Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment

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Aims: To compare different approaches to modelling the distribution of willingness to pay using stated preference data on Tanzanian Clinical Officers' job choices.

Methods: We use mixed logit models to estimate the distribution of willingness to pay (WTP) for various job attributes. In particular we compare the standard approach of specifying the distributions of the coefficients and deriving WTP as the ratio of two coefficients (estimation in preference space) to specifying the distributions for WTP directly at the estimation stage (estimation in WTP space). The latter approach has been found to produce more realistic WTP estimates in applications in other fields of economics but has to our knowledge not been applied before in the health economics literature.

Data: We use data from a discrete choice experiment on the choice of health service jobs among Tanzanian final-year students training to be Clinical Officers.

Results: When allowing for preference heterogeneity in terms of wages the willingness to pay estimates derived from the preference space models turn out to be unrealistically high for many of the job attributes while those estimated directly in WTP space are more realistic. The models in preference space fit the data better than the corresponding models in WTP space although the difference between the best fitting models in the two estimation regimes is minimal.

Conclusions: The results in this application suggest that sensitivity testing using a variety of model specifications, including estimation in WTP space, is recommended when using mixed logit models to estimate willingness to pay distributions.

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1. Introduction

Health economists have a long tradition of estimating measures of willingness to pay (WTP) for goods and services. Willingness to pay measures are considered useful for several reasons. First, they can directly inform policy makers by providing information about how much people value some goods or services and can thus inform the pricing of these goods or services (Hanley et al. 2003). Second, WTP measures can be important inputs in economic evaluations such as cost benefit analyses (Loomes 2001; Negrín et al. 2008; Oliver et al. 2002). Third, WTP measures can be a convenient tool to make relative comparisons and rankings of the desirability of goods and services.

It is possible to estimate WTP measures in many ways; for instance the researcher can ask respondents directly how much they are willing to pay for a certain service or good. However, there are problems with methods like or similar to this. Such questions are cognitively difficult to answer directly and respondents may have incentives to answer strategically (Arrow et al. 1993; Hanley et al. 2003). Alternatively, WTP measures can be derived from discrete choice models estimated using either revealed preference data or data from discrete choice experiments (DCEs). In these cases, the WTP for an alternative attribute can be calculated as the ratio of the attribute coefficient to the price coefficient (Train, 2003).

Mixed logit models are the state of the art tool applied in analysis of discrete choices and they are increasingly applied in health economics (Hall et al. 2006; Hole 2008; King et al. 2007; Lancsar et al. 2007; Negrín et al. 2008; Paterson et al. 2008; Regier et al. 2009). The mixed logit model makes it possible to account for heterogeneity in preferences which are unrelated to observed characteristics and it has been shown that any discrete choice random utility model can be approximated by an appropriately specified mixed logit model (McFadden & Train 2000). When estimating the mixed logit model the researcher specifies that the distribution of preferences follow a particular distribution, for instance a normal distribution. The parameters of this distribution, such as the mean and the standard deviation in the case of a normal distribution, are then estimated using either classical or Bayesian estimation techniques. Since the WTP for an attribute is given by the ratio of the attribute coefficient to the price coefficient, the WTP from a mixed logit model is given by the ratio of two randomly distributed terms. Depending on the choice of distributions for the coefficients this can lead to

WTP distributions which are heavily skewed and that may not even have defined moments. A common approach to dealing with this potential problem is to specify the price coefficient to be fixed. This is a convenient assumption as in this case the distribution of the willingness to pay for an attribute is simply the distribution of the attribute coefficient scaled by the fixed price coefficient. The problem is that it is often unreasonable to assume that all individuals have the same preferences for price (Meijer & Rouwendal 2006), so this approach implies an undesirable trade off between reality and modelling convenience. An alternative approach which allows the preferences for price to be heterogeneous is to specify that the price coefficient is log-normally distributed. This ensures that the WTP measures have defined moments since the price coefficient is constrained to be positive, but the resulting WTP distribution can be highly skewed which may produce unrealistic estimates of the means and standard deviations of WTP.

Train and Weeks (2005) suggest that a way to circumvent this problem is to estimate the mixed logit model in WTP space rather than in preference space. This involves estimating the distribution of willingness to pay directly by re-formulating the model in such a way that the coefficients represent the WTP measures. The researcher then makes a priori assumptions about the distributions of WTP rather than the attribute coefficients. This approach has been found to produce more realistic WTP estimates in applications in other fields of economics but has to our knowledge not been applied before in the health economics literature.

In this study we compare the preference and WTP space approaches to modelling the distribution of willingness to pay using stated preference data on Tanzanian Clinical Officers' job choices. We find that the results differ between the estimation regimes, suggesting that careful sensitivity testing is necessary when using mixed logit models to estimate willingness to pay distributions.

The paper is organised as follows. Section 2 provides a brief review of the use of mixed logit models to estimate willingness to pay in the health economics literature. Literature from other fields of economics where willingness to pay is estimated directly in WTP space is also discussed. Sections 3 and 4 present the methodology and the data applied in the study. Section 5 presents the results and section 6 offers some concluding remarks.

2. Literature review

2.1 The use of mixed logit models to estimate willingness to pay in the health economics literature

Although the mixed logit model is becoming increasingly popular in the field of health economics there are still relatively few health-related studies that have used mixed logit models to estimate willingness to pay measures. Among these studies the majority focus on the mean or median on the WTP distribution while other aspects such as the skew and spread of the distribution have received less attention. In the following we will present a brief review of these studies with a particular focus on how their findings relate to estimating WTP.

Paterson et al. (2008) study smokers' preferences for increased efficacy and other attributes of smoking cessation therapies. Using a mixed logit model they calculate willingness to pay for different treatments among groups of smokers. They find evidence of substantial preference heterogeneity and demonstrate that allowing for heterogeneity both improves the fit of the model and enhances our understanding of the smokers' preferences. The WTP for the non-monetary attributes calculated at the median of the coefficient distributions is reported.

Hole (2008) examines patients' preferences for the attributes of a general practitioner appointment using mixed and latent class logit models. Significant preference heterogeneity is found for all attributes including cost and the mixed and latent class logit models fit the data considerably better than the standard logit model. The WTP distributions are found to be right-skewed as the mean WTP is substantially higher than the median WTP.

King et al. (2007) analyse patients' preferences for managing asthma using mixed logit models with random intercepts. They find that the mixed logit models fit the data better than a standard logit and that a substantial amount of heterogeneity is unaccounted for by observable characteristics. The modelling results are used to derive willingness to pay measures but in this case the WTP estimates are fixed as only the constant terms are specified to be random.[1]

[1] The authors state that this is due to the relatively low sample size in their application.

Negrín et al. (2008) apply mixed logit models to analyse the willingness to pay for alternative policies for patients with Alzheimer's disease. All coefficients are specified to be normally distributed and both maximum simulated likelihood and hierarchical Bayes methods are used to estimate the models. The authors find that there is significant heterogeneity in the preferences for all the attributes including cost. The authors report WTP measures calculated at the means of the coefficient distributions.

Regier et al. (2009) analyse preferences regarding genetic testing for developmental delay using mixed logit models estimated using hierarchical Bayes and maximum simulated likelihood. WTP measures are derived from the coefficients in the estimated models and it is demonstrated that different distributional assumptions affect the WTP estimates. In particular it is noted that when the cost parameter is assumed to be log normally distributed some WTP estimates are found to be very high. The authors mention that estimation in WTP space may be an alternative approach but do not pursue that option in their paper.

2.2. Estimation of mixed logit models in WTP space

Train and Weeks (2005) show that WTP estimates can be estimated directly in a mixed logit model by re-formulating the model in such a way that the estimated parameters represent the parameters of the WTP distribution rather than the parameters of the usual coefficients. They call this estimation in WTP space as opposed to the conventional approach which they call estimation in preference space. The advantage of their approach is that the researcher specifies the WTP distribution directly and therefore avoids the rather arbitrary choice of WTP distribution that arises from dividing the coefficients of the non-monetary attributes by the cost coefficient.

The WTP space method is not yet widely used, probably partly because it has not been implemented in standard statistical software packages. It has been applied in a few studies, however, in particular within the disciplines of environmental economics and marketing (Balcombe et al. 2008; Balcombe et al. 2009; Scarpa et al. 2008; Sonnier et al. 2007; Train & Weeks 2005). Train and Weeks (2005) and Sonnier et al. (2007) use stated preference data on the choice of cars with different fuel systems and cameras to compare the performance of models in WTP space to models in preference space. Both studies use hierarchical Bayes to estimate the mixed logit models and their results are similar in that they find that the models in preference space fit the data better than the models estimated in WTP space. However, the models in WTP space were found to produce more realistic WTP measures. Scarpa et al. (2008) use revealed preference data on destination choices in the Alps to estimate models in preference and WTP space using both maximum simulated likelihood and hierarchical Bayes. In their application the model in WTP space both fits the data better and produces more realistic WTP estimates and the authors therefore conclude that there is not necessarily a trade off between goodness of fit and reasonable WTP estimates.

3. Methodology

The utility person *n* derives from choosing job *j* in choice situation *t* is specified as a function of the wage, w_{njt}, and other non-monetary attributes of the job, x_{njt}:

$$U_{njt} = \alpha_n w_{njt} + \beta_n' x_{njt} + \varepsilon_{njt} \qquad (1)$$

where α_n and β_n are individual-specific coefficients for the wage and the other attributes of the job and ε_{njt} is a random term. We assume that ε_{njt} is extreme value distributed with variance given by $\mu_n^2(\pi^2/6)$, where μ_n is an individual-specific scale parameter. Train and Weeks (2005) show that dividing equation (1) by μ_n does not affect behaviour and results in a new error term which is IID extreme value distributed with variance equal to $\pi^2/6$:

$$U_{njt} = \lambda_n w_{njt} + c_n' x_{njt} + \varepsilon_{njt} \qquad (2)$$

where $\lambda_n=\alpha_n/\mu_n$ and $c_n=\beta_n/\mu_n$.[2] Train and Weeks (2005) call this specification the model in preference space. By using the fact that WTP for the attributes is given by $\gamma_n=c_n/\lambda_n$ equation (2) can be re-written as:

$$U_{njt} = \lambda_n [w_{njt} + \gamma_n' x_{njt}] + \varepsilon_{njt} \qquad (3)$$

which is what Train and Weeks (2005) call the model in WTP space. Models (2) and (3) are of course behaviourally equivalent but the key thing to note is that standard assumptions regarding the distributions of λ_n and c_n in the preference space model can lead to unusual

[2] Strictly speaking we should introduce new notation for U_{njt} and ε_{njt} to show that these are now equal to U_{njt}/μ_n and ε_{njt}/μ_n but for the sake of readability we follow Train and Weeks (2005) here.

distributions for WTP. Assuming that λ_n and c_n are normally distributed, for example, implies that γ_n is a ratio of two normals which does not have defined moments. This is an unlikely choice of distribution for WTP if this was specified directly as we do in the WTP space model.

The coefficients in the preference space and WTP space models can be estimated by using maximum simulated likelihood or Bayesian methods (Train 2003). Contrary to most of the applications of the WTP space model in the literature we estimate the models using maximum simulated likelihood in the present paper.

4. Data

We use data from a discrete choice experiment on the choice of health service jobs among Tanzanian final-year students training to be Clinical Officers (COs). The aim of the experiment was to elicit the students' preferences for different features of health service jobs in order to advice Tanzanian policy makers on how rural jobs can be made more attractive to Tanzanian health workers (Kolstad 2008). Clinical Officers are health workers with the same length of education as nurses, but with a more clinical orientation. They are in reality often functioning as medical doctors, and this is in particular evident in the rural districts of Tanzania. However, the job preferences among this important group of health workers have not been given much attention earlier.

320 finalists (around 60% of all CO finalists in Tanzania in 2007) from 10 randomly selected schools participated in the DCE. All finalists in the selected schools were invited to participate and the data were mostly collected during school time, on the school premises. This largely explains the response rate of around 96%, which is unusually high for a DCE. After excluding incomplete responses and respondents from countries other than Tanzania we were left with an estimation sample of 296 respondents.

The attributes in the choice experiment were chosen following extensive literature searches and early in-depth interviews to identify the most important aspects of health service jobs. We used a D-optimal design based on the covariance matrix of a multinomial logit model with all the coefficients set equal to zero to construct the hypothetical choice situations. The result was a set of 32 choice situations that were randomly divided into two blocks. Each respondent was presented with 16 choice situations where each of these represented the choice between two hypothetical jobs. The jobs consisted of seven attributes which included the wage of the job, education prospects and other characteristics related to the location of the job and the facilities of the workplace. The attributes and the design of the DCE are described in more detail in (Kolstad 2008).

5. Results

5.1 Models in preference space

Table 1 shows the results for the models in preference space.[3] Model 1 is a simple logit model and model 2 is a mixed logit model with independent random coefficients for all the attributes except wage. These two models were included as benchmark specifications as they are both common in the DCE literature. Model 3 is equivalent to Model 2 except that it allows for preference heterogeneity in terms of wages and Model 4 also allows for non-zero correlations between the wage coefficient and the other coefficients and between the education coefficients. Given the high number of random coefficients in the model we decided that a model with a completely unrestricted correlation matrix would be too demanding to estimate and we therefore allow for non-zero correlations between the coefficients that to us seemed more likely to be correlated *a priori*[4]. In all the mixed logit models, the coefficients for wage, education, infrastructure and equipment are given a log-normal distribution[5], while the rest of the coefficients are normally distributed. We use 1000 Halton draws in the estimation of the mixed logit models with independent coefficients and 2500 Halton draws to estimate the model with correlated coefficients.[6]

In general the coefficients in the models in Table 1 have the expected signs and the estimates are fairly consistent across models in terms of signs and significance. All else equal the respondents prefer a job with higher wages and they prefer to have the possibility of further

[3] The mixed logit models in preference space are estimated in Stata using the *mixlogit* command (Hole, 2007). The models in WTP space are estimated using a modified version of this command. All models were estimated using alternative starting values to reduce the likelihood of the algorithm getting trapped in a local optimum.
[4] The selection of correlations was informed by evidence from interviews with a subset of the respondents.
[5] We report the parameters of the log-normal distribution rather than the underlying normal distribution, although the latter parameterisation was used at the estimation stage. The standard errors of the parameters are calculated using the delta method.
[6] We increased the number of draws in the estimation of the more complex model as this was needed to produce stable results.

education after 2, 4 and 6 years to no further education. They prefer a job where sufficient equipment is provided to one without sufficient equipment and a job which offers decent housing and infrastructure to one that does not. In terms of location the respondents prefer to work in a district headquarter to working in a regional headquarter or in a location which is a 3-hour (or longer) bus ride from the district headquarters. The least popular location is the capital, Dar es Salaam. This may seem surprising but there are several plausible explanations for this finding. Living costs are very high in Dar es Salaam compared even to other cities in Tanzania, but perhaps more importantly the likelihood of being in charge of a health facility and to be able to practice as a clinician is smaller in Dar es Salaam, where most of the "real" doctors are based. The coefficients for the workload attribute and for being located in a regional headquarter are insignificant in all the models.[7] The constant term is also found to be consistently insignificant, which is expected since a significant constant term would indicate a preference for job "A" over job "B" (or vice versa) net of the influence of the alternative attributes. Since no information is provided about the jobs apart from the attributes the constant term should theoretically be equal to zero. The constant is nevertheless often included in the model as a test for specification error and we follow that convention here.

The results in Table 1 show that there is a substantial amount of heterogeneity in the preferences for the various job attributes. In all the mixed logit models there is evidence of significant heterogeneity in the preferences for equipment, infrastructure, workload and education after 2 years of service. In addition Models 3 and 4 show significant heterogeneity in the preferences for working in Dar es Salaam and, importantly, in the preferences for the wage attribute. The latter finding implies that model 2 where the wage parameter is assumed to be fixed is too restrictive.

The correlations between the estimated coefficients in model 4 are reported in Table 2. It can be seen from the table the coefficients are in general quite highly correlated, in particular the education coefficients. This finding seems plausible as a person that value education after 4 years highly is also likely to value education after 2 years highly. The wage coefficient is also found to be highly correlated with the coefficients for education. For policy purposes, it is important to be aware of the possible implications of this finding; strong preferences for education do not necessarily reflect a genuine preference for knowledge and skills, but may

[7] See the discussion in Kolstad (2008) for some possible explanations of this finding.

indirectly capture preferences for higher salaries which are strongly related to higher education in Tanzania. The wage coefficient is also found to be positively correlated with the coefficient for improved infrastructure, while the coefficient for sufficient equipment is negatively correlated with the wage coefficient. This indicates that those who put a high weight on working at a facility with sufficient equipment and drugs are less concerned with high wages, suggesting that at least some of the COs are motivated by other factors than mere economic incentives.

We find that the goodness of fit increases with the flexibility of the model. Model 4, which allows the coefficients to be correlated fits the data better than Model 3 in which they are assumed to be independent. Models 3 and 4 both have considerably better fit than Model 2, which is another indication of the significant preference heterogeneity in terms of wages in the data. As expected the worst performing model is the standard logit which does not allow for any preference heterogeneity. This result is confirmed by all the applied information criteria: the log likelihood and the Akaike (AIC) and Swartz (BIC) criteria.

5.2 Willingness to pay in preference space

Table 3 shows the mean, median and standard deviation of the willingness to pay measures derived from Models 1-4.[8] The mean willingness to pay for education opportunities, decent infrastructure and a health facility with sufficient equipment is generally high. The respondents are willing to sacrifice the largest amount of their salary to have the opportunity to continue their education after 2 years of service. The ranking of these attributes varies somewhat between the models with independent coefficients (Models 1-3) and the model with correlated coefficients (Model 4). The main difference is that in the latter model education after 4 years is ranked higher than in the other models.

The means of the WTP measures derived from Models 1 and 2 are quite similar and substantially lower than those from Models 3 and 4 in which the wage coefficient is specified to be random. The mean willingness to pay for decent infrastructure, for instance, increases from 237.03 TSH per month in Model 2 to 465.913 TSH per month in Model 3. When

[8] These figures are calculated by using simulation. The simulated WTP distributions are obtained by dividing draws from the distributions of the non-monetary coefficients by draws from the distributions of the wage coefficient. 10,000 draws were used in the calculations.

bearing in mind that the starting salary for a public CO is just above 200.000 TSH per month the WTP values from Model 3 and 4 seem very high. The question is whether this increase in the mean WTP reflects the models' ability to capture preference heterogeneity in terms of wages or whether it is an artefact of the particular distribution we have chosen for WTP. It can be seen that the WTP distributions are highly skewed as the absolute value of the median is consistently much lower than the mean. The introduction of correlation between the coefficients decreases the means of the WTP measures somewhat, but their distributions are still highly skewed. The standard deviations of the WTP measures are also very large in models 3 and 4. Again this may simply reflect a high degree of preference heterogeneity but it may also be a result of our choice of distributions for the coefficients and hence WTP.

The correlations between the WTP measures derived from Models 3 and 4 are shown in Tables 4a and 4b. It can be seen from the tables that there is a high degree of correlation between the WTP measures. In particular, the WTP for provision of decent housing is positively correlated with WTP for education and for working in a district headquarter. The WTP for the different education levels are highly correlated with each other. The WTP for sufficient equipment is more highly correlated with the other WTP measures in model 4 than in model 3 while the other WTP measures are more highly correlated in model 3.

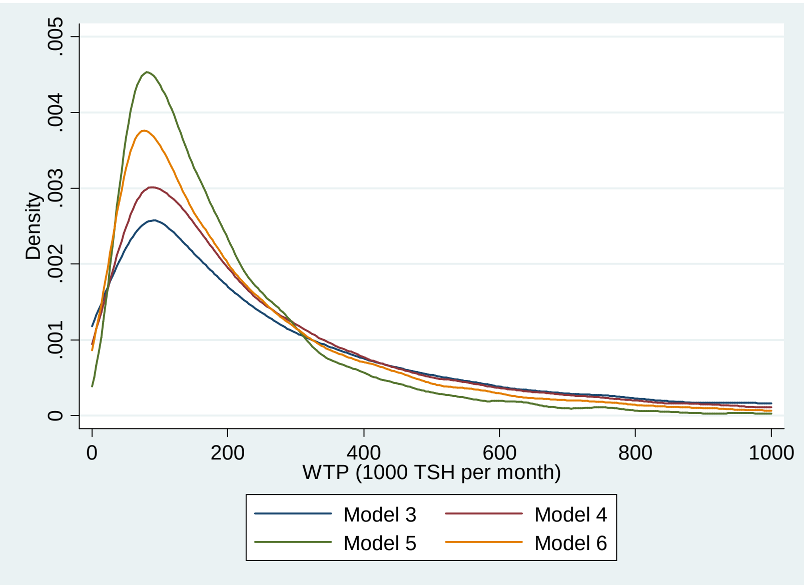
5.3 Models in WTP space

Table 5 presents the estimates from the models in WTP space. Models 5 and 6 in this table are analogous to models 3 and 4 in preference space in that all the attribute coefficients are assumed to be random but the coefficients in model 5 are independent while some of the coefficients in model 6 are allowed to be correlated. In particular, the non-monetary attributes are specified to be correlated with the wage coefficient and the coefficients for education after 2, 4 and 6 years are specified to be correlated with each other. As in the preference space models the coefficients for wage, education, infrastructure and equipment are given log-normal distributions, while the rest of the coefficients are normally distributed. In this case, however, the chosen distributions for the non-monetary attributes represent the distributions of WTP for these attributes. Both models are estimated using 2500 Halton draws.

It is evident from the table that the means of the WTP measures are much lower than those derived from the corresponding models from preference space. This is in line with the findings in Sonnier et al. (2007), Train and Weeks (2005) and Scarpa et al. (2008). It is also interesting to note that the means of the WTP measures in Models 5 and 6 are similar to those derived from the simplest models in preference space (Models 1 and 2).

The standard deviations of the WTP measures are generally high, indicating that there is a substantial amount of heterogeneity in the respondents' preferences, although the standard deviations are substantially smaller than in preference space. Similarly, the WTP distributions for the log-normally attributes are skewed as the means are much larger than the medians, but less so than the WTP distributions estimated in preference space. Figures 1 and 2 show the distribution of willingness to pay for improved infrastructure and education after 2 years derived from Models 3-6.[9] These figures demonstrate that the estimated WTP distributions from the WTP space models (Models 5 and 6) are more peaked than those from the preference space models which have very long tails.

Figure 1. Willingness to pay for improved infrastructure



It should also be noted that there evidence of significant heterogeneity in the WTP for housing and for education after 6 years of service in WTP space but not in preference space. This observation demonstrates the possibility of obtaining different qualitative results depending on the estimation regime. We also find some evidence of this when analysing the implied ranking of the means of the WTP distributions for the different attributes. The ranking differs

[9] These are kernel density plots based on 10,000 random draws from the coefficient distributions in the case of the preference space models (which are then divided by draws from the distribution of the cost coefficient to produce WTP) and WTP distributions in the case of the WTP space models.

between the preference space and WTP space models, although education after 2 years of service is the most highly ranked attribute according to all the models.

Figure 2. Willingness to pay for education after 2 years

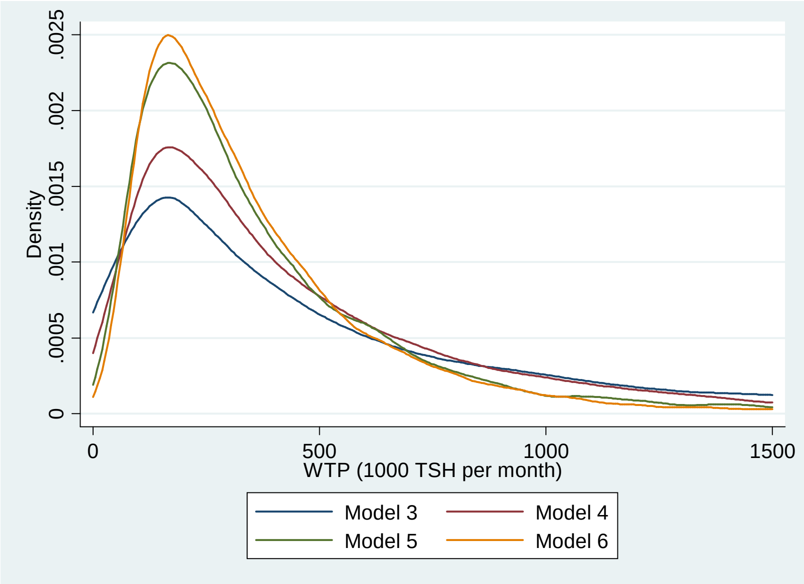


Table 6 shows the correlations between the WTP measures and the wage coefficient and the WTP for education derived from Model 6. It can be seen that the WTP for sufficient equipment is negatively correlated with the wage coefficient. This suggests that respondents who find the facilities of the workplace especially important are less concerned with higher wages which confirms our result in preference space. The consistent pattern of highly correlated willingness to pay for education is not found in WTP space, however. The WTP measures for education after 2 and 4 years are highly correlated, but education after 6 years is found to be negatively correlated with education after 2 and 4 years. This observation may be an indication that COs see education after 6 years as something qualitatively different from education after a shorter time of service.

By comparing Tables 1 and 5 it can be seen that the fit of the models in WTP space is not as good as that of the corresponding models in preference space. This is in line with Train and Weeks (2005) and Sonnier et al. (2007), while Scarpa et al. (2008) find that the WTP space model fits their data better. The result in the present application is not as clear-cut as it may seem at first glance, however. For all practical purposes the difference in goodness of fit between Model 4 and Model 6 is negligible according to all the applied information criteria. Regardless of the estimation regime there is a more substantial difference in fit between the models which allow the coefficients to be correlated (Models 4 and 6) and the models in which the coefficients are assumed to be independent (Models 3 and 5). It is also worth noting that both the models estimated in WTP space fit the data better than the preference space model with a fixed wage coefficient. These results imply that allowing for non-zero correlations between the coefficients and for heterogeneity in the preferences for the wage attribute affect the fit of the model more than whether the model is estimated in preference or WTP space.

6. Concluding remarks

Due to practical considerations it is common to specify the coefficient for the monetary attribute in choice models to be fixed. This specification represents a trade-off between realism and modelling convenience as it is often unrealistic to assume that all respondents have the same preferences regarding the price of a good or the wage of a job. Relaxing the assumption of preference homogeneity is not straightforward, however, as it may lead to implausible distributions for willingness to pay. In this paper we compare models estimated in preference and WTP space and find that the estimated willingness to pay distributions differ markedly in the two estimation regimes. When the preferences for wage are allowed to be heterogeneous the means of the WTP distributions estimated in preference space turn out to be unrealistically high for many of the attributes while those estimated directly in WTP space are more realistic.

The models in preference space fit the data in our study better than the corresponding models in WTP space, but this distinction is not clear-cut as the best fitting models in the two estimation regimes have very similar goodness of fit. Allowing for heterogeneity in the preferences for wages and allowing for non-zero correlations between the coefficients is found to affect the goodness of fit of the models more than whether the model is estimated in preference or WTP space.

Our results suggest that sensitivity testing using a variety of model specifications, including estimation in WTP space, is recommended when using mixed logit models to estimate willingness to pay distributions.

References

Arrow K, Solow R, Portney P, Leamer E, Radner R, Schumann H. 1993. Report of the NOAA panel of contingent valuation *Federal Register* 10:4601-14

Balcombe K, Bailey A, Chalak A, Fraser I. 2008. Modifying willingness to pay estimates where respondents mis-report their preferences. *Applied Economics Letters* 15:327 - 30

Balcombe K, Chalak A, Fraser I. 2009. Model selection for the mixed logit with Bayesian estimation. *Journal of Environmental Economics and Management* 57:226-37

Hall J, Fiebig DG, King MT, Hossain I, Louviere J. 2006. What influences participation in genetic carrier testing? Results from a discrete choice experiment. *Journal of Health Economics* 25:520-37

Hanley N, Ryan M, Wright R. 2003. Estimating the monetary value of health care: Lessons from environmental economics. *Health Economics* 12:3-16

Hole AR. 2008. Modelling heterogeneity in patients' preferences for the attributes of a general practitioner appointment. *Journal of Health Economics* 27:1078-94

King MT, Hall J, Lancsar E, Fiebig D, Hossain I, et al. 2007. Patient preferences for managing asthma: results from a discrete choice experiment. *Health Economics* 16:703-17

Kolstad JR. 2008. How to make rural jobs more attractive to health workers. Findings from a discrete choice experiment in Tanzania., Working paper 15/2008, Department of Economics, University of Bergen

Lancsar E, Hall J, King M, Kenny P, Louviere J. 2007. Patient preferences for managing asthma: Results from a discrete choice experiment. *Respirology* 12:127-36

Loomes G. 2001. The use of cost-effectiveness thresholds outside the health sector. In *Cost-effectiveness Thresholds: Economic and Ethical Issues*, ed. A Towse, C Pritchard, N Devlin. London: Office of Health Economics

McFadden D, Train K. 2000. Mixed MNL for discrete response. *Journal of Applied Econometrics* 15:447-70

Meijer E, Rouwendal J. 2006. Measuring Welfare Effects in Models with Random Coefficients. *Journal of Applied Econometrics* 21:227-44

Negrín MA, Pinilla J, León CJ. 2008. Willingness to pay for alternative policies for patients with Alzheimer's Disease. *Health Economics, Policy and Law* 3:257-75

Oliver A, Healey A, Donaldson C. 2002. Choosing the method to match the perspective: economic assessment and its implications for health-services efficiency *Lancet* 359:1771-4

Paterson RW, Boyle KJ, Parmeter CF, Neumann JE, Civita Pd. 2008. Heterogeneity in preferences for smoking cessation. *Health Economics* 17:1363-77

Regier DA, Ryan M, Phimister E, Marra CA. 2009. Bayesian and classical estimation of mixed logit: An application to genetic testing. *Journal of Health Economics 28:598-610*

Scarpa R, Thiene M, Train K. 2008. Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps. *American Journal of Agricultural Economics* 90:94-1010

Sonnier G, Ainslie A, Otter T. 2007. Heterogeneity distributions of willingness-to-pay in choice models. *Quantitative Marketing Economics* 5:313-31

Train KE. 2003. *Discrete Choice Methods with Simulation*: Cambridge University Press

Train KE, Weeks M. 2005. Discrete choice models in preference space and willingness-to-pay space. In *Application of simulation methods in environmental and resource economics*, ed. R Scarpa, A Alberini, pp. 1-16. Dordrecht: Springer

Table 1: Results from models in preference space

	Model 1	Model 2	Model 3	Model 4
Mean				
District headquarter (ref. 3 miles+ from district HQ)	.216***	.239***	.229***	.182**
	(.0701)	(.0795)	(.0838)	(.0883)
Regional headquarter (ref. 3 miles+ from district HQ)	.021	.002	.021	.034
	(.0650)	(.0724)	(.0774)	(.0807)
Dar es Salaam (ref. 3 miles+ from district HQ)	-.308***	-.369***	-.375***	-.355***
	(.0771)	(.0880)	(.0982)	(.1067)
Decent housing offered (ref. no house provided)	.216***	.250***	.275***	.348***
	(.0493)	(.0582)	(.0627)	(.0716)
Normal workload (ref. heavy workload)	-.063	-.072	-.028	.062
	(.0482)	(.0564)	(.0623)	(.0707)
Sufficient equipment (ref. insufficient equipment)	.413***	.561***	.603***	.651***
	(.0433)	(.0835)	(.0889)	(.0889)
Decent infrastructure (ref. poor infrastructure)	.716***	.891***	1.016***	1.182***
	(.0381)	(.0675)	(.0820)	(.1062)
Education after 6 years of service (ref. no education)	.354***	.383***	.447***	.594***
	(.0931)	(.1067)	(.1149)	(.1490)
Education after 4 years of service (ref. no education)	.707***	.817***	.956***	1.308***
	(.0747)	(.0889)	(.0947)	(.1540)
Education after 2 years of service (ref. no education)	1.149***	1.588***	1.884***	2.703***
	(.0687)	(.1458)	(.1735)	(.3395)
Wage	.003***	.004***	.005***	.008***
	(.0002)	(.0002)	(.0005)	(.0008)
Constant	-.017	.002	-.019	-.027
	(.0398)	(.0457)	(.0487)	(.0508)
SD				
District headquarter (ref. 3 miles+ from district HQ)		.005	.011	.101
		(.1676)	(.1941)	(.1727)
Regional headquarter (ref. 3 miles+ from district HQ)		.010	.053	.010
		(.1748)	(.2801)	(.2618)
Dar es Salaam (ref. 3 miles+ from district HQ)		.190	.466***	.552***
		(.2906)	(.1764)	(.1736)
Decent housing offered (ref. no house provided)		.012	.0685	.223
		(.2421)	(.2743)	(.1657)
Normal workload (ref. heavy workload)		.321***	.295**	.397***
		(.1147)	(.1432)	(.1234)
Sufficient equipment (ref. insufficient equipment)		1.135**	1.125***	1.046***
		(.4459)	(.4097)	(.3580)
Decent infrastructure (ref. poor infrastructure)		.809***	.905***	1.161***
		(.1383)	(.1760)	(.2282)
Education after 6 years of service (ref. no education)		.169	.264	.382
		(.2693)	(.1922)	(.2814)
Education after 4 years of service (ref. no education)		.371*	.314	1.393***
		(.1983)	(.2300)	(.3421)
Education after 2 years of service (ref. no education)		1.491***	1.753***	4.040***
		(.3714)	(.4078)	(1.081)
Wage			.006***	.011***
			(.0013)	(.0024)
Log Likelihood	-2424.2108	-2335.4964	-2266.7905	-2226.2604
AIC	4872.422	4714.993	4579.581	4498.521
BIC	4949.811	4856.874	4727.911	4646.851

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

Table 2: Correlation between coefficients in preference space

	Wage	Education after 6 years of service	Education after 4 years of service	Education after 2 years of service	District headquarter	Regional headquarter	Dar es Salaam	Decent housing offered	Normal workload	Sufficient equipment	Decent infrastructure
Wage	1	.700***	.415***	.605***	.250**	-0.118	0.057	.242*	.235**	-.255**	.433***
Education after 6 years of service		1	.393**	.689***							
Education after 4 years of service			1	.935***							
Education after 2 years of service				1							

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

Table 6: Correlation between coefficients in WTP space

	Wage	Education after 6 years of service	Education after 4 years of service	Education after 2 years of service	District headquarter	Regional headquarter	Dar es Salaam	Decent housing offered	Normal workload	Sufficient equipment	Decent infrastructure
Wage	1	.005	-.057	-.003	-.268	-.054	.255**	-.073	.403***	-.534***	-.565***
Education after 6 years of service		1	-.593***	-.613***							
Education after 4 years of service			1	.914***							
Education after 2 years of service				1							

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 3: WTP in preference space (1000 TSH per month)

	Model 1	Model 2	Model 3	Model 4
District headquarter				
Mean	67.16	63.053	104.062	66.56
Median		63.053	67.07	36.95
SD		1.216	123.893	106.02
Regional headquarter				
Mean	6.566	.62	9.834	15.42
Median		.62	4.58	7.94
SD		2.801	40.4627	26.20
Dar es Salaam				
Mean	-95.637	-97.731	-168.846	-173.55
Median		-97.731	-84.66	-60.47
SD		50.309	378.809	556.80
Decent housing offered				
Mean	67.171	65.736	125.001	123.40
Median		65.736	78.85	67.18
SD		3.040	155.511	229.21
Normal workload				
Mean	-19.506	-19.318	-12.880	-21.38
Median		-19.318	-6.27	7.87
SD		85.873	211.807	332.56
Sufficient equipment				
Mean	128.145	149.165	276.982	376.82
Median		67.34	87.59	81.25
SD		283.689	802.445	1320.67
Decent infrastructure				
Mean	222.369	237.03	465.913	353.03
Median		175.47	224.12	201.22
SD		214.534	795.362	535.30
Education after 6 years of service				
Mean	110.021	100.842	202.336	161.45
Median		92.05	114.05	117.87
SD		45.374	312.782	151.59
Education after 4 years of service				
Mean	219.547	215.842	438.931	378.87
Median		195.61	266.07	215.23
SD		98.171	599.306	553.84
Education after 2 years of service				
Mean	356.758	415.804	849.356	561.64
Median		302.06	403.59	356.27
SD		391.905	1498.37	681.22

Table 4a: Correlation between WTP derived from models in preference space with uncorrelated coefficients.

	Education after 6 years of service	Education after 4 years of service	Education after 2 years of service	District headquarter	Regional headquarter	Dar es Salaam	Decent housing offered	Normal workload	Sufficient equipment	Decent infrastructure
Education after 6 years of service	1									
Education after 4 years of service	.7073	1								
Education after 2 years of service	.5261	.6109	1							
District headquarter	.7700	.9187	.6534	1						
Regional headquarter	.1774	.2498	.2239	.2766	1					
Dar es Salaam	-.4208	-.4883	-.3373	-.5348	-.1477	1				
Decent housing offered	.7103	.8733	.6136	.9444	.2925	-.5034	1			
Normal workload	.0305	-.0092	.0326	-.0167	-.0404	.0288	-.0383	1		
Sufficient equipment	.3441	.3745	.2840	.4150	.0561	-.2345	.3667	.0461	1	
Decent infrastructure	.5850	.6394	.4626	.6876	.1941	-.3824	.6301	-.0471	.3116	1

Table 4b: Correlation between WTP derived from models in preference space with correlated coefficients

	Education after 6 years of service	Education after 4 years of service	Education after 2 years of service	District headquarter	Regional headquarter	Dar es Salaam	Decent housing offered	Normal workload	Sufficient equipment	Decent infrastructure
Education after 6 years of service	1									
Education after 4 years of service	.5252	1								
Education after 2 years of service	.5080	.8895	1							
District headquarter	.4771	.3559	.1689	1						
Regional headquarter	.7226	.5106	.3145	.6853	1					
Dar es Salaam	-.4215	-.2764	-.1649	-.4488	-.5939	1				
Decent housing offered	.3429	.2852	.1494	.2518	.3579	-.1617	1			
Normal workload	-.3753	-.2721	-.2116	-.3501	-.3934	.2097	-.1109	1		
Sufficient equipment	.4952	.3927	.2793	.5339	.5488	-.3707	.3011	-.2259	1	
Decent infrastructure	.3041	.2220	.0403	.4282	.6154	-.424	.1263	-.3311	.3663	1

Table 5: Results from models in WTP space

	Model 5			Model 6		
	Mean	Median	SD	Mean	Median	SD
District headquarter (ref. 3 miles+ from district HQ)	37.090***	37.090***	14.894	24.854*	24.854*	7.924
	(-14.1432)	(-14.1432)	(43.0253)	(13.4141)	(13.4141)	(12.2174)
Regional headquarter (ref. 3 miles+ from district HQ)	-11.186	-11.186	3.335	-.230	-.230	50.643***
	(14.2000)	(14.2000)	(33.0508)	(12.8775)	(12.8775)	(10.3719)
Dar es Salaam (ref. 3 miles+ from district HQ)	-84.068***	-84.068***	135.792***	-83.210***	-83.210***	126.821***
	(20.7431)	(20.7431)	(28.9353)	(24.4425)	(24.4425)	(18.7309)
Decent housing offered (ref. no house provided)	72.747***	72.747***	63.742***	87.463***	87.463***	65.038***
	(12.6159)	(12.6159)	(18.4233)	(13.4433)	(13.4433)	(11.5766)
Normal workload (ref. heavy workload)	7.731	7.731	94.455***	11.804	11.804	71.571***
	(13.7237)	(13.7237)	(17.0008)	(20.9490)	(20.9490)	(10.4749)
Sufficient equipment (ref. insufficient equipment)	114.762***	40.445***	304.745***	204.330***	43.749**	932.186
	(17.3201)	(13.172)	(118.4856)	(62.9274)	(20.391)	(925.5536)
Decent infrastructure (ref. poor infrastructure)	205.190***	147.670***	197.960***	261.636***	165.283***	321.050***
	(14.7631)	((12.753)	(33.2395)	(30.6796)	(15.368)	(76.1500)
Education after 6 years of service (ref. no education)	63.987***	52.251**	45.229	68.559***	52.940**	56.415**
	(22.654)	(25.568)	(31.1601)	(18.6993)	(22.657)	(27.4704)
Education after 4 years of service (ref. no education)	186.686***	137.997***	170.093***	202.079***	125.110***	256.325***
	(19.0917)	(19.624)	(18.3648)	(23.8156)	(17.687)	(54.9961)
Education after 2 years of service (ref. no education)	389.776***	285.748***	361.601***	369.465***	281.871***	313.084***
	(32.3037)	(23.977)	(76.0636)	(31.2732)	(20.815)	(76.5505)
Wage	0.009***	0.006***	0.010***	0.012***	0.006***	0.021**
	(0.0015)	(0.0005)	(0.0035)	(0.0026)	(0.0007)	(0.0084)
Constant	-13.256			-18.858**		
	(8.9806)			(7.9583)		
Log Likelihood	-2277.7386			-2227.6365		
AIC	4601.477			4501.273		
BIC	4749.807			4649.603		

* significant at 10% level, ** significant at 5% level, *** significant at 1% level