Does One Size Fit All? Investigating Heterogeneity in Men's Preferences for Benign Prostatic Hyperplasia Treatment Using Mixed Logit Analysis

Article *in* Medical Decision Making · October 2009

DOI: 10.1177/0272989X09341754 · Source: PubMed

CITATIONS
21

READS
50

5 authors, including:

Barbara Eberth
Newcastle University
14 PUBLICATIONS **137** CITATIONS
SEE PROFILE

Verity Watson
University of Aberdeen
77 PUBLICATIONS **1,339** CITATIONS
SEE PROFILE

Mandy Ryan
University of Aberdeen
126 PUBLICATIONS **6,038** CITATIONS
SEE PROFILE

Gillian Barnett
8 PUBLICATIONS **260** CITATIONS
SEE PROFILE

Does One Size Fit All? Investigating Heterogeneity in Men's Preferences for Benign Prostatic Hyperplasia Treatment Using Mixed Logit Analysis

Barbara Eberth, PhD, Verity Watson, PhD, Mandy Ryan, PhD, Jenny Hughes, MA, Gillian Barnett, MSc, BSc Hons

In this study, the authors demonstrate how mixed logit analysis of discrete choice experiment (DCE) data can provide information about unobserved preference heterogeneity. Their application investigates unobserved heterogeneity in men's preferences for benign prostatic hyperplasia (BPH) treatment. They use a DCE to elicit preferences for seven characteristics of BPH treatment: time to symptom improvement, sexual and nonsexual treatment side effects, risks of acute urinary retention and surgery, cost of treatment, and reduction in prostate size. They investigate the importance of these characteristics and the trade-offs men are willing to make between them. Preferences are elicited from a sample of 100 men attending an outpatient clinic in Ireland. The authors find all treatment characteristics are significant determinants of treatment choice. There is significant preference heterogeneity in the population for four treatment characteristics: time to symptom improvement, treatment reducing prostate size, risk of surgery, and sexual side effects. The importance of preference heterogeneity at the policy level within the context of shared decision making is discussed. ***Key words:*** *benign prostatic hyperplasia; preference heterogeneity; choice behavior; discrete choice experiments.* ***(Med Decis Making 2009;29:707–715)***

Benign prostatic hyperplasia (BPH) is a chronic and progressive disease that results in prostatic enlargement. The impact of BPH includes irritative (frequency, urgency, or nocturia) and/or obstructive (weak stream, hesitancy) symptoms when passing urine. If BPH patients are inappropriately treated or treatment is unsuccessful, they are at risk of symptom deterioration over time, acute urinary retention (AUR), and surgery.[1,2] Since the early 1990s, the management of BPH patients has advanced significantly. The treatment options for men with symptomatic BPH include active monitoring, medical therapy (α-blockers or 5α-reductase inhibitors [5ARIs]), or surgery. Each of the medical interventions available has different characteristics and there is uncertainty about which treatment option is best for individual patients.[3] In this article, we report the results of a study examining men's preferences for medical treatment of BPH focusing specifically on the characteristics of α-blockers and 5ARIs.

Patient involvement in the decision-making process has been shown to increase compliance with

Received 20 October 2008 from Health Economics Research Unit, University of Aberdeen, Aberdeen, UK (BE, VWA, MR); GlaxoSmithKline, Rathfarnham, Dublin, Ireland (JH); and formerly of GlaxoSmithKline, Middlesex, UK, currently of Gillian Barnett and Associates, Donegal, Ireland (GB). This work was undertaken at Health Economics Research Unit (HERU), University of Aberdeen. Financial support for this study was provided by the University of Aberdeen, the Health Foundation, the Chief Scientist Office of the Scottish Government Health Directorates (Barbara Eberth, Verity Watson, and Mandy Ryan), and GlaxoSmithKline (Jenny Hughes). Gillian Barnett was employed by GlaxoSmithKline at the time she conducted the work. The funding agreement ensured the authors' independence in designing the study, interpreting the data, writing, and publishing the report. The following authors are employed by the sponsor GlaxoSmithKline: Jenny Hughes, and Gillian Barnett at the time she conducted the work. Revision accepted for publication 7 April 2009.

Address correspondence to Barbara Eberth, PhD, Health Economics Research Unit, Institute of Applied Health Sciences, University of Aberdeen, Polwarth Building, Foresterhill, Aberdeen AB24 3DS, UK; telephone: 0044 (0) 1224 555181; fax: 0044 (0) 1224 550926; e-mail: b.eberth@abdn.ac.uk.

DOI: 10.1177/0272989X09341754

treatment and satisfaction with the outcome.[4] Thus, it is important to know how individuals' treatment preferences vary in the population. Commonly, studies report the mean effect for the population. However, several authors have stated that accounting for heterogeneity is important in medical decision making.[5,6] For example, Sculpher and Gafni (in 2001) suggest that subgroup analysis would allow preference heterogeneity to be included in cost-effectiveness decisions.[6] Zaric (in 2003) goes further and suggests that all information, including the distribution of heterogeneity, should be included in cost-effectiveness analysis.[5] Although Zaric[5] was referring to population heterogeneity in the probability of illness, the argument is also relevant for preference heterogeneity and indeed other forms of heterogeneity.

One method to involve individuals in decision making is a discrete choice experiment (DCE).[7–10] The distinctive feature of a DCE is the assumption that the utility (satisfaction or benefit) individuals derive from a good or service is based on the characteristics of the good and not the good per se.[11] Typically, DCE participants are presented with multiple choice sets, each containing two or more hypothetical scenarios. Each scenario is defined by the same set of characteristics; these characteristics take different levels within a given choice set. In each choice set, participants are asked to indicate the scenario they would choose, and this is assumed to be the scenario that gives the highest utility. When choosing between scenarios individuals are assumed to make trade-offs between the levels presented for the characteristics. This allows estimation of the relative significance of treatment characteristics and reveals how these affect the utility an individual obtains from treatment. Trade-offs between the characteristics of alternative treatments, as measured by the marginal rate of substitution between treatment characteristics, can also be estimated. If a price proxy (money attribute) is included, marginal willingness to pay (WTP),[12] a monetary measure of benefit, for a unit change in the treatment characteristic can be calculated.

In this study, we elicit the preferences of men at risk of BPH for medical treatment using a DCE. We explored the resulting data to determine if there is significant preference heterogeneity in the sample. In DCEs, preference heterogeneity has traditionally been explored through subgroup analysis and interaction terms.[9,13,14] This approach is limited by the need to define a priori hypotheses regarding how respondents' characteristics influence their preferences. We apply an alternative approach, the mixed logit (ML), or random parameters logit, and investigate unobserved preference heterogeneity by allowing the model parameters to vary across individuals. This approach does not use subgroups of the population to identify preference heterogeneity, and therefore provides a more general alternative to subgroup analysis. Although the ML[15,16] is beginning to be viewed as the ''state of the art'' in discrete choice modeling,[15] applications in health care are limited: it was recently applied to DCE data eliciting preferences for asthma treatment and participation in genetic carrier testing.[17,18] The ML method is outlined in further detail in the Methods and Model section. The results of the ML model and estimates of marginal WTP[12] are presented in the Results section. In the Discussion section, we discuss how the results can be used to inform policy recommendations and suggest implications for shared decision making.

METHODS AND MODEL

In this study, we use the same DCE questionnaire as Watson and others.[19] Treatment characteristics were based on the characteristics of α-blockers (tamsulosin and doxazosin) and 5ARI (dutasteride) treatments reported in published randomized, double blind, placebo-controlled trials.[20–22] These characteristics were: the most commonly cited drug-related sexual (decreased libido, abnormal ejaculation, and impotence) and nonsexual (headache and dizziness) side effects; time to symptom improvement; the effect of medication on prostate size; and the chance of acute urinary retention or surgery after 2 years of treatment. To these six characteristics a price proxy, defined as the monthly cost of treatment, was added to permit the calculation of marginal WTP.[19]

The treatment characteristics and their assigned levels are reported in Table 1. This study differs from Watson and others[19] in two respects. First, Watson and others[19] use data collected from a random sample of men in the general UK population; our data are collected from men attending a urology outpatient clinic. Second, Watson and others applied a multinomial logit and investigated observed preference heterogeneity using subgroup analysis. The authors found all treatment characteristics to be significant treatment choice determinants; the most important characteristics were the sexual side effects, which were least desired. Sexual side effects were less important for men with moderate compared with mild symptoms, although those men

Table 1 Treatment Characteristics and their Associated Levels

Characteristic	Levels
Time to symptom improvement	1 month, 3 months, 6 months
Treatment decreases prostate size	Yes (1), no (0)
Sexual side effects	None Decreased libido Impotence Abnormal ejaculation
Nonsexual side effects	None Headache Dizziness
Treatment cost (€):	10, 20, 30, 50
Chance of AUR (%)[a]	2, 4, 6
Chance of surgery (%)	2, 4, 6

a. AUR, acute urinary retention (complete inability to urinate).

with mild symptoms were more concerned about time to symptom improvement and AUR risk. In this study, we apply the ML model to investigate unobserved preference heterogeneity.

The characteristics and levels result in 2592 ($3^4 \times 4^2 \times 2^1$) possible combinations. To reduce the number of profiles presented to respondents, the software programme SPEED was used to generate two sets of 16 profiles that satisfied the criteria of level balance and orthogonality.[23] To create choice sets these two designs were randomly paired.[24] A third no-treatment alternative was added to each choice set, giving respondents the option of being nondemanders. A sample choice set is depicted in Figure 1.

The DCE was administered to a random sample of 100 Irish men ages 30 or older who were attending an outpatient clinic. Attendance at the clinic was not specifically related to BPH. The sampling strategy was based on broad quota controls on age and social class to ensure a representative sample was obtained. Ethics committee approval and consent was obtained. Each respondent received the questionnaire and an information sheet describing BPH and the two alternative treatment options (5ARI and α-blocker medication with their respective side effects and times to symptom improvement). Both the questionnaire and the information sheet are available on request from the authors. Data on respondents' demographic characteristics and International Prostate Symptom Score[25] were also collected.

Responses from the DCE were analyzed using an ML model and software package NLOGIT 4.0.[26] The ML model is derived by allowing for preference heterogeneity in the multinomial logit model (MNL) using parameter mixing.[27] Selected parameters of

Characteristics of the treatment	Drug treatment A	Drug treatment B	No drug treatment
Time to symptom improvement	3 month	1 month	No improvement
Treatment reduces prostate size	No	Yes	No
Sexual side effects from treatment	Decreased sexual desire	Unable to get or maintain an erection	None
Nonsexual side effects from treatment	None	Headache	None
Monthly cost of drug treatment	€30	€10	€0
Chance of having acute urinary retention after 2 years	2%	6%	4%
Chance of surgery after 2 years	4%	2%	4%
Which treatment would you prefer? Please insert a tick in the box under the drug treatment you would prefer. ***Tick one box only.***			

Figure 1 Example of a discrete choice experiment choice set.

the MNL model are permitted to vary according to prescribed statistical distributions. Thus, preference heterogeneity in the population is incorporated into the model by treating the coefficients as random rather than fixed parameters.

The MNL modeling approach is based on random utility theory.[28] Thus, we assume that respondents know their preferences with certainty, even though the researcher cannot perfectly observe them. As such, the utility U_{njs} respondent $n=1,\ldots,N$, receives from treatment alternative $j=1,\ldots,J$, in choice situation $s=1,\ldots,S$, is given by

$$U_{njs}=\beta' x_{njs}+\varepsilon_{njs} \text{ with } \beta\sim f(\beta;\theta). \quad (1)$$

The systematic component is given by $\beta' x_{njs}$ where x is a vector of K treatment characteristics observed by the researcher (in this case the characteristics of BPH treatment) and β a vector of unknown parameters to be estimated. The unobserved random component is ε_{njs}. The K-dimensional vector β has probability density function $f(\beta;\theta)$, with θ containing all the parameters of the distribution of β in the population. The unobserved random component ε_{njs} is assumed to be independently and identically distributed extreme value type I and independent of β and x_{njs}. We further assume independence across the random elements in the β vector.

Given equation 1, conditional on β, the probability that respondent n chooses alternative j in choice situation s is

$$\Pr_{njs}(\beta)=\frac{e^{\beta' x_{njs}}}{\sum_{j=J_n} e^{\beta' x_{njs}}}, \quad (2)$$

which is a logit probability.

When a common distribution (such as a normal or log-normal distribution) is specified for any characteristic coefficient, the integrations underpinning the log-likelihood are not analytically tractable.[15] In this case, estimation proceeds by simulated maximum likelihood. For each coefficient specified as random, simulated maximum likelihood takes a specified number of draws $\beta^{(r)}(r=1,\ldots,R)$. from the distribution of the coefficient $f(\beta;\theta)$ For each draw the logit in equation 2 is calculated. The mean of the logits approximates the choice probability. For further detail on ML estimation see Train.[16]

DATA ANALYSIS

Following conventional practice, the systematic utility derived from treatment, $V=\beta' x_{njs}$ is assumed to be a linear additive function of the treatment characteristics. Thus, our estimating equation is

$$\begin{aligned} V=&\beta_0+\beta_1 Time+\beta_2 Size+\beta_3 S\_Dec+\beta_4 S\_Abej\\ &+\beta_5 S\_Imp+\beta_6 Surg+\beta_7 NS\_Head+\beta_8 NS\_Dizz\\ &+\beta_9 Cost+\beta_{10} Aur. \end{aligned} \quad (3)$$

We assume that β_k, $K=1-6$ are random and independently normally distributed with mean μ_K and standard deviation σ_K to be estimated. Estimates of $\hat{\beta}_0$ and $\hat{\beta}_7$ – $\hat{\beta}_{10}$ remain fixed. By assuming that the price coefficient is fixed, the marginal WTP for the random treatment characteristics is distributed according to the characteristic's distribution.

The alternative specific constant for treatment, β_0, is interpreted as the average effect of unobserved treatment characteristics on the utility of treatment relative to no treatment. The coefficients (β_1–β_{10}) represent the relative importance of a unit change in each characteristic on treatment utility. A priori expectations are that, on average, less time to symptom improvement, no side effects, a lower risk of acute urinary retention or surgery, a lower treatment cost, and a decrease in prostate size are preferred.

Interpretation of the coefficients depends on their unit of measurement. Thus β_1 shows the effect on treatment utility of a one-month increase in symptom improvement time, whereas β_9 represents the effect on treatment utility of a €*1* increase in treatment cost. The sexual and nonsexual side effects and prostate size characteristics are represented by dummy variables and their coefficients are interpreted relative to the base category. Thus β_5 indicates the effect of impotence as a side effect compared with no sexual side effects (the base category).

A statistically significant estimated standard deviation (σ_K) provides evidence of preference heterogeneity for that treatment characteristic. Preference heterogeneity can either be a difference in strength of preference (the magnitude of the estimated coefficient) or a difference in direction of preference (the sign of the estimated coefficient). An insignificant standard deviation ($\sigma_K=0$) is evidence that preferences for that treatment characteristic do not vary in the population and can be adequately represented by the mean for the whole population.

The information derived from the ML model, contained in the estimated means (μ_K) and standard deviations (σ_K) of an independent normally distributed random coefficient, permits the calculation of the proportion of the population for whom a treatment characteristic has a positive or negative effect. This is defined as $\Phi(\mu/\sigma)$, where Φ is the standard normal

cumulative distribution function.[16] For instance, for the characteristic ''treatment decreases prostate size'' the estimated mean and standard deviation can be used to identify the proportion of the population with a preference for shrinking medication (a positive coefficient) compared with the proportion of the population with a preference for relaxing medication (a negative coefficient).

The marginal WTP is calculated as the negative of the ratio of the treatment characteristic of interest (numerator) and the price proxy (denominator). For instance, $-(\beta_{10}/\beta_9)$ measures marginal WTP for a 1% decrease in the risk of acute urinary retention.

Model goodness of fit is assessed using the likelihood ratio (LR) test statistic; it compares the log-likelihood of the specified model with a model containing no explanatory variables.[28] Alternative model specifications were considered. In particular, we varied the coefficients that were specified as random and their specified distributions. The final model was the most parsimonious model that best fits the data based on LR tests and the Akaike information criterion.

RESULTS

The age of the 100 sampled men ranges from 34 to 69 years (mean 52 years, median 52 years, SD 8.92 years) and the average income is in the range of €30,000 to €39,999. Three men have previously been treated for BPH, two of whom have previously undergone surgery for BPH. When asked whether they have experienced AUR, 11 indicate that they have. International Prostate Symptom Score responses indicate that 70% of the sample report mild (0 to 7), 24% medium (8 to 19), and 5% severe (20 to 35) symptoms (1% declined to complete the International Prostate Symptom Score questionnaire).

The results of the ML model are shown in Table 2. Estimated mean and standard deviations are reported for the random coefficients, and average estimates are reported for the fixed parameters. All characteristics are statistically significant and have the expected signs, thereby validating the theoretical model.

The LR test statistic, with a χ^2 value of 1198.482, is consistent with the hypothesis that the ML model with 16 parameters explains the data better than the alternative model, which includes only a constant term. The significant negative alternative specific constant indicates that medication is preferred over no medication. As expected, respondents prefer lower waiting times to symptom improvement, a reduction in prostate size, and reduced risk of AUR or surgery after 2 years of medication. Among the sexual side effects, impotence is the least desired followed by decreased libido, and abnormal ejaculation. The nonsexual side effects, headache and dizziness, also have a statistically significant negative coefficient, meaning that, on average, these side effects are not desired. Cost is negative and significant at the 10% level ($P = 0.086$) indicating that, on average, lower cost is preferred to higher cost of medical treatment.

The standard deviations of the random coefficients are statistically significant, providing evidence of preference heterogeneity in the population for the characteristics specified as random. Under the model assumptions, the risk of surgery coefficient is normally distributed: $N(-0.366, 0.352^2)$ The results suggest that 85% of the population prefer treatment with a lower risk of surgery after two years; however, 15% would choose a treatment with a higher risk of requiring surgery (all other things equal). An argument for the latter is that surgery may be perceived to offer a cure. On average treatment decreasing prostate size is preferred compared with treatment leaving the prostate enlarged. The distribution of the coefficient reveals that 69.5% of the population are in favor of treatment reducing prostate size, whereas 30.5% prefer to take medication leaving the prostate enlarged. From a clinical perspective this finding is important. Symptom relief occurs faster with α-blockers but symptom relief is the only benefit that patients receive. However, 5ARIs reduce prostate size, but symptom relief is not immediate. We find, on average, respondents prefer treatment with no sexual side effects. The distributions of the coefficients for the sexual side effects reveal that 93% prefer treatment without sexual side effect impotence, 87% without sexual side effect decreased libido, and 77.3% without sexual side effect abnormal ejaculation. With respect to waiting time to symptom improvement, 97% of the population prefer shorter waiting times and 3% are willing to wait longer. Intuitively we would not expect individuals to prefer longer waiting times. There are two explanations for this. First, some respondents may not consider this characteristic to be important when making a choice. Second, this finding may be a statistical artifact arising from the assumption of normally distributed coefficients. The distribution of the coefficient waiting time to symptom improvement is presented in Figure 2.

Table 2 column 4 shows respondents' marginal WTP for a unit change in each treatment characteristic. For example, marginal WTP for a 1% reduction in

Table 2 Regression Resultsa and Marginal Willingness to Pay Estimates (€)

		Mixed logit[b]		WTP[c]		Preference Interpretation
Constant (no treatment)	Coefficient	−3.382	(7.540)	375.78		Drug treatment v. no drug treatment
Time to symptom improvement	Mean	−0.108	(−2.262)	12.00	(32.33)	For a 1-month reduction in waiting time
	SD	0.291	(6.036)			
Treatment decreases prostate size	Mean	1.102	(4.090)	122.44	(241.44)	For decreased prostate
	SD	2.173	(7.292)			
Sexual side effects						
Impotence	Mean	−3.759	(−7.856)	417.67	(281.22)	For move from side effect to no side effect
	SD	2.531	(7.220)			
Decreased libido	Mean	−2.136	(−7.309)	237.33	(205.78)	For move from side effect to no side effect
	SD	1.852	(8.064)			
Abnormal ejaculation	Mean	−1.467	(−4.596)	163.00	(216.78)	For move from side effect to no side effect
	SD	1.951	(8.402)			
Nonsexual side effects						
Headache	Coefficient	−0.836	(−2.861)	92.89		For move from side effect to no side effect
Dizziness	Coefficient	−0.633	(−2.726)	70.33		For move from side effect to no side effect
Cost of drug treatment	Coefficient	−0.009	(−1.716)			
Risk characteristics:						
AUR	Coefficient	−0.201	(−3.436)	22.33		For a 1% decrease in AUR risk
Surgery	Mean	−0.366	(−6.092)	40.67	(39.11)	For a 1% decrease in surgery risk
	SD	0.352	(5.104)			
Pseudo R^2	.3567					
χ^2	1249.610					
Log likelihood	−1126.383					
LR test χ^2(df)	1198.482 (16)					
Number of respondents	100					
Number of observations	4782					

Note: WTP, willingness to pay; AUR, acute urinary retention; LR, likelihood ratio

a. Of the 100 respondents who completed the questionnaire, 96 completed all 16 choice sets, 2 completed 15 choice sets, and 2 completed 14 choice sets. As such, the analysis is based on 1594 $[(96 \times 16) + (2 \times 16) + (2 \times 14)]$ completed choices.

b. We specified 1000 Halton draws and convergence was achieved after 37 iterations. The *t* statistics are in parentheses.

c. WTP estimates are based on the regression results in column 3 and rounded to 2 decimal places. The standard deviations are in parentheses.

the risk of AUR two years after treatment is €22.33 $[(-0.201/-0.009)]$. For the random treatment characteristics, in addition to the marginal WTP, the standard deviation of marginal WTP can be estimated. Marginal WTP for a one-month reduction in time to symptom improvement is normally distributed with a mean of €12.00 $[(\beta_{Time}/\beta_{Cost}) = -0.108/-0.009]$ and a standard deviation of €32.33 $[(\sigma_{Time}/\beta_{Cost}) = -0.291/-0.009]$.

DISCUSSION

We applied an ML model to investigate unobserved preference heterogeneity in responses to a DCE eliciting preferences for BPH treatment. Information about preference heterogeneity may help physicians understand individuals' preferences for treatment, as well as inform policy decisions. We found evidence of preference heterogeneity. For

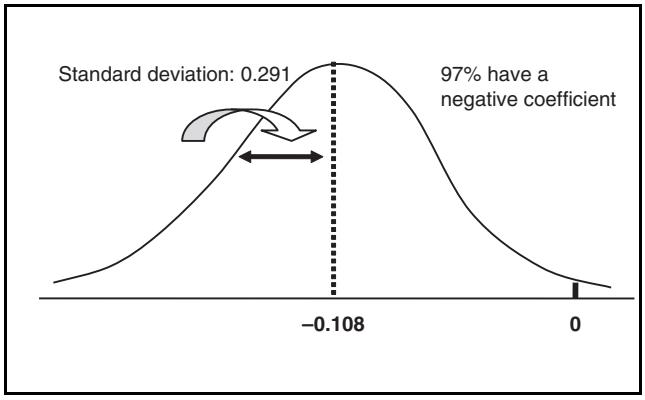

Figure 2 Distribution of coefficient for time to symptom improvement in the population.

example, although, on average, sexual side effects have a negative effect on respondents' treatment choice, the magnitude of this effect varies in the population. Similarly, although 69.5% of men prefer treatment that reduces prostate size (shrinking medication), 30.5% of men prefer treatment that leaves the prostate enlarged (relaxing medication). Ignoring preference heterogeneity may result in low uptake of, and poor adherence to, medication.

Preferences for treatment characteristics were not specific to one therapy. Although men prefer the rapid improvement in symptoms provided by α-blockers, they also gain utility from a 5ARI treatment that reduces prostate size. This indicates that combination therapies provide more utility to some men than monotherapies.[29] Within the medical profession, there is growing acceptance of combination therapy in the management of BPH. Recent clinical evidence found that the combination of an α-blocker and 5ARI (dutasteride) resulted in significantly greater improvements in symptoms, peak urinary flow, and BPH-related health status compared with those of monotherapy alone for men with moderate to severe BPH.[30] Combination therapies will increase treatment costs. Whether the additional costs are justified by the increase in utility requires further research.

A number of limitations should be noted when interpreting the results. First, the specified model makes several assumptions that could be relaxed in future work. The assumption of uncorrelated random parameters can be relaxed to introduce correlations across the random parameters. Second, the DCE asked respondents to make repeated choices; however, we assumed independence of the stochastic error across choices, alternatives, and individuals. This could be relaxed to incorporate error correlations across choices via estimation of preference parameters for each individual in the sample conditional on the choices they have been observed to make.[31] Error correlations across the utility of alternatives can be estimated via an error components logit to identify alternative specific unobserved preference heterogeneity independent of preference heterogeneity uncovered through the random parameters.[32] Third, the study design assumed a main effects model implying the effect of each treatment characteristic on utility to be independent of other characteristics. This main-effects-only design is in line with other DCE studies in health economics.[9] However, respondents' preferences for one characteristic may depend on the level of another characteristic. Future work should investigate two-way and higher-order interaction preferences for health care.[9] Fourth, bladder outlet obstruction is affected by dynamic (muscle) elements as well as prostate size. This dynamic characteristic was not included in the DCE. Further work is needed to determine if respondents differentiate between effect on dynamic elements and effect on prostate size when choosing treatment.

Although the results indicate that unobserved preference heterogeneity exists, it does not say where. Both observed and unobserved preference heterogeneity could be further explored by allowing for observed preference heterogeneity around the mean of a random parameter via interaction with sociodemographic characteristics of the respondent (such as income group). An alternative approach would be to use a latent class model.[33] Both approaches could be considered in future research.

Eliciting the preferences of men under the age of 40 at a urology outpatient clinic will result in a sample with prostitis/chronic pelvic pain, not BPH. An alternative inclusion criterion would be to target those referred with lower urinary tract symptoms, indicative of bladder outlet obstruction secondary to BPH. Future research should explore how preferences differ across different sections of the population. Patients with familiarity of the condition and experience of symptom and treatments may have better formed preferences. The ML model could be informative for such a comparison. Whereas subgroup analysis may result in statistically significant mean preference differences between groups, the ML model will indicate whether the estimated preference distributions of the two groups are statistically different.

Differences in preferences across patient groups or between patients and the general public raise the question of ''whose preferences count.'' Gafni argues that the views of the community are relevant.[34] Others have questioned whether respondents with little or no experience of a condition or treatment can provide preference information. Only three men in our sample reported previously receiving treatment for BPH. To help ensure informed preferences all respondents were provided with an information sheet prior to completing the DCE. This conveyed technical aspects of BPH to men who may feel uncomfortable talking about the prostate gland, balancing this against how much information respondents can feasibly comprehend. The information sheet described BPH and how it affects urinary flow, BPH symptoms, treatment options and side effects, and the consequences if BPH is left untreated. Visual aids as well as descriptive text were included to aid understanding. More research is needed to consider how experience, familiarity, and the information (both context and format) provided influence preferences.

From a policy perspective an important question is how the results of models that estimate preference heterogeneity can be used in decision making. We have argued that considering mean effects only can disguise important information in heterogeneous populations. The mean effect is a useful measure for policy recommendations if everybody in the population receives a welfare gain (or at least no welfare loss) and the distinction between individuals is in the magnitude of their welfare gain. However, if two polarizing views exist and two treatments were required to accommodate these opposing preferences, a policy recommendation based on the population average may, in the worst case scenario, represent a welfare loss to both groups. However, we do not have data on the costs or resource implications of BPH treatment; thus we cannot use the results of the DCE in a cost-benefit analysis. An important area for future research is to investigate how preference heterogeneity would impact on cost-benefit or cost-effectiveness decisions.

In summary, this study investigates heterogeneity in men's preferences for BPH treatment using an ML model. By modeling unobserved preference heterogeneity, a further layer of data, about how preferences vary in the population, is uncovered. Although this is clearly important, future research is required, relaxing the modeling assumptions and comparing preferences across different groups. A further challenge at the policy level is to incorporate such heterogeneity into a decision-making framework. This is an exciting avenue for future research.

ACKNOWLEDGMENTS

We are grateful to all respondents who completed the DCE. Financial support from the University of Aberdeen, the Health Foundation, GlaxoSmithKline, and the Chief Scientist Office of the Scottish Government Health Directorates are gratefully acknowledged. The Health Economics Research Unit is funded by the Chief Scientist Office of the Scottish Government Health Directorates. The views expressed in this article are those of the authors. We thank the editor and referees for comments on a previous version of this article.

REFERENCES

1. Emberton M, Andriole G, de la Rosette J, Djavan B, Hoefner K, Vela Navarrete R, et al. Benign prostatic hyperplasia: a progressive disease of aging men. Urology. 2003;61:267-273.

2. Pickard R, Emberton M, Neal D. The management of men with acute urinary retention. Br J Urol. 1998;81:712–20.

3. Stoevelaar H, Van De Beek C, Casparie A, McDonnell J, Nijs H. Treatment choice for benign prostatic hyperplasia: a matter of urologist preference? J Urol. 1999;161:133-138.

4. Garraway W, Lee R, Collins G. High prevalence of benign prostatic hypertrophy in the community. Lancet. 1991;338:469-471.

5. Zaric GS. The impact of ignoring population heterogeneity when Markov models are used in cost-effectiveness analysis. Med Decis Making. 2003;23:379–96.

6. Sculpher M, Gafni A. Recognizing diversity in public preferences: the use of preference sub-groups in cost-effectivness analysis. Health Econ. 2001;10:317–24.

7. Ryan M, Farrar S. Using conjoint analysis to elicit preferences for health care. BMJ. 2000;320:1530–3.

8. Ryan M, Gerard K. Using discrete choice experiments in health economics: moving forward. In: Scott T, Maynard A, Elliott R, eds. Advances in Health Economics. Chichester: John Wiley & Sons; 2003.

9. Ryan M, Gerard K. Using discrete choice experiments to value health care programmes: current practice and future research reflections. Appl Health Econ Health Policy. 2003;2:55–64.

10. Fiebig D, Louviere J, Waldman D. Contemporary issues in modelling discrete choice experimental data in health economics. 2005; Available from: http://wwwdocs.fce.unsw.edu.au/economics/staff/DFIEBIG/ContemporaryissuesHEv120Apr05.pdf. Accessed 25.08.2008.

11. Lancaster K. A new approach to consumer theory. J Political Econ. 1966;74:132–57.

12. Ryan M, Gerard K, Amaya-Amaya M. Using Discrete Choice Experiments to Value Health and Health Care. Dordrecht: Springer; 2007.

13. McIntosh E, Ryan M. Using discrete choice experiments to derive welfare estimates for the provision of elective surgery: implications of discontinuous preferences. J Econ Psychol. 2002;23:367–82.

14. Scott A. Identifying and analysing dominant preferences in discrete choice experiments: an application in health care. J Econ Psychol. 2002;23:383–98.

15. Hensher D, Greene W. The mixed logit model: the state of practice. Transportation. 2003;30:133–76.

16. Train K. Discrete Choice Methods with Simulation. New York: Cambridge University Press; 2003.

17. Lancsar E, Hall J, King M, et al. Using discrete choice experiments to investigate subject preferences for preventive asthma medication. Respirology. 2007;12:127–36.

18. Hall J, Fiebig D, King M, Hossain I, Louviere J. What influences participation in genetic carrier testing? Results from a discrete choice experiment. J Health Econ. 2006;25:520–37.

19. Watson V, Ryan M, Brown CT, Barnett G, Ellis BW, Emberton M. Eliciting preferences for drug treatment of lower urinary tract symptoms associated with benign prostatic hyperplasia. J Urol. 2004;172(6 Part 1):2321–5.

20. Fawzy A, Braun K, Lewis G, Gaffney M, Ice K, Dias N. Doxazosin in the treatment of benign prostatic hyperplasia in normotensive patients: a multicentre study. J Urol. 1995;154:105–109.

21. Lepor H. Phase III multicentre placebo-controlled study of tamsulosin in benign prostatic hyperplasia. Tamsulosin Investigation Group. Urology. 1998;51:892–900.

22. Roehrborn C, Boyle P, Nickel J, Hoefner K, Andriole G. Efficacy and safety of a dual inhibitor of 5-alpha-reductase types 1 and 2 (dutasteride) in men with benign prostatic hyperplasia. Urology. 2002;60:434–41.

23. Bradley M. User's Manual for the Speed Version 2.1 Stated Preference Experiment Editor and Designer. Hague: Hague Consulting Group; 1991.

24. Hensher DA, Rose JM, Greene WH. Applied Choice Analysis. A Primer. Cambridge: Cambridge University Press; 2005.

25. Barry M, Fowler F, Mulley A, Henderson J, Wennberg J. Patient reactions to a program designed to facilitate patient participation in treatment decisions for benign prostatic hyperplasia. Med Care. 1995;33:771-787.

26. Greene W. NLOGIT Version 4.0 Reference Guide. Castle Hill: Econometric Software; 2007.

27. Johnson NL, Kotz S, Kemp AW. Univariate Discrete Distributions. New York: Wiley; 1993.

28. McFadden D. Conditional logit analysis of qualitative choice behavior. In: Zarembka P, ed. Frontiers of Econometrics. New York: Academic Press; 1974.

29. Roehrborn C, Siami P, Barkin J, Damiao R, Montorsi F. POD-06.02: the effects of dutasteride, tamsulosin, and combination therapy on lower urinary tract symptoms and Qmax in men with BPH and prostatic enlargement: two-year results from the Combination of Avodart(R) and Tamsulosin (CombAT) study. Urology. 2007;70(3 Suppl 1):19. 29th Congress of the Société Internationale d'Urology. Podium Session POD-06.02.

30. Roehrborn CG, Siami P, Barkin J, Damião R, Major-Walker K, Morrill B, et al. The effects of dutasteride, tamsulosin and combination therapy on lower urinary tract symptoms in men with benign prostatic hyperplasia and prostatic enlargement: 2-year results from the CombAT study. J Urol. 2008;179:616-621.

31. Revelt D, Train K. Specific Taste Parameters and Mixed Logit. Working Paper No. E00-274. Berkeley: Department of Economics, University of California; 2000.

32. Greene WH, Hensher DA. Heteroscedastic control for random coefficients and error components in mixed logit. Transportation Research Part E. 2007;43:610–623.

33. Greene WH, Hensher DA. A latent class model for discrete choice analysis: contrasts with mixed logit. Working Paper ITS-WP-02-08. Sydney: Institute of Transport Studies, University of Sydney and Monash University; 2002.

34. Gafni A. Willingness-to-pay as a measure of benefits: relevant questions in the context of public decisionmaking about health care programs. Med Care. 1991;29:1246-1252.