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The influence of individuals in forming collective household preferences for water quality

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The influence of individuals in forming collective household preferences for water quality

Abstract

Preference for water quality and its nonmarket valuation can be used to inform the development of pricing policies and long term supply strategies. Tap water quality is a household concern. The objective status quo varies between households and not between individuals within households, while charges are levied on households not individuals. Individual preferences differ from collective preferences. In households where there are two adults, we examine the preferences of each separately and then as a couple in collective decisions. We show the level of influence each has in developing the collective decision process. We use discrete choice experiments to model preference heterogeneity across three experiments on women, men and on both. We propose a random utility model which decomposes the error structure in the utility of alternatives so as to identify the individual influence in collective decisions. This approach to choice data analysis is new to environmental economics.

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1. Introduction

Tap water is a typical complex good that is provided at the household level and which can be decomposed into a number of attributes. While tap water is certainly a good familiar to all members of households, each member may display substantially different tastes for its attributes. Because of the composite nature of welfare changes in household water supply, due to this intra-household heterogeneity of taste, conducting stated surveys based on a representative of the household might lead to misleading results. This is an important issue from the empirical viewpoint and motivates our study.

The theoretical and applied literature on household economics has made substantial progress in modelling joint preferences in marketing and transport (Arora and Allenby, 1999; Adamowicz et al., 2005; Hensher et al., 2008; Marcucci et al., 2010), whereas with few exceptions (Dosman and Adamowicz 2006, Bateman and Munro 2005, Strand 2007, Beharry-Borg et al. 2009) less progress has been made in terms of empirical applications in the field of non-market valuation. Investigating preferences from choice data coming from group decisions, rather than individual decisions, requires the ability to handle latent correlations amongst individual and joint choices in a structured manner. In the context of tap water, results obtained from disentangling individual preferences in group decisions have important implications for both policy and survey practice. These implications are of particular salience when preference surveys are designed to inform the process of definition or/and negotiation of water tariff between water utilities and regulatory bodies in charge of evaluating the adequacy of the tariffs and the economic management of investment by water utilities. At the time of data collection for this study this was of particular relevance in Italy, where recent legislation was intended to shift the control of water supply to newly constituted local water network utilities, with the intent of directing water management to be more responsive to market forces. The debate over this legislation proposal has been relegated to backstage after the results of a national referendum (12-13 June 2011 on the composition of water tariffs), but the focus on cost efficiency and social benefits is still driving the debate.

In this study we use data from a widely employed form of stated preference survey for multi-attribute goods, choice experiments (Adamowicz et al., 1998). The salient feature of the data collection is that members of households have provided choice responses first as individuals, and then jointly as a family. To adequately investigate preference heterogeneity of household members for tap water one of the main issues is how to empirically measure these differences, considering that results can be quite sensitive to choice of model specification. Previous work usefully employed power function approaches based on the concept that the household's indirect utility is determined by a convex combination (a power function) of the indirect utility of man and woman (Dosman and Adamowicz 2006). This was later extended to power functions at the single attribute level. That is, the contribution of each attribute to the household's utility function was modelled as a convex combination (Beharry, Hensher and Scarpa 2009), with the power parameter specified as a household specific random component.

Within this context, we now explore the use of an innovative modelling approach, that we call structural choice modelling (hereafter SCM). SCM is an alternative econometric framework for modelling choice data using latent variables, by combining data generated from separate but related surveys and thereby simultaneously modelling choice outcomes from several DCEs (Rungie, 2011; Rungie et al., 2010, 2011; Coote et al., 2011). With respect to previous applications in environmental economics this approach allows two advantages: (*i*) the incorporation of latencies and (*ii*) the simultaneous estimation of structural causal factors from individual and joint choice.

SCM is designed to incorporate latent variables and structural equations into the analyses of DCEs and, more generally, into choice processes (McFadden, 1974; 2001). There are indeed several important precursors to SCM. Firstly, factor analytic models have been used to study brands in a product category. This is as if "brand" is an attribute and the individual brands are levels. Factors have been applied across brands and other attributes by Elrod (1988), Elrod and Keane (1995), Keane (1997) and Walker (2001). Secondly, factor analytic models have also been applied to the characteristics of respondents by using indicator variables (Walker, 2001; Ashok et al., 2002; Morikawa et al., 2002; Temme et al., 2008; Bolduc and Daziano, 2010; Yáñez et al., 2010; Hess and Stathopoulos, 2011). Thirdly, methods using latent variables have been developed for the analysis of combined RP and SP data (Ben-Akiwa and Morikawa, 1990; Hensher et al., 1999; Louvier et al., 1999; Ben-Akiva et al., 2002; Louviere et al., 2002; Morikawa et al., 2002). The various approaches differ in the nature of the covariates employed; in the first the covariates are the attributes of the alternatives and in the second the characteristics of the respondents. However, all approaches rely on similar mathematics.

SCM adapts this mathematics to extend the analysis of the attributes. In particular, it adds to the factor analytics the capacity to specify simultaneous equations and correlations (Jöreskog, 1970, 1973; Bollen, 1989; Jöreskog and Sörbom, 1996) and it exploits the potential relationships between uses and choice outcomes (Rungie, 2011; Rungie et al., 2011; Coote et al., 2011).

In the traditional random coefficient model (e.g. Ben-Akiwa et al., 1997; McFadden and Train, 2000; Dube et al., 2002; Train, 2009), the coefficients for each covariate are independent random variables with means and variances estimated from the data; i.e. the variance covariance matrix, denoted by Σ, is either diagonal or with off-diagonal elements that refer to only covariances between random coefficients. In SCM the coefficients have a multivariate distribution where, through the parsimonious use of factor analytics in the form of simultaneous equations and correlations, Σ can be significantly more complex, yet structured. Although to be practical, the number of parameters must not be excessive. In addition competing models, i.e. competing specifications for the structure of Σ, can be empirically evaluated. In other words, the factor analytics are used to bring testable correlation structures to the error component nature of mixed logit models. The contribution of SCM is in its capacity to specify and evaluate competing models for how preferences for attributes are related. Error component models, of the type explored to define flexible substitution patterns between alternatives (Brownstone and Train 1999, Herriges and Phaneuf 2002, Thiene and Scarpa 2008) can also be seen as special cases of SCM specifications.

The present study adds to the existing literature in several ways. First, it is one of the few existing applications of structural choice models to investigate latency in preference heterogeneity. Second, to our knowledge this is the first empirical study using this approach in the field of environmental and resource economics. Ultimately, it is one of the few contributions using data from more than two choice experiments that are simultaneously modelled within a natural group, such as the couple.

The rest of the paper is organized as follows. The next section illustrates the methodology. Survey and data are described in section 3, whereas section 4 defines model specifications and provides a discussion of result estimates. The last section concludes.

2. Methods

In this section we start by laying out a notation that we then use to move from the conventional and by now quite familiar mixed logit model to what we call a structural (equation) choice model or SCM. In the latter latent variables are brought to bear so as to develop a plausible structure of correlation across the determinants of choices. In our application we focus on a plausible structure between choice by members of the same residential unit (man and woman) and their joint deliberations. Specifically, we try to account for influences of individual taste coefficients of single respondents in a household as latent determinants of choice in the joint household decisions. Following Rungie et al. (2011) it is conceptually desirable to cast the approach around the familiar random utility framework.

Traditional random utility theory (McFadden, 1974; 2001; Train, 2009) states that alternative *i* is perceived to deliver utility u_i. This is composed of a systematic component v_i, and an error term, ε_i, which may be GEV or Gumbel distributed[1].

$$u_i = v_i + \varepsilon_i \tag{1}$$

The systematic components, v, are specified to be linear combinations of the m covariates in the vector x with random coefficients grouped in the vector β. To illustrate the structural choice model proposed here Rungie et al. (2011) used a notation and approach that is borrowed from the

[1] For simplicity the subscripts for the individual, the choice set and alternative within the choice set are omitted.

conventions employed in the broad literature of structural equation modelling and adapted to choice modelling. However, this would not be a familiar notation for those who, such as this audience, have been exposed to the conventional mixed logit notation. So, in order to facilitate the understanding of the proposed notation we proceed as follows. We note that in random parameter logit with a continuous mixture of taste the individual taste coefficient for a given attribute x_k is composed of two additive terms: the mean value of the taste parameter for the k^{th} covariate β_k and its random idiosyncratic component $\sigma_k \tilde{\beta}_{kn}$, where $\tilde{\beta}_{kn}$ is the random component drawn by some distribution (perhaps standard normal) for the n^{th} individual and σ_k is the dispersion parameter for this random element to be estimated. So, omitting the subscript i for the single choice selection and n for the respondent, the conventional mixed logit notation for the systematic component of the utility is given by

$$v = \Sigma_k \, (\beta_k + \sigma_k \tilde{\beta}_k) x_k. \tag{2}$$

Rather than being a single random entity, in the SCM $\tilde{\beta}_k$ can be expressed as a structural equation:

$$\tilde{\beta}_k = a_{k,1}\tilde{\beta}_1 + \cdots + a_{k,m}\tilde{\beta}_m + \delta_k \tag{3}$$

where the $a_{.,.}$ are elements from a matrix of regression parameters and the $\delta_.$ are elements from a vector of random components, from which after estimation measures of fit, such as the classic R-squares, can be derived. These help to evaluate the overall model and the suitability of the proposed constructs.

From the above equations, it can be seen that the variance-covariance matrix of $\tilde{\beta}$ is considerably more structured than a simple diagonal matrix. In other words, specific correlation structures can be imposed on the coefficients for the covariates. In a way, structural choice modeling (SCM) can be seen as an extension of error component modeling of the mixed logit model as described in Brownstone and Train (1999), Train (2009) and Herriges and Phaneuf (2002) in the context of flexible substitution patterns.

Typically, the random components δ in equation (3) are specified to have Gaussian distributions, but other distributions can also be assumed. In estimation via simulated maximum likelihood the expectation of mixtures of choice probabilities is obtained via variance reduction techniques based on quasi-random draws. In this application we use Halton draws for their well-known equidispersion properties (Train 1999), but others can be used (Baiocchi 2005).

From the above it should be apparent that two special cases of the utility structure underlying observed choice that we presented so far—the traditional fixed and random coefficient models—need not be addressed by means of SCM. Indeed standard software packages can be used and results from identical models on the same data will differ slightly due to differences in maximization algorithms and features of simulation techniques. In what follows we use SCM to create an 'Influence Model', which is designed to uncover the latent structure of correlated choices in couples. Specifically, we focus on the influences between men and women individual preferences and their joint choices as couples. In the process we highlight some stylized identification issues that are typical of SCM. We do so by presenting utility specifications in both the preference and WTP-space for panel data, which are the most frequently utility specifications used in non-market valuation studies from DCEs. For a discussion of the advantages and disadvantages of the two approaches in non-market valuation the interested reader is directed to Train and Weeks (2005), Scarpa, Thiene and Train (2008), and to Daly, Hess and Train (2012).

3. Survey and Data

The study is based on survey data collected with face-to-face DCEs interviews of 80 couples. One group of 20 couples was sampled in the city of Torino in the North-West. A second group of 60 couples was obtained in the city of Vicenza, in the North-East. The two locations in terms of water quality are similar for a variety of reasons not discussed here, but mainly linked to their proximity to the Alps. The motivation for investigating preferences for residential tap-water is to be found in the recently debated reforms of the national legislation regulating water utilities, which considered shifting the control of water supply to newly constituted authorities with the intention to make water supply more market driven. This would turn out to be challenging for municipalities, because it will force them to implement a series of changes in water utility management by merging water management utilities across local authorities and creating new locally regulated commercial entities. Therefore, local water authorities (Integrated Water Services) are interested in investigating preference heterogeneity for tap water quality attributes to strategically define water tariffs across city locations.

3.1 Data

The data used here come from an explorative and preliminary survey specifically designed to prepare a more complex data collection, which will be the subject of another application. The application provided here is for the purpose of proof of concept. As mentioned above, reported results are based on interviews of 80 couples, which in total provided 1,920 choice responses from 8 choice tasks with four alternatives each. Choices were expressed by 160 respondents individually (80 men and 80 women) which then also provided 80 sets of joint decisions.

In the survey, respondents were asked to choose among alternatives described using the same attribute structure, which differed on the basis of four quality attributes relating to drinking water characteristics plus the cost (Chlorine Odour, Chlorine Taste, Water Turbidity, Calcium Carbonate Stains and Cost). Cost was described as an additional amount of money people would pay in the water bill over a year. In particular, respondents were asked to choose among water service supply contracts displaying different levels of water supply characteristics or “water service factors” to use a term commonly employed in similar utility studies (Willis and Scarpa 2005) and in the UK water industry. The attributes and the relative levels are reported in table 1. Respondents were asked to choose between the frequencies of events in which they could smell (odour) and/or taste chlorine (once a day, once a week, once a month, never or always). Turbidity due to fine air bubbles was also considered. Its levels included its absence, and its presence in a mild, medium and extreme form. Due to the hardness of water in this area calcium carbonate staining in pipes is quite a concern and the effect of presence/absence of staining was also investigated. In the survey respondents faced four alternatives in each choice set, where one alternative was always the status quo and involved no additional cost. An example of choice set is reported in table 2.

The design of the survey was finalized by contacting and interviewing experts employed by local utilities supplying Integrated Water Services (water supply as well as water treatment services). These provided specific and technical information which turned out to be valuable in the selection of the attributes levels. This information was supplemented with suggestions provided by technicians from public institutions involved in the management of such water services. The combined information was then used to conduct repeated focus groups, the results from which were then used to design the choice experiments. The complete questionnaire was then tested in the field in a pilot survey, which also provided priors for the coefficient values to be used in the Bayesian design.

The choice data from each household were collected first with man and woman conducting individual experiments and being asked their individual preferences. Then, it proceeded by asking man and woman to join together in a choice exercise to select favourite alternatives for the household. In this way for each household we collected 3 sets of choices, one for the man, one for the woman and one for the household.

3.2 Experimental design

The survey employed a sequentially adapted experimental design and one of the aims of the research was to use the information collected with the first design as a prior to inform the subsequent ones. In particular, in the survey was used a sequential efficient Bayesian design. The purpose was to ensure a high accuracy of the estimates despite the relatively small sample size affordable. One of the main advantages of such an approach is that as more responses are collected during the course of the survey, gradually more accurate information becomes available on the priors of the population, thereby increasing the efficiency of the final estimates and decreasing the potential for mis-specification (Kanninen 2002; Scarpa et al. 2007; Ferrini and Scarpa 2007; Scarpa and Rose, 2008; Kerr and Sharp, 2010; Vermeulen et al., 2011).

In the Turin sample, the overall survey design was articulated in subsequent phases, as additional information was sequentially collected in six waves of sampling. Each sample wave used a different *WTP_b-efficient* design[2] developed using Bayesian priors (as indicated by the subscript "b"), derived by combining the information collected in all previous waves. The initial prior information was gathered from the pre-test and the pilot survey; the first wave of interviews then informed in turn the design of the following waves. At the end of waves 1-6 basic multinomial logit models were estimated so as to provide priors for the efficient design of the subsequent sample wave. Each respondent tackled 8 choice tasks.

For the second group of respondents in Vicenza we employed a Bayesian D-efficient design (Sandor and Wedel, 2001; Ferrini and Scarpa, 2007; Rose and Bliemer, 2009), derived on the basis of existing information on parameter estimates previously obtained from the previous study. The

[2] Specifically, the *WTP_b-efficient* criterion was adopted to select the fraction of the full factorial to be used as a design in the sequence of sub-samples. This is based on the minimization of the expected variance of some non-linear functions of the utility coefficients, namely the sum of the variances of the marginal willingness to pay estimates. Considering that different attributes can be described in different units, as in the case at hand, Scarpa and Rose (2008) point out that the minimisation process of variance sum across marginal WTPs with uneven unit of measurement may result in an unsatisfactory outcome. To overcome such a limitation, they suggest the adoption of a criterion that maximizes the minimum *t*-value for the marginal WTP. This choice places more emphasis on the attribute whose WTP was estimated with least accuracy, as measured by the *t*-value. We note in passing that Bayesian WTP-efficiency has also been found to provide designs with higher robustness to outliers and less prone to producing extreme WTP estimates (Vermeulen et al., 2010).

point estimates from the earlier Turin study were used to inform the prior distribution on the Bayesian design for Vicenza, while the standard errors were used to define the variances of the distributions of priors. The probabilities in the derivation of the design were obtained via simulation using 200 Halton draws.

3.3 Sampling

The survey focussed on couples and the preferences of their two members. As a consequence it focussed on modelling joint choices as functions of primitive individual preferences of the two members of the couple (man and woman).

The survey developed in several stages. The first stage aimed at selecting households that could be considered as “couples” into a sampling frame. These were subjects living in a stable relationship with a partner. Then the sampling was randomly executed on this frame.

During the second stage, respondents were asked whether they would be willing to participate in the survey. They were contacted by mail first and then by telephone. Once both partners agreed on participation, the interviewer would fix an appointment to visit the couple. At the household’s house, they were debriefed jointly and given the stated preference tasks.

Importantly, in order to avoid that any difference in choice across individuals of the same household could be due to differences in choice tasks, each respondent within a given household unit was given the same sequence of choice tasks. These tasks were performed first individually, so as to derive individual preferences, and then jointly. When performed individually, respondents were asked their individual preferences. When performed jointly, they were asked to negotiate a mutually satisfying outcome for the couple.

4. Model specifications and estimates

In what follows we first illustrate the specifications of indirect utility for the preference space model because it is the most commonly employed. Later we will show the changes required for the WTP-space panel model.

4.1 Model specifications and rationale

The choice data is made of responses to three identical discrete choice experiments (DCEs) conducted separately. With y_{w} we denote the responses by women (DCE 1), with y_{m} those by men (DCE 2) and with y_{j} the joint responses provided as a couple (DCE 3). To simultaneously model choice probabilities for the separate DCEs the three data matrices were stacked at the household level. In each DCE the alternatives were described by using five attributes, three of which had 4 levels defined as unimproved and 3 levels of improvement. In this study these were then aggregated into a dummy-coded variables denoting extreme improvement (the level of a disturbance was reduced to "never"). The fourth attribute (*stain*) had two levels and was also coded as a single dummy variable denoting the "presence" of stains. The fifth attribute was the cost (tariff) which was coded numerically in Euros. Because of dummy coding with each attribute (except cost) and the alternative specific constant for the status-quo in total there were six identifiable coefficients for the indirect utility function.

To evaluate the identification power of the SCM influence model in explaining unobserved heterogeneity we compare it with two standard logit specifications. In total, three logit probability models have been specified and estimated for the three data sets: (*i*) the *fixed coefficient model*, (*ii*) the *random coefficient model*, and (*iii*) the *influence model*. First, the fixed coefficient logit model was estimated, from which a mean value estimate (β_k) for each attribute coefficient is obtained. Next, the well-known restrictive assumptions of the fixed coefficient logit model were relaxed by estimating a random coefficient panel model; this, besides mean values (β_k), provided estimates of the dispersion parameter (σ_k) for the random coefficients of each covariate.

Ultimately and more importantly, we pose the following question: is there a structural link in the heterogeneity within the joint DCE and the heterogeneity in the separate DCEs by men and women? The influence model specifies these links, in that the utilities for the joint decisions are also a function of the individual utilities for women and men. Each utility in the joint DCE model is simultaneously specified to be a linear function of the equivalent utilities in the women and men DCEs. By doing so we wish to investigate if and, in case, to what extent, the joint decision making process of couples is influenced by individuals. Within this exploration, as we will show, we can also answer the question of whether women or men are most affecting joint decisions.

In the equations and model specifications below the attributes are referred to as follow: odour=OD, taste=TS, turbidity=TR, stain=ST, cost=CO and status quo=SQ.

4.2 The Random Coefficient Model

In this model, the four water factor services—odour, taste, turbidity and stain—are assumed to have random coefficients. The other two attributes—cost and status quo—are given fixed coefficients.

For women's individual choices the random coefficient model involves the following indirect utilities:

$$
\begin{aligned}
v^{OD,w} &= \left(\beta^{OD,w} + \sigma^{OD,w}\tilde{\beta}^{OD,w}\right)x^{OD,w} \\
v^{TS,w} &= \left(\beta^{TS,w} + \sigma^{TS,w}\tilde{\beta}^{TS,w}\right)x^{TS,w} \\
v^{TR,w} &= \left(\beta^{TR,w} + \sigma^{TR,w}\tilde{\beta}^{TR,w}\right)x^{TR,w} \\
v^{ST,w} &= \left(\beta^{ST,w} + \sigma^{ST,w}\tilde{\beta}^{ST,w}\right)x^{ST,w} \\
v^{CO,w} &= \beta^{CO,w}x^{CO,w} \\
v^{SQ,w} &= \beta^{SQ,w}x^{SQ,w}
\end{aligned} \tag{4}
$$

and, for alternative *i*,

$$\mu_i^w = v_i^{OD,w} + v_i^{TS,w} + v_i^{TR,w} + v_i^{ST,w} + v_i^{CO,w} + v_i^{SQ,w} + \varepsilon_i^w \tag{5}$$

For men’s individual choices and the joint decisions the random coefficient model repeats the same structure.

4.3 The Influence Model

While the random coefficient model introduces heterogeneity across the panel of choices it does not uncover any latent structure of choice between members of the same household. In particular, no relation exists between the primitive of the utility function of the individuals in their choices and their joint choice. Behaviourally this is clearly counter-intuitive and contrary to empirical findings reporting corroborating evidence in favour of such correlation (Dosman and Adamowicz 2006; Beharry, Hensher and Scarpa, 2009; Scarpa, Thiene and Hensher 2012). To account for this we propose an SCM that elaborates further on the random coefficient model by imposing structure in the correlation of the $\tilde{\beta}$ s, but only for the joint choices. As in the random coefficient model the primitive of the utility for women individual choices are expressed as independent random coefficients.

$$\begin{aligned}\tilde{\beta}^{OD,w} &= \delta^{OD,w}\\ \tilde{\beta}^{TS,w} &= \delta^{TS,w}\\ \tilde{\beta}^{TR,w} &= \delta^{TR,w}\\ \tilde{\beta}^{ST,w} &= \delta^{ST,w}\end{aligned} \qquad (6)$$

The four random components δ in (6) have independent standard Gaussian distributions leading to a model for the women’s individual choices identical to the random coefficient model in (4). For men’s individual choices the influence model repeats the same structure.

Things are different for the joint decisions, which have random components specified as linear combinations applied to the primitive utilities:

$$\tilde{\beta}^{OD,j} = a^{OD,w}\tilde{\beta}^{OD,w} + a^{OD,m}\tilde{\beta}^{OD,m} + \delta^{OD,j}$$
$$\tilde{\beta}^{TS,j} = a^{TS,w}\tilde{\beta}^{TS,w} + a^{TS,m}\tilde{\beta}^{TS,m} + \delta^{TS,j} \qquad (7)$$
$$\tilde{\beta}^{TR,j} = a^{TR,w}\tilde{\beta}^{TR,w} + a^{TR,m}\tilde{\beta}^{TR,m} + \delta^{TR,j}$$
$$\tilde{\beta}^{ST,j} = a^{ST,w}\tilde{\beta}^{ST,w} + a^{ST,m}\tilde{\beta}^{ST,m} + \delta^{ST,j}$$

where a denotes the regression coefficients. The four random components δ in (7) have independent Gaussian distributions with means zero but with standard deviations to be estimated from the data (error components). Then, the indirect utilities are:

$$v^{OD,j} = \left(\beta^{OD,j} + \sigma^{OD,j}a^{OD,w}\tilde{\beta}^{OD,w} + \sigma^{OD,j}a^{OD,m}\tilde{\beta}^{OD,m} + \sigma^{OD,j}\delta^{OD,j}\right)x^{OD,j}$$
$$v^{TS,j} = \left(\beta^{TS,j} + \sigma^{TS,j}a^{TS,w}\tilde{\beta}^{TS,w} + \sigma^{TS,j}a^{TS,m}\tilde{\beta}^{TS,m} + \sigma^{TS,j}\delta^{TS,j}\right)x^{TS,j}$$
$$v^{TR,j} = \left(\beta^{TR,j} + \sigma^{TR,j}a^{TR,w}\tilde{\beta}^{TR,w} + \sigma^{TR,j}a^{TR,m}\tilde{\beta}^{TR,m} + \sigma^{TR,j}\delta^{TR,j}\right)x^{TR,j} \qquad (8)$$
$$v^{ST,j} = \left(\beta^{ST,j} + \sigma^{ST,j}a^{ST,w}\tilde{\beta}^{ST,w} + \sigma^{ST,j}a^{ST,m}\tilde{\beta}^{ST,m} + \sigma^{ST,j}\delta^{ST,j}\right)x^{ST,j}$$
$$v^{CO,j} = \beta^{CO,j}x^{CO,j}$$
$$v^{SQ,j} = \beta^{SQ,j}x^{SQ,j}$$

The heterogeneity of the women's individual choices is exogenous, specified by the independent δ in (6). So too is the heterogeneity of the men's individual choices. However, in (7) the heterogeneity for the *joint* decisions is now a combination of an exogenous effect, specified as the δ, and an endogenous effect, specified by including the $\tilde{\beta}^{\cdot,w}$ and $\tilde{\beta}^{\cdot,m}$ terms.

As discussed below, the influence model was fitted to the data in two similar forms, the full model (Full) and a slightly simplified model (S) without redundancies, which in the empirical analysis shows to fit the data just as well.

4.4 Preference space estimates

All models have been estimated by using DiSCos (Rungie, 2011)[3]. The estimates of the mean values of the preference space model with fixed taste coefficients, reported in Table 3, show expected signs and high significance for all attributes. All coefficients for the "never" smell and taste for chlorine and the no turbidity display positive intensities of taste. Women show less inclination to adhere to the status-quo than men and what emerges from joint decisions.

Table 4 reports the statistics for the fit of the various preference space models. As it can be noted by comparing the log-likelihood values, the random coefficient model (see Table 5 for result estimates) performs better than the fixed model, as one would expect. Nevertheless the influence model gives the best fit. The improvement in terms of performance is substantial, with more than 70 points, thereby supporting our hypothesis of existence of a latent structure in the unobserved heterogeneity. Information criteria that penalize for over parameterization, such as AIC, AIC3 and BIC, are concordant to indicate this model to provide best fit.

4.4.1 Identification of the Influence Model

The SCM model might be challenging in its identification requirements. It is easy to establish if a SCM is identified: (*i*) If the Hessian matrix cannot be inverted then the model is not identified; (*ii*) If many of the more substantive parameters have *t*-values close to zero then most likely there is also a problem with identification. Confounding occurs when two parameters are not identified but their product is. The result is a ridge in the plot of the log likelihood function. The Hessian may not be invertible but if it is some of the standard errors will be quite large; (*iii*) If fixing individual parameters to zero, or some other theoretically justifiable value, does not reduce the optimum log likelihood and fit of the model, then the parameter need not be estimated from the data.

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[3] Structural choice models were estimated by means of a software program called DiSCos (Rungie, 2011) and written in MatLab by using 10,000 Halton draws. Estimation of each model with relatively good starting values took about a week in a Dell M6500 quad core 64 bit computer.

Through practical experience guidelines are developing for creating properly identified SCMs. To reduce the risk of confounding, a usual practice, which is discussed further below, is to fix the standard deviations of the random components δ to one.

The influence model as it is described above has 42 parameters. There are three DCEs, women, men and joint, each with six attributes creating a total of 18 mean estimates in β. In each DCE four attributes, OD, TS, TR and ST, have random coefficients with dispersion parameters σ creating a total of 12. The same four attributes in the women and men experiments influence the preferences in the joint experiment creating a total of 8 regression parameters a. Finally, as in (7), the four δ in the joint experiment each have a standard deviation to be estimated. Thus, there are in total 42 parameters to estimate from the data. Not all are identified.

In the joint DCE, for any one attribute, (7) indicates a confounding between three parameters; the regression coefficients a, the dispersion parameter σ and standard deviation of δ. One of the three is not identified. As a comparison, in the women and men experiments the standard deviation of δ is fixed to one leading to the remaining dispersion parameter, σ, being identified. Exploratory data analysis indicated that for the joint experiment a similar approach of fixing the standard deviation of δ to one was not appropriate as it reduced the ability to interpret the regressions parameters a. As an alternative, the standard deviation of δ were free to be estimated from the data, and some regression parameters, a, were fixed. This led to the (full) influence model having 38 identified parameters. The results are in Table 4.

Specifically, for the influence of the women on the joint DCE the regression parameters were all fixed to one; i.e. $a^{OD,w} = a^{TS,w} = a^{TR,w} = a^{ST,w} = 1$. This is as if the influence of the women were standardized. The influence of the men on the joint experiment is then evaluated by comparing the equivalent regression parameters, $a^{OD,m}$, $a^{TS,m}$, $a^{TR,m}$ and $a^{ST,m}$, to the standard of one. But the model does not assume there is influence, not does it impose it. In the joint DCE the combined roles of the dispersion parameter, σ, and the standard deviation of the random component δ determine the relative exogenous and endogenous effects on heterogeneity. The degree of influence is determined by the data. The results are discussed below but first we examine the goodness-of-fit for the four regressions in (7) by focussing on their R-squares.

4.4.2 Simplifying the influence model

The R-squares for the four regressions equations in the Influence Model (Full) are reported in Table 6. The estimates of the standard deviations for the four δ in (7) were all so close to zero that the R-squares are all 100%. The result does not indicate that the decision making in the joint experiment was deterministic when conditioned on the women and men experiments. Rather, the result indicates that all the heterogeneity in the joint experiment can be accounted for by heterogeneity from the separate women and men experiments and that the expressions $\delta^{OD,j}$, $\delta^{TS,j}$, $\delta^{TR,j}$ and $\delta^{ST,j}$ in (7) do not contribute to the fit of the model. This is a strong result, but it is unsurprising. The DCEs for women and men were conducted first. Then the joint DCE was conducted immediately after. Apart from the heterogeneity influencing the women and men DCEs, there was no opportunity for a new exogenous source of heterogeneity to influence the joint DCE.

Consequently, the model in (7) was simplified as in (9); the regression parameters, a, for women were fixed to one and standard deviations for the δ in the joint experiment were fixed to zero, giving rise to the following latent structure:

$$
\begin{aligned}
\tilde{\beta}^{OD,j} &= \tilde{\beta}^{OD,w} + a^{OD,m}\tilde{\beta}^{OD,m} \\
\tilde{\beta}^{TS,j} &= \tilde{\beta}^{TS,w} + a^{TS,m}\tilde{\beta}^{TS,m} \\
\tilde{\beta}^{TR,j} &= \tilde{\beta}^{TR,w} + a^{TR,m}\tilde{\beta}^{TR,m} \\
\tilde{\beta}^{ST,j} &= \tilde{\beta}^{ST,w} + a^{ST,m}\tilde{\beta}^{ST,m}
\end{aligned}
\qquad (9)
$$

Table 4 shows this simpler form of the influence model (denoted by (S) from “simplified”) fitted the data just as well, confirming the redundancy of parameters in the full influence model. This reduced form is the model we use to evaluate the influence. Further results for the influence model (S), as are given in Tables 7 and 8, and are discussed below.

4.4.3 Evaluating Influence

The estimates of the regression coefficients, a, are shown in Table 7. The influence of men on the attribute of odour in joint choices was greater than the influence of women. Conversely, the influence of women in joint choices was greater on the other three qualitative attributes, taste, turbidity and stain.

Aggregating over (the square of) the regression parameters for the four attributes identifies that women provided 58% of the heterogeneity in the joint experiment and men 42%. This conclusion, that women have greater influence, is further demonstrated by applying two constraints to the influence model (S). First, only women are specified as influencing the heterogeneity in the joint experiment, and second, only men. The results in Table 9 for these two models again show clearly that women have greater influence on the heterogeneity in the joint DCE than men.

4.5 Willingness-to-pay space for the influence model

In willingness-to-pay space a strictly positive random component, λ, is applied multiplicatively to the systematic component of utility (Train and Weeks 2005). Since λ operationalises heterogeneity for scale and for the cost coefficient simultaneously, the cost coefficient in the indirect utility in the influence model in WTP space is set to -1.

Thus for women's individual choices the model from (4) has $\beta^{CO,w}$=-1 and is:

$$
\begin{aligned}
v^{OD,w} &= \lambda^{w}\left(\beta^{OD,w} + \sigma^{OD,w}\tilde{\beta}^{OD,w}\right)x^{OD,w} \\
v^{TS,w} &= \lambda^{w}\left(\beta^{TS,w} + \sigma^{TS,w}\tilde{\beta}^{TS,w}\right)x^{TS,w} \\
v^{TR,w} &= \lambda^{w}\left(\beta^{TR,w} + \sigma^{TR,w}\tilde{\beta}^{TR,w}\right)x^{TR,w} \\
v^{ST,w} &= \lambda^{w}\left(\beta^{ST,w} + \sigma^{ST,w}\tilde{\beta}^{ST,w}\right)x^{ST,w} \\
v^{CO,w} &= \lambda^{w}(-1)x^{CO,w} \\
v^{SQ,w} &= \lambda^{w}\beta^{SQ,w}x^{SQ,w}
\end{aligned}
\tag{10}
$$

For men's individual choices and the joint decisions the random coefficient model in WTP space repeats the same structure.

Similarly for the joint decisions (8) becomes:

$$
\begin{aligned}
v^{OD,j} &= \lambda^{j}\left(\beta^{OD,j} + \sigma^{OD,j}a^{OD,w}\tilde{\beta}^{OD,w} + \sigma^{OD,j}a^{OD,m}\tilde{\beta}^{OD,m} + \sigma^{OD,j}\delta^{OD,j}\right)x^{OD,j} \\
v^{TS,j} &= \lambda^{j}\left(\beta^{TS,j} + \sigma^{TS,j}a^{TS,w}\tilde{\beta}^{TS,w} + \sigma^{TS,j}a^{TS,m}\tilde{\beta}^{TS,m} + \sigma^{TS,j}\delta^{TS,j}\right)x^{TS,j} \\
v^{TR,j} &= \lambda^{j}\left(\beta^{TR,j} + \sigma^{TR,j}a^{TR,w}\tilde{\beta}^{TR,w} + \sigma^{TR,j}a^{TR,m}\tilde{\beta}^{TR,m} + \sigma^{TR,j}\delta^{TR,j}\right)x^{TR,j} \\
v^{ST,j} &= \lambda^{j}\left(\beta^{ST,j} + \sigma^{ST,j}a^{ST,w}\tilde{\beta}^{ST,w} + \sigma^{ST,j}a^{ST,m}\tilde{\beta}^{ST,m} + \sigma^{ST,j}\delta^{ST,j}\right)x^{ST,j} \\
v^{CO,j} &= \lambda^{j}(-1)x^{CO,j} \\
v^{SQ,j} &= \lambda^{j}\beta^{SQ,j}x^{SQ,j}
\end{aligned}
\tag{11}
$$

The random coefficient λ has a lognormal distribution giving rise to two additional parameters, the mean μ_λ and standard deviation σ_λ of the normally distributed $\ln(\lambda)$. The joint scale, λ^j, is a function of the scales for woman, λ^w, and man, λ^m, and an error term λ^δ where:

in the linear form

$$
\ln\left(\lambda^{j}\right) = a^{\lambda,w}\ln\left(\lambda^{w}\right) + a^{\lambda,m}\ln\left(\lambda^{m}\right) + \ln\left(\lambda^{\delta}\right)
\tag{12}
$$

and in the multiplicative form

$$\left(\lambda^{j}\right)=\left(\lambda^{w}\right)^{a^{\lambda,w}}\left(\lambda^{m}\right)^{a^{\lambda,m}}\left(\lambda^{\delta}\right) \tag{13}$$

With eight new parameters to be estimated (μ_λ mean and σ_λ for each of three λ and two a^λ) and three former parameters fixed to -1 (the price coefficients, for women, men and joint) the influence model in willingness-to-pay space increases the number of parameters by 5 to a new total of of 39. Comparing information criteria reported in Table 10 to Table 4 shows the WTP space model fits the data better than the preference space models, even accounting for parameter proliferation.

The estimates for the *a* parameters are in Tables 11. The estimates for the distribution parameters of ln(λ) are in Table 12, where the total joint mean and dispersion is calculated using (12). The earlier preference space results in Table 3 report partworths for cost of -0.06 for woman and man and -0.04 for joint. The plot of the three log normal distributions for λ in WTP space in Figure 1 show results of a similar order and again the joint is lower. The upper tails represents the cases where there is a higher willingness to pay. There are more individuals in the upper tail for man and less for joint. An interpretation is that in the joint decisions extreme WTP positions mostly held by men are moderated down by women.

The estimates of the remaining parameters, in Table 13, can be compared with Table 8. The estimated means for cost in preference space in Table 8 are -.05 for woman, -.07 for man and -.04 for joint. By comparison, for WTP space in Table 8, the same parameters are all fixed to -1. Consequently, all other estimates in Table 8 are necessarily 20 times higher. Once this multiplicative scaling effect of λ has been accounted for the estimates for WTP space for each attribute are still higher, about double, but the order of importance of the attributes is unchanged.

98% of the variability in the joint ln(λ) is accounted for by the variability in the crude ln(λ) for woman and man. Thus the result for preference space that joint decisions can be accounted for by the individual woman and man decisions is confirmed in the WTP space for the heterogeneity in the random behaviour of λ. In the joint decisions there is no other or new source of heterogeneity apart from the primitive man and woman decisions. Table 11 shows that again man has more influence on Odour but overall, as measured now through ln(λ), woman, at 66%, has much more influence than man at 32%.

The pooled willingness to pay for each attribute is the product of λ and the various forms of β as in (9) to (12). The median results, reported in Table 14, show that removing Stain has the highest value and improvement in Taste the least. For Taste, Turbidity and Stain the joint decision is an averaging of the primitive decisions but not so for Odour where the dynamics of the joint decision raises the WTP. The first quartiles for Stain show the results for those willing to pay more. In every case for these quartiles the man has higher willingness to pay which is moderated in the joint decision by women. Conversely the first quartiles, and third for Stain, show the results for those with willingness to pay less. The joint decision raises this small willingness to pay for Turbidity and Stain. Finally, the correlations of women with joint and men with joint in Table 15 show the same pattern as seen before. Women have much more influence in the joint decisions than men, especially, as shown in the quartile behaviours, in the case of men with extreme (low or high) WTPs.

5. Conclusions

The study of preferences underlying group decisions can be conducted by adequately developed surveys and the data of which are consistently analyzed by employing specifically developed choice models. While previous work has mostly employed power function approaches at the individual indirect utility level (Dosman and Adamowicz 2006) or at the single attribute level (Beharry, Hensher and Scarpa 2009), we offer an "influence model" based on a special structure of the idiosyncratic components of the joint choice. This is a special case of a broader approach to choice modeling developed by Rungie et al. (2011) and Coote et al. (2011) called structural choice modeling. As a proof of concept, we explore this approach in a small sample but high quality set of discrete choice experiments conducted in households and investigating preferences for tap water. Tap water is a multi-attribute good that is appreciated differently by each member of a household. Yet, one single contract provides this utility at the household level. Household preferences should hence be based on joint decisions by members of the household. In an identical choice experiment conducted first individually and separately by husband and wife, and then jointly, we find that a structural model of choice greatly improves model fit.

We stop short of deriving estimates of welfare measures for specific policies because we favor the uncovering of structure in the heterogeneity of joint decisions. Overall we find the preliminary results worth of attention and the modeling approach informative. Further research should focus on other plausible specifications of influence across individual and joint choice as well as on deriving welfare estimates for specific policy proposals. Future work should also explore the predictive power of the model for joint group decisions in observations held out of sample during estimation, but based on the individual preferences of the group.

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Table 1. Description of the qualitative attributes

Variable name	Attribute		Description of attribute and level
O_ALWAYS	OD	Odour	chlorine odour always
O_MONTH	OD	Odour	chlorine odour once a month
O_WEEK	OD	Odour	chlorine odour once a week
O_NEVER	OD	Odour	chlorine odour never
T_ALWAYS	TS	Taste	chlorine taste always
T_MONTH	TS	Taste	chlorine taste once a month
T_WEEK	TS	Taste	chlorine taste once a week
T_NEVER	TS	Taste	chlorine taste never
NO_TURB	TR	Turbidity	no turbidity from fine air bubbles
MILD_TURB	TR	Turbidity	mild turbidity from fine air bubbles
MED_TURB	TR	Turbidity	medium turbidity from fine air bubbles
EXTR_TURB	TR	Turbidity	extreme turbidity from fine air bubbles
STAIN	ST	Stain	presence of calcium carbonate staining in pipes

Table 2. Example of choice-set.

Which of the following alternative would you choose?	**A**	**B**	**C**	**D**
Chlorine odour:	Always	1 day per week	1 day per month	None
Chlorine taste:	Always	1 day per week	Never	
Turbidity:	Absent	Medium	Extreme	
Calcium carbonate staining:	No	Yes	Yes	
Additional WTP in the bill per year	18€	5€	6€	
Choice	☐	☐	☐	☐

Table 3. Preference Space Fixed Model.

	Women		Men		Joint	
	M	|*t*-value|	μ	|*t*-value|	μ	|*t*-value|
Odour	0.85	9.30	0.79	8.30	0.89	8.35
Taste	0.28	2.86	0.27	2.66	0.31	2.73
Turbidity	0.85	8.95	0.79	8.58	1.04	10.57
Stain	-1.90	9.04	-1.63	7.87	-1.90	8.12
Cost	-0.06	4.78	-0.06	5.54	-0.04	3.53
Status Quo	-0.06	0.29	0.32	1.94	0.48	2.97

Table 4. Preference Space   Summary of model statistics.

Model	Number of Parameters	Log Likelihood	BIC	AIC	AIC3
Fixed Coefficient	18	-1343.42	2778	2723	2741
Random Coefficient	30	-1267.18	2687	2594	2624
Influence (Full)	38	-1200.36	2594	2477	2515
Influence (S)	34	-1200.36	2573	2469	2503

Table 5. Preference Space Random Coefficient Model.

Means	Women		Men		Joint	
	μ	|*t*-value|	μ	|*t*-value|	μ	|*t*-value|
Odour	1.01	7.93	0.98	7.26	1.02	8.18
Taste	0.30	2.38	0.30	2.24	0.34	2.29
Turbidity	1.00	7.31	1.04	7.20	1.19	9.24
Stain	-3.69	6.00	-3.04	5.71	-3.14	2.60
Cost	-0.05	3.15	-0.07	5.41	-0.04	3.55
Status Quo	0.10	0.39	0.43	2.23	0.52	2.83
Dispersions	σ	|*t*-value|	σ	|*t*-value|	σ	|*t*-value|
Odour	0.42	2.84	0.64	3.02	0.00	0.00
Taste	0.44	2.22	0.48	2.69	0.66	3.90
Turbidity	0.58	4.27	0.71	4.46	0.46	2.82
Stain	2.48	2.19	1.88	4.84	1.94	1.72

Table 6. Preference Space   Result goodness-of-fit for the Influence Model (Full).

Attribute	R Square %
Odour	100
Taste	100
Turbidity	100
Stain	100

Table 7 Preference Space Result estimates of the regression coefficient, a, for the Influence Model (S).

Attribute	Women	Men	
	a^w	a^m	|t-value|
Odour	fixed to 1	1.34	1.89
Taste	fixed to 1	0.47	1.69
Turbidity	fixed to 1	0.81	2.43
Stain	fixed to 1	0.42	2.34

Table 8 Preference Space The reduced form of the Influence Model (S).

	Women		Men		Joint	
Means	μ	|t-value|	μ	|t-value|	μ	|t-value|
Odour	1.07	8.22	0.94	6.64	1.23	7.59
Taste	0.26	2.08	0.25	1.95	0.39	2.39
Turbidity	1.07	7.68	0.97	7.36	1.48	8.91
Stain	-4.70	5.24	-3.39	5.35	-5.23	4.85
Cost	-0.05	3.35	-0.07	5.29	-0.04	3.68
Status Quo	0.15	0.59	0.45	2.37	0.63	3.29
Dispersions	σ	|t-value|	σ	|t-value|	σ	|t-value|
Odour	0.52	4.45	0.75	5.20	0.37	2.72
Taste	0.50	3.70	0.43	2.47	0.65	4.46
Turbidity	0.63	5.06	0.64	4.13	0.61	4.26
Stain	3.08	5.28	2.04	4.01	2.83	3.67

Table 9. Preference Space Summary of constrained model statistics.

Model	Number of Parameters	Log Likelihood	BIC	AIC	AIC3
Women Influence Only	30	-1214.52	2581	2489	2519
Men Influence Only	30	-1227.23	2607	2514	2544

Table 10. WTP Space Summary of model statistics, (cf Table 4).

Model	Number of Parameters	Log Likelihood	BIC	AIC	AIC3
Influence (S)	39	-1095.13	2388	2268	2307

Table 11. WTP Space Estimates of the regression coefficient, *a*, for the Influence Model (S) , (cf Table 7).

Attribute	Women		Men	
	a^w	|*t*-value|	a^m	|*t*-value|
Odour	fix to 1		1.55	1.88
Taste	fix to 1		0.24	0.57
Turbidity	fix to 1		1.05	1.68
Stain	fix to 1		0.75	1.73
Lambda	0.61	4.51	0.37	3.39

Table 12. WTP Space Result estimates of the normal distribution parameters for ln(λ) in the Influence Model (S).

	Women		Men		δ Joint		Total Joint
ln(λ)	Estimate	|*t*-value|	Estimate	|*t*-value|	Estimate	|*t*-value|	
μ	-2.76	5.45	-2.01	6.29	-0.76	0.89	-3.20
σ	1.70	6.14	1.92	5.60	0.20	0.99	1.28

Table 13. WTP Space Result estimates of the other parameters for the Influence Model (S), (cf Table 8).

Means	Women		Men		Joint	
	μ	|*t*-value|	μ	|*t*-value|	μ	|*t*-value|
Odour	28.81	2.10	19.92	6.10	59.36	2.00
Taste	4.31	1.24	4.38	2.30	10.62	1.02
Turbidity	29.60	2.56	22.31	6.44	67.03	1.89
Stain	-155.28	1.80	-112.36	4.54	-279.13	1.43
Cost	fixed to -1		fixed to -1		fixed to -1	
Status Quo	18.13	1.27	12.09	2.99	50.76	1.48
Dispersions	σ	|*t*-value|	σ	|*t*-value|	σ	|*t*-value|
Odour	10.58	2.37	16.49	4.67	17.15	1.55
Taste	10.78	2.43	6.12	4.61	19.43	1.71
Turbidity	13.68	2.14	12.59	7.09	22.16	1.36
Stain	101.68	1.69	55.93	4.25	115.25	1.70

Figure 1 Probability density function for λ

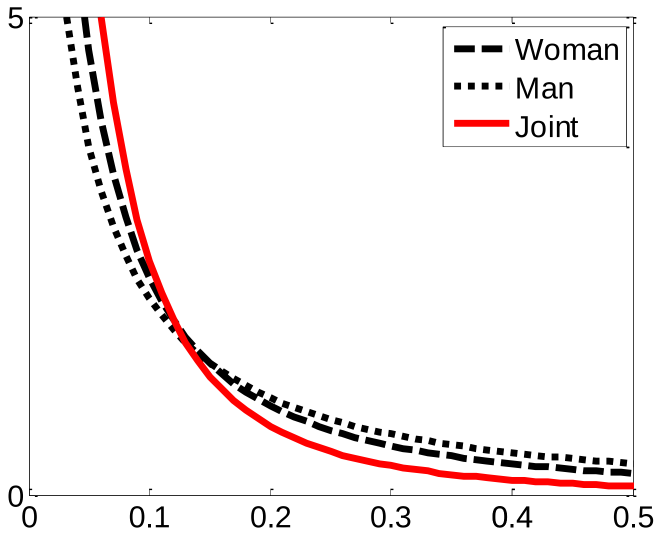

Table 14. WTP Space Distributions of pooled willingness to pay (the product of λ and the various forms of β).

	First Quartile			Median			Third Quartile		
	Women	Men	Joint	Women	Men	Joint	Women	Men	Joint
Odour	0.51	0.29	0.74	1.67	1.78	2.08	5.45	8.24	5.48
Taste	-0.09	0.00	-0.06	0.12	0.29	0.26	0.86	1.78	1.12
Turbidity	0.47	0.56	0.90	1.63	2.43	2.41	5.49	9.90	6.20
Stain	-27.97	-50.43	-25.85	-7.67	-12.79	-9.93	-1.84	-3.10	-3.59

Table 15 WTP Space Pooled willingness to pay correlations - women and men with joint.

	Women	Men
Odour	0.56	0.27
Taste	0.61	0.10
Turbidity	0.59	0.25
Stain	0.52	0.24