Determining the change in welfare estimates from introducing measurement error in non-linear choice models

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Abstract

Observed and unobserved characteristics of an individual are often used by researchers to explain choices over the provision of environmental goods. One means for identifying what is typically an unobserved characteristic, such as an attitude, is through some data reduction technique, such as factor analysis. However, the resultant variable represents the true attitude with measurement error, and hence, when included into a non-linear choice model, introduces bias in the model. There are well established methods to overcome this issue, which are seldom implemented. In an application to preferences over two water source alternatives for Perth in Western Australia, we use structural equation modeling within a discrete choice model to determine whether welfare measures are significantly impacted by ignoring measurement error in latent attitudes, and the advantage to policy makers from understanding what drives certain attitudes.

Keywords: contingent valuation; attitudes; structural equation modeling; recycled water

1 Introduction

A key consideration in utilising attitudes in behavioural analysis is that they are unobservable, or latent, and can only be inferred from other data[1]. For example, an individual's attitude towards the environment may be revealed by their membership of an environmental organisation. However, any one measure may not entirely capture the attitude, and typically attitudes are measured using a number of indicator variables. As such these latent variables are measured with error.

The term 'measurement error' refers to one of two types of error: error in the raw data or error in capturing a latent variable (Wansbeek and Meijer, 2000). The former refers to,

[1] The integration of the economic choice literature and the psychology literature on attitudes leads to some replication in the concept of 'latent' variables. Utility itself is usually treated as an unobserved latent variable in any model of choice, while latent variables in the psychology literature usually represent some attitude or behavioural construct that is revealed through secondary responses. Strictly, both are latent variables, existing within some posited hierarchical structure. The term 'latent' in this thesis is used to describe the underlying behavioural constructs, while recognising utility as a specific latent variable of particular significance in the choice decision.

for example respondents overstating their income or errors in the data collection technique used. The latter, which is the focus of this paper, is where observed variables are used as a proxy for the unobservable latent and hence may not entirely capture its true value (Wansbeek and Meijer, 2000; Greene, 1997). Including variables measured with error in non-linear choice models is a recognised issue in the econometrics literature (Everitt 1984; Greene 1997; Wansbeek and Meijer 2000). As identified by Train et al. (1987), the problem is that by not accounting for the uncertainty in the measure of the latent (which is induced through its measurement via multiple items), parameter bias is introduced into subsequent non-linear models that employ the variable.

A literature review reveals a small number of studies that have investigated the sensitivity of estimates to using latent variables with varying levels of measurement error. However, all have restricted their analysis to identifying bias in model parameter estimates (Carroll et al. 1984; Morikawa et al. 2002; Rabe-Hesketh, Skrondal and Pickles 2003). For example, Morikawa et al. (2002) compared two approaches for including latent attitudes in a travel mode choice model: sequential inclusion of fitted values generated in LISREL and simultaneous estimation of latents via full information maximum likelihood[2]. First, they found that including the latent attitudes into the choice model significantly improved its goodness of fit. Second, whilst the parameter estimates in the choice model were similar, the simultaneous estimation process produced more efficient estimates. A somewhat more comprehensive analysis by Rabe-Hesketh et al. (2003) examines the sensitivity of parameter estimates to variation in the measurement error variance within a particular latent variable. They show that as the measurement error variance within a latent variable increases, the parameter estimate is biased in a continuous fashion.

With the increasing use of psychology theories to explain preferences over bundles of public goods, and their reliance on proxy variables to measure underlying latents, it is likely that the use of biased parameters to estimate welfare values is prevalent in the

[2] LISREL is a statistical package used to undertake structural equation modelling.

applied economics literature[3]. A review of several studies reveals that the common approach used by non-market valuation practitioners to incorporate latents within a non-linear choice model has been to treat them as if measured without error. For example, Cooper et al. (2004) use factor scores to incorporate various motivation measures towards the environment (i.e., human value and natural value) to explain choices over a set of environmental goods. In a comprehensive search of the environmental valuation literature, the authors found several studies that use attitudes to explain choices (Kotchen and Reiling, 2000; Bateman et al., 2006; Milon and Scrogin, 2006; Kotchen and Moore, 2007; van den Bergh, 2008; Spash et al., 2009; Cai et al., 2010) however none that specifically account for measurement error in the attitudinal variables included in the discrete choice models.

Perhaps a reason for this is that a significant shortfall in the existing literature is that the affect of error measured variables on welfare estimates, which economists are most interested in, is not quantified. This paper extends previous analyses by investigating the effect of measurement error on welfare estimates. The issue is addressed by comparing two approaches to including the latent variables within the discrete choice model: factor scores, generated via a factor analysis, and structural equation modelling (SEM). The merits of both are explored and the welfare estimates derived from each approach are compared.

2 An approach to account for measurement error

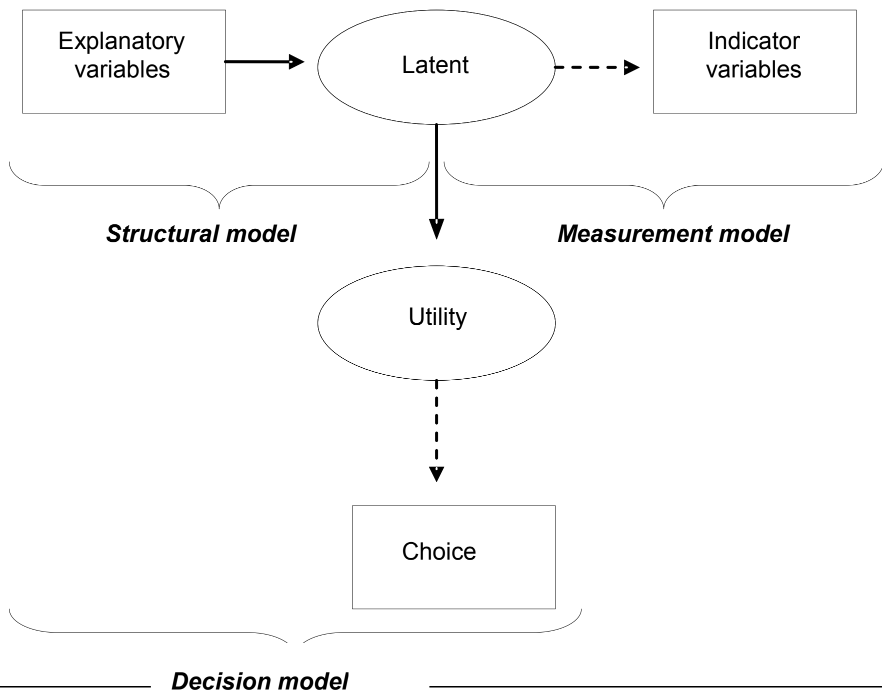
One approach to account for measurement error in latent variables is to estimate them simultaneously with the choice model, using structural equation models. Structural equation modelling (SEM) refers to a set of statistical models that seek to explain relationships among multiple variables. The key advantages of the SEM approach, with respect to estimating latents, is identified by Hair et al. (2006) as the ability to: (1) estimate multiple and interrelated dependence relationships; (2) represent unobserved concepts in these relationships and account for measurement error in the estimation

[3] Attitudes are a hypothetical construct which represent an individual's objective evaluation of an event, a person, a 'thing' or place, generally referred to as the attitude object.

process; and (3) define a model that explains the entire set of relationships in the available data.

A framework for using SEM within an economic choice model, is depicted in Figure 1. The latent attitude is treated as endogenous, and measured by indicators through a 'measurement' model. One can also model the determinants of an attitude, by specifying an effect of an explanatory variable on the latent variable(s) through a structural model. The latent and additional explanatory variables are then used to explain the observed choice, denoted as the decision model. The measurement and structural models specified for each latent, and the decision are all estimated simultaneously. In principle this integrated model structure is generic: the decision model may apply to revealed or stated preferences, and the latter may accommodate any form of choice format. Similarly, a number of alternative specifications could be employed to describe the measurement model.

Figure 1 Integrated latent variable and choice model.



Note: Figure adapted from Ben-Akiva et al. (1999, p.195)

For the purposes of maintaining consistency in the following theoretical explanation, a latent is defined as an unobservable construct (which could be an attitude) that is measured by indicators (which could be responses to survey questions), and a covariate is an observed variable (which could be a socio-demographic characteristic). For the purposes of this section, the decision model is generic and specified as:

$$P(Z = 1) = f(\eta_j, x), \tag{1}$$

where the observed choice, Z, is a function of a set of latent variables, η_j, and observed variables, x.

Following Muthèn and Sattora (1995), the outline of the SEM approach for simultaneous estimation of the latent variables, η_j, with the decision model of equation (1) is given below. For the structural model, a set of linear structural relations for j groups of observed units are specified for the m-dimensional latent variable vector η regressed on a q-dimensional observed variable vector x such that:

$$\eta_j = \alpha + B\eta_j + Kx_{1j} + \zeta_j, \tag{2}$$

where α is an m-dimensional vector of intercept parameters, B is an $m \times m$ matrix of regression slope parameters, K is a $m \times q$ matrix of regression slopes, and ζ_j is a m-dimensional vector of residuals. The latent is assumed to follow a normal distribution but no distributional assumptions are made about x_j. The estimation of the latent is augmented by the measurement model for a given latent j:

$$y_{ji} = \upsilon + \Lambda\eta_j + \varepsilon_j, \tag{3}$$

where y_{ji} is a vector of observed responses (of dimension p) to the set of indicator variables appropriate to j, υ is a p-dimensional parameter vector of intercepts, Λ is a p-parameter matrix of coefficients (loadings) for regressions of the indicator variables on the latent variable in the structural relations, and ε_j is a p-dimensional vector of random residuals (measurement errors).

Often, the observed responses to indicator variables generated by the underlying latent are often restricted to a small number of categories with nonequidistant steps i.e., rating scales. By assuming a continuous distribution there is potential for a critical mismatch between the assumptions underlying the statistical model and the empirical characteristics of the data to be analysed. This mismatch between theoretical assumptions and the empirical characteristics of the data has potentially serious consequences for the validity of the conclusions drawn from the analysis (Muthèn 1983; Flora and Curran 2004). In this case the measurement model is supplemented by a threshold model, which relates each observed categorical response y_{ji} to a latent continuous response y^*_{ji}, and it is assumed that the latter is determined by equation 3 It is assumed that:

$$
y_{ji} = \begin{cases} 0\ if - \infty < y^* \leq \kappa_1 \\ 1\ if\ \kappa_{1i} < y^* \leq \kappa_2 \\ \vdots\ \vdots \qquad \vdots \\ S\ if\ \kappa_{Si} < y^* \leq \infty \end{cases} \tag{4}
$$

where the number of thresholds is equal to S-1.

In structural equation models large numbers of variables make identification a fundamental consideration for model estimation. The restrictions required are model specific and likely to depend on the software package used for estimation and the properties of the hypothesised model.

Despite numerous studies which have employed attitudes to explain preferences over environmental goods, all have preferred to use factor scores as the means for incorporating the attitudes in a two-step process, rather than the simultaneous estimation of the decision model and the latents, which can be done using SEM. However there are some examples in the travel choice literature where unobservable constructs, such as ride comfort and convenience, have been included into the travel choice model by using SEM (Morikawa et al. 2002; Temme et al. 2008).

Key to the uptake SEM in the environmental valuation field is identifying the impediments and benefits to its use. The impediments to using SEM in an economic framework are thought to be twofold. First, the return on investment from increasing the complexity of the estimation model could be perceived by the practitioner as low, and contributing little to the interpretation of the results. However, Johansson-Stenman and Konow (2010) suggest that including, for example fairness judgments, is likely to lead to improved empirical predictive power, richer descriptive theories, and greater policy relevance. The second issue is that the effect of biased parameters on results from subsequent analyses is unquantified, and hence largely unconsidered by practitioners. Both issues will be addressed by this paper.

In addition to accounting for measurement error within the latents, the benefit from using SEM to estimate attitudinal variables lies in the flexibility of the structural model, which allows for relationships to be specified between a latent variable and observed, exogenous variables such as socio-demographic traits (i.e., simultaneously identifying the latent and explaining its variation among individuals). The literature provides some examples where relationships between demographic variables, such as gender and age, and attitudes are estimated. For example, Zelezny et al. (2000) conclude that females show more concern for the environment than men, and Torgler et al. (2010) find that older European citizens are more likely to hold higher levels of environmental morale for reduce littering in public places. Basically, identifying these additional relationships adds richness to the analysis, providing assistance in the communication of the results to policy makers.

3 Experiment

3.1 Case study

In a changing climate, securing drinking water supplies is a prominent issue for decision makers. In the capital city of Western Australia, Perth, the State government and water service provider, the Water Corporation, have developed a water source plan to secure the city's future drinking water needs. Perth already has one operational and one planned desalination facility; however the focus of the latest water source plan, Water Forever, is on a 60 percent increase in water recycling within the next 50 years (Water Corporation 2009). The most promising means available for achieving this improvement is via groundwater replenishment, which is the indirect use of recycled wastewater. However, the biggest impediment to the uptake of using recycled wastewater for human consumption is the acceptability of this water source by the local community. There are numerous examples of recycled wastewater schemes, particularity in Australia and the United Stated, that have failed to gain significant public acceptance and have hence never been implemented.

The basis for valuation studies is the acceptability of an innovation, contingent upon an alternative. In this study we seek to elicit preferences for a groundwater replenishment scheme, given the alternative is a second desalination plant. A brief description of both desalination and groundwater replenishment is provided below. It should be noted that both schemes use the same purification process, namely reverse osmosis, and both have the capability to provide the same amount of water into the drinking water supply: it is the source of feed water that differs.

Desalination is the removal of salt from water, by using a physical filter barrier to separate the salt ions from the water. The process can be used with a wide range of salt water concentrations of salt water, from which both potable water and water suitable for commercial and industrial applications can be produced. The desalination process has been used to generate substantial quantities of potable water in several countries, most notably Saudi Arabia (Water Corporation 2006).

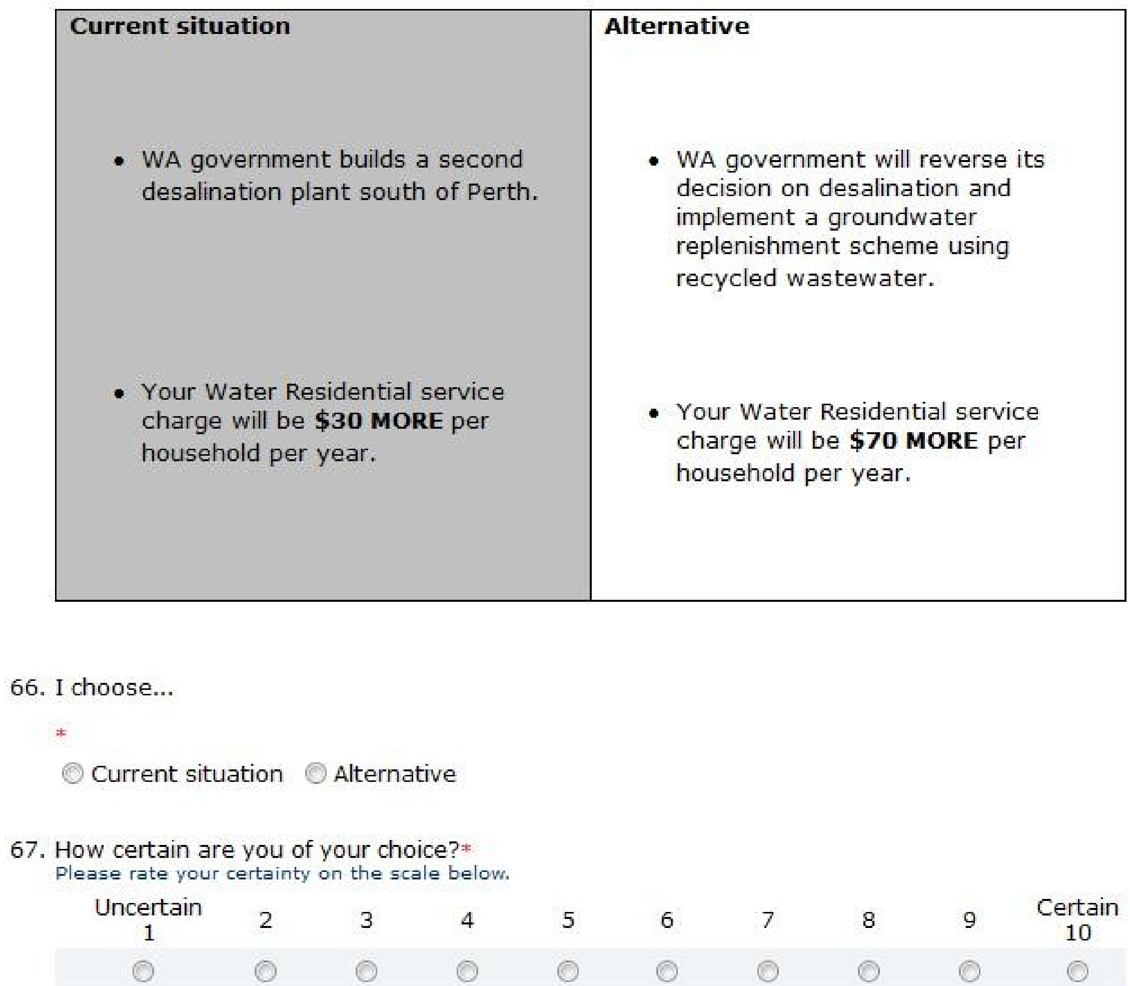
Groundwater replenishment describes the practice of using highly treated wastewater to augment surface water or groundwater sources. The most common source product for water recycling is sewage, and here the term 'recycled wastewater' will refer to recycling sewage. Sewage is an attractive input source for water recycling as there is a continuous supply of product that can be accessed relatively easily through established treatment plants (Toze 2006). Essentially the wastewater is treated through reverse osmosis, injected into an underground aquifer where it remains until extraction and more treatment before being used in the potable water supply.

The advantage of indirectly using recycled water through a groundwater system is that the retention time of the recycled wastewater in the groundwater supply means the probability of drawing out the recycled wastewater with any remnant chemical and pharmaceuticals is reduced. In addition, the time interval between injection and extraction imposes a safety buffer for the water provider in case of treatment failure or the detection of adverse environmental affects (Rodriguez et al. 2009). Until extraction, the recycled wastewater is used to service groundwater dependent environmental systems (such as wetlands) and mitigate saltwater intrusion into coastal aquifers (Water Corporation 2006).

3.2 Economic values

A multiple bounded dichotomous choice question format was used to elicit preferences for the water source option. However, to allow for clear comparisons between the two approaches to including attitudes in the discrete choice model, the complexity of the choice model is minimised by using only the first DC response for each individual in the analysis (i.e. treating the data as a single bound discrete choice). Each respondent was asked if they would be willing to pay (WTP) an amount or willing to accept (WTA) a reduction in their annual water service fee for the introduction of a groundwater replenishment scheme rather than a second desalination plant, which had at the time of the survey (September 2007) been recently approved by the State government. The payment vehicle used is the existing Water Residential service charge, which is an independent annual fee for the purposes of funding new water sources. The bid amounts offered ranged from $130 compensation to a $150 payment, in intervals of $30. An example of a CV question that requires respondents to pay is provided in Figure 2.At the time the survey was administered, a $30 increase in each households Water Residential service fee had been announced by the State Government to accommodate the cost of the second desalination, and hence this increase was reflected in the status quo option of all choice exercises. The six available bid offers (-$130, -$100, -$70, $70, $100, $130) were randomly assigned across the sample population.

Figure 2 An example payment offer presented to respondents.



Current situation	Alternative
• WA government builds a second desalination plant south of Perth. • Your Water Residential service charge will be **$30 MORE** per household per year.	• WA government will reverse its decision on desalination and implement a groundwater replenishment scheme using recycled wastewater. • Your Water Residential service charge will be **$70 MORE** per household per year.

66. I choose...

*

Current situation   Alternative

67. How certain are you of your choice?*

Please rate your certainty on the scale below.

Uncertain 1	2	3	4	5	6	7	8	9	Certain 10

3.3 Attitudinal variables

The general attitudes towards water resources and the environment, and specific attitudes towards each policy alternative, groundwater replenishment and desalination, were captured using Likert (Likert 1932) and Semantic differential (Osgood et al. 1957) scaled questions. The questions pertaining to each attitude were replicated from surveys by Porter et al. (2005) and Nancarrow et al. (2008). Each question is designed to capture some aspect of each attitude, and these questions have been extensively validated by these researchers. The general attitudes are termed *general trust*, *equity* and *environmental obligation*, and a description of each is provided in Table 1.

As the decision variable denotes a choice between two water schemes we use relative attitudes, which are a composite of the individuals attitude towards the groundwater replenishment scheme relative to their attitude towards the desalination scheme. As the questions used to generate the attitudes specific to each scheme are based on identically worded indicator questions, direct comparisons between scores on matching indicator questions can be made. The score for each *relative* indicator, for each relative attitude, is generated by subtracting the desalination attitude score from the GR scheme attitude score. For example, an individual that scored the fairness of the GR scheme as 5, highly fair, and scored the perceived fairness of the desalination scheme as 3, neutral, would be assigned a relative fairness score of 2. Since the scores on each indicator question are derived from five point scales, an individual can receive a score for each relative indicator that ranges from -4 to 4. The implication of this process is that any equivalent difference in indicators is treated as an equivalent relative indicator (i.e. 5-3 is equivalent to 3-1).

Table 1 Description of attitudes.

Variable	Interpretation
General trust	Positive scores mean more general trust Negative scores mean less general trust
Equity	Positive scores mean a positive equity attitude Negative scores mean a negative equity attitude
Environmental obligation	Positive scores mean greater environmental obligation Negative scores mean less environmental obligation
Relative emotion	Positive scores mean GR is perceived as less emotive than desalination Negative scores mean GR is perceived as more emotive than desalination
Relative fairness	Positive scores mean GR is perceived as more fair to various users than desalination Negative scores mean GR is perceived as less fair to various users than desalination
Relative benefits	Positive scores mean GR is perceived as more beneficial than desalination Negative scores mean GR is perceived as less beneficial than desalination
Relative perceived outcome	Positive scores mean GR is perceived to have more outcomes than desalination Negative scores mean GR is perceived to have less outcomes than desalination
Relative risk	Positive scores mean GR is perceived as more risky than desalination Negative scores mean GR is perceived as less risky than desalination
Relative trust in agencies	Positive scores mean agencies are trusted more to manage GR than desalination Negative scores mean agencies are trusted less to manage GR than desalination

The reliability of the latent construct refers to the consistency of measurement. In other words, the reliability is the degree to which the indicator questions explain the same underlying latent. The reliability measure essentially identifies the amount of random measurement error present within the latent construct, which will be important when considering the comparison of welfare estimates generated from each approach. The reliability measures calculated are Cronbach alpha and coefficient H. The formulas for coefficient H can be found in Hancock and Mueller (2001), and Cronbach alpha in Cronbach (1951). The key difference between the two measures is that for coefficient H, the reliability of the construct will always be larger than the reliability of a single indicator, meaning that the Cronbach alpha measurement results in a lower bound estimate of the true reliability. The Cronbach alpha and coefficient H estimates for each latent attitude are provided in Table 2.

Table 2 Code, number of indicators, Cronbach alpha and coefficient H estimates for each latent attitude.

Latent variable	Latent code	Number of indicators	Cronbach alpha	Coefficient H
General trust	1	4	.89	.92
Equity	2	3	.79	.85
Environmental obligation	3	3	.78	.79
Relative fairness	4	3	.92	.96
Relative emotion	5	4	.95	.98
Relative risk	6	4	.94	.98
Relative perceived outcomes	7	4	.93	.93
Relative benefits	8	4	.94	.96
Relative agency trust	9	3	.81	.82

3.4 Covariates

The covariates are observed measurable characteristics of the individual. Specifically, they pertain to the socio-demographic status, level of prior information, and the respondents experience with recycled wastewater. A description of each is given in Table 3.

Table 3 Description of observed individual characteristics.

Variable	Description	Coding
Tertiary	What is your highest level of education?	1= University, trade or technical qualification 0= Other
Male	What is your gender?	1= Male 0= Female
Income	Which category best describes your gross annual household income (before tax)?	22= Less than $22,000 36= $22,001 to $50,000 62.5= $50,001 to $75,000 87.5= $75,001 to $100,000 113.5= $100,001 to 125,000 125= Over $125,000
Age	Which category best describes your age?	24= Less than 24 years 31.5= 24 to 39 years 47.5= 40 to 50 years 61.5= 56 to 65 years 71.5= 66 to 75 years 75= Over 75 years
Information	Are you aware of any new water supply and management options that are happening to improve Perth drinking water?	1= Options listed 0= No options listed
No children	Which category best describes the number of children you have in your household?	1= No children 0= Children
Tap	When drinking water from your home, how is it primarily sourced?	1= Tap 0= Through a water filter or bottled water
Illness	Have you suffered from any illness caused by drinking poor quality water?	1= Yes 0= No/ don't' know
Country	Have you lived in another country where recycled wastewater was used for drinking?	1= Yes 0= No/ don't know
House	How is your property structured?	1= Detached house 0=Semi-detached; townhouse/ villa; unit/ flat

3.5 Survey implementation

A web-based survey was used to collect the response data. As the survey was administered via a web based panel, the survey was closed when the quota was filled, and a response rate is therefore not reported. In total, there were 470 useable responses collected. The sample was representative of the Perth population.

4 Econometric specification

4.1 Discrete choice model

The choice model defines the unobserved utility difference Z^* associated with the two alternatives offered, and a model for choice between desalination and recycled wastewater such that:

$$Z^* = \beta_1 A + \gamma x + \tau\eta + \epsilon, \tag{5}$$

$$Z = \begin{cases} 1\ if\ Z^* > T \\ 0\ otherwise, \end{cases} \tag{6}$$

where Z^* is the unobserved utility difference between the options being considered, Z is the observed choice outcome, x represents observed covariates, η represents unobserved latent variables, and γ and τ represent vectors of parameters. The intercept in the expression for the latent is constrained to equal zero, and a threshold, T, is freely estimated as Mplus adopts this normalisation. Note that T will be the negative of the intercept estimated in a conventional specification.

The error term ε follows a normal distribution that leads to a standard probit model of choice, such that:

$$P(Z = 1|\eta x) = \Phi(\eta, x, \beta), \tag{7}$$

where the vector of regressors for the latents η and covariates x are assumed to influence the outcome *Z*. The covariates are observed exogenous variables and the latents are normally distributed continuous variables.

4.2 The factor scores approach

Under the factor scores approach, the first step is to generate an estimate of the attitude score for each individual and each attitude. The attitudes are estimated via a reduced form of equation (2), such that each construct is simply assumed to be a random variable, ζ_j, with a particular distribution. Hence, the structural model is reduced to:

$$\eta_j = \alpha + \zeta_j, \tag{8}$$

where α is an m-dimensional vector of intercept parameters and ζ_j is a m-dimensional vector of residuals.

The measurement model and the threshold model are as specified in equation (3) and (4), respectively, and used simultaneously with equation (8) to estimate the latent distributions for each attitude and each individual.

The factor scores for each attitude and each individual can then be generated using a variety of methods. Mplus uses a posterior distribution approach (Muthèn and Muthèn 2007). Posterior distributions are generated for each parameter vector and each individual and the expected posterior distribution is the mean of these estimates.

The factor scores, generated for each individual, are included as variables along with other covariates in the decision model (equations 5, 6 and 7). In this study, possible relationships between attitudes and covariates and correlations between attitudes are not identified[4].

4.3 The SEM approach

To incorporate the attitudinal variables in this model (specified as η in equation 4) a reduced form of equation (2) is used. A set of linear structural relations for j groups of observed units are specified for the m-dimensional latent variable vector η regressed on a q-dimensional observed variable vector x such that:

$$\eta_j = \alpha + Kx_j + \zeta_j, \qquad \zeta_j \sim N(0, \varphi) \tag{9}$$

where α is an m-dimensional vector of intercept parameters, K is a $m \times q$ matrix of regression slopes, and ζ_j is a m-dimensional vector of residuals. A measurement model (equation 3) and threshold model (equation 4) is defined for each latent. The restrictions imposed in equations (3), (4) and (9) defined for each latent are to standardise $\upsilon = 0$ and $\alpha = 0$, whilst κ_i is freely estimated (i.e. the intercepts in the structural and measurement models are constrained, while all thresholds are allowed to vary) (Muthèn and Satorra 1995). The latents and the decision model (5-7) are then estimated simultaneously.

5 Results

5.1 Factor scores approach

The model is estimated in the statistical package Mplus (Muthèn and Muthèn 2007), and will be referred to as the *factor scores model*. As the attitudes are represented by discrete values in a single variable the integration points needed are tractable for maximum likelihood estimation of the β parameters. All the attitudes and covariates defined in

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[4] To incorporate these effects a third step would be required, whereby the factor score is interacted with the covariate, a second variable created and subsequently entered into the choice model. Given the focus is on determining the effect, on welfare estimates, of excluding measurement error in the latent this will not be undertaken here.

Tables 1 and 3 are tested in the model. The significant variables in explaining choice are reported in Table 4, and the McFadden R-square fit measure (reported at the end of Table 4) indicates that 62 percent of the variation in the data is explained by the model.

Table 4 Parameter estimates (Est.) and standard errors (S.E) from the factor scores model.

Discrete choice model			
Variable	Est.	(S.E)	P>|z|
Threshold	.230**	(.076)	.000
Relative fairness	.459**	(.076)	.000
Relative emotion	.229**	(.060)	.000
No children	.290*	(.148)	.050
Bid	-.007**	(.000)	.000
Model fit measure	Obtained value		
McFadden's R-square	0.62		

*Indicates significance at the 10 percent level; **Indicates significance at the 5 percent level; Log-Likelihood = -197

The bid variable has a negative sign, meaning that as the bid amount offered increased the respondent's acceptance of groundwater replenishment is likely to decrease. This finding conforms to expectation from economic theory, which stipulates that as the price of a good increases, its consumption will decrease. The threshold parameter, which is important for deriving subsequent welfare estimates, is significant.

5.2 SEM approach

All covariates and latents were tested within the model, which is estimated in Mplus (Muthèn and Muthèn 2007). The increasing dimensions of integration with the addition of each latent variable means maximum likelihood is not always possible for model estimation. There are nine attitudes that are potentially significant in explaining the choice between GR and desalination, hence, the model is estimated first by robust weighted least squares, which is recommended by Muthèn and Muthèn (2007) for models containing more than 3 latent variables. As only two attitudes are significant in explaining choice, relative fairness and relative emotion, the final model can be estimated using maximum likelihood.

Table 5 reports the results from the estimated model, which will henceforth be referred to as the *integrated model*. Whilst the model was estimated simultaneously, for the benefit of clarity the results are provided in three sections for each sub-model. The first section, the discrete choice sub-model, provides the parameter estimates and standard errors for the significant variables explaining the response to the CV question (specified in equations 5, 6 and 7). The second section, the structural sub-models, reports the significant relationships between the *covariates* and significant latents (specified in equation 9) and the *correlation structure* between the latents. Note that there are potentially two effects of a covariate: the direct effect of a covariate within the discrete choice model, and an indirect effect of the covariate within the structural model. However, for this data no variable is significant in both models. The third section, the measurement sub-model, reports the loading parameters for each indicator (specified in equation 3). The thresholds (specified in equation 4) provide no benefit to the interpretation of the results and hence are provided in appendix 1, Table A5.

The values for the fit measures are the standard measure recommended in the applied SEM literature, and they are reported at the end of Table 5. The Comparative Fit Index (CFI; Bentler 1990), Tucker Lewis Index (TLI; Tucker and Lewis 1973), and Root Mean Square Error of Approximation (RMSEA; Steiger and Lind 1980) all fall within the recommended ranges provided in Table 5. The Chi-square value complies with the recommended fit value, in that the fitted model's covariance structure is not significantly different from the observed covariance matrix, at the 5 percent level.

Table 5 Parameter estimates (Est.) and standard errors (S.E) from the integrated model.

Discrete choice sub-model

Variable	Est.	(S.E)
Threshold	.431**	(.094)
Relative fairness	.399**	(.080)
Relative emotion	.234**	(.062)
No children	.284*	(.150)
Bid	-.007**	(.001)

Structural sub-model	Relative fairness		Relative emotion	
Covariates	Est.	(S.E)	Est.	(S.E)
Tertiary	.563**	(.179)	.408*	(.211)
Age	-.014**	(.005)	-	-
Information	-	-	.354**	(.173)
Country	.310*	(.190)	-	-
Correlation structures	Est.	(S.E)	Est.	(S.E)
Emotion	2.905**	(.367)	-	-

Measurement sub-models

	Loadings			Loadings	
Fairness	Est.	(S.E)	Emotion	Est.	(S.E)
$y^*_{4,1}$	1.000	(fixed)	$y^*_{5,1}$	1.000	(fixed)
$y^*_{4,2}$	.856**	(.081)	$y^*_{5,2}$	.588**	(.052)
$y^*_{4,3}$	1.808**	(.300)	$y^*_{5,3}$	1.455**	(.182)
			$y^*_{5,4}$	1.037**	(.102)

Model Fit measures	Obtained value	Recommended value
Chi-Square	22.84 (15), p = .088	p > .05
CFI	.999	≥ .95
Tucker Lewis Index	.999	≥ .95
RMSEA	.033	≤ .05

*Indicates significance at the 10 percent level; **Indicates significance at the 5 percent level; Log-likelihood = -4343

5.3 Welfare estimates

Median welfare estimates, which are interpreted as the value at which 50% of the population are willing to pay, are generated both for a representative individual with sample-average characteristics, and for differing levels of a variety of characteristics. The equations for calculating the median welfare estimates using the parameter estimates from the factor score and integrated model are outlined below.

The probit response function is generally written as:

$$P(Z = 1) = \Phi(\alpha + \beta_1 A + \gamma x + \tau\eta), \tag{10}$$

where α is an intercept value, β_1 is the coefficient for the bid variable A, and γ and τ are parameter vectors for covariates x and latent variables η.

However, note that in Tables 4 and 5 a threshold, denoted below as T, is estimated in Mplus instead of an intercept.[5] To generate a median welfare estimate for the quantity of A such that there is a 50:50 chance of acceptance, the term in brackets in equation (10) has to equal zero, such that:

$$-T + \beta_1 A + \gamma x + \tau\eta = 0. \tag{11}$$

Hence, the median welfare estimate (denoted A^*) is found as:

$$A^* = \frac{T - \gamma x - \tau\eta}{\beta_1}, \tag{12}$$

where γ is a p-dimensional parameter coefficient vector for p covariates, x, τ is a m-dimensional parameter coefficient vector for the m latent variables represented by η, and β_1 is the coefficient on the bid parameter.

[5] The threshold is equivalent to (-ve) of the intercept value.

Table 6 Mean, standard deviation (S.D), minimum (min) and maximum values (max), and the 5th and 95th percentiles for latent and socio demographic variables that are significant in the factors scores and integrated models.

Variable	Mean	S.D	5%, 95%	Min, Max
Both models				
No children	0	(.50)	-	-.5, .5
Information	0	(.46)	-	-.7, .3
Tertiary	0	(.50)	-	-.56, .45
Country	0	(.34)	-	-.13, .87
Age	0	(12.77)	-	-25.36, 25.64
Factor scores model				
Relative fairness	0	(.85)	-1.39, 1.42	-2.68, 2.26
Relative emotion	0	(.88)	-1.51, 1.40	-2.59, 2.85
SEM model				
Relative fairness	0	(1.76)	-2.87, 2.87	-5.93, 4.83
Relative emotion	0	(2.11)	-3.69, 3.2	-6.87, 7.69

[1] The variables information, tertiary, country and age are used to calculate indirect effects on relative fairness and emotion through the structural models.

As the mean of each relative latent is zero by construction, and (for ease of derivation) all covariates are defined as mean deviations (see Table 6), under each approach the median welfare estimate for an individual with average characteristics reduces to:

$$\mathrm{A}^* = \frac{T}{\beta_1}. \tag{13}$$

It is also of interest to identify how changes in an individual's characteristics impact on the median welfare estimate. We do that by varying (in sequence) the level of the individual characteristics. The covariates are varied to their maximum and minimum values, and for the latent variables the 5% and 95% percentiles are used (see Table 6).

The median welfare estimate given changes in the covariates that are present in the decision model is calculated using:

$$\Delta A^* = \frac{-\gamma \Delta x}{\beta_1}, \tag{14}$$

The median welfare estimate given changes in the latents is calculated using:

$$\Delta A^* = \frac{-\tau \Delta \eta}{\beta_1}, \tag{15}$$

These welfare estimates are reported in Table 7, for both the integrated and factor score models. Apart from the characteristic under consideration, all other characteristics are held at sample average means.

To determine whether the welfare estimates differed significantly, Krinsky-Robb tests (Krinsky-Robb 1986) were used for the comparison between welfare estimates generated from each set of model parameters. The P-values, which denote the difference in welfare estimates generate from each approach, are reported in the last column of Table 7.

Table 7, Welfare estimates and standard errors (in parenthesis) derived from the integrated model and factor scores model, and the difference, in P-values, between the welfare estimates.

Status	Factor scores model	Integrated model	Difference
Direct effects on choice	Est. (S.E)	Est. (S.E)	P-value
Median	-62.22** (12.05)	-62.59** (14.07)	.502
Children	-89.95** (17.45)	-83.84** (18.67)	.389
No children	-41.49** (15.49)	-41.34** (17.24)	.493
Relatively unfair	-231.03** (40.10)	-235.43** (42.25)	.474
Relatively fair	110.22** (35.03)	110.25** (36.59)	.503
Relatively adverse emotion	-180.73** (37.06)	-183.92** (39.19)	.476
Relatively positive emotion	47.89 (31.35)	42.34 (31.55)	.451

*Indicates significance at the 10 percent level; **Indicates significance at the 5 percent level

Given that the covariates (exogenous respondent characteristics) have been used in the discrete choice and structural models, they potentially impact the welfare calculation at two levels: directly through the choice model and indirectly via their impact on the latent variables[6]. The vector of coefficients for the regressions of covariates on latents that is captured in the structural model (equation 9) is denoted by *K*. In other words, the change in the median welfare estimate is a combination of the effect of a unit change in covariates, *x*, in the choice model and/or the structural model. However, as no covariate is significant in both the discrete choice and structural models, we need consider only the impact of changes in covariates that influence the latent, calculated as:

$$\Delta A^* = \frac{-\tau_c K_c \Delta x_c}{\beta_1} \tag{16}$$

These welfare estimates, derived only for the integrated model, are reported and compared with the sample average mean welfare estimate in Table 8.

[6] If there were direct and indirect effects of *x*, the welfare estimate would be calculated as the sum of equation 13 and 15.

Table 8 Indirect effects of the covariates on choice as mediated through relative fairness and relative emotion.

	W_{SEM}	Difference to the median (P-value)
Median	-62.59**(14.07)	-
Indirect effects through relative fairness		
Has a tertiary education	-47.68** (14.47)	.219
No tertiary education	-81.57** (16.61)	.189
Age bracket 24 to 39 years	-47.41** (14.84)	.243
Age bracket 40 to 55 years	-61.29** (14.03)	.472
Age bracket 56 to 65 years	-72.56** (15.06)	.312
Age bracket 66 to 75 years	-81.24** (16.72)	.185
Has lived in a country with recycled wastewater	-45.33** (17.15)	.211
Has not lived in a country with recycled wastewater	-65.26** (14.29)	.451
Indirect effects through relative emotion		
Has a tertiary education	-57.16** (14.29)	.375
No tertiary education	-69.55** (14.99)	.350
Has prior knowledge	-59.45** (14.08)	.426
No prior knowledge	-69.91** (15.09)	.365

*Indicates significance at the 10 percent level; **Indicates significance at the 5 percent level

6 Discussion

6.1 Implications of measurement error

The few studies that have investigated the issue of including variables measured with error in non-linear models and provide evidence that the measurement error biases the parameter estimate. However no evidence is offered as to whether this bias is then transferred to subsequent estimates that are derived from the model parameters. Of particular issue is whether the partworths are influenced, given they are derived as the ratio of parameters.

The findings show that the welfare estimates generated from the factor scores and SEM approaches are near identical (Table 7), which is expected given all the parameter estimates in each model are similar. In considering the reason behind this result we refer back to Table 2, where the Cronbach alpha and coefficient H are provided as a reliability measure of each latent. Both measures can have values that range from 0 to 1, with values closer to 1 indicating a more reliably measured latent. The Cronbach alpha and coefficient H are 0.92 and 0.96 for relative fairness, and 0.95 and 0.98 for relative emotion. This means that for relative fairness more than 92 percent of the variation in the observed indicator responses is explained by the relative fairness attitude, and for relative emotion more than 95 percent of the variation in the observed indicator responses is explained by the relative emotion attitude. The remaining percentage of the observed variance is classed as random measurement error (Kline 2006). The general consensus within the SEM literature is that a Cronbach alpha of greater than 0.7 indicates a reliable latent construct (Hair et al. 2006) and this study confirms that where the reliability of a latent variable is greater than 0.92, the researcher can expect no significant bias in the model parameters and hence subsequent welfare estimates.

6.2 Policy relevant findings

The individual characteristics driving the tradeoff between schemes and welfare estimates for use by policy makers will now be discussed. The discussion is based on the results from the integrated model, as it is the most comprehensive.

Here, the sample average median estimate is $62, which compliments the only other study to investigate welfare values for a recycled wastewater scheme. Blamey et al. (1999) reported that on average, Canberra residents require $55 compensation per person to accept a drinking water supply scheme that would inject recycled wastewater into the potable water supply. However past studies have not investigated the influence of observed individual characteristics and psychological drivers on individual welfare values, and more generally the tradeoff between attitudes and efficiency for environmental policies has received limited attention in the literature. As indicated by the positive coefficient on relative fairness and relative emotion in both models, respondents who scored the groundwater replenishment scheme as fairer and/ or less adversely emotive than the desalination scheme were more likely to vote for it. Of the studies that have investigated recycled wastewater acceptance psychological repugnance (Bruvold and Ward 1972; Alhumoud et al. 2003; Nancarrow et al. 2008), perceived risk (Marks et al. 2008; Dolnicar and Schäfer 2008) and trust in institutions are consistently highlighted to be important factors in people's decision to accept recycled wastewater for human use. The fact that risk and trust attitudes are no longer important in choice may suggest that the introduction of an opportunity cost in this study has influenced which attitudes are now brought to bear. In addition, relative emotion is not as strong in influencing groundwater replenishment scheme acceptance as relative fairness. This is observed by comparing the welfare estimates generated for relative fairness and relative emotion, which are given under column three in Table 7. Respondents who reported high perceptions of scheme fairness, relative to desalination, are predicted to correspond to the majority of the community willing to pay for the groundwater replenishment scheme, by at least $110 per individual. In contrast, those who perceived the groundwater replenishment scheme as less adversely emotive, compared to the desalination scheme, were not willing to pay for it. This is an important finding and suggests that the perceived fairness of a recycled wastewater scheme to current and future community members, as well as the environment, can impact is acceptability.

The studies that have highlighted certain attitudes as significant impediments to recycled wastewater acceptability offer little guidance as to the population groups the policy maker can target to improve relevant attitudes to recycled wastewater rejection. The advantage of the current analysis is the simultaneous parameterisation of the latents through the structural models, which allows identification of approaches to mitigating emotive reactions to recycled wastewater. The welfare estimates from the indirect effects of covariates on relative fairness and relative emotion are presented in Table 8, along with measures of difference to the median sample average welfare estimate. Under the conventional approach taken in environmental stated preference studies this aspect could not be simultaneously accounted for[7].

There are no significant changes to the median welfare estimate given indirect changes in the covariates. However, some useful directions to policy makers as to what characteristics on an individual are likely to drive relative fairness and relative emotion. Respondents with a tertiary education, younger respondents and those who had lived in another country that uses recycled wastewater in the potable supply, were more likely to perceive the groundwater replenishment scheme as fair to all users, compared to the second desalination scheme. From the policy maker's perspective identifying experience as a contributing factor in high fairness perceptions is perhaps the most useful of these characteristics, as exposing the community to trial groundwater replenishment schemes is likely to prove fruitful. In fact, access to the site of a trialled localised groundwater replenishment scheme was recently made available to the Perth community.

Responses to relative emotion are likely to be less adverse, relative to the desalination scheme, if the respondent reported a higher level of information and a tertiary education. This finding suggests that by improving the amount of education provided to the community, specifically on future water source options, the emotive response to the groundwater replenishment scheme will improve.

Family structure, specifically respondents who do not have children, is likely to influence the acceptability of the GR scheme. A possible interpretation of this finding is that respondents with children are more concerned with the future outcomes of a recycled wastewater schemes. This result has received limited attention in the acceptance literature, and of the two studies which have investigated the effect of family structure on acceptance Po et al. (2005) found no relationship between family structure and intentions to drink recycled water (although it was noted that households with children under the age of eighteen were under represented in their sample) and Tziakis et al. (2009) found farmers with children wanted to pay less for recycled water.

[7] One could use regression analysis to investigate which observed characteristics explain attitudes, however we found no evidence of this additional step in the relevant literature.

7 Conclusion

The primary aim of this paper was to determine whether, first, the current practice for including attitudes into discrete choice models induces bias in subsequent welfare estimates, and second present a statistically sound and tractable method for incorporating attitudes into a choice model, which provides benefits in terms of added interpretation of the results.

In considering the issue of measurement error in non-linear model and the effect of this on subsequent estimates, the findings suggest that for latents which are measured extremely well (i.e., low residual measurement error) there is likely to be little or no effect on subsequent welfare estimates from moving to the SEM approach. Further research using data sets with varying levels of factor reliability is required to fully quantify these effects of parameter bias on subsequent welfare estimates.

Although measurement error is a non-issue in this particular case study, benefits and drawbacks from using SEM to incorporate attitudes into discrete choice models can be identified. From an efficiency viewpoint, SEM provides a more efficient estimation process as the generation of latents and specification of indirect effects through the structural model can be incorporated into a simultaneous estimation process. In this case study, where attitudes contribute a significant amount to explaining choice over water source schemes, understanding what drives them is especially useful for improving policy acceptance within the community.

From a practical viewpoint, the researcher must consider whether expending addition resources, in terms of software and time required to learn the technique, justify the efficiency gains. If the latent constructs generated are initially assessed as reliably measured, factor scores (and subsequent regression analysis of the covariates on each factor) may provide a more tractable approach without compromising the validity of the welfare estimates.

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Appendix 1

Table A5 Threshold parameter estimates (Est.) and standard errors (S.E) from the integrated model, reported in section 5.2, Table 5.

Measurement models	
Relative fairness	Est. (p-value)
$y^*_{4,1}$	-5.0**; -3.8**; -2.3**; -.9**; 1.5**; 2.9**; 5.1**
$y^*_{4,2}$	-4.7**; -4.4**; -2.9**; -1.7**; -.1; 1.0**; 2.1**; 3.0**
$y^*_{4,3}$	-8.1**; -6.2**; -4.0**; -2.1**; 1.2**; 3.1**; 5.1**; 7.2**
Relative emotion	Est. (p-value)
$y^*_{5,1}$	-5.4**; -3.7**; -1.9**; -.6**; 1.7**; 3.3**; 5.5**; 7.2**
$y^*_{5,2}$	-4.0**; -2.8**; -1.8**; -.8**; .7**; 1.8**; 2.9**; 3.8**
$y^*_{5,3}$	-7.5**; -5.3**; -2.8**; -.7**; 2.7**; 5.0**; 7.6**
$y^*_{5,4}$	-6.0**; -4.4**; -2.4**; -.8**; 1.9**; 4.3**; 6.0**; 7.5**

*Indicates significance at the 10 percent level; **Indicates significance at the 5 percent level.