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Uncovering the Nexus Between Attitudes, Preferences and Behavior in Sociological Applications of Stated Choice Experiments

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Abstract: Multifactorial survey experiments such as stated choice experiments are used more and more frequently in social science research. In this paper, based on an experimental study on ethical and political consumption, we explore the potential of hybrid choice models to explicitly model latent psychological factors such as attitudes, overcoming a possible endogeneity bias and misrepresentation of causality. To this end, we employ a hybrid latent class choice model (HLCCM) in which the latent class structure allocates individuals to classes according to underlying latent attitudes that also influence the answers to attitudinal questions. This allows, in line with sociological action theories, a theory guided testing of preference segmentation and modification caused by attitudes. We compare the complex hybrid latent class choice model with less complex models that do not take the latent variable nature of attitudes into account and discuss in which cases less complex models might be more appropriate.

However, the HLCCM always has the advantage of providing structure for theory testing and is therefore a useful tool to uncover preference heterogeneity, preference modification and decision making processes in sociological and other social science research.

Keywords: attitudes, hybrid choice model, latent class analysis, stated choice experiment, stated preferences

Acknowledgements: We thank two anonymous reviewers for their helpful comments. The data used in this study was collected as part of the Trilateral Research Project "The Economic Integration of Agriculture in Israel and Palestine," for which the generous support of the German Research Foundation (DFG) is acknowledged. Petr Mariel acknowledges financial support from the Spanish Ministry of Economy and Competitiveness through grant ECO2017-82111-R and the Basque Government through grant IT-642-13 (UPV/EHU Econometrics Research Group).

1 Introduction

While factorial surveys have been widely used in sociological research since decades (see Wallander 2009 for an overview) other multifactorial survey designs such as stated choice and conjoint experiments are still novel for most sociologists (but see Auspurg and Hinz 2014, 2015; Beyer and Liebe 2015; Liebe et al. 2016). In stated choice experiments respondents are asked to choose from an array of behavioral alternatives, which vary in a number of attributes, the alternative they favor most. This design allows researchers to estimate the effect of each attribute on respondents' stated choices. Stated choice experiments (SCEs) originated in marketing and transportation economics (Louviere et al. 2000) and became popular in many subfields of economics including transportation, health and environmental economics because they provide a means of measuring preferences for product attributes even if the good in question is hypothetical. It is important to stress that SCE are *not* identical with or a special case of conjoint experiments. The main difference is the theoretical foundation of SCE which is based on random utility theory (see Auspurg and Hinz 2015; Louviere et al. 2010 for a detailed discussion). This theoretical foundation – a rational-choice framework – is in-principle in line with many sociological action theories assuming that individuals choose from behavioral alternatives the one that gives the highest level of satisfaction or utility (Kroneberg and Kalter 2012; Bruch and Feinberg 2017). Applications of SCE in sociology include studies on the social embeddedness in trust situations (Buskens and Weesie 2000), ethical consumption (Andorfer and Liebe 2013) and discrimination (Beyer and Liebe 2015). Both, SCE and conjoint experiments are also used in political science research for example regarding the admission of immigrants (Hainmueller and Hopkins 2015; Bansak et al. 2016), climate agreements (Bechtel and Scheve 2013) and ethnic voting (Carlson 2015).

Most studies using SCEs focus on the main effects of choice attributes. However, more recently the relationship between those attributes and further explanatory variables like socio-

demographics and attitudinal concepts became a major concern since it is more realistic and theoretically meaningful to assume preference heterogeneity within a given population. Theoretically derived explanatory variables like attitudes can be expected to considerably increase the explanatory power of choice models. In principle these variables can be directly included in a choice model. Yet, some authors have questioned this approach because the integration of attitudinal questions as error free explanatory variables in a choice model biases model results (Ben-Akiva et al. 2002a,b). These authors argue that it is crucial to account for the fact that attitude measures must be understood as latent indicators of an unobserved "true" (psychic) state. To add attitude measures directly to the models could potentially lead to an endogeneity bias and misrepresentation of causality. Endogeneity bias means that errors of the structural equation of indicators for attitudes might be correlated with the error of the choice model ("[...] unobserved effects that influence both a respondent's choice and his/her responses to indicator questions," Daly et al. 2012: 269). Misrepresentation of causality refers to the argument that responses to indicator questions do not necessarily have a causal relationship with behavioral choices.

In this paper, we demonstrate that, based on an action-theoretic framework, hybrid choice models can be a useful tool to model preference heterogeneity and modification in a population and hence to overcome potential endogeneity bias and causal misrepresentation regarding attitudinal effects. Hybrid choice models extend the specification of the traditional random utility model by incorporating additional decision protocols and enrich the underlying behavioral characterizations. These extensions comprise, among others, flexible disturbances (e.g., factor analytic) to mimic more complex error structures and to allow for the explicit modeling of latent psychological factors such as attitudes. However, the term "hybrid choice model" is an umbrella concept for different choice modeling techniques. In the following we focus on latent class structures to uncover preference heterogeneity and segmentation as well

as latent variable approaches to integrate attitudinal effects and to investigate preference modification. We demonstrate that this type of hybrid choice model, an integrated choice and latent variable model, is especially valuable for sociological and other social science research.

In our empirical application we investigate the relationship between attitudes and choice behavior in a SCE study of ethical and political consumption that was carried out in Germany in 2012 and investigates the preferences for so-called "Peace products" – goods that are jointly produced by Israeli and Palestinian producers. Ethical and political consumption research deals with consumer behavior that takes not only a product's quality and price into account, but also the political, social, and environmental effects of its production and marketing (e.g., Stolle et al. 2005, Andorfer and Liebe 2012). Friedman (1996) distinguishes between "boycotts", or negative buying behavior, and "buycotts", or positive buying behavior. Boycotting denotes refusal to buy products and services that are associated with negative political, social, and environmental (i.e. external) effects. Buycotting refers to the deliberate purchase of products that are perceived to reduce negative or generate positive external effects. Organic production is another ethical product characteristic considered in our study; organic crops are grown without pesticides and herbicides and are therefore associated with environmental and human health benefits compared with conventionally produced crops.

In our study respondents had to evaluate different types of olive oils which varied regarding *production method* (organic, non-organic), *origin* (Italy, Israel, Palestinian Territories, and jointly produced by Israeli and Palestinian producers, so called "Peace Products") and *price*. Theoretical determinants explaining the purchase of products with ethical attributes include pure altruism, impure altruism or warm glow giving, social and personal norms, trust, and object related attitudes (Stolle et al. 2005; Liebe 2014). In our case we concentrate specifically on relevant discriminatory attitudes towards Jews, Arabs as well as attitudes towards the Israel-

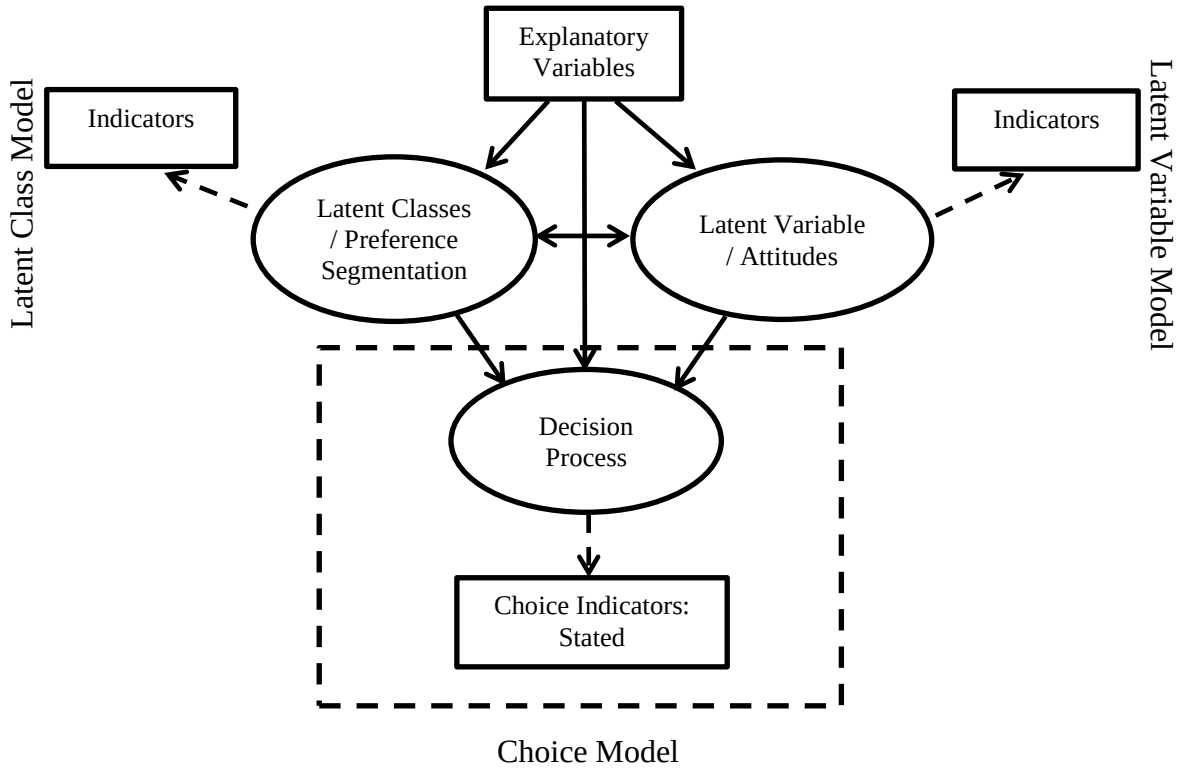
Palestinian conflict, all of them can be expected to affect stated preferences for products from Israel, Palestinian territories and Peace products.

In the following we discuss how the hybrid choice modeling framework relates to economic and sociological theory. This is followed by a presentation of our stated choice experiment, a description of the results and a discussion on the advantages and disadvantages of hybrid choice modeling as a method to uncover processes of decision making which are closely linked to action theories.

2 The Interplay of Attitudes, Preferences and Choice Behavior

We discuss the relationship between attitudes, preferences and choice behavior (decision making) within the hybrid choice modeling framework as pictured in Figure 1. The standard explanatory chain in social science research holds that attitudes affect preferences which in turn affect behavior. However, what makes behavioral research difficult is the fact that attitudes and preferences are theoretical, latent constructs that cannot be directly observed by researchers. This has consequences for the adequate modeling of decision and action theories in sociology and other social sciences. We therefore first introduce the basic theoretical idea behind the SCE method as it was developed in economic research. Second, we discuss one specific approach for capturing preference heterogeneity in a population (i.e. not all individuals have the same "tastes"), an assumption that is very plausible in most behavioral studies. Third, we specify how attitudes can be linked to preferences and choice behavior by taking into account that they are latent variables. It has to be stressed that in what follows, theory and statistical modeling are discussed hand in hand because the statistical models are used to represent the theoretical arguments. This is one strength of choice modeling compared to other modeling approaches for testing theories in social science research such as including theory-oriented variables in a regression model without taking the underlying behavior model or assumptions into account.

Figure 1: Hybrid Choice Model of Decision Making (simplified, adapted from Walker and Ben-Akiva 2001; Ben-Akiva et al. 2002a)



Theory-guided Mapping of Preferences

Many theoretical explanations of sociological phenomena rest on the idea that behavioral choices are associated with outcomes that can be expressed in terms of utility or satisfaction for the decision maker (Voss and Abraham 2000; Kroneberg and Kalter 2012). For example, occupational choice is related to monetary characteristics such as income and non-monetary characteristics such as flexible hours (Boskin 1974; Bender et al. 2005). Explicitly or implicitly, many researchers assume that choosing an occupation depends on a (linear) combination of these relevant characteristics and that individuals choose the behavioral alternative with the highest utility or level of satisfaction (or employ another decision rule). Such theory building (also Opp 1999) can be found with regard to political participation, migration, environmental behavior, deviant behavior etc. (e.g., Hechter and Kanazawa 1997; Kroneberg and Kalter 2012; Wittek et al. 2012; Tutić and Liebe 2017). In empirical studies researchers try to disentangle the effects/importance (e.g., utility weights) of each of these characteristics.

While these sociological theories are often not defined well in a formal manner within (sociological) rational choice theory (i.e. wide variants of RCT, Opp 1999; Tutić and Liebe 2017 for a critical discussion), they are fairly close to ideas developed in economic choice theory (McFadden 1986) that underlies the stated-choice-experiment (SCE) method. The starting point is "[…] the economists' standard model of the choice process, a theory of rational choice in which individuals collect information on alternatives, use the rules of probability to convert this information into perceived attributes, and then go through a cognitive process that can be represented as aggregating the perceived attribute levels into a stable one-dimensional utility index which is then maximized" (McFadden 2001: 336).

SCEs are motivated by the consideration that the effects of the characteristics or attributes of a good can be separated (Louviere et al. 2000: 2), an idea, which was explicitly developed for example in Lancaster's (1966: 133) characteristics theory of value: "The chief technical novelty lies in breaking away from the traditional approach that goods are the direct objects of utility and, instead, supposing that it is the properties or characteristics of the goods from which utility is derived." Assuming a decision rule, most often utility maximizing behavior, SCE can be used to map preferences and hence to investigate the relevance and importance weights that individuals place on the characteristics of a good or behavioral alternative. SCEs thereby can be used to test parts of sociological action theories, for example regarding the relevance of theoretical variables for behavioral outcomes and models of rational choice. In principle, other decision rules including loss aversion and elimination by aspects can also be tested (Chorus 2014).

Originally, in the standard model of the choice process sociological and social-psychological behavioral determinants such as beliefs, attitudes and perceived social norms were typically not considered. This led to the formulation of the *random* utility maximization model (RUM) which followed a basic idea that Thurstone (1927) had introduced in a paper on comparative judgment,

now accounting for "errors in perception" (McFadden 1986: 279; 2001). Among others, McFadden (1974) developed models to introduce randomness in the utility maximization model in order to being able to consider "psychophysical" phenomena such as attitudes. His multinomial/conditional logit model is the baseline for analyzing stated choice/preference data in line with (economic) choice theory and is described by a set of structural equations, represented by the utilities of alternative j for respondent n in the choice occasion t as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} = ASC_j + \beta' x_{njt} + \varepsilon_{njt}, \quad (1)$$

for a total of J alternatives, N individuals and T choice occasions. V_{njt} represents a systematic component and ε_{njt} a random variable following an extreme value type I distribution with location parameter 0 and scale parameter 1. The term V_{njt} depends usually on *observable* attributes (x_{njt}) and the vector of estimated attribute parameters β which, as mentioned above, indicate the importance of choice attributes such as occupational attributes or ethical components of consumer products. In (1), ASC_j is an alternative specific constant for alternative j normalized to zero for one of the J alternatives due to the identification of the model. We assume that the decision maker n obtains from an alternative j in a choice occasion t a certain level of utility U_{njt}. The decision maker chooses the alternative that provides the highest utility. The discrete choice behavioral model states, therefore, that an alternative i is chosen by decision maker n in choice occasion t if and only if $U_{nit} > U_{njt}, \forall j \neq i$.

The baseline theory and corresponding model is represented by the box with dashed lines in Figure 1. The decision process itself is a black box or theoretical/latent variable for researchers (ovals in Figure 1) but preferences for behavioral attributes and choice behavior can be observed in the field or in experiments such as stated preference experiments. Other non-observable characteristics of decision making are attributed to the error term (the "randomness" part).

Theory-guided Mapping of Preference Segmentation

The baseline theory and model rely on the assumption that a population can be represented by one preference parameter for each choice attribute considered in the analysis. The analysis does not take into account that individuals might differ in their preferences. However, this is often unrealistic. In the following we modify the standard theoretical model by including latent segmentation (latent classes) in a population. This is especially useful in sociological applications where researchers often expect distinct groups in society to differ in their preferences and characteristics (occupational preferences, ethnic preferences, political preferences, etc.). While the latent segmentation approach seems rather exploratory at first sight, it can also be used to capture groups of individuals and model their characteristics as theoretically derived determinants of class membership. Another benefit of the approach lies in its ability to estimate group sizes. This gives an idea about how large groups with different behavioral preferences in a population are.

The standard Latent Class Choice Model (LCCM), as part of our more complex hybrid model, is defined as follows: given the membership of class c_s, the probability of respondent's n sequence of choices i is given by

$$\Pr(y_n^t|c_s, x_n) = \prod_{t=1}^{T_n} \frac{\exp(ASC_i^{c_s} + \beta'_{c_s} x_{nit})}{\sum_{j=1}^{J} \exp(ASC_j^{c_s} + \beta'_{c_s} x_{njt})}, \tag{2}$$

where y_n^t is the sequence of choices over the T_n choice occasions for respondent n. Equation (2) is a product of standard logit probabilities. If the probability of membership to a latent class c_s of respondent n is defined as π_{n,c_s}, the unconditional probability of a sequence of choices can be derived by taking the expectation over all C classes, that is

$$P_n = \Pr(y_n^t|x_n) = \sum_{s=1}^{C} \pi_{n,c_s} \prod_{t=1}^{T_n} \frac{\exp(ASC_i^{c_s} + \beta'_{c_s} x_{nit})}{\sum_{j=1}^{J} \exp(ASC_j^{c_s} + \beta'_{c_s} x_{njt})}. \tag{3}$$

The class allocation probabilities π_{n,c_s} are usually modelled by using a logit structure, where the utility of a class is a function of a constant and socio-demographic variables. To the extent

that the inclusion of these variables in the so-called membership function is motivated by (sociological) theories LCCM can investigate "processes" of preference formation/modification.

Therefore, the class allocation probabilities π_{n,c_s} depend on constant a $\mu_{0,s}$, m socio-demographic variables $Z_{1n}, Z_{2n}, \dots, Z_{mn}$ of individual n and corresponding parameters (φ_{1s},φ_{2s}, … , φ_{ms}), that is

$$\pi_{n,c_s} = \frac{\exp(\mu_{0,s}+\varphi_{1s}Z_{1n}+\varphi_{2s}Z_{2n}+\cdots+\varphi_{ms}Z_{mn})}{\sum_{s=1}^{C}\exp(\mu_{0,s}+\varphi_{1s}Z_{1n}+\varphi_{2s}Z_{2n}+\cdots+\varphi_{ms}Z_{mn})}. \quad (4)$$

For one of the classes, the parameters for the constant $\mu_{0,s}$ and socio-demographic variables (φ_{1s},φ_{2s}, … , φ_{ms}) are fixed to zero for the purpose of normalization.

Linking Attitudes and Preference Segmentation/Modification

To integrate attitudinal measures in SCE for capturing preference modification and for testing assumptions in sociological and social-psychological theories such as the attitude-behavior relationship (e.g., Ajzen 1988; Bohner and Dickel 2011), the most obvious thing to do might be the inclusion of interaction terms between attitudinal items and choice attributes in the standard model or, for example, in the membership function of a LCCM (e.g., Ojea and Loureiro, 2007). However, from a theoretical point of view this is problematic because sociological and psychological concepts such as attitudes are latent constructs and thus comprised of an observable and unobservable part. *Endogeneity bias* and *misrepresentation of causality* are the two main reasons discussed in the literature for using a latent variable approach to capture attitudinal effects (Ben-Akiva et al. 2002a; Vij and Walker 2016 for a discussion). Endogeneity bias refers to correlations between indicators for attitudes and the error of the choice model. Misrepresentation of causality means that responses to indicator questions do not necessarily have a causal relationship with behavioral choices. A potential endogeneity bias

and misrepresentation of causality can be avoided by employing a latent variable model as shown on the right-hand side in Figure 1.

For example, in a hybrid model framework including two latent variables representing two attitudinal concepts measured by items using a 5-point response scale, the class allocation probabilities π_{n,c_s} depend on a constant $\mu_{0,s}$, the two latent variables (LV_{1n}, LV_{2n}), m socio-demographic variables $Z_{1n}, Z_{2n}, \dots, Z_{mn}$ of individual n and corresponding parameters (λ_{1s},λ_{2s}) and (φ_{1s},φ_{2s}, $\dots$, φ_{ms}), that is

$$\pi_{n,c_s} = \frac{\exp(\mu_{0,s}+\lambda_{1s}LV_{1n}+\lambda_{2s}LV_{2n}+\varphi_{1s}Z_{1n}+\varphi_{2s}Z_{2n}+\cdots+\varphi_{ms}Z_{mn})}{\sum_{s=1}^{C}\exp(\mu_{0,s}+\lambda_{1s}LV_{1n}+\lambda_{2s}LV_{2n}+\varphi_{1s}Z_{1n}+\varphi_{2s}Z_{2n}+\cdots+\varphi_{ms}Z_{mn})}. \quad (5)$$

For one of the classes, the parameters for the constant $\mu_{0,s}$, the latent variables ($\lambda_{1s}, \lambda_{2s}$), and the socio-demographic variables ($\varphi_{1s}, \varphi_{2s}, \dots, \varphi_{ms}$) are fixed to zero for the purpose of normalization.

The next part of such a hybrid model is formed by measurement equations relating the ordinal responses to the attitudinal items to the latent variables. The ℓth indicator of all L_q indicators for respondent n is defined as

$$I_{q\ell n} = m(LV_{qn}, \zeta_q) + v_{qn}, \quad (6)$$

where the indicator $I_{q\ell n}$ is a function of latent variables LV_{qn} and a vector of parameters ζ_q. The specification of v_{qn} determines the behavior of the measurement model and depends on the nature of the indicator. In some studies the distribution of the indicator was approximated by a normal distribution (Glerum, Atasoy and Bierlaire, 2014) and therefore the error v_{qn} was assumed to be normal. In other studies, as also in the present one, the discrete nature of the indicator leads to the use of models for ordinal outcomes (Daly et al. 2012). Given an ordinal response scale, the measurement equations base on threshold functions. For a discrete indicator with 5 levels $i_1, i_2, \dots, i_5$ such that $i_1 < i_2 < \cdots < i_5$ the measurement equation for individual n is modelled as an ordered logit model for the latent variable as

$$I_{q\ell n} = \begin{cases} i_1 & if \quad -\infty < LV_{qn} \leq \tau_{q\ell 1} \\ i_2 & if \quad \tau_{q\ell 1} < LV_{qn} \leq \tau_{q\ell 2} \\ & \vdots \\ i_5 & if \quad \tau_{q\ell 4} < LV_{qn} < \infty \end{cases}. \tag{7}$$

where $\tau_{q\ell k}$ are thresholds that need to be estimated.

The last part of our hybrid model is formed by the second set of structural equations relating the latent variables to the individual characteristics. That is for the q-th latent variable of total Q defined as

$$LV_{qn} = \gamma_{q1} Z_{1n} + \gamma_{q2} Z_{2n} + \cdots + \gamma_{qm} Z_{mn} + \omega_{qn}, \tag{8}$$

where $Z_{1n}, Z_{2n}, \ldots, Z_{mn}$ are socio-demographic variables and ω_{qn} are random disturbances that are assumed to be normally distributed with a zero mean and standard deviation $\sigma_{q\omega}$.

The model is estimated by maximum simulated likelihood. The estimation involves maximizing the joint likelihood of the observed sequence of choices (P_n) defined in (3) and the observed answers to the attitudinal questions $L_{I_{q\ell n}}$, where $L_{I_{q\ell n}}$corresponds to the usual log-likelihood function of an ordered logit model (Long 1997). The two components are conditional on the given realization of the latent variable LV_{qn}. Accordingly, the log-likelihood function of the model is given by integration over ω_{qn}:

$$LL(\beta, \mu, \gamma, \zeta, \tau) = \sum_{n=1}^{N} ln \int_{\omega} (P_n \prod_{\ell=1}^{L_q} \prod_{q=1}^{Q} L_{I_{q\ell n}})\, g(\omega) d. \tag{9}$$

Thus, the joint likelihood function (9) depends on parameters of the utility functions defined in (3), the parameters used in the allocation probabilities (5), the parameters for the socio-demographic interactions in the latent variable specification defined in (8), and the parameters for the measurement equations defined in (6) and (7). Daly et al. (2012) describe different identification procedures. In this application, we follow the Bolduc normalization by setting $\sigma_\omega = 1$.

To summarize, our application of a hybrid choice model is not only in line with economic or consumer theory – implying e.g. common price and income effects – but can also accommodate sociologically relevant concepts such as beliefs, subjective norms, and attitudes, the latter being usually explicitly modeled based on a latent variable model. In other words: hybrid choice models account for the finding that "demographic, economic, and social variables can modify preferences" (McFadden 1987: 278). In this respect it is also a powerful tool for sociological and other social science research because in line with many action-theoretic models in sociology and other social sciences stated choice experiments combined with the random utility model and latent class and latent variable modelling can uncover the relevance of behavioral characteristics as well as theoretical determinants of preference modification such as beliefs and attitudes.

3 A Stated Choice Experiment on Ethical and Political Consumption

3.1 Experimental design

In our stated choice experiment (SCE) study respondents were shown choice sets with three different extra virgin olive oil alternatives and were asked to state which one of these olive oils they would buy. There was also a "none of those" option. The latter was included to map a realistic shopping situation in a supermarket as closely as possible. Each olive oil was characterized by a combination of attribute levels referring to organic production (yes, no), origin (Israel, Palestinian Territories, Peace Product, Italy), and price (3, 6,10,15 Euro).

Respondents were told that all of the olive oils are extra virgin (the highest quality) and packaged in ½-litre bottles. The Peace products were explained in the survey by means of the following text: "The examples of food products that you will see below vary in price, production methods and country of origin. A special characteristic is that some of these examples are of so-called *Peace Products*, which are the result of joint projects that are designed to foster

cooperation between farmers from Israel and from the Palestinian Territories. The Palestinian and the Israeli partners in these projects benefit equally from the sales of these *Peace Products*. The income generated from the sale of these products is used to promote joint Israeli-Palestinian social projects."

Since the full factorial of all attribute-level combinations (three alternatives with three attributes of two, four, and four levels, respectively) is very large, we worked with a fractional factorial design. Specifically, using the software Ngene (2018), we employed an optimal orthogonal in the differences (OOD) design (see Burgess and Street 2005). Orthogonality ensures that the influence of a single attribute can be determined independently from the influences of the others. Besides orthogonality, the choice design was constructed to minimize the overlap between attribute levels across alternatives in a choice set, thus forcing respondents to make trade-offs between the single attributes. We obtained 20 choice sets which were blocked into four groups of five sets each, and each respondent answered one such group. Figure 2 gives an example of the choice sets employed in the survey. Each respondent was asked to picture him/herself in front of a supermarket shelf to select the product that he/she would choose.

Figure 2: Example of a choice set used in the study

Characteristics	**Olive Oil A (500ml)**	**Olive Oil B (500ml)**	**Olive Oil C (500ml)**	**None of them**
Organic	Yes	Yes	No	
Origin	Peace Product	Palestinian Territories	Italy	
Price	10 Euro	3 Euro	6 Euro	
I choose… (please click on)	O	O	O	O

The experimental design also included a test of context effects; respondents were randomly assigned to one of two groups in the web survey. The first group had to answer questions

measuring anti-Arabic and anti-Semitic attitudes *before* the CE. In the second group these questions were posed *after* the CE. Apart from this variation, all other aspects of the CE and the attitudinal items were identical in both groups. In this study we focus on the theory-guided modeling of the relationship between attitudes, preference and choice behavior and not the order effect (see Liebe et al. 2016 for a more detailed analysis of the order effect present in this data and Table S2 in the supplementary material for a HLCCM taken the order effect and attitudes as latent variables into account; the findings on preference modification are largely similar to the ones presented below).

3.2 Data and variables

The data were collected via a web-survey in Germany which was carried out by a survey organization in 2012 (quota-controlled sample regarding gender and age). All respondents were members of the organization's access panel which is based on self-selection. Respondents received a small reimbursement from the survey organization for participating. 3,876 panel members were invited to take part in the survey. Of those invited, 652 finished the survey. This amounts to a response rate of 17%, taking all types of dropouts including "closed quota" into account. We obtained 440 usable interviews containing no missing values on the variables that are important for this study. In the sample, 53% are women. Mean age is 42 years (SD = 13.26, Min = 18, Max = 77) and 43% of the respondents have higher education (at least upper secondary education).

The questionnaire contained several statements, which were answered on a five-point response scale, to measure anti-Semitic and anti-Arab attitudes that were assumed to have a major impact on respondents' decisions to buy products from the Middle East. Table 1 gives an overview of the items we used to measure those concepts. The underlying approach of attitudes refers to Eagly and Chaiken's (1993, 1) notion of a "psychological tendency" that is expressed by the

evaluations of an object, in this case the devaluating of persons perceived as “Jewish” and “Arab,” respectively. Anti-Semitic and anti-Arab attitudes refer to ethnical essentialistic devaluations of what is perceived to be a homogenous group, that of “Jews” or “Arabs.” In order to control for acquiescence effects (Lentz 1938; Peabody 1966), that is, the tendency to agree with survey statements in situations of uncertainty, each construct was operationalized using two benevolent and two hostile items. For anti-Semitism the two hostile statements refer to classical stereotypes, namely deceitfulness (item 2) and anti-Semitic conspiracy theories (item 3). In contrast, items 1 and 4 entail favorable statements of Jews, the rejection of which is assumed to indicate prejudiced beliefs. Analogous to anti-Semitism, attitudes towards the group of “Arabs” are measured using two items with hostile (items 1 and 3) and two items with benevolent phrasing (items 2 and 4). The answers to these items and corresponding additive indices of anti-Semitism and anti-Arabism are very similar between treatments.

Anti-Semitism can be considered to be one of the most socially undesirable topics in Germany. In such an environment, where norms of anti-anti-Semitism are perceived to be publicly enforced, we observe the tendency to “camouflage” (see Holz 2001) direct anti-Semitism and use ways of “detour communication” (Bergmann and Erb 1986, 1991), the most important one being “Israel-related anti-Semitism” (or: “anti-Zionism”; see Klug 2003). Hence, we included a measure representing this second, indirect dimension of anti-Semitic attitudes in the survey. In this case we used three items, one of which was framed in a positive way, the other two in a negative way (see Table 1). The items reflect previous findings (see Judaken 2007) showing that Israel-related anti-Semitism on the one hand tries to justify negative attitudes towards Jews by blaming Israel’s politics (item 5) and on the other hand denies Israel its right to defend itself (item 6). Finally, it compares Israel’s politics to those of the Third Reich by using vocabulary like “extermination” (item 7).

Table 1: Statements used to measure anti-Semitism and anti-Arabism

anti-Arabism	anti-Semitism
Direct anti-Arabism	Direct anti-Semitism
1. "I can understand that for some people Arabs are unpleasant." (see Decker et al., 2010)	1. "The Jewish culture must be protected against its enemies." (see Beyer and Liebe 2010)
2. "In my opinion most Arabs are peaceful people." (see Cohrs et al., 2002)	2. "Jews are more likely than others to use shady practices to get what they want." (see Decker and Brähler 2006)
3. "I am mistrustful of Arabs."	3. "Jews have too much influence in the world." (see Bergmann and Erb1991)
4. "I would not have any problems living in a neighborhood with many Arabs." (see Leibold and Kühnel 2006)	4. "I do not make a distinction between Jews and other people." (see Bergmann and Erb, 1991)
Palestine-related anti-Arabism	Israel-related anti-Semitism
5. The Palestinians should not be permitted to establish an independent state.	5. As a consequence of Israel's policy, I find Jews increasingly dislikeable.
6. The living conditions of the Palestinian population must be improved.	6. Israel has a right to defend itself.
7. The Palestinians are an extremely militant people.	7. Israel is conducting a war of extermination against the Palestinians.

Note: All items were measured on a five-point response scale (strongly disagree, disagree, neither agree nor disagree, agree, strongly agree). Disagreement (disagree, strongly disagree) with positively connoted items ranges between 7% and 31% and agreement (agree, strongly agree) with negatively connoted items between 7% and 29%.

To a lesser degree, but still, anti-Arabic attitudes are affected by anti-discrimination norms as well. Consequently and in line with the approach we applied for the measure of anti-Semitism, we used three items to collect data on "Palestine-related anti-Arabism" (see Table 1). The basic idea again is that statements articulating an outright denial of the rights of Palestinians as well as a stereotypical characterization of Palestinians as being generally violent are used as a more legitimate way to articulate direct anti-Arabism.

4 Results

In the following, using a step-by-step approach, we first present the baseline model assuming no preference heterogeneity in the data. We then present the results of a latent class choice model (LCCM) taking unobserved heterogeneity (i.e. preference segmentation) into account. This model is presented without and with attitudinal variables in the class membership function. Subsequently, results from a hybrid latent class choice model (HLCCM) which explicitly represents the attitudinal effects in a latent variable model are shown. Model components of the LCCM and HLCCM were estimated simultaneously. All models were estimated using PythonBiogeme (Bierlaire 2003; Bierlaire 2008).

The baseline model

The conditional logit model presented in Table 2 shows that respondents, on average, disfavour products from Israel and Palestinian Territories compared to products from Italy. They have a positive and statistically significant preference for organic products compared to non-organic products. Yet, they do not value Peace products significantly more than products from Italy. In line with economic theory we find that higher prices decrease the likelihood to choose a product.

Table 2: Estimation of the Conditional Logit Model (CLM)

LogL	-2,401.262		
K	8		
N	2,195		
	Est.		rob.t
ASC2	0.242	**	3.62
ASC3	0.022		0.31
ASC4	-1.96	**	-17.63
Organic	0.481	**	8.09
Israel	-0.738	**	-8.66
Palestine	-0.622	**	-7.52
Peace	0.0143		0.18
Price	-0.225	**	-27.03

Note: ** $p < .01$, * $p < .05$, $^{+}$ $p < 0.10$. Robust *t*-statistics (rob.t) have been computed by the use of BHHH matrix (Berndt et al., 1974) as described in Bierlaire (2009: 65).

Preference Segmentation

The first task when specifying a latent class model is to determine the number of classes. Table 3 reports goodness-of-fit criteria for different numbers of classes of latent class choice model (LCCM) and the corresponding hybrid latent class choice model (HLCCM). As expected, the log-likelihood decreases as the number of classes increases in the two models. The values of AIC, BIC and CAIC indicate for the LCCM a solution with four classes. However, for the HLCCM case, BIC indicates a solution with three classes while the AIC favours the model with four classes. Since the AIC tends to overestimate the number of classes (McLachlan and Peel 2000), and parsimony, especially in this complex hybrid choice framework, is considered to be important, the models selected and presented below have three classes.

Table 3: Goodness-of-fit criteria for different numbers of classes in the latent class model (LCCM) and hybrid latent class model (HLCCM)

	LCCM		
	2 Classes	*3 Classes*	*4 Classes*
LogL	-2,143.0	-2,041.4	-1,993.3
K	20	32	44
N	2,195	2,195	2,195
AIC	4,325.9	4,146.8	**4,074.6**
BIC	4,439.8	4,329.0	**4,325.1**
CAIC	4,439.8	4,329.0	**4,325.1**

	HLCCM		
	2 Classes	*3 Classes*	*4 Classes*
LogL	-9,918.7	-9,816.8	-9,790.5
K	95	106	117
N	2,195	2,195	2,195
AIC	2,0027.4	1,9845.6	**1,9815.1**
BIC	2,0568.4	**2,0449.2**	2,0481.3
CAIC	2,0568.4	**2,0449.2**	2,0481.3

The systematic component V_{njt} of (1) corresponding to class c_s is according to the definition of choice attributes and levels defined as

$$V_{n1t}^{c_s} = \beta_{Organic}^{c_s} Organic_{n1t} + \beta_{Israel}^{c_s} Israel_{n1t} + \beta_{Palestine}^{c_s} Palestine_{n1t} + \beta_{Peace}^{c_s} Peace_{n1t} + \beta_{Price}^{c_s} Price_{n1t}$$

$$V_{n2t}^{c_s} = ASC_2^{c_s} + \beta_{Organic}^{c_s} Organic_{n2t} + \beta_{Israel}^{c_s} Israel_{n2t} + \beta_{Palestine}^{c_s} Palestine_{n2t} + \beta_{Peace}^{c_s} Peace_{n2t} + \beta_{Price}^{c_s} Price_{n2t} \quad (10)$$

$$V_{n3t}^{c_s} = ASC_3^{c_s} + \beta_{Organic}^{c_s} Organic_{n3t} + \beta_{Israel}^{c_s} Israel_{n3t} + \beta_{Palestine}^{c_s} Palestine_{n3t} + \beta_{Peace}^{c_s} Peace_{n3t} + \beta_{Price}^{c_s} Price_{n3t}$$

$$V_{n4t}^{c_s} = ASC_4^{c_s},$$

where $Organic$, $Israel$, $Palestine$, and $Peace$ are binary coded variables representing the respective attribute level (references being none-organic and Italian products). *Price* represents the only non-categorical attribute of the corresponding alternative.

Key findings of the LCCM

Table 4 shows the results of the 3-Class-LCCM including the explanatory variables gender, age and education in the class membership function (4).

Table 4: Estimation of the Latent Class Choice Model (LCCM)

LogL	-2,041.4								
K	32								
N	2,195								
	Class 1			*Class 2*			*Class 3*		
Class size	*18%*			*45%*			*37%*		
	Est.		*rob.t*	*Est.*		*rob.t*	*Est.*		*rob.t*
ASC2	0.18		0.71	-0.51	**	-2.58	0.26	*	2.42
ASC3	-0.25		-0.71	-0.46	*	-2.27	0.09		0.64
ASC4	-1.05	**	-2.86	-5.09	**	-10.22	-2.76	**	-6.82
Organic	-0.22		-0.76	0.64	*	2.17	0.63	**	3.75
Israel	-3.54	**	-5.82	-0.66	**	-3.04	-0.72	**	-4.08
Palestine	-2.43	**	-5.03	-0.42		-1.47	-0.56	**	-2.92
Peace	-1.83	**	-5.78	0.17		0.84	0.25	+	1.72
Price	-0.21	**	-5.19	-0.61	**	-9.36	-0.09	**	-4.80
Membership									
Constant				2.09	**	3.33	2.26	**	3.27
Women				-0.45		-1.49	-0.37		-1.09
Age				-0.02	*	-2.06	-0.04	**	-2.94
Education				0.38		1.08	0.76	*	2.14

Note: ** $p < .01$, * $p < .05$, + $p < 0.10$. Robust *t*-statistics (rob.t) have been computed by the use of BHHH matrix (Berndt et al., 1974) as described in Bierlaire (2009: 65).

In line with microeconomic theory classes 1, 2 and 3 show a negative price effect. We also see that the price effect varies across classes. With respect to preference segmentation related to ethical and political consumption, the three latent classes can be described as follows:

Class 1 (no ethical consumption): Respondents who are assigned with the highest probability to this class value products from Israel and the Palestinian territories as well as the Peace product significantly more negatively than products from Italy. They do not value organic products significantly differently compared to non-organic products. Overall, this class tends to have no taste for ethical consumption. The estimated class size is 18%.

Class 2 (weak ethical consumption): Respondents who are likely to be members of this class with an estimated size of 45% significantly and slightly disvalue products from Israel compared to products from Italy. They neither show statistically significant differences in the valuation of products from Palestinian territories and products from Italy nor regarding the Peace product and products from Italy. Yet, class members prefer organic products over non-organic products.

Class 3 (strong ethical consumption): Respondents who are likely to be members of this class value products from Israel and Palestinian territories more negatively than products from Italy. They have a preference for organic over non-organic products as well as the (ethical) Peace product over products from Italy. The corresponding parameter estimates are all statistically significant and the estimated class size is 37%.

The effects of the variables included in the class membership function – gender, age and education – indicate that older respondents are less likely to be members of one of the two classes with ethical preferences compared to the class with no ethical preferences. Higher educated individuals are more likely to be assigned to the class with strong ethical preferences compared to the class with no ethical preferences. The education and age effects are in line with studies on ethical and political consumption (see Roessel and Schenk 2017), although some

studies found only mixed evidence regarding the age of (political) consumers (e.g. Starr 2009). Compared with the three class model, we obtain the same substantial results in a four class model where we find another class with no taste for ethical consumption and additionally no significant price sensitivity (see Table S1, suppl. material). Higher educated individuals are more likely to be a member of this fourth class compared with the first class with no ethical preferences. Yet, this reference class reveals much stronger negative preferences for products from Israel and the Palestinian territories and as well as for the Peace product. Therefore, the overall conclusion derived from the three class model is consistent with the findings of the four-class model: higher educated individuals are more likely to be members of the "ethical consumption" classes.

Preference Segmentation Taking Attitudinal Effects into Account

Table 5 shows the results of a LCCM including additive indices for anti-Semitism (Mean = 17.62, SD = 5.05, Min = 7, Max = 35, Cronbach's alpha = 0.78) and anti-Arabism (Mean = 17.95, SD = 4.78, Min = 7, Max = 32, Cronbach's alpha = 0.78) in the membership function. Basically, this model shows the same results as the LCCM on preference segmentation presented in Table 4. There is a class with no ethical consumption (estimated size of 11%), one with weak ethical consumption (size of 25%) and another with a strong ethical consumption pattern (size of 64%). Also, age and education have the same effects in terms of direction and statistical significance as the model without attitudes.

In order to test the attitude-behavior relationship we have to focus now especially on class differences regarding the origin of the products. Class 1 (no ethical consumption) seems very peculiar in this regard since individuals belonging to this group generally disvalue products from the Middle East including the Peace product. We now assume that this preference structure is based on respective attitudes, that is, anti-Semitic and anti-Arab prejudices. Thus, there

should be a positive effect of the respective attitudinal indices. What we see in Table 5 backs this hypothesis: high anti-Semitism and anti-Arabism scores decrease the likelihood to belong to Class 2 (weak ethical consumption) or Class 3 (strong ethical consumption) compared to Class 1 (no ethical consumption). All corresponding effects are statistically significant, except the effect of anti-Arabism on class membership in Class 2. These findings seem to clearly indicate that individuals are less likely to buy products from regions whose inhabitants they despise.

This is in line with the literature of the filed. The topic of boycotting Israeli products has made it into the news recently with the case of the BDS movement (BDS standing for "Boycott, Divestment and Sanctions") which has been controversially discussed as being potentially anti-Semitic because it demands a general boycott of Israeli goods and even citizens (Nelson and Brahm 2014). Our research now shows that indeed, as some scholars already demonstrated using qualitative data (Hirsh 2007; Wistrich 2010; Herf 2013), the boycott of Israeli goods and even of Peace products can be related to anti-Semitic motives.

There are no studies yet on anti-Arab boycotts and, even more surprisingly, only a small amount of literature that deals with the relationship of Xenophobia and political consumption. But the few studies that exist indicate that prejudiced attitudes can indeed become the basis of consumption preferences and respective behavior (e.g. Harun and Shah 2013; Shah and Ibrahim 2016).

Table 5: Estimation of the latent class choice model (LCCM) including attitudes in the membership function

LogL	-2,027.262								
K	36								
N	2,195								
AIC	4,126.52								
AIC3	4,162.52								
BIC	4,331.51								
	Class 1			*Class 2*			*Class 3*		
Class size	11%			25%			64%		
	Est.		rob.t	Est.		rob.t	Est.		rob.t
ASC2	0.20		0.79	-0.49	*	-2.43	0.27	*	2.53
ASC3	-0.18		-0.55	-0.50	*	-2.30	0.09		0.75
ASC4	-0.98	*	-2.49	-5.16	**	-9.73	-2.88	**	-6.43
Organic	-0.19		-0.60	0.70	*	2.36	0.62	**	4.08
Israel	-3.48	**	-5.54	-0.70	**	-2.82	-0.68	**	-3.68
Palestine	-2.32	**	-5.30	-0.51		-1.40	-0.51	*	-2.35
Peace	-1.77	**	-5.68	0.14		0.64	0.29	+	1.85
Price	-0.21	**	-4.85	-0.63	**	-7.79	-0.10	**	-4.40
Membership									
Constant				4.86	**	4.40	6.17	*	5.39
Women				-0.56	+	-1.83	-0.57		-1.62
Age				-0.02	*	-1.96	-0.04	*	-2.68
Education				0.31		0.86	0.69	+	1.91
anti-Arabism				-0.06		-1.55	-0.08	*	-2.17
anti-Semitism				-0.09	**	-3.05	-0.13	**	-3.43

Note: ** p < .01, * p < .05, + p < 0.10. Robust *t*-statistics (rob.t) have been computed by the use of BHHH matrix (Berndt et al., 1974) as described in Bierlaire (2009: 65).

Key findings of the HLCCM

Table 6 presents the estimated parameters of the HLCCM, taking into account latent discriminatory attitudes and including explanatory variables for both class membership and the latent variables (as pictured in Figure 1). This allows for testing whether ethical or political consumption is linked to discriminatory attitudes taking into account a potential endogeneity bias, causal misrepresentation and attitude heterogeneity (i.e. how attitudes depend on respondents' characteristics). The first block of Table 6 represents the coefficients of the systematic component V_{njt} defined in (10). The second block includes the coefficients of the class allocation probabilities defined in (5). The third block contains the coefficients of the structural equations of the latent variables defined in (8) and the last two blocks are devoted to the measurement equations (6) and (7).

Table 6: Estimation of the hybrid latent class choice model (HLCCM)

LogL	-9,807.456
K	112
N	2,195
AIC	1,9838.91
AIC3	1,9950.91
BIC	2,0476.63

	Class 1			*Class 2*			*Class 3*		
Class size	18%			45%			37%		
	Est.		*rob.t*	*Est.*		*rob.t*	*Est.*		*rob.t*
ASC2	0.18		0.72	-0.49	*	-2.42	0.27	*	2.54
ASC3	-0.21		-0.63	-0.49	*	-2.31	0.09		0.75
ASC4	-1.04	**	-2.85	-5.14	**	-9.78	-2.80	**	-6.96
Organic	-0.22		-0.71	0.69	*	2.34	0.62	**	4.03
Israel	-3.54	**	-5.78	-0.70	**	-2.87	-0.69	**	-3.75
Palestine	-2.38	**	-5.18	-0.50		-1.44	-0.52	*	-2.46
Peace	-1.82	**	-6.06	0.14		0.66	0.28	+	1.83
Price	-0.21	**	-5.55	-0.62	**	-8.20	-0.10	**	-4.60
The class allocation probabilities equations									
Constant				2.34	**	3.52	2.50	**	3.39
anti-Arabism				-0.30		-1.45	-0.49	*	-2.23
anti-Semitism				-0.45	*	-2.22	-0.61	*	-2.41
Women				-0.60	+	-1.95	-0.61	+	-1.73
Education				0.29		0.81	0.67	+	1.84
Age				-0.02	+	-1.88	-0.03	*	-2.59

Latent variable structural equations

	anti-Arabism			anti-Semitism		
	Est.		*rob.t*	*Est.*		*rob.t*
Women	-0.13		-1.25	-0.16		-1.49
Eduation	-0.21	+	-1.92	-0.08		-0.73
Age	0.00		0.45	0.01	*	2.07

Measurement equations

Coefficients of the LV

	anti-Arabism			anti-Semitism		
	Est.		*rob.t*	*Est.*		*rob.t*
ζ_{q1}	1.91	**	8.94	1.20	**	6.83
ζ_{q2}	1.88	**	8.13	2.43	**	7.39
ζ_{q3}	3.51	**	6.26	2.26	**	7.59
ζ_{q4}	1.60	**	8.10	1.62	**	7.90
ζ_{q5}	1.05	**	6.59	1.91	**	8.90
ζ_{q6}	0.77	**	5.06	0.77	**	4.72
ζ_{q7}	1.35	**	7.31	1.17	**	7.10

Thresholds

	anti-Arabism			anti-Semitism		
	Est.		*rob.t*	*Est.*		*rob.t*
τ_{q11}	-3.08	**	-7.80	-2.11	**	-6.98
δ_{q12}	1.83	**	9.51	1.87	**	11.50

δ_{q13}	2.38	**	12.21	2.10	**	12.83
δ_{q14}	2.12	**	9.69	1.02	**	7.26
τ_{q21}	-2.53	**	-6.17	-0.51		-0.98
δ_{q22}	2.50	**	11.35	1.93	**	9.05
δ_{q23}	3.11	**	12.14	2.45	**	9.08
δ_{q24}	2.20	**	6.11	1.61	**	5.61
τ_{q31}	-3.54	**	-4.77	-1.12	*	-2.33
δ_{q32}	2.87	**	7.01	1.71	**	9.00
δ_{q33}	3.68	**	7.73	2.57	**	10.15
δ_{q34}	2.80	**	6.36	1.50	**	6.41
τ_{q41}	-2.91	**	-7.89	0.46		1.26
δ_{q42}	1.76	**	9.82	1.67	**	10.56
δ_{q43}	2.16	**	12.12	1.42	**	7.34
δ_{q44}	1.51	**	8.70	1.11	**	4.65
τ_{q51}	-1.06	**	-4.70	-1.85	**	-4.29
δ_{q52}	1.60	**	12.21	2.09	**	10.90
δ_{q53}	2.29	**	11.88	2.20	**	11.27
δ_{q54}	1.27	**	4.67	1.84	**	8.15
τ_{q61}	-1.30	**	-7.07	-2.04	**	-9.17
δ_{q62}	1.99	**	14.32	1.92	**	12.49
δ_{q63}	2.14	**	10.66	2.52	**	14.85
δ_{q64}	1.13	**	4.19	0.96	**	5.39
τ_{q71}	-2.36	**	-7.82	-2.60	**	-8.52
δ_{q72}	1.84	**	10.74	1.36	**	8.50
δ_{q73}	2.72	**	13.47	2.59	**	14.74
δ_{q74}	2.12	**	7.00	1.59	**	9.54

Note: ** $p < .01$, * $p < .05$, $^{+}$ $p < 0.10$. Robust *t*-statistics (rob.t) have been computed by the use of BHHH matrix (Berndt et al., 1974) as described in Bierlaire (2009: 65).

In class 1, 2 and 3 we find again a negative price effect. The higher the price the less likely it is to choose a product alternative. With respect to preference heterogeneity or segmentation, the three latent classes in the HLCCM can be described as follows:

Class 1 (strong discrimination / no ethical consumption): Respondents assigned with the highest probability to this class with an estimated size of 18% value products from Israel and Palestinian territories as well as the (ethical) Peace Product much more negatively compared to products from Italy. They do not differentiate between organic and non-organic products.

Class 2 (weak discrimination / weak ethical consumption): This class, with an estimated size of 45%, gathers respondents who are very likely to disfavour products from Israel compared to

products from Italy. Members of Class 2 do significantly prefer organic products over non-organic products and do not make a significant difference in the valuation of Peace products compared to Italian products.

Class 3 (no discrimination / strong ethical consumption): Finally, respondents who are likely to be a member of this class with an estimated size of 37% value products from Israel and Palestinian territories significantly more negatively than products from Italy. Yet, they significantly prefer Peace products over products from Italy and organic products over non-organic products.

There are two latent variables in our HLCCM representing anti-Arab and anti-Semitic attitudes LV_{1n} and LV_{2n}, which, in our case, are a function of three socio-demographic variables: gender, age, and education. The equation (8) becomes therefore

$$LV_{qn} = \gamma_{q1} Women_{1n} + \gamma_{q2} Age_{2n} + \gamma_{q3} Education_{3n} + \omega_{qn}. \quad (11)$$

The third block of Table 6 presents the estimation of the parameters γ. There are two statistically significant relations: the latent variable representing "anti-Arab attitudes" correlates with our measure of education and the latent variable "anti-Semitic attitudes" correlates with age. Higher educated respondents (i.e. at least upper secondary education) show lower values of the latent variable concerning "anti-Arab attitudes" and older respondents have higher values on the latent variable concerning "anti-Semitic attitudes." These findings are line with other studies (e.g. Quinley and Glock 1979; Johnson 1992; Kurthen et al. 1997) and go beyond the LCCM including attitudes as explanatory variables in the class membership function.

The last two blocks of Table 6 are devoted to the measurement equations (6) and (7). The five-level Likert scale responses presented in the first column of Table 4 are related through ζ in equation (6) to the first latent variable and responses presented in the second column of Table 4 relate to the second latent variable. The coefficients ζ of all 14 indicators presented in

Table 6 are clearly statistically significant showing strong relations between the two latent variables and the attitudinal indicators.

The last part of Table 6 presents estimation of the thresholds defined in (7). For estimation purposes the thresholds has been redefined as

$$\tau_{q\ell 2} = \tau_{q\ell 1} + \delta_{q\ell 1}, \tau_{q\ell 3} = \tau_{q\ell 2} + \delta_{q\ell 2} \text{ and } \tau_{q\ell 4} = \tau_{q\ell 3} + \delta_{q\ell 3}.$$

The third block of Table 6 presents the coefficients of the class allocation probabilities defined in (5) which are in our model respondent specific and are a function of the latent variables LV_{1n} and LV_{2n} as well as the variables representing gender, age, and education. These two latent variables depend on the random error terms ω_{qn} as defined in (8), meaning that the allocation probabilities themselves follow a random distribution.

After the estimation of the model the allocation probabilities in the LCCM can be computed for each individual n according to (4). As these probabilities vary among individuals Table 5 and Table 6 presents their mean values as class sizes. In the HLCCM the allocation probabilities contain latent variables and these by definition depend on random errors (8). That is why we simulated the class allocation probabilities in the HLCCM according to (5). We use 10,000 draws for each latent variable of each respondent according to (11), combining the estimated parameters γ with corresponding values of socio-demographic variables and adding generated random errors ω. Similar to LCCM, the class sizes in Table 6 represent the mean values for HLCCM.

Key findings on LVs and sociodemographic variables

Compared with *Class 1 (strong discrimination / no ethical consumption)* higher values on the latent variable anti-Semitism statistically significantly decrease the likelihood to be allocated to *Class 2 (weak discrimination / weak ethical consumption).* Therefore, the latent variable "anti-Semitic attitudes" suggests that individuals with negative attitudes towards Jews and

Israel are more likely to be members of the class with the lower probability to choose products from Israel (i.e. Class 1). The latent variable anti-Arabism does not affect the allocation probability of *Class 2*. Further, compared with *Class 1* higher values on both LVs (anti-Semitic attitudes *and* anti-Arab attitudes) significantly decrease the likelihood to be allocated to *Class 3 (no discrimination / strong ethical consumption)*, the class which compared to Class 1 shows smaller effects of the variables "Israel" and "Palestine."

Thus, there emerges the general pattern that higher values on the latent variables correspond with stronger negative preferences for products from Israel and Palestinian territories as well as the Peace product. As already indicated before and now backed up by a correctly specified statistical model, negative attitudes and respective stated behavioral preferences show a robust correlation.

Regarding socio-demographics we found similar to the LCCM that women are less likely to be members of *Class 2 (weak discrimination / weak ethical consumption)* and *Class 3 (no discrimination / strong ethical consumption)*, higher educated respondents are more likely to be assigned to *Class 3* and older respondents are less likely to be assigned to both *Class 2* and *Class 3*. The corresponding effects are (weakly) statistically significant. The negative effect for women might be present because the purchase of Peace Products as a type of political consumption is strongly related to political conflicts and previous research found a tendency that women, on average, seem to show lower rates of political interest than men (see Verba et al. 1997) and that women are less active regarding political participation than men (see Roessel and Schenk 2017: 5). Yet, there is no comparable research specifically concerning the Peace product as an ethical product because this is a novel aspect of our study. Studies on other topics such as the purchase of Fair Trade products, however, show that women, on average, have stronger preferences for political consumption than men (Roessel and Schenk 2017).

Another way of quantifying and presenting differences in preferences is to calculate marginal rates of substitution between choice attributes (see Holmes et al. 2017). If one of the choice attributes includes costs, i.e. a price, marginal willingness to pay (MWTP) values can be calculated by dividing the coefficient value of the non-monetary attribute by the coefficient value of the monetary attribute and multiplying this quotient by minus one [e.g. for the Peace product $-1 \times \left(\beta_{Peace}^{c_s}/\beta_{Price}^{c_s}\right)$]. We use this approach to compare preferences across latent classes. Table 7 presents simulated MWTP values based on results of the HLCCM (see Mariel et al. 2015 for details on how to calculate these values). We find, for example, for *Class 1 (strong discrimination / no ethical consumption)* a MWTP of -8.63 Euro for the Peace product compared to a product from Italy and -1.05 Euro for organic products compared to non-organic products. These values amount to 2.90 Euro and 2.33 Euro, respectively, for *Class 3 (no discrimination / strong ethical consumption)*. Accordingly, due to a positive likelihood to be a member of Class 3, higher educated individuals are more likely to have a positive willingness to pay for Peace products and organic products than less educated individuals.

Table 7: Marginal Willingness to Pay Values (MWTP) in Euro per Class for the HLCCM

	Class 1			*Class 2*			*Class 3*		
Class size	*18%*			*45%*			*37%*		
Attribute	MWTP	95% CI		MWTP	95% CI		MWTP	95% CI	
Organic	-1.05 n.s.	-3.97	1.87	1.11	0.19	2.03	6.37	2.33	10.42
Israel	-16.77	-24.32	-9.22	-1.12	-1.90	-0.35	-7.15	-11.97	-2.32
Palestine	-11.28	-16.90	-5.66	-0.80 n.s.	-1.87	0.26	-5.32	-10.14	-0.51
Peace	-8.63	-12.32	-4.93	0.23 n.s.	-0.45	0.90	2.90	-0.42	6.22

Note: Confidence intervals (CI) were estimated using the delta method; n.s. denotes that the underlying effect of the attribute in the HLCCM is statistically insignificant at the 10% level.

Figure 3 summarizes the estimations of class sizes across the different model variants presented in Tables 4, 5 and 6. The distribution of the allocation probabilities of the LCCM including attitudes as explanatory variables in the membership function (3B) is very different from the

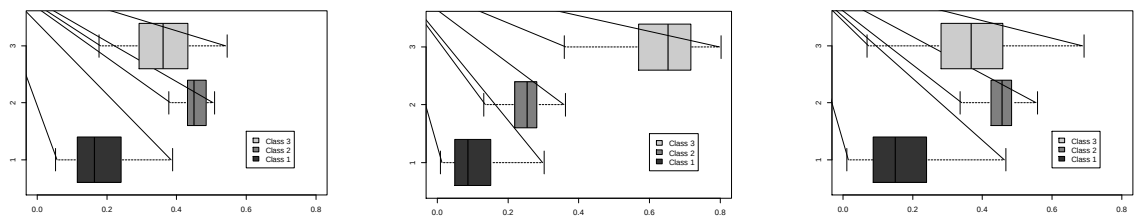
distribution of the allocation probabilities of the LCCM including socio-demographic variables only (3A) and from the distribution of the allocation probabilities of the HLCCM (3C). For example, based on the LCCM without attitudes and the HLCCM we would conclude that mean values for the size of Class 3 (no discrimination/strong ethical consumption) is 37% in both cases. Yet, based on the LCCM, directly including attitudes in the membership function, we would estimate a size of 64% for the "same" (no discrimination/strong ethical consumption) Class 3. This can be due to the fact that the direct inclusion of attitudes in the membership function does not account for their possible endogeneity and can thus lead to a bias in the estimation of the parameters of the membership function. The extent of the bias depends on the correlation of the random error term contained in the attitude measure and the error of the underlying model of the membership function. Figure 3A and 3C present substantially different estimates of class sizes in the population than Figure 3B because there is no endogenous variable present in the membership function in 3A and endogeneity is properly addressed via HLCCM treatment in 3C.

Figure 3: Estimated Allocation Probabilities and Class Sizes for three Model Variants

3A) LCCM without attitudes

3B) LCCM directly including attitudes in the class membership function

3C) HLCCM including attitudes as latent variables



5 Discussion and Conclusions

Stated choice experiments (SCEs) have already been applied in various areas of the social sciences. While we think that they are a promising approach that should be used more often, it is crucial to correctly specify the models especially if preference heterogeneity can be assumed.

SCEs, based on a theoretical framework and behavioral assumptions such as utility maximization, can single out the effect of specific behavioral attributes such as the importance of a product's characteristics that are related to ethical considerations (i.e. the mode and origin of its manufacturing). However, individuals typically differ regarding their preferences. Hence, often a modeling framework fitting all individuals with just a single parameter is based on unrealistic assumptions. Fortunately, it is one of the benefits of SCEs that they are able to capture preference heterogeneity by integrating explanatory measures, especially attitudinal ones. It is common in sociology and social psychology to assume at least a substantial correlation between attitudes and behavioral preferences. In our case, for example, we tried to answer the question if individuals with prejudices (i.e. negative attitudes) are indeed more likely to "boycott" products from respective countries. SCEs offer an opportunity to study such attitude effects on preference formation/modification.

However, as has been shown in this study, modeling attitude-preference-behavior relationships in a theoretically appropriate way is a rather complex task because attitudes are latent variables. This is the main motivation for using hybrid choice models which can take into account the latent variable nature of attitudes and other concepts such as normative beliefs. In a step-by-step approach and theory-guided manner we have shown how, based on SCE data, preferences can be mapped, preference segmentation can be studied and explained, and how attitudinal effects on preference modification can be captured. In doing so we assumed (random) utility maximizing behavior which is a widespread implicit or explicit assumption, also in sociological applications of Rational Choice Theory (even if the assumption is criticized, Hechter and Kanazawa 1997; Voss and Abraham 2000; Kroneberg and Kalter 2012).

Yet, hybrid choice models are a flexible tool to model different decision rules including random utility maximization, random regret minimization, elimination-by-aspects as well as combinations of decision rules (Chorus 2014 for an overview). This opens up the possibility of

systematically studying and comparing decision making processes in a controlled experimental environment. This great potential for sociological research should be explored in future studies. Our study has exemplified how decision-making processes and assumption of behavioral theories in the social sciences can be modeled more directly using SCE. Therefore, the method complements other methods such as "standard" survey research and insights from laboratory and field experiments regarding individual decision making. Potential areas of applications of SCE are manifold and include educational decision making, migrating, voting, discrimination, and bureaucracy.

Taking results from the vast number of SCE studies from transportation research, health economics, environmental economics and marketing into account, it seems obvious that also research in sociology and other social sciences has to deal with questions of preference heterogeneity and modification. However, given the high estimation costs of hybrid latent class choice models – in our case the model included 112 parameters – it seems reasonable to ask whether it is really worth the effort. The answer to this question given in the literature is not straightforward (Mariel and Meyerhoff 2016; Vij and Walker 2016). For example, it is shown and argued (see Vij and Walker 2016) that under certain conditions a LCCM without latent variables can capture non-biased estimates and is in line with assumptions about causality. Further, sociological concepts such as values, general attitudes, and social norms, which, depending on the context, can be assumed to be very stable over time, create less need for a complex modeling approach because endogeneity bias should be rather low or non-existent.

Also, if in applied research the interest is to investigate whether there is a "significant relationship" between general attitudes and (choice) behavior, a model without latent variables might be sufficient, even if it is biased to some extent. This is demonstrated in our study with the LCCM including attitudes as explanatory variables in the membership function. Both, the model with and without latent variables show that there is a systematic and statistically

significant relationship between discriminatory attitudes and behavior. Yet, the estimated class sizes differ remarkable between the models and it can be assumed that, in our case, the more complex model (HLCCM) represents the population better than the less complex model (LCCM). Further, especially if specific attitudes are of interest, it has to be kept in mind that reverse causality is possible. This has been shown in the context of stated choice experiments, for example, in a study on travel mode choice (Kroesen et al. 2017) where there is evidence that behavior influences attitudes more than vice versa. But reverse causality is better captured in a more comprehensive modeling framework taking the causal structure explicitly into account. Again, SCEs provide an experimental environment to study such effects of reverse causality which might also be relevant in sociological and other social science applications.

Despite valuable reasons for employing less complex models to test theoretical relationships in SCE data, there will always remain a clear advantage of the complex model: "Unlike simpler choice models, ICLV [Integrated Choice and Latent Variables] models provide a mathematical framework for testing and applying complex theories of behavior, and lend structure and meaning to underlying sources of heterogeneity" (Vij and Walker 2016: 212). Since the theoretically guided explanations of heterogeneity in attitudes, preferences and behavioral choices are at the core of social research in sociology, political science and other social sciences, we think that the approach presented in this paper is a useful complement to the researcher's toolbox.

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