Preferences for prioritizing kidney transplants. Exploring preference heterogeneity using mixed logit, and latent class.

By Michael Clark[1], Domenico Moro[2], Dennis Leech[3], Anil Gumber[4], Ala Szczepura[1], Nick West[5], and Robert Higgins[5].

[1] Warwick Medical School, University of Warwick.
[2] Third Sector Research Centre, University of Birmingham.
[3] Economics Department, University of Warwick.
[4] School of Applied Health Professions, University of East Anglia.
[5] Nephrology Department, University Hospital, Coventry.

Aims: We published an analysis considering whether preferences for transplantation varied between defined patient groups. This used interaction dummy variables, to examine preference heterogeneity. Here we consider whether using more advanced methods is more appropriate.

Methods: We analyzed discrete choice experiment (DCE) data using random effects logit, conditional logit, mixed logit, latent class, and conditional logit with dummy variables.

Data: 863 patient responses elicited using a DCE.

Results: Goodness of fit (Mc Faddens R^2 and proportion of responses predicted by the model) improved as we moved from random effects logit / conditional logit, to mixed logit, or latent class. Mixed logit and latent class models highlighted preference heterogeneity for a number of attributes. However, the full extent of preference heterogeneity for defined groups (i.e. ethnic minorities) only becomes apparent using interaction dummies.

Conclusions: Mixed logit and latent class models are welcome editions to the health economist's tool box. Basic models presenting average valuations mask preference heterogeneity exposed by mixed logit / latent class. However, when differences are anticipated for defined respondent groups using interaction dummy variables is more appropriate than sole reliance upon mixed logit / latent class.

Background.

In the UK, in January 2011, 6,610 patients awaited renal transplantation (rising 8% annually since 2004), and in 2009-10, 1,482 received deceased donor transplants, and 1,038 received live donor transplants [1]. Growing imbalance between demand and supply, led to the Organ Donation Taskforce Report [2] outlining initiatives to increase organ supply by 50% within 5 years. Despite this, demand will outstrip supply despite increased supply, so criteria do need to be in place to allocate the limited supply of kidneys which are available for transplantation. Efficiency requires organs be transplanted to patients deriving greatest health benefit. Equity of access concerns may conflict with efficiency ones. Patients waiting a long time may be given a transplant on equity grounds, even if someone else who has not waited as long obtains greater health benefits from transplantation.

In 2006 UK transplant policy was re-appraised. Existing policy disadvantaged those with less common tissue types and blood groups, especially ethnic minorities [3]. African Caribbeans and Asians have a 3-4 times greater risk of end stage renal disease [2], related to higher prevalence of type 2 diabetes in African Caribbean and Asians [4]. Increased risk of renal disease in these groups is also related to increased risk of hypertension [5] and combined cardiovascular disease [6]. Moreover, ethnic minorities donate fewer organs [6], so are less able to obtain closely matched transplants.

The re-appraissal reduced priority attached to HLA tissue matching, allowing consideration of other criteria [7]. New guidelines [8] suggested more priority should be given to long waiters and paediatric and younger adult recipients. USA and Australian research indicated these changes would be acceptable to professionals and patients [9,10].

DCEs have been increasingly used to address priority setting issues in healthcare in primary care [11], and secondary care [12,13]. Some DCE transplantation work has been published, including work assessing factors influencing willingness to donate body parts [14] and a United Kingdom (UK) DCE establishing priorities for liver transplantation [15, 16] . In renal transplantation the first published DCE findings emanated from this study [17] which was conducted in the UK. There has also been some recent renal DCE research relating to patient and healthcare professional preferences for chronic kidney disease (CKD) care more generally (including kidney transplantation) in Canada [18].

Aims.

Our earlier paper [17] solely assessed whether patient preferences vary by ethnicity and gender. This paper begins by using random effects logit and then conditional logit for baseline models which do not assess whether preferences are heterogeneous. We then assess whether preferences are heterogeneous using mixed logit, and latent class modeling (to assess whether preferences differ across respondents in general). We also run a conditional logit model with interaction dummy variables to assess whether preferences vary comparing non-ethnic minority and ethnic minority respondents. In our earlier paper [17] we examined differences in preferences for non-white patients vs. all other patient respondents, and South Asian patients vs. all other patient respondents using random effects probit with dummy variables. The definition of ethnic minority respondent used in this paper is broader than that used in our previous analysis in that it includes both white and non-white ethnic minority respondents (white ethnic minority respondents, had not been classed as ethnic minorities in our earlier published analysis [17]). Recently a number of discrete choice experiment analyses have been conducted which also assess preference heterogeneity [19, 20, 21, 22, 23, 24, 25]. The aim of this paper is to assess whether conducting additional analysis to establish whether preferences are heterogeneous is worthwhile in our pre-existing DCE dataset, and to compare alternative methods (mixed logit, latent class, and conditional logit with interaction dummy variables for sub-groups). We do this to establish whether these methods represent an improvement upon methods which do not cater for preference heterogeneity (i.e. a baseline random effects logit model, and a baseline conditional logit model).

Methods.

This DCE involves respondents making choices, about which one of two hypothetical transplant recipients (differing in characteristics) should receive a kidney. DCE respondents trade-offs are established so weightings given to different recipient characteristics (attributes) are quantified. The pilot study began in 2005, the main study began in 2006. Final data analysis was during 2010-11.

1) Pilot exercise.

We developed a pilot DCE questionnaire using SPEED [26]. Attributes and level selection, was mainly informed by discussions with clinicians. We paired choices generated by SPEED to minimize attribute overlap and level imbalance [27]. We interviewed 60 respondents (who completed questionnaires and ranked potential attributes) to inform attribute and level selection. Respondents included 41 patients including 8 ethnic minorities, 16 healthcare professionals, 1 donor, 1 carer, and a renal Consultants secretary). They completed a DCE questionnaire, and ranked attributes (as described in the questionnaire and written on cards) in priority order. Pilot respondents could also suggest other potential attributes, and details of these were written on cards. They then ordered cards in order of priority. Most respondents (n = 56) came from the University Hospital, Coventry, including 4 ethnic minorities. Another 4 ethnic minority patients came from Ealing NHS Trust to boost minority responses. Pilot DCE attributes and levels included: Waiting time (levels: 1 month, 2 years, or 10 years); tissue match (levels: non-favourable, favourable, and perfect,); employment status (levels: unemployed, part-time, or full time); number of dependent children or adults (levels: 0, 1, or 4); extra years of life expectancy (levels: 1, 5 or 12 years); recipient age (levels: 20, 45, or 70 years); and other recipient diseases (levels: healthy accept for kidney disease, kidney disease plus a condition affecting activities [asthma], and kidney disease plus a condition affecting daily activities [severe arthritis]).

2) Attributes and levels - final DCE.

We analyzed the pilot data using Random Effects Probit and all the attributes (with the exception of the employment status attribute) proved significant at the 5% level. Early during piloting respondents expressed disquiet about the employment attribute, arguing it represented unwarranted discrimination against the retired or those unemployed because of illness. We therefore asked respondents whether this should be an attribute, and most respondents said ‘no’, so we dropped it. However findings from attribute rankings suggested the following warranted inclusion. Most respondents thought people with adult and child dependents ought to be prioritized, so the dependents attribute was amended to include adults. Age was considered relevant but the recipient age ceiling was reduced to 65, because clinicians suggested transplantation was unlikely amongst over 65s. The separate life expectancy and other recipient diseases attributes although highly ranked, resulted in unrealistic DCE scenarios. One pairwise choice resulted in a choice between a 70 year old with severe arthritis with 12 years life expectancy, and a 45 year old without co-morbidities having shorter life expectancy.The comparison did not make sense, since you expect a 45 year old without co-morbidities to have longer life expectancy than a 70 year old with severe arthritis. So we replaced the life expectancy attribute with one relating to whether a potential recipient had diseases predominantly affecting life expectancy. This resulted in more realistic scenarios, improving DCE identification and efficiency properties. Other highly ranking attributes included patient compliance / whether illness was self-inflicted. This assumed a higher ranking than it normally would because the pilot exercise arose when George Best (a former

international football player) was dying after liver transplantation because of ongoing alcohol misuse. We wanted to prevent health professionals preferences over-riding respondents preferences, but healthcare professionals rightly pointed out kidney disease rarely arises because of alcohol misuse, so the issue was not pertinent. Also healthcare professionals pointed out that those who are thought likely to abuse their bodies or be non-compliant would not be transplanted. So we excluded this attribute. Table 1 indicates final attributes and levels.

Table 1: Final attributes and levels.

Attribute	**Variable name**	**Levels**	**Interpretation of coefficients.**
Time spent awaiting transplantion.	wait	1 month, 2 years, and 10 years.	Indirect utility of each 1 year reduction in transplant recipient waiting time.
Tissue type matching.	tiss	Non-favourable match: 86% average kidney survival rate post-transplant. Favourable match: 89% average kidney survival rate post-transplant. Perfect match: 90% average kidney survival rate post-transplant.	Indirect utility of prioritizing people for each 1% improvement in kidney survival.
How many child or adult dependents recipients have	dep	None, 1, or 4 dependents.	Indirect utility of each additional dependent.
Recipient age	age	20 years, 45 years, and 65 years	Indirect utility for each 1 year reduction in recipient age.
Diseases predominantly affecting life expectancy	dis1	Moderate disease (uncontrolled hypertension or obesity) & Kidney disease rather than no disease affecting life expectancy (other than Kidney disease).	Indirect utility of having moderate rather than no disease predominantly affecting life expectancy.
	dis2	Severe disease (heart attack, stroke, or diabetes with complications) rather than no disease affecting life expectancy (other than Kidney disease).	Indirect utility of having severe disease rather than no disease predominantly affecting life expectancy.
Diseases predominantly affecting quality of life	ill1	Moderate disease (mild asthma) rather than no disease affecting quality of life (other than Kidney disease)	Indirect utility of having moderate disease rather than no disease predominantly affecting quality of life.
	ill2	Severe disease (severe arthritis) affecting quality of life rather than no disease affecting quality of life (other than Kidney disease)	Indirect utility of having severe disease rather than no disease predominantly affecting quality of life.

DCE attributes and levels were explained in the questionnaire preamble. We expected respondents to prioritize those waiting longer for a transplant on equity grounds, so anticipated a positive coefficient on a years less wait. The questionnaire preamble explained transplant survival rates obtained from UK Transplant were contingent upon donor / recipient tissue match,and said categories included perfect matches (90% 12 month transplant survival rate when all 6 tissue types match); favourable matches (89% 12 month transplant survival rate when 4-5 tissue types match); or non-favourable matches (86% 12 month survival rate when less than 4 tissue types match). On efficiency grounds we thought respondents would generally prefer to transplant to recipients with the highest chance of success, so improvements in kidney survival would be positively valued, but, some ethnic minority groups might not have this preference if there are a lack of organs closely matching their own. We considered that recipients with child or adult dependents or more dependents would be prioritized because more people benefit from recipients improved health if they care for others, so we expected a positive coefficient. All other things being equal you expect older patients to benefit less from a transplant because they have a lower life expectancy, so the coefficient on reductions in recipient age should be negative. We anticipated respondents for efficiency reasons would prioritize those with no diseases predominantly affecting life expectancy over those with moderate diseases predominantly affecting life expectancy, and those with severe diseases predominantly affecting life expectancy over those with no diseases predominantly affecting life expectancy, so expected negative coefficients. Likewise we anticipated respondents would value prioritizing those with no disease predominantly affecting quality of life to those with moderate diseases predominantly affecting quality of life, and those with no diseases predominantly affecting quality of life to those with severe diseases predominantly affecting quality of life, so expected negative coefficients.

3) Development of final DCE.

We wanted to force a choice, so used a binary dependent model, because in reality transplant decisions have to be made, and medical professionals face a forced choice when allocating kidneys because of donor scarcity. Moreover pilot interviews revealed many respondents felt uncomfortable with deciding who to transplant. Therefore having a ‘cannot decide’ option would have triggered such responses from respondents who in reality were not indifferent, so we forced a choice. We could have allowed choices between more than 2 potential recipients using a multinomial model, or had more attributes and levels, but this would complicate decision making [28]. Moreover, many renal patients suffer from fatigue, so we wanted to avoid complexity, because when complexity increases respondents may be more inclined to use simplifying heuristics [29] compromising response reliability.

The final DCE design did not use SPEED, but was again an Orthogonal Main Effects Plan (OMEP) design involving independent valuation of attributes. To ensure a perfectly orthogonal design we used an OMEP design supplied by leading DCE designers [30] improving efficiency. We blocked 18 choices into 2 blocks of 9 questions (versions A and B) to reduce respondent fatigue, otherwise the patient questionnaire would have had 13 not 10 pages. Respondents chose between transplanting patient A or B. For example for one choice patient A waited 2 years; had an 89% chance of 1 year transplant success; had 4 dependents; was 20 years; had severe diseases predominantly affecting life expectancy (heart attack, stroke, or diabetes with complications); but no diseases predominantly affecting quality of life except Kidney disease. Patient B waited 10 years; had a 90% chance of 1 year transplant success; had no dependents; was 45 years; had

no diseases predominantly affecting life expectancy except kidney disease; and had moderate disease affecting quality of life (mild asthma).

4) Questionnaire distribution.

The National Kidney Federation included a flyer and freepost envelope in 'Kidney Life' (circulation c.20,000) inviting patients, carers, donors, or healthcare professionals to request questionnaires. Members of the British Organ Donor Society had questionnaires posted to them. We sent questionnaires to healthcare professionals listed in UK transplants service directory, and targeted non-transplanting units with transplant coordinators or transplant physicians. To increase ethnic minority responses we provided translated questionnaires. A reputable translation organization was used to translate questionnaires into Punjabi, Hindi, Bengali, Gujarati, and Urdu. The bilingual researcher administering the questionnaires upon non-English speaking patients then checked the questionnaires translations accuracy, and chased ethnic minority patient responses obtaining 18 additional responses from Ealing NHS Trust, and 5 from University Hospital, Coventry.

5) Econometric / statistical analysis.

All data econometric analysis was conducted in STATA. We first used a Random Effects logit (model 1), to establish stakeholder preferences. Variables are defined in table 1.

$$Y = \beta_0 + \beta_1 wait + \beta_2 tiss + \beta_3 dep + \beta_4 age + \beta_5 dis1 + \beta_6 dis2 + \beta_7 ill1 + \beta_8 ill2 + \mu + \xi$$

(Model 1)

Y is the binary dependent variable, μ is the random effects error term and ξ is the general error term. We then used conditional logit (model 2). With the conditional logit model choice amongst alternatives is modeled as function of the characteristics of the alternatives, so it is well suited to estimating behavioural models [31].

$$Y = \beta_1 wait + \beta_2 tiss + \beta_3 dep + \beta_4 age + \beta_5 dis1 + \beta_6 dis2 + \beta_7 ill1 + \beta_8 ill2 + \xi$$

(Model 2)

In order to establish whether there was preference heterogeneity we used Generalized Linear Latent and Mixed Models (GLAMMs) [32]. We first ran a mixed logit model (model 3) [33]. The mixed logit model establishes the mean value of coefficients, and then has a secondary layer of regressors with coefficients indicating the standard deviation (denoted by the SD prefix) of each of the regressors.

$$Y = \beta_1 wait + \beta_2 tiss + \beta_3 dep + \beta_4 age + \beta_5 dis1 + \beta_6 dis2 + \beta_7 ill1 + \beta_8 ill2 + \beta_9 SDwait + \beta_{10} SDtiss$$

$$+\beta_{11} SDdep + \beta_{12} SDage + \beta_{13} SDdis1 + \beta_{14} SDdis2 + \beta_{15} SDill1 + \beta_{16} SDill2 + \xi$$

(Model 3)

After running a mixed logit model we ran a latent class model (model 4). In order to determine the optimum number of classes for the latent class model we increased the

number of classes until the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) suggested we had the optimum number of classes. We continued to increase the number of classes by one class until the AIC and BIC figures stopped falling and began to increase. Both the AIC and BIC reached their lowest level when the model had 4 latent classes, and then began to increase as the number of latent classes increased to 5. Consequently, the AIC and BIC suggested that the optimum number of latent classes for the latent class model was 4. So in the results section we present results for a latent class model with 4 latent classes (model 4). Here the latent class that variables relate to is indicated by the letters _lc1, _lc2, _lc3, and _lc4 respectively at the end of variable names.

$$Y = \beta_1 wait\_lc1 + \beta_2 tiss\_lc1 + \beta_3 dep\_lc1 + \beta_4 age\_lc1 + \beta_5 dis1\_lc1 + \beta_6 dis2\_lc1 + \beta_7 ill1\_lc1$$

$$+\beta_8 ill2\_lc1 + \beta_9 P2\_1 + \beta_{10} wait\_lc2 + \beta_{11} tiss\_lc2 + \beta_{12} dep\_lc2 + \beta_{13} age\_lc2 + \beta_{14} dis1\_lc2$$

$$+\beta_{15} dis2\_lc2 + \beta_{16} ill1\_lc2 + \beta_{17} ill2\_lc2 + \beta_{18} P2\_2 + \beta_{19} wait\_lc3 + \beta_{20} tiss\_lc3 + \beta_{21} dep\_lc3$$

$$+\beta_{22} age\_lc3 + \beta_{23} dis1\_lc3 + \beta_{24} dis2\_lc3 + \beta_{25} ill1\_lc3 + \beta_{26} ill2\_lc3 + \beta_{27} P2\_3 + \beta_{28} wait\_lc4$$

$$+\beta_{29} tiss\_lc4 + \beta_{30} dep\_lc4 + \beta_{31} age\_lc4 + \beta_{32} dis1\_lc4 + \beta_{33} dis2\_lc4 + \beta_{34} ill1\_lc4 + \beta_{35} ill2\_lc4 + \xi$$

(Model 4)

Model 5, is a conditional logit model which compares ethnic and non-ethnic minority patient preferences. The ethnic minority patient category included all patients in an ethnic category except 'White British.' Y, μ, and ξ are as previously defined, D_E is a dummy variable, $D_E = 1$, for ethnic minorities, 0 otherwise.

$$Y = \beta_0 + \beta_1 wait + \beta_2 tiss + \beta_3 dep + \beta_4 age + \beta_5 dis1 + \beta_6 dis2 + \beta_7 ill1 + \beta_8 ill2 +$$

$$\beta_9 D_E + \beta_{10} D_E wait + \beta_{11} D_E tiss + \beta_{12} D_E dep + \beta_{13} D_E age + \beta_{14} D_E dis1 + \beta_{15} D_E dis1 + \beta_{16} D_E ill1 + \beta_{17} D_E ill2$$

$$+\xi$$

(Model 5)

Model 5 establishes whether preferences differ between ethnic and non-ethnic minority patients. If β_9 is significant it suggests non-attribute specific differences in preferences between ethnic and non-ethnic minority patients. If ethnic minority interaction dummies ($\beta_{10....}\beta_{17}$) are significant, it indicates preferences differ between ethnic minorities and non-ethnic minorities for significant associated attribute(s).

6) Statistical methods for Marginal Rate of Substitution (MRS).

MRS indicates the ratio of changes in other attributes to changes in waiting times (see table 2) We used the Delta method [34] using command 'nlcom' in STATA, for 95% confidence intervals, to establish statistical significance.

Table 2: Calculating MRS – Valuing attributes compared to a 1 year difference in waiting time .

Models 1, 2, & 3 **Variable**	 **MRS**		
wait			
tiss	β_2 / β_1		
dep	β_3 / β_1		
age	β_4 / β_1		
dis1	β_5 / β_1		
dis2	β_6 / β_1		
ill1	β_7 / β_1		
ill2	β_8 / β_1		
Model 4 **Variable**	 **MRS – Latent class 1**	**Model 4** **Variable**	 **MRS – Latent class 2**
wait		**wait**	
tiss	β_2 / β_1	**tiss**	β_{11} / β_{10}
dep	β_3 / β_1	**dep**	β_{12} / β_{10}
age	β_4 / β_1	**age**	β_{13} / β_{10}
dis1	β_5 / β_1	**dis1**	β_{14} / β_{10}
dis2	β_6 / β_1	**dis2**	β_{15} / β_{10}
ill1	β_7 / β_1	**ill1**	β_{16} / β_{10}
ill2	β_8 / β_1	**ill2**	β_{17} / β_{10}
Model 4 **Variable**	 **MRS – Latent class 3**	**Model 4** **Variable**	 **MRS – Latent class 4**
wait		**wait**	
tiss	β_{20} / β_{19}	**tiss**	β_{29} / β_{28}
dep	β_{21} / β_{19}	**dep**	β_{30} / β_{28}
age	β_{22} / β_{19}	**age**	β_{31} / β_{28}
dis1	β_{23} / β_{19}	**dis1**	β_{32} / β_{28}
dis2	β_{24} / β_{19}	**dis2**	β_{33} / β_{28}
ill1	β_{25} / β_{19}	**ill1**	β_{34} / β_{28}
ill2	β_{26} / β_{19}	**ill2**	β_{35} / β_{28}
Model 5 **Variable**	 **Non-ethnic minority MRS**	**Model 5** **Variable**	 **Ethnic minority MRS**
wait		**wait**	
tiss	β_2 / β_1	**tiss**	$(\beta_2 + \beta_{11}) / (\beta_1 + \beta_{10})$
dep	β_3 / β_1	**dep**	$(\beta_3 + \beta_{12}) / (\beta_1 + \beta_{10})$
age	β_4 / β_1	**age**	$(\beta_4 + \beta_{13}) / (\beta_1 + \beta_{10})$
dis1	β_5 / β_1	**dis1**	$(\beta_5 + \beta_{14}) / (\beta_1 + \beta_{10})$
dis2	β_6 / β_1	**dis2**	$(\beta_6 + \beta_{15}) / (\beta_1 + \beta_{10})$
ill1	β_7 / β_1	**ill1**	$(\beta_7 + \beta_{16}) / (\beta_1 + \beta_{10})$
ill2	β_8 / β_1	**ill2**	$(\beta_8 + \beta_{17}) / (\beta_1 + \beta_{10})$

Wald tests using 'testnl' in STATA for model 4 considered whether MRS differed significantly between the 4 latent classes for a given variable. So for example the Wald test conducted relating to tissue match is $\beta_2 / \beta_1 = \beta_{11} / \beta_{10} = \beta_{20} / \beta_{19} = \beta_{29} / \beta_{28}$. Wald tests using 'testnl' for model 5 established whether MRS differed significantly between ethnic minority vs. non-ethnic minority patients. Thus to establish (model 5) whether preferences for tissue matching differed between ethnic and non-ethnic minorities, the hypothesis is $\beta_2 / \beta_1 = (\beta_2 + \beta_{11}) / (\beta_1 + \beta_{10})$ i.e. was tissue match MRS for non-ethnic and ethnic minorities identical ($p \leq 0.05$ indicates a difference at the 5% level).

Results.

Sample.

Table 3: Sample characteristics.

	Patients (n = 863)
AGE	
Mean age	54. 75years
GENDER	
Male	480 (55.62%)
Female	383(44.38%)
ETHNICITY	
White (British)	762 (88.19%)
White ethnic minorities	24 (2.78%)
Non-white ethnicity (excluding Asians)	17 (1.97%)
Non-white ethnicity (Asians)	43 (4.98%)
Not indicated	13 (1.51%)
DEPENDENT CHILDREN	
0	718 (83.19%)
1	70 (8.11%)
2	48 (5.56%)
3	12 (41.39%)
> 3	7 (0.81%)
Not indicated	8 (0.93%)
DEPENDENT ADULTS	
0	717 (83.08%)
1	113 (13.09%)
2	16 (1.85%)
> 2	6 (0.70%)
Not indicated	11 (1.27%)

Table 3 indicates respondent characteristics. UK Renal Registry data [35, 36] was used to assess patient sample representativeness. Of the 850 / 863 patients who indicated ethnicity, 762 / 850 patients (89.65%) were white (British), and 24 / 850 (2.82%) were white ethnic minorities, so 92.47% are white. UK incidence data [35] suggested 79.7% of renal patients are white, so whites are over-represented in our survey. Overall, 60 / 850

(7.06%) patients indicating ethnicity were non-white, compared with a 20.3% incidence rate [35], 43 / 60 non-white patients were South Asians (4.98% of those indicating ethnicity) compared to a 10.5% incidence [35]. 480/863 patients (55.62%) were male, 383 / 863 (44.38%) were female. Graphically presented Renal Registry data [35] reassuringly indicated slightly higher proportions of male than female patients across age groups. Average sample patient age was 54.75 years (median 56.9 years), and Renal Registry data median age (57.3 years) was virtually identical [35].

The patient sample comprised: 440 / 863 (50.98%) with successful transplants and 116 / 863 (13.44%) whose transplant failed. Renal Registry prevalence data [36] suggests 46.9% of patients have successful transplants (close to our figure). There is no incidence / prevalence data for other categories.

Results.

Model 1 (Random effects logit).

Table 4: Random effects logit (model 1).

Attribute	**Coefficient**	**MRS**	**p-value for MRS**
wait	.1333**		
tiss	.1440**	1.08**	0.000
dep	.1894**	1.42**	0.000
age	--.0101**	-0.08**	0.000
dis1	-.1004*	-0.76*	0.030
dis2	--1.641**	-12.30**	0.000
ill1	..1738**	1.30**	0.004
ill2	.0712	0.53	0.234
Mc Fadden R^2	0.1726	**Proportion of values accurately predicted by the model**	64.20%

***** Indicates significance at the 5% level, but no at the 1% significance level
** Indicates significance at the 1% level.

Results from the random effects logit model 1 (table 4) suggest that patients value a 1% improvement in the 12 month kidney transplant survival rate of 1% significantly (MRS=1.08) slightly more than a 1 year additional wait (the denominator for MRS). Patients also value prioritizing those with more dependent adults or children more, and MRS is significant and equals1.42 for each additional dependent. Potential transplant recipients who are older are prioritized less (MRS = -0.08). Those with a moderate disease (uncontrolled hypertension or obesity) & Kidney disease affecting life expectancy rather than no disease other than kidney disease are prioritized less than those with no disease affecting life expectancy (apparent because the MRS on dis1 is negative and = -0.76). Likewise those with a severe disease (heart attack, stroke, or diabetes with complications) affecting life expectancy rather than no disease other than kidney disease affecting life expectancy are prioritized far less than those with no disease (apparent because the MRS on dis2 is negative and = -12.30).

Those with moderate disease (mild asthma) rather than no disease affecting quality of life (other than Kidney disease) are prioritized more than those with no disease affecting quality of life (MRS on ill1 is significant and = 1.30), this may be because many patient respondents themselves may have moderate diseases affecting quality of life. The MRS for ill2 is insignificant, suggesting that having severe rather than no disease affecting quality of life should not be a significant determinant of who is prioritized for transplants according to our patient group (a somewhat unexpected result).

Model 2 (Conditional logit).

Table 5: Conditional logit (model 2).

Attribute	**Coefficient**	**MRS**	**p-value for MRS**
wait	.0968**		
tiss	.1151**	1.19**	0.000
dep	.1550**	1.60**	0.000
age	-.0090**	-0.09**	0.000
dis1	-.0961*	-0.99*	0.036
dis2	-1.290**	-13.33**	0.000
ill1	-.0206	-0.21	0.757
ill2	-.0050	-0.05	0.938
Mc Fadden R^2	0.2199	**Proportion of values accurately predicted by the model**	71.14%

***** Indicates significance at the 5% level, but no at the 1% significance level
** Indicates significance at the 1% level.

As expected the conditional logit model performs better than random effects logit in terms of measures of goodness of fit (Mc Fadden $R^2$and the proportion of values accurately predicted by the model). Results from model 2, (table 5) again suggest that patients value a 1% improvement in the 12 month kidney transplant survival rate of 1% significantly (MRS=1.19). Patients also value prioritizing those with more dependent adults or children more, and MRS is significant and equals 1.60 for each additional dependent. Potential transplant recipients who are older are prioritized less (MRS = -0.09). Those with a moderate disease (uncontrolled hypertension or obesity) & Kidney disease affecting life expectancy rather than no disease other than kidney disease are prioritized less than those with no disease affecting life expectancy (apparent because the MRS on dis1 is negative and = -0.99). Likewise those with a severe disease (heart attack, stroke, or diabetes with complications) affecting life expectancy rather than no disease other than kidney disease affecting life expectancy are prioritized far less than those with no disease (apparent because the MRS on dis2 is negative and = -13.33).The MRS for ill1 and ill2 are both insignificant, suggesting that having moderate or severe diseases affecting quality of life should not be a determinant of who is prioritized for transplants according to our patient group.

Model 3 (Mixed logit).

The mixed logit results (model 3, table 6) also suggest that that patients value a 1% improvement in the 12 month kidney transplant survival rate of 1% significantly (MRS=1.24). Patients also value prioritizing those with more dependent adults or children more, and MRS is significant and equals 1.82 for each additional dependent. Potential transplant recipients who are older are prioritized less (MRS = -0.08). dis1 is insignificant suggesting that those with moderate diseases affecting life expectancy are not prioritized more than those with no diseases affecting life expectancy. However, those with a severe disease (heart attack, stroke, or diabetes with complications) affecting life expectancy rather than no disease other than kidney disease affecting life expectancy are prioritized far less than those with no disease (apparent because the MRS on dis2 is negative and = -13.44). The MRS for ill1 and ill2 are both insignificant, suggesting that having moderate or severe diseases affecting quality of life should not be a determinant of who is prioritized for transplants. Most importantly in terms of investigating preference heterogeneity the mixed logit results suggest that preference heterogeneity is statistically significant with respect to the variables wait, dep, age, and dis2. Given that wait is the denominator used to calculate MRS, this suggests that preference heterogeneity might impact upon estimated MRS when a latent class model is used.

Table 6: Mixed logit results (model 3)

Attribute	**Coefficient**	**MRS**	**p-value for MRS**
Mean			
wait	.1210**		
tiss	.1506**	1.24**	0.000
dep	.2201**	1.82**	0.000
age	-.0099**	-.08**	0.000
dis1	-.0838	-.07	0.123
dis2	-1.626**	-13.44**	0.000
ill1	-.0400	-.33	0.619
ill2	.0387	.32	0.622
Standard deviation			
wait	-.0568**		
tiss	-.0207		
dep	.2145**		
age	-.0145**		
dis1	.0362		
dis2	1.172**		
ill1	.0957		
ill2	.0159		
Mc Fadden R^2	0.2411	**Proportion of values accurately predicted by the model**	72.78%

***** Indicates significance at the 5% level, but not at the 1% significance level
** Indicates significance at the 1% level.

Model 4 (Latent class model).

Table 7: Latent class model results (AIC and BIC) according to the number of classes in the model.

	Class 1	Class 2	Class 3	Class 4	Class 5
AIC	8415.54	7889.75↓	7714.96↓	7482.22↓	7545.94↑
BIC	8476.75	8019.81↓	7913.88↓	7750.00↓	7882.57↑

We kept running latent class models with increasing numbers of latent classes until both the AIC and BIC figures ceased to improve. Both figures continued to improve (i.e. declined) until the model had 4 classes (table 7). They then began to deteriorate when a model was applied with 5 latent classes. We therefore used a model with 4 latent classes, and some of the results are presented in table viiii. Results not presented in table viiii are the fact that the probability of belonging to latent class 1 is 0.3017; probability of belonging to latent class 2 is 0.1983; probability of belonging to latent class 3 is 0.1768; and the probability of belonging to latent class 4 is 0.3233.

MRS figures suggest (table 8) that MRS with respect to tissue match (the value of a 1% change in the likelihood of a kidney transplant succeeding for 12 months or more compared to someone waiting one year longer) is always significant and positive, and varies from a 1.28 low, to a 1.73 high across the 4 latent classes suggesting that patients value prioritizing those with a better tissue match between recipient and donor. Wald test results (table 9) do not support the hypothesis that MRS for tissue match varies across latent classes (p=0.4069). The MRS relating to prioritizing those with an extra dependent adult or child varies from a low of 0.20 to a high of 3.70 across the 4 latent classes, so MRS is very sensitive to class membership for prioritizing those with more dependents, implying that there is quite a lot of preference heterogeneity with respect to valuing having dependents. This is confirmed by the Wald test (p=0.000) which suggests that MRS for 'dep' varies across latent classes. MRS relating to the age of recipients varies. Intuitively we would expect people to prioritize younger rather than older recipients (because younger recipients generally have more potential to benefit from a transplant) so we expect the sign on MRS with respect to being a year older to be negative. Interestingly however the coefficient changes sign across latent classes. It is positive and significant for classes 1 and 2 (0.13 and 0.11 respectively) and only becomes negative and significant in classes 3 and 4 (-0.54 and -0.042 respectively). This preference heterogeneity is confirmed by the Wald test for MRS for 'age' which confirm that MRS differs across latent classes (p=0.000). The coefficient upon 'dis1' is not significant in latent classes 1 and 4. In latent class 2, MRS is positive and significant at 5.32 and in latent class 3 it is also positive and significant but higher at 14.52. Wald test results suggest that MRS for 'dis1' varies across latent classes (p=0.000). MRS for dis2 is always significant. In latent class 2 it is positive at 3.23, but in classes 1, 3, and 4 it is negative, it is -24.59 in latent class 1, -11.10 in latent class 3, and -5.36 in latent class 4. Wald test results suggests that MRS for 'dis2' varies across latent classes (p=0.000).

The MRS for 'ill1' is significant in latent classes 1 and 2 but insignificant in classes 3 and 4. In latent class 1 it is 11.17, and in latent class 2 it is 5.35. Wald test results suggest that MRS for 'ill1' varies significantly across latent classes (p=0.000). MRS for 'ill2' is significant in classes 1, 2, and 3. It is 5.83 in class 1, 9.98 in class 2, and 6.11 in class 3, but insignificant in class 4. Wald test results also suggest that MRS for 'ill2' varies significantly across latent classes (p=0.000). Therefore the general picture emerging

from the 4 class latent class model is that MRS differs across latent classes for every variable except 'tiss' (tissue match). This suggests that adopting econometric modeling which allows for preference heterogeneity is appropriate.

Table 8: Latent class model (model 4) results for 4 Latent Classes.

Attribute	Coefficient	MRS	p-value
wait_lc1	.1986**		
tiss_lc1	.2541**	1.28**	0.000
dep_lc1	.1465**	0.73*	0.012
age_lc1	.0254	0.13**	0.008
dis1_lc1	.1421	0.72	0.541
dis2_lc1	-4.883**	-24.59**	0.000
ill1_lc1	2.219*	11.17**	0.000
ill2_lc1	1.157	5.83*	0.014
P2_1	-.0691		
wait_lc2	4.198**		
tiss_lc2	6.673**	1.59**	0.000
dep_lc2	0.853**	0.20**	0.000
age_lc2	0.441**	0.11**	0.000
dis1_lc2	22.34**	5.32**	0.000
dis2_lc2	13.56**	3.23**	0.000
ill1_lc2	22.47**	5.35**	0.000
ill2_lc2	41.91**	9.98**	0.000
P2_2	-.489**		
wait_lc3	0.252**		
tiss_lc3	0.435**	1.73**	0.000
dep_lc3	0.648**	2.57**	0.000
age_lc3	-0.136**	-0.54**	0.000
dis1_lc3	3.659**	14.52**	0.000
dis2_lc3	-2.798**	-11.10**	0.000
ill1_lc3	-0.253	-1.00	0.535
ill2_lc3	1.50**	6.11**	0.002
P2_3	-.0604**		
wait_lc4	.064**		
tiss_lc4	.0838**	1.30**	0.000
dep_lc4	0.2388**	3.70**	0.000
age_lc4	-0.003	-.042	0.329
dis1_lc4	-0.164*	-2.55	0.069
dis2_lc4	-0.346*	-5.36**	0.002
ill1_lc4	-0.250*	-3.87	0.051
ill2_lc4	-0.152	-2.36	0.205
Mc Fadden R^2	0.3115	**Proportion of values accurately predicted by the model**	83.48%

***** Indicates significance at the 5% level, but not at the 1% significance level
** Indicates significance at the 1% level.

Table 9: Latent class model (model 4) Wald test results for MRS.

MRS	Wald test hypothesis	p-value of Wald test
tiss	$\beta_2 / \beta_1 = \beta_{11} / \beta_{10} = \beta_{20} / \beta_{19} = \beta_{29} / \beta_{28}$	0.4069
dep	$\beta_3 / \beta_1 = \beta_{12} / \beta_{10} = \beta_{21} / \beta_{19} = \beta_{30} / \beta_{28}$	0.0000
age	$\beta_4 / \beta_1 = \beta_{13} / \beta_{10} = \beta_{22} / \beta_{19} = \beta_{31} / \beta_{28}$	0.0000
dis1	$\beta_5 / \beta_1 = \beta_{14} / \beta_{10} = \beta_{23} / \beta_{19} = \beta_{32} / \beta_{28}$	0.0000
dis2	$\beta_6 / \beta_1 = \beta_{15} / \beta_{10} = \beta_{24} / \beta_{19} = \beta_{33} / \beta_{28}$	0.0000
ill1	$\beta_7 / \beta_1 = \beta_{16} / \beta_{10} = \beta_{25} / \beta_{19} = \beta_{34} / \beta_{28}$	0.0000
ill2	$\beta_8 / \beta_1 = \beta_{17} / \beta_{10} = \beta_{26} / \beta_{19} = \beta_{35} / \beta_{28}$	0.0000

Model 5 (Conditional logit with interaction dummy variables for ethnic minorities).

Table: 10: Conditional logit with interaction dummy variables (model 5) for ethnic minority groups (88 out of 863 are ethnic minorities).

Variable	Coefficient for non-ethnic minorities	MRS for non-ethnic minorities.	Coefficient for dummy variables for ethnic minorities	MRS for ethnic minority patients	Wald test p-values
wait	.0099**	1	-.0174	1	
tiss	.1242**	1.25** (1.00 / 1.49)	-.0609	0.51 (-1.15 / 0.13)	p=0.0000
dep	.1584**	1.59** (1.36 / 1.83)	-.0114	0.026 (-0.55/ 0.60)	p=0.0000
age	-.0096**	-0.10** (-0.07/-0.13)	.0040	0.13 (-.08 / 0.10)	p=0.0413
dis1	-.1333	-1.34 (-0.37 / -2.31)	-.2748	2.61 (-0.16 / 5.39)	p=0.0163
dis2	-1.397**	-14.05** (-12.57 / -15.57)	.8108**	6.74** (3.92 / 9.56)	p=0.0000
ill1	-.0324	-0.33** (-1.74 / 1.09)	.0650	0.60 (-3.28 / 4.49)	p=0.6887
ill2	-.0440	-0.44** (-1.84 / 5.03)	.2359	2.31 (-1.44 / 6.07)	p=0.2234
Mc Fadden R^2	0.2235		**Proportion of values accurately predicted by the model**	**73.69%**	

***** Indicates significance at the 5% level, but no at the 1% significance level
** Indicates significance at the 1% level.

Results for model 5 (table 10) suggest that MRS differs in a statistically significant manner between ethnic minorities and non-ethnic minorities with respect to wait, tiss,dep, age, dis1 and dis2. Non-ethnic minority respondents value prioritizing recipients with a closer tissue match positively, but ethnic minorities do not (MRS is insignificant). Non-ethnic minorities would prioritize recipients with dependents (dep is positive and significant), but amongst ethnic minorities MRS for dep is insignificant. Non-ethnic minorities would prioritize older recipients less (MRS for age is negative and significant), but amongst ethnic minorities MRS for age is insignificant. Non-ethnic minorities have a negative MRS for dis1 which is -1.34, but ethnic minorities have a positive MRS of 2.61. Both figures for MRS are insignificant, and the Wald test does suggest that MRS differs significantly between the 2 groups. For dis2, MRS is negative and significant amongst non-ethnic minorities (-14.05) amongst ethnic minorities though it is positive and significant (6.74). This suggests that non-ethnic minorities would not prioritize those with severe disease affecting life expectancy over those with no disease affecting life expectancy, whereas ethnic minorities would prioritize those with severe diseases affecting life expectancy over those with no disease (perhaps because ethnic minorities are more likely to suffer from severe diseases affecting life expectancy). Amongst non-ethnic minorities ill1 is negative and significant (-0.33) suggesting that those with moderate disease affecting quality of life are a lower priority for transplantation than those with no diseases affecting quality of life. Amongst ethnic minorities though MRS is of the same sign but insignificant (Wald tests do not suggest that MRS differs between non-ethnic minorities and ethnic minorities with respect to ill1). Amongst non-ethnic minorities ill2 is negative and significant (-0.44) amongst ethnic minorities though. MRS is insignificant (Wald tests do not suggest that MRS differs between non-ethnic minorities and ethnic minorities with respect to ill2).

Conclusions.

Baseline findings (models 1 and 2) which do not consider whether preferences are heterogeneous or not (models 1 and 2) are broadly supportive of 2006 revisions to UK kidney transplant policy, which prioritized long waiters and young adults. These analyses show this shift in policy is justified, but suggest that other criteria (i.e. prioritizing those with dependents) ought to be considered when UK transplant policy is re-appraised.

Models 3 and 4 (mixed logit and latent class) are general models which can be used to assess the extent to which preferences are heterogeneous. Both analyses highlight the fact that preferences for some variables are heterogeneous. The mixed logit results suggest that preferences are statistically significantly different with respect to 4 / 8 of the variables (wait, dep, age, and dis2) indicated by a statistically significant measure of standard deviation.

For the latent class model we deployed a slightly different measure of heterogeneity. We considered it logical to normalize our valuation of all of the other variables in terms of waiting time (wait). So we used ‘wait’ for the denominator to derive MRS. We then used Wald tests to test for equality of MRS for each variable across the 4 latent classes. Both the mixed logit and latent class results provided no support for the view that preferences for ‘tiss’ (prioritizing those with a close tissue match between recipient and donor) are heterogeneous.

The Wald test results (table 9) though for the latent class model (model 4) suggested that preferences differed across latent classes for all the other variables (i.e. 6 / 7 of the measures of MRS). If you take these findings at face value some people might take them to imply that the latent class results indicated more preference heterogeneity than mixed logit results (for which only 4 / 8 variables had a statistically significant standard deviation).

This result should not be unexpected. This is because our mixed logit results indicated that there is preference heterogeneity with respect to the variable 'wait'. Since the variable 'wait' is the denominator that we use to derive MRS for the latent class model, it follows that we always use a denominator to derive MRS which is subject to preference heterogeneity. Moreover, since our Wald tests for MRS look at variation across 2 variables, whereas the mixed logit standard deviation measure of heterogeneity assesses heterogeneity only with respect to one variable, it is hardly surprising that a our Wald test measures for the 4 class latent class model seem to imply more evidence of heterogeneity than mixed logit results.

Something that needs highlighting however is the fact that whilst both the mixed logit and latent class model results provide no evidence of preference heterogeneity with respect to the tissue match attribute (tiss), this is at odds with the findings of the conditional logit model with dummy variables (model 5). This model has dummy variables for ethnic minority patient respondents. Many ethnic minorities would be disadvantaging themselves as an ethnic group if they favoured prioritizing recipients with a close tissue match between donor and recipient. This is because low levels of organ donation amongst some ethnic minority groups, mean that many ethnic minorities are far less likely to be able to get a closely tissue matched transplant. Therefore the fact that model 5 results showed that non-ethnic minorities would prioritize recipients with a close donor tissue match (MRS = 1.59 for 'tiss' and highly significant) whereas MRS for 'tiss' is not significant amongst ethnic minorities (a difference also highlighted by the Wald test result [p=0.000]) made intuitive sense. However, had we not employed a model like model 5 to establish whether preferences differ between non-ethnic minorities and ethnic minorities differ we may have reached the misleading conclusion (based upon mixed logit and latent class results) that there is no preference heterogeneity with respect to the tissue match attribute. This finding suggests that we cannot just rely upon blanket application of mixed logit or latent class models in order to pinpoint variations in preferences. Instead if we anticipate that preferences might vary between defined respondent groups, we ought to use dummy variable models to test for this. The model 5 results in this paper, and those reported in our earlier analysis [17] suggest that both time spent waiting and the quality of tissue match between donor and recipient are of importance to non-ethnic minority patients, but that amongst ethnic minority patients closeness of tissue match is not a significant determinant of patient preferences. So our findings raise significant issues about kidney transplant allocation to those from ethnic minority groups. Without modelling for possible differences in preferences between ethnic and non-ethnic minority respondents, we would not have obtained this result.

We obtained 908 patient responses, and 863 of these proved to be complete enough to be amenable to data analysis using all 5 econometric models. Both mixed logit and latent class models highlighted the fact that preferences did appear to be heterogeneous across many variables. This was not an unsurprising result given that we had such a large sample for analysis. However, mixed logit and latent class models proved insufficiently sensitive to highlight the possibility of preference heterogeneity with respect

to the variable 'tiss'. Only when a model using interaction dummy variables for ethnic minority groups was used, did preference heterogeneity for this attribute between ethnic groups prove apparent. We would also suggest that deploying interaction dummy variable models can be particularly useful in that it provides an extra layer of information. This is because you are not just testing for preference heterogeneity per se (as with mixed logit or latent class models). Instead through the use of well specified dummy variables you can pinpoint the presence or absence of preference heterogeneity with respect to defined sample characteristics. Such models therefore confer additional information about how preferences vary between defined respondent groups.

References.

1. NHS Blood and Transplant: **Weekly Statistics**. [http://www.uktransplant.org.uk/ukt/statistics/latest_statistics/latest_statistics.jsp]. 3rd February 2011.

2. Department of Health: **Organs for transplants: a report from the Organ Donation Taskforce**. [http--www.dh.gov.uk-prod_consum_dh-groups-dh_digitalassets-@dh-@en-documents-digitalasset-dh_082120.pdf]. 16th January 2008.

3. Higgins RM, West N, Edmumds ME, et al: **Effect of a strict HLA matching policy on the distribution of cadaveric kidney transplants to Indo-Asian and white European recipients: regional study.** *British Medical Journal*, 1997, **315:** 1354-1355.

4. Raleigh VS: **Diabetes and hypertension in Britain's ethnic minorities: implications for the future of renal services.** *British Medical Journal*,1997, **314:** 209-212.

5. Norris KC, Tareen N, Martins D, & Variri ND: **Implications of ethnicity for the treatment of hypertensive kidney disease, with an emphasis on African Americans.** *Nat Clin Pract Nephrol*, 2008, **4(10):** 538-49.

6. Cappuccio FP, Oakeshott P, Strazzullo P, & Kerry SM: **Application of the Framington risk estimates to ethnic minorities for primary prevention of heart disease in general practice.** *British Medical Journal*, 2002, **327(7420):** 919.

7. Koenne RA: **Should the allocation of cadaveric kidneys for transplantation be based on HLA matching?** *Nephrol Dial Transplant*, 2002, **17(5):** 884-6.

8. NHS Blood and Transplant [formally UK Transplant]: **2006 Kidney allocation scheme.** [http:// www.uktransplant.org.uk-ukt-about_transplants-organ_allocation-kidney_(renal)-renal_organ_sharing_principles-kidney_allocation_scheme_2006-v8.doc.url]

9. Louis ON, Sanker P, & Ubel PA: **Kidney transplantion candidates' views of the transplant allocation system.** *J Gen Intern Med*, 1997, **12:** 478-84.

10. Browning CJ, & Thomas SA: **Community values and preferences in transplantation organ allocation decisions.** *Social Science and Medicine*, 2001, **52:** 853-61.

11. Rubin G. Bate A. George A, et al: **Preferences for access to the GP: a discrete choice experiment.** *British Journal of General Practice*, 2006, **56:** 743-748.

12. Youngkong S, Baltussen R, Tantivess S, et al: **Criteria for priority setting of HIV / AIDS interventions in Thailand.** *BMC Health Services Research,* 2010, **10:** 197

13. Allepuz A, Espallargues M, Moharra M, et al: **Prioritisation of patients on waiting lists for hip and knee arthroscopies and cataract surgery.** *BMC Health Services Research,* 2008, **8:** 76.

14. Bennett R, & Savani S: **Factors influencing the willingness to donate body parts for Transplantation.** *Journal of Health and Social Policy*, 2004,**18(3):** 61-85.

15. Ratcliffe J, & Buxton M: **Patients' preferences regarding the process and outcomes of life-saving technology. An application of conjoint analysis to liver transplantation.** *International Journal of Technology Assessment in Health Care*, 1999, **15(2):** 340-51.

16. Ratcliffe J: **Public preferences for the allocation of donor liver grafts for transplantation**. *Health Economics*, 2000, **9:** 137-48.

17. Clark M.D, Gumber AK, Leech D, et al: **Prioritising patients for renal transplantation? Analysis of patient preferences for kidney allocation according to ethnicity and gender.** *Diversity in Health and Care,* 2009, **6:** 181-191.

18. Davison SN, Kromm SK, & Currie GR: **Patient and health professional preferences for organ allocation and procurement, end-of-life care and organization of care for patients with chronic kidney disease using a discrete choice experiment.** Nephrology, Dialysis, Transplant, 2010, **25:** 2334-2341.

19. Eberth B, Watson V, Ryan M, et al**: Does one size fit all? Investigating heterogeneity in men's preferences for benign protostatic hyperplasia treatment using mixed logit analysis**. *Medical Decision Making,* Nov-Dec 2009: 707-715.

20. Kjaer T, & Gyrd-Hansen D: **Preference heterogeneity and choice of cardiac rehabilitation program: Results from a discrete choice experiment.** *Health Policy.* 2008, **85:** 124-132.

21.Hole AR: **Modelling heterogeneity in patients' preferences for the attributes of a general practitioner appointment.** *Journal of Health Economics,* 2008, **27:** 1078-1094.

22. Kruk ME, Johnson JC, Gyakobo M, et al: **Rural practice preferences among medical students in Ghana: a discrete choice experiment.** *Bull World Health Organ,* 2010, **88:** 333-341.

23. Chan-Halbrendt C, Lin T, et al: **Hawaiian residents preferences for Miconia control program attributes using conjoint analysis and latent class analysis.** *Environmental Management,* 2010, **45:** 250-260.

24. Cunningham CE, Deal K, Rimas H, et al: **Modelling the information preferences of children with mental health problems.** *J Abnorm Child Psychol.* 2008, **36:** 1123-1138.

25. Cunningham CE, Vailancourt T, Rimas H, et al: **Modelling the bullying prevention program preference: A discrete choice conjoint analysis.** *J Abnorm Child Psychol.* 2009, **37:** 929-943.

26. Bradley M: **User's manual for the speed version 2.1 stated preference editor and designer.** Hague Consulting Group. 1991.

27. Huber J, & Zwerina K:**The importance of utility balance in efficient choice designs.** *Journal of Marketing Research.* 1996, **XXXIII:** 307-317.

28. Amaya-Amaya M, Gerard K, & Ryan M: **Discrete choice experiments in a nutshell.** In *Using Discrete Choice Experiments to Value Health Care*, Edited by Ryan M, Gerard K, Amaya-Amaya: Springer; 2008: 13-46.

29. Lloyd AJ: **Threats to the estimation of benefit: are preference elicitation methods accurate?** *Health Economics.* 2003; **12:** 393-402.

30. Street DJ, Burgess L, & Louviere J: **Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments,** *International Journal of Research Marketing*, 2005, **22:** 459-470.

31. Hoffman SD, & Duncan GJ: **Multinomial and Conditional Logit Discrete-Choice Models in Demography.** ***Demography.*** **August 1988, 25(3): 415-427.**

32. Rabe-Hesketh S, Skrondal A, & Pickles A: **GLLAMM Manual.** U.C Berkeley *Division of Biostatistics Working Paper Series.* **Paper 160**, University of California, Berkeley.

33. Hole AR. **Estimating mixed logit models using maximum simulated likelihood.** *The Stata Journal.* ***vv(ii):*** *1-13.*

34. Wooldridge JM: **Economic analysis of cross section and panel data.** Cambridge MA, MIT press; 2002.

35. Byrne C, Ford D, Glig J, et al: **ESRD incident rates in 2008: national and centre-specific analyses**. Chapter 3, UK Renal Registry report. [http://www.renalreg.org]. 2008

36. Byrne C, Steenkamp R, Castledine C, et al: **ESRD prevalent rates in 2008 national and centre-specific analyses**. Chapter 4, UK Renal Registry report. [http://www.renalreg.org]. 2008.