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Socio Economic Implications For Individual Responses to Air Pollution policies in EU +27

The use of Discrete Choice Exercises for estimating socio-economic acceptability of air quality policies: investigation on the possibility of interaction between DCA and GAINS model.

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Introduction

It is universally recognized that poor air quality has adverse impacts on human health and ecosystems. However, the total impact of current levels and trends of air pollution alongside current policies and those which may be implemented in the near future is not well known to the public. Many questions remain about how to better integrate policy options and expert knowledge and how well broad policy initiatives are accepted by people and their communities. Public acceptability affects the policy effectiveness. Acceptability has been suggested as one of the main dimensions of attitudes and has been used as an indicator for assessing them in a number of studies. As reported in section 1, literature on policy acceptability has shown that the perceived policy effectiveness is an important element for their acceptability. In turn, the design of a policy influences people's way of thinking about its effectiveness and legitimacy. Furthermore, individual characteristics are also important when evaluating policy acceptability. Especially what others think and do, reflecting a social norm, influences how effective people believe policies are, and thus their acceptability.

In recent years, individuals' preferences have been increasingly used to analyse environmental aspects and, in particular, air quality issues. This information was used to support policy makers in the decision-making process, especially for non-market goods. With Discrete Choice Experiments (DCEs)[1] is possible to describe, explain and predict choices between two or more "choice alternatives". They investigate people's preferences and their potential behaviour, identifying variables affect individuals' choices.

Environmental valuation with DCEs is playing an increasingly significant role in environmental decision making processes. Hoyos (2010) reviewed the state of the art of environmental valuation with DCEs. Birol, Karousakis, and Koundouri (2006) assisted policy makers in formulating efficient and sustainable wetland management policies in accordance with the European Union Water Framework Directive (2000/60/EC), by providing results of a valuation study on the Cheimaditida wetland (Greece). DCEs were used to estimate the values

[1] As supported by Jordan J. Louviere, Flynn, and Carson (2010), 'Discrete Choice Experiments' and 'Conjoint Analysis' terms are not to be considered synonymous. Traditional Conjoint Analysis is based on Conjoint Measurement, while Discrete Choice Experiments are based on Random Utility Theory and related Random Utility Models. This theory is well-tested and strongly associated with error components whose properties play key roles in parameter estimates and welfare measures derived from Discrete Choice Experiment data collection. For the SEFIRA WP4 pilot survey, we use and refer to what Jordan J. Louviere et al. (2010) intend for Discrete Choice Experiment survey.

of changes in several ecological, social and economic functions that Cheimaditida wetland provides to the Greek public. The results reveal that there is considerable preference heterogeneity across the public and, on average, they derive positive and significant values from sustainable management of this wetland. The estimated economic benefits of sustainable wetland management are weighed against the costs of alternative wetland management scenarios. Results of this cost benefit analysis can aid in the design of socially optimal policies for sustainable management of the Cheimaditida wetland, with possible implications for other similar wetlands in Greece and the rest of Europe.

This report aims at providing the informed reader of the different existing options and “the way we are going” to use DCEs within the SEFIRA project. For these reasons the report is structured as follows: § 1 deals with the public acceptability of air quality policies. In particular, after reviewing the definition of public acceptability (§ 1.1), the main drivers and characteristics that affect public acceptance of a policy are briefly described (§ 1.2). Starting from considerations on the *state of the art* of policy measures used to improve air quality in Europe, § 2 reports the distinction of the main technical and non-technical measures using a behavioural approach (§ 2.1). Moreover, the how and where non-technical measures are currently considered in Integrated Assessment Models (IAMs) is also addressed (§ 17). § 3, 4 and 5 describe two quantitative methodologies that analyse air quality measures differentiated by a low or high degree of behavioural components. We refer at the IAMs and in particular at the *Greenhouse gas - Air pollution Interactions and Synergies* (GAINS) model and at the DCEs. In particular, § 5 explores methodological guidelines of DCMs related also to the SEFIRA WP4 pilot survey. Conclusions of the report synthetizes the main steps focused. Further details such as an overview of the most common DCMs with the methodological details and equations, a glossary, a list of acronyms etc. are reported in the Annexes.

1. Public acceptability of air quality policies

This section aims at defining and characterizing the idea of "public acceptability" of air quality policies. In § 1.1, acceptability is explored and the main drivers and characteristics which affect the public policy acceptance are briefly described in § 1.2 with related subsections.

1.1. Defining acceptability

There is broad consensus that public acceptance is crucial for a successful introduction and operation of policies, and must be taken into account by authorities who intend to introduce such measures. However, a common finding to the different fields in which public acceptability has been analysed is the lack of conceptual clarity, regarding definitions, methodology and general research frameworks. In fact, the notion of acceptability may express, according to the specific analysis, in various concepts such as support, agreement, feasibility, propensity to vote for, favourable reaction, etc. Only a few authors have attempted to formulate a clear and systematic definition (Jens Schade & Schlag, 2003; Viegas, Macario, Goller, & Raux, 2000). Vlassenroot, Brookhuis, Marchau, and Witlox (2010, p. 165) define acceptability as the way how potential users will react and act if a certain measure (or device) is implemented. The 'acceptance' term by J. Schade and Schlag (2000, p. 25) "*defines respondents attitudes including their behavioural reactions after the introduction of a measure*", and the 'acceptability' term "*describes the prospective judgment of measures to be introduced in the future*".

Moving from an individual to a collective point of view of the acceptability, since 1991 the 'public (or social) acceptability' concept was used, continuing to present an inadequate understanding of the meaning of acceptability (Stankey & Clark, 1991). From an economic point of view, acceptability is explained by Mayeres and Proost (2003) as "*any major pricing or taxation reform* [that] *will be accepted only if it shows a welfare gain or no welfare loss for a sufficiently large majority of the voters*"[2].

An important paradox is the difference between public acceptability of a measure and expert's appraisal of their effectiveness. For instance, in contrast to some transport planners and

[2] In addition, an interesting study on the understanding the role of the emotions when making choice is carried out by Araña and León (2009) with reference to individual preferences for alternative policy measures in the urban areas.

economists, who favour road pricing as an instrument to solve today's transport problems, the public is still quite sceptical about road pricing measures (Vrtic, Schuessler, Erath, & Axhausen, 2007).

Often acceptability is mainly related to specific measures or regulatory schemes. This is due to the fact that policy makers would be most interested in schemes and measures that will have the greatest acceptability or popularity amongst the general public. One field of research where acceptability of policy instruments has been more extensively explored is in the transport sector, where researchers mostly examined the acceptability of road pricing schemes (e.g. Di Ciommo, Monzón, & Fernandez-Heredia, 2013; Eriksson, Garvill, & Nordlund, 2006, 2008; J. Schade & Baum, 2007; J. Schade & Schlag, 2000; Jens Schade & Schlag, 2003). There are relevant studies also in the energy sector (e.g. Soerensen, Hansen, Hansen, & Hammarlund, 2003; Strazzera, Mura, & Contu, 2012). The main objectives of these studies were to identify which factors, drivers and individual characteristics affect the (public) acceptability of a specific policy. Jens Schade and Schlag (2003) stated that the acceptability of a system has been seen primarily as determined by attitudes and influenced by additional system-specific characteristics. In many cases, the social psychological attitude theory of planned behaviour (Ajzen, 1991) which describes the relation between attitudes and behaviour has been used as a theoretical basis. Although a general acceptance theory does not exist, it is undisputed, that attitudes are of great relevance for agreeing or disagreeing with something. Jens Schade and Schlag (2003) reviewed the main factors which contribute to the overall low public acceptability of pricing measures in transport and hence hinder its enforcement. J. Schade and Schlag (2000) and Schlag and Teubel (1997), using an heuristic model, defined the main drivers determining acceptability. Across all the measure-related and person-related factors which affect the public acceptability, the most important are synthetically explained in § 1.2. In the literature on DCMs, the acceptance is synonymous of preference so the most accepted solution is referred to the most preferred policy alternative included in the choice experiments. The public acceptability has been widely analysed via DCEs (Bristow, Wardman, Zanni, & Chintakayala, 2010; Chiu & Tzeng, 1999; Marcucci, Stathopoulos, Gatta, & Valeri, 2012; Poortinga, Spence, Demski, & Pidgeon, 2012; Jens Schade & Schlag, 2003; Viegas et al., 2000; Zhang, Yu, & Zou, 2011).

1.2. Drivers affecting public acceptability

In the literature there is a wide list of drivers affecting policy acceptability from an individual perspective. However, there are a number of factors that are generally known as having a major role in the acceptability (or non-acceptability) of a policy. Traditionally, policy decisions by policy makers or authorities are taken paying limited attention to the impact they have on various social groups. In the last three decades the environmental policy field has seen growing conflicts and policy makers have been often under public scrutiny if not openly criticized or contested (Pellizzoni and Osti 2003, Pellizzoni and Ylönen 2012). Now, policy making on the matter is much more complex due for instance to: i) the coexistence of multiple perspectives, ii) the need to develop and present multiple arguments taking into account those different points of view, iii) the need to educate public opinion, iv) establish compromises with multiple social groups and stakeholders in order to achieve main public goal, and v) avoiding serious damage to interests of any of those groups (Viegas & Macario, 2002). The aim of this section is to provide a synthesis of the most important and used (in empirical applications) policy acceptability drivers.

1.2.1. Problem perception

The perception of poor air quality as a problem is a necessary precondition for regarding problem solving measures as important (Bickersta & Walker, 2001; European Commission Eurobarometer, 2013; Steg & Vlek, 1997). It is assumed that high problem awareness will lead to increased willingness to accept solutions for the perceived problems. In the case of air quality problems related to traffic congestion, a multitude of studies has shown that perception of mobility-related problems is particularly high in densely populated regions (e.g. Jones, 2001). Yet, empirical findings on the influence of problem perception on acceptability are inconsistent. Although several studies found a relationship between problem perception and acceptability of various pricing measures (e.g. de Groot & Schuitema, 2012; Rienstra, Rietveld, & Verhoef, 1999), other results show that the groups perceiving traffic congestion as one of the biggest problems reject road pricing more strongly than groups perceiving mainly environmental problems (e.g. Harsman, Pädam, & Wijkmark, 2000). Authors suggest that this pattern might reflect a doubt among people about the efficiency of road pricing. Nevertheless, respondents' attitudes between the cities considered in the survey differ significantly.

1.2.2. Social norms

Social acceptability of a social object has to do with cultural norms and social representation of acceptable or dangerous behaviour within a group. Anthropology studies on acceptability show why different environmental cultures affect so much acceptability and effectiveness of norms (Douglas, 1985). Perceived social norms and perceived social pressure refer to perceived opinions of significant others (family, friends) and the importance of the others' opinions for the individual (Ajzen, 1991). More precisely, social norms refer to the respondents' assumption about whether his/her significant other would think that he/she should accept the strategy. These normative beliefs are concerned with the likelihood that important referent individuals or groups approve a given behaviour. Moreover, the more favourable the perceived social norm is with respect to a presented pricing strategy, the stronger should be an individual's acceptability of the strategy (Jacobson, Christensen, Prince, Cordova, & Eldridge, 2000). Environmental friendly behaviour can described as a "social dilemma": a conflict between individual and collective interests. According to Dawes (1980) a social dilemma has two basic characteristics: (1) each individual is better off when he/she acts in his/her own interest and (2) all individuals are better off when they cooperate.

1.2.3. Knowledge about options

Environmental awareness research has established that knowledge about the right action is a necessary but not a sufficient prerequisite for conservation-conscious behaviour (e.g. Bell, Fisher, Baum, & Greene, 1990). So, any new measure of the different sectors depends on good user information. Among other issues, the background of the problem, the aims of the measure, and its concrete realisation have to be clearly explained and understood by the public (Schlag, 1998). Although this causal connection has not been settled yet, previous studies show that well-known demand management measures meet with a higher rate of acceptability than unknown measures (MIRO, 1995). It is usually hypothesised that a higher effectiveness evaluation depends on how well known the measure is, and that this effectiveness judgment has an influence on acceptability. But findings are inconsistent. Steg and Vlek (1997) found information having a negative effect, with a lot of information leading to a higher assessment of effectiveness but, compared with a less informed control group, to a significantly lower acceptability of restrictive measures. In psychological terms, a distinction must be made between whether a person feels to be well or badly informed or whether he/she actually is well or badly informed. Hence, a differentiation is made between the so-called objective knowledge and the subjective assessment of the own knowledge (J. Schade & Schlag, 2000).

The level of risk acceptability often depends on the advantages and disadvantages of a specific activity as evaluated from different perspectives (Marchi, Pellizzoni, & Ungaro, 2001). According to Watzlawick, Beavin, and Jackson (1967), the communication of environmental issues involves the exchange of information between four specific categories: experts, citizens, public and private institutions. The degree of information actually transferred is proportional to the level of trust credited by users to the information sources. For this reason risk perception is strongly tied with risk communication. Communication with general public and expertise public role becomes a strategic instrument of environmental governance (Lidskog & Sundqvist, 2011).

1.2.4. Perceived effectiveness and efficiency

If someone recognizes air quality problems and their consequences (problem perception), and identifies at least in part the aims of changing these problems (e.g. reducing traffic congestion, declining environmental damage, etc.), he/she has to answer to the crucial question, of whether the proposed measures are appropriately effective and efficient. Effectiveness refers to the degree to which the aims of the measure can be reached. Efficiency, on the other hand, is related to the cost-benefit relation of a concrete measure (e.g. road pricing) compared to other possible measures (e.g. access restriction) (Beuthe *et al.,* 2004). Because the complex efficiency criterion is difficult to investigate and to communicate, up to now the perceived effectiveness has been mostly examined (e.g. MIRO, 1995). Relating to road pricing measures, results highlight a lower degree of perceived effectiveness such as the congestion reduction (Luk & Chung, 1997). Here, lower scores in perceived effectiveness usually correlate with lower acceptability of the particular measure and vice versa. However, studies aimed at defining a causal relationship between them are missing (Jens Schade & Schlag, 2003). Lastly, Rienstra et al. (1999, p.190) highlight that "*strategic responses on perceived effectiveness may occur when respondents try to justify their rejection of painful policy by claiming that they perceive them as ineffective*".

1.2.5. *Equity and fairness*

A key factor affecting the behaviour of individuals is the (social) fairness of the measure. However, there remains some uncertainty over this concept, expressing itself in the prevailing confusion over related definitions (equity, justice, fairness), which require clarification (Jens Schade & Schlag, 2003). First of all, we need to distinguish among a normative, individual and descriptive perspective. The normative perspective (usually the economic approach) asks from a societal viewpoint which distribution of e.g. outcomes should be considered fair.

Giuliano (1994) reports that equity like an economic concept primarily refers to the real distribution of costs and benefits within society. Here, equity primarily refers to the distribution of costs and benefits. From a psychological point of view perceived justice, among others, is of major concern as a basic requirement for acceptability. Justice, as people perceive it, may differ from objective distribution of costs and benefits but surely depends on it as one major parameter influencing personal perceptions. And, as with most personally mediated perceptions, it differs not only between different situations and people in the same situation and even between people with comparable objective costs and benefits. Therefore, besides rational cost-benefit calculations additional variables, which also influence the personal cost-benefit ratio, must be taken into account. Moreover, Viegas (2001) tentatively operationalizes equity as personal outcome expectations. The more people perceive advantages following the introduction of a given measure the more they will be willing to accept it.

1.2.6. *Socio-economic and system characteristics*

Apart from intangible individual characteristics (e.g. perceptions, evaluations, etc.), the policy acceptability (also for those related to the air quality field) depends on the individual socio-economic status and additional characteristics related to the implemented policy. Socio-economic relationships of agency and power, as well as spatial and social distribution of risk have an impact on acceptability and related social behaviour (Buzzelli, Jerrett, Burnett, & Finkelstein, 2003).

Particular attention is paid to the income role. Following economic theory, it is to be expected that low income groups should be more opposed to pay for the introduction of quality measures because of their higher marginal utility of money, and their decreased willingness to pay to reduce externalities. In particular, Rienstra et al. (1999) find that the lowest income group perceived pricing measures as most effective, and also, that the income level had no significant impact on the support for pricing measures. Further, analysing the relation among other socio-economic variables and the "problem awareness", "perceived effectiveness" and "support of policies", they point out that the personal features of respondents have the lowest impact on the policy acceptability. Regarding the system characteristics implemented by the measure, Harrington, Krupnick, and Alberini (2001) find that complex systems (such as time-based and delay-based charging) may not be accepted and that systems with a known charge are preferable to systems with an unknown charge.

In synthesis in order to capture how and if different air quality policies can reach their objectives it is important to understand the correlation between the different dimensions of acceptability and every single policy design. In fact, acceptability is a necessary precondition for regarding problem solving measures as important. However, acceptability drivers are many and differ from one another, and some choices are needed. Some of the possible policy acceptability drivers that can be studied are: individual policy cost effectiveness; how people are willing to accept changes in their individual life style; how people evaluate economic fairness of the policy; how people evaluate intergenerational equity. Some of these drivers will be used in the SEFIRA WP4 pilot project.

2. Classifying technical and non-technical measures using a behavioural approach

The debate on air quality measures is important because the results of every single policy depend on the interaction among the different acceptability drivers and their synergic effect. Part of the actual debate is on the technical or non-technical nature of policy instruments. The distinction between technical and non-technical measures is provided in § 2.1, highlighting the role of the behavioural dimensions. This standard classification is relevant but if the research focus is on policy acceptability, more attention should be due to understand how policy efficacy is related to behavioural components that determine policy acceptability. It follows that understanding the relationship between behavioural components and acceptability drivers might support policy makers in the design of successful air quality policies.

Currently, IAMs are widely used to support the EC and national policy makers to identify portfolios of measures that improve air quality and reduce greenhouse gas emissions at least cost. § 2.2 presents if and how technical and non-technical measures are included in different IAMs currently used.

2.1. Introducing the distinction

In the literature on the different types of air quality measures, several definitions are used and there is a striking absence of theoretical motivation of the different definitions and classifications of these types of measures. Catarina Sternhufvud, Belhaj, and Åström (2006) define non-technical and technical measures. There is to date no consensus upon the definition of non-technical measures and the distinction with technical measures and there will always be borderline cases irrespective of the chosen definition (Sternhufvud *et al.* 2006).

Technical measures are seen mainly as *end-of-pipe* measures, i.e. measures that intervene at the end of production process, while non-technical measures are seen as structural and involving behavioural changes (Schucht, 2005) in consumption patterns. This definition is likely to be too simplistic. Supported by economic incentives, the non-technical measures are not completely independent from technology changes even if they are implemented towards changing the behaviour of technology users (C. Sternhufvud, Belhaj, & Åstrom, 2006).

Therefore, the definition itself and the assumptions used for non-technical measures assessment could result in an evaluation process lacking in robustness. Some authors define them as measures where the behaviour of people changes such as to reduce a given environmental impact (e.g. Barrett, 2005). Moreover, Catarina Sternhufvud et al. (2006) compare the changes of input and output when incorporating a measure, instead of only focusing on changes in emission factors and activity data. Input and output reflect a firm's production where and input is the resources required for the production of the commodity and output is the produced commodity. With an example of a car production facility, in a technical measure (e.g. particle filters aiming at reducing emissions from the car production process) the input consists in labour, energy and raw material while output is the car. The particle filter does not affect the mix or quantity of production input in order to produce the output to any larger extent. However, a non-technical measure (e.g. change in work routines that enables energy savings) will affect the quantity or the mix of input to production. It is this change that causes the emission reduction.

In the literature several attempts have been made in order to group and classify differently technical and non-technical measures. For instance, D'Elia, Bencardino, Ciancarella, Contaldi, and Vialetto (2009) list possible air quality measures divided by type of related sector (energy, domestic and road transport), distinguishing between technical and non-technical measures. The classification proposed in Table 1 focuses not so much on the standard technical and non-technical distinction but rather on the level of membership that each policy has with its "behavioural component" (see the last two columns on the right-hand side of Table 1). Here intended as the level of individual effort needed in order to have a successful policy (i.e. the individual willingness to improve a certain behaviour). Remembering Barret definition´s (2005) the behavioural component of a specific policy is how the behaviour of people has to change in order to favour the achievement of a given environmental target.

Table 1 - List of possible measures and their degree of behavioural content

Type of sector	Specific measure	Low degree of behavioural content	High degree of behavioural content
Energy	Photovoltaic		X
	Wind	X	
	Hydroelectric	X	
	Geothermic Well	X	
	Urban Waste incineration with heat recovery	X	
	District heating Plant	X	
	Biogas recovery in agricultural and in farming sectors	X	
Domestic	High efficiency domestic boilers		X
	Energy efficiency in building		X
	Residential heat meter		X
	Heat pumps		X
	Regulation of residential biomass, oil and coal use		X
	Efficiency improvements in fireplaces and stoves		X
	Solar heating systems		X
	Incentives for shift to natural gas in domestic boilers		X
Road Transport	Low emission zones		X
	Road traffic restriction		X
	Pollution charge		X
	Car sharing		X
	Motorway speed limits		X
	Bike sharing		X
	Incentives for new cars	X	
	Incentives for new diesel heavy duty	X	
	Particulate filter	X	
	Incentive for alternative fuel cars	X	
	New methane service stations	X	
	Incentives for biofuel public transport	X	
	Opening new rail lines	X	
	Opening new underground lines	X	
	Cycle paths		X
	Modal shift from cars/lorries to ships		X
	Bus investment (new buses, service extension)	X	
	Rationalizing load transport in urban area	X	

Source: *our elaboration on D'Elia et al. (2009)*

2.2. Modelling technical and non-technical measures

Integrated assessment models currently used in air quality policy development are based on an interdisciplinary approach, involving atmospheric science, technology and economics, to support *ex ante* decision-making by combining quantitative models representing different systems and scales into a framework for integrated assessment (Janssen *et al.,* 2009). Typically, these models make use of mainly technical measures and are organized in a modular structure, in which modules encapsulating knowledge from the different scientific disciplines are coupled in accordance with the question raised by the decision maker. Such modular approaches need to respect several stages of the model development process, modularisation and integration on a conceptual, numerical, and technical level (Hinkel, 2009). Integrated assessment models have been developed to identify portfolios of measures that improve air quality and reduce greenhouse gas emissions at least cost. Such models bring together scientific knowledge and quality-controlled data on future socio-economic driving forces of emissions, on the technical and economic features of the available emission control options, on the chemical transformation and dispersion of pollutants in the atmosphere, and the resulting impacts on human health and the environment.

Over time, different models have been developed and applied such as the ASAM (*Abatement Strategies Assessment Model*) (Oxley & ApSimon, 2007; Warren & ApSimon, 1999), the MERLIN (*Multi-pollutant, Multi-effect Assessment of European Air Pollution Strategies: the Integrated Approach*) models (Reis, Nitter, & Friedrich, 2005) etc. Drouet and Reis (2012) provide a synthetic overview of these models by type of policy impacts analysed (Figure 1). For the past 20 years, the RAINS (*Regional Air Pollution Information and Simulation*) model (Schöpp, Amann, Cofala, Heyes, & Klimont, 1999), and its extension to incorporate greenhouse gases, known as GAINS model (Amann *et al.,* 2011), has been used as a commonly shared tool in the key negotiation processes in Europe that led to international agreements on harmonized emission control strategies in the EU and the UNECE.

Figure 1 – Overview of the integrated assessment models

Name	Emission model	Air quality model	Reference
Global			
Global Health Impacts	MESSAGE	TM5	Rao et al. (2012)
Regional			
MERG	MARKAL	SCA	James et al. (1985)
RAINS	PRIMES	EMEP	Alcamo and Hordijk (1990)
ASAM	EMEP/CASM	RAINS	ApSimon et al. (1994)
SAMI	EMS-95/Mobile5b	URM-1ATM,...	Odman et al. (2002)
EC4MACS	GAINS	TM5,EMEP,...	EC4MACS (2007)
SIMCA	CEP/SMOKE	CMAQ	Borge et al. (2008)
GAMES	POEM-PM	TCAM	Carnevale et al. (2008)
MINNI	RAINS-Italy	FARM	D'Elia et al. (2009)
Mexico2050	E3MG	p-TOMCAT	Barker et al. (2010)
GAINS	GAINS	EMEP	Amann et al. (2011)
RIAT	GAINS	NNET(TCAM)	Carnevale et al. (2012)
Urban			
GENEVA	MARKAL-lite	TAPOM-lite	Carlson et al. (2004)
BRUTAL	iMOVE	ADMS-Urban,...	Oxley et al. (2009)
LEAQ	ETEM	TAPOM-lite	Zachary et al. (2011)

Source: Drouet and Reis (2012, slide n.6)

Air pollution strategies developed within the framework of Convention on Long-range Trans-boundary Air Pollution (CLRTAP) and Corporate Average Fuel Economy (CAFE) regulations are mainly based on technical measures to abate air pollution for which the potential emission reduction and costs often can be estimated and used in IAM. More recently, non-technical measures have been put forward as an important complement to technical measures in future air pollution strategies.

Considering the aim of this section, the models of greatest concern to analyses if and how technical and non-technical measures are considered are RAINS, MERLIN and GAINS. The RAINS model (Amann *et al.*, 2004) analysis technical measures such as end-of-pipe technologies, and a few non-technical measure limited to the agricultural and transport sectors. Technical measures are used in the emission optimization process via their effect on emission factors from production. Behavioural and structural changes are used through alternative exogenous scenarios of the driving forces through policy assessment tools (for instance, TREMOVE), but not internalised into the RAINS optimization process.

The MERLIN model includes macro-economic effects and cost-benefit assessment in the optimization not included in the RAINS model. The economic evaluation of benefits of reducing the environmental impact of air pollutants is included in the search for optimal emission controls. This model uses a different approach to emission abatement, which enables inclusion of non-technical measures in the emission abatement calculations (UCL, 2004).

In the GAINS model, the classification between behavioural changes, structural and technical measures is the same as in RAINS (Klaassen et al., 2004). But, unlike RAINS, efficiency improvements and fuel substitution are included in the model as possible measures, since much of the Greenhouse Gas (GHG) abatement options are to be found in these structural measures. A wide range of *technical measures* has been developed to capture emissions at their sources before they enter the atmosphere. Emission reductions achieved through these options neither modify the driving forces of emissions nor change the structural composition of energy systems or agricultural activities. GAINS considers several hundred options for greenhouse gases and about 1,500 pollutant-specific *end-of-pipe* measures for reducing SO2, NOx, VOC, NH3 and PM emissions and assesses their application potentials and costs. It considers also *structural measures* that supply the same level of (energy) services to the consumer but with less polluting activities. This group of measures includes fuel substitution (e.g. switch from coal to natural gas) and energy conservation/energy efficiency improvements. The GAINS model introduces such structural changes as explicit control options. Lastly, *behavioural changes* (e.g. changes in lifestyles, legal traffic restrictions, pollution taxes, emission trading systems, etc.) are not internalized in the GAINS optimization process, but reflects such changes through alternative exogenous scenarios of the driving forces.

Many mitigation measures involve significant changes in the current infrastructures of energy systems, industry and the housing sector, as well as changes in the personal behaviour of people, with important positive or negative side-effects on a wide range of other, non-climate related aspects (Amann *et al.,* 2008, p. 5).

The potential and cost to implement non-technical measures are generally difficult to estimate and the effects of these measures are quite intricate since they often involve complex human psychology (Brand *et al.,* 2000). Due to these difficulties, up to date they have only to a limited extent been included in IAMs, mainly as exogenous elements in scenario analysis.

However, the attention of experts and policy makers, the increased awareness and attention to pollution effects on human health by the general public and the change of attitude towards more environmentally friendly behaviour (e.g. *peer-to-peer car sharing*[3]) is promoting this topic as an urgent issue to be addressed. On this point, the IAMs represent a powerful tool and many efforts are going in that direction (UCL, 2004). The scientific debate is open, suggesting the need of integrating non-technical measures in IAMs and in future air pollution strategies.

This section addresses the technical and non-technical issue related to air quality measures. In particular, we propose a new classification of these measures based on the behavioural content inherent in each measure, highlighting the importance of behavioural dimension of measures. Various IAMs are currently used to support national and European policy makers to identify portfolios of measures that improve air quality and reduce GHG emissions at least cost. Considering the increased attention and use toward non-technical measures (especially behavioural), SEFIRA project explores the possibility of using DCE information in different models that mainly deals with technical measures. The DCE pilot survey is the first step to show how it is possible to obtain information on individual willingness to accept a particular environmental policy.

[3] The *peer-to-peer car sharing* is developed in the last few years around the world. Generally, car sharing is a service provided by the local public administration or a by a private firm. However, always more frequently are individuals, car owners, who voluntarily, make their vehicles available for others to rent for short periods of time. This practice greatly reduces carbon emissions, reduces congestions, incidents, and improves city environments.

3. The GAINS model and current air quality modelling

The GAINS model (http://gains.iiasa.ac.at) explores cost-effective multi-pollutant emission control strategies that meet environmental objectives on air quality impacts (on human health and ecosystems) and greenhouse gases.

In this section GAINS, used as the main reference model to rank air quality measures based on cost-effective optimization, is briefly described mainly explaining where and how non-technical measure are considered and modelled in all GAINS modules.

3.1. Model characteristics

The GAINS model is an integrated assessment model that brings together information on the sources and impacts of air pollutant and greenhouse gas emissions and their interactions. GAINS is an extension of the earlier RAINS (Regional Air Pollution Information and Simulation) model, which addressed air pollution aspects only. GAINS combines data on economic development, the structure, control potential and costs of emission sources, the formation and dispersion of pollutants in the atmosphere and an assessment of environmental impacts of pollution. GAINS addresses air pollution impacts on human health from fine particulate matter and ground-level ozone, vegetation damage caused by ground-level ozone, the acidification of terrestrial and aquatic ecosystems and excess nitrogen deposition) of soils, in addition to the mitigation of greenhouse gas emissions. GAINS describes the inter-relations between these multiple effects and the range of pollutants (SO2, NOx, PM, NMVOC, NH3, CO2, CH4, N2O, F-gases) that contribute to these effects at the European scale.

GAINS assesses, for each of the 43 countries in Europe, the costs and impacts of more than 1000 measures to control the emissions to the atmosphere. It computes the atmospheric dispersion of pollutants and analyses the costs and environmental impacts of pollution control strategies.

3.2. Typical features and results

In its 'scenario mode', the number of "what-if" scenarios that can be explored with the GAINS model is limited, which makes it impossible to fully explore the consequences of even the most important permutations of emission control measures in all economic sectors of several dozens of countries. Thus, in practice such scenarios address a limited number of technology-related emission control rationales, but cannot deliver a systematic analysis of environmentally driven emission control strategies.

The GAINS 'optimisation mode' provides an important element of a "science based" rationale as a basis for emission reduction accords. By calculating country- and sector-specific reduction requirements for any exogenously specified environmental target, the GAINS optimisation can provide results that are of immediate relevance to negotiators because they meet the spatial and temporal scales that are relevant for decision makers. The optimisation is also attractive because, while striving for a common target (e.g., equal environmental improvement for all Parties), it considers environmental and economic differences between Parties that lead to objectively justifiable differences in abatement efforts.

Resulting inequalities in abatement burdens are based on scientifically determined differences in environmental sensitivities, atmospheric dispersion characteristics or emission source structures. It is also important that the optimisation problem as set up in the GAINS model does not provide an absolute and unique answer to the pollution control problem. Actual results of an optimisation run depend on the environmental objectives (e.g., the acceptable environmental risk) as established by the negotiators, the goal function (minimization of total emission control costs), and the problem framing (e.g., the exclusion of changes in the energy systems, which cannot be directly influenced by environmental policies in Europe). All these settings are subject to negotiations, and the optimisation results are critically influenced by the policy choices on these issues. Thus, the GAINS model does not internalise policy choices, but deliberately leaves room for decisions of negotiators.

In its optimization mode, GAINS identifies the least-cost balance of emission control measures across pollutants, economic sectors and countries that meet user-specified air quality and climate targets. For policy analyses, GAINS provides for each country, economic sector and pollutant allocation of emission reduction measures that would meet targets on improved human health and ecosystems protection.

3.3. Data sources

GAINS relies to the maximum possible extent on internationally published statistics (e.g., on the EUROSTAT energy balances and agricultural activities), as well as on national emission inventories that have been submitted by countries to the European Environment Agency and EMEP.

Projections of future economic activities are taken as exogenous input from studies that have applied sectorial models. These include the PRIMES energy model, the CAPRI agricultural model, and the TREMOVE transport model. Calculations of the dispersion of pollutants in the atmosphere are based on results of the EMEP model, and ecosystems impacts are estimated using the CCE impact assessment tools. Linkages between all these models and GAINS have been developed under the EC4MACS project (www.ec4macs.eu).

3.4. Documentation

A detailed description of the GAINS model can be found at http://www.iiasa.ac.at/rains/review.html, as well as in Amann *et al.* (2011) and their references, for a special focus on the methodological issues see Amann (2012), for examples of the GAINS model applications see Slento et al. (2009) and Wagner (2010).

3.5. The treatment of non-technical emission control options in the GAINS model

While the GAINS model includes a large variety of technical means for reducing emissions, it does not include the simulation of behavioural changes of consumers that influence demand for energy, transport and agriculture; also responses of the energy and agricultural markets towards higher emission control costs are outside its systems boundaries, and it does not address effects that higher pollution control costs might have on the transfer of production to third countries.

The main rationale for excluding such effects from the immediate GAINS analysis is the interest to maintain transparency and manageability of the GAINS model. Instead of incorporating all complex relations that are relevant for these aspects into one super-model, a network of specialized models that address these aspects in more detail has been created through the EC4MACS (European Consortium for the Modelling of Air pollution and Climate Strategies) project (www.ec4macs.eu).

Table 2 – Main strength and weak points related to the GAINS model

Strengths	Weakness
A comprehensive, interdisciplinary integrated perspective of the costs, health and environmental effects and monetary benefits of a large range of emission control measures in Europe	Emission control options include only technical measures.
Based on latest, peer reviewed, science	Consumer preferences and behavioural changes are not included in the GAINS portfolio of measures
Incorporating quality-controlled input data for all European countries, validated in an extensive series of bilateral consultations with national experts	GAINS does not assess macro-economic feedbacks of emission control measures (although they are addressed in the EC4MACs model suite)
A systems approach to quantify interactions and co-benefits of air pollution policies with other policy objectives	
Interactive access to input data and results on the Internet	
Since 1985 used in all major international negotiations on air pollution control accords in Europe (under the Convention on Long-range Transboundary Air Pollution and the European Union)	

4. Discrete Choice Models to study air quality policy acceptability drivers

This section is aimed at synthetically explaining what DCMs are and how they work, using a non-technical language. Appropriate references are proposed through the report to further deepen the different relevant methodological issues. A glossary is provided in Annex 1 in order to explain the meaning of specific terms used in the DCM literature.

4.1. A definition

DCEs are based on a long-standing, well-tested theory of choice behaviour that can take inter-linked behaviours into account (§ 4.4). Many DCE applications resemble the traditional conjoint analysis simply because they are based on survey questions about combinations of attribute-levels. The key difference between a conjoint analysis and a DCE lies in the critical role of error components. In fact, for the conjoint analysis the error components' treatment is an afterthought, while for discrete choice experiments it is the starting point. Furthermore, Jordan J. Louviere et al. (2010) highlight that in the academic literature of different fields there is a misuse of the two terminologies. During the 1980s it became common to suggest that discrete choice experiments were "just another type of conjoint analysis" by calling them "choice-based conjoint analyses". However, the Random Utility Theory basis of discrete choice experiments is very different from conjoint measurements[4].

DCMs are statistical technique aimed at modelling the way people choose between a set of alternatives. They help researchers in analysing and predicting how people's choices are influenced by their personal characteristics and by the available alternatives. The alternatives could be referred to different products, services, policies etc. Each alternative is described by a set of specific features, called attributes, which in turn are described by attributes-levels. Making individuals' trade-offs between the various attributes-levels, the individual (decision maker) chooses the preferred alternative that yields greatest satisfaction or 'utility'. Using

[4] For further details see Jordan J. Louviere et al. (2010).

Stated Preference[5] data DCMs allow to *ex ante* evaluate products, services or policies still not present in the market or not yet implemented (M. Ben-Akiva, Bierlaire, Bolduc, & Walker, 2008; M. Ben-Akiva & Lerman, 1985; Jordan J. Louviere, Swait, & Hensher, 2000; Luce, 1959; McFadden, 1981; K. E. Train, 2002).

The Utility is postulated to be a function of both observable (or deterministic) and unobservable (or random) part of the utility as follows:

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

where V_{ni} is the deterministic part of the utility derived from the alternative i by the decision maker n, and ε_{ni} is the associated random utility (error term unknown to the analysts).

4.2. Stated and Revealed Preferences

There are two types of survey approaches: those soliciting evidence on past consumer decisions and behaviour (*Revealed Preference*, RP) and those using consumer responses to hypothetical questions (*Stated Preference*, SP).

SP data are stated choices obtained through an *ad hoc* interview in which respondents are directly asked about their hypothetical choice situations. Moreover, it is also possible to collect real information on actual choices made by individuals, called RP data, even if not always RP data can be collected for instance with reference to not real choice alternative (for instance, a new policy option or a new product). Both types of data have *pros* and *cons* highlighted for instance by M. Ben-Akiva (2008) and Sanko (2001).

The main advantage of the SP approach is that hypothetical and non-existent alternatives (in our case, measures) can be included in the experiment. Therefore, new methods and innovations can be included in the alternatives and the model results can be used for predictions and calculation of future market shares or acceptability. Furthermore, the personal and environmental limitations that might exist in real-life situations from which RP data are collected, can be broadened. A sophisticate approach is to combine both RP and SP data in order to avoiding both the main respective disadvantages.

[5] This type of data is briefly described in the following section.

4.3. A framework for the theory of choice

DCMs are interested in the behaviour of a large number of individuals or organizations expressed in terms of aggregate quantities (e.g. market demand for a service, acceptability for a measure). However, the aggregate behaviour is explicitly the result of individual choices (M. Ben-Akiva & Lerman, 1985). Moreover, the modelling of the individual behaviour is the core of all predictive models of aggregate behaviour.

A choice is characterized by a sequential decision-making process that includes several steps. M. Ben-Akiva and Lerman (1985) suggested that this complex process defines preliminarily the following important elements:

1. *The decision maker*: defining the decision-making entity and its characteristics. The unit of decision making can be an individual or a group of people (e.g. household, firm, government agency).
2. *The alternatives*: determining the options available to the decision maker. The individual has a universal set of alternatives. In the DCEs, the single decision maker considers a subset of alternatives taken from the universal one, previously chosen by the researcher[6]. This process is usually referred to as *choice set generation*. These alternatives are both feasible to him\her and known during the decision process. The feasibility of an alternative is defined by a variety of constraints such as physical availability, monetary resources, time availability, informational constraints etc. Generally, these alternatives are *specific* or *labelled*. However, there is another approach that does not name the alternatives (i.e. the researcher defines *generic* or *unlabelled* alternatives)[7].
3. *The attributes of alternatives*: measuring the benefits and costs of an alternative to the decision maker. The attractiveness of an alternative is evaluated in terms of a vector of attribute values. These values are measured on a scale of attractiveness that can be ordinal (e.g. car is the fastest transport mode) or cardinal (e.g. travel cost equal to 2€). The alternatives could be homogeneous within the choice experiment (e.g. cheese, milk), in this case the "generic" alternative is just a vector of quantities of such goods, services or policy tested, referring only to the quantities. When the alternatives are heterogeneous the

[6] For further details on the two-stage process generally used to select the few alternatives to include in a choice experiment see D.A. Hensher, Rose, and Greene (2005, p. 104).
[7] For further details on the differences between labelled and unlabelled choice experiment see § 5.1.2.

decision maker could have different choice sets, evaluate different attributes and assign different values for the same attribute at the same alternative.

4. *The decision rule*: describing the process used by the decision maker to choose an alternative. It describes how the decision maker makes a choice. It describes the mechanisms to process the information available and arrive at a unique choice. There are many types of decision rules. An exhaustive list is proposed by Svenson (1979). The main decision rules can be classified as follows:

   a) *Dominance*: an alternative is dominant with respect to another if it is better for at least one attribute and no worse for all other attributes. This rule is also used to eliminate inferior alternatives from a choice set. For instance, M. Ben-Akiva and Lerman (1985, p. 36) propose a commuter modal choice example in which the availability of an additional public transport mode (e.g. subway line) is tested. This new hypothetical public transport can be eliminated from an individual's choice set if it has an equal fare and level of comfort, but longer travel time. It is highly unlikely that the existence of a transport mode that is faster, cheapest and most comfortable.

   b) *Satisfaction*: every attribute assumes a level that serves as a satisfaction criterion. This may be defined as a "level of aspiration" based on the decision maker's expectations of the attainable, derived from his\her current information and previous experiences. Used in combination with other decision rules (e.g. dominance) it could be more effective, for example a commuter set upper limits on the travel time and cost to be met by car and bus, and car is the chosen because of a higher level of comfort.

   c) *Lexicographic rules*: Supposing that the attributes are ranked by their level of "importance", the decision maker chooses the alternative that is the most attractive for the most important attribute. For instance, the commuter first considers travel time and eliminates the walk mode as the lowest alternative. If cost is considered as second and the bus fare is smaller than the car travel cost, then the bus will be selected.

   d) *Utility*: The attractiveness of an alternative, expressed by a vector of attributes values, is reducible to a scalar. This defines for each alternative an index that represents the associated utility. The utility is a measure that the decision maker attempts to maximize through his\her choice. The assumption of a single index is based on the notion of trade-offs or compensatory-offsets[8] that a decision maker is using explicitly or implicitly in comparing different attributes[9].

The combination of two of these rules generates new rules. For instance, the lexicographic and satisfaction rules together create the “elimination by aspects” rule. It process begins with the most important attribute and eliminates the alternatives that do not meet its criterion level (Tversky, 1972).

4.4. The background of Discrete Choice Experiments

The basic problem confronted by DCEs is the modelling of the choice from a set of mutually exclusive and collectively exhaustive set of alternatives. DCEs are based on the microeconomic approach of consumer behaviour based on the utility maximization under a budget constrain (M. Ben-Akiva & Lerman, 1985). The individual is modelled through his/her selection of alternative with the highest utility among those available at the time the choice is made. The theoretical basis of DCMs can be found in characteristics theory of demand, welfare theory and consumer theory (Lancaster, 1966). Obviously, it is impossible to predict exactly and always the alternative chosen by all individuals. Also for this reason, the concept of random utility was introduced in DCEs, as previously done in mathematical psychology by Thurston (1927). The utility of alternatives are considered random variables, so the probability that an alternative is chosen is defined as the probability that it has the greatest utility among the available alternatives[10].

Following Hanemann (1984), the consumer decision can be separated into a discrete/continuous choice: which good to choose and how much of the chosen good to consume. In the context of a choice experiment, the decision is constructed so that the discrete choice is isolated. Given the public nature of many non-market goods, each individual is able to choose only one alternative from the choice set, considering both its cost and its continuous

[8] The three previous decision rules are non-compensatory, meaning that positive evaluation of an attribute does not compensate for (i.e. is not balanced against) a negative evaluation of some other attribute. On the contrary, the utility decision rule allows for a negative evaluation or performance on a particular attribute to be compensated for by a positive evaluation on another attribute.
[9] The all previous decision rules are non-compensatory.
[10] For further details on the evolution from the economic consumer theory to the discrete and probabilistic choice one see M. Ben-Akiva and Lerman (1985, pp.39-57).

dimension[11]. The economic model underlying a DCE is intrinsically linked to the statistical model adopted: it conditions the design of the survey and the analysis of data. As a consequence, undertaking a DCE can be considered as an integrated and cyclical process in which an economic model describing the issue under analysis is permanently revised as new information is gathered from the experimental design, experts' advice, focus groups and pilot surveys. A comprehensive overview of this valuation method can be found in M. Ben-Akiva and Lerman (1985); D.A. Hensher et al. (2005); J.J. Louviere (1988); Jordan J. Louviere et al. (2000); K. E. Train (2002). The Random Utility Models[12] are the most used models for the estimation of transport demand (Cascetta & Pappola, 2001). The user's choice is a "discrete choice", as it is carried out between a finite set of transport alternatives (Domenich & McFadden, 1975). Anderson, Palma, and Thiesse (1992) and Jordan J. Louviere et al. (2000) show that the concept of utility is a convenient theoretical device that allows to associate an index to specific level of satisfaction to the consumption of a particular good/service. The attractiveness of an alternative can be quantitatively measured with a set of attributes (Lancaster, 1966). In particular, the user associates, for each available alternative, a utility function that translates the level of satisfaction generated by the specific alternative (Cherchi, 2003). A rational user with perfect discrimination capacity and unlimited capacity of information processing, will choose the alternative which possesses the highest degree of utility (Lancaster, 1966).

McFadden (1981) and Manski (1973), criticizing the perfect power of discrimination and the unlimited capacity of information processing introduce the concept of random utility to explain phenomena that might otherwise seem an irrational claim. In fact, it is possible that the decision maker changes its choice over time. It is more realistic, therefore, to assume that the choice of an individual, given a specific choice set of alternatives, is not unique, but follows a probability distribution, since it is not possible to know and represent precisely the utility perceived by the decision maker. It follows that the utility must be specified not only as a function of a deterministic component, but also as a function of a stochastic component, which represents the set of unknown variables (and/or non-observable) of the utility function. The probabilistic choice model is reasonably the most suitable to represent the choices of individuals. Manski (1977) identifies four different sources of uncertainties which are

[11] For a formal description, the interested reader may refer to Alpizar, Carlsson, and Martinsson (2001) or Haab and McConnell (2002).
[12] The *constant utility approach* also exists and is mainly used in the mathematical psychology. It hypothesizes that the utilities of alternatives are constant and that the choice probability for an individual are functions parameterized by those utilities.

respectively related to the following issues: *a)* attributes are not always observable, *b)* changes in individuals' tastes cannot be observed, *c)* measurement errors, and *d)* instrumental variables (*proxy*). Luce (1959) introduced the Independence and Irrelevant Alternatives (IIA) axiom, to facilitate the experimental measurement of choice probabilities. Combining the ideas of Marschak (1960) and Luce (1959) in a model, McFadden (1974) proposed the Multinomial Logit (MNL) model.

The DCMs are a big family. In the last years, important improvements were carried out in taking in consideration individual preference heterogeneity. However, the most recent challenge in modelling through DCMs is the inclusions of individual's attitudes and perceptions towards the tested attributes and assess their impact on choice through Integrated Choice and Latent Variable models (Alvarez-Daziano & Bolduc, 2009; M. D. Ben-Akiva et al., 1999; Bolduc & Alvarez-Daziano, 2010; Di Ciommo et al., 2013; Jensen, Cherchi, & Mabit, 2013). For a synthetic overview of the most applied DCMs see Annex 2.

4.5. Applications of Discrete Choice Experiments

DCEs have been successfully used in many fields in order to: *i)* analyse individual preferences towards a set of options (such as goods, services, policies); *ii)* predicting demand (or acceptance) for a new option and define optimum pricing; *iii)* analyse the degree of competition between different items and the market penetration; *iv)* simulate the *ex-ante* impact of potential policy based on attributes' changes; *v)* estimating the willingness to pay/to accept for e.g. an improvement of the service quality, a decrease of the travel time etc.; *vi)* analyse product (or service) viability testing; *vii)* testing variations of product/service/policy attributes; and *viii)* understand brand value.

DCEs have been used for the first time in the field of *marketing* (e.g. brand choice). Marketing researchers use them to study consumer demand and to predict competitive business responses, enabling choice modellers to solve a range of business problems, such as pricing, product development, and demand estimation problems. The most relevant examples were carried out by Allenby, Arora, and Ginter (1995); Allenby and Rossi (1999); Andrews, Ainslie, and Currim (2002); Gilbride, Lenk, and Brazell (2008); Kessels, Goos, and Vandebroek (2006); Sándor and Wedel (2005); Yu, Goos, and Vandebroek (2009).

Also in the *transportation* sector, DCEs have a long and established history. For instance, transport mode choice, vehicle choice, airport choice, airlines choice and destination choice are among the many choices over time analysed. The most relevant examples were carried out by Adler (2001); Ahn, Jeong, and Kim (2008); C.R. Bhat (1995); Di Ciommo et al. (2013); Eriksson et al. (2008); Ewing and Sarigöllü (1998); Glerum, Themans, and Bierlaire (2011); David A. Hensher, Rose, and Greene (2008); Hsu and Chen (2005); Khan (2007); Kupfer (2012).

Since the mid-1990's, the interest in the use of the SP theory and methods has increased dramatically in agricultural and food economics, environmental and resource economics and health economics (Jordan J. Louviere et al., 2010). The first application of the DCMs in the context of environmental resources was reported by Adamowicz, Louviere, and Williams (1994). In the last decades, the number of applications has significantly increased and DCEs have become a popular SP method for environmental valuation (e.g. recreation choice, water quality improvement).

The most relevant examples were carried out by Bristow *et al.* (2010); Day *et al.* (2012); Fezzi, Bateman, and Ferrini (2013); Hindsley, Landry, and Gentner (2011); Jessoe (2013).

More recently, DCEs have been largely also in the following fields:

a) *Housing* (e.g. residential location): Gabriel and Rosenthal (1989); Potoglou and Kanaroglou (2007);

b) *Post and telecommunications* (e.g. choice of residential telephone service): Miravete (2002); Sell, Mezei, and Walden (2014);

c) *Energy* (e.g. appliance type choice): Goett, Hudson, and Train (2002); David Revelt and Train (1998);

d) *Health and social care* (e.g. healthcare program choice, patients' preferences in the treatment of prostate cancer): Bakker and Jacob Trip (2013); Cameron and DeShazo (2013); Ryan (2004);

e) *Insurance* (e.g. car insurance choice): Artís, Ayuso, and Guillén (2002); Hall (2004); Keane (2004); Wen, Wang, and Lan (2005);

f) *Labor* (e.g. occupation choice): Blundell, Duncan, McCrae, and Meghir (2000); Fuller, Manski, and Wise (1982); Van Soest (1995);

g) *Agriculture* (e.g. Christmas tree market choice): Davis and Wohlgenant (1993); Zapata, Sambidi, and Dufour (2007);

h) *Food* (e.g. salmon choice): Frode, Atle, Gro, and Kari (2005).

In the DCEs of SEFIRA pilot project, *un-labelled* alternatives will be included in the choice experiments in order to describe a generic air quality policy, probably referred to a specific sector (e.g. transport, agriculture, household etc.). This approach allows us the identification and use of all alternatives within the universal se of alternatives, avoiding alternative-specific parameter estimates.

4.6. Strengths and weaknesses of Discrete Choice Models

This section aims to provide a synthetic overview of the main strengths and weak points of the DCE methodology. They are summarized in Table 3.

Although DCE surveys are demanding in terms of time and cost of planning and realization and, dealing with individual choices, the time horizon of these choices should necessary be limited (due to the possible preference instability), many benefits can be gained from their implementations. In particular, DCMs estimate psychological trade-offs that consumers make when evaluating several attributes together, measuring preferences at the individual level. Even if SPs are not related to observed/real preferences, with a consequent probability of not reflect what they state with their actual behaviours, the possibility to have an *ex ante* evaluation of product/policy options, before their introduction into the real-life context might provide important indications for policy makers, firms and researchers (such as the willingness-to-pay/accept measures for setting price). DCEs are based on a statistical technique used to determine how people value different features that make up an individual product or service. DCEs have the potential to reduce problems such as expressions of symbolic values, protest bids, and some of the other sources of potential bias associated with contingent valuation. Respondents may find some trade-offs difficult to evaluate, because they are unfamiliar. In addition, if the number of attributes or levels of attributes is increased, the complexity and the number of comparisons increase. This may lead to fatigue and loss of interest, and the application of simplified decision rules. However, with a careful planning of the survey these drawbacks can be avoided or limited. In addition, if appropriately designed, the ability to model interactions between attributes can be used to develop needs based segmentation analysis. Furthermore, DCEs minimizes many of the biases that can arise for instance in contingent valuation studies where respondents are presented with the unfamiliar and often unrealistic task of putting prices on nonmarket amenities. Moreover, repeated nature of the choice experiments, however controlled in the estimation process, makes it difficult for the respondent to behave strategically.

Table 3 – Main strength and weak points related to the Discrete Choice Experiments

Strengths	Weakness
Estimation of trade-offs between attributes-levels.	Time consuming, high cost and high knowledge necessary to implement DCEs.
Estimation of the level of customer demand for alternative service products in non-monetary terms.	Complex models and estimation procedures.
En-ante assessment of new products/policy options.	Limited time horizon of individual preferences.
Enables welfare impacts to be estimated for multiple scenarios.	Respondents may be unfamiliar with the good or service being valued and not have an adequate basis for articulating their true value.
Calculation of the willingness-to-pay/willingness-to-accept and value of the time measures.	Respondents may fail to take questions seriously because the financial implications of their responses are not binding.
Potentially reduces the incentive for respondents to behave strategically.	Not realism in stated preference (e.g. stated intentions of willingness to pay may exceed true feelings).
Most biases can be eliminated by careful survey design and implementation.	Important limits provided by the “Utility maximization” assumption.
It allows creating decision support system tools for policy recommendation.	Cognitive complexity of the choice experiments.
Is being constantly improved to explore, for instance, latent variables that capture attitudes and perceptions of the decision makers (e.g. Integrated Choice and Latent Variable model).	The framing or presentation format of the choice experiment leads consumers to attribute-wise processing of information

Note: DCEs = Discrete Choice Experiments.

5. How to design Discrete Choice Experiments: methodological guidelines

The DCEs are based on the generation and analysis of individual choice data. As mentioned before, several choice experiments, each containing a set of mutually exclusive hypothetical alternatives between which respondents are asked to choose their preferred one, are collected. The main point is that individual choices imply implicit trade-off between the levels of the attributes in the different alternatives included in a choice set. Experimental designs are used to construct choice sets, so that the attributes are uncorrelated and therefore yield unconfounded estimates of the parameters. The resulting choices are finally analysed to estimate the contribution that each attribute and level add to the overall utility of the individuals (Hoyos, 2010). We aim this section on briefly explaining of the main steps of the processes used in generating a DCE survey. For further details on the generation of the experimental design see D.A. Hensher et al. (2005, p. 100). The process generally used to implement a DCE survey is shown in § 5.1, and § 5.2 highlights the main *pros* and *cons* of this instrument.

5.1. Discrete Choice Experiment survey process: six phases

The SP data deals with experiments rather than real observations. This implies that the process of setting up a SP is more complex than collect RP data. Moreover, SP surveys' results are affected by the quality of the surveys' planning and realization. Furthermore, time and financial resources are needed to prepare and administer choice experiments. In fact, setting up a SP survey requires a number of stages and important decisions that necessarily affect the result. Table 4 summarizes it.

Table 4 - Steps to set up a DCE survey

Phases	Steps
A	Problem definition
B	Experimental design definition
C	Questionnaire structure and context
D	Data collection and sampling strategy
E	Model estimation and interpretation
F	Internal and external validity tests

Source: our elaboration on D.A. Hensher et al. (2005)

5.1.1. Phase A - Problem definition

The research objectives have to be clearly identified. An optimum clarity and knowledge of the research problem constitutes a preferential element to ensure the realization of a valid survey tool. In the SEFIRA project the main aim is to analyse the individual preferences toward the public acceptability of air quality policies. The focus is on the understanding of the importance and related weight that selected drivers (policy characteristics) have in determining individual policy acceptability through respondents' choices. Furthermore, by carrying out segmentation analysis (thanks to the socio-economic data collected), we will highlight socio-economic differences in the individual preferences toward the acceptability of air quality policies.

5.1.2. Phase B - Experimental design definition

The generation of the experimental design implies a series of important decision such as to:

1) *Identify and select of the alternatives, attributes, attribute-levels and range of the attribute-levels*: with reference to the identification and selection of attributes to include in choice experiments, these decisions are of extreme importance because all the subsequent analyses focus on the attributes previously selected. Typically,

the attributes are not more than five[13] (Aaker & Day, 1990), while the attribute-levels should be limited to three or four. Obviously, the number of the selected attributes depends at the research topic analysed and at the type of method selected for the administration of the interviews. However, attributes are selected reviewing the academic literature on that topic. Not always these analyses are complemented by qualitative analysis such as focus groups. The latter are very important mainly for the definition of the attribute-levels and their range.

2) *Use labelled or unlabelled alternatives in the choice experiments*: the decision to use label versus unlabelled choice experiments is very important. An unlabelled choice experiment is characterised by generic choice alternatives. Each alternative has a generic title such as "Alternative 1". This means that the decision maker does not have other information than this. When a choice alternative has a specific title such as "Car" these choice experiments are called labelled. It is important to highlight that unlabelled choice experiments do not require the identification and use of all alternatives within the whole set of choice alternatives. Furthermore, unlabelled experiments require the estimation of general parameters which are the same for any choice profiles. On the contrary, using labelled experiments the estimated alternative specific constants could be specified for each alternative (Bates, 2011; D.A. Hensher *et al.,* 2005). For instance, this type of choice experiment fits very well if the goal of the analyst is also to test the brand name of a product, to estimate market share and willingness to pay measures.

3) *Decide the experimental design strategy*: having identified attributes, attributes-levels and their range, the analyst must take decisions on the type of experimental design to be used. Different types of design exists: full factorial design, fractional factorial design, orthogonal design, and efficient design[14]. A full factorial design contains all possible levels of the attributes[15]. Due to the enormous amount of possible combination that usually is produced by a full factorial design, analyst chooses a portion of it. Therefore, a sub-set of a full factorial is called fractional factorial design. The selection of the sub-set of combinations is often random. An experimental design is defined orthogonal when it satisfies attribute level balance

[13] For instance, in the DCM literature generally, the number of attributes is ranging from 4 to 6, while for more complex issues, the number is ranging from 6 to 9 attributes.
[14] For further details see D.A. Hensher et al. (2005, p. 109).
[15] For instance, if there are 2 alternatives (transport mode 1 and 2), with 5 attributes and 3 attribute-levels, the total number of possible combinations is (3*3*3*3*3) * (3*3*3*3*3) = 32*5 = 50.049.

and all parameters are independently estimable. In particular, orthogonal design ensures that the attributes-levels are spread over all choice experiments, and that attribute level combinations do not exhibit a certain (positively or negatively correlated) pattern (M. C. J. Bliemer & Rose, 2011). The main reasons for using orthogonal design are three: 1) allow for an independent estimation of the influence of each design attribute on choices, 2) are easy to construct even if only for a limited number of combinations of attribute levels, 3) are historically linked to the estimation of linear models where orthogonality prevents multicollinearity[16] and minimizes the variance of the parameter estimates. In the last few years, efficient experimental designs have developed. It is defined 'efficient' if the design yields data that enables parameters estimation with as low as possible standard errors. An efficient design, assuming specific *a priori* for the parameters, calculates the Asymptotic Variance-Covariance matrix (the roots of the diagonal of this matrix are the asymptotic standard errors). There exist different measures of efficiency, including the *D-error*[17], the *A-error*[18], the *S-optimality*[19] (M. C. Bliemer & Rose, 2005; M. C. J. Bliemer & Rose, 2010).Using the *blocking* function, it is possible to split the original design into smaller designs.

[16] Multicollinearity is a statistical phenomenon in which two (or more) covariates in a multiple regression model are highly correlated (Farrar & Donald, 1967).
[17] D-efficiency is the most common approach to measuring efficiency of experimental designs (Ferrini & Scarpa, 2007). D-efficient designs minimise D-error, which is defined as: $D_z - error = \det(\Omega_1(X,0))^{1/H}$, where H is the number of parameters to be estimated, X is the experimental design, $0 = \beta$ is the parameter value (*a priori*) when there are no information about it.
[18] The A-error looks at the variances and not at the covariances. The experimental design with the lowest A-error is called A-optimal. The A-error is calculated as:
$A_p - error = \frac{tr(\Omega_1(X,\beta))}{H}$, where H is the number of parameters to be estimated, X is the experimental design, $0 = \beta$ is the parameter value (*a priori*) when there are no information about it.
[19] This efficiency measure is related to the sample sizes required to estimate each parameter (attribute) significantly. This experimental design is optimized for sample size for each attribute.

4) *Use a full or partial profile for the choice experiments*: if the analyst would use many attributes making difficult for the respondent to take decision considering all of them at the same time, a partial profile design[20] could be applied. In fact, respondents often are non-compensatory[21] in their choice behaviour, making their choices based on one or a limited group of attributes. Therefore, to prevent this so-called lexicographic behaviour, the attributes shown to the respondents should be limited, according to the topic analysed (Green, 1974). Generally, when the researcher selects a limited number of attributes a full profile design for the choice experiments is implemented.

5) *Define the number of choice experiments to be administered to each respondent*: this decision is important and related to different aspects of the survey such as the type of the experimental design used, number of alternatives, attributes, attributes-levels and their range, type of administration technique used to administer interviews etc[22].

6) *Choose the type of answer for the choice experiments*: another important aspect of the choice experiment is the type of answer. The 'choice', 'ranking' and 'rating' options exist. According to the type of answer chosen, the technique of data analysis and the reliability of the results obtained varies (Aaker & Day, 1990; Johnson & Desvousges, 1997; J.J. Louviere, 1988). With the choice option, the respondents have to pick one of the two, three or more alternatives available in the choice experiment. A main critical aspect could be due to the low level of information obtainable despite this drawback the approach is nevertheless the fastest and easiest to implement, and more realistically reproducing the real decision-making processes of the respondent[23]. In the ranking option, the interviewee orders the proposed alternatives according his/her own preferences from the best to the worst. In contrast with the choice, this option implies that the

[20] In a full profile for choice experiments, alternatives are described by all the selected attributes, while in a partial profile one, the alternatives are characterized by few attributes that generally change over choice experiments administered to the respondents.
[21] A behaviour is non-compensatory if positive evaluation of an attribute does not compensate for (i.e. is not balanced against) a negative evaluation of some other attributes.
[22] For further details on the learning and fatigue during DCEs see Savage and Waldman (2008).
[23] With this type of answer, the analyst will know only the first choice while with the others approach he/she will collect information on each of the other chosen alternatives.

respondent constraints own preference in a final choice. Moreover, before we get their preferences, respondents must examine all qualities of all alternatives, and this makes the choice exercise more complex and time-consuming. On the other hand, however, it has the undeniable advantage of giving a high level of information. Lastly, in the rating option, very similar to the ranking option, the interviewee ranks each of the available choice profiles and assigns to each of them a scalar value according to his/her own preferences. The decision between one of these options is affected by some aspects such as the number of attributes and levels to be investigated, the type of experimental design used, the maximum number of choice experiments that will be administered to each respondent, and the type of econometric analysis that the analyst want to perform with the collected data.

Relating to the SEFIRA pilot project, we defined the attributes, attribute-levels and their ranges in collaboration with IIASA and KINGS partners. As highlighted above, this step is very important and it is necessary the cooperation between the research unit of UNIURB and IIASA. From a list of all possible attributes, we selected the most important five. Due to the constraints that the CAWI[24] survey provides for the DCE technique (see below § 5.1.4), we will use two unlabelled alternatives in the choice experiments, each characterized by five attributes with, in turn, up to four levels each. Due to the limited number of attributes that we can test, the full profile option for the choice experiment is our choice, asking to the respondent to answer with the 'choice' option. Preliminary evaluations on the choice of the experimental design strategy are addressed toward a fractional factorial design or an orthogonal design one.

5.1.3. Phase C - Questionnaire structure and context

Usually, a DCM questionnaire includes different sections. The first one is almost always an introductory section where socio-economic and behavioural data of the respondent (and his/her family) are collected. Obviously, these questions depend from the issue analysed. The second one proposes a series of choice experiments, which are the core of the questionnaire[25]. The third section deals with attitudinal aspects of respondents toward the research problem and/or specific aspects such as the perceived complexity of the questionnaire. A few studies

[24] For further details see § 5.1.4.
[25] Where possible in addition at the SP choice experiments, also the RP one is collected.

include a further forth section where the interviewer answers some questions on the perceived attention and interest of respondents and other general comments provided by the respondents during the interview administration are included. Moreover, the choice context should be specified providing respondents a synthetic description in which they will have to do a choice, defining also the time horizon in which the respondents should imagine to do that choice.

The SEFIRA questionnaire will be structured as follows: after a first section focused on the socio-economic data of the respondent, a few choice experiments on choice policy acceptability will follow. In the next section, attitudinal data on environmental and social issues will be collected as well. Relating to the choice context definition, in the SEFIRA pilot study the focus is on the air quality policy evaluation with a short and medium time frame of reference.

5.1.4. Phase D - Data collection and sampling strategy

The data collection phase is related to different important aspects such as the selection of the place where to administer the interviews, the method used to administer them and the definition of the sampling strategy. There are different methods to collect choice experiment data ranging from *Pencil And Paper Instrument* (PAPI), *Computer Assisted Telephone Interviewing* (CATI), *Computer Assisted Self-Interviewing* (CASI) to *Computer Assisted Personal Interviewing* (CAPI). In the last years, also internet-related methods are increasingly used, such as the *Electronic Mail Survey* (EMS) and the *Internet Electronic Survey* (IES), as examples of the more general *Computer-Assisted Web Interviewing* (CAWI). For a detailed explanation see Leeuw, Hox, and G.Snujkers (1995). The most used and suitable technique related to DCEs is the CAPI one. Sarasua and Meyer (1996) provided a list of the main advantages of using the CAPI method: interesting and flexible presentation format; consistent format across the interviewers and the respondents; automatic and updating questions; automatic data coding and storage; speed up the recording times of the answers; possibility to insert checks to avoid wrong input answers; reduce the percentage of non-responses (in particular those caused by errors in the registration phase). If choice experiments present a limited number of attributes a computer-assisted web interviewing (CAWI) survey could be suitable. However, it is important to remember that this choice depend on different aspects such as the phenomenon analysed, the sampling size and strategy, the experimental design, the response mode used and the time and budget constraints of the investigation. Recently, a mixed mode of interviews administration is frequently used due to the possibility to avoid the specific disadvantages of each technique, in particular using web-based methods. The selection of the place to administer the interviews is mainly related to the studied topic. For instance, in the transport literature of DCMs, interviews are generally administered on transport-related places (e.g. rail/bus/gasoline station, inside airport, on-board railway/bus etc.). A few studies administer interviews also in non-transport related places (e.g. shopping centres and waiting rooms of banks, dentists, beauticians etc.) in order to interview non-transport users (potential demand) (e.g. Valeri, 2013).

Another important decision is the sampling strategy. Sampling is the process of selecting a relatively small group of people from a specific population to be analysed. In applied research, a complete census is often impracticable, while the goal of sampling is to assess clusters efficiently and effectively by designing and executing representative sample plans. In fact, to consider a selection of people, rather than a census, has numerous advantages such as time and cost savings, more in-depth information, lower total error and greater practicality. Although different types of errors might occur (sampling error, sample bias, and non-sampling error), there are two main different sampling methods: *probabilistic* and *non-probabilistic*[26] methods. In the DCM literature, the *probabilistic* sampling strategy is widely applied. Across the different types of this group of sampling strategy, *simple random* (each element of the population an equal and known chance of being selected for inclusion in the sample), *stratified* (it is a modified type of random sample, often used when sub-groups of the population are of special interest to the researcher), *cluster* (similar to the previous one, the difference refers to the selection of a random sample of subgroups rather than a random sample from each subgroup) and *systematic* (it is initiated by randomly selecting a digit, *n*, and then selecting a sample element at every *nth* interval, depending on the size of the population and the sample size requirement) strategies are applied. In an exploratory survey, 30-60 individuals are sufficient. However, for a segmentation analysis, 200 individuals for each subgroup are needed (Orme, 1998). Furthermore, increasing the sample size increases the probability that the sample mean approaching that of the population. The Statistics literature suggests using a sample size n what allows to verify the follows inequality: $\frac{n*t*a}{c} > 500$ where t is the number of observations collected by each respondent, a is the number of alternatives (excluded the 'non-choice' option), and the c is the number of parameters to estimate.

[26] The most commonly utilized *non-probability* sampling techniques are: *convenience*, *judgment*, and *quota*.

Relating to the SEFIRA project, interviews will be administered mainly using a CAWI technique. Therefore, the public acceptability will necessarily be studied through a rather simple choice experiment structure (number of alternatives, attributes, attribute-levels) in order to make alternatives clear to the interviewee. The questionnaire will be previously tested through a pilot survey.

We are considering the possibility to complement this method administering further interviews through the SEFIRA web site. According to the analysed topic, the survey will be carried in five countries (Sweden, Germany, Italy, Poland, United Kingdom) and the sample will be nationally representative. We will be able to disaggregate results down to NUTS level 3 so that we will be able to consider potential respondent's differences according to type of living environment, both rural and urban areas. The population target is defined as active people who both use car/motorcycle for their mobility and eat red meat and/or dairy products, even occasionally.

5.1.5. Phase E - Model estimation and interpretation

After a data cleaning phase, DCMs' estimation and interpretation steps is needed. From the logit model family, the simplest DCM is the MNL model. It is the standard logit model; exhibiting the Independence from Irrelevant Alternatives (IIA) property it implies proportional substitution across alternatives[27] (K. E. Train, 2002, p. 80). Often this property results too restrictive and incapable to capture all sources of correlation explicitly. For this, more flexible DCMs were used also to explore preference heterogeneity.

The Generalized Extreme Value (GEV) models are a large class of models with a variety of substitution patterns. For all alternatives, the unobserved portions of utility are jointly distributed as a GEV, allowing for correlations over alternatives and it is a generalization of the univariate extreme value distribution that is used for standard logit models (e.g. Karlstrom, 2001). When all correlations are zero, the GEV model becomes standard logit. One of the most used GEV model is the Nested Logit Model applied in different fields such

[27] This property means that the ratio of probabilities of choosing any two alternatives is independent of the choice set. A first advantage of this property is its ability to deal with a large set of alternatives to estimate a model on a sub-set of these alternatives. A second one, is that if one were only interested in a respondent's choice between two alternatives, even if the choice set contains multiple alternatives, providing the IIA property holds, the MNL can make estimates on this sub-set.

as transportation, energy, housing, telecommunications etc. (e.g. Forinash & Koppelman, 1993).

Different variants are developed over time such as the Cross-Nested Logit model, that allows for multiple overlapping nests (e.g. M. Ben-Akiva & Bierlaire, 1999), the Ordered GEV model, in which the correlation in the unobserved utility between any two alternatives depends on their proximity in the ordering (e.g. C.R. Bhat, 1998), the Paired Combinatorial Logit model in which each pair of alternatives constitutes a nest with its own correlation (e.g. Chu, 1989), and the Generalized Nested Logit model that includes the Paired Combinatorial Logit model and other Cross-Nested Logit models as special cases.

Further flexible models are increasingly used such as the Random Parameter (or Mixed) (RPL) Logit model that allow for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (e.g. Boyd & Mellman, 1980). The RPL models could be derived under a variety of different behavioural specifications with the related specific interpretation. For instance, it is possible to distinguish between the Random Parameter and Error Component Logit models (e.g. Chandra R. Bhat & Castelar, 2002). The Error Component Logit (ECL) model type instead represents the error components that create correlations among utilities for the different alternatives (e.g. Beville & Kerr, 2010).

These two model types could be also used together (e.g. Greene & Hensher, 2007). Instead of capturing correlations among alternatives, the analyst might to allow the variance of the unobserved factors to differ over the alternatives. This type of model is called Heteroskedastic Extreme Value model. It implies that there is no correlation in unobserved factors over alternatives but the variance of the unobserved factors is different for each alternative (e.g. Greene, Hensher, & Rose, 2006). In the last few years, the use of a further type of DCMs is spreading. It is called Integrated Choice and Latent Variable Model (ICLV). Its first application is referred to M. D. Ben-Akiva et al. (1999). This model is composed of a discrete choice model and a latent variable model, allowing to take in consideration latent psychological factors such as attitudes and perceptions (e.g. Alvarez-Daziano & Bolduc, 2009; Bolduc & Alvarez-Daziano, 2010).

All the previously cited DCMs have specific interpretation of the results.

A further explanation of some of these models is reported in Annex 2[28]. Because of the SEFIRA project aim to highlight socio-economic characteristics, flexible and practical DCMs will be tested in particular those models that allow for preference heterogeneity (e.g. RPL, ECL, ICLV models).

5.1.6. Phase F - Internal and external validity tests

The last phase regards internal and external validity tests. The first type of tests is used for instance to verify if the individual preferences are rational[29] (only rational choices are analysed with DCMs). The second one is useful to verify if the estimated DCM replicates in a sufficient manner the real individual preferences (Rotaris, 2005). All the main validity tests will be run.

5.2. Constraints for the SEFIRA discrete choice pilot survey

The SEFIRA project will administer the discrete choice interviews using the CAWI technique. Considering the complexity of the analysed issue, the range of possible air quality measures that can be considered, and the pilot character of the study, public acceptability will be studied through a rather simple choice experiment which has a limited number of alternatives, attributes and attribute-levels. Choice experiments will be calibrated on a justifiable cognitive effort of the interviewee (and previously tested through a pilot survey).

[28] In addition, a detailed explanation on tests and practical issues in choosing and developing DCMs is reported in Chapter 7 in M. Ben-Akiva and Lerman (1985, p.154).

[29] According to the Rational Choice Theory, the 'rationality' means that an individual acts as if balancing costs against benefits to arrive at action that maximizes personal advantage (Friedman, 1953). All decisions are postulated as mimicking such a rational process.

Summary and next steps

The actual debate on air quality measures focuses mainly on the technical or non-technical nature of policy instruments. Policies that belong to the set of non-technical measures seem to offer the scope for assessing acceptability to the general public compared with technical measures, in that they often imply more significant changes in the lifestyles of individuals. They also often offer different ways of analysing a problem and therefore embody choices and 'trade-offs'. This standard classification is relevant but if the research focus is on policy acceptability more attention should be dedicated to understand how policy efficacy is related to behavioural components that determine policy acceptability. It follows that understanding the correlation between behavioural components and acceptability drivers may become significant in the design of successful air quality policies.

At present he majority of air quality improvements are due to the implementation of technical measures (analysed by IAMs), whose public acceptability level as well as social perception of the policy effectiveness are rather unknown. In fact, as emerged from § 2.2, behavioural changes (e.g. changes in lifestyles, legal traffic restrictions, pollution taxes, emission trading systems, etc.) are not internalised in the optimisation process of most widespread IAMs. On the contrary, such changes are reflected by alternative exogenous scenarios of the driving forces.

Attention paid by policy makers and experts in better understanding the socio-economic and individual implications of non-structural measures, is substantially increasing. The level of community participation and sharing has to be extensively assessed, described and studied through the use of new methodologies and interdisciplinary approaches. In this direction, DCMs are a robust and widespread quantitative methodology for the study of individual preferences.

Within WP4 of the SEFIRA project, this will be done building a pilot choice experiment. Such an experiment will enable us to identify and test a methodology capable to increase the knowledge of specific policy drivers (attributes) that belong to air quality policies and that could influence their degree of acceptability.

DCEs allow: 1) not only to have a weight of the importance of the selected policy acceptability drivers, but also to detect the trade-offs that individuals make between the different levels; 2) in the DCE the social aspects related to individual choices will be taken into considerations (e.g. "social dilemma", etc.) and socio-economic data of respondents will be used in order to perform segmentation analysis, highlighting socio-economic differences in the air quality acceptability across the selected countries.

Policy acceptability is related to four main aspects:

i. *The drivers that affects and characterize the acceptability measure* (§ 1)

The "acceptability" concept (§ 1.1) and the main drivers by which it is influenced (§ 1.1) are synthetically defined: the problem perception (§ 1.2.1), the social norms (§1.2.2), the knowledge about options (§ 1.2.3), the perceived effectiveness and efficiency (§ 1.2.4), equity and fairness of a measure (§ 1.1), and socio-economic and system characteristics (§ 1.2.6). However, there are many different acceptability drivers are, and some choices are needed in order to select those drivers to be included in the WP4 pilot DCE. In this specific context, the cooperation between the SEFIRA partners from the University of Urbino (UNIURB), the International Institute for Applied System Analysis (IIASA) and the King's College of London (KINGS) allowed us to narrow the full list of drivers (around #30) to four drivers: i) the cost of the policy (individual annual cost paid to implement such policy); ii) the level of personal engagement (how people are willing to accept changes in their individual life style such as the decrease required in the use of car/motorcycle, decrease required in the consumption of red meat and/or dairy product); iii) the temporal horizon of the policy (time required for the policy to give its beneficial effects on air quality); iv) the improvement of human health (reduction of premature deaths caused by the atmospheric pollution).

ii. Types of measures (§ 2)*:*

The factors affecting policy acceptability are one on the key issues, a second one is distinction between technical and non-technical measures provided in § 2.1, in which it has been highlighted the role of their behavioural dimensions. The literature provides different definitions for technical and non-technical measures. In the present report, we propose an additional one. Our focus is not on the standard technical and non-technical distinction, but rather on the level of "behavioural component" of each policy (see the last two columns on the right-hand side of Table 1). The "behavioural component" in this report is the level of individual effort needed in order to have a successful policy (i.e. the individual willingness to improve a certain behaviour). It follows that understanding the relationship between behavioural components and acceptability drivers might support policy makers in the design of successful air quality policies.

Various IAMs (§ 2.2) are currently used in order to support national and European policy makers to identify portfolios of measures that improve air quality and reduce GHG emissions at least cost, these models make use of mainly technical measures. Considering the increased attention toward non-technical measures (especially behavioural), the SEFIRA project proposes to investigate the feasibility of cooperation between DCMs and integrated assessment models mainly dealing with technical measures in view of potentially more complex model integrations.

iii. *Quantitative Models used to analyse used measures* (§ 3-4-5)

After having highlighted the differences between technical and non-technical measures and how they are incorporated into IAMs (§ 2), we synthetically presented the widely used GAINS model. Referring mainly to technical measures that involve a low level of behavioural components, GAINS model performs a cost-effectiveness optimization in order to select the more cost-effective air quality policies to implement.

Afterwards DCMs are presented as a quantitative instrument to analyse non-technical measures (§ 4-5). We synthetically explain what DCMs are and how they work, using a non-technical language.

A glossary is provided in Annex 2 in order to define specific terms used in the DCM literature. While theoretical DCM issues are detailed in § 4, methodological guidelines on how to set up and apply a DCE are shown in § 5.

With DCEs is possible to elicit individual preferences for potential new air quality policies, analysing their *ex ante* acceptability. Requiring respondents to make individuals' trade-offs between various policy drivers (so-called attributes-levels), DCMs allow the estimation of the respondent sensitivity toward each policy characteristics, included in the choice experiments, and their related weight. The literature in different fields recognise that simply asking human beings to rate/choose their preferred item from a list will generally yield no more information than the fact that human beings want all the benefits and refuse the costs, as done for instance by

European Commission Eurobarometer (2013). DCE requires individuals to make trade-offs between two or more choice options. In other words, they give information on the weight that each attribute (and each attribute-level) has on respondents' choices. The six important steps of a DCM model are described; these deals with the problem definition, experimental design and questionnaire setting and administration to model estimation and interpretation. One of the most important is the definition of the *choice set* elements: alternatives, attributes, attributes-levels and their range. In this experimental phase we don't have the possibility of an extended and comparative evaluation in the choice of the attributes. For this reason we opted for establishing a multi-disciplinary open discussion between all the partners involved in the Working Package 4 that developed in various meetings at national and international level.

iv. *Possible integration between models*

The potential cooperation between DCM and IAMs will be briefly explored by considering the role of non-structural measures (especially behavioural ones), in the selection process of air quality measures.

As emerged in § 4, it is well known that a key element for a successful policy is the social acceptance of that the policy, strictly related to the understanding of the trade-off between different attributes that characterise the policy in term of acceptability. Therefore, an interesting research direction seems to find methodologies working on the understanding of socio-economic dynamics (preference heterogeneity) that affect the policy acceptability and, consequently, the effectiveness and efficiency of the policy. In the SEFIRA project the use of a DCE to study air quality acceptability will be tested.

Annexes

1. Defining terminology

This section is aimed at providing common practical knowledge through examples about DCMs finalized to be used for the SEFIRA Project (Table 5).

Table 5 – Common WP4 glossary

List of terms	Summary description	Examples
Policy package	it is a bundle of measures	A set of air quality measures
Measure	It is a single policy intervention	Photovoltaic, energy efficiency building, road traffic restriction
Attribute [1, 2, .. n]	It describes a measure	Fairness, Mortality
Attribute-level [a, b, .. m]	It describes the attribute range/wideness	Measure cost: 0€, 10€, 25€, 50€ Mortality: 10% death reduction, 25% death reduction, 50% death reduction
Alternative	It is a choice option characterized by a mixed bundle of attributes-levels	Alternative X: 1a, 2b, .. 3n Alternative Y: 1c, 2b, .. 3m Alternative Z: ….
Choice experiment	It is a choice exercise (scenario) including more alternatives	
Experimental design	It is a plan for running an experiment and it is often displayed as a matrix	Full factorial design, fractional factorial design, orthogonal design, efficient design Bayesian design.

2. Overview of the most common Discrete Choice Models

As mentioned in § 25, the Utility, $U_{ni} = V_{ni} + \varepsilon_{ni}$, using $V_{ni} = \sum_k \beta_k x_{nik}$, could be expressed also as follows:

$$U_{in} = ASC_i + \beta_{1ni} X_{1ni} + \beta_{2ni} X_{2ni} + ... + \beta_{Nni} X_{Nni} + \varepsilon_{ni}$$

where ASC_i is the Alternative Specific Constant representing the net average effect of omitted variables (relative to the base); including the ASCs when estimated by maximum likelihood procedure, the logit is able to replicate the aggregate choice shares. $X_{1ni}...X_{Nni}$ are the deterministic part of the utility characterized by the attributes and individual socio-economic data. $\beta_{1ni}....\beta_{Nni}$ are the estimated attribute coefficients.

Following the example provided by the Department for Transport (2013) on modal choice (transport sector), if the analyst is interested in analysing the importance of Travel Time (TT) and Travel Cost (TC) drivers on choice, an appropriate representation of the individual Utility would be as follows: $V_{ni} = \beta_{TT} TT_{ni} + \beta_{TC} TC_{ni}$

where β_{TT}, β_{TC} are the estimated taste parameters to Travel Time and Travel Cost, respectively. Since both attributes are perceived as 'bad' in term of utility, they will appear with a negative coefficient, $\beta_{TT}, \beta_{TC} < 0$.

Logit models relate probability of choosing alternative i from J alternatives as follows:

$$P_{ni} = \frac{e^{\mu V_{ni}}}{\sum_{nj \in J} e^{\mu V_{nj}}}$$

where μ is a strictly positive scale parameter. The probability of person n choosing alternative i is:

$$\mathrm{P_n(i) = P(U_{in} > U}_{jn})$$

and the probability of choosing alternative j is:

$$\mathrm{P_n(j) = 1\text{-}P}_n\mathrm{(i)}$$

The observed inconsistencies in the choice behaviour are taken to be a result of observational deficiencies on the part of the analyst. The individual selects the alternative with the highest utility. However, the utility are unknown by the analyst. For this reason, the choice probability of the alternative i is equal to the probability that its utility is greater or equal to the utilities related to the other alternatives in the choice set C_n (M. Ben-Akiva & Lerman, 1985). Generally, it is possible to generalize as follows: $P(i \mid C_n) = P[U_{ni} \geq U_{nj}, all\ j \in C_n]$.

Following this approach the choice probabilities are derived by assuming a joint probability distribution for the set of random utilities: $\{U_{ni}, i \in C_n\}$.

Manski (1973, 1977) identifies four different sources of randomness: unobserved attributes, unobserved taste variations, measurement errors and imperfect information and instrumental (or proxy) variables. In order to estimate a specific random utility model, it is required an assumption about the joint probability distribution of the full types of errors: $\{\varepsilon_{ni}, i \in C_n\}$.

Depending on the different assumptions made on the error type (e.g. Independent and Identically Distributed - IID), different random logit models are developed over time.

Moving from the basic MNL, the Mixed Logit model refers to a generalized modelling framework which maintains the IID Extreme Value Type I error term, but uses simulated maximum likelihood estimation to allow coefficients to be estimated over a specified distribution (D.A. Hensher & Greene, 2003; Hess & Train, 2011; Daniel McFadden & Kenneth Train, 2000; K. Train, 1998; K. E. Train, 2002). There are two general specifications, the random parameters and the error components specification. They differ in expressing heterogeneity in the different components of the model. The RPL model allows preference coefficients in deterministic utility to be estimated over continuous distributions, by simulating (taking draws) around the MNL estimates according to a pre-specified distribution. This allows representing the preference heterogeneity over the population. These taste distributions involve both mean and variance estimates. Zero taste variations in the estimated parameters cause the collapse of the RPL to the MNL model. There is a great deal of latitude in investigating different distributional forms[30]. The RPL can be estimated using a

[30] The most common distribution are: *normal*: $\beta_i = \beta + \sigma v_i, v_i \rightarrow N[0,1]$ (D. McFadden & K. Train, 2000); *triangular*: $\beta_i = \beta + \sigma v_i, v_i \rightarrow Triangle[-1.1]$ (D. Revelt & Train, 2000);

panel formulation which allows correlation across individual's choices and relaxes IID. Incorporating variance around parameter means overcomes the restrictive IIA property (M. Ben-Akiva & Lerman, 1985; D.A. Hensher et al., 2005; K. E. Train, 2002).

Starting from:

$$P(y_{is} = j) = \frac{\exp(\alpha_{ji} + \beta_{ik}' x_{jis})}{\sum_{q=1}^{J} \exp(\alpha_{qi} + \beta_{ik}' x_{qis})}$$

The RPL model takes form by allowing individual parameter estimates β_i in the vector β. Where:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik}$$

In this formulation β_k is the population mean, v_{ik} is individual specific heterogeneity, with mean 0 and standard deviation equal to 1. σ_k is the standard deviation of the distribution β_{ik} around β_k. The analysts observe X and estimate β_k and σ_k. They test if alternative parametric distribution chosen for β_k and σ_k offers a better approximation of the population preferences (Beville & Kerr, 2010). The previous specification can be extended to allow for heterogeneity in the random parameter means and variances (Greene et al., 2006). To allow σ_{ki} being heteroscedastic, the specification is extended to: $\sigma_{ik} = \sigma_k \exp(\omega_k' hr_i)$

where ω_k are parameters which capture variance heterogeneity in the random parameters in the systematic utility part and hr_i are observed variables of the individual. The means are allowed to be heterogeneous according to observed variables, z_i of the individual where, δ_k, are parameters which capture the mean shift. β_{ik} can be specified as: $\beta_{ik} = \beta_k + \delta' z_i + \sigma_k v_{ik}$

As before, ε represents the unobserved portion of utility. For each individual's level of unobserved utility, the error term, ε, is random. However, in the RPL model framework, compared to MNL one, correlation is induced in ε. This correlation partially relaxes the IID assumption. The RPL model can be further generalized to allow variance differences to be captured in unobserved utility at the alternative specific level. These error components

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lognormal: $\beta_i = \exp(\beta + \sigma v_i), v_i \rightarrow N[0.1]$ (M. Ben-Akiva, Bolduc, & Bradley, 1993); *uniform*: $\beta_i = \beta + \sigma v_i, v_i \rightarrow U[-1.1]$ (D. Revelt & Train, 2000) For the full list see Nlogit version 4.0 (2010, p. 125).

completely relax the IID assumption of MNL, allowing individuals' substitution patterns to become fully flexible. Theoretically, Error Components can be estimated for each alternative. The simulation procedure is the same as the random parameters - draws are taken from a predetermined distribution and the results are average. Parameters are arrived at which maximize the simulated log-likelihood.

The Error Component specification can be estimated in addition to the random parameter specification as specified below:

$$P(y_{is} = j) = \frac{\exp(\alpha_j + \beta_{ik}' x_{jis} + \sum_{m=1}^{M} d_{jm}\theta_m E_{im})}{\sum_{q=1}^{J} \exp(\alpha_{qi} + \beta_{ik}' x_{qis} + \sum_{m=1}^{M} d_{qm}\theta_m E_{im})}$$

where E_{im} are individual specific random error terms, $m = 1,......M$, $E_{im} \sim N[0,1]$, θ_m is the scale factor for error component m, and d_{jm} is equal to 1 if E_{im} appears in the utility for alternative j and 0 otherwise. A number of studies have combined random parameters with error components (Beville & Kerr, 2010; Cherchi, Cirillo, & Ortuzar, 2009; Greene & Hensher, 2007; Greene et al., 2006; Hess & Train, 2011).

Taking into account for the heteroscedasticity in the ε_j distribution, the previous formula is becomes:

$$P(y_{is} = j) = \frac{\exp[\alpha_j + \beta_{ik}' x_{jis} + \sum_{m=1}^{M} d_{jm}\theta_m \exp(\gamma_m ' he_i) E_{im}]}{\sum_{q=1}^{J} \exp[\alpha_{qi} + \beta_{ik}' x_{qis} + \sum_{m=1}^{M} d_{qm}\theta_m \exp(\gamma_m ' he_i) E_{im}]}$$

where $\exp(\gamma_m ' he_i)$ is heterogeneity in the variance of the error terms which are captured by, he_i, individual characteristics.

3. Examples of Discrete Choice Experiment surveys with labelled and unlabelled choice exercises

Below are reported the main choice set elements of two DCE applications, differentiated by the type of alternatives used (labelled versus unlabelled).

Paper 1:

"*Stated preferences of Finnish private homeowners for residential heating systems: A discrete choice experiment*".

Authors: Rouvinen and Matero (2013).

Alternatives: 6 labelled (specific) heating system alternatives: wood pellet boiler, solid wood fired boiler, district heat, electricity, ground heat (pump) and oil boiler.

Attributes:	wood pellet boiler	solid wood fired boiler	district heat	electricity	ground heat pump	oil boiler
Investment cost	13,000	10,000	10,000	9,000	10,000	5,000
Operating cost (euro/year)	1,500	950	1,400	3,100	1,150	3,150
CO2 emissions	1,300	600	3,300	1,100	400	9,000
Fine particle emissions	1,400	1,100	1,100	120	220	40
Requirement own work	2 hours/month	20 hours/month	None	None	None	15 min/month
I CHOOSE:	☐	☐	☐	☐	☐	☐

Attributes: 5 attributes - investment cost, annual operating cost, CO2 emissions, fine particle emissions and required own work.

Example of the choice experiment:

CHOICE 1

	Programme A	OR	Programme B
Waiting time	2 months		8 months
Distance travelled	5 miles		30 miles
Total health benefit	40 QALYs		20 QALYs
Share of health benefits	*For best off group:* 20% *For worst off group:* 20%		*For best off group:* 10% *For worst off group:* 30%

Which programme would you give priority to: *(please tick one)*
Programme A ☐
Programme B ☐

Paper 2:

"*Examining the attitudes and preferences of health care decision-makers process in relation to access, equity and cost-effectiveness: A discrete choice experiment*".

Authors: Ratcliffe, Bekker, Dolan, and Edlin (2009).

Alternatives: 2 generic health programme alternatives: Programme A, Programme B.

Attributes: 4 attributes - total health benefit from each programme, the share of total health benefits, the waiting time to receive specialist, the distance travelled to hospital to receive treatment.

Example of the choice experiment:

The main aspect that affects the reliability of DCM results is a not well-defined frame for a choice experiment. On this point, it is possible to use unlabelled (or generic) alternative in the choice experiment (as done in the "health care programme case study" – Paper 2) but it is well defined and limited to the health sector and with specific and "easy to understand" attributes (e.g. waiting time to receive specialist: two months). This allowed to produce (estimated) coefficients related to a generic health care programme and not specific, for instance, of the booking system for ultrasound services. This approach allows knowing about common individual preferences across all the different types of health care services.

However, it is also possible to use a labelled (specific) choice experiment (as done in the "residential heating system case study" – Paper 1), necessarily related to a specific measure. In the reported example, the aim of the study was to analyse the individual preferences among wood pellet boilers, solid wood fired boilers, district heat, electricity, ground heat (pump) and oil boiler heating systems, i.e. specific types of heating systems. With this approach it is possible to estimate the heating system specific parameters.

4. List of Acronyms

ASC: Alternative Specific Constant

CAPI: Computer-Assisted Personal Interviewing

CASI: Computer-Assisted Self-Interviewing

CAPI: Computer-Assisted Telephone interviewing

CAWI: Computer-Assisted Web Interviewing

DCE: Discrete Choice Experiment

DCM: Discrete Choice Model

ECL: Error Component Logit

GAINS: Greenhouse Gas and Air Pollution Interactions and Synergies

GEV: Generalized extreme value

GHG: Greenhouse gas

IIA: Independence of Irrelevant Alternatives

IID: Independent and Identically Distribution

MNL: Multinomial Logit

RP: Revealed Preference

RPL: Random Parameter Logit

SEFIRA: Socio-Economic implications For Individual Responses to Air Pollution Policies in EU +27

SP: Stated Preference

References

A. Lòpez-Pita, F. Robusté. (2003). *The Madrid-Barcelona high-speed line.* Paper presented at the Institution of Civil Engineers.

Aaker, D.a., & Day, G.S. (1990). *Marketing Research* (Vol. IV edition). New York: Wiley.

Adamowicz, W., Louviere, J., & Williams, M. (1994). Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities. *Journal of Environmental Economics and Management, 26*(3), 271-292. Adler, Nicole. (2001). Competition in a deregulated air transportation market. *European Journal of Operational Research 129*, 337-345.

Ahn, Jiwoon, Jeong, Gicheol, & Kim, Yeonbae. (2008). A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete-continuous choice approach. *Energy Economics, 30*(5), 2091-2104.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179-211.

Allenby, G.M., Arora, N., & Ginter, J.L. (1995). Incorporating prior knowledge into the analysis of conjoint studies. *Journal of Marketing Research, 32*, 152-162.

Allenby, G.M., & Rossi, P.E. (1999). Marketingmodels of consumer heterogeneity. *Journal of Econometrics, 89*, 57-78.

Alpizar, F., Carlsson, F., & Martinsson, P. (2001). Using choice experiments for non-market valuation. *Economic Issues, 8*, 83-110.

Alvarez-Daziano, Ricardo, & Bolduc, Denis. (2009). *Canadian consumers' perceptual and attitudinal responses toward green automobile technologies: an application of Hybrid Choice Models*. Paper presented at the 2009 EAERE-FEEM-VIU European Summer School in Resources and Environmental Economics: Economics, Transport and Environment.

Amann, Markus. (2012). The GAINS Integrated Assessment Model: IIASA for the European consortium for Modelling of Air Pollution and Climate Strategies - EC4MACS.

Amann, Markus, Bertok, Imrich, Borken-Kleefeld, Jens, Cofala, Janusz, Heyes, Chris, Höglund-Isaksson, Lena, Winiwarter, Wilfried. (2011). Cost-effective control of air quality and greenhouse gases in Europe: Modeling and policy applications. *Environmental Modelling & Software, 26*(12), 1489-1501.

Amann, Markus, Bertok, Imrich, Borken, Jens, Cofala, Janusz, Heyes, Chris, Hoglund, Lena, Winiwarter, Wilfried. (2008). GAINS: potentials and costs for GHG mitigation in Annex I Countries (Methodology). Laxemburg: IIASA.

Amann, Markus, Cofala, Janusz, Heyes, Chris, Klimont, Zbigniew, Mechler, Reinhard, Posch, Max, & Schöpp, Wolfgang. (2004). RAINS model review 2004 – 1 Modelling of emission control potentials and costs. Laxenburg: IIASA.

Anderson, S., Palma, A. De, & Thiesse, J.F. (1992). *Discrete Choice Theory of Product Differentiation*. Cambridge: MIT Press.

Andrews, R.L., Ainslie, A., & Currim, I.S. (2002). An empirical comparison of logit choice models with discrete versus continuous representations of heterogeneity. *Journal of Marketing Research, 39*, 479-487.

Araña, Jorge E., & León, Carmelo J. (2009). Understanding the use of non-compensatory decision rules in discrete choice experiments: The role of emotions. *Ecological Economics, 69*(8-9), 2316-2326.

Artís, Manuel, Ayuso, Mercedes, & Guillén, Montserrat. (2002). Detection of automobile insurance with discrete choice models and misclassified clamins. *The Journal of Risk and Insurance, 69*(3), 325-340.

Bakker, Sjoerd, & Jacob Trip, Jan. (2013). Policy options to support the adoption of electric vehicles in the urban environment. *Transportation Research Part D: Transport and Environment, 25*(0), 18-23.

Barrett, M. (2005). *The potential for use of alternative scenarios for implementation of NTM in IAM*. Paper presented at the Workshop on the Importance of Non-Technical Measures for Reductions in Emissions of Air Pollutants and How to Consider Them in Integrated Assessment Modelling, Goteborg, Sweden.

Bates, J. (2011). Implementation of Panel Data with Unlabeled Alternatives. Retrieved Retrieved from: http://tech.groups.yahoo.com/group/biogeme/message/1632

Bell, P.A., Fisher, J.D., Baum, A., & Greene, T.C. (1990). *Environmental Psychology*: Harciurt Brace Jovanovich College Publishers.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short-term travel decisions. In R. Hall (Ed.), Handbook of Transportation Science, International Series in Operations Research and Management Science (Vol. 23). Kluwer.

Ben-Akiva, M., Bierlaire, M., Bolduc, D., & Walker, J. (2008). *Discrete Choice Analysis*.

Ben-Akiva, M.D., McFadden, T., Gärling, D., Gopinath, J., Walke, J., Bolduc, D., . . . Rao, V. (1999). Extended Framework for Modeling Choice Behavior. *Marketing Letters, 10*(3), 187-203.

Ben-Akiva, Moshe. (2008). *Stated Preference Surveys. Presented at the Discrete Choice Analysis: Predicting Demand and Market Shares*. École Polytechnique Fédérale de Lausanne, Switzerland.

Ben-Akiva, Moshe, Bolduc, D., & Bradley, M. (1993). Estimation of travel choice models with randomly distributed values of time. *Transportation Research Record, 1413*, 88-97.

Ben-Akiva, Moshe, & Lerman, Steven. (1985). *Discrete choice analysis: theory and application to travel demand*. Cambridge, London: The MIT Press.

Beville, Stephen, & Kerr, Geoffrey. (2010). *Fishing For More Understanding: A Mixed Logit-error Component Model of Freshwater Angler Site Choice*. Paper presented at the 4th World Congress of Environmental Resource Economists, Montreal, Quebec.

Bhat, C.R. (1995). A heteroscedastic extreme value model of intercity travel mode choice. *Transportation Research B, 29*(6), 471-183.

Bhat, C.R. (1998). Accommodating variations in responsiveness to level-of-service measures in travel mode choice modelling. *Transportation Research A, 32*(7), 495-507.

Bhat, Chandra R., & Castelar, Saul. (2002). A unified mixed logit framework for modeling revealed and stated preferences: formulation and application to congestion pricing analysis in the San Francisco Bay area. *Transportation Research Part B: Methodological, 36*(7), 593-616.

Bickersta, Karen, & Walker, Gordon. (2001). Public understandings of air pollution: the localisation' of environmental risk. *Global Environmental Change, 11*, 133-145.

Birol, E., Karousakis, K., & Koundouri, P. (2006). Using a choice experiment to account for preference heterogeneity in wetland attributes: the case of Cheimaditida wetland in Greece. *Ecological Economics, 60*, 145-156.

Bliemer, M.C., & Rose, J.M. (2005). Efficiency and Sample Size Requirements for StatedChoice Studies (pp. ITLS-WP-05-08). Sydney: Institute of Transport and Logistics Studies, University of Sydney.

Bliemer, Michiel C. J., & Rose, John M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B: Methodological, 44*(6), 720-734.

Bliemer, Michiel C. J., & Rose, John M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A: Policy and Practice, 45*(1), 63-79.

Blundell, R., Duncan, A., McCrae, J., & Meghir, C. (2000). The labour market impact of the working families–tax credit. *Fiscal Studies, 21*, t5-104.

Bolduc, Denis, & Alvarez-Daziano, Ricardo. (2010). On estimation of Hybrid Choice Models.

Boyd, J., & Mellman, R. (1980). The Effect of Fuel Economy Standards on the U.S. Automotive Market: An Hedonic Demand Analysis. *Transportation Research B, 14*(5), 367-378.

Brand, Christian, Moon, David, Watkiss, Paul, Hartje, Johannes, Sessa, Carlo, Ricci, Andrea, Vantelon, Alain. (2000). CANTIQUE deliverable 6 - final report: TÜV Immissionsschutz und Energiesysteme GmbH.

Bristow, Abigail L., Wardman, Mark, Zanni, Alberto M., & Chintakayala, Phani K. (2010). Public acceptability of personal carbon trading and carbon tax. *Ecological Economics, 69*(9), 1824-1837.

Buzzelli, M., Jerrett, M., Burnett, R., & Finkelstein, N. (2003). Spatiotemporal Perspectives on Air Pollution and Environmental Justice in Hamilton - Canada 1985-1996. *Annals of the Association of American Geographers, 93*, 557-573.

Cameron, Trudy Ann, & DeShazo, J. R. (2013). Demand for health risk reductions. *Journal of Environmental Economics and Management, 65*(1), 87-109.

Cascetta, E., & Pappola, A. (2001). Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. *Transportation Research C, 9*, 249-263.

Cherchi, Elisabetta. (2003). *Il valore del tempo nella valutazione dei sistemi di trasporto*. Milano: FrancoAngeli.

Cherchi, Elisabetta, Cirillo, C., & Ortuzar, J. de D. (2009). *A mixed logit mode choice model for panel data: accounting for different correlation over time periods.* Paper presented at the International Choice Modelling Conference, Harrogate.

Chiu, Yi-Chang, & Tzeng, Gwo-Hshiung. (1999). The market acceptance of electric motorcycles in Taiwan experience through a stated preference analysis. *Transportation Research Part D: Transport and Environment, 4*(2), 127-146.

Chu, C. (1989). *A paired combinatorial logit model for travel demand analysis.* Paper presented at the Fifth World Conference on Transportation Research, Ventura.

D'Elia, I., Bencardino, M., Ciancarella, L., Contaldi, M., & Vialetto, G. (2009). Technical and Non-Technical Measures for air pollution emission reduction: The integrated assessment of the regional Air Quality Management Plans through the Italian national model. *Atmospheric Environment, 43*(39), 6182-6189.

Davis, George C., & Wohlgenant, Michael K. (1993). Demand Elasticities from a Discrete Choice Model: The Natural Christmas Tree Market. *American Journal of Agricultural Economics, 75*(3), 730-738.

Dawes, R.M. (1980). Social dilemmas. *Annual Review of Psychology, 31*, 169-193.

Day, Brett, Bateman, Ian J., Carson, Richard T., Dupont, Diane, Louviere, Jordan J., Morimoto, Sanae, Wang, Paul. (2012). Ordering effects and choice set awareness in repeat-response stated preference studies. *Journal of Environmental Economics and Management, 63*(1), 73-91.

de Groot, Judith I. M., & Schuitema, Geertje. (2012). How to make the unpopular popular? Policy characteristics, social norms and the acceptability of environmental policies. *Environmental Science & Policy, 19–20*(0), 100-107.

Department for Transport. (2013). Supplementary Guidance - Bespoke Mode Choice Models. London: Transport Appraisal and Strategic Modelling (TASM) Division - DfT.

Di Ciommo, Floridea, Monzón, Andrés, & Fernandez-Heredia, Alvaro. (2013). Improving the analysis of road pricing acceptability surveys by using hybrid models. *Transportation Research Part A: Policy and Practice, 49*(C), 302-316.

Domenich, Thomas, & McFadden, Daniel. (1975). *Urban Travel Demand - A Behavioural Analysis*. Amsterdam: North Holland Publishing.

Douglas, M. (1985). Risk Acceptability According to the Social Sciences (Vol. 11). New York: Russell Sage Foundation Social Research Perspectives Occasional Report on Current Topics.

Drouet, L., & Reis, L. Aleluia. (2012). Implementation of a Full Air Quality Model in an Integrated Assessment Model: The Luxembourg Energy Air Quality model.

Eriksson, Louise, Garvill, Jörgen, & Nordlund, Annika M. (2006). Acceptability of travel demand management measures: The importance of problem awareness, personal norm, freedom, and fairness. *Journal of Environmental Psychology, 26*(1), 15-26.

Eriksson, Louise, Garvill, Jörgen, & Nordlund, Annika M. (2008). Acceptability of single and combined transport policy measures: The importance of environmental and policy specific beliefs. *Transportation Research Part A: Policy and Practice, 42*(8), 1117-1128.

European Commission Eurobarometer. (2013). Attitudes of Europeans towards air quality - report.

Ewing, G.O., & Sarigöllü, E. (1998). Car fuel-type choice under travel demand management and economic incentives. *Transportation Research Part D: Transport and Environment, 3*(6), 429-444.

Farrar, D.E., & Donald, R.R. (1967). Multicollinearity in Regression Analysis: The Problem Revisited. *Review of Economics and Statistics, 49*(1), 92-107.

Ferrini, S., & 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*, 342-363.

Fezzi, Carlo, Bateman, Ian J., & Ferrini, Silvia. (2013). Using revealed preferences to estimate the Value of Travel Time to recreation sites. *Journal of Environmental Economics and Management*.

Forinash, C.V., & Koppelman, F.S. (1993). Application and Interpretation of Nested Logit Models of Intercity Mode Choice. *Transportation Research Record, 1413*, 98-106.

Friedman, Milton. (1953). Essays in Positive Economics. *The University of Chicago Books*, 334.

Frode, Alfnes, Atle, Guttormsen, Gro, Steine, & Kari, Kolstad. (2005). *Consumers' willingness to pay for the color of salmon:a choice experiment with real economic incentives*. Paper presented at the American Agricultural Economics Association, 2005 Annual meeting, Providence.

Fuller, W.C., Manski, C., & Wise, D. (1982). New Evidence on the Economic Determinants of Post-secondary Schooling Choices. *Journal of Human Resources, 17*(4), 477-498.

Gabriel, S.A., & Rosenthal, S.S. (1989). Household location and race: estimates of a multinomial logit model. *The Review of Economics and Statistics, 17*(2), 240-249.

Gilbride, T.J., Lenk, P.J., & Brazell, J.D. (2008). Market share constraints and the loss function in choice-based conjoint analysis. *Marketing Science, 27*, 995-1011.

Giuliano, G. (1994). Equity and Fairness Considerations of Congestion Pricing. *Curbing Gridlock: Peak-Period Fees To Relieve Congestion, 2*, 250-279.

Glerum, Aurelie, Themans, Michael, & Bierlaire, Michel. (2011). *Modeling demand for electric vehicles: the effect of car users' attitudes and perceptions*. Paper presented at the Second International Choice Modeling Conference.

Goett, Andrew, Hudson, Kathleen, & Train, K. (2002). Customer Choice Among Retail Energy Suppliers. *Energy Journal, 21*(4), 1-28.

Green, P.E. (1974). On the Design of Choice Experiments Involving Multifactor Alternatives. *Journal of Consumer Research, 1*(2), 61–68.

Greene, William H., & Hensher, David A. (2007). Heteroscedastic control for random coefficients and error components in mixed logit. *Transportation Research Part E: Logistics and Transportation Review, 43*(5), 610-623.

Greene, William H., Hensher, David A., & Rose, John. (2006). Accounting for heterogeneity in the variance of unobserved effects in mixed logit models. *Transportation Research Part B: Methodological, 40*(1), 75-92.

Haab, T.C., & McConnell, K.E. (2002). *Valuing environmental and natural resources*. Cheltenham, UK: Edward Elgar Publishing Limited.

Hall, Jane. (2004). Can we design a market for competitive health insurance? *CHERE discussion paper, 53 (February)*.

Hanemann, W.M. (1984). Discrete/continuous models of consumer demand. *Econometrica, 52*, 541-561.

Harrington, Winston, Krupnick, Alan J., & Alberini, Anna. (2001). Overcoming public aversion to congestion pricing. *Transportation Research Part A: Policy and Practice, 35*(2), 87-105.

Harsman, B., Pädam, S., & Wijkmark, B. (2000). Ways and Means to Increase the Acceptance of Urban Road Pricing *Deliverable D4. EU-project PRIMA*: Funded by the European Commission.

Hensher, D.A., & Greene, W.H. (2003). Mixed logit models: state of practice. *Transportation, 30*(2), 133-176.

Hensher, D.A., Rose, J.M., & Greene, W.H. (2005). *Applied Choice Analysis: A Primer*. Cambridge: Cambridge University Press.

Hensher, David A., Rose, John M., & Greene, William H. (2008). Combining RP and SP data: biases in using the nested logit 'trick' – contrasts with flexible mixed logit incorporating panel and scale effects. *Journal of Transport Geography, 16*(2), 126-133.

Hess, S., & Train, K. (2011). Recovery of inter- and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B, 45*(7), 973-990.

Hindsley, Paul, Landry, Craig E., & Gentner, Brad. (2011). Addressing onsite sampling in recreation site choice models. *Journal of Environmental Economics and Management, 62*(1), 95-110.

Hinkel, J. (2009). The PIAM approach to modular integrated assessment modelling. *Environmental Modelling & Software, 24*(6), 739-748.

Hoyos, David. (2010). The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics, 69*(8), 1595-1603.

Hsu, Chaug-Ing, & Chen, Yu-Chiang. (2005). A Model on Market Share Distribution between Air Transportation, High-Speed Rail, and Automobiles. *Journal of the Eastern Asia Society for Transportation Studies, 6*, 2003-2018.

Jacobson, N.S., Christensen, A., Prince, S.E., Cordova, J., & Eldridge, K. (2000). Integrative behavioral couple therapy: An acceptance based, promising new treatment for couple discord. *Journal of Consulting and Clinical Psychology, 68*, 351-355.

Janssen, S., Ewert, F., Li, H., Athanasiadis, I.N., Wien, J.J.F., Thérond, O., . . . Ittersum, M.K. van. (2009). Defining assessment projects and scenarios for policy support: use of ontology in integrated assessment and modelling. *Environmental Modelling & Software, 24*(12), 1491-1500.

Jensen, Anders Fjendbo, Cherchi, Elisabetta, & Mabit, Stefan Lindhard. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment, 25*(0), 24-32.

Jessoe, Katrina. (2013). Improved source, improved quality? Demand for drinking water quality in rural India. *Journal of Environmental Economics and Management, 66*(3), 460-475.

Johnson, F.R., & Desvousges, W.H. (1997). Estimating Stated Preferences with Rated-Pair Data: Environmental, Health, and Employment Effect of Energy Programs. *Journal of Environmental and Management, XXXIV*(1), 79-99.

Jones, P.M. (2001). Gaining Public Support for Road Pricing through a package Approach. *Traffic Engineering and Control, 4*, 194-196.

Karlstrom, A. (2001). Developing Generalized Extreme Value Models Using the Pickands' Representation Theorem.

Keane, Michael P. (2004). *Modeling Health Insurance Choice Using the Heterogeneous Logit Model*. Paper presented at the Center for Health Economics Research and Evaluation (CHERE), , Sydney, Australia.

Kessels, R., Goos, P., & Vandebroek, M. (2006). A comparison of criteria to design efficient choice experiments. *Journal of Marketing Research*, 409-419.

Khan, Omer. (2007). *Modelling passenger mode choice behaviour using computer aided stated preference data.* (PhD thesis (IF49)), Queenseland University of Technology.

Klaassen, G., Amann, Markus, Berglund, C., Cofala, J., Hoeglund-Isaksson, L., Heyes, C., Winiwarter, W. (2004). The Extension of the RAINS Model to Greenhouse Gases. Laxenburg: IIASA.

Kupfer, Franziska. (2012). *The airport choice for scheduled freighter operations in Europe.* (PhD thesis), University of Antwerp, Antwerp.

Lancaster, K. (1966). A new approach to Consumer Theory. *Journal Pol. Economics, 74*, 321-157.

Leeuw, E.D., Hox, J.J., & G.Snujkers. (1995). The Effect of Computer-Assisted Interviewing on Data Quality: A Review. *Journal of Market Research Society, XXXVII*(4), 325-344.

Lidskog, R., & Sundqvist, G. (2011). *Governing the Air. The Dynamics of Science, Policy and Citizen Interaction*. Cambridge: MIT Press.

Louviere, J.J. (1988). *Analyzing Decision Making: Metric Conjoint Analysis*. Newbury Park, California: SAGE.

Louviere, Jordan J., Flynn, Terry N., & Carson, Richard T. (2010). Discrete Choice Experiments Are Not Conjoint Analysis. *Journal of Choice Modelling, 3*(3), 57-72.

Louviere, Jordan J., Swait, Joffre D., & Hensher, David A. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press.

Luce, R.D. (1959). *Individual Choice Behavior: A Theoretical Analysis*: Dover Publications.

Luk, J., & Chung, E. (1997). Public acceptance and technologies for road pricing (Vol. Research Report n. 307). Vermont: ARRB Transport Research Ltd.

Manski, F. (1973). *The Analysis of Qualitative Choice.* Department of Economics, MIT, Cambridge.

Manski, F. (1977). The Structure of Random Utility Models. *Theory and Decision, 8*, 228-254.

Marchi, B. De, Pellizzoni, L., & Ungaro, D. (2001). *Il rischio ambientale*. Bologna: Il Mulino.

Marcucci, E., Stathopoulos, A., Gatta, V., & Valeri, Eva. (2012). A Stated Ranking Experiment to Study Policy Acceptance: The Case of Freight Operators in Rome's LTZ. *Italian Journal of Regional Science, 11*(3), 11-30.

Marschak, J. (1960). Binary-choice constraints and random utility indicators. In K. J. Arrow, S. Karlin & P. Suppes (Eds.), *Mathematical Methods in the Social Sciences* (pp. 312–329). Stanford: Stanford University Press.

Mayeres, Inge, & Proost, Stef. (2003). Reforming transport pricing: an economic perspective on equity, efficiency and acceptability. In B. S. J. Schade (Ed.), Economic Perspective on Equity and Acceptability: Acceptability of Transport Pricing Strategies: Elsevier Science.

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

McFadden, Daniel. (1981). *Econometrics Models of Probabilistic Choice, Structural Analysis of Discrete Data*. Cambridge: MIT Press.

McFadden, Daniel, & Train, Kenneth. (2000). Mixed MNL models of discrete response. *Journal of Applied Econometrics, 15*, 447-470.

Miravete, E. (2002). Estimation demand for local telephone service with asymmetric information and optional calling plans. *Review of Economic Studies, 69*, 943-971.

MIRO. (1995). MIRO Final Project. Brussels: Delivareble 8 to the European Commission, DG XIII DRIVE Programme.

Nlogit version 4.0. (2010). Student Reference Guide. *W.H. Greene, Econometric Software Inc.*

Orme, B. (1998). Sample Size Issue for Conjoint Analysis Studies.

Oxley, T., & ApSimon, H. (2007). Space, time and nesting Integrated Assessment Models. *Environmental Modelling & Software, 22*, 1732-1749.

Poortinga, Wouter, Spence, Alexa, Demski, Christina, & Pidgeon, Nick F. (2012). Individual-motivational factors in the acceptability of demand-side and supply-side measures to reduce carbon emissions. *Energy Policy, 48*(0), 812-819.

Potoglou, D., & Kanaroglou, P.S. (2007). Household demand and willingness to pay for clean vehicles. *Transportation Research Part D: Transport and Environment, 12*(4), 264-274.

Ratcliffe, Julie, Bekker, Hilary L., Dolan, Paul, & Edlin, Richard. (2009). Examining the attitudes and preferences of health care decision-makers in relation to access, equity and cost-effectiveness: A discrete choice experiment. *Health Policy, 90*, 45-57.

Reis, S., Nitter, S., & Friedrich, R. (2005). Innovative approaches in integrated assessment modelling of European air pollution control strategiese - Implications of dealing with multi-pollutant multi-effect problems. *Environmental Modelling & Software, 20*, 1524-1531.

Revelt, D., & Train, K. (2000). Customer-specific taste parameters and mixed logit *Working Paper 00-274*. Berkeley: University of California.

Revelt, David, & Train, K. (1998). Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level. *Review of Economics and Statistics, 80*(4), 647-657.

Rienstra, S. A., Rietveld, P., & Verhoef, E. T. (1999). The social support for policy measures in passenger transport. - A statistical analysis for the Netherlands. *Transportation Research Part D: Transport and Environment, 4*(3), 181-200.

Rotaris, Lucia. (2005). Linee guida per la progettazione delle indagini di analisi congiunta. In E. Marcucci (Ed.), *I modelli a scelta discreta per l'analisi dei trasporti - teoria, metodi e applicazioni*: Carocci editore.

Rouvinen, S., & Matero, J. (2013). Stated preferences of Finnish private homeowners for residential heating systems: A discrete choice experiment. *Biomass and Bioenergy, 57*(0), 22-32.

Ryan, Mandy. (2004). Discrete choice experiments in health care. *BMJ2004, http://dx.doi.org/10.1136/bmj.328.7436.360*.

Sándor, Z., & Wedel, M. (2005). Heterogeneous conjoint choice designs. *Journal of Marketing Research, 42*, 210-218.

Sanko, Nobuhiro. (2001). *Guidelines for Stated Preference Experiment Design.* (Master thesis), School of International Management Ecole Nationale des Ponts et Chaussées, Rue de la Fontaine, France.

Sarasua, W.A., & Meyer, M.D. (1996). New technologies for household travel surveys. In Transportation Research Board (Ed.), *Conference on Household Travel Surveys: New Concepts and Research Needs*. Irvine, California.

Savage, S.J., & Waldman, D.M. (2008). Learning and fatigue during choice experiments: a comparison of online and mail survey modes. *Journal of Applied Econometrics*(23), 351-371.

Schade, J., & Baum, M. (2007). Reactance or acceptance? Reactions towards the introduction of road pricing. *Transportation Research Part A, 41*, 42-48.

Schade, J., & Schlag, B. (2000). Acceptability of urban transport pricing. *VATT research reports, Helsinki*.

Schade, Jens, & Schlag, Bernhard. (2003). Acceptability of urban transport pricing strategies. *Transportation Research Part F: Traffic Psychology and Behaviour, 6*(1), 45-61.

Schlag, B., & Teubel, U. (1997). Public acceptability of transport pricing. *IATSS Research, 21*, 134-142.

Schöpp, W., Amann, M., Cofala, J., Heyes, C., & Klimont, Z. (1999). Integrated assessment of European air pollution emission control strategies. *Environmental Modelling & Software, 14*, 11-19.

Schucht, S. (2005). *Including structural changes into IAM: some ideas and possible implications*. Paper presented at the Workshop on the Importance of Non-Technical Measures for Reductions in Emissions of Air Pollutants and How to Consider Them in Integrated Assessment Modelling, Goteborg, Sweden.

Sell, Anna, Mezei, József, & Walden, Pirkko. (2014). An attitude-based latent class segmentation analysis of mobile phone users. *Telematics and Informatics, 31*(2), 209-219.

Slento, Erik, Nielsen, Ole-Kenneth, Hoffmann, Leif, Winther, Morten, Fauster, Patric, Mikkelsen, Mette Hjorth, & Gyldenkoerne, Steen. (2009). NEC-2020 Emission Reduction Scenarios. Assessment of intermediary GAINS emission reduction scenarios for Denmark aiming at the upcoming 2020 National Emission Ceiling EU directive (Vol. NERI TEchnical Report n. 746). Denmark: National Environmental Research Institute, Aarhus University.

Soerensen, Hans Christian, Hansen, Lars Kjeld, Hansen, Rune, & Hammarlund, Karin. (2003). European Thematic Network on Wave Energy: Public acceptability: EMU and Hammarlund Consulting.

Stankey, G.H., & Clark, R.N. (1991). *Social aspects of New Perspectives in Forestry: a problem analysis*. Milford, PA.

Steg, L., & Vlek, C. (1997). The Role of Problem Awareness in Willingness-to-Change Car-Use and in Evaluating Relevant Policy Measures. In T. Rothengatter & E. C. Vaya (Eds.), *Traffic and Transport Psychology* (pp. 465-475). Amsterdam: Pergamon.

Sternhufvud, C., Belhaj, M., & Åstrom, S. (2006). The Feature of Non Technical Measures and Their Importance in Air Pollutant Reduction – Applied to Two Meta Analysis *IVL Report B1656*.

Sternhufvud, Catarina, Belhaj, Mohammed, & Åström, Stefan. (2006). The feature of Non technical measures and their importance in air pollutants reduction - applied to two meta-analysis. Stockholm: IVL Swedish Environmental Research Institute.

Strazzera, Elisabetta, Mura, Marina, & Contu, Davide. (2012). Combining choice experiments with psychometric scales to assess the social acceptability of wind energy projects: A latent class approach. *Energy Policy, 48*(0), 334-347.

Svenson, O. (1979). Process descriptions of decision-making. *Organizational Behavior and Human Performance, 23*, 86-112.

Thurston, K. (1927). A law of comparative judgement. *Psychological Review, 34*, 273-286.

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

Train, Kenneth E. (2002). *Discrete choice methods with simulations*. Cambridge: Cambridge University Press.

Tversky, A. (1972). Elimination by aspects: a theory of choice. *Psychological Review, 79*, 281-299.

UCL. (2004). Deliverable 2 - Non-technical emissions abatement options (MERLIN model). London: University College London.

Valeri, Eva. (2013). *Air and rail transport in the Rome-Milan corridor: competition policy implications based on a discrete choice analysis.* University of Trieste, PhD thesis, unpublished work.

Van Soest, A. (1995). Structural models of family labor supply: a discrete choice approach. *Journal of Human Resources, 30*, 63-88.

Viegas, J. (2001). Making urban road pricing acceptable and effective: Searching for quality and equity in urban mobility. *Transport Policy, 8*, 289-294.

Viegas, J., & Macario, R. (2002). *Price Acceptability in the transport sector*. Paper presented at the MC_ICAM Conference on Acceptability of Transport Pricing strategies, Dresden.

Viegas, J., Macario, R., Goller, L., & Raux, C. (2000). Socio-economic principles for price acceptability: Deliverable D2 - EU-project PATS, funded by the European Commission, 4th framework Transport RTD.

Vlassenroot, Sven, Brookhuis, Karel, Marchau, Vincent, & Witlox, Frank. (2010). Towards defining a unified concept for the acceptability of Intelligent Transport Systems (ITS): A conceptual analysis based on the case of Intelligent Speed Adaptation (ISA). *Transportation Research Part F: Traffic Psychology and Behaviour, 13*(3), 164-178.

Vrtic, M., Schuessler, N., Erath, A., & Axhausen, K. W. (2007). Design elements of road pricing schemes and their acceptability.

Wagner, Fabian. (2010). Estimating co-benefit with GAINS model - Examples from India and China.

Warren, R.F., & ApSimon, H.M. (1999). Uncertainties in integrated assessment modelling of abatement strategies: illustrations with the ASAM model. *Environmental Science & Policy, 2*, 439-456.

Watzlawick, Beavin, & Jackson. (1967). Communications theorist Paul Watzlawick dies.

Wen, C.-H., Wang, M.-J., & Lan, L.W. (2005). Discrete choice modeling for bundled automobile insurnce policies. *Journal of the Eastern Asia Society for Transportation Studies, 6*, 1914-1928.

Yu, J., Goos, P., & Vandebroek, M. (2009). Efficient conjoint choice designs in the presence of respondent heterogeneity. *Marketing Science, 28*, 122–135.

Zapata, Hector O., Sambidi, Pramod R., & Dufour, Elizabeth A. (2007). *Choice Models in Policy Analysis*. Paper presented at the Southern Agricultural Economics Association Annual Meetings, Mobile, Alabama.

Zhang, Yong, Yu, Yifeng, & Zou, Bai. (2011). Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV. *Energy Policy, 39*(11), 7015-7024.