The role of attitudes in determining individual behavior in transportation - from psychology to discrete choice modeling

A dissertation presented by

Antonio Borriello

Submitted to the

Faculty of Economics
Università della Svizzera Italiana

For the degree of

Ph.D. in Economics

Thesis Committee:

Prof. Rico Maggi, supervisor, Università della Svizzera italiana
Prof. Massimo Filippini, internal examiner, Università della Svizzera italiana
Prof. Kay Axhausen, external examiner, ETH Zürich

January 2017

"If we knew what it was we were doing, it would not be called research, would it?"

Albert Einstein

Contents

Introduction 5
References 12
Chapter 1. Exploiting Evaluative Space Grids to stochastically measure ambivalence/indifference 14
Abstract 14
1.1. Introduction 15
1.2. Ambivalence and indifference measures 19
1.3. Methodology 24
1.3.1. Tobit Model: Indirect (scores) approach 24
1.3.2. Ordered Logit model approach: Direct (observed ratings) approach 25
1.4. Empirical data 29
1.5. Estimation sample results 31
1.5.1. Tobit Model: Indirect (scores) approach 31
1.5.2. Ordered Logit model approach: Direct (observed ratings) approach 32
1.6. Out of sample results 37
1.6.1. Tobit Model: Indirect (scores) approach 37
1.6.2. Ordered Logit model approach: Direct (observed ratings) approach 38
1.7. Discussion and conclusions 39
References 42
Chapter 2. The implementation of the Evaluative Space Grid in a hybrid choice model to overcome the disadvantages of measuring attitudes using common scales. 45
Abstract 45
2.1. Introduction 46
2.2. Evaluative Space Grid (ESG) 49
2.3. Methodology 50
2.4. Empirical data 54
2.4.1. Sample composition 54
2.4.2. Structure of the questionnaire: SP experiment 55
2.4.3. Structure of the questionnaire: attitudinal questions 57
2.5. The model 58
2.6. Results 62
2.6.1. Structural model 62
2.6.2. Measurement model 63

2.6.3. Discrete choice model 66
2.6.4. Effect of latent variables 68
2.7. Discussion and conclusions 71
References 74
Chapter 3. Generalized versus localized attitudinal responses in discrete choice 77
Abstract 77
3.1. Introduction 78
3.2. Theoretical background 81
3.3. Case study 82
3.3.1. The survey 82
3.3.2. The evaluative space grid (ESG) 85
3.3.3. Sample composition 86
3.4. Model 87
3.5. Results 89
3.5.1. Localized attitudes 91
3.5.2. Structural equation model 94
3.5.3. Choice model 98
3.5.4. Discussing the different models 100
3.6. Conclusions 101
References 104
Conclusion 107

Introduction

This dissertation is the outcome of a PhD program in Economics focused on modelling individual preferences in the context of transportation. Its ambition is to improve the understanding of individual choices using discrete choice model techniques (HDCM). The framework of HDCM consists of the simultaneous estimation of two processes, a structural equation model and a choice model. Whilst the former explores the composition of the psychological factors, the latter predicts individual choices among a set of discrete alternatives. This methodology was proposed by McFadden (1986) in response to the critiques of behavioral economics regarding the acceptance of individual rationality in the context of choice behavior. Indeed, behavioral economists disagree with the bounded rationality of economic agents and suggested a wider theoretical framework according to which psychological, social, cognitive, and emotional factors play a notable role in determining economic decisions of individuals (Kahneman et al., 1991; Kahneman and Ritov, 1994; Kahneman et al., 1999; Thaler, 1980 and 1985). In accordance with this theoretical framework, McFadden states that "the theory of the economically rational utility-maximizing consumer, interpreted broadly to admit the effects of perception, state of mind, and imperfect discrimination, provides a plausible, logically unified foundation for the development of models of various aspects of market behavior" (p. S14, 1980). Hybrid discrete choice model represents a technique able to incorporate the irregularities and idiosyncratic features of choice behavior, due to perceptions, attitudes information processing, context and cognitive processes, into the systematic and invariant features typical of the random utility model (Ben-Akiva *et al.*, 2002). Within this framework, the random utility model (RUM) assumes that the characteristics of the decision-maker and the attributes of the alternatives affect the decision process leading to the revealed choice. The RUM is enhanced with several extensions, such as the inclusion of flexible disturbances, a latent segmentation of the population or of latent psychological factors, which reduce the error computed in modeling individual preferences.

In this setting, this dissertation aims at refining the way psychological factors are explored and framed in the context of hybrid discrete choice model and includes three original articles, which are presented as separate chapters. In any article, a methodological section, containing the innovation of the econometrics steps, is followed by empirical work, based on datasets collected in the context of transportation. Nevertheless, it is important to stress that the methodology described in this thesis can be applied to any context. The first two chapters elucidate the advantages of using the Evaluative Space Grid (ESG; Larsen *et al.*, 2009), which is an instrument to measure attitudinal indicators, in the framework of HDCM. Since the introduction of this methodology, numerous adaptations of the econometric framework have been proposed in order to make the model more suitable for specific cases (among others, mixed models, latent class models, multiple discrete-continuous models). However, whilst the choice model part has evolved, the methodology employed for exploring the psychological factors remained mostly unchanged. The rigidity of the structural equation model clashes with the innovative and remarkable findings concerning the psychological aspects leading to the choice. In order to reduce this "gap", the first two chapters of this dissertation attempt to improve the way psychological aspects are explored and are connected to the choice model in the framework of HDCM. Data were collected through a survey conducted in the context of a Swiss National Science Foundation project, namely PostCar World. Respondents, from three different linguistic regions of Switzerland, completed a stated preference experiment on mode choice for commuting purpose and stated their attitudes towards the *pleasure of driving* and *environmental inclination*, using the Evaluative Space Grid instrument.

A notable concern discussed in psychology related to the measurement of psychological factors, which may also affect the modeling of individual preferences, regards the distinction of individuals having an ambivalent or indifferent attitude. Indeed, common response measures for evaluating attitudes, emotions and affect, such as Likert and semantic differential scales, are unable to distinguish these two categories of individuals. Indifference implies that a subject has no interest in the stimuli being studied, being truly neutral in their attitude, reflected by low positive and negative reactions towards the object under evaluation. Ambivalence, on the other hand, suggests that the subject experiences both positive and negative valence towards the stimuli. When measured using traditional attitudinal scales, both attitudes will likely result in the subject choosing the neutral option of the scale (Kaplan, 1972; Thompson *et al.*, 1995). To overcome this issue, Larsen *et al.* proposed using the Evaluative Space Grid, which is a single-item measure of positivity and negativity. This instrument follows the theoretical model proposed by Cacioppo and Berntson (1994), namely the Evaluative Space Model, who demonstrate that both positive and negative feelings towards an object act as two distinct systems, allowing for the independent and simultaneous assessment of positive/negative attitudes towards an object. According to this theory, an increase in positive (negative) feelings is not necessarily connected to a decrease of negative (positive) feelings. This finding has resulted in the literature distinguishing between the concepts of ambivalence and indifference.

In several papers, ambivalence and indifference have been measured mainly by means of deterministic indices (Kaplan, 1972; Thompson *et al.*, 1995), which fail to recognize that recorded answers are the result of underlying psychological latent constructs, and hence are imprecise expressions of an individual's true attitude towards an object. Assuming attitudes are latent constructs, and hence not directly measurable, the use of scores seems anachronistic. In this chapter, we suggest two different approaches to model attitudes collected by means of ESGs according to their latent nature.

The first approach follows the scoring scheme proposed by Audrezet *et al.*'s (2016), who calculate a (censored) deterministic score based on the individual response. We propose modelling this score by means of a Tobit model, in which the latent dependent variable is predicted via socio-demographic variables. It is worth noting that the model accounts for censoring of the dependent variable, consistent with the bounds imposed when generating attitudinal scores using the approach proposed by Audrezet *et al.*.

In the second approach, using the observed attitudinal data captured using the ESG response mechanism, we demonstrate how attitudinal data can be analyzed using a system of ordered logit models. Also these models respect the assumption that the observed outcome obtained from the response mechanism used is based on a latent construct. Such latent variable is decomposed into two parts, a modelled component, and an unobserved error term which is randomly distributed over the population of interest. The model produces not only an estimate of the value of the latent variable based on the observed or modelled component used to explain the latent variable, but more importantly, the stochastic nature of the error term translates into a probabilistic prediction of the response outcome. By simultaneously estimating independent ordered logit models for the positive and negative domains of the ESG, the approach allows for separate latent processes to explain probabilistically the positive and negative domains of attitudes. Nevertheless, it is also possible to determine to what degree the two processes are related by accounting for the correlation. Finally, by placing restrictions on the parameter estimates derived from the various models, it is also possible to test to what degree different latent processes exist across the positive and negative attitudinal domains. It is our argument that for many applied fields, such as social behavior, political behavior and marketing, the distinction between individuals having an ambivalent or indifferent attitude is of primary importance and can add efficacy and efficiency to policies.

The second chapter of this dissertation illustrates the econometric steps to include the ESG in the framework of a hybrid discrete choice model. The rationale of this work stems from the inaccurate measurement of attitudes, which is common practice when modelling individual choices in transportation. From an econometric point of view, an attitude is a variable that cannot be directly measured (latent) but that can be defined through some indicators (or observable variables, items) net of an error. The first problem concerns the number of indicators used to define the attitude itself: because of their latent nature, the higher the number of observable variables suitable to measure the attitude, the lower the error computed in the measuring process will be. Therefore, the omission of relevant observable variables in defining an attitude increases the randomness of the latent variable and, as a consequence, reduce its efficacy. A second problem is the misspecification of the attitude itself. In many studies, choice modelers use a “direct measure” of what actually is a latent construct (e.g. the latent variable *comfort,* which should be measured by means of observable indicators, becomes a categorical attribute in the choice model) generating high aggregation of content. A poor discrimination of content is also caused by the positioning of the items, used for measuring attitudes, along the latent continuum. Otherwise stated, whilst psychologists include items with a positive, neutral and negative valence covering the entire latent continuum domain when exploring an attitude (i.e. they use appropriate wording aimed at capturing a possible positive, neutral and negative outcome of the attitude), choice modelers usually use only items with an extreme positive or a negative valence. A consequence of the lower discrimination and information is the aggregation of individuals with an indifferent or ambivalent attitude in choice modeling applications when a common response mechanism (e.g. Likert scale) is used. Indeed, as explained in the first chapter of this thesis, these two categories of respondents select the central values of the scale, making the segmentation unfeasible. To this aim, we propose using the Evaluative Space Grid, rather than a Likert scale to collect attitudinal variables. This tool is able to disentangle individuals with an indifferent and an ambivalent attitude, as well as those with a positive and a negative inclination. This chapter has a twofold ambition. From a theoretical perspective, it integrates the ESG in the framework of discrete choice modelling: the grids are modelled, in the structural equations, by means of two latent variables, representing positive and negative domains respectively, whilst, in the measurement equations, two ordered logit regressions link the observables items to the latent variables. The hybrid choice model does not include any specific parameters to measure a direct effect of indifference and ambivalence on the alternatives. Rather, probabilities of revealing an ambivalent or indifferent attitude are foreseen using the results of the structural equation model. In addition to the methodological contribution, this work tests the hypothesis that individuals with ambivalent and indifferent attitudes have different preferences in a context of transportation mode choice for commuting trips and therefore the distinction of such categories becomes of primary importance for making policies more effective. In particular, we show that subjects who consider commuting by private car comfortable/handy and uncomfortable/challenging at the same time (individuals revealing ambivalence) reveal different preferences from those who judge commuting by private car neither comfortable/handy nor uncomfortable/challenging (individuals having indifferent attitude), for 7 out of 8 alternatives of transport. Furthermore, respondents who have ambivalent and indifferent attitudes also respond differently if the proposed alternatives experience a change in cost, travel time or density of the transportation system. It is our argument that choice modelers use a limited number of items because of time and cost constraints, quality of responses and simplicity for defining an attitude. We partially share this practice but we do suggest to use a different tool (i.e. ESG) to measure attitudes, which is more appropriate when it is not possible to collect a large number of observable variables or specific items with a neutral valence. Furthermore, the ESG allows by construction the segmentation of respondents in case of high aggregation of content, limiting misspecification issues. Distinguishing individuals with an ambivalent and indifferent attitude is as important as identifying those with a positive and negative inclination. In different contexts, researchers showed that indifferent and ambivalent individuals act differently (Costarelli and Colloca, 2004; Yoo, 2010; Thornton, 2011) and such a distinction can suggest more effective policies. Nevertheless, to the best of my knowledge, so far no study in transportation research has provided any evidence on the different behavior of individuals having an indifferent or ambivalent attitude, whilst any research exploiting a hybrid choice model provides insights on the difference between subjects with a positive or negative attitude (such as environmental, pro/against-car, pro/against sharing modes inclinations).

The last chapter of this dissertation enters an ongoing debate in the psychological literature on the stability of attitudes and shows that different types of attitudes have a significant and notable impact on individual choices. Data was collected through an ad hoc survey conducted among people living and travelling in Sydney, who were asked to respond to the same attitudinal question, both prior to undertaking the choice experiment, and after each stated choice task. Within the psychological literature there appear to exist three different schools of thought as to whether or not attitudes are largely fixed or transient. The first school of thought identifies attitudes as long term stable constructs which are “memory-based”. According to this vision, an attitude towards an object is linked to one or more global evaluations that is brought to the mind once the object is encountered. This has led, for example, to the development of the MODE (in case of one evaluation, Fazio, 1990) and MCM (in case of more than one evaluations, Petty *et al.*, 2007) attitudinal model frameworks. The second school of thought assumes that attitudes are developed “on the spot”, being short term situational specific constructs. The APE model, proposed by Gawronski and Bodenhausen (2007), and the connectionist models, suggested by Schwarz (2007) and Conrey and Smith (2007), assume that associative and propositional processes linked to attitude formation are sensitive to contextual influences and that attitudes are constructed at the time a specific situation occurs as the evaluative judgments are formed only when required rather than being stored in longer term memory. A mediating vision on attitude formation assumes that they are created via a mixture of both short and long-term influences. This intermediate view of attitude formation, represented by models such as the IR model (Cunningham and Zelazo, 2007; Cunningham *et al.*, 2007), assume that evaluative processes towards objects are part of an iterative cycle where the current evaluation of a stimuli can be adjusted as new contextual and motivational information arises, and that adjustments to attitudes occurs in an iterative manner over time resulting in an updated evaluation according to the specific stimuli and context faced. The approach adopted in this work allows for an examination as to how attitudinal responses vary as the attribute levels of the alternatives presented within the experiment change over repeated choice tasks. The evidence shows the importance of specifying both long-term stable constructs and short term situational specific attitudes when exploring the role of psychological factors on the decision-making process. Understanding the temporal stability of attitudes is critical to transportation planning and research given the link between attitudes and behavior. Indeed, if attitudes are a precursor towards action, one mechanism to change travel behavior may be via the ability of transport planners to change attitudes, exploiting the classical models of attitude change, such as the elaboration likelihood model (Petty and Wegener, 1999), or the heuristic/systematic model (Chen and Chaiken, 1999).

In conclusion, this dissertation embodies a “journey” through the way attitudes are treated in the framework of hybrid discrete choice models. The trigger of this research is the opportunity to improve the analysis of psychological factors which drive individual choices. The contribution is instrumental, by suggesting the use of the Evaluative Space Grid for measuring attitudes, methodological, by showing the econometric steps for including such an instrument in the framework of a hybrid choice model, and structural, by recommending the use of long-term stable and short-term situational specific attitudes when exploring the role of psychological factors on individual behavior.

References

Ajzen I., 1985. From Intentions to Actions: A Theory of Planned Behavior. In: Kuhl J., Beckmann J. (Eds.) Action Control. SSSP Springer Series in Social Psychology. Springer, Berlin, Heidelberg.

Audrezet, A., Olsen, S.O., Tudoran, A.A., 2016. The GRID scale: a new tool for measuring service mixed satisfaction. *Journal of Services Marketing* 30(1), 29 – 47. doi: 10.1108/JSM-01-2015-0060

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, J., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., Munizaga, M.A., 2002. Hybrid choice models: progress and challenges. *Marketing Letters* 13(3), 163 – 175.

Cacioppo, J.T., Berntson, G. G., 1994. Relationship between attitudes and evaluative space: a critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin* 115(3), 401 – 423. doi: 10.1037/0033-2909.115.3.401

Chen, S., Chaiken, S., 1999. The heuristic-systematic model in its broader context. In S. Chaiken & Y. Trope (Eds.), Dual process theories in social psychology, 73 - 96. New York: Guildford Press.

Conrey, F.R., Smith, E.R., 2007. Attitude representation: attitudes as patterns in a distributed, connectionist representational system. *Social Cognition 25*, Special Issue: What is an Attitude?, 718-735. https://doi.org/10.1521/soco.2007.25.5.718.

Costarelli, S., Colloca, P., 2004. The effects of attitudinal ambivalence on pro-environmental behavioral intentions. *Journal of Environmental Psychology* 24(3), 279 – 288. doi: 10.1016/j.jenvp.2004.06.001

Cunningham, W.A., Zelazo, P.D., 2007. Attitudes and evaluations: a social cognitive neuroscience perspective. *Trends in Cognitive Sciences 11*, 97 – 104.

Cunningham, W.A., Zelazo, P.D., Packer, D.J., Van Bavel, J.J., 2007. The iterative reprocessing model: a multilevel framework for attitudes and evaluation. *Social Cognition* 25(5), 736 – 760.

Fazio, R.H., 1990. Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. In M.P. Zanna (Ed.), Advances in experimental social psychology. 23, 75-109. New York: Academic Press.

Gawronski, B., Bodenhausen, G.V., 2007. Unraveling the processes underlying evaluation: attitudes from the perspective of the APE model. *Social Cognition* 25, 687–717.

Kahneman, D., Knetsch, J., Thaler, R., 1991. The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives* 5, 193 – 206.

Kahneman, D., Ritov, I., 1994. Determinants of stated willingness to pay for public goods: a study in the headline method. *Journal of Risk and Uncertainty* 9, 5 – 38.

Kahneman, D., Ritov, I., Schkade, D., 1999. Economic preferences or attitude expressions?: an analysis of dollar responses to public issues. Journal of Risk and Uncertainty 19, 203 – 235.

Kaplan, K. J., 1972. On the ambivalence-indifference problem in attitude theory and measurement: A suggested modification of the semantic differential technique. *Psychological Bulletin* 77, 361-372. doi: 10.1037/h0032590

Larsen, J.T., Norris, C.J., McGraw, A.P., Hawkley, L.C. and Cacioppo, J.T., 2009. The evaluative space grid: a single-item measure of positivity and negativity. *Cognition and Emotion* 23(3), 453-480. doi: 10.1080/02699930801994054

McFadden, M., 1980. Econometric models for probabilistic choice among products. The Journal of Business 53(3-2): Interfaces between marketing and economics, S13 - S29.

McFadden, M., 1986. The choice theory approach to market research. *Marketing Science* 5(4). Special issue on consumer choice models, 275 – 297.

Petty, R.E., Wegener, D.T., 1999. The elaboration likelihood model: current status and controversies. In S. Chaiken & Y. Trope (Eds.), Dual process theories in social psychology, 41 -72. New York: Guildford Press

Petty, R.E., Briñol, P., DeMarree, K.G., 2007. The meta-cognitive model (MC) of attitudes: implications for attitude measurement, change, and strength. *Social Cognition* 25.

Schwarz, N., 2007. Attitude construction: evaluation in context. *Social Cognition* 25(5), 638 – 656.

Thaler, R., 1985. Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization* 1, 39 – 60.

Thaler, R., 1985. Mental accounting and consumer choice. *Marketing Science* 4(3), 199 – 214.

Thompson, M.M., Zanna, M.P. and Griffin, D.W., 1995. Let's not be indifferent about (Attitudinal) ambivalence. In Petty, R.E. and Krosnick, J.A. (Eds), Attitude Strength: Antecedents and Consequences, (pp. 361-386) Lawrence Erlbaum, Mahwah, NJ.

Thornton, J.R., 2011. Ambivalent or indifferent? Examining the validity of an objective measure of partisan ambivalence. *Political Psychology* 32(5), 863-884. doi: 10.1111/j.1467-9221.2011.00841.x

Yoo, S.J., 2010. Two types of neutrality: ambivalence versus indifference and political participation. *The Journal of Politics* 72(1), 163-177. doi: 10.1017/S0022381609990545

Chapter 1. Exploiting Evaluative Space Grids to stochastically measure ambivalence/indifference

Antonio Borriello[1], John M. Rose[2], Rico Maggi[1]

[1]Università della Svizzera italiana, [2]University of Technology of Sydney

Abstract

Common response measures for evaluating emotions and affect such as Likert and semantic differential scales are unable to distinguish between indifference and ambivalence. The Evaluative Space Model (Cacioppo and Berntson, 1994) has been used to demonstrate that both positive and negative feelings towards an object act as two distinct systems: an increase in positive (negative) feelings is not necessarily connected to a decrease of negative (positive) feelings. This finding has resulted in the literature distinguishing between the concepts of ambivalence and indifference. As with other previous works however, ambivalence and indifference have been calculated mainly by means of deterministic indices (Kaplan, 1972; Thompson *et al.*, 1995), which fail to recognize that the answers recorded are the result of underlying psychological latent constructs, and hence are imprecise measures of an individual's true attitude towards an object. Here, we suggest two approaches to modelling data obtained from an Evaluative Space Grid (ESG, Larsen *et al.*, 2009), both of which are consistent with treating such data as if it were generated from latent psychological constructs. In the first approach, we propose modelling attitudinal scores derived from an ESG using Tobit models, whereas in the second approach, we discuss using ordered logit models to model the ESG ratings directly. Using the later approach, we are able to model the probability of individuals having an ambivalent, indifferent, or unipolar attitude (positive or negative) towards an object, as well as demonstrate that respondents use different latent processes in selecting negative and positive responses within the ESG.

Keywords*:* ambivalence, evaluative space grid, ordered regression

1.1. Introduction

Central to social psychology is the study and measurement of attitudes. Over time, the precise definition of attitudes has changed, from one that broadly encompassed cognitive, affective, motivational, and behavioral components, to one that now simply reflects an individual's likes and/or dislikes for some stimuli (see Schwarz and Bohner 2001 for a historical overview of attitudes). Whilst ideally, one would capture an individual's attitude directly using some form of subjective measure, the ability, and likelihood, of individuals to provide socially desirable or acceptable responses to subjective questions makes the use of objective measures far more practical in empirical settings, particularly when dealing with attitudes related to delicate subject matter (Priester and Petty, 1996; Clark *et al.*, 2008).

The first known attempt to measure attitudes (or opinions which reflect attitudes) was conducted by Thurstone (1928). Thurstone postulated that attitudes exist on an abstract continuum, at the extremities of which lie those who are either strongly in favor of, or strongly against, with those in between exhibiting varying degrees of favor or disfavor, and even indifference. To measure attitudes towards prohibition, pacifism/militarism, and the role of the church, Thurstone developed between 80 and 100 statements and asked subjects to place each statement on an 11 point scale defined by a central neutral point, with five points located to either side. Subjects were told that statements placed further to the left of neutral indicate an increasingly negative attitude towards the object being evaluated, whilst statements placed to the right of neutral represent an increasingly positive attitude towards the object. Other than the neutral center and direction of attitude, no visual or verbal cues were provided to subjects as to the precise meaning or value each point on the scale represented.

Building on the work of Thurstone, Likert (1932) proposed a scale based on the measurement of different statements (items) of which subjects were asked to express their level of agreement/disagreement. Like Thurstone's scale, the items contained within the Likert scale include an equal number of positive and negative positions symmetrically sited around a neutral point. However unlike Thurstone's scale, the values of each Likert item are spaced equally, which is made known to subjects responding to the scale. Further progress on the measurement of attitudes was made when Osgood (1964) proposed a semantic differential scale to measure attitudes. It uses a series of opposing pairs of adjectives, anchored at the extremities of a continuum, to measure attitudes towards a single object of interest. Using this scale, Osgood was able to detect three unique dimensions related to the evaluative concept these being, *evaluation* (measured by pairs like good vs bad), *potency* (e.g., strong vs weak) and *activity* (e.g., active vs passive).

Independent of the precise scale employed, subjects are assumed to compute the net difference between positive and negative opinions, beliefs, and feelings towards the stimuli under study, and select a position on the scale that best reflects their overall attitude towards the object being evaluated. Typically, values to the right of the defined neutral point are used to reflect increasingly positive opinions or feelings, whilst values to the left of neutral reflect increasingly negative attitudes towards the object under study. As such, strong positive and negative responses and weak positive and negative responses flow outward relative to the neutral center of the scale. When the neutral point of the scale is chosen however, the interpretation provided by traditional attitudinal scales is somewhat ambiguous insofar as it is not possible to distinguish between the subject being indifferent towards the stimuli under study, or ambivalent towards it (Kaplan, 1972; Thompson *et al.*, 1995).

Unfortunately, the distinction between indifference and ambivalence is important to the understanding of attitudes in social psychology, making the lack of ability of standard measurement tools to distinguish between the two problematic. Indifference implies that a subject has no interest in the stimuli being studied, being truly neutral in their attitude, reflected by low positive and negative reactions towards the object under evaluation. Ambivalence on the other hand suggests that the subject experiences both positive and negative valence towards the stimuli, which when measured using traditional attitudinal scales, will likely result in the subject choosing the neutral option of the scale.

However, there exist an ongoing debate within the recent literature as to whether or not individuals can experience opposing feelings towards the same object. Russell and Carroll (1999) proposed a mutually exclusive paradigm that is a bipolar view where two opposite feelings (in the mentioned paper the authors refer to happiness/sadness) lie at the opposite ends of a latent continuum and for which co-endorsement is not permissible. Recently Tay and Kuykendall (2016) revised this bipolar model and suggested an "updated" version in which individuals who experience moderate amounts of happiness can also experience moderate amounts of sadness, even if mixed feelings are less likely to co-occur when the positive or negative feeling is very strong. An opposite theory has been proposed by Cacioppo and Berntson (1994) who envisaged a bivariate framework, named the Evaluative Space Model (ESM), where positive and negative feelings (or attitudes) can be experienced at the same time also with high intensities.

Following the theoretical framework proposed by Cacioppo and Berntson, Larsen *et al.* (2009) proposed a "single-item measure of positivity and negativity" which they termed the *evaluative space grid* (ESG). The ESG contrasts positive and negative stimuli related to an attitude, posing two 5 points scales on *x* and *y* axes. Using the ESG, subjects are asked to select one of over 25 cells that best reflects their simultaneous negative and positive feelings towards the stimulus under study, as shown in Figure 1.

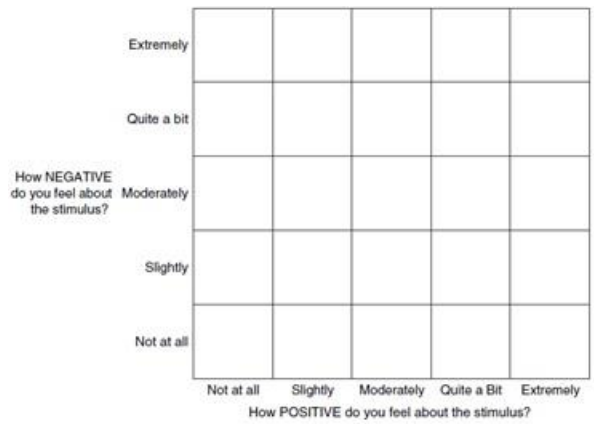

Figure 1: Evaluative space grid, taken from Larsen *et al.* (2009)

The grid is designed to differentiate between four different attitudes; (1) positive (high positive and low negative), (2) negative (low positive and high negative), (3) indifference (low positive and negative), and (4) ambivalence (moderate to high positive and negative), as suggested by the ESM. The positioning of these different types of responses are shown in Figure 2.

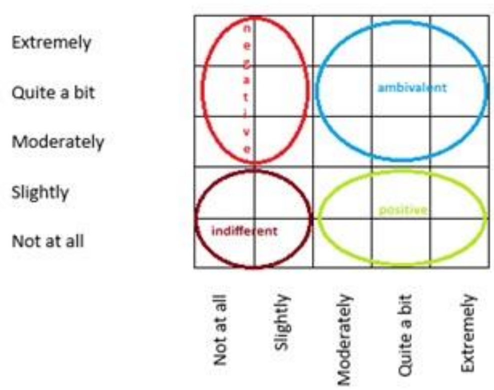

Figure 2: ESG subdivision in four different areas.
Indifference (bottom left), positive (bottom right), negative (top left), ambivalent (top right).

The current work does not seek to address the aforementioned debate on the mutual exclusiveness of feelings or attitudes, nor does it seek to validate a new scale. Rather, the aim of this chapter is to examine different ways in which attitudinal data can be modelled, drawing on existing modelling approaches drawn from the consumer behavior literature. The ESG is suitable to discern between indifference and ambivalence, as well as positive and negative attitudes, and can be useful for instance in the framework of the modelling processes we explore herein. Indeed, indifferent and ambivalent respondents have been treated with no distinction so far in this field as they occupy the same position on a Likert scale, even if psychologists agree that they can behave differently (Costarelli and Colloca, 2004; Yoo, 2010; Thornton, 2011).

Our interest in the ESG is further driven by the distribution of the responses collected through an empirical survey. In fact, as opposed to the findings of Tay' and Kuykendall's (2017) in which only 7 out of 166 respondents reported having an ambivalent emotion (six respondents reported being "moderately" happy and sad whilst one respondent reported being "very" happy whilst simultaneously being "moderately" sad), a significant proportion of respondents in the current data reported simultaneous strong positive and negative attitudes, suggesting that empirically it is possible to have both a strong positive and negative attitude. Figure 3 shows the proportion of respondents responding to the bipolar ESG questions related to the "practicality of driving the car for commuting purposes" versus the "difficulty of driving the car for commuting reasons". Based on the responses obtained, 38.72% of respondents are categorized as having a positive attitude towards driving, 23.57% a negative attitude, 1.35% are considered indifferent, whilst the remaining 36.36% can be classed as being ambivalent towards driving.

Negative attitude					
5	5.05%	3.03%	0.67%	0.67%	0.00%
4	1.68%	9.76%	6.73%	2.69%	0.67%
3	0.67%	3.37%	12.1%	11.8%	1.01%
2	0.00%	0.34%	1.68%	14.8%	8.75%
1	1.01%	0.00%	1.01%	3.03%	9.43%
	1	2	3	4	5
			Positive attitude		

Figure 3: Distribution of responses of the ESG.
Color formatting: green indicates a high probability of selecting the cell, whilst red indicates a low probability.

Respondents completing the survey completed six ESG questions designed to explore attitudes held towards private car usage and mode choice within a commuting setting. Given that the aim of the current chapter is methodological rather than to introduce a new scale for measuring the attitudes towards the private car, we present the results for one grid related to how handy/challenging it is to commute by private car. We note however that the proportion of the ambivalent responses for the remaining grids ranges from 26% to 67%. The analysis for the other grids is available upon request.

The remainder of the chapter is organized as follows. In the next section we review several measures used so far to compute a score for the ambivalence and introduce a different and more appropriate way of dealing with this latent underlying predisposition. Ambivalence measures used so far are mostly deterministic, and as a consequence, they fail to recognize that recorded answers are the result of underlying psychological latent constructs. Exploiting the ESG response mechanism, we suggest two different econometric approaches to explain such data, a tobit and an ordered logit model, which respect the assumption that attitudes are latent constructs and, as such, they treat the ambivalence rating in a stochastic manner.

We then describe in detail both the Tobit and ordered logit models, after which we discuss the survey instrument and empirical data. Next, we provide a detailed discussion of the results obtained from of the modelling process, including the results of applying the various models to a hold-out sample. Finally, we close with a general discussion of the findings, before providing general concluding comments.

1.2. Ambivalence and indifference measures

Kaplan (1972) devised an approach using a semantic differential scale where subjects were first told to consider only positive aspects of the stimuli under study before completing the scale, after which they were told to think only about negative aspects of the stimuli, before being asked to answer the exact same scale. The degree to which a subject is ambivalent towards the object is then computed for each item of the scale as

$$\left(P_i + N_i\right) - \left|P_i - N_i\right|, \tag{1}$$

where P_i and N_i represent respectively the positive and the negative assessment on the two scales for item *i,* using a split scale which is operationalized by converting negative coded values of the scale to be positive. Higher values for Equation (1) represent a greater degree of ambivalence towards the item. Mathematically, Equation (1) is equivalent to doubling the score of the weakest evaluated item. For example, assuming a split four-points scale for item *i*, consider the situation where a subject is observed to answer 2 for the positively framed question, and 4 for the negatively framed question. Substituting P_i = 2 and N_i = 4 into Equation (1) gives a score of 4, which is equal to twice the lower rating of P_i = 2.

Likewise, consider a subject whose answers are $P_i = 3$ and $N_i = 2$. Equation (1) returns a value of 4, twice the lower rated value of $N_i = 2$. As demonstrated by the previous two examples however, it is possible for different subjects to obtain the same score, despite displaying different positive and negative attitudes towards the same object, such that Equation (1) fails to respect the important property of similarity.

Alongside the concept of similarity, research into ambivalence has also identified the property of "intensity" as being important for purposes of measurement. As discussed by Conner and Spark (2002), ambivalence requires the measurement of both "(a) the "intensity" of people's feelings (i.e., both how positive and negative those feelings may be) about an attitude object and (b) the "similarity" of the intensity of positive and negative feelings".

Recognizing this, Thompson *et al.* (1995) proposed an alternative index to compute ambivalence, this being

$$\left(P_i + N_i\right)/2 - \left|P_i - N_i\right|, \tag{2}$$

where the first component given as an average represents the intensity of ambiguity whilst the second component given as an absolute value represents the similarity of the attitudinal components being measured.

Assuming the same two subject responses as before, based on Equation (2), the score for subject 1 is now 1, whilst the score for subject 2 becomes 1.5. The higher score for subject 2 occurs due to the greater similarity between their positive and negative evaluations for the same item relative to the first subject.

The use of sequentially structured conversely framed questions has been criticized within the literature given that such an approach has the potential to induce subjects to reveal distorted preferences, particularly if for the second set of questions they attempt to display consistent answers with the preferences given to the first set of questions asked. For this reason, Larsen *et al.* (2009) proposed using a "single-item measure of positivity and negativity" which is the Evaluative Space Grid. The ESG is designed to recover the independent and simultaneous assessment of positive/negative attitudes towards an object, and has since been validated in different fields such as psychology and social behavior (e.g., Audrezet, 2014; Audrezet *et al.*, 2016). The grid is designed to differentiate between ambivalence and indifference, as well as positive and negative attitudes.

By treating the axis of the grid as separate responses, it is possible to compute the degree of ambivalence a subject has towards an object using the indices previously described. Audrezet *et al.* (2016) proposed an alternative index using the ESG to study overall satisfaction with bank services. Their proposed method seeks to simultaneously combine the level of satisfaction and dissatisfaction held for an object by an individual (i.e., the overall satisfaction score should decrease (increase) as the dissatisfaction (satisfaction) rating increases along the vertical (horizontal) axis). Based on the bilinear model, the Audrezet *et al.* score is given as

$$S(i,j)=(b+2)i+bj-1-6b, \tag{3}$$

where i and j represent respectively the score on the positive and negative axis of the grid, and $-1<b\leq 0$. Any arbitrary value within the constraint can be chosen for *b*, however Audrezet *et al.* recommend choosing a value of *b* = -0.5. Independent of the value of *b* chosen, $S(i,j)$ will range between 1 (i.e., $S(1,5)$) and 9 (i.e., $S(5,1)$). Maximum ambivalence is achieved for the rating pair of "extremely dissatisfied" – "extremely satisfied" (top-right quadrant, $S(5,5)$), with a score of 7 given *b* = -0.5. Maximum indifference is observed to occur for the rating pair of "not at all dissatisfied" – "not at all satisfied" (bottom-left quadrant, $S(1,1)$), with a score of 3, assuming once more *b* = -0.5.

Before selecting a model however, there exists the problem of how to code the observed responses. Whilst it might be logical to assign a value of 1 to the bottom left of the grid (i.e., *S*(1,1)) and 25 to the top right of the grid (i.e., *S*(5,5)), the appropriate coding of the remaining cells is somewhat less apparent. For example, it is possible to code cell *S*(1,2) as 2 or assign cell *S*(2,1) the same value, Likewise, a valid argument could be made to also code cell *S*(2,2) as 2. As such, any coding of the grid will likely be arbitrary, as will the results of any model estimated on the data. For this reason, we propose in the first instance using the Audrezet *et al.* (2016) score calculated using Equation (3). Use of the Audrezet *et al.* score however poses additional problems in that the resulting score is bounded between the values of 1 and 9, which must also be accounted for in any model selected.

In the current chapter, we do not seek to argue either for or against any of the various techniques of response analysis discussed above, but rather we seek to address how best to analyse attitudinal data captured in such a way that it is capable of disentangling indifference from ambivalence type responses. Using the ESG response approach, we propose two different econometric models to explain such data, although we note that the methods proposed are not limited to data captured using the ESG response mechanism.

Using the Audrezet *et al.* score, and given our selection criteria, we propose using the Tobit model to analyse such data. We do so for two reasons. Firstly, the model is analogous to the familiar linear regression model, whilst accounting for censoring of the dependent variable, consistent with the bounds imposed when generating attitudinal scores using the approach proposed by Audrezet *et al.* The similarity to linear regression means further that model is capable of prediction, consistent with our second model selection criteria. Secondly, the Tobit model is also consistent with the assumption that the observed outcome is derived from some underlying form of latent structure.

The Tobit model is capable of modelling attitudinal scores and although there exists nothing inherently wrong with this model itself, a number of potential concerns exist about the data to which the model is to be applied. Firstly, the score itself is dependent on the value of *b* chosen by the analyst, making the dependent variable somewhat arbitrary. Again, as with assigning values to each of the cells of the ESG, this may render the results of any model also arbitrary. Secondly, even if the score distinguishes between indifference and ambivalence, as well as unipolar positive and negative attitudes, its interpretation is not very clear. Indeed, the score ranges from one to nine, where the lowest and the highest values identify respectively an individual with negative and positive attitudes and in between, a score of three categorizes an indifferent respondent whilst a score of seven an ambivalent one. Such a "bipolar" score, is not clearly interpretable when a value of two or eight is returned for a respondent. Third, the derived score represents a transformation of the observed ESG rating, and as such, we are in fact modelling a latent variable associated to explain this transformed variable, which in turn is related to the actual answer given by the respondent. Thus, whilst we argue for use of the Tobit model to model attitudinal scores based on ESG ratings tasks, we would suggest that a model that deals specifically with the observed ratings and not some intermediary transformation, whilst also avoiding issues of how to code the responses, would be more suitable for understanding the full gamut of attitudinal outcomes.

Using the observed attitudinal data captured using the ESG response mechanism, we demonstrate how attitudinal data can be analysed using a system of ordered logit models. Underlying such models is the assumption that the observed outcome obtained from the response mechanism used is based on a latent construct, which is further decomposed into two parts, a modelled component, and an unobserved error term which is randomly distributed over the population of interest. The model produces not only an estimate of the relative value of the latent variable based on the observed or modelled component used to explain the latent variable, but more importantly, the stochastic nature of the error term translates into a probabilistic prediction of the response outcome. By simultaneously estimating independent ordered logit models for the positive and negative domains of the ESG, the approach allows for separate latent processes to explain probabilistically the positive and negative domains of attitudes. Further, by allowing for an additional term that is common between the different models, it is also possible to determine to what degree the two processes might be correlated. Finally, by placing restrictions on the parameter estimates derived from the various models, it is also possible to test to what degree different latent processes exist across the positive and negative attitudinal domains.

Our main criteria for selecting an appropriate model rests with the contention that attitudes based on psychometric survey questions should be treated as indicators of underlying latent psychological factors rather than as directly observed measurements of said factors (see Borsboom, 2008). The assumption that attitudes are latent constructs implies any survey response provided by an individual represent imperfect measures of that respondent's true attitude towards a given object and renders many forms of analysis incapable of appropriately dealing with such data. This is because the selected mode of analysis should firstly explain the underlying latent construct related to the response rather than deal directly with the actual observed response itself, and secondly, the assumed imprecision of the response suggests that the selected rating should be treated in a stochastic as opposed to deterministic manner. A secondary criterion we impose for selecting a model is the ability of the model to forecast future responses. For many psychological studies, forecasting future responses may be of little interest, with a simple tabulation of attitudinal scores derived from some population being sufficient for understanding attitudes towards an object under study. Nevertheless, in many applied fields, being able to predict how attitudes may develop or change over time, or even what attitudes may exist in other non-sampled populations represents an important challenge. For example, understanding how attitudes towards climate change given differences in the socio-demographic make-up of different regions may help in more targeted communications from governments and non-government organizations designed to shift attitudes. Likewise, understanding differences in attitudes towards alternative transport modes may help transport planners design and build large scale transport infrastructure based on future socio-demographic trends within a city.

Within the chapter, we make use of a sample of respondents from Lugano, Switzerland, who completed a survey related to their attitudes towards driving. Based on a sample of 296 respondents, we first split the sample into an estimation and hold out sample, after which we compute an attitudinal score for each respondent based on the method proposed by Audrezet *et al.* (2016). Using this data, we then estimate a Tobit model using sociodemographic variables as independent variables to test for any systematic patterns that might explain the derived score. Next, using the same attitudinal data, we estimate a series of ordered logit models to test different possible data generation processes underlying the specific values chosen within the ESG response mechanism. Finally, for both models, we apply the modelled results to the hold-out sample to test out of sample model performance.

1.3. Methodology

In this section, we discuss two models, the Tobit model, and the ordered logit model which will be used to analyze the data.

1.3.1. Tobit Model: Indirect (scores) approach

To model the results obtained from an ESG response task, we first compute the scores using the equation derived by Audrezet *et al.* (2016) for each individual respondent, *n*. Assuming a value for *b* = -0.5, the resulting scores will be bounded between 1 and 9. Using the computed scores as the dependent variable, we next analyze this data using a Tobit model with censoring at both of these upper and lower bounds. Rather than model the dependent variable directly, as with traditional regression type techniques, the attitudinal score in the Tobit model is treated as a latent variable, which is explained via a linear function such that

$$S_n^*\left(i,j\right)=\theta' q_n+\xi_n, \quad (4)$$

where $S_n^*\left(i,j\right)$ is the latent variable explaining the derived score, θ is a vector of parameters associated with socio-economic characteristics, q_n, and ξ_n is a random disturbance term, distributed $\xi_n \sim i.i.d.N\left(0,\sigma_n^2\right)$.

Given that empirically we observe the computed attitudinal score rather than the latent variable, $S_n^*\left(i,j\right)$, and based on the truncation of the computed attitudinal score, the structure of the model is such that

$$S_n(i,j)=\begin{cases} S_n^*(i,j) & if\ S_L(i,j)<S_n^*(i,j)<S_U(i,j) \\ S_L(i,j) & if\ S_n^*(i,j)\leq S_L(i,j) \\ S_U(i,j) & if\ S_n^*(i,j)\geq S_U(i,j) \end{cases} \tag{5}$$

where $S_n^*(i,j)$ is as per equation (1), and $S_L(i,j)$ and $S_U(i,j)$ are the lower and upper bounds of the score, equal to 1 and 9 respectively.

The parameters of the model, θ and σ_n are estimated using maximum likelihood estimation techniques. The log-likelihood function of the model is given as

$$\begin{aligned}\log L_N^T = &\sum_{S_n(i,j)=S_L(i,j)} \log\Phi\left[\left(S_L(i,j)-\theta' q_n\right)/\sigma_n\right] + \sum_{S_n(i,j)=S_U(i,j)} \log\left[1-\Phi\left[\left(S_U(i,j)-\theta' q_n\right)/\sigma_n\right]\right] \\ &+ \sum_{S_n(i,j)=S_n^*(i,j)} -0.5\left[\log(2\pi)-\log\left(\frac{1}{\sigma}\right)^2+\left[\left(S_n(i,j)-\theta' q_n\right)/\sigma\right]^2\right],\end{aligned} \tag{6}$$

where Φ represents the cumulative density function of a standard normal distribution.

In the current study, we obtain the parameter estimates of the Tobit model based on an estimation sample, which we subsequently apply to a holdout sample. The predicted outcomes for the holdout sample are computed using Equation (7).

$$E\left[S_n^*(i,j)\,|\,q_n\right]=S_L(i,j)\Phi_L+S_U(i,j)(1-\Phi_U)+(\Phi_U-\Phi_L)\theta' q_n+\sigma_n(\phi_L-\phi_U), \tag{7}$$

where $\phi_b=\phi\left[\left(S_n(i,j)-\theta' q_n\right)/\sigma_n\right], \forall b=S_L(i,j),S_U(i,j),$ where ϕ is the probability density function of a standard normal distribution, and $\Phi_b=\Phi\left[\left(S_n(i,j)-\theta' q_n\right)/\sigma_n\right], \forall b=S_L(i,j),S_U(i,j),$ where Φ is as previously defined.

The final model is estimated using the extension NLOGIT 6 of the econometric and statistical software package LIMDEP.

1.3.2. Ordered Logit model approach: Direct (observed ratings) approach

In the previous section, we provided details of the Tobit model, which we apply to the attitudinal scores derived from the observed ratings obtained from an ESG task. Rather than model an intermediary transformation of the ratings task, we now discuss the ordered logit model, which can be used to model directly the observed ESG ratings outcome. To understand the model, let *n* represent subject and *r* the response for the i^{th} indicator variable or item in a survey. The analyst observes a discrete outcome y_{nir} for subject *n*, representing a point on a non-observable continuous latent variable, U_{ni}. The latent variable U_{ni} and discrete observed outcome y_{nir} are therefore intrinsically linked, with subjects characterized as having higher values of U_{ni} being more likely to select higher level categories based on the rating scale used. Hence, the observed response is assumed to be determined by the level of U_{ni}, such that if U_{ni} exceeds some psychological threshold, τ_{ir}, category *r* will be selected, else one of the preceding categories will be chosen. Assuming a response mechanism with five response categories, the assumed choice process may be represented as

$$\begin{aligned} &y_{ni1} = 1,\ if\ \ \tau_{i1} > U_{ni}, \\ &y_{ni2} = 1,\ if\ \ \tau_{i2} > U_{ni} > \tau_{i1}, \\ &\vdots \qquad\qquad \vdots \\ &y_{ni5} = 1,\ if\ \ U_{ni} > \tau_{i4}. \end{aligned} \tag{8}$$

We assume that the latent variable may be explained, or proxied, in part, by observable data, such as by gender, income, etc.; however given that it is unlikely that such data will be fully capable of explaining an individual's attitudes towards an object, we decompose U_{ni} into two components, an observed component and stochastic component, such that $U_{ni} = V_{ni} + \varepsilon_{ni}$. For simplicity, we assume a linear additive specification for the observed component of the latent variable, such that $V_{ni} = \sum_{k=1}^{K} \beta_{ik} x_{nik}$, where x_{nik} represents the *k*th socio-demographic characteristic of subject *n*, and β_{ik} the marginal contribution to the latent variable associated with the *k*th socio-demographic characteristic. The remaining term, ε_{ni}, is a stochastic term representing the idiosyncratic impact on U_{ni}, not directly modelled in V_{ni}. Under the assumption that ε_{ni} is distributed extreme value type 1 over the population, and assuming a five category scale, the probability that respondent *n* will choose category *r* for item *i* is

$$P_{nir} = \begin{cases} \dfrac{\exp(\tau_{i1} - V_{ni})}{1 + \exp(\tau_{i1} - V_{ni})}, r = 1 \\ \dfrac{\exp(\tau_{ir} - V_{ni})}{1 + \exp(\tau_{ir} - V_{ni})} - \dfrac{\exp(\tau_{ir-1} - V_{ni})}{1 + \exp(\tau_{ir-1} - V_{ni})}, \forall\ 1 < r < 5, \\ 1 - \dfrac{\exp(\tau_{i4} - V_{ni})}{1 + \exp(\tau_{i4} - V_{ni})}, \forall r = 5. \end{cases} \tag{9}$$

Rather than treat survey responses to attitudinal data as deterministic, Equation (9) suggests that each response can be chosen up to a modelled probability for any given respondent. That is, for each response category associated with response item *i*, we estimate the probability distribution for all possible outcomes for each respondent *n*.

In the current study, in order to identify ambivalence, we use the ESG response mechanism so that subjects can reveal simultaneously positive and negative attitudes towards the object under study. As such, we capture two discrete outcomes, y_{nir}, and y_{njr}, representing the concurrent positive and negative attitude dimensions held toward an object respectively. Both the positive or negative items are therefore assumed to provide a discrete representation of two separate, yet potentially correlated, continuous latent variables, U_{ni}, and U_{nj}.

The modelling approach we propose is flexible insofar as it is able to handle multiple theoretical perspectives as to possible relationships that might exist between U_{ni} and U_{nj}. The most restrictive assumption possible is to assume the same psychological process underlies the choice of positive and negative outcomes for some stimuli, such that $U_{ni} = U_{nj}$. Under this scenario, the same socio-demographic characteristics enter into V_{ni} and $V_{nj,}$ whilst the marginal contribution of each socio-demographic characteristic is held constant across the two functions (i.e., $\beta_{ik} = \beta_{jk}$). Differences in responses in the negative and positive domains occur only via differences in the psychological thresholds for the two outcomes, τ_i, and τ_j. If τ_i is assumed to equal τ_j, then the responses are assumed to be perfectly correlated across the positive and negative domains. A less restrictive assumption consistent with the Evaluative Space Model (ESM) allows for the possibility that positive and negative attitudes arise from different psychological processes (Cacioppo and Berntson, 1994; Cacioppo *et al.*, 1997; Cacioppo, *et al.*, 1999). Here, whilst the same socio-demographic characteristics may enter into V_{ni} and $V_{nj,}$ the marginal contribution for each can differ across both domains (i.e., $\beta_{ik} \neq \beta_{jk}$). The least restrictive specification, also consistent with the ESM, allows for different subsets of socio-demographic characteristics to be used to explain the observed positive and negative responses for the same stimuli. Under the last two scenarios, it is possible to treat $\tau_i = \tau_j$ or $\tau_i \neq \tau_j$, the outcome of which should be determined empirically.

We further extend the modelling framework to allow for the possible correlation of the stochastic components of U_{ni} and U_{nj}. We do this by the addition of a random term to the two observed components of the latent variables, such that

$$U_{ni} = \sum_{k=1}^{K} \beta_{ik} x_{nik} + \eta_{ni} + \varepsilon_{ni}, \tag{10a}$$

$$U_{nj} = \sum_{k=1}^{K} \beta_{jk} x_{njk} + \eta_{nj} + \varepsilon_{nj}, \tag{10b}$$

where

$$\begin{bmatrix} \eta_{ni} \\ \eta_{nj} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right), -1 \le \rho \le 1. \tag{11}$$

Given that neither η_{ni} and η_{nj} are associated with an observable variable, both terms represent additional sources of error associated with U_{ni} and U_{nj} respectively, with correlation equal to ρ. To estimate the additional error structure described in Equation (11), we rely on a process known as Cholesky decomposition, which is shown in Equation (12). The specific Choleksy matrix used in this context is the lower triangular matrix described by the first matrix in the right-hand side of Equation (12).

$$\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ 0 & \sqrt{1-\rho^2} \end{bmatrix}. \tag{12}$$

The bivariate distribution given in Equation (11) is obtained from independent $N(0,1)$ distributions, q_{n1} and q_{n2} such that

$$\begin{aligned} \eta_{ni} &= q_{n1}, \\ \eta_{nj} &= q_{n1}\rho + q_{n2}\sqrt{1-\rho^2}. \end{aligned} \tag{13}$$

With the above background, we note that the probability of observing subject n selecting the r^{th} response category for items i and j are

$$P_{ni}^{*} = \int_{\eta_i} y_{nir} P_{nir} f\left(\eta_i \mid \Omega_\rho\right) d\eta_i, \text{ and} \tag{14a}$$

$$P_{nj}^{*} = \int_{\eta_j} y_{njr} P_{njr} f\left(\eta_j \mid \Omega_\rho\right) d\eta_j, \tag{14b}$$

where Ω_ρ represents the covariance structure given in Equation (11).

The objective for the analyst is to estimate the parameters, $\beta_{ik}, \beta_{jk}, \tau_i, \tau_j$ and ρ. Typically we would use maximum likelihood estimation to locate the parameters of interest, however given that the integrals in Equations (14a) and (14b) do not have a closed form solution, we resort to using simulated maximum likelihood to estimate the model parameters. The log-likelihood function of the ordered logit model is given as

$$\log L_N^L(\beta,\tau,\rho \mid X,Y) = \sum_{n=1}^{N} \log\left(P_{ni}^* P_{nj}^*\right). \tag{15}$$

The final model is estimated using Python-Biogeme version 2.4 (Bierlaire, 2016), using 20,000 Modified Latin Hypercube Sample (MLHS) draws to approximate the integrals in Equations (14a) and (14b) (see Hess *et al.*, 2006).

As with the Tobit model, we estimate the various ordered logit models on an estimation sample, after which we apply the parameter estimates to a holdout sample. The application of the model to the holdout sample further requires simulation of the integrals required to compute the probabilities given in Equations (14a) and (14b). To remain consistent with the estimation process, we also use 20,000 MLHS draws for this purpose.

1.4. Empirical data

Data was collected in Lugano, a city in the Italian speaking part of the Switzerland, from September 2014 to May 2015. Using a paper and pencil questionnaire, a sample of 296 respondents were interviewed about their attitudes towards car use. A screening criteria for the survey was imposed such that sampled respondents had to be below the age of 44 years at the time of completing the survey (mean age was 22.6). The sample consisted of mainly native Italian speakers (91 percent), who held a current driver license, where mostly female (52 percent), and whose current occupation is as a student (77 percent, with the remainder being either workers or apprentices). The majority of the sample reported earning less than 30,000 CHF/year (80 percent). Ninety two percent of the sample reported having access to a car in their household, with the average number of days in which the car was in use (with the respondent acting as either the driver or as a passenger) being equal to 3.8 days per week. The obvious non-representativeness of the sample does not pose an issue for the present study given that the objective of the work is methodological rather than empirical in nature.

Respondents completing the questionnaire were instructed as to how to interpret and complete the ESG task. A trained interviewer provided a verbal description of the task and demonstrated the process via an example that was not related to the topic of interest. Overall, respondents completed six ESGs, each of which was framed with the statement “Depending on your experience, you think that driving is…”. In completing the six ESG questions, respondents were asked to consider only commuting trips (to university or workplace). The full list of the six pairs of adjectives included relaxing vs stressful, enjoyable vs boring, safe vs risky, flexible vs binding, comfortable vs uncomfortable, and handy vs challenging.

A pre-pilot and pilot of the instrument (involving 80 students from Univeristà della Svizzera italiana) found that respondents were easily able to understand four of the six adjective pairs in the context of a commuting trip (these being relaxing versus stressful, enjoyable versus boring, safe versus risky, comfortable versus uncomfortable). The precise meaning of the two remaining pairs, flexible versus binding, and handy versus challenging, however, were found to be less obvious to respondents. As such, the meaning of these two pairs was emphasized during the survey, with respondents informed that flexible versus binding referred to whether it was possible or not to change a selected route mid trip as a result of changing circumstances such as in the case of an accident, whilst handy versus challenging referred to more practical issues such as the timing for leaving home, ease of locating parking, and whether it is necessary to transfer to a different transport mode during the trip. An example grid is given in Figure 4.

Figure 4: Example of ESG in the survey

For the final analysis, we randomly removed data from 71 respondents, leaving a total of 225 observations for each grid to estimate models on. The data from the 71 respondents was then used to form a hold-out sample to allow for an out of sample validation of the estimated models. We report the results of the model estimation exercise and out of sample validation task in the sections that follow.

1.5. Estimation sample results

In this section, we present the results for the Tobit model estimated using the Audrezet *et al.* (2016) scores, followed by the results obtained from a series of ordered logit models estimated directly on the observed responses. For purposes of expediency, we report the results for a single ESG question, that being a trade-off between the positive ‘handy’ and negative ‘challenging’ anchors (see Figure 4). The results for the remaining five ESG questions are similar to the results reported here and are available from the authors upon request.

1.5.1. Tobit Model: Indirect (scores) approach

Table 1 presents the Tobit model results obtained from the estimation sample consisting of 225 respondents. Overall, the model is statistically significant as represented by the ANOVA fit measure (p-value <0.001). A dummy variable for whether a respondent uses a private vehicle as their main mode of transport or not, the log of how many days a car is used on average, and an interaction between the respondents age squared and a dummy representing whether the respondent is classed as having a low level of income, where found to be statistically significant variables explaining the derived attitudinal score. The positive parameter for the private mode dummy variable suggests that respondents who use a household owned vehicle for travel are more likely to have a higher attitudinal score than those who rely on public transport for the ‘handy’-‘challenging’ ESG question. Similarly, those who use a car more often are also likely to have a higher attitudinal score for this same question, although each additional day of use produces a diminishing increase in the score. Finally, holding income constant, older respondents are likely to have a lower score for the ‘handy’-‘challenging’ ESG question, whilst holding age constant, lower income respondents are also likely to have lower score for this question.

	Par.	(*t*-rat.)
Constant	5.2860	(10.35)
Private mode of transport	0.6655	(2.02)
log(car use)	0.8435	(3.71)
Age^2 × Income(Low)	-0.0019	(-2.46)
Sigma	2.4151	(18.72)
Model fit		
LL(0)	-1401.244	
LL(β)	-493.909	
ANOVA fit measure	0.000	

Table1: Tobit model results

We present the above discussion in vague generalities as the model results highlight major limitations with using a transformative score such as that suggested by Audrezet *et al.* (2016) for the purposes of prediction and modelling. To demonstrate, the maximum score for ambivalence, 7, will be achieved for cell *S*(5,5), whilst the maximum score possible, 9, representing a positive attitude towards the object, will be obtained for cell *S*(5,1). Unfortunately, distinguishing between these two outcomes is somewhat difficult based on the model results presented. Similarly, distinguishing between indifference and a negative attitude towards the object being measured is also somewhat difficult. For this reason, we now turn to using a series of ordered logit models to model the responses directly, as opposed to some transformation of the responses.

1.5.2. Ordered Logit model approach: Direct (observed ratings) approach

Based on the single ESG question, Table 2 presents the results for two models based on the estimation sample segment of the data. For the first model, M1, we constrain the parameter estimates to have the same magnitude but opposite signs between the positive and negative domains of the ESG question, whilst simultaneously allowing for different psychological thresholds for the two outcomes. As such, model M1 assumes a single underlying decision process to explain the observed positive and negative outcomes of the ESG. In the second model, M2, all parameters of the model are estimated free of any such constraints, thus allowing for distinct decision processes to explain the positive and negative responses within the ESG question. Based on the log-likelihood ratio test (see e.g., Hensher, Rose and Greene, 2015), both models provide a statistical improvement in terms of model fit when compared to the null model (M1: $\chi^2_{12} = 213.336, p - value < 0.001;$ M2: $\chi^2_{17} = 129.876, p - value < 0.001$), with model M2 providing a better statistical fit for the data when compared to model M1 ($\chi^2_5 = 13.106, p - value = 0.004$).

	M1: Single utility function				M2: Dual utility functions			
	Par.	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*
	Handy		*Challenging*		*Handy*		*Challenging*	
Latent variables								
Age (less than 26)	-	-	-	-	1.229	(3.05)	-	-
Number of day exercise (per week)	-	-	-	-	-	-	-0.190	(-2.08)
Number of day car use (per week)	0.241	(4.37)	-0.241	(-4.37)	0.257	(4.28)	-0.181	(-3.04)
Income (less than 50,000)	-	-	-	-	-1.191	(-2.01)	0.717	(1.76)
Main mode of transport privately owned	0.543	(2.02)	-0.543	(-2.02)	0.598	(2.00)	-	-
Italian cultural background	-0.750	(-1.81)	0.750	(1.81)	-1.050	(-2.45)	-	-
Threshold parameters								
τ_1	-2.583	(-5.57)	-2.620	(-5.34)	-2.898	(-3.60)	-2.268	(-5.03)
τ_2	-0.937	(-2.25)	-1.065	(-2.26)	-1.208	(-1.55)	-1.079	(-2.16)
τ_3	0.357	(1.25)	0.522	(2.13)	0.135	(0.46)	0.509	(2.07)
τ_4	2.345	(9.91)	2.288	(8.38)	2.209	(8.74)	2.276	(8.23)
Correlation parameter								
ρ	-0.646	(-8.28)	-	-	-0.589	(-6.606)	-	-
Model fit								
LL(0)	-772.530				-724.247			
LL(β)	-665.862				-659.309			
ρ^2	0.138				0.090			
Adj. ρ^2	0.029				0.016			
AIC	1355.724				1352.618			

Table 2: Ordered logit model results

Turning first to model M1, three socio-demographic characteristics where found to be related to the two underlying latent variables used to explain the values selected for both the 'handy' and 'challenging' axes on the ESG question. Frequent car users and respondents whose main mode of transport is privately owned were found to have a higher relative value for the latent variable associated with 'handy', whilst those with an Italian cultural background have a lower relative value, *all else being equal*. This suggests that respondents who more often use the car have a higher probability of holding a more positive position on the 'handy' axis of the ESG question, whilst those with an Italian cultural background have a higher probability of holding a less positive position for the same domain, *ceteris paribus*. The converse is true for the 'challenging' domain of the ESG question. The negative ρ parameter for the model suggests that after accounting for the influence the socio-demographic characteristics have on explaining the attitudes towards driving, respondents are more likely to select values within the ESG along the direction of the diagonal of the grid.

The threshold parameters of the model also tell a story. The large negative and statistically significant parameters for the first threshold suggest that the latent variable will need to be sizably negative for the lowest values of the grid to be chosen for both the positive and negative axes, *all else being equal*. A similar pattern emerges also for the largest positive and statistically significant parameters. Examining the relative differences between the threshold parameters also suggests that keeping the value of the underlying latent variable constant, respondents will be observed to have a higher probability of selecting larger values for the challenging axis than for the handy axis, *ceteris paribus*, except for the third value. This is because the relative differences between the threshold levels is greater for the positive ‘handy’ domain than for the negative ‘challenging’ domain, and hence the same latent variable value is more likely to exist within a higher threshold range for ‘challenging’ than for ‘handy’.

A different picture emerges from model M2 however. Without the constraints on the parameter estimates, different influences are observed to be related to the positive and negative components of the ESG question. For the positive ‘handy’ domain of the ESG, being of a lower age, using a car more often, and using a private vehicle as a main mode of transport all have a positive and statistically significant influence on the underlying latent variable for this construct. As such, respondents who fit the above description will be predicted to have a higher probability of selecting a more positive value in the ESG along the ‘handy’ domain. Conversely, those with a lower income and those with an Italian background are predicted to select lower values along this axis. Lower income respondents are also predicted to select higher values for the ‘challenging’ domain of the ESG, whilst those who tend to exercise more, or use the car more often are less likely to report driving ‘challenging’.

Based on the above results, Model M2 suggests different latent structures operate across the positive and negative domains of the ESG. To demonstrate, consider an individual younger than 26 who exercises five days a week, never uses a car but uses other privately owned means of transport, has an income higher than 50,000 CHF/year, and is not of Italian heritage. For such a person, and ignoring the correlation parameter, the model predicts values for the positive and negative domain latent variables of 1.828 and -0.231 respectively. In comparison, for the same individual, the first model would predict values for the two latent variables of 0.543 and -0.543 respectively.

The correlation parameter, ρ, has the same sign of that obtained from model M1. The negative ρ parameter suggests that after accounting for the influence the socio-demographic characteristics have on explaining the attitudes towards driving, respondents who are observed to select high values on one axis of the grid are more likely to select lower values along the opposite axis, *all else being equal*.

The relative differences between the threshold parameters is also similar to those obtained from the first model, with greater differences being observed for the 'handy' axis of the ESG than for the ''challenging' axis, with the exception of the third value. Nevertheless, given different structures are modelled for each latent variable, care needs to be taken in interpreting these differences, as unlike the results obtained from model M1, the same socio-demographic profile will likely return different values for the positive and negative domains, and hence their position relative to the threshold parameters is no longer fixed.

In order to understand how well the model predicts, Figure 5 presents the probabilities for the ESG based on the observed sample outcomes alongside the predicted outcomes obtained from the model. By and large, the model appears to predict reasonably over the grid, however the model tends to slightly struggle with zero observation cells, assigning small but non-zero probabilities and to under predict the cells on the diagonal, especially at the extremities. The problem with the diagonal is likely due to an empirical lack of relevant socio-demographic variables to explain this aspect of attitude.

	H1	H2	H3	H4	H5
C5	0.0533	0.0311	0.0000	0.0089	0.0000
C4	0.0089	0.0978	0.0756	0.0311	0.0044
C3	0.0000	0.0400	0.1244	0.1244	0.0089
C2	0.0000	0.0044	0.0222	0.1333	0.0756
C1	0.0133	0.0000	0.0089	0.0356	0.0978

(a) Actual probabilities

	H1	H2	H3	H4	H5
C5	0.0069	0.0139	0.0167	0.0217	0.0101
C4	0.0197	0.0412	0.0512	0.0694	0.0339
C3	0.0267	0.0595	0.0787	0.1154	0.0623
C2	0.0161	0.0383	0.0543	0.0870	0.0529
C1	0.0070	0.0173	0.0258	0.0443	0.0297

(b) Predicted probabilities

Figure 5: Estimation sample actual versus predicted outcomes

To further highlight the workings of the model, reported in Figure 6 are the predicted outcomes of four respondents using model M2. The socio-demographic profiles of the four different respondents are shown in Table 3. To compute the probabilities shown in Figure 5, 500 MLHS draws were used to simulate the correlated error term of the model. As shown in Figure 5, rather than predict one outcome per respondent, the model predicts for each individual the probabilities for all possible outcomes being observed. In order to obtain a probability for each individual to exhibit a particular attitude, it is also possible to sum the computed probabilities across several cells for the same individual. Thus for example, summing the six cells that make up the top left hand corner of the grid (cells C1:H3 to C2:H5), it becomes possible to compute the probability that a given individual will have a negative attitude towards driving. The remaining attitudinal types can be computed by summing the appropriate cells, as shown in Figure 2. The probabilities for each individual exhibiting different attitudes are given in Table 4.

	Individual 1	Individual 2	Individual 3	Individual 4
Age (less than 26)	0	1	0	1
Number of day car use (per week)	0	0	0	7
Income (less than 50,000)	1	1	1	0
Main mode of transport privately owned	0	1	0	1
Italian cultural background	1	0	1	0
Number of day exercise (per week)	0	0	7	7

Table 3: Example respondents

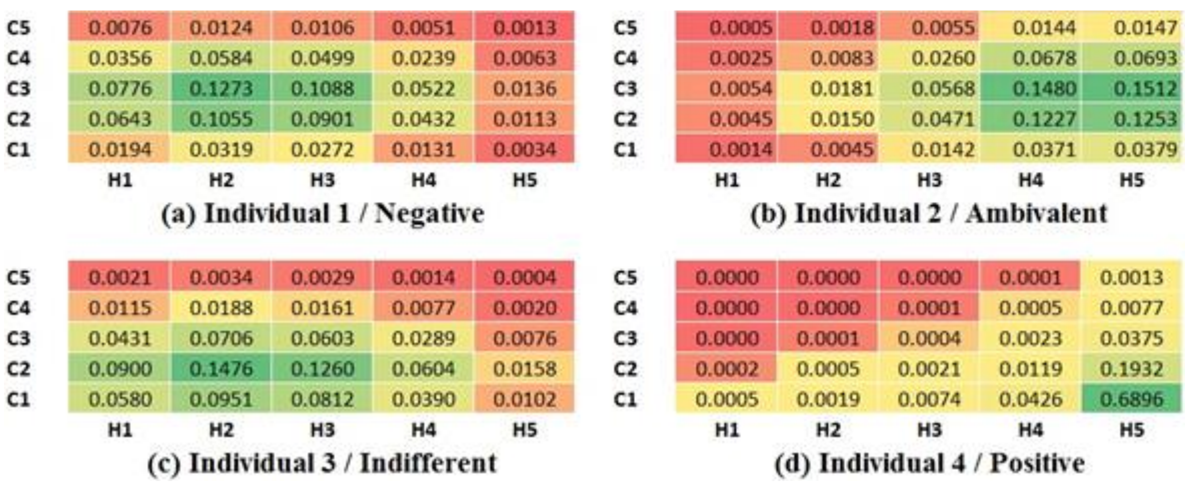

Figure 6: Individual probabilities for 4 different example ESGs. Probabilities accord to a scale red (low) to green (high).

From Table 4, it can be seen that individual 1 has the highest probability of being associated with a negative attitude towards driving, although there is respectively a 0.2716 and 0.2212 probability that they may be classed as being ambivalent or indifferent towards driving. Respondent 2 has the greatest probability of being classed as being ambivalent towards driving, however there is also a significant probability (i.e. 0.3842) that they could also be considered as having a positive attitude towards driving. Individual 3 is most likely to be indifferent towards driving even if they show a 0.3327 probability to have a positive attitude towards driving, whilst individual 4 has the highest probability of being classed as having a positive attitude towards driving. The important take-away however is that each individual has a non-zero probability of being described under each type of attitudinal response. In this sense the model is truly stochastic, meaning that two individuals with the same socio-demographic profile will have the same probability outcomes, however this does not preclude different outcomes being actually observed in practice.

	Individual 1 (Negative)	**Individual 2 (Ambivalent)**	**Individual 3 (Indifferent)**	**Individual 4 (Positive)**
Negative	**0.3189**	0.0366	0.1494	0.0002
Positive	0.1884	0.3842	0.3327	**0.9469**
Indifferent	0.2212	0.0254	**0.3906**	0.0032
Ambivalent	0.2716	**0.5538**	0.1273	0.0498

Table 4: Probabilities for four individuals displaying different attitudinal responses

1.6. Out of sample results

In this section, we use the hold-out sample to test how well the models perform when predicting to another sample of respondents. We start with applying the Tobit model to the hold-out sample before applying the second ordered logit model, model M2, to the same sample.

1.6.1. Tobit Model: Indirect (scores) approach

For each respondent in the hold out sample, we compute the attitudinal scores based on their real ESG responses, and compare these to the predicted scores derived by applying Equation (7) using the respondent's socio-demographic characteristics as well as the model parameters reported in Table 1. Figures 7 and 8 plot the Kernel Density Functions for the predicted versus actual scores, and predicted values versus residuals values respectively. What both figures demonstrate is that the predicted values for the hold out sample are clustered between 4 and 7.5, and fail to systematically predict either low or high scores. Examination of both the model parameters and sample explains why this is the case. The large statistically significant constant contrasts with the smaller model parameters, which alongside a lack of variation in the socio-demographic profiles of either sample, means that the predictions from the model tend to be distributed within a small range around the constant term. This finding suggests that those wishing to adopt this approach should ensure that the sample has adequate variation in terms of the explanatory variables adopted, as well as information on a wide range of such variables.

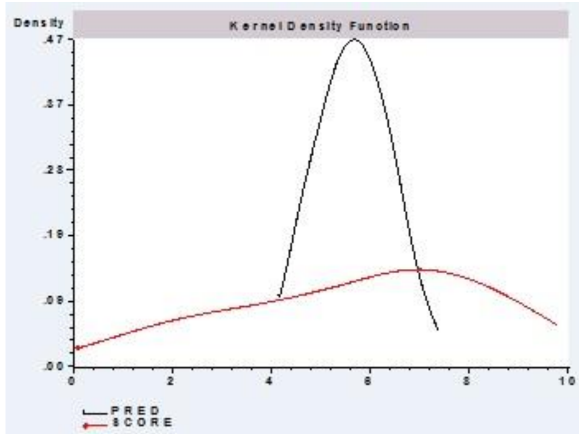

Figure 7: Kernel density functions for predicted versus actual scores

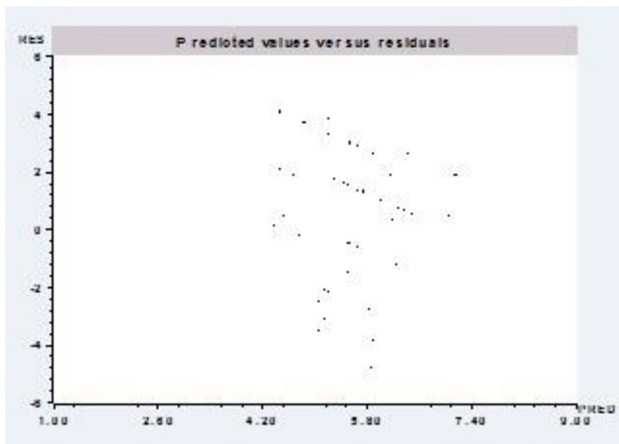

Figure 8: Scatter plot of predicted versus residual scores

1.6.2. Ordered Logit model approach: Direct (observed ratings) approach

Similar to how we applied the Tobit model to the hold-out sample, in this section, we use the socio-demographic characteristics of each respondent assigned within the hold out sample to predict the ESG outcomes using the ordered logit model M2. These predictions are then compared to the actual outcomes. Figure 9 presents the results of this exercise. The model tends to under predict the cells at in the lower right quadrant of the grid associated with positive attitudes towards driving. The results suggest that whilst overall, the socio-demographic characteristics are good predictors of ESG response, had alternative socio-demographic characteristics been collected within the survey, then these may have acted as better proxies for responses associated with the lower right quadrant of the grid.

	H1	H2	H3	H4	H5
C5	0.0423	0.0282	0.0282	0.0000	0.0000
C4	0.0423	0.0845	0.0423	0.0141	0.0141
C3	0.0282	0.0141	0.1127	0.0986	0.0141
C2	0.0000	0.0000	0.0000	0.1972	0.1268
C1	0.0000	0.0000	0.0141	0.0141	0.0845

(a) Actual probabilities

	H1	H2	H3	H4	H5
C5	0.0053	0.0123	0.0161	0.0220	0.0103
C4	0.0161	0.0383	0.0510	0.0713	0.0350
C3	0.0240	0.0583	0.0807	0.1196	0.0645
C2	0.0153	0.0386	0.0558	0.0888	0.0536
C1	0.0068	0.0175	0.0262	0.0439	0.0287

(b) Predicted probabilities

Figure 9: Actual probabilities versus predicted probabilities

To complete this discussion, we present in Table 5, a series of statistics measuring the prediction error of the model, both within and out of sample. Although simply summary measures, the results show that the model appears to perform slightly better within sample than out of sample, with the largest absolute error observed occurring for cell H5:C1 (i.e. 0.0680).

	Within Sample	Out of Sample
$\|Maximum\ error\|$	0.0680	0.1084
$\|Sum\ of\ error\|$	0.6854	0.8214
$\|Average\ error\|$	0.0274	0.0329
$E(Error^2)$	0.0010	0.0017

Table 5: Within and out of sample prediction errors

1.7. Discussion and conclusions

The ability to model attitudes in the manner described here is important, given that ambivalence and indifference may be largely indistinguishable using traditional methods. We propose two different econometric models to best analyze data collected by means of the ESG response mechanism, although the methods proposed are not limited to such a type of data, but can be applied to any type of data collected using rating scales.

The internal mechanisms that led to the two types of attitudes may be very different, as too the experiences of individuals who are either ambivalent or indifferent. For example, an individual who is ambivalent towards an object may experience internal conflict (Sengupta and Johar, 2002; Tang *et al.*, 2014), defined by unpleasant or uncomfortable feelings (Festinger, 1957; Heider, 1946; Newby-Clark *et al.*, 2002; Van Herreveld *et al.*, 2009), which may result in attempts to resolve the internal turmoil, whilst an individual who is indifferent towards the same object is unlikely to show any reaction other than a completely neutral one. For this reason, it is crucial to understand who these individuals are: the ESG is a highly recommended tool to achieve this aim, and its proper use exploiting distribution function, as suggested in this work, can add value to its potentialities.

It is our argument that for many applied fields, such as social behavior, political behavior and marketing, the distinction between ambivalent and indifferent can add efficacy and efficiency to policies. For instance, in marketing identifying common individual characteristics which lead more likely to assess a product or service both satisfying and unsatisfying, can suggest the producer on which cluster to focus the efforts in order to increase the probability of satisfaction.

Thompson *et al.* (1995) modified the ambivalence index by Griffin in order to take into account two different domains of ambivalence, cognitive and affective. A continuum of our research is to link two (or more) ESGs, in order to relate different domains of ambivalence. Moreover, our additional interest is to test whether and to what extent ambivalent and indifferent individual's act differently (Costarelli and Colloca, 2004; Yoo, 2010; Thornton, 2011) in a transport context, connecting attitudes towards driving collected by means of ESGs and mode choices.

Two alternative approaches presented in this work are applied to ESG response type questions. Such an instrument, different from traditional Likert and semantic differential type scales, allows the researcher to detect various attitudinal outcomes towards an object, including ambivalence and indifference, alongside the more commonly measured positive and negative attitudinal outcomes. To date, whilst there exist several tools to measure ambivalence, including the use of subjective measures (Priester and Petty, 1996; Clark *et al.*, 2008), response time (Bargh *et al.*, 1992; Fazio *et al.*, 1986), indices based on the scores of two separate semantic differential scales (Kaplan, 1972; Katz and Hass, 1988; Thompson *et al.*, 1995), mouse tracking (Schneider *et al.*, 2015), and scores captured in 2D space using a bilinear model exploiting an ESG response mechanism (Audrezet *et al.*, 2016), each of these approaches have been criticized due to a number of potentially severe limitations. Subjective measures may led to biased conclusions given respondents are able to easily provide socially desirable or acceptable responses, whilst use of response times remains largely a black box, with little to no way available to infer the true mental process resulting in attitudes. Mouse tracking studies remain hard to replicate when many respondents are involved, and indices and scores whilst easy to implement, assume that the response mechanism from which they are derived is a perfect measure of attitudes. Assuming attitudes are latent constructs, and hence not directly measurable, the use of scores seems anachronistic. For this reason, the models we suggest treat attitudes based on psychometric survey questions as indicators of underlying latent psychological factors rather than as directly observed measurements of said factors. An additional advantage of the proposed models, is their ability to forecast future responses (i.e. predict out of sample). In many applied fields, such as environmental or transport economics in which such psychological methods are commonly used, being able to predict how attitudes may develop or change over time, or even what attitudes may exist in other non-sampled populations, can support policy makers in their decisions.

Based on the Audrezet *et al.* (2016) scoring scheme, we use a Tobit model to demonstrate how such scores can be appropriately modeled in practice. The Tobit model assumes an underlying latent structure to predict the observed outcome, in this case the attitudinal score. The latent variable within the model is predicted via socio-demographic variables. In the current chapter, whilst the model is theoretically consistent with the view that attitudes are latent constructs, we find the model performance to be somewhat lacking, providing poor predictive power. We argue however that this finding is not the result of model misspecification but rather due to having a small number of socio-demographic variables available for use, as well as a lack of variation in terms of the socio-demographic variables we do have available.

We offer a second model, the ordered logit model, as an alternative means to model ESG response data. By estimating two simultaneous ordered logit models, we demonstrate that it is possible to model the observed outcomes of the grid, rather than a transformation of the observed outcomes. By modelling the observed outcomes as opposed to an intermediary transformation, we show how it is possible to model up to a probability, various attitudinal outcomes, something the Tobit model struggles with. Within the chapter, we are able to demonstrate how alternative specifications of the model can be used to test different theoretical frameworks associated with attitudes. In this vain, we use the system of models to model (1) positive and negative items being driven by the same factors exploiting a unique distribution function for both axes (e.g., if gender is positively significant, males have a higher probability of scoring high positive and negative values than females), and (2) different factors affect the positive and the negative items assuming total independence between them (e.g., being a male could lead more likely to higher values for positive item but could not have a significant effect for the negative one), whilst in both cases allowing the unobserved factors to be related by means of a correlation term. As with the Tobit model, we find selection of socio-demographic characteristics is crucial to the predictive ability of the model.

References

Audrezet, A., 2014. L'ambivalence des consommateurs: proposition d'un nouvel outil de mesure. *Business administration. Universite Paris Dauphine - Paris IX. French.*

Audrezet, A., Olsen, S.O., Tudoran, A.A., 2016. The GRID scale: a new tool for measuring service mixed satisfaction. *Journal of Services Marketing* 30(1), 29 – 47. doi: 10.1108/JSM-01-2015-0060

Bargh, J. A., Chaiken, S., Govender, R., Pratto, F., 1992. The generality of the automatic attitude activation effect. *Journal of Personality and Social Psychology* 62, 893 – 912. doi: 10.1037/0022-3514.62.6.893

Bierlaire, M., 2016. PythonBiogeme: a short introduction, Technical report TRANSP-OR 160706. Transport and Mobility Laboratory, ENAC, EPFL. Retrieved from: http://biogeme.epfl.ch/documentation/pythonfirstmodel.pdf

Borsboom, D., 2008. Latent variable theory. *Measurement* 6, 25 – 53. doi: 10.1080/15366360802035497

Cacioppo, J.T., Berntson, G. G., 1994. Relationship between attitudes and evaluative space: a critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin* 115(3), pp. 401 – 423. doi: 10.1037/0033-2909.115.3.401

Cacioppo, J.T., Gardner, W.L., Berntson, G. G., 1997. Beyond bipolar conceptualizations and measures: the case of attitudes and evaluative space. *Personality and Social Psychology Review* 1(1), 3 – 25. doi: 10.1207/s15327957pspr0101_2

Cacioppo, J.T., Gardner, W.L., Berntston, G.G., 1999. The affect system has parallel and integrative processing components: form follows function. *Journal of Personality and Social Psychology* 76(5), 839 – 855. doi: 10.1037/0022-3514.76.5.839

Clark, J. K., Wegener, D. T., Fabrigar, L. R., 2008. Attitudinal ambivalence and message-based persuasion: motivated processing of proattitudinal information and avoidance of counterattitudinal information. *Personality & social psychology bulletin,* 565 – 577. doi: 10.1177/0146167207312527

Conner, M., Sparks, P., 2002. Ambivalence and Attitudes, *European Review of Social Psychology* 12, 37 –70. doi: 10.1002/0470013478.ch2

Costarelli, S., Colloca, P., 2004. The effects of attitudinal ambivalence on pro-environmental behavioral intentions. *Journal of Environmental Psychology* 24(3)*,* 279 – 288. doi: 10.1016/j.jenvp.2004.06.001

Fazio, R. H., Sanbonmatsu, D. M., Powell, M. C., Kardes, F. R., 1986. On the automatic activation of attitudes. *Journal of Personality and Social Psychology* 50, 229–238. doi: 10.1037/0022-3514.50.2.229

Festinger, L., 1957. *A theory of cognitive dissonance.* Evanston, IL: Row, Peterson.

Heider, F., 1946. Attitudes and cognitive organization. *Journal of Psychology* 21*,* 107-112. doi: 10.1080/00223980.1946.9917275

Hensher, D.A., Rose, J.M. and Greene, W.H., 2015. *Applied Choice Analysis*, Second Edition, Cambridge University Press, Cambridge.

Hess, S., Train, K. and Polak, J., 2006. On the use of modified latin hypercube sampling (MLHS) method in the estimation of mixed logit model for vehicle choice, *Transportation Research Part B* 40(2), 147–163*.* doi: 10.1016/j.trb.2004.10.005

Kaplan, K. J., 1972. On the ambivalence-indifference problem in attitude theory and measurement: A suggested modification of the semantic differential technique. *Psychological Bulletin* 77, 361-372. doi: 10.1037/h0032590

Katz, I., Hass, R. G., 1988. Racial ambivalence and American value conflict: Correlational and priming studies of dual cognitive structures. *Journal of Personality and Social Psychology 55,* 893–905. doi: 10.1037/0022-3514.55.6.893

Larsen, J.T., Norris, C.J., McGraw, A.P., Hawkley, L.C. and Cacioppo, J.T., 2009. The evaluative space grid: a single-item measure of positivity and negativity. *Cognition and Emotion* 23(3), 453-480. doi: 10.1080/02699930801994054

Likert, R., 1932. A technique for the measurement of attitudes. *Archives of Psychology,* R. S. Woodworth Editor, 140, New York.

Newby-Clark, I.R., McGregor, I., Zanna, M.P., 2002. Thinking and caring about cognitive inconsistency: When and for whom does attitudinal ambivalence feel uncomfortable? *Journal of Personality and Social Psychology* 82, 157-166. doi: 10.1037/0022-3514.82.2.157

Osgood, C. E., 1964. Semantic differential technique in the comparative study of cultures. *American Anthropologist* 66(3), *171 – 200.* doi: 10.1525/aa.1964.66.3.02a00880

Priester, J.R., Petty, R.E., 1996. The gradual threshold model of ambivalence: relating the positive and negative bases of attitudes to subjective ambivalence. *Journal of Personality and Social Psychology* 71, 431–449. doi:10.1037/0022-3514.71. 3.431

Russell, J. A., Carroll, J. M., 1999. On the bipolarity of positive and negative affect. Psychological Bulletin 125, 3–30.

Schneider, I.K., van Harreveld, F., Rotteveel, M., Topolinski, S., van der Pligt, J., Schwarz, N., Koole, S.L., 2015. The path of ambivalence: tracing the pull of opposing evaluations using mouse trajectories. *Front. Psychol.* 6(996)*.* doi: 10.3389/fpsyg.2015.00996

Schwarz, N., Bohner G., 2001. The construction of attitudes. Manuscript of a chapter in A. Tesser and N. Schwarz. *Intrapersonal processes*, *Blackwell Handbook of Social Psychology,* 436 – 457. Oxford, UK. Blackwell.

Sengupta, J. Johar, G.V., 2002. The effects of inconsistent attribute information on the predictive value of product attitudes: toward a resolution of opposing perspectives. *Journal of Consumer Research* 29(1), 39-56. doi: 0093-5301/2003/2901-0003

Tang, T., Fang, E. Wang, F., 2014. Is neutral really neutral? The effects of neutral user-generated content on product sales. *Journal of Marketing* 78(4), 41-58.

Tay, L., Kuykendall L., 2017. Why self-reports of happiness and sadness may not necessarily contradict bipolarity: a psychometric review and proposal. *Emotion Review* 9(2), 146-154*.* doi: 10.1177/1754073916637656.

Thompson, M.M., Zanna, M.P. and Griffin, D.W., 1995. Let's not be indifferent about (Attitudinal) ambivalence. In Petty, R.E. and Krosnick, J.A. (Eds), *Attitude Strength: Antecedents and Consequences*, (pp. 361-386) Lawrence Erlbaum, Mahwah, NJ.

Thornton, J.R., 2011. Ambivalent or indifferent? Examining the validity of an objective measure of partisan ambivalence. *Political Psychology* 32(5), 863-884. doi: 10.1111/j.1467-9221.2011.00841.x

Thurstone, L.L., 1928. Attitudes can be measured. *American Journal of Sociology* 33, 529 – 554.

Van Herreveld, F., Van der Pligt, J., De Liver, Y., 2009. The Agony of Ambivalence and Ways to Resolve It: Introducing the MAID Model. *Personality and Social Psychology* 13(45). DOI: 10.1177/1088868308324518.

Yoo, S.J., 2010. Two types of neutrality: ambivalence versus indifference and political participation. *The Journal of Politics* 72(1), 163-177. doi: 10.1017/S0022381609990545

Chapter 2. The implementation of the Evaluative Space Grid in a hybrid choice model to overcome the disadvantages of measuring attitudes using common scales.

Antonio Borriello[1], Stefano Scagnolari[1]

[1]Università della Svizzera italiana

Abstract

The study of latent variables, and in particular of attitudes, contributes to a better understanding of individual preferences and behavior and it is now common practice within transportation literature. However, the procedure of attitude measurement is still not optimal. Two major issues are the misspecification of the attitude itself and in the number of suitable items used for defining the psychological factor. The incorrect measurement entails a poor representation of individuals on the latent continuum and a less precise definition of the latent variable itself.

These issues become even more relevant when a Likert scale is used. Indeed, the neutral point of this scale is selected by both individuals having an ambivalent and an indifferent attitude, and the poor representation makes impossible to distinguish these categories. Nevertheless, such a distinction can be very profitable for policy reasons. To overcome this issue and to suggest more effective policies, we propose using the Evaluative Space Grid (ESG), which is a single-item measure of positivity and negativity, to collect attitudinal variables. This tool can distinguish between individuals with indifferent and ambivalent attitudes, as well as those with positive and negative inclinations.

This work models the ESG using a pair of ordered logit regressions and suggests a procedure to include this approach in the framework of hybrid choice models. Furthermore, it endeavors to shed light on the preferences of individuals having indifferent and ambivalent inclinations in a transportation context, showing the hypothesis that their preferences are different for commuting trips.

Keywords: Attitude measurement, hybrid choice model, Evaluative Space Grid, Ambivalence, Indifference.

2.1. Introduction

The integration of psychological factors in transportation literature is a fundamental key for understanding individual behavior. In the last two decades, hybrid choice models, which explore the influence of attitudes on individuals’ choices as well as their composition, became quite popular and widespread. In this work we focus on a new way of measuring an attitude with the scope of exploring individuals’ behavior and the choices they make in a transportation context.

Psychologists define an attitude as "the sum-total of a man's inclinations and feelings, prejudice or bias, preconceived notions, ideas, fears, threats and convictions about any specific topic” (Thurstone and Chave, 1929). From an econometric point of view, an attitude is a variable that cannot be directly measured (latent) but that can be defined through some indicators (or observable variables) net of an error. The first attempt to measure an attitude was made by Thurstone (1928), who measured the inclination towards prohibition, pacifism/militarism, and religion. Thurstone developed between eighty and one-hundred statements and asked subjects to place each statement on an 11-point scale defined by a central neutral point, with five points located to either side. Likert (1932) refined Thurstone’s work and proposed a scale based on the measurement of different statements (items) of which subjects were asked to express their level of agreement/disagreement. At the present time, this instrument is considered being the gold standard for measuring attitudes and it is the most common tool in psychology or in applied fields like transportation.

Because of their latent nature, the higher the number of observable variables suitable to measure the attitude, the lower the error computed in the measuring process. Consider as an example the measurement of passengers’ loyalty to public transport modes. Shiftan *et al.* (2015) measure this attitude using twenty-six items representing affective, conative, action and cognitive facets of loyalty, as well as hedonic value, comfort, convenience and reliability. The assessment of the latent variable “loyalty to public transport modes” depends on how much variance of that attitude the items are able to explain. Omitting constructs such as e.g. comfort or reliability would increase the randomness of the latent variable and, as a consequence, reduce its efficacy.

The use of a limited number of measurable items for defining an attitude and the misspecification of the attitude itself are the main problems emerging in several papers in transportation mode choice. Indeed, researchers who focus on the study of attitudes from a psychological perspective generally exploit a larger set of suitable items for defining a latent construct than researchers who model the behavioral consequences of the attitudes. In a study aimed at segmenting "the population of day trip travelers into potential 'mode switchers' using cluster analysis", Anable (2005) employs respectively twenty-four and twenty-seven items to represent the general attitude towards the car and its alternatives. In an application of the Theory of Planned Behavior designed to understand the factors influencing the car use for commuting, Abrahamse *et al.* (2009) assess the general attitude towards the car using a set of seven items. The attitude pro-car is instead defined by Atasoy *et al.* (2012) by using three items in a hybrid choice model with latent classes for a sample of Swiss respondents. The observable variables adopted to proxy the latent construct, measure two specific aspects of the attitude (convenience and flexibility of the car) and therefore, several important aspects were not included in the construction of the attitude, decreasing its explained variance. Analogous differences on the number of items used, can be found for the definition of the attitude "environmental concerns", which, referring to the papers by Mokhtarian *et al.* (2001), Ory, Mokhtarian (2005), Anable (2005), Prillwitz and Barr (2011), has been defined using on average 8 items, whilst Johansson *et al.* (2006), Atasoy *et al.* (2012), Hess *et al.* (2013) and Bahamonde-Birke, Hanappi (2016), employ on average 4.5 items to outline the same attitude. Rundmo *et al.* (2011) define the safety perceived for public and private means using five and seven items respectively, whereas Daziano and Bolduc (2013), and Raveau *et al.* (2010) use only two items to explore the same latent constructs. The general satisfaction with public transport and soft modes has been explored by Prillwitz and Barr (2011), who use ten and nine items respectively, whereas a general satisfaction for commuting has been measured using one item by Abou-Zeid and Ben-Akiva (2011).

An inappropriate specification of the attitude can be observed in the study by Domarchi *et al.* (2008), who investigate the effect of the attitudes towards car and public transport on mode choice by means of two items. Using "direct measure" of what actually is a latent construct, they generate high aggregation of contents. Indeed, respondents can associate the question "For me, using car / public transport to arrive to work is good'' with several aspects, like its convenience, its flexibility and its cost inter alia. A similar misspecification of the latent variable can be also found in Bolduc *et al.* (2008) and Bolduc and Daziano (2010), who use a considerable number of items (eight) to define the "appreciation of new car features", but who measure directly "safety" and "reliability", which clearly are latent variables. It is also a common practice to treat a latent construct as an attribute of the choice experiment: for instance, Espino *et al.* (2003) and Espino *et al.* (2006) define "comfort" as an attribute with generic categories "low – standard or medium – high".

In order to validate a new scale for measuring an attitude, psychologists consider numerous items related to it and then, using techniques of variable reduction, cut out the less informative indicators. The main reason why choice modelers employ a limited number of items concerns the way the survey is designed in a choice experiment setting: the questionnaire usually contains a section with six/ten choice tasks as well as sociodemographic questions. The addition of a long list of attitudinal indicators would make the filling of the survey time consuming and quite demanding, affecting the quality of the responses, as well as (and maybe mainly) the cost for distributing the survey (using an internet panel, respondents are paid according to the time spent completing the questionnaire). Furthermore, many researchers are not aware of the existing literature in transportation psychology and the list of items useful for identifying the attitude is usually discussed within a focus group with experts in the field, who are choice modelers themselves and rarely psychologists. A further difference between the definition of a scale in psychology and choice modeling consists in the positioning of the items along the latent continuum. Psychologists include items with a positive, neutral and negative valence covering the entire latent continuum domain (i.e. they use appropriate wording aimed at capturing a possible positive, neutral and negative outcome of the attitude), whilst choice modelers usually use items with an extreme positive or a negative valence.

The lower discrimination and information lead to an aggregation of individuals with an indifferent or ambivalent attitude in choice modeling applications. Indeed, the central value on a Likert scale can express indifference as well as ambivalence. Indifference implies that an individual has no interest in the stimuli being studied, revealing a low positive and negative reaction; ambivalence, on the other hand, suggests that the subject experiences both a moderate or high positive and negative valence towards the stimuli. A correct distinction between these two categories of respondents is fundamental for understanding behavior and suggesting more effective policies. As a matter of fact, it has been shown that indifferent and ambivalent individuals act differently in contexts such as political elections and environmental behavior (Costarelli and Colloca, 2004; Yoo, 2010; Thornton, 2011).

In this chapter, we propose to measure attitudes using a different tool, namely Evaluative Space Grid (ESG, Larsen *et al.*, 2009), rather than the Likert scale, to allow the differentiation between ambivalence and indifference, as well as positive and negative attitudes. This work has a twofold ambition: from a theoretical perspective, it endeavors to integrate the ESG in the framework of discrete choice modelling in order to avoid the aggregation of individuals positioned on the neutral part of a latent continuum; the empirical contribution concerns testing the hypothesis that individuals with indifferent and ambivalent attitudes towards the private car use for commuting behave differently in the context of transport mode choice.

The remainder of the chapter is organized as follows. In the next sections, we first introduce the ESG tool, proposed by Larsen *et al.*, and the methodology, which elucidates the econometric steps to define a hybrid choice model including the evaluative space grid, and we then present the sample, the survey as well as the model we use to analyze it. The following section shows the results obtained through the hybrid choice model and in particular the differences amongst different categories of respondents, namely those including individuals with a positive, negative, indifferent and ambivalent attitude towards the private car use for commuting trips. We conclude the chapter summarizing the major evidence and discussing the benefits of using the evaluative space grids in a hybrid choice model in the context of transport.

2.2. Evaluative Space Grid (ESG)

The studies on the neutral part of the latent continuum started decades ago and the first attempt to measure ambivalence was made by Kaplan (1972) who derived a simple formula using the respondents' assessment of a Likert item. However, the common Likert scale is not suitable to measure ambivalence and indifference, even if it contains items with both a positive and a negative valence. Indeed, the use of sequentially structured conversely framed questions has been criticized within the literature given that such an approach has the potential to induce subjects to reveal distorted preferences, particularly if for the second set of questions they attempt to display consistent answers with the preferences given to the first set of questions asked. For this reason, Larsen *et al.* proposed using a "single-item measure of positivity and negativity" which they termed the *evaluative space grid*. The ESG is designed to recover the independent and simultaneous assessment of positive/negative attitudes towards an object, and has since been validated in different fields such as psychology and social behavior (e.g., Audrezet, 2014; Audrezet, Olsen and Tudoran, 2016). This tool follows the theoretical framework of Evaluative Space Model (ESM) proposed by Cacioppo and Bernston (1994), who suggested that positive and negative feelings can be experienced at the same time, also with strong intensities.

The ESG contrasts positive and negative stimuli towards an attitude, posing two 5 points scales on *x* and *y* axes. Subjects are asked to select one of over 25 cells that best reflects their simultaneous negative and positive feelings towards the stimulus under study, as shown in Figure 1. The grid is designed to differentiate between four different attitudes: (1) positive (high positive and low negative), (2) negative (low positive and high negative), (3) indifference (low positive and negative), and (4) ambivalence (moderate to high positive and negative).

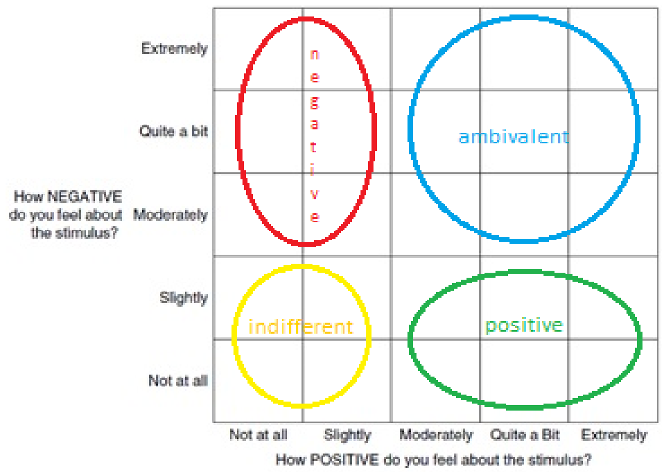

Figure 1: Evaluative space grid. Audrezet (2014) suggests the following division of the grid: bottom left cells identify an indifferent individual (yellow); bottom right cells classify a subject with a positive attitude (green); the top left cells (red) categorize an individual with a negative attitude; top right cells identify a subject with an ambivalent attitude.

2.3. Methodology

In this section, we discuss the methodology applied to incorporate the Evaluative Space Grid in a choice model framework. To model the ESG, we use two ordered logit regressions which take into account the ordinal nature of the tool. Three types of relationships are defined in the hybrid discrete choice model as follows.

Let consider *n* respondents who face a choice set composed by *J* alternatives. The chosen alternatives is $k_n = \arg\max((U_{nj} = f_1(X_j, W_n, Y_j, G_n; a, d, c, v_{nj}) \mid n = 1,\ldots,N; j = 1,\ldots,J)$, where X_j is a vector of attributes for alternative *J*, W_n represents a vector of socio-economic variables describing individual *n*, G_n indicates the vector of l latent variables, whilst the matrix Y_j defines which latent variables are inserted in the utility function of alternative *J*. The impacts of these latent variables are measured by the vector *c*, whilst vectors *a* and *d* represent the impact that attributes and socioeconomic variables have on the utility of the alternative respectively. The error term ν_{nj} is i.i.d. extreme value type 1. The analyst can define the function $f_1(g)$ according to the data.

Latent variables are determined by a series of structural relationships. We assume that they may be explained, or proxied, by observable data, such as gender, income, etc.. However, given that such data are not fully capable of explaining an individual's attitudes towards an object, we decompose G_{nl} in two parts, an observed component and a stochastic component, such that $G_{nl} = O_{nl} + \psi_{nl}$. For simplicity, we assume a linear additive specification for the observed component of the latent variable, such that $O_{nl} = bW_{nl}$ where W_{nl} represents the vector of socio-demographic characteristic of subject *n* associated to the latent variable l, and b is the vector containing the marginal contribution to the latent variable associated with the socio-demographic characteristics. The remaining term ψ_{nl} is a stochastic term representing the idiosyncratic impact on G_{nl}, not directly modelled in O_{nl}, following a Normal distribution with zero mean and variance $\sigma^2_{\psi_l}$.

Attitudinal response y_{ni} for the *i^th^* indicator variable (or item) is a categorical variable modelled by a measurement equation, whose general formulation is $y_{ni} = \delta_i + d_i G_n + \varepsilon_{ni}$, where δ_i is a constant, G_n is the vector of the latent variables whose effect on the response is measured by the vector d_i (note that this vector may contains zero values if the latent variables do not have an impact on a given item). The specification of ε_{ni} determines the type of measurement model: through this work we assume that ε_i is distributed as extreme value type 1 over the population for any item and, therefore, we use an ordered logit to model the attitudinal responses. Hence, the level of G_{nl} determines the observed responses such that if G_{nl} exceeds some psychological threshold, τ_{irl}, category *r* will be selected, else one of the preceding categories will be chosen.

Assuming a five category scale, the probability that respondent *n* will choose category *r* for item *i* is

$$P_{nir} = \begin{cases} \dfrac{\exp(\tau_{i1l} - O_{ni})}{1+\exp(\tau_{i1l} - O_{ni})}, r = 1 \\ \dfrac{\exp(\tau_{irl} - O_{ni})}{1+\exp(\tau_{irl} - O_{ni})} - \dfrac{\exp(\tau_{irl-1} - O_{ni})}{1+\exp(\tau_{irl-1} - O_{ni})}, \forall\ 1 < r < 5, \\ 1 - \dfrac{\exp(\tau_{i4l} - O_{ni})}{1+\exp(\tau_{i4l} - O_{ni})}, \forall r = 5. \end{cases} \tag{1}$$

Equation (1) suggests that each response can be chosen up to a modelled probability for any given respondent. That is, for each response category associated with response item *i*, we estimate the probability distribution for all possible outcomes for each respondent *n*. We define an indicator variable γ_{nir}, such that $\gamma_{nir} = 1$ if category *r* is chosen by individual *n* for item *i* and 0 otherwise.

Up to this point, we followed the methodology described in Daly *et al.* (2012). However, in this work we collect the attitudes using the Evaluative Space Grid response mechanism, rather than a common Likert scale, to allow simultaneous assessment of positive and negative attitudes towards the object under study. Therefore, we capture two discrete outcomes per any grid, y_{ni}^{+} and y_{ni}^{-}, representing the concurrent positive and negative dimensions of the attitude for item *i* respectively. Both the positive or negative dimensions are assumed to provide a discrete representation of two separate, yet potentially correlated, continuous latent variables, $G_{nl}^{+} = b^{+}W_{nl}^{+} + \psi_{nl}^{+}$ and $G_{nl}^{-} = b^{-}W_{nl}^{-} + \psi_{nl}^{-}$. The modelling approach we propose follows the assumption of the ESM, which allows for the possibility that positive and negative attitudes arise from different psychological processes. In order to explain the observed positive and negative responses for the same stimuli, we use different subsets of socio-demographic characteristics (W_{nl}^{+} and W_{nl}^{-}). We further extend the modelling framework to allow a pattern of possible correlation of the stochastic components of G_{nl}^{+} and G_{nl}^{-}. We do this by constructing the random terms of the positive and negative components of the latent variables as

$$\psi_{nl}^{+} = t_{nl}^{+} \qquad (2a)$$

$$\psi_{nl}^{-} = t_{nl}^{+} * \rho + t_{nl}^{-}(\sqrt{1-\rho^{2}}) \qquad (2b)$$

where t_{nl}^{+} and t_{nl}^{-} are random draws following a Normal distribution with zero mean and unit variance (note that ψ_{nl}^{-} still follows the same distribution). Given that neither ψ_{nl}^{+} and ψ_{nl}^{-} are associated with an observable variable, both terms represent additional sources of error associated with G_{nl}^{+} and G_{nl}^{-} respectively, with correlation equal to ρ. To estimate the additional error structure, we rely on a Cholesky decomposition.

Two discrete outcomes are modelled in the measurement equations, such that

$$y_{ni}^{+} = \delta_{i}^{+} + d_{i}^{+}G_{n}^{+} + \varepsilon_{ni}^{+} \qquad (3a)$$

$$y_{ni}^{-} = \delta_{i}^{-} + d_{i}^{-}G_{n}^{-} + \varepsilon_{ni}^{-} \qquad (3b)$$

Positive (negative) outcome, $y_{ni}^{+}(y_{ni}^{-})$, depends on the positive (negative) domain of the latent variable, $G_n^{+}(G_n^{-})$ and its effect on the attitudinal response is measured through the vector $d_i^{+}(d_i^{-})$. Under this scenario, it is possible to treat $\tau_{irl}^{+}=\tau_{irl}^{-}$ or $\tau_{irl}^{+}\neq\tau_{irl}^{-}$, the outcome of which should be determined empirically. The objective of the analyst is to estimate the parameters included in the three types of relationships. However, for identification issues, it is necessary to impose some constraints. First, the normalization of the scale for the measurement equation should be considered. Ben-Akiva *et al.* (1999) suggested to normalize to 1 the impact of one the attitudinal indicators d_i^{+} (d_i^{-}) of each of the latent variables and estimate the variances of the errors in the structural equation (σ_{ψ}^{2}); Bolduc *et al.* (2005) instead, proposed to normalize the variances to 1 and to estimate d_i^{+} (d_i^{-}) for the whole set of indicators. Second, the simultaneous estimation of the constants δ_i^{+} (δ_i^{-}) in the measurement equations and the first threshold τ_{i1l}^{+} (τ_{i1l}^{-}) used in the ordered logit is unfeasible and therefore only one of the two parameters should be included into the model.

With the above background, we define the probability of observing subject *n* selecting the $r^{th}(s^{th})$ response category for item $i^{+}(i^{-})$ conditional on latent variables and hence on Σ_{ψ} (variance-covariance matrix of $\psi_{nl}^{+},\psi_{nl}^{-}$) as

$$P(y_{ni}^{+}\mid G^{+})=\prod_{r=1}^{5}P_{nir}^{+\,\gamma_{nir}^{+}} \tag{4a}$$

$$P(y_{ni}^{-}\mid G^{-})=\prod_{s=1}^{5}P_{nis}^{-\,\gamma_{nis}^{-}} \tag{4b}$$

The conditional and unconditional probabilities of observing individual *n* selecting the vector of responses $y_n^{+}(y_n^{-})$ are defined as

$$P(y_n^{+}\mid G^{+})=\prod_{i=1}^{I}y_{ni}^{+} \tag{5a}$$

$$P(y_n^{-}\mid G^{-})=\prod_{i=1}^{I}y_{ni}^{-} \tag{5b}$$

$$P(y_n^{+})=\int_{\psi^{+}}P(y_n^{+}\mid G^{+})dF_{\psi^{+}}\psi^{+} \tag{6a}$$

$$P(y_n^{-})=\int_{\psi^{-}}P(y_n^{-}\mid G^{-})dF_{\psi^{-}}\psi^{-} \tag{6b}$$

where $F_{\psi^{+}}\psi^{+}(F_{\psi^{-}}\psi^{-})$ is the distributions of $\psi^{+}(\psi^{-})$.

The unconditional probability of observing subject *n* choosing the *j*^th^ alternative is:

$$P_n(j) = \int_{\psi^+}\int_{\psi^-} P_n(j \mid G^+, G^-)\, dF_{\psi^+}\psi^+ dF_{\psi^-}\psi^- \tag{7}$$

where $P_n(j \mid G^+, G^-)$ is the individual probability conditioned on the latent variables G^+ and G^-. It follows that the unconditional joint probability of observing subject *n* choosing the *j*^th^ alternative and selecting the vector of responses $y_n^+(y_n^-)$ is

$$P_n = P_n(j)P(y_n^+)P(y_n^-) \tag{8}$$

or, if the researcher assumes independency among any ESG and the choice model, it is possible to integrate after the product,

$$P_n = \int_{\psi^+}\int_{\psi^-} P_n(j \mid G^+, G^-)P(y_n^+ \mid G^+)P(y_n^- \mid G^-)\, dF_{\psi^+}\psi^+ dF_{\psi^-}\psi^- \tag{8b}$$

The final log-likelihood function is therefore

$$LL = \sum_{n=1}^{N} \log(P_n) \tag{9}$$

Given that the integrals in equation 7 do not have a closed form, simulated maximum likelihood estimation has to be used to locate the parameters of interest.

2.4. Empirical data

In this section we present the sample and the types of data we used for the analysis. The survey contains a stated preference experiment on transportation mode choice consisting in six choice tasks and three evaluative space grids employed to collect attitudes towards commuting to work or university by a private car.

2.4.1. Sample composition

Data was collected from September 2014 to September 2016 in Lugano, Lausanne and Zurich, three different cities in Switzerland representing three different linguistic parts of the country, Italian, French and German respectively. Using a paper and pencil questionnaire, a sample of 595 respondents were interviewed about their attitudes towards car use and their preferences for commuting trips. The sample is mainly composed by university students (87%), with the remainder being either workers or apprentices. In the present work, the focus on younger respondents (the mean age of the sample is

21.9) occurred for two reasons. First, experience suggests that it is easier to collect data from students; second, younger respondents display a higher degree of heterogeneity in terms of travel behavior, and use alternative commuting modes more frequently than older respondents, generating more valuable information (see e.g., Whalen *et al.*, 2013; Khattak *et al.*, 2011). Fifty-five percent of respondents are male and large part of the sample lives either in the Italian or French speaking areas (39 and 37 percent respectively), with the remainder living in the German speaking area (13 percent) and abroad (11 percent). The majority of the respondents reports not having any earnings (49 percent) or earning less than 30,000 CHF/year (40 percent). Eighty-three percent of the sample reports having access to a car in their household, with the average number of days in which the car was in use (with the respondent acting as either the driver or as a passenger) being equal to 2.81 days per week. The average number of days per week in which respondents do sports (any activity, individual or collective, that lasts for at least 30 minutes) is 2.44.

2.4.2. Structure of the questionnaire: SP experiment

The questionnaire includes a specific section with a stated preference experiment, consisting of the mode choices for a commuting trip: respondents are asked to imagine a near future (five years) in which they live in the city where they have been interviewed, have a position consistent with their education and have to work in the city center. Every morning they are assumed to commute for a distance equal to the average commuting distance (Mikrozensus Mobilität und Verkehr, 2010) which is respectively 2.6, 4.3 and 4.45 km (one way) in Lugano, Lausanne and Zurich. Travel time, monthly cost and the transport system densities, as well as a hypothetical wage that respondents would earn, vary across choice tasks. We collect individual preferences looking at a near future for two main reasons: first, we tried to make the framework more realistic given that the set of alternatives includes an innovative but inexistent transportation system, namely moving walkways; second, given that the sample is mainly composed of students who do not earn any (or do earn low) wages, we can have insights on the impact of expected wages on transportation mode choice.

Eight transportation modes compose the set of alternatives, however respondents can only choose among a subset of them. The group of private alternatives comprises private car (PC), motorbike (MO), electric bike (EB) and conventional bike (BI) and it varies among respondents. The set of public modes includes bus, train and metro (aggregated as a unique alternative and labelled PT), car-sharing (CS), carpooling (CP), moving walkways (MW) and is the same for any respondent. The moving walkways system is an innovative transportation mode which is described to be installed on the main sidewalks of the city, totally free and uncovered. Its width allows two passenger lanes and the length is 200 m on average (in order to allow to get off and on), with a speed varying between 12 and 15 km/h. We consider carpooling as public mode in a sense that it is not a "purchasable-private" alternative. The set of alternatives is kept constant among choice tasks for the same respondent. Table 2 contains different combinations of private alternatives, which can be presented to the respondents. We do not include the combinations "motorbike + e-bike/bike" and "e-bike + bike" because we expect one alternative to be dominant. For example, in a situation in which an individual is asked to choose between e-bike and bike for commuting, the latter alternative is dominated, generating no valuable information.

1	Private car + conventional bike
2	Motorbike
3	E-bike
4	Private car + motorbike
5	Private car + e-bike
6	Conventional bike

Table 2: Different set of alternatives.

Three attributes describe the alternatives: monthly cost (CST), one-way travel time (TT) and move or being moved (DST) are defined by three levels, different for Lugano, Lausanne and Zurich. The monthly cost comprises the purchase and maintenance costs for MO, BI and EB, whilst for PC and CP it includes the parking cost in the city center, as well the purchase and maintenance costs. The DST is a proxy of the system density indicating the walking km needed to cover the commuting distance. Furthermore, any choice task presents a value representing the monthly wage defined accordingly to the median wage (± 25%) for workers five years after obtaining a master degree (in any field).

The software Ngene 1.1.2 (Ngene, 2014) is used to compute an efficient design (Rose *et al.*, 2008; Rose and Bliemer, 2008) with two blocks. To avoid very unreal situations, we exclude from the design combinations with the highest value for DST and the lowest for TT for public transport and moving walkway. We design twelve choice tasks (six for each block) for any subset of alternatives. The same procedure is used for the three different cities, generating 3 (cities) * 6 (combinations) different designs. The resulting D-errors range from 0.002 (private car + conventional bike combination in Lausanne) to 0.05 (private car + e-bike combination in Lausanne). Summarizing, any respondent faces six choice tasks, according to the city, the combination of private means and the block to which he or she is randomly assigned. Table 3 shows an example of a choice task for a respondent living in Lugano.

	Monthly wage: 7500 CHF					
	Public Transport	**Conventional bike**	**Moving Walkway**	**Private car**	**Car-sharing**	**Car-pooling**
Travel time	14 min	10 min	23 min	14 min	20 min	21 min
Monthly Cost	45 CHF/ month	4 CHF/ month	free	260 CHF/ month	190 CHF/ month	80 CHF/ month
Move or being moved	1.0 walking km	Whole route by bike	1.0 walking km	0.2 walking km	1.0 walking km	0.3 walking km
Choice	□	□	□	□	□	□

Table 3: example of choice task for a respondent living in Lugano, whose set of private alternatives contains a private car and a conventional bike

2.4.3. Structure of the questionnaire: attitudinal questions

The second section of the survey contains attitudinal questions measured using the evaluative space grids. This tool is quite recent and it is not commonly employed in surveys aimed at measuring attitude. To make sure that respondents could complete the questionnaire in a proper way, a trained interviewer provided a verbal description of the task and demonstrated the process via an example that was not related to the topic of interest. Overall, respondents completed six ESGs, three of which are used here and are framed with the statement “Depending on your experience, you think that driving is…”. In completing the six ESGs, respondents were asked to consider only commuting trips (to university or workplace). The full list of the three pairs of adjectives includes *flexible* vs *binding*, *comfortable* vs *uncomfortable*, and *handy* vs *challenging*.

A pre-pilot and pilot of the instrument (involving 80 students from Univeristà della Svizzera italiana) found that respondents were hardly able to understand two of the three adjective pairs in the context of a commuting trip. Indeed, *flexible* vs *binding*, and *handy* vs *challenging*, were found to be less obvious to respondents. As such, the meaning of these two pairs was emphasized during the survey, with respondents informed that *flexible* vs *binding* referred to whether it was possible or not to change a selected route mid trip as a result of changing circumstances such as in the case of an accident, whilst *handy* vs *challenging* referred to more practical issues such as the timing for leaving home, ease of locating parking, and whether it is necessary to transfer to a different transport mode during the trip. An example grid is given in Figure 2.

Figure 2: Example of ESG in the survey

The distribution of the responses for the evaluative space grids used for the subsequent analysis is displayed in Figure 3. In contrast to the Evaluative Space Model suggested by Cacioppo and Bernston (1994), Tay and Kuykendall (2017) proposed an “updated bipolar model” according to which individuals who experience moderate amounts of happiness can also experience moderate sadness, but mixed feelings are less likely to co-occur with strong intensities. Indeed, authors reported that in their experiment only 7 out of 166 respondents had an ambivalent emotion. The distribution of the responses in this experiment shows a very distant pattern and confirms the Evaluative Space Model. Specifically, 43 percent, 31 percent and 37 percent of respondents reported considering commuting by car moderate-high *flexible/binding*, *comfortable/uncomfortable* and *handy/challenging*, respectively.

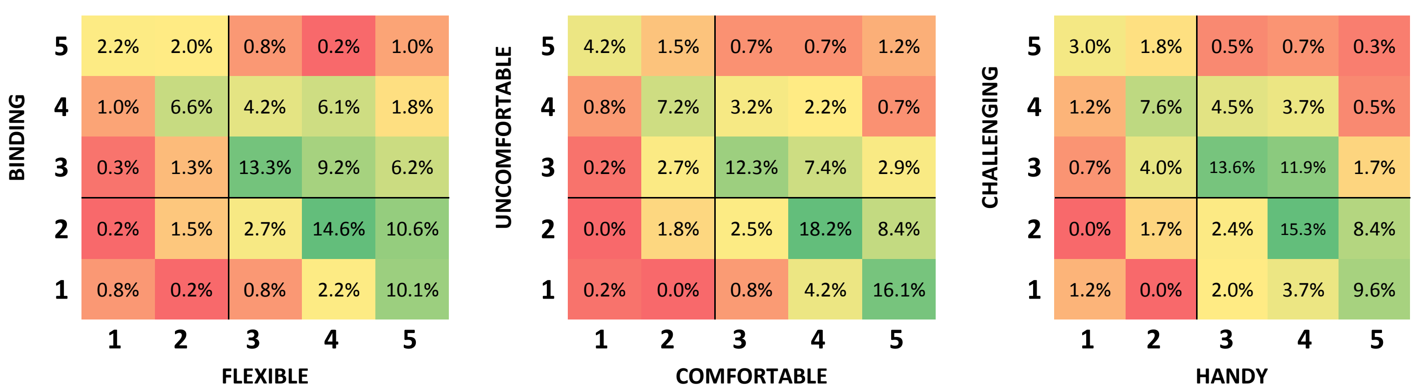

Figure 3: distribution of responses for the ESGs.

2.5. The model

Before running a hybrid choice model, we perform a factor analysis on the items collected using the grids (*flexible*, *binding*, *comfortable*, *uncomfortable*, *handy* and *challenging*) in order to properly design the latent construct. The analysis shows that *flexible* and *binding* do not belong to the same latent construct as they show high values of uniqueness and therefore they are removed from the analysis. The second column in Table 4 reports the coefficients of the four remaining items: *comfortable* and *handy* have a positive impact on the latent variable *practicality and convenience of using the private car for commuting purposes*, whilst *uncomfortable* and *challenging* have a negative effect. In other words, an individual who assigns a higher value to the items *comfortable* and *handy* (*uncomfortable* and *challenging*), is more likely to assess commuting by car practical and convenient (impractical and inconvenient). The internal consistency of the construct is measured through Cronbach's alpha which is large enough, meaning that the items explain the same construct.

Variable	Practicality	Uniqueness
Comfortable	0.8061	0.3501
Uncomfortable	-0.7862	0.3818
Handy	0.7087	0.4978
Challenging	-0.6675	0.5545
Cronbach's alpha	0.8317	

Table 4: Exploratory factor analysis.
Items *flexible* and *binding* are removed as they present a high value of uniqueness.

Following the evidence of the exploratory factor analysis which suggests a unique factor, we create two opposite domains of the same latent variable (G_n^+ and G_n^-), as explained in the methodology section. Specifically, two latent variables measure the positive and the negative realms of *practicality and convenience of using the private car for commuting purposes*, respectively. A different set of socio-economic variables explain the latency in the structural equations:

$$G_n^+ = b_{age}^+ Age_n^+ + b_{c\_use}^+ Car\_use_n^+ + b_{Ita}^+ Ita_n^+ + b_{Fr\_Sp}^+ Fre * Spo + b_{Pub\_Fuse}^+ Pub * Fr\_use + \psi_n^+ \quad (10a)$$

$$G_n^- = b_{pri}^- Pri + b_{c\_use}^- Car\_use + b_{car\_av}^- Car\_av + b_{stud}^- Stud + \psi_n^- \quad (10b)$$

The *practicality and convenience of using the private car for commuting purposes* is function of age, number of days of car use per week, a dummy variable representing native Italian speakers, the interaction between native French speakers and the number of days of sport as well as a further interaction indicating respondents who commute with a public mean but who use the private car frequently (more three or more days per week, both as a passenger or driver). The latent variable measuring the *impracticality and inconvenience of using the private car for commuting purposes*, instead, depends on a dummy variable equals to 1 if the respondent actually commutes by a private mean, the number of days of car use per week (note that we specify two different parameters in equations (10a) and (10b)), car availability and student status. We adopt the normalization suggested by Bolduc *et al.* and, as a consequence, we only estimate the effects of the socio-economic variables on the latent variables and we fix the standard deviation of the error terms to one. Nevertheless, the parameter capturing the correlation between the positive and negative domains of the latent variable is estimated.

The latent variable G_n^+ explains the observable items *comfortable* and *handy*, whilst *uncomfortable* and *challenging* depend on G_n^-. Different psychological thresholds are set for different latent variables. Furthermore, to allow a more flexible and congruent specification of the link between the latent variable and the related items, we set specific psychological thresholds in the measurement equations, hypothesizing that the same value of the latent construct can correspond to different categories for different related items. As a matter of example, Figure 4a shows the value that an individual has on the positive domain of the latent variable practicality (3.56), which corresponds to category 5 on the measurable variable *comfortable* and to category 4 on *handy*. The psychological thresholds for the negative domain are also different from the ones used for the positive realm (Figure 4b). In total, the number of thresholds to be estimated in the model is given by the number of items * the number of categories per item – 1, that equals to 4 * (5 – 1) = 16 in our specification.

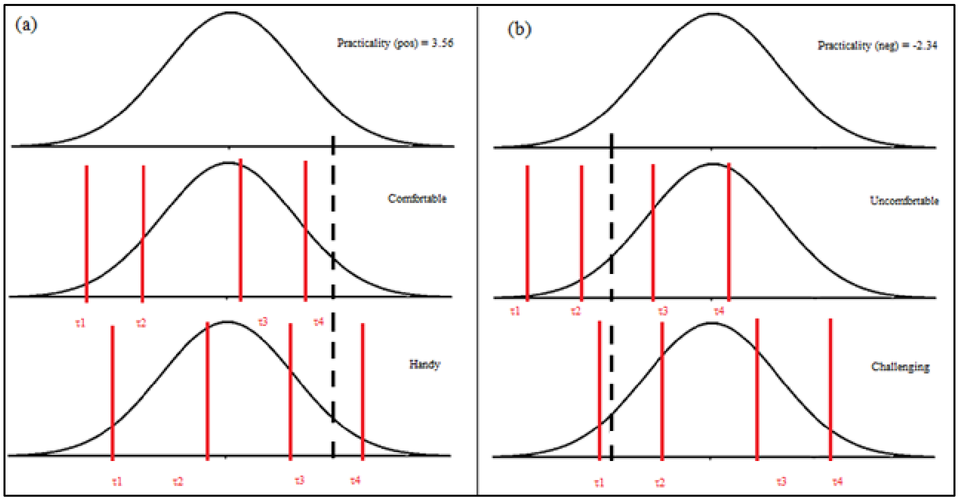

Figure 4: psychological thresholds specific for item and for latent variable. (a) Positive latent variable G_n^+. (b) Negative latent variable G_n^-. The first distribution in both figures represents the distribution of the latent variable whereas the second and the third describe the distributions of the observable variables *comfortable* (4a)/*uncomfortable* (4b) and *handy* (4a)/*challenging* (4b), respectively.

Furthermore, as described in the methodology section, for identification reason, the constants of each measurement equation (eq. 11a-d)) are set to zero allowing the estimation of the first psychological threshold.

$$y_{n,comf} = d_{comf} G_n^+ + \varepsilon_{n,comf} \tag{11a}$$

$$y_{n,handy} = d_{handy} G_n^+ + \varepsilon_{n,handy} \tag{11b}$$

$$y_{n,disc} = d_{disc} G_n^- + \varepsilon_{n,disc} \tag{11c}$$

$$y_{n,chall} = d_{chall} G_n^- + \varepsilon_{n,chall} \tag{11d}$$

In the choice model, whilst the attributes travel time and move or being moved are assumed to have a linear effect on the utilities, cost is inserted with a logarithmic transformation. Utility functions of the alternatives also depend on two latent constructs (namely, the positive and negative domains of *practicality and convenience of using the private car for commuting purposes*), an error component as well as individual characteristics. Specifically, we hypothesize that G^+ and G^- have a positive effect on the car-based alternatives (private car, car-sharing and carpooling) and on the motorized non-car based alternatives (bus, train, metro and motorbike), respectively. We further assume that private alternatives (bike, private car, motorbike and e-bike) share within the subset an amount of heterogeneity, not detected by the socio-economic variables and by the latent variables, to be captured by an error component.

The model specification does not consider any specific parameter to measure indifference and ambivalence. Indeed, the utility functions in the choice model only rely on latent variable scores, measuring the positive and the negative realms of *practicality and convenience of using the private car for commuting purposes*. Probabilities of revealing an ambivalent or indifferent attitude are foreseen using the results of the structural equation model.

The final model is estimated using Python-Biogeme version 2.4 (Bierlaire, 2016), using 10,000 Modified Latin Hypercube Sample (MLHS) draws to approximate the integrals in Equations (5a) – (5b) – (6) (see Hess *et al.*, 2006).

2.6. Results

This section contains general results of the hybrid choice model and a focus on the preferences of different categories of individuals, specifically those who are indifferent or ambivalent towards the practicality and the convenience of commuting by a private car. Furthermore, we show how ambivalent and indifferent subjects respond to changes in the attribute levels.

2.6.1. Structural model

Table 5 reports the coefficient estimates for the structural model. The latent variable *practicality and convenience of using the private car for commuting purposes* is positively affected by number of days of car use. It appears reasonable that individuals who use the car more often (either as a driver or passenger) have a higher probability of considering the use of the private car for commuting purposes practical and convenient. On the other hand, older individuals, those who are native Italian speakers, French native speakers who do sport more often during the week and frequent car users who take public means for commuting purposes, show a lower probability of assessing commuting by car practical and convenient, all the rest being equal.

The number of days a private car is used also explains the latent variable unpracticality and inconvenience, but in an opposite direction. That is, the more an individual uses a car, the lower the probability of assessing commuting by car as inconvenient and unpractical, ceteris paribus. In addition, this latent variable presents a lower value for students and for those who actually commute by a private mean, whereas it has a higher value for those who have access to a private car in their household. This latter result can be explained looking at the sample composition: only seventeen percent of respondents do not have a car available in the household and, consequently, have never commuted by private car. This segment likely idealizes the efficacy of commuting using this alternative, underestimating the challenges and the inconveniences that individuals, who actually had the opportunity of commuting by car, experience.

It is worth noting that, as hypothesized, the positive and the negative domains of the latent variable measuring the ease of commuting by car are correlated: the parameter measuring the correlation ρ, equals 0.575 and indicates a higher probability of observing individual assessments lying on the main diagonal of the ESG. This finding empirically demonstrates the evaluative space model described by Cacioppo and Bernston, since a high (low) value of the positive latent variable G^+ is associated with a high (low) value of the negative latent variable G^-, proving that positive and negative feelings can be experienced at the same time with strong intensities.

	Structural model			
	Practicality and convenience of commuting by car		*Unpracticality and inconvenience of commuting by car*	
	Par.	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*
Age	-0.046	(-2.73)	-	-
Italian native speaker	-0.381	(-2.98)	-	-
Number of days using the car (per week)	0.112	(6.48)	-0.044	(-2.75)
French native speaker * Number of days doing sport	-0.118	(-2.96)	-	-
Frequent car user * Main mode of transport (public)	-0.212	(-2.30)	-	-
Car available to use	-	-	0.159	(1.76)
Student	-	-	-0.184	(-1.89)
Main mode of transport privately owned	-	-	-0.248	(-3.00)
Correlation parameter ρ	0.575	(9.02)		

Table 5: coefficient estimates for the latent variables.

2.6.2. Measurement model

The latent variable G^+ has a positive impact on both the observable items: the coefficients measuring the effect of *practicality and convenience of using the private car for commuting purposes* on *comfortable* and *handy* are 2.17 and 2.76, respectively (Table 6). The latent variable G^- has a positive impact on *uncomfortable* (1.92) and on *challenging* (2.55), even if for the latter the significance is borderline (p-value = 0.09). In other words, an individual with a higher positive (negative) latent attitude will be more likely to assess commuting by car highly comfortable and handy (uncomfortable and challenging), all the rest being equal.

Psychological thresholds are statistically different within the same latent variable (that is $\tau_{i,comf} \neq \tau_{i,handy}$, for i = 1, … , 4) as well as between the two latent variables, indicating that the positive (negative) domain of convenience and practicality of commuting by car affects differently the perception of observable items *comfortable* and *handy* (*uncomfortable* and *challenging*).

	Measurement model							
	Practicality and convenience of commuting by car				*Unpracticality and inconvenience of commuting by car*			
	Par.	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*
	Comfortable		*Handy*		*Uncomfortable*		*Challenging*	
d	2.17	(3.53)	2.76	(2.63)	1.92	(2.44)	2.55	(1.69)
	Threshold parameters							
τ_1	-6.95	(-3.67)	-8.18	(-3.27)	-2.54	(-3.38)	-3.69	(-2.22)
τ_2	-4.81	(-2.23)	-5.62	(-1.85)	-0.33	(-0.28)	-1.07	(-0.42)
τ_3	-3.15	(-8.35)	-3.46	(-5.95)	1.48	(3.49)	1.56	(1.79)
τ_4	-0.79	(-2.08)	-0.19	(-0.27)	3.17	(7.94)	4.15	(4.79)

Table 6: coefficients estimates for the measurement model.

The structural equation model based on the evaluative space grids identifies four different categories of respondents, according to the inclination pro/against and indifferent/ambivalent towards the comfort and practicality of using the private car for commuting purposes. The model computes for any individual the probabilities for all possible outcomes being observed, that are the probabilities of the individual assessing commuting by car comfortable (from 1 to 5) and uncomfortable (from 1 to 5), as well as handy and challenging, according to his own socio-economic characteristics and the thresholds defined by the measurement model. The socio-demographic profiles and the resulting probabilities of four different respondents are shown, as a matter of example, in Table 7 and Figure 5 respectively.

	Individual 1 **Indifferent**	**Individual 2** **Ambivalent**	**Individual 3** **Negative**	**Individual 4** **Positive**
Age	21	23	20	22
Native speaker	Fre	Ita	Fre	Ita
Number of days using the car (per week)	0	2	0	7
Number of days doing sport (per week)	3	3	3	1
Main mode of transport (private/public)	Priv	Pub	Pub	Priv

Table 7: Example of four different respondents

By using the ESG tool rather than a Likert scale, it becomes possible to correctly identify the probabilities of an individual revealing any attitude, including indifference and ambivalence. Using 500 MLHS draws to simulate the error terms of the model and following the partition suggested by Audrezet (2014) shown in Figure 1, we compute the probability for each individual to exhibit a particular attitude towards the convenience and the practicality of using the private car for commuting purposes, for both ESG1 (measuring *comfortable/uncomfortable*) and ESG2 (measuring *handy/challenging*) (Figure 5). Specifically, individual 1 displays the highest probability of considering commuting by car neither comfortable/handy nor uncomfortable/challenging (bottom left corner probabilities equal to 0.989 and 0.992 for ESG1 and ESG2 respectively), whilst respondent 2 has the greatest probability of being classed as being ambivalent towards commuting by car in both grids. Individual 3 has the highest probability of considering commuting by car uncomfortable and challenging (i.e. 0.984 for ESG1 and 0.997 for ESG2), whereas individual 4 has the highest probability of assessing the commuting by car comfortable and handy.

	COMFORTABLE/UNCOMFORTABLE							HANDY/CHALLENGING						
Indifferent	0.011						0.000	0.008						0.000
	5	0.0003	1E-08	1E-09	2E-10	2E-11		5	4E-05	6E-11	5E-12	6E-13	2E-14	
	4	0.0015	4E-08	5E-09	1E-09	1E-10	1	4	5E-04	8E-10	6E-11	7E-12	3E-13	1
	3	0.0091	3E-07	3E-08	6E-09	6E-10		3	0.007	1E-08	8E-10	1E-10	4E-12	
	2	0.0803	2E-06	3E-07	6E-08	6E-09		2	0.087	1E-07	1E-08	1E-09	5E-11	
	1	0.9088	3E-05	3E-06	6E-07	7E-08		1	0.906	1E-06	1E-07	1E-08	5E-10	
	0.989	1	2	3	4	5	4E-06	0.992	1	2	3	4	5	0.000
Ambivalent	0.0176						0.967	0.011						0.987
	5	0.0014	0.0103	0.0459	0.2749	0.326		5	6E-04	0.007	0.054	0.436	0.193	
	4	0.0005	0.004	0.0177	0.1059	0.126	1	4	2E-04	0.003	0.022	0.175	0.077	1
	3	0.0002	0.0011	0.005	0.03	0.036		3	3E-05	3E-04	0.002	0.019	0.008	
	2	3E-05	0.0002	0.001	0.0057	0.007		2	2E-06	2E-05	2E-04	0.001	6E-04	
	1	4E-06	3E-05	0.0001	0.0007	8E-04		1	2E-07	2E-06	1E-05	1E-04	5E-05	
	0.000	1	2	3	4	5	0.015	0.000	1	2	3	4	5	0.002
Negative	0.984						0.001	0.997						0.000
	5	0.6517	0.0026	0.0003	6E-05	6E-06		5	0.685	3E-04	2E-05	3E-06	1E-07	
	4	0.2555	0.001	0.0001	2E-05	2E-06	1	4	0.281	1E-04	9E-06	1E-06	5E-08	1
	3	0.0728	0.0003	3E-05	7E-06	7E-07		3	0.031	1E-05	1E-06	1E-07	5E-09	
	2	0.0138	5E-05	6E-06	1E-06	1E-07		2	0.002	1E-06	8E-08	9E-09	4E-10	
	1	0.0017	7E-06	7E-07	2E-07	2E-08		1	2E-04	8E-08	6E-09	7E-10	3E-11	
	0.016	1	2	3	4	5	0.000	0.002	1	2	3	4	5	0.000
Positive	0.001						0.063	0.001						0.062
	5	4E-06	3E-05	0.0001	0.0009	0.001		5	2E-07	3E-06	2E-05	2E-04	1E-04	
	4	2E-05	0.0001	0.0006	0.0038	0.004	1	4	3E-06	3E-05	3E-04	0.003	0.002	1
	3	0.0001	0.0008	0.0037	0.0222	0.027		3	4E-05	4E-04	0.003	0.034	0.02	
	2	0.0007	0.005	0.0223	0.134	0.16		2	3E-04	0.003	0.025	0.244	0.141	
	1	0.0013	0.0096	0.0425	0.2554	0.305		1	3E-04	0.004	0.031	0.309	0.179	
	0.017	1	2	3	4	5	0.919	0.008	1	2	3	4	5	0.930

Figure 5: Individual probabilities revealing 4 different attitudes. Probabilities accord to a scale red (low) to green (high). Corner values identify the probabilities of being classified negative (top-left), ambivalent (top-right), positive (bottom-right) and indifferent (bottom-left) towards commuting by car.

2.6.3. Discrete choice model

The estimates of the choice model, which includes an error component in addition to the latent variables, are shown in Table 8. The alternative specific constant parameters suggest that young Swiss respondents prefer to commute by private car all the rest being equal. Following, carpooling, motorbike and car-sharing are favored to public transport, bike, e-bike and moving walkway, revealing a pronounced inclination for car-based alternatives, all rest being equal. The walking distance (move or being moved attribute) has a negative impact on all the alternatives, so have the travel time and the log(monthly cost), ceteris paribus. Respondents are willing to pay 6 CHF more per month, based on an expense of 15 CHF per month (average monthly cost of bike and e-bike), for saving about five percent of the commuting time per day (that is saving about 45 minutes per month). The willingness to pay per month for saving five percent of the commuting time per day for PT, PC, CS, CP and MO is 46 CHF, based on an expense of 150 CHF per month (average monthly cost of the alternatives listed above). Hypothetical low (different for cities, on average about 6500 CHF/month) and medium wages (on average about 8800 CHF/month) have a positive impact on non-car-based alternatives, or otherwise stated, having a high wage increases the probability of commuting by PC, CS and CP, which are the most expensive alternatives in the experiment.

The estimates of the socio-economic variables indicate that individuals who commute by a private mean have a higher probability of choosing a private mean for the hypothetical commute trip too, whilst those who conduct an active life, doing sport two or more times per week, are more likely to choose an active transportation mean (i.e. bike, e-bike or moving walkway), all the rest being equal. The cultural background of an individual affects the mode choice for commuting: German native speakers display a higher probability of choosing public transport, bike, e-bike and moving walkway, and similarly Italian native speakers prefer non-car-based alternatives. However, the impact of the dummy variable indicating an Italian cultural background is much lower than the one representing a German cultural background. Gender has a significant effect on the utility of carpooling and in detail, male respondents have a lower probability of considering carpooling an appealing alternative. This finding can be due to a higher attention of females for environmental issues (see among others Patterson *et al.*, 2005; Bolduc *et al.*, 2008). Inter-alternative correlation exists within the set of private alternatives and it is captured by the error component, meaning that these alternatives share common heterogeneity not detected by the socio-economic variables.

The latent variable measuring the positive domain of convenience and practicality of using the private car for commuting purposes, G^+, has a positive effect (3.28) on the utility functions of the car-based alternatives (PC, CS, CP) in the choice model, suggesting that individuals who have a positive attitude towards the convenience of the private car use for commuting trips show a higher probability of choosing private car, car-sharing and carpooling than those who have a neutral or negative attitude, ceteris paribus. Conversely, the latent variable measuring the negative domain G^- has a positive impact (2.79) on the utility functions of PT and MO, suggesting that subjects who consider commuting by car challenging and uncomfortable have a higher probability of choosing public transport (train, bus, metro) and motorbike than those who have a less negative attitude, all the rest being equal.

	Choice model		
Alternative specific constants	*Par.*	*(Rob. t-test)*	*Alternative specifications*
Public Transport (PT)	-4.92	(-3.74)	
Bike (BI)	-9.03	(-4.58)	
Moving Walkway (MW)	-8.24	(-4.33)	
Private Car (PC)	-	-	
Car-sharing (CS)	-4.13	(-8.72)	
Carpooling (CP)	-2.96	(-5.15)	
Motorbike (MO)	-3.93	(-2.84)	
Electric bike (EB)	-6.29	(-3.04)	
Attributes			
Log(monthly cost)	-0.564	(-2.18)	PT, PC, CS, CP, MO
Log(monthly cost)	-0.433	(-2.13)	BI, EB
Travel time	-0.173	(-14.71)	PT, PC, CS, CP, MO
Travel time	-0.177	(-9.31)	BI, EB
Move or being moved	-1.43	(-11.13)	
Low Wage	2.60	(11.96)	PT, BI, MW, MO, EB
Medium Wage	1.03	(6.21)	PT, BI, MW, MO, EB
Socio-economic characteristics			
Actual mode for commuting (private)	0.943	(3.15)	BI, PC, MO, EB
Italian native speaker	-0.804	(-1.71)	PC, CS, CP
German native speaker	2.47	(2.81)	PT, BI, MW, EB
Sportsman	0.703	(2.33)	BI, MW, EB
Male	-0.858	(-1.78)	CP
Error components			
Private means	-2.60	(-15.38)	BI, PC, MO, EB
Latent variables			
G^{+}	3.28	(14.19)	PC, CS, CP
G^{-}	2.79	(13.88)	PT, MO

Table 8: estimates of the choice model. The last column contains the alternatives whose utilities depend on the corresponding parameter (for instance, the parameter measuring Low Wage is included in PT, BI, MW, MO and EB utility functions). If the cell is blank, the parameter is included in the whole set of alternatives.

2.6.4. Effect of latent variables

The combined effect of positive and negative attitudes towards the convenience and the practicality of using the private car for commuting purposes is observed assigning respondents to four different categories (i.e. positive, negative, indifferent and ambivalent), according to simulated individual scores. In detail, we first compute the latent variable scores according to the structural model specification and then, using the specific sets of psychological thresholds estimated for the different grids, we can allocate any respondent to a different category for any grid. As an example, let us consider a subject whose scores on the latent variables G^+ and G^- are -5 and 3.5 respectively. According to the psychological thresholds of the grid *comfortable* vs *uncomfortable*, this subject has a high probability of selecting the cell (2:5) in the ESG1, revealing a high propensity for judging commuting by car uncomfortable (negative attitude). However, the same subject exhibits an ambivalent attitude towards the dichotomy *handy*/*challenging* having a high probability of selecting the cell (3:4) in the ESG2. One of the main strength of the evaluative space grid is its ability to distinguish subjects who are torn between a positive and a negative attitude, and who can be therefore either ambivalent or indifferent. Indeed, the tool proposed by Likert to measure attitudes fails in distinguishing these categories, which are merged together on the neutral point of the scale.

We calculate and use market shares for the eight alternatives using 500 MLHS draws to simulate the error components for testing the hypothesis that individuals with an indifferent attitude have different preferences of those who have an ambivalent attitude (a table containing market shares is available upon request). Guaranteed that individuals who consider commuting by private car convenient and practical have different preferences from those who consider it inconvenient and unpractical, we then compare market shares for indifferent and ambivalent categories using Welch's t-tests. Table 9 displays the test outcomes: a key finding is that thirteen out of sixteen t-tests reject the null hypothesis of equality (with a p-value < 0.1), suggesting that individuals who have an ambivalent attitude towards the convenience and the practicality given by the usage of the private car for commuting purposes reveal different preferences for the mode choice in a commuting trip than those who exhibit an indifferent attitude.

	PT	*BI*	*MW*	*PC*	*CS*	*CP*	*MO*	*EB*
ESG1	Rej 0.01	Rej 0.1	Rej 0.05	Rej 0.01	Rej 0.01	Rej 0.01	Acc	Rej 0.05
ESG2	Rej 0.01	Rej 0.05	Acc	Rej 0.01	Rej 0.01	Rej 0.01	Acc	Rej 0.01

Table 9: Welch's t-tests Ambivalent vs Indifferent market shares. Null hypothesis: equal market shares. "Rej 0.01 (0.1)" = reject the null hypothesis (p-value < 0.01 (0.1)); "Do not Rej" = cannot reject the null hypothesis (p-value > 0.1).

INCREASE IN TRAVEL TIME BY 10%

	PT				BI				PC			
	GRID 2		GRID 3		GRID 2		GRID 3		GRID 2		GRID 3	
	amb	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*
mean	-1.35	-2.25	-1.59	-2.43	-1.95	-0.22	-1.82	-0.01	-1.16	-2.20	-1.03	-2.06
var	0.63	0.27	0.68	0.07	0.61	0.21	0.61	0.00	0.62	0.19	0.60	0.12
p-value	**0.000**		**0.031**		**0.004**		**0.000**		**0.000**		**0.033**	

INCREASE IN MONTHLY COST BY 10%

	PT				BI				PC			
	GRID 2		GRID 3		GRID 2		GRID 3		GRID 2		GRID 3	
	amb	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*	*amb*	*ind*
mean	-0.92	-1.64	-1.11	-1.82	-0.67	-0.06	-0.63	0.00	-1.21	-2.68	-1.08	-2.67
var	0.37	0.17	0.39	0.03	0.02	0.01	0.03	0.00	0.66	0.00	0.65	0.00
p-value	**0.001**		**0.025**		**0.002**		**0.000**		**0.000**		**0.000**	

INCREASE IN MOVE OR BEING MOVED BY 10%

	PT				BI	PC			
	GRID 2		GRID 3		**This alternative has DST = 0**	GRID 2		GRID 3	
	amb	*ind*	*amb*	*ind*		*amb*	*ind*	*amb*	*ind*
mean	-0.56	-0.95	-0.64	-1.03		-0.40	-0.65	-0.49	-1.25
var	0.14	0.05	0.14	0.03		0.12	0.04	0.15	0.06
p-value	**0.044**		**0.040**			**0.064**		**0.028**	

Table 10: elasticities for market shares and travel time (top table), market shares and cost (mid table), market shares and density (bottom table). The bold values, reported in the last row of any table, represent the p-values computed for a Welch's t-test. Null hypothesis: equal elasticities between ambivalent and indifferent categories.

A further important finding is that individuals who have an ambivalent attitude towards the practicality and convenience of using the private car for commuting purposes react differently to a change in the attribute levels than those who possess an indifferent attitude. Indeed, after calibrating the model, we measure the responsiveness of the market shares to a change in travel time, cost and move or being moved for the different alternatives. For brevity, we only show here the elasticities for public transport, bike and private car, which are the most used transportation means within the four categories. Upon request, authors the elasticities for all categories and change in attribute levels can be provided.

Evidence shows that indifferent individuals respond more actively to a change in travel time, cost and density (i.e. move or being moved) for public transport and private car than ambivalent subjects, whilst the latter category of persons displays a larger elasticity for bike. Table 10 shows that a 10 percent increase in travel time for public transport reduce the market share of 1.35 percent or 1.59 percent (according to ESG1 and ESG2 categorizations) and 2.25 percent or 2.43 percent for ambivalent and indifferent subjects respectively. A similar pattern is displayed for a 10 percent increase in travel time for private car, whilst for bike, the market shares are reduced more for the ambivalent category (1.95 and 1.82 percent according to ESG1 and ESG2 classifications) than for the indifferent category (0.22

percent according to ESG1 and 0.01 percent according to ESG2). An analogous scheme is reported for a 10 percent increase in cost and density. The null hypothesis stating that individuals having an ambivalent attitude display the same elasticity of those having an indifferent attitude is rejected in all the tests.

Summarizing, the results contained in this section confirm the hypothesis that individuals possessing an ambivalent or indifferent attitude have different preferences and different behaviors. Tests on the differences in market shares and elasticities are consistent with the findings of previous works suggesting that distinguishing individuals with an ambivalent and indifferent attitude is as important as identifying those with a positive and negative inclination as they tend to act differently.

2.7. Discussion and conclusions

The definition of attitudes in transportation literature presents substantial differences according to the type of study. Psychologists use numerous measurable variables having a different valence (from extreme negative to extreme positive) to shape an attitude, whilst researchers who mainly focus on the consequent behavior of the attitudes employ a limited number of items, with either an extreme positive or negative valence. In several applications in choice modelling the randomness of the latent variable (attitude) is increased because of the use of a reduced set of items, entailing a less precise definition of the attitude itself and a poor representation of individuals on the latent continuum. In some studies, attitudes are inserted in the discrete choice experiment as an attribute and are measured using a qualitative ordered scale (low – medium – high). Such a misspecification of the latent construct entails an even larger randomness of the attitude (for instance, respondents can identify with "comfort" the quality of the seats, the presence of air conditioning, the space for standing and several more observable variables).

The Likert scale, which is the gold standard tool for measuring the observable variables in transportation, is appropriate for distinguishing subjects with a positive or negative valence, but it is not suitable for disentangling persons with indifferent and ambivalent inclinations, who lie both on the neutral point of the latent continuum (central values of the scale). The Evaluative Space Grid, proposed by Larsen *et al.*, is a single-item measure of positivity and negativity following the theoretical framework of Evaluative Space Model, stating that positive and negative feelings can be experienced at the same time, also with strong intensities. The ESG is purposely designed to differentiate between ambivalence and indifference, as well as positive and negative attitudes. The differentiation between subjects having an ambivalent and indifferent attitude, which cannot be realized with a Likert scale, can provide further insights to policy makers, who can study ad hoc policies on different segments of the population. As a matter of fact, it has already been shown, in contexts such as politic elections and environmental behavior (Costarelli and Colloca, 2004; Yoo, 2010; Thornton, 2011), that indifferent and ambivalent individuals act differently.

This work proposes a methodology to include the ESG in the framework of hybrid choice models: the grids are modelled, in the structural equations, by means of two latent variables, representing positive and negative domains respectively, and, in the measurement equations, two ordered logit regressions link the observables items to the latent variables. It is worth noting that the hybrid choice model does not include specific parameters to measure a direct effect of indifference and ambivalence on the alternatives. The lack of these parameters could suggest the use of common items measured with a Likert scale. However, even if the econometrics behind the construction of latent variables is the same, using the evaluative space grid tool preserves the correct collection of data aimed at measuring the ambivalence and indifference, which could bring to biased results if sequentially structured conversely framed questions are used. A possible follow-up of this research is the introduction of specific parameters in the hybrid choice model measuring the effect of indifference and ambivalence, using a categorical method for defining the four different types of attitudes.

In addition to the methodological contribution, this work tests the hypothesis that indifferent and ambivalent individuals display different preferences in a context of transportation mode choice for commuting trips and therefore the distinction of such categories becomes of primary importance for policy motives. In particular, we show that subjects who consider commuting by private car comfortable/handy and uncomfortable/challenging at the same time (ambivalent individuals) reveal different preferences from those who judge commuting by private car neither comfortable/handy nor uncomfortable/challenging (indifferent individuals), for 7 out of 8 alternatives of transport. Furthermore, these categories also respond differently if the proposed alternatives experience a change in cost, travel time or density of the transportation system. Specifically, the elasticity is larger for individuals with an indifferent attitude when travel time, cost and density for public transport and private car increase, whilst subjects having an ambivalent attitude display a larger elasticity when similar changes occur for bike.

The inclusion of attitudes in studies modeling individuals' preferences obtained great appreciation because of possible implications for policy purposes. Indeed, specific campaign for individuals who have, for instance, a strong inclination towards environmental concerns or attachment to the car can be adopted. This work moves one step forward, claiming that it is important to consider also the segment of individuals having a neutral inclination, that is subjects revealing an ambivalent or indifferent attitude. Once the composition of these clusters has been identified, it is possible to draw even more powerful and effective policies.

References

Abou-Zeid, M., Ben-Akiva, M., 2011. The effect of social comparisons on commute well-being. *Transport Policy* 19, 93–104.

Abrahamse, W., Steg, L., Gifford, R., Vlek, C., 2009. Factors influencing car use for commuting and the intention to reduce it: a question of self-interest or morality? *Transportation Research Part F* 12, 317–324.

Anable, J., 2005. 'Complacent Car Addicts' or 'Aspiring Environmentalists'? Identifying travel behaviour segments using attitude theory. *Transport Policy* 12, 65 – 78.

Atasoy, B., Glerum, A., Bierlaire, M., 2012. Attitudes towards mode choice in Switzerland. Report TRANSP-OR 110502. Transport and Mobility Laboratory, EPFL.

Audrezet, A., 2014. L'ambivalence des consommateurs: proposition d'un nouvel outil de mesure. *Business administration. Universite Paris Dauphine - Paris IX. French.*

Audrezet, A., Olsen, S.O., Tudoran, A.A., 2016. The GRID scale: a new tool for measuring service mixed satisfaction. *Journal of Services Marketing* 30(1), 29 – 47. doi: 10.1108/JSM-01-2015-0060

Bahamonde-Birke, F. J., Hanappi, T., 2016. The potential of electromobility in Austria: Evidence from hybrid choice models under the presence of unreported information. *Transportation Research Part A* 83, 30-41.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 1999. Integration of Choice and Latent variable Models. Massachusetts Institute of Technology, Cambridge.

Bierlaire, M., 2016. PythonBiogeme: a short introduction, Technical report TRANSP-OR 160706. Transport and Mobility Laboratory, ENAC, EPFL. Retrieved from: http://biogeme.epfl.ch/documentation/pythonfirstmodel.pdf

Bolduc, D., Daziano, R., 2010. On estimation of hybrid choice models. In book: Choice Modelling: the state-of-art and the state-of-practice, Publisher: Emerald, Editors: S. Hess and A. Daly, 259 -287.

Bolduc, D., Boucher, N., Daziano, R., 2008. Hybrid Choice Modeling of New Technologies for Car Use in Canada. *Journal of the Transportation Research Board* 2082, Transportation Research Board of the National Academies

Bolduc, D., Ben-Akiva, M., Walker, J.L., Michaud, A., 2005. Hybrid Choice Models with Logit Kernel: Applicability to Large Scale Models, in M.E.H. Lee-Gosselin and S.T. Doherty, eds. *Integrated Land-Use and Transportation Models: Behavioral Foundations*, Emerald Group Publishing, 275-302.

Cacioppo, J.T., Berntson, G. G., 1994. Relationship between attitudes and evaluative space: a critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin* 115(3), 401 – 423. doi: 10.1037/0033-2909.115.3.401

Costarelli, S., Colloca, P., 2004. The effects of attitudinal ambivalence on pro-environmental behavioral intentions. *Journal of Environmental Psychology* 24(3), 279 – 288. doi: 10.1016/j.jenvp.2004.06.001

Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behavior. *Transportation* 39, 267 – 297. DOI:10.1007/s11116-011-9351-z

Daziano, R., Bolduc, D., 2013. Incorporating pro-environmental preferences toward green automobile technologies through a Bayesian Hybrid Choice Model. *Transportmetrica* 9(1), 74 – 106.

Domarchi, C., Tudela, A., Gonzalez, A., 2008. Effect of attitudes, habit and affective appraisal on mode choice: an application to university workers. *Transportation* 35, 585–599. DOI 10.1007/s11116-008-9168-6

Espino, R., De Dios Ortuzar, J., Roman, C., 2003. Analysing the effect of latent variables on willingness to pay in mode choice model. Association for European transport.

Espino, R., De Dios Ortuzar, J., Roman, C., 2006. Analysing demand for suburban trips: A mixed RP/SP model with latent variables and interaction effects. *Transportation* 33, 241 – 261. DOI 10.1007/s11116-005-2299-0

Habib, K. M. N., Kattan, L., Islam, M. T., 2011. Model of personal attitudes towards transit service quality. *J. Adv. Transp.* 45, 271–285.

Hess, S., Shires, J., Jopson, A., 2013. Accommodating underlying pro-environmental attitudes in a rail travel context: Application of a latent variable latent class specification. *Transportation Research Part* D 25, 42–48.

Hess, S., Train, K. and Polak, J., 2006. On the use of modified latin hypercube sampling (MLHS) method in the estimation of mixed logit model for vehicle choice, *Transportation Research Part B* 40(2), 147–163. doi: 10.1016/j.trb.2004.10.005

Johansson, M. V., Heldt, T., Johansson, P., 2006. The effects of attitudes and personality traits on mode choice. *Transportation Research Part A* 40, 507–525.

Kaplan, K. J., 1972. On the ambivalence-indifference problem in attitude theory and measurement: A suggested modification of the semantic differential technique. *Psychological Bulletin 77*, 361-372. doi: 10.1037/h0032590

Khattak, A., Wang, X., Son, S., Agnello, P., 2011. University student travel in Virginia: is it different from the general population? *Transportation Research Record* 2255, 137 – 145.

Larsen, J.T., Norris, C.J., McGraw, A.P., Hawkley, L.C. and Cacioppo, J.T., 2009. The evaluative space grid: a single-item measure of positivity and negativity. *Cognition and Emotion* 23(3), 453-480. doi: 10.1080/02699930801994054

Likert, R., 1932. A technique for the measurement of attitudes. Archives of Psychology, R. S. Woodworth Editor, 140, New York.

Mikrozensus Mobilität und Verkehr, 2010. Bundesamt für Statistik: https://www.bfs.admin.ch/bfs/de/home.html

Mokhtarian, L.P., Salomon, I., Redmond, L.S., 2001. Understanding the demand for travel: it’s not purely ‘derived’. *Innovation* 14(4), 355 – 380.

Ngene 1.1.2 User Manual & Reference Guide, 2014. http://www.choice-metrics.com/download.html

Ory, D.T., Mokhtarian, P.L., 2005. When is getting there half the fun? Modeling the liking for travel. *Transportation Research Part* A 39, 97–123.

Patterson, Z., Haider, M., Ewing, G., 2005. A gender-based analysis of work trip mode choice of suburban Montreal commuters using stated preference data. *Transportation Research Record: Journal of the Transportation Research Board 1924*, 85 – 93. doi: 10.3141/1924-11.

Prillwitz, J., Barr, S., 2011. Moving towards sustainability? Mobility styles, attitudes and individual travel behavior. *Journal of Transport Geography* 19, 1590–1600.

Raveau, S., Daziano, R., Yanez, M.F., Bolduc, D., de Dios Ortuzar, J., 2010. Sequential and simultaneious estimation of hybrid discrete choice models: Some new findings*.* *Transportation Research Record Journal of the Transportation Research Board* 2156(1), 131 – 139.

Rose, J.M., Bliemer, M.C.J., 2008. Stated preference experimental design strategies, in Hensher, D.A. and Button, K.J. (eds.) Handbook of Transport Modelling, Elsevier, Oxford, Ch. 8, 151-180.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.C., 2008. Designing efficient stated choice experiments involving respondent based reference alternatives. *Transportation Research Part B* 42(4), 395-406.

Rundmo, T., Nordfjærn, T., Iversen, H. H., Oltedal, S., Jørgensen, S. H., 2011. The role of risk perception and other risk-related judgements in transportation mode use*. Safety Science* 49, 226–235.

Shiftan, Y., Barlach, Y., Shefer, D., 2015. Measuring passenger loyalty to public transport modes. *Journal of Public Transportation* 18(1).

Tay, L., Kuykendall L., 2017. Why self-reports of happiness and sadness may not necessarily contradict bipolarity: a psychometric review and proposal. *Emotion Review* 9(2), 146-154*.* doi: 10.1177/1754073916637656.

Thornton, J.R., 2011. Ambivalent or indifferent? Examining the validity of an objective measure of partisan ambivalence*. Political Psychology* 32(5), 863-884. doi: 10.1111/j.1467-9221.2011.00841.x

Thurstone, L.L., 1928. Attitudes can be measured. *American Journal of Sociology* 33, 529 – 554.

Thurstone, L.L., Chave, E.J., 1929. The measurement of attitude. Chicago: University of Chicago Press.

Whalen, K.E., Páez, A., Carrasco, J.A., 2013. Mode choice of university students commuting to school and the role of active travel. *Journal of Transport Geography 31, 132 – 142.*

Yoo, S.J., 2010. Two types of neutrality: ambivalence versus indifference and political participation. *The Journal of Politics* 72(1), 163-177. doi: 10.1017/S0022381609990545

Chapter 3. Generalized versus localized attitudinal responses in discrete choice

Antonio Borriello[1], John M. Rose[2]

[1]Università della Svizzera italiana, [2]University of Technology of Sydney

Abstract

In his theory of planned behavior, the psychologist Ajzen illustrates that psychological factors are precursor of behavior. Following this theoretical framework, in the last decades many researchers explored the importance of attitudes and perceptions in determining choice behavior in a transportation setting. A more recent debate within the psychological literature concerns the stability of attitudes. The first school of thought argues that attitudes embody long-term stable constructs which are "memory-based" (*generalized attitudes*), and it contrasts the idea that attitudes are short-term situational specific concepts, constructed at the time a specific situation occurs (*localized attitudes*). A mediating classification of attitudes consists in defining attitudes as created via a mixture of both short and long-term influences.

The current practice when modeling individual choices consists in employing only generalized attitudes. This paper examines the stability of attitudes within a stated choice experiment framework and shows the importance of including localized attitudes when modeling preferences.

Subjects are asked to provide responses to the same attitudinal questions, both prior to undertaking the choice experiment, and after each stated choice task they complete as part of the survey. Evidence shows that generalized and localized attitudes diverge for most of the respondents and their impact on individual choices is substantial. Additionally, considering generalized and localized attitudes separately, only captures partial information related to the psychological process leading to the choice. Finally, the omission of localized attitudes may potentially lead to inconsistent estimates as is the case of the willingness to pay.

Keywords: stability of attitudes, individual preferences, willingness to pay

3.1. Introduction

Over the past four decades, discrete choice models (DCM) have become the dominant method for modelling and understanding traveler preferences and behavior. Estimation of DCMs requires analysts to specify separate utility functions for the different alternatives present within a given market of interest. Typically, these utility functions are defined in terms of the attributes of the alternatives being examined, the characteristics of the decision makers, or some combination of the two. By observing how variations in the attributes of the alternatives or characteristics of the decision makers systematically vary with the observed choices within the market, the influence on choice behavior of each attribute describing the alternatives and/or characteristic of the individual decision makers can be determined in the form of utility weights. Based on the overall combined utility values derived for each alternative within the model, the probability that each alternative will be chosen is then calculated, which subsequently provides a direct mapping between the individual specific choice environment described within the data and overall market behavior.

Despite being somewhat less used in practice, early theorists identified the importance that the attitudes and perceptions held by different decision makers towards both the objects being considered, and towards more general life concerns, can play on choice behavior. For example, McFadden (1980), based on theories of consumer behavior, discussed the importance of including attitudinal data within the DCM framework, stating "The theory of the economically rational utility-maximizing consumer, interpreted broadly to admit the effects of perception, state of mind, and imperfect discrimination, provides a plausible, logically unified foundation for the development of models of various aspects of market behavior." Currim (1981) and Swait (1994) demonstrated how generalized attitudes and perceptions can be used to build models with segmented preferences resulting in improved forecasting and model fits for both stated preference and revealed preference data sets. Citing even earlier work on hybrid conjoint models (e.g., Green *et al.* 1981 and Green 1984) as his inspiration, McFadden (1986) derived the theoretical framework for the hybrid choice model (HCM) allowing for the inclusion of both generalized attitudes and alternative specific perceptions, to enter the utility functions of a DCM via a latent variable structure. The model was first operationalized by Train *et al.* (1987) to explore the impact of attitudes upon rate scheduling for public utilities, whilst Swait (1994) used a similar modelling structure to model preferences for different beauty products. Similar conceptual frameworks were made operational using various transportation contexts by Morikawa (1989), Morikawa *et al.* (1990), Hensher (1990), Ben-Akiva and Morikawa (1990), Vieira (1992) and Ben-Akiva and Boccara (1993).

Of late, the inclusion of attitudinal and perceptual data within DCMs has become increasingly popular with a spate of recent papers examining how attitudes and perceptions influence bicycle choice (e.g., Maldonado-Hinarejos *et al.* 2014), the relationship between mode choice and the built environment (e.g., Van Acker *et al.* 2011), and automobile choice (e.g., Daziano and Bolduc 2013a). Other recent papers have explored methodological issues related to how best to incorporate attitudes and perceptions within the DCM framework (e.g., Ben-Akiva *et al.*, 2002; Daziano and Bolduc, 2013b; Raveau *et al.*, 2012; Vij and Walker, 2016). More recently, Bahamonde-Birke *et al.* (2017) have argued that there exists a difference between attitudes and perceptions, where attitudes are defined as “a mindset or a tendency to act in a particular way due to both an individual’s experience and temperament” (Allport, 1935), whereas perceptions represent the organization, identification and interpretation of sensory information aiming at representing and understanding the environment (Schacter *et al.*, 2011). In spite of the earlier cited work which explicitly discussed the different role that generalized attitudes and perceptions have on choice, Bahamonde-Birke *et al.* (2017) argue that previous work has tended to ignore this distinction treating the two concepts interchangeably.

Thus, despite recent attention, the idea that attitudes and perceptions play a significant role in choice behavior is not new. The focus of the current paper is to examine the stability of attitudes within a stated choice experiment framework. As such, we do not seek to explore explicitly the role of perceptions, which as discussed above, has been shown to play an important role in describing choice behavior. Our interest in the temporal stability of attitudes stems from an ongoing debate within the psychological literature where there appear to exist three different schools of thought as to whether or not attitudes are largely fixed or somewhat transient. The first school of thought identified assumes that attitudes are long term stable constructs which are “memory-based” such that an attitude towards an object is linked to one or more global evaluations that brought to the mind once the object is encountered. This has led for example to the development of the MODE (in case of one evaluation, Fazio, 1990) and MCM (in case of more than one evaluations, Petty *et al.*, 2007) attitudinal model frameworks. The second school of thought related to the temporal stability of attitudes is to assume that attitudes are short term situational specific constructs that are developed “on the spot”. For example, Gawronski’ and Bodenhausen (2007) propose what they call the APE model which assumes that associative and propositional processes linked to attitude formation are sensitive to contextual influences. Similarly, Schwarz (2007) and Conrey' and Smith (2007) propose what have been termed connectionist models for attitude formation. These connectionist models posit that attitudes are constructed at the time a specific situation occurs and that evaluative judgments are formed only when required rather than being stored in longer term memory. The third school of thought on attitude formation assumes that attitudes are created via a mixture of both short and long-term influences. This intermediate view of attitude formation, represented by models such as the IR model (Cunningham and Zelazo, 2007; Cunningham *et al.*, 2007), assume that evaluative processes towards objects are part of an iterative cycle where the current evaluation of a stimuli can be adjusted as new contextual and motivational information arises, and that adjustments to attitudes occurs in an iterative manner over time resulting in an updated evaluation according to the specific stimuli and context faced. Through this work we refer to long term stable attitudes as *generalized*, whilst short term situational specific constructs are labelled *localized.* We refer the interested reader to Bohner and Dickel (2011) or Crano and Prislin (2006) for further discussions related to the debate on the temporal nature of attitude formation.

Understanding the temporal stability of attitudes is critical to transportation planning and research given the link between attitudes and behavior as explained by the theory of planned behavior (Ajzen, 1985) which has become the dominant theoretical framework adopted within the literature. This is because, if attitudes are a precursor towards action, one mechanism to change travel behavior may be via the ability of transport planners to change attitudes. The classical models of attitude change, such as the elaboration likelihood model (Petty and Wegener, 1999), or the heuristic/systematic model (Chen and Chaiken, 1999), rely on the introduction of new stimuli, such as a message or advertisement, which when processed by the individual, can result in an attitude change alongside a change in behavior. Such theories are used in part to motivate travel behavior change programs, such as TravelSmart (Red3, 2005).

The current chapter reports the results of a stated choice experiment where respondents are asked to provide responses to the same attitudinal question, both prior to undertaking the choice experiment, and after each stated choice task they complete as part of the survey. The approach adopted allows for an examination as to how attitudinal responses vary as the attribute levels of the alternatives presented within the experiment change over repeated choice tasks. The survey approach allows for an examination of the path dependence of attitudinal changes within a stated choice framework, as well as an investigation as to how previously stated attitudes can affect current decisions.

The remainder of the paper is organized as follows. In the next section we briefly introduce the methodology and then present case study, focusing on the structure of the survey and the sample used for the analysis. The following sections contain the specification of the model used to analyze the data and a discussion of the results. Finally, we conclude the paper summarizing the main findings and the benefit of considering psychological aspects constructed in the situation based on currently accessible information, as well as general attitudes pre-stored in memory.

3.2. Theoretical background

An overview of the general framework of hybrid discrete choice model is presented in this section (see Walker, 2001; Ben-Akiva *et al.*, 2002; Daly *et al.*, 2012 for a more detailed explanation of the methodology). A HDCM consists of a simultaneous estimation of two distinct processes, a structural equation model and a discrete choice model. Whilst the former explores and defines the structure of the psychological factors using two types of relationships (structural and measurement equations), the latter determines individuals' preferences.

Let consider *n* respondents who face a choice set composed by *J* alternatives and let assume that the decision makers are rational, choosing the alternative that maximizes the personal utility. The chosen alternatives is

$$k_n = \arg\max((U_{nj} = f_1(X_j, W_n, Y_j, G_n; a, d, c, \nu_{nj}) \mid n = 1, ..., N; j = 1, ..., J) \qquad (1)$$

where X_j is a vector of attributes for alternative *J*, W_n represents a vector of socio-economic variables describing individual *n*, G_n indicates the vector of l latent variables, whilst the matrix Y_j defines which latent variables are inserted in the utility function of alternative *J*. The impacts of these latent variables are measured by the vector *c*, whilst vectors *a* and *d* represent the impact that attributes and socioeconomic variables have on the utility of the alternative respectively. The error term ν_{nj} is i.i.d. extreme value type 1. The analyst can define the function $f_1(g)$ according to the data.

A latent variable is defined in the structural equation as a function of observable data (such as individual characteristics and alternative features) plus a stochastic component (ψ_{nl}) which is typically assumed to be Normal distributed with zero mean and a certain covariance matrix:

$$G_{nl} = bW_{nl} + pX_{jl} + \psi_{nl} \tag{2}$$

The attitudinal response y_{ni} for the i^{th} indicator variable (or item) is a (categorical) variable modelled by a measurement equation. Its general formulation is

$$y_{ni} = \delta_i + d_i G_n + \varepsilon_{ni} \tag{3}$$

where δ_i is a constant, the vector d_i measures the effect of the latent variable on the attitudinal response (note that this vector may contains zero values if the latent variables do not have an impact on a given item) and ε_{ni} is an error term. According to its specification, the type of measurement model is determined (for example ordered logit or ordered probit).

The objective of the analyst is to estimate the parameters included in the three types of relationships. To do so, it is necessary to maximize the likelihood of jointly observing the vector of choices and indicators *k* and *y*. The parameters of interest are then estimated using technique of simulated maximum likelihood, employing random draws to describe the probability distributions associated with the latent variables.

It is worth noting that the methodology used for defining the measurement equations in this work slightly differs from the standard practice because the attitudinal indicators are collected by means of the ESG instrument. The reader can refer to the previous chapter of this thesis for a detailed explanation of the method.

3.3. Case study

3.3.1. The survey

The ad hoc experiment set up for this paper allows us to explore the role that different types of attitudes play in explaining the decision-making process in transportation. Differently from the common HDCM practice that only employs attitudes stored in memory, we hypothesize that attitudes can change according to the situation and therefore the researcher should consider such divergences when modelling the travel demand.

The questionnaire consists of four parts. In the first section, the overall opinion on trains is collected through indicators measuring the overall satisfaction/dissatisfaction (Figure 1). Such indicators represent the manifestation of generalized attitudes and are function of socio-economic variables. The instrument used to collect attitudes is the evaluative space grid (ESG) proposed by Larsen *et al.* (2009).

A grid can replace a set of indicators measured with a semantic differential scale without any loss of information and it is suitable for collecting either a specific or a general attitude, affecting notably on the length of our survey. In the next section, we describe such an instrument more appropriately.

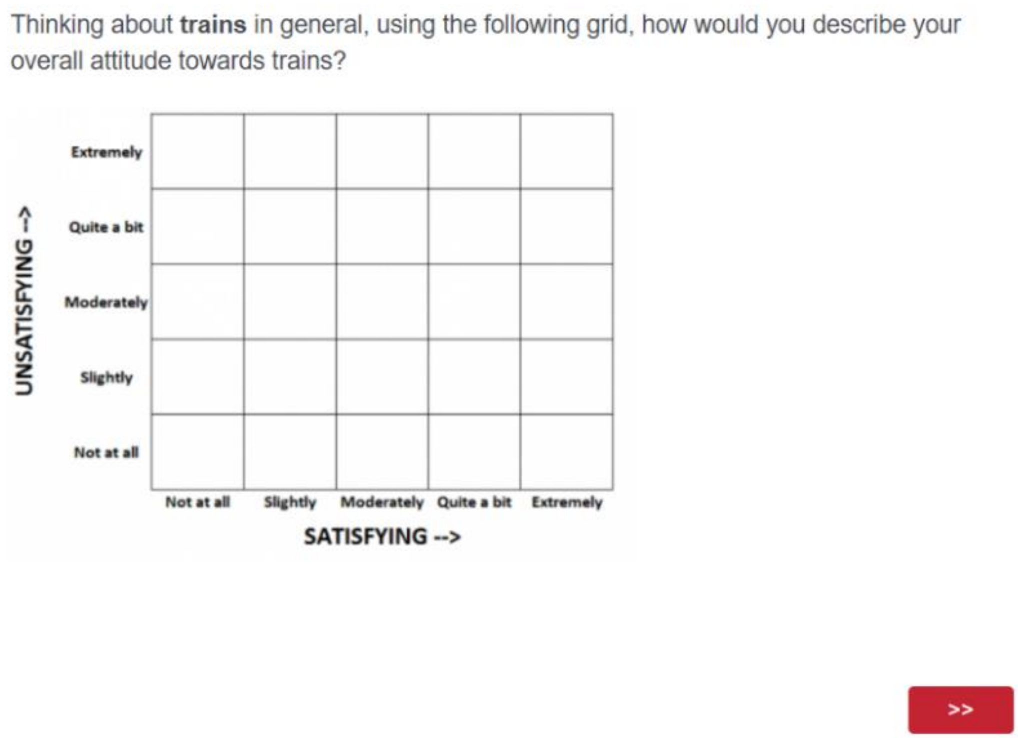

Figure 1: Evaluative space grid for measuring the general satisfaction/dissatisfaction towards trains.

In the second section, respondents are asked to describe their last trip taken by train defining, among other characteristics, access time, waiting time, travel time, transfer time, egress time, fare, crowd on the platform, seat availability and temperature in the train. In addition, the localized satisfaction/dissatisfaction towards this trip is collected using a further ESG. In the next section, interviewees are expected to assess their satisfaction/dissatisfaction for six alternative train services, pivoted around the one they recently took (Figure 2). The expected attitude of a hypothetical offer, being constructed on the spot, represents a localized attitude.

Shown below are the levels of the service of a new alternative for the same trip you described before.

	Trip characteristic	New Alternative
GETTING TO THE TRAIN	Access time	5
	Waiting time	4
	Description of the train platform	
ON THE TRAIN	Travel time on the train	6
	Time spent waiting for transfer(s)	2
	Seat availability	No
	Fare paid	$4.56
	Temperature on the train	Pleasant
GETTING TO THE FINAL DESTINATION	Egress time	5

Assuming that you are taking the exactly same trip again, how satisfied/unsatisfied do you think you would be with the above alternative?

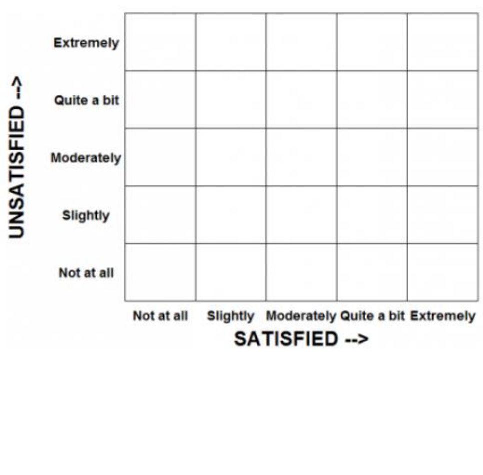

Figure 2: Example of a hypothetical train service and ESG related to it.

Following, the hypothetical train services pivoted around the actual are used in a stated preference experiment consisting in six choice tasks with two alternatives. Respondents are asked to choose between the same train service he/she described in section two (reference alterative) and the hypothetical train service (stated alternatives) for taking the exactly same trip they described. Figure 3 displays a screen capture representing an example of choice task. The software Ngene 1.1.2 (Ngene, 2014) is used to maximize the D-efficiency for a pivotal design (Rose *et al.*, 2008; Rose and Bliemer, 2008) with four blocks.

For the trip you described to us, consider a situation where you have two alternative means of transport, the mode you actually used or a new train with different levels of services. We would like you to study both alternatives and choose the one that you would most likely use if you had to repeat the trip.

	Trip characteristic	Current Alternative	New Alternative
GETTING TO THE TRAIN	Access time	4	5
	Waiting time	3	4
	Description of the train platform		
ON THE TRAIN	Travel time on the train	8	6
	Time spent waiting for transfer(s)	2	2
	Seat availability	Yes	No
	Fare paid	$3.65	$4.56
	Temperature on the train	Pleasant	Pleasant
GETTING TO THE FINAL DESTINATION	Egress time	6	5

CURRENT ALTERNATIVE NEW ALTERNATIVE

>>

Figure 3: Example of choice task.

It is worth noting that we collect attitudinal indicators for the localized attitudes before presenting the choice experiment, as we want to test the hypothesis that psychological factors explain the behavior and not that behavior builds the attitude. In closing, the last section of the survey asks for socio-economic information of the respondents.

3.3.2. The evaluative space grid (ESG)

The ESG is designed to collect the independent and simultaneous assessment of positive/negative attitudes towards an object, and it has been validated in different fields such as psychology and social behavior (e.g., Audrezet, 2014; Audrezet, *et al.*, 2016). This tool follows the theoretical framework of

Evaluative Space Model (ESM) proposed by Cacioppo and Bernston (1994), who suggested that positive and negative feelings can be experienced at the same time, also with strong intensities. The ESG contrasts positive and negative stimuli towards an attitude, posing two 5 points scales on *x* and *y* axes. Subjects are asked to select one of over 25 cells that best reflects their simultaneous negative and positive feelings towards the stimulus under study, as shown in Figure 4. The grid is designed to differentiate between four different attitudes: (1) positive (high positive and low negative), (2) negative (low positive and high negative), (3) indifference (low positive and negative), and (4) ambivalence (moderate to high positive and negative).

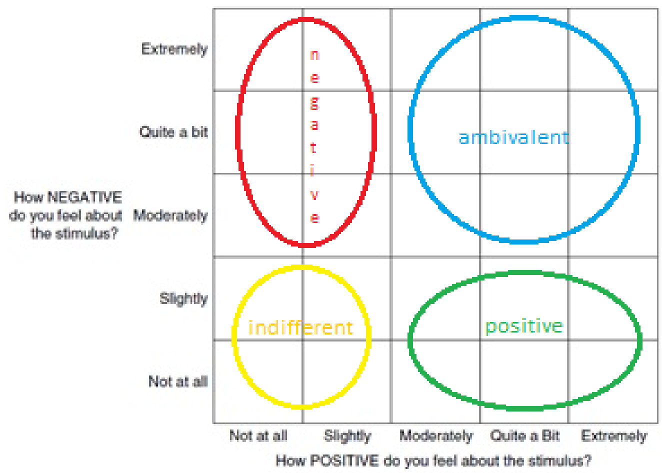

Figure 4: Evaluative space grid. Audrezet (2014) suggests the following division of the grid: bottom left cells identify an indifferent individual (yellow); bottom right cells classify a subject with a positive attitude (green); the top left cells (red) categorize an individual with a negative attitude; top right cells identify a subject with an ambivalent attitude.

Audrezet *et al.* (2016) proved that the ESG performs as well as the semantic differential scale with respect to different criteria (such as reliability and discriminant, convergent, nomological and predictive validity) and it captures more information (allows to measure separately indifference and ambivalence) with the advantage of being a single-item measure.

3.3.3. Sample composition

Data was collected using an online panel in April 2017 and consists in a sample of 340 respondents (mean age 47.3) who recently took a trip by train in Sydney, for any purpose (going from/to work 34.12 percent; working trip 7.06 percent; shopping 7.65 percent; leisure 29.12 percent; visiting friends or relatives 7.94 percent; other 14.11 percent). Eighty-six percent of respondents has an Australian citizenship, male respondents account for forty-seven percent of the sample and twenty-three percent of interviewees state to have never had a bad experience with trains. Fourteen percent of the sample does not provide the income, six percent has no income and the average weekly income of those who declare it amounts to 1113 AUD. The sample is mainly composed by workers (sixty-three percent) and retired (seventeen percent), with the remainder being students, full time homemakers and unemployed and seekers.

3.4. Model

The specification used to analyze the data consists of a structural equation model in which the attitudes are defined as latent variables and are linked to the attitudinal indicators and to a discrete choice model. Two latent variables measure the generalized satisfaction/dissatisfaction towards the train system whilst twelve more latent variables evaluate the localized satisfaction/dissatisfaction for the last train service the respondents experienced as well as the hypothetical services presented in the SP experiment. Latent variables describing the satisfaction (either generalized and localized) are linked to the corresponding attitudinal indicator measuring the positive domain (x axis on the ESG), whilst the negative domain of the evaluative space grid (y axis) represents the manifestation of the latent variable measuring the dissatisfaction (either generalized and localized). Figure 5 shows the framework of the structural equation model: generalized satisfaction and dissatisfaction are defined by individual characteristics whilst localized satisfaction and dissatisfaction, created in response to a stimulus, also depend on the attributes of the environment/alternatives. In addition to the parameters measuring the effect of the latent variable on the corresponding attitudinal indicator, we estimate two different sets of threshold parameters for the ordered logit models for the positive and negative domains, which we hypothesize not to vary for different choice tasks.

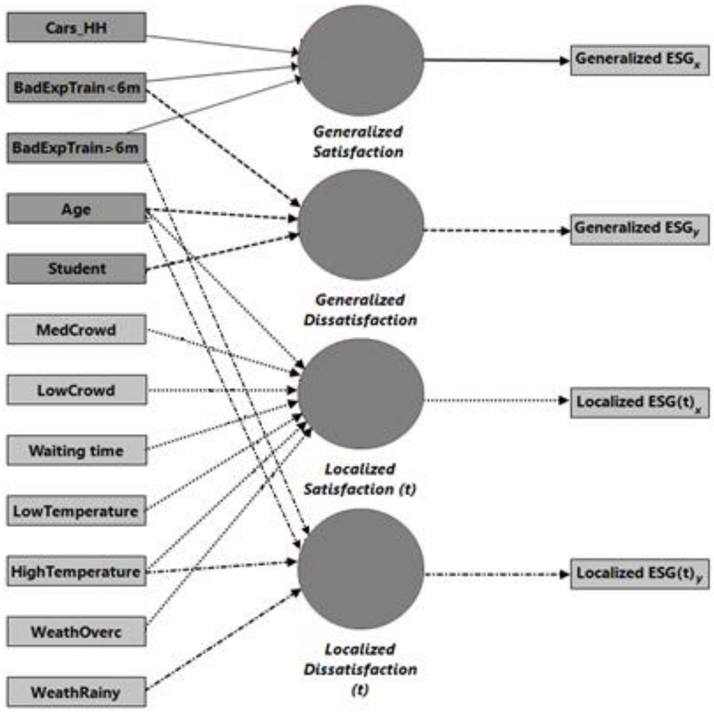

Figure 5: structural equation model framework. The *t* (= 1, …, 6) for Localized ESG indicates the choice task. Dark and light grey rectangles on the left-hand side represent individual characteristics and attributes of the environment/attitudes, respectively.

The choice model reflects the structure of the stated preference experiment, consisting of two utility functions representing the train service described by the respondents in section two and a hypothetical alternative train service. The alternatives depend on individual characteristics, attributes of the train service as well as of the latent variables measuring the generalized and localized satisfaction/dissatisfaction. The attributes describing the features of the trip are inserted in both utility functions and their effect is measured through generic parameters, whereas the individual characteristics are inserted in the utility function of the reference alternative. It is important to note that we hypothesize the effect of cost to be heterogeneous among respondents and to be distributed lognormally.

We assume that the generalized satisfaction and dissatisfaction have an effect on the reference alternative, whilst the localized attitudes influence the utility of the stated alternatives. The localized satisfaction and dissatisfaction for the reference alternative are defined using the same set of parameters of the other localized attitudes (stated alternatives); nonetheless, they do not enter any utility function. Differently from the localized satisfaction/dissatisfaction for the stated alternatives, we would expect these attitudes to have a positive effect on the reference alternative. However, such a specification performs worse than the one adopted in this paper. Therefore, we measure the localized satisfaction/dissatisfaction for the reference alternative with the only scope of capturing the influence of the regressors and not of explaining the choice process.

In the result section we compare this model (hereafter full model, FM) with five different specifications, which are briefly illustrated below.

Model 1 (M1) – MNL:

The first model is a multinomial logit model in which the reference and stated alternatives are described by the attributes listed above as well as socio-economic variables.

Model 2 (M2) – MMNL:

The mixed multinomial logit assumes a random taste variation for the parameter measuring the effect of *cost* on the alternatives, specifically defined to follow a lognormal distribution.

Model 3 (M3) – HDCM using only the generalized attitudes:

Model 3 is defined as a hybrid choice model. The structural equations of M3 consist of two latent variables measuring the generalized satisfaction/dissatisfaction towards the train system explained by individuals' characteristics. In the choice model, the latent variables are expected to affect the utility associated with the reference alternative.

Model 4 (M4) – HDCM using only the localized attitudes towards the last trip taken:

In this model we explore the effect of the localized satisfaction/dissatisfaction towards the last trip on the utility function of the reference alternative.

Model 5 (M5) - HDCM using the localized attitudes towards the hypothetical train services:

The specification of this model only differs from the FM because of the omission of the generalized satisfaction/dissatisfaction towards the train system.

3.5. Results

This section includes a specific analysis on the importance of localized attitudes followed by the general results of the full hybrid choice model. The detailed results of the different models (M1 – M5) are not presented here for brevity reasons; however, the main findings are discussed.

GENERALIZED

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	2.94%	1.47%	1.76%	1.18%	2.94%
4	1.18%	6.18%	5.00%	5.88%	1.47%
3	0.59%	1.47%	15.59%	6.47%	0.88%
2	0.29%	4.12%	2.94%	12.94%	5.29%
1	0.59%	0.88%	1.47%	6.76%	9.71%

LOCALIZED (ACT)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	3.24%	0.59%	0.00%	2.35%	4.41%
4	1.47%	2.35%	3.24%	5.29%	1.47%
3	0.29%	6.47%	12.94%	8.24%	0.88%
2	0.88%	2.65%	2.35%	11.47%	1.76%
1	1.18%	0.29%	3.24%	10.00%	12.94%

LOCALIZED (HYP 1)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	3.24%	0.88%	0.59%	0.88%	1.76%
4	1.47%	5.00%	5.29%	5.88%	1.76%
3	1.18%	5.29%	18.53%	6.47%	0.59%
2	0.88%	4.41%	6.18%	8.53%	0.88%
1	3.53%	0.88%	3.24%	6.76%	5.88%

LOCALIZED (HYP 2)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	8.82%	1.18%	0.88%	0.88%	2.65%
4	2.06%	7.65%	4.71%	5.29%	0.29%
3	2.65%	6.47%	14.12%	6.18%	0.29%
2	2.35%	4.71%	5.29%	7.06%	1.76%
1	5.00%	0.88%	3.53%	2.65%	2.65%

LOCALIZED (HYP 3)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	12.65%	3.24%	1.18%	0.29%	2.35%
4	5.88%	6.18%	3.53%	6.47%	0.29%
3	2.06%	5.29%	12.65%	2.94%	1.18%
2	1.47%	5.00%	4.41%	5.29%	0.29%
1	7.65%	2.06%	2.94%	2.06%	2.65%

LOCALIZED (HYP 4)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	7.94%	2.94%	2.06%	1.18%	2.35%
4	4.41%	4.41%	5.29%	3.82%	2.35%
3	1.47%	4.71%	14.12%	5.00%	0.88%
2	1.18%	4.71%	6.76%	6.47%	0.88%
1	5.59%	1.47%	4.12%	2.35%	3.53%

LOCALIZED (HYP 5)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	15.88%	2.94%	0.59%	0.88%	0.88%
4	3.24%	10.00%	2.35%	3.24%	1.18%
3	4.12%	4.71%	14.41%	5.00%	0.29%
2	1.47%	8.53%	3.24%	2.65%	0.88%
1	6.18%	2.65%	2.65%	1.47%	0.59%

LOCALIZED (HYP 6)

UNSATISFYING \ SATISFYING	1	2	3	4	5
5	5.59%	0.88%	0.29%	0.29%	1.18%
4	2.65%	5.00%	3.24%	7.65%	0.29%
3	1.76%	8.24%	14.12%	7.06%	1.18%
2	2.35%	8.53%	5.29%	6.76%	0.29%
1	2.06%	3.24%	3.24%	4.71%	4.12%

Table 1: Distribution of responses of the ESGs

3.5.1. *Localized attitudes*

Table 1 shows the distribution of responses of the Evaluative Space Grids used for the analysis. The color formatting indicates that the greener the cell, the higher the frequency of respondents selecting that cell. Analyzing the distributions, it clearly emerges the importance of collecting localized attitudes. Indeed, respondents seem reporting different attitudes according to the specific situation they are facing, and the differences become more evident when the generalized satisfaction/dissatisfaction is compared to the localized attitudes for hypothetical train services.

Table 2 compares the generalized attitude and localized satisfaction/dissatisfaction for the last trip taken. By construction, the numerical difference between the evaluation of two evaluative space grids ranges from -4 to 4 for both the positive and the negative axes. For example, if a respondent considers the general train system extremely satisfying and moderately unsatisfying (cell 5:3 in general ESG) and the first hypothetical alternative very satisfying and very unsatisfying (cell 4:4 in SP1 grid), the difference will be equal to 1 and -1 for the positive and the negative axes, respectively. The central cell (highlighted in green) represents the frequency of respondents who reveal the same attitude for the last trip and for the generalized satisfaction/dissatisfaction towards the trains system. The localized satisfaction/dissatisfaction for the last trip is slightly different from the generalized satisfaction/dissatisfaction for forty-eight percent of respondents (difference included within the range (-1,1) but 0) whilst is very different for nineteen percent of them.

4	0	0	0	1	**1**	1	0	0	0
3	0	0	0	0	**3**	1	0	1	0
2	0	0	3	7	**9**	4	1	0	0
1	0	1	5	16	**38**	12	1	0	0
0	**0**	**1**	**1**	**23**	**113**	**28**	**2**	**0**	**0**
-1	0	0	2	12	**23**	11	2	0	0
-2	0	1	0	1	**5**	0	1	1	0
-3	0	1	0	1	**2**	0	0	0	0
-4	0	0	0	0	**4**	0	0	0	0
	-4	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**

Table 2: Matrix of differences between ESGs measuring the generalized satisfaction towards the train and the localized satisfaction towards the last train service experienced. Numbers identify the frequencies of respondents revealing that combination of differences for x and y axes. A green cell classifies a high frequency, a red cell identifies a low frequency.

Figure 6 reports the matrices of differences among all collected grids, representing either generalized and localized attitudes. Using a color formatting, it is possible to visually notice the distribution of the frequencies, highlighted by green cells if the frequency is high, and red cells if the frequency is low. Even though the highest value is always observed at the central cell of any matrix, the presence of non-null frequencies in most of the remaining cells (light green or yellow) suggests that the localized attitudes change according to the situation for several respondents.

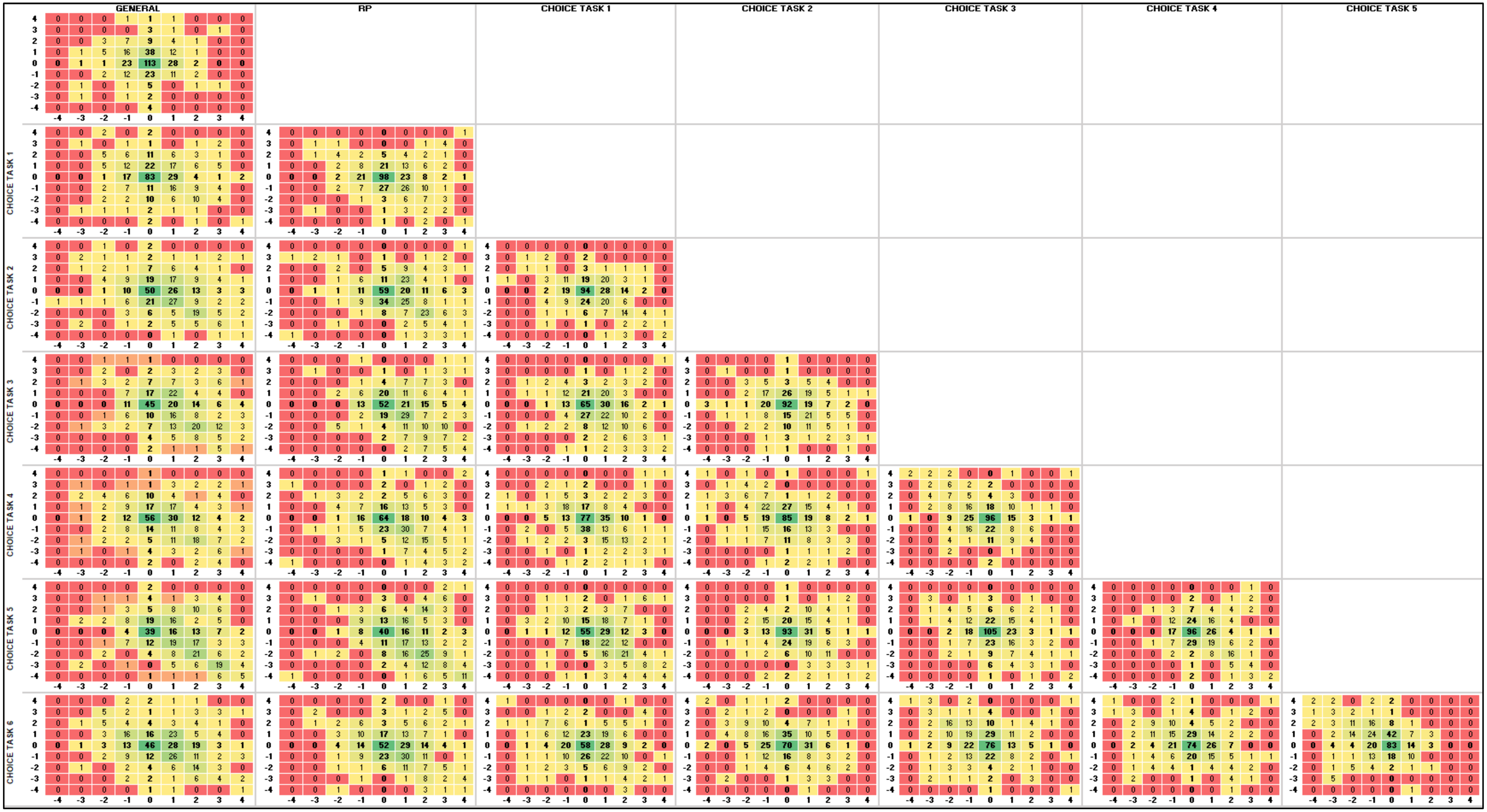

Figure 6: Cross-table including the matrices of differences. By column, the generalized attitude towards the train service (GENERAL), the localized attitude for the last train service (RP) and for the hypothetical train services (CHOICE TASK 1 – 6). By row, the localized attitude for the last train service (RP) and for the hypothetical train services (CHOICE TASK 1 – 5).

A further evidence emerging from testing the similarity of the generalized and localized attitudes is a memory effect, or state dependency. The analysis of the average Euclidian distances for any pair of ESGs collected through the survey (Table 3) reveals that two consecutive grids display a higher similarity than any other pair (except for choice task 3 - choice task 4, which presents an average Euclidian distance larger than choice task 3 - choice task 5). As a matter of example, let consider the second column of Table 3: the average Euclidian distance between the localized attitudes towards the last train service (RP) and the first hypothetical service (CT1) is 1.287, quite smaller than any other distance in the column, indicating that the localized attitude towards the last train service is more similar to the one towards the first hypothetical service than to any other one.

	GEN	RP	CT1	CT2	CT3	CT4	CT5	CT6
GEN								
RP	1.038							
CT1	1.453	1.287						
CT2	1.805	1.741	1.300					
CT3	2.049	1.975	1.580	1.322				
CT4	1.838	1.775	1.454	1.403	1.370			
CT5	2.227	2.286	1.830	1.358	1.261	1.316		
CT6	1.794	1.723	1.546	1.453	1.510	1.480	1.414	

Table 3: average Euclidian distances

The analysis of the differences of attitudinal indicators highlights the importance of considering localized attitudes when modelling individual behavior. Indeed, if generalized and localized attitudes capture different aspects of the mental process leading to the choice, the omission of such factors may potentially lead to incorrect estimates, as their contribution in explaining the choice will be absorbed by the error term.

3.5.2. Structural equation model

Table 4 reports the coefficient estimates for the structural model. The generalized satisfaction is negatively affected by the number of cars in respondent's household as well as by the past experience travelling by train. A higher probability of having a lower generalized satisfaction towards trains is revealed by respondents who have more cars available in the household and by those who have had a bad experience travelling by train, with more recent experiences (less than six months) impacting more than older ones (more than six months ago). Conversely, a bad experience within the last six months increases the probability that an individual has higher generalized dissatisfaction towards trains. This latent variable is also affected by a logarithmic transformation of age (the older the respondent, the lower the generalized dissatisfaction) and by the individual occupation (students have a higher probability of revealing a lower generalized dissatisfaction). The latent variables measuring the localized satisfaction and dissatisfaction are negatively affected by age and a logarithmic transformation of age, respectively. That is, an older respondent has a higher probability of displaying an indifferent attitude towards the train system, whilst an ambivalent attitude is more likely to be held by a younger individual. As for the generalized dissatisfaction, those who have had a bad experience with a train service in the last six months are more likely to display a higher localized dissatisfaction towards the train service. The weather affects the localized satisfaction/dissatisfaction: indeed, travelling in an overcast day has a negative impact on the localized satisfaction whilst a rainy day has a positive effect on the localized dissatisfaction. As concerns other features of the trip, the localized satisfaction is influenced by the crowd on the platform (the lower the better) and negatively by the waiting time. A pleasant temperature on the train (reference alternative) increases the localized satisfaction whilst only a high temperature seems to have a negative impact on the localized dissatisfaction. Finally, the parameters capturing the correlation between the positive and negative domains of the latent variables (i.e. within generalized satisfaction/dissatisfaction and localized satisfaction/dissatisfaction) are not statistically different from zero, suggesting that the mental processes bringing to the positive and negative assessments on the ESGs are independent.

	Structural model							
	Generalized Satisfaction		*Generalized Dissatisfaction*		*Localized Satisfaction*		*Localized Dissatisfaction*	
	Par.	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*
Age	-	-	-	-	-0.016	(-6.42)	-	-
Log(Age)	-	-	-0.607	(-1.87)	-	-	-0.382	(-2.22)
Cars in the hh	-0.197	(-1.96)	-	-	-	-	-	-
Occupation = student	-	-	-0.838	(-1.63)	-	-	-	-
Bad exp. Train 6 months	-0.728	(-2.21)	0.817	(2.70)	-	-	0.241	(2.09)
Bad exp. Train > 6 m	-0.452	(-1.65)	-	-	-	-	-	-
Weather = Overcast	-	-	-	-	-0.249	(-2.24)	-	-
Weather = Rainy	-	-	-	-	-	-	0.199	(1.66)
Crowd = Low	-	-	-	-	0.555	(7.06)	-	-
Crowd = Medium	-	-	-	-	0.256	(4.02)	-	-
Temperature = Low	-	-	-	-	-0.870	(-8.45)	-	-
Temperature = High	-	-	-	-	-0.872	(-10.07)	0.427	(6.11)
Waiting time	-	-	-	-	-0.026	(-3.47)	-	-
Correlation parameters								
ρ_0	-0.195	(-1.14)						
ρ_1	-0.038	(-0.51)						

Table 4: coefficient estimates for the latent variables.

Based on the findings reported in the previous section where respondents revealed a memory effect compiling the localized attitudinal indicators, we inserted a further variable assessing the similarity between consecutive perceptual indicators in any latent variable measuring the localized satisfaction/dissatisfaction. Specifically, the absolute value of the difference between two consecutive ESGs (for both the positive and the negative indicators) is found to be significant for eleven out of twelve localized latent variables (Table 5). Otherwise stated, the similarity of two consecutive assessments influences the localized satisfaction/dissatisfaction through the stated preference experiment. Keeping the ESG shown in Figure 4 in mind, the sign of the parameters suggests the position of the individuals who are more likely to give different assessment for two consecutive levels of (hypothetical) train services. As a matter of example, the parameter *Difference Satisfaction 2_1* suggests that larger is the $abs(y_{1,sat} - y_{2,sat})$, higher is the probability that the individual has a lower localized satisfaction for the train service presented in choice task 2. Similarly, larger is the $abs(y_{1,dis} - y_{2,dis})$, higher is the probability that the subject considers the same train service dissatisfying. Considering these results, it is possible to conclude that the respondents who assess ESG1 and ESG2 differently, are more likely to describe the train service presented in choice task 2 dissatisfying. Opposite is the case of the assessment of ESG6 where the parameters measuring the effects of $abs(y_{5,sat} - y_{6,sat})$ on the localized satisfaction/dissatisfaction of the hypothetical train service shown in choice task 6 are positive and negative, respectively. As a result, respondents who assess ESG5 and ESG6 differently, are more likely to describe satisfying the train service presented in choice task 6.

	$abs(y_{t,sat} - y_{t+1,sat})$ $abs(y_{t,dis} - y_{t+1,dis})$	
	Par.	*(Rob. t-test)*
Difference Satisfaction 1_RP	-0.668	(-4.53)
Difference Dissatisfaction 1_RP	0.171	(1.99)
Difference Satisfaction 2_1	-0.346	(-3.26)
Difference Dissatisfaction 2_1	0.432	(5.94)
Difference Satisfaction 3_2	-0.138	(-1.72)
Difference Dissatisfaction 3_2	0.330	(3.36)
Difference Satisfaction 4_3	0.180	(2.83)
Difference Dissatisfaction 4_3	-0.027	(-0.24)
Difference Satisfaction 5_4	-0.470	(-7.43)
Difference Dissatisfaction 5_4	0.432	(3.73)
Difference Satisfaction 6_5	0.494	(8.60)
Difference Dissatisfaction 6_5	-0.51	(-2.33)

Table 5: coefficient estimates for the differences of two consecutive indicators.

Table 6 contains the coefficient estimates for the measurement model. The parameters measuring the effect of the latent variables on the attitudinal indicators are significant and positive, indicating that a greater generalized/localized satisfaction/dissatisfaction increases the probability that respondents attribute a higher value to the corresponding attitudinal indicator. The estimates of the two sets of thresholds for the ordered logit models are shown in the bottom part of Table 6.

	Measurement model			
	Par.		*(Rob. t-test)*	
Generalized Satisfaction 1	1.17		(7.24)	
Generalized Dissatisfaction 1	0.936		(6.54)	
Localized Satisfaction RP	1.38		(10.90)	
Localized Dissatisfaction RP	1.78		(11.09)	
Localized Satisfaction t=1	1.21		(9.36)	
Localized Dissatisfaction t=1	1.76		(12.38)	
Localized Satisfaction t=2	1.79		(13.15)	
Localized Dissatisfaction t=2	1.88		(14.10)	
Localized Satisfaction t=3	2.37		(15.53)	
Localized Dissatisfaction t=3	1.96		(10.23)	
Localized Satisfaction t=4	2.31		(14.63)	
Localized Dissatisfaction t=4	1.64		(9.03)	
Localized Satisfaction t=5	2.43		(15.83)	
Localized Dissatisfaction t=5	1.51		(11.02)	
Localized Satisfaction t=6	2.28		(15.28)	
Localized Dissatisfaction t=6	1.44		(10.07)	
Threshold parameters				
	Satisfaction		*Dissatisfaction*	
	Par.	*(Rob. t-test)*	*Par.*	*(Rob. t-test)*
τ_1	-5.49	(-16.29)	-4.04	(-3.45)
τ_2	-3.61	(-9.65)	-2.49	(-2.11)
τ_3	-1.61	(-11.65)	-0.75	(-6.43)
τ_4	0.68	(4.29)	0.90	(7.39)

Table 6: coefficient estimates for the measurement model.

3.5.3. Choice model

The estimates of the full hybrid choice model are displayed in the last column of Table 7. The parameters measuring the effect of egress and travel times on the alternatives are significant and negative, indicating a decreasing utility for an increase in these attributes. Similarly, an increase in cost is perceived as a detriment, even if individuals display heterogeneous sensibility to this parameter. Indeed, the parameter related to cost is assumed lognormal distributed, resulting in a distribution with a positive skew. Having a seat available on the train increases the probability of having a higher utility. As concerns the socioeconomic characteristics, respondents who always select the same alternative in the six choice tasks (non-traders) and those who prefer to be by themselves rather than being in crowded places (comfortable = alone) have a higher probability of choosing the reference alternative whilst those who prefer individual but not motorized transportation means (i.e. taxi or Uber service) for visiting friends and relatives display a lower probability of choosing this alternative. Other socioeconomic characteristics do not seem to have a direct impact on the process of choice, but they do have an indirect impact via generalized and localized attitudes. The estimates of the generalized satisfaction and dissatisfaction indicate that higher the satisfaction (dissatisfaction), higher (lower) the probability of choosing the reference alternative. An important finding of this work is the significant effect of the localized attitudes on the individual preferences. A higher satisfaction (dissatisfaction) measured for the hypothetical train services increases (decreases) the probability of choosing the stated alternative. To the best of our knowledge, no previous paper has measured the impact of localized attitudes on the decision-making process in the context of transportation.

	Choice model					
Attributes	M1	M2	M3	M4	M5	FM
ASC RP	-0.304 (-1.42)	-1.65 (-2.15)	0.195 (0.60)	4.27 (2.73)	-0.103 (-0.49)	0.405 (0.41)
Access Time	-0.031 (-1.73)	-	-	-	-	-
Travel Time	-0.036 (-5.40)	-0.0386 (-5.23)	-0.040 (-5.09)	-0.040 (-5.02)	-0.033 (-4.75)	-0.023 (-3.02)
Egress Time	-0.028 (-3.63)	-0.029 (-3.05)	-0.039 (-3.80)	-0.038 (-3.92)	-0.036 (-4.14)	-0.030 (-3.52)
Cost (μ)	-0.246 (-3.90)	-1.687 (-4.17)	-1.43 (-4.23)	-1.44 (0.344)	-1.447 (-4.73)	-1.655 (-4.52)
Cost (σ)	-	1.820 (4.87)	1.64 (5.17)	1.66 (5.02)	1.422 (4.96)	1.642 (4.67)
Seat availability	0.612 (5.43)	0.701 (5.29)	0.632 (4.83)	0.603 (4.60)	0.753 (6.04)	0.683 (5.50)
Temperature Low	-0.535 (-4.77)	-0.674 (-5.47)	-0.836 (-3.97)	-	-	-
Temperature High	-1.02 (-6.06)	-1.16 (-5.83)	-1.650 (-4.28)	-	-	-
Crowd Low	0.247 (2.58)	0.433 (3.21)	-	-	-	-
Crowd Medium	-	0.278 (2.17)	-	-	-	-
Individual characteristics						
Non-Trader	1.86 (5.12)	1.86 (4.91)	2.610 (8.57)	2.60 (8.87)	2.015 (5.11)	1.927 (5.18)
Train for leisure trips	-	-	-	-	0.404 (1.65)	-
Car for leisure trips	-	-	0.307 (1.64)	0.314 (1.81)	0.425 (1.95)	-
Train for working trips	-	-	-	-	-0.310 (-2.07)	-
Age	0.008 (1.73)	-	-	-	-	-
Log(Age)	-	0.341 (1.70)	-	-	-	-
Uber/Taxi for visiting	-1.90 (-7.73)	-1.42 (-4.99)	-1.840 (-5.04)	-	-	-1.13 (-4.42)
Occ. = Student	0.452 (1.84)	0.519 (1.95)	0.501 (1.65)	-	-	-
Comfortable = Alone	-	-	-	-	-	-0.235 (-1.65)
Latent variables						
Generalized pos. attitude	-	-	1.92 (2.04)	2.17 (3.45)	-	0.451 (1.92)
Generalized neg. attitude	-	-	1.70 (1.71)	1.89 (2.99)	-	-0.428 (-1.81)
Localized pos. attitude	-	-	-	-	0.026 (0.31)	0.315 (2.35)
Localized neg. attitude	-	-	-	-	-0.045 (-0.52)	-0.463 (-2.39)
Willingness to pay						
	8.79 AUD/h	12.54 AUD/h	10.01 AUD/h	10.15 AUD/h	8.52 AUD/h	7.22 AUD/h

Table 7: coefficient estimates for the choice model. In brackets robust t-test.

3.5.4. Discussing the different models

In this paragraph, we present the results of the best specification derived for any model and discuss the major differences. However, performances of these models are not directly comparable. In models M4 – M5 (as for the FM), the temperature on the train and crowd on the platform affect the choice through the localized satisfaction/dissatisfaction. In models M1 – M2 – M3 instead, in addition to travel and egress times, cost and seat availability, the attributes access time (only in M1), crowd on the platform (in M1 – M2) and temperature on the train directly influence the utility functions of the alternatives. According to the results of both models, respondents prefer less crowd on the platform and pleasant temperature on the train.

Looking at M3 and M4, the parameters measuring the effect of the generalized satisfaction (for M3) and the localized satisfaction for the last trip (for M4) indicate that higher the satisfaction, higher the probability of choosing the reference alternative. A similar pattern emerges also for the parameters related to the generalized and localized (for the last trip) dissatisfaction, even if the magnitude is lower. Specifically, M3 suggests that a respondent, with a pronounced generalized dissatisfaction towards trains, prefers the reference alternative to the SP. This result may indicate that the last trip that the respondent took by train was, conversely, a satisfying experience. However, the partial information on the attitudes captured in M3, which does not consider localized attitudes for the last trip, makes the result less straightforward to explain. Along the same line, a respondent with higher dissatisfaction for the last trip who still prefers the reference alternative (M4) can be interpreted as a nonsense. Again, M4 does not include the localized attitudes for the stated alternatives, which can be perceived even worse than the last trip experienced by the respondent.

Finally, the latent variables proxying the localized satisfaction/dissatisfaction have no significant effect on the choice of the alternative (M5). This latter result embodies a further proof of the importance of considering generalized and localized attitudes altogether when exploring individual preferences. Indeed, when the effects of the generalized/localized attitudes are analyzed separately, the parameters may not be able to capture sufficient information or their effects can be the sum of different aspects and therefore, the impact of the psychological factors on the mode choice can become biased.

An interesting discussion concerns the value of the willingness to pay (WTP) estimated using different models and reported in the last row of Table 7. The values refer to the median of a lognormal distribution for the models including a random parameter for *cost* (from M2 to FM) and to the mean value for the multinomial logit model. Focusing on the models including a random parameter for cost, it is worth noting that increasing the number of latent variables used in the structural equation model, the WTP decreases. That is, whilst the mixed multinomial logit suggests that the median respondent is willing to pay 12.54 AUD for saving one-hour of travel time, the hybrid choice models including two latent variables, measuring respectively the generalized and the localized (towards the last trip taken) satisfaction/dissatisfaction (M3 – M4), suggest a WTP of about 10 AUD. According to M5, which includes twelve latent variables determining the localized satisfaction/dissatisfaction for the hypothetical alternatives, the median respondent is willing to pay 8.52 AUD to save one hour of trip by train, which is about 15% less than the value found for specifications M3 and M4. An even lower WTP emerges from the FM, in which both the generalized and the localized satisfaction and dissatisfaction are included. Here, fourteen latent variables are specified, resulting in a WTP of 7.22 AUD, which is about 25% less than the model including only the generalized attitudes. This result is consistent with the literature (Abou-Zeid *et al.*, 2010; Walker *et al.*, 2010; Guevara, 2015; Vij, Walker, 2016) showing that the inclusion of latent variables and measurement indicators reduces the bias due to omitted variables or measurement error. In our case, additional significant latent variables further reduce the measurement bias. The information added by considering localized attitudes is likely to be dispersed in the error term of the alternative in a model that do not consider psychological factors at all or does only consider generalized attitudes, generating a less precise value for the willingness to pay for saving travel time. Such a finding may also question the accuracy of the WTP estimated in similar settings within transportation literature given that the common practice is to include only generalized attitudes when estimating HDCMs.

3.6. Conclusions

This chapter focuses on the role of attitudes in determining individual choice behavior and examines the temporal stability of generalized attitudes within a stated choice experiment framework. Within the psychological literature, there exist three different schools of thought as to whether or not attitudes are largely fixed or somewhat transient. The first school of thought identified assumes that attitudes are long term stable constructs which are "memory-based" such that an attitude towards an object is linked to one or more global evaluations that brought to the mind once the object is encountered. The second school of thought related to the temporal stability of attitudes assumes that attitudes are short term situational specific concepts that are constructed at the time a specific situation occurs and that evaluative judgments are formed only when required rather than being stored in longer term memory. The third school of thought on attitude formation suggests that attitudes are created via a mixture of both short and long-term influences, assuming that evaluative processes towards objects are part of an iterative cycle where the current evaluation of stimuli can be adjusted as new contextual and motivational information arises.

The current chapter reports the results of a stated choice experiment where respondents are asked to provide their generalized and localized attitude towards a train service. The approach adopted allows for an examination as to how attitudinal responses vary as the attribute levels of the alternatives presented within the experiment change over repeated choice tasks. Comparing the attitudinal indicators, it emerges that the generalized and localized attitudes are different for most of the respondents and the farer the hypothetical train services are presented in the stated preference experiment, the weaker the stability of the attitude is. In addition, this divergence also appears comparing localized attitudes specific of the hypothetical situations and it increases when comparing two hypothetical train services more distant in time. The comparison of attitudinal indicators highlights the necessity of exploring the effect that localized attitudes have on individual choice. The results of the stated preference experiment conducted in this work reveal that both generalized and localized attitudes have a significant impact on individuals' choices. In our experiment, the models analyzing generalized and localized attitudes separately only capture partial information related to the psychological process leading to the choice and, consequently, the interpretation of the results may be tricky. Furthermore, the omission of localized attitudes may potentially lead to inconsistent estimates, as their contribution in explaining the choice will be absorbed by the error term. A demonstration is given by the value of the WTP obtained by different hybrid choice model specifications, which decreases as the number of latent variables measuring attitudes increases. Specifically, a model including generalized and localized attitudes presents a willingness to pay about 25% lower than a specification including only generalized attitudes and 40% lower than a specification without any attitude.

The evidence of this work proves the importance of specifying both generalized and localized attitudes when exploring the role of psychological factors on the decision-making process. The inclusion of attitudes with different temporal stability provides more consistent estimates and it appears to be critical to transportation planning and research given the link between attitudes and behavior as explained by the theory of planned behavior. Indeed, if attitudes are a precursor towards action, one mechanism to change travel behavior may be via the ability of transport planners to change attitudes, using for example the introduction of new stimuli, such as a message or advertisement, which when processed by the individual, can result in an attitude change alongside a change in behavior.

References

Abou-Zeid, M., Ben-Akiva, M., Bierlaire, M., Choudhury, C., Hess, S., 2010. Attitudes and value of time heterogeneity. *Applied Transport Economics A Management and policy perspective*, 523 – 545.

Ajzen I., 1985. From Intentions to Actions: A Theory of Planned Behavior. In: Kuhl J., Beckmann J. (Eds.) *Action Control*. SSSP Springer Series in Social Psychology. Springer, Berlin, Heidelberg.

Allport, G.W., 1935. Attitudes. In Handbook of Social Psychology, C Murchinson, 798 – 844. Worcester, MA: Clark Univ. Press.

Audrezet, A., 2014. L'ambivalence des consommateurs: proposition d'un nouvel outil de mesure. *Business administration. Universite Paris Dauphine - Paris IX. French.*

Audrezet, A., Olsen, S.O., Tudoran, A.A., 2016. The GRID scale: a new tool for measuring service mixed satisfaction. *Journal of Services Marketing* 30(1), 29 – 47. doi: 10.1108/JSM-01-2015-0060

Bahamonde-Birke, F.J., Kunert, U., Link, H., Ortúzar, J., 2017. About attitudes and perceptions – Finding the proper way to consider latent variables in discrete choice models. *Transportation* 44, 475–493. DOI 10.1007/s11116-015-9663-5

Ben-Akiva, M., Boccara, B., 1993. Discrete choice models with latent choice sets. Working paper, Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Ben-Akiva, M., Morikawa, T., 1990. Estimation of travel demand models from multiple data sources. International Symposium on Transportation and Traffic Theory, Yokohama, Japan.

Ben-Akiva, M.E., Walker, J.L., Bernardino, A.T., Gopinath, D.A., Morikawa, T. and Polydoropoulou, A., 2002. Integration of choice and latent variable models. In H.S. Mahmassani (ed.), *In Perpetual Motion: Travel Behaviour Research Opportunities and Challenges*. Pergamon, Amsterdam.

Bohner, G., Dickel, N., 2011. Attitudes and attitude change. *Annual Review of Psychology* 62, 391 – 417.

Cacioppo, J.T., Berntson, G. G., 1994. Relationship between attitudes and evaluative space: a critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin* 115(3), 401 – 423. doi: 10.1037/0033-2909.115.3.401

Chen, S., Chaiken, S., 1999. The heuristic-systematic model in its broader context. In S. Chaiken & Y. Trope (Eds.), Dual process theories in social psychology, 73 - 96. New York: Guildford Press.

Conrey, F.R., Smith, E.R., 2007. Attitude representation: attitudes as patterns in a distributed, connectionist representational system. *Social Cognition* 25, *Special Issue: What is an Attitude?*, 718-735. https://doi.org/10.1521/soco.2007.25.5.718.

Crano, W.D., Prislin, R., 2006. Attitudes and Persuasion. *Annual Review of Psychology* 57, 345 – 374.

Cunningham, W.A., Zelazo, P.D., 2007. Attitudes and evaluations: a social cognitive neuroscience perspective. *Trends in Cognitive Sciences* 11, 97 – 104.

Cunningham, W.A., Zelazo, P.D., Packer, D.J., Van Bavel, J.J., 2007. The iterative reprocessing model: a multilevel framework for attitudes and evaluation. *Social Cognition* 25(5), 736 – 760.

Currim, I., 1981. Using segmentation approaches for better prediction and understanding from consumer mode choice models. *Journal of Marketing Research* 18, 301-309.

Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. *Transportation* 39(2), 267-297.

Daziano, R. A., Bolduc, D., 2013a. Incorporating pro-environmental preferences toward green automobile technologies through a Bayesian Hybrid Choice Model. *Transportmetrica A: Transport Science* 9(1), 74 - 106.

Daziano, R. A., Bolduc, D., 2013b. Covariance, identification, and finite-sample performance of the MSL and Bayes estimators of a logit model with latent attributes. *Transportation* 40(3), 647-670.

Fazio, R.H., 1990. Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. *In M.P. Zanna (Ed.), Advances in experimental social psychology.* 23, 75-109. New York: Academic Press.

Gawronski, B., Bodenhausen, G.V., 2007. Unraveling the processes underlying evaluation: attitudes from the perspective of the APE model. *Social Cognition* 25, 687–717.

Green, P., 1984. Hybrid Models for Conjoint Analysis: An Expository Review. *Journal of Marketing Research* 21, 155-169.

Green, P., Goldberg, S., Montemayor, M., 1981. A Hybrid Utility Estimation Model for Conjoint Analysis. *Journal of Marketing* 45(1), 33-41. doi:10.2307/1251718

Guevara, C.A., 2015. Critical assessment of five methods to correct for endogeneity in discrete choice models. *Transportation Research Part A* 82, 240 – 254.

Hensher, D., 1990. Hierarchical stated response design – an application to bus user preferences. *Logistics and Transportation Review* 26(4), 299 – 321.

Larsen, J.T., Norris, C.J., McGraw, A.P., Hawkley, L.C. and Cacioppo, J.T., 2009. The evaluative space grid: a single-item measure of positivity and negativity. *Cognition and Emotion* 23(3), 453-480. doi: 10.1080/02699930801994054

Maldonado-Hinarejos, R., Sivakumar, A., Polak, J.W., 2014. Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach. *Transportation* 41, 1287–1304. DOI 10.1007/s11116-014-9551-4

McFadden, M., 1980. Econometric models for probabilistic choice among products. *The Journal of Business* 53(3-2): Interfaces between marketing and economics, S13 - S29.

McFadden, M., 1986. The choice theory approach to market research. *Marketing Science* 5(4). Special issue on consumer choice models, 275 – 297.

Morikawa, T., 1989. Incorporating stated preference data in travel demand analysis. Unpublished phD dissertation, Dept. of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Morikawa, T., Ben-Akiva, M., Mc Fadden, D., 1990. Incorporating psychometric data in econometric demand models. Prepared for presentation at the Banff Invitational symposium on consumer decision-making and choice behavior, Canada.

Ngene 1.1.2 User Manual & Reference Guide, 2014. http://www.choice-metrics.com/download.html

Petty, R.E., Briñol, P., DeMarree, K.G., 2007. The meta-cognitive model (MC) of attitudes: implications for attitude measurement, change, and strength. *Social Cognition* 25.

Petty, R.E., Wegener, D.T., 1999. The elaboration likelihood model: current status and controversies. In S. Chaiken & Y. Trope (Eds.), *Dual process theories in social psychology*, 41 -72. New York: Guildford Press.

Raveau, S., Yanez, M., Ortúzar, J., 2012. Practical and empirical identifiability of hybrid discrete choice models. *Transportation Research Part B: Methodological* 46, 1374–1383. DOI: 10.1016/j.trb.2012.06.006.

Red3, 2005. Evaluation of Australian TravelSmart Projects in the ACT, South Australia, Queensland, Victoria and Western Australia: 2001–2005, Report to the Department of Environment and Heritage and State TravelSmart Program Managers. Accessed from: http://www.travelsmart.gov.au/publications/evaluation-2005.html

Rose, J.M., Bliemer, M.C.J., 2008. Stated preference experimental design strategies, in Hensher, D.A. and Button, K.J. (eds.) Handbook of Transport Modelling, Elsevier, Oxford, Ch. 8, 151-180.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.C., 2008. Designing efficient stated choice experiments involving respondent based reference alternatives. *Transportation Research Part B* 42(4), 395-406.

Schacter, D.L., Gilbert, D.T., Wegner, D.M., 2011. Psychology (2nd edition). New York: Worth.

Schwarz, N., 2007. Attitude construction: evaluation in context. *Social Cognition* 25(5), 638 – 656.

Swait, J., 1994. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of retailing and consumer services* 1(2), 77 – 89.

Train, K.E., McFadden, D.L., Goett, A.A., 1987. Consumer attitudes and voluntary rate schedules for public utilities. *The review of economics and statistics* 69(3), 383 – 391.

Van Acker, V., Mokhtarian, P.L., Witlox, F., 2011. Going soft: on how Subjective Variables Explain Modal Choices for Leisure Travel. *European journal of transport and infrastructure research* 11(2), 115-146.

Vieira, L., 1992. The value of service in freight transportation. PhD dissertation, Dept. of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B* 90, 192 – 217.

Walker, J.L., 2001. *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*. Massachusetts Institute of Technology.

Walker, J., Li, J., Srinivasan, S., Bolduc, D., 2010. Travel demand models in the developing world: correcting for measurement errors. *The International Journal of Transportation Research* 2(4), 231 – 243.

Conclusion

This dissertation focuses on the way psychological factors, in particular attitudes, are treated in choice modeling in the context of transportation. Here, the common practice adopted is still very distant from the one used in psychological literature and therefore it is not always accurate. The dissertation proposes procedures and methods to improve the measurement of psychological variables to be used in choice modeling. The use of the Evaluative Space Grid to collect attitudinal indicators represents the main contribution of this dissertation, as this has been employed in all the works. The first two chapters show in details the benefits of using this tool when modeling individual preferences. If the researcher aims at suggesting policies for different segments of the population based on psychological variables (for example environmental friendly, attached to the car, pro adventures, etc.), then the ESG is the perfect tool to employ. Indeed, this instrument improves the segmentation helping policy makers to draw more specific and effective policies. The last chapter is no longer focused on the instrument itself, rather it shows the importance of considering different types of attitudes when modeling individual preferences. Nevertheless, the ESG can be modeled as suggested in chapters one and two to take into account the possibility that respondents can have a neutral satisfaction as the outcome of two different attitudes, which are indifference and ambivalence.

The importance that psychological variables have on individual behavior is the foundation of this dissertation. Since McFadden proposed the framework of hybrid discrete choice models (1986), several papers showed the role that attitudes, perceptions and beliefs have on determining individual preferences and choices in a transportation context. One of the most used techniques that connects the exploration of psychological factors to the study of individual preferences is hybrid discrete choice modeling. Whilst the choice modeling part has been improved in the last decades, introducing for examples mixed models, latent class models and discrete-continuous models, not much attention has been paid for the structural equation model, which aims at exploring the psychological aspects of the respondent. The trigger of this research is the opportunity to improve the analysis of psychological factors which drive individual choices.

This dissertation contributes to this literature in a threefold way. The first contribution is instrumental, by suggesting the use of the Evaluative Space Grid for measuring attitudes, the second one is methodological, by showing the econometric steps for including such an instrument in the framework of a hybrid choice model, and the final one is structural, by recommending the use of long-term stable and short-term situational specific attitudes when exploring the role of psychological factors on individual behavior.

The first chapter focuses on the importance of distinguishing between individuals having indifferent and ambivalent attitudes, as well as positive and negative inclinations. Traditional methods for measuring attitudes, such as Likert scale, semantic differential scale or conversely framed questions, help the researcher to segment the population of individuals having positive and negative attitudes, however these tools aggregate individuals revealing a neutral inclination. The Evaluative Space Grid (ESG), proposed by Larsen *et al.* (2009), instead, allows the researcher to detect various attitudinal outcomes towards an object, including ambivalence and indifference, alongside the more commonly measured positive and negative attitudinal outcomes. Such an instrument has already been used in psychology and in marketing studies to assess ambivalence and indifference by means of a deterministic score. However, assuming attitudes are latent constructs, hence not directly measurable, the use of scores seems anachronistic. The first chapter includes an approach, based on two simultaneous ordered logit models, which considers the latent nature of the attitudes. Using this procedure, it is possible to model up to a probability any attitudinal outcome. An additional advantage of the proposed model, is its ability to forecast future responses (i.e. predict out of sample). In many applied fields, such as environmental or transport economics in which such psychological methods are commonly used, being able to predict how attitudes may develop or change over time, or even what attitudes may exist in other non-sampled populations, can support policy makers in their decisions.

The second chapter of this dissertation describes the methodology to include the ESG in the framework of hybrid choice models. In brief, structural equations consist of two latent variables, representing positive and negative domains respectively, explained by individual characteristics and linked by a correlation term; measurement equations consist of two ordered logit regressions which connect the observables items to the latent variables. In addition to the methodological contribution, this chapter tests the hypothesis that individuals having indifferent and ambivalent attitudes display different preferences in a context of transportation mode choice for commuting trips. Furthermore, these categories also respond differently if the proposed alternatives experience a change in the attributes of the alternatives. The inclusion of attitudes in studies modeling individuals' preferences is very helpful for policy purposes. Indeed, policy makers may target their campaign specifically for individuals who have, for instance, a strong positive or negative inclination towards environmental concerns or attachment to the car. This work helps policy makers draw even more powerful and effective policies, showing that it is important to consider also the segment of individuals having a neutral inclination, i.e. subjects revealing an ambivalent or indifferent attitude, as their choices and their reaction to an incentive may be different.

The last chapter of the dissertation enters a debate in psychological literature on the temporal stability of attitudes. Here, a hybrid choice model explores the impact that long-term stable constructs (generalized attitudes) and short-term situational specific concepts (localized attitudes) have on individual behavior. Generalized and localized attitudes are measured through a stated preference experiment in the context of transportation. Whilst the inclusion of stable psychological constructs is common practice, the exploration of the role of attitudes constructed on the spot is new to transportation literature. Evidence shows that generalized and localized attitudes are different for most respondents and that both types of attitudes have a significant impact on individuals' choices. Furthermore, the omission of localized attitudes may potentially lead to inconsistent estimates, as their contribution in explaining the choice will be absorbed by the error term, as demonstrated by the value of the WTP obtained by different hybrid choice model specifications. Specifically, evidence shows that including both types of attitudes decreases the amount that respondents are willing to pay to save travel time. The inclusion of attitudes with different temporal stability appears to be critical to transportation planning and research given the link between attitudes and behavior as explained by the Theory of Planned Behavior. Indeed, if attitudes are a precursor towards action, one mechanism to change travel behavior may be via the ability of transport planners to change attitudes, using for example the introduction of new stimuli, such as a message or advertisement, which when processed by the individual, can result in an attitude change alongside a change in behavior.

The methodology and the procedures presented in this dissertation, together with the empirical case studies proposed, represent a tiny contribution to what is possible to achieve importing ad hoc procedures from psychology to applied fields like transportation. Psychological literature contains numerous debates on factors influencing individual behavior, such as attitudes, perceptions, beliefs and social norms, and therefore further effort and investigation is required by applied researchers in this direction. Several advances have been done in modeling individual behavior in the last decades, and importing new instruments or testing theoretical frameworks suggested by psychologists may further contribute to improve the representation of individual behavior.