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Background

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Abstract

This paper examines the distribution of preferences in a sample of patients who responded to a discrete choice experiment on the choice of general practitioner appointments. In addition to standard logit, mixed and latent class logit models are used to analyse the data from the choice experiment. It is found that there is significant preference heterogeneity for all the attributes in the experiment and that both the mixed and latent class models lead to significant improvements in fit compared to the standard logit model. Moreover, the distribution of preferences implied by the preferred mixed and latent class models is similar for many attributes.

Keywords: discrete choice experiment; mixed logit; latent class logit

JEL classification: I10; C25

1 Introduction

Data from health related discrete choice experiments (DCEs) are usually analysed using probit or logit models or random effects extensions of these (see Ryan and Gerard, 2003, for a review). These approaches produce estimates of the mean taste weights attributed to the attributes in the experiment by the sampled individuals. Further, if a cost attribute or a proxy for cost is included in the experiment the taste weights can be used to derive estimates of mean willingness to pay for the attributes. It is likely, however, that individuals have different preferences, and that some of the preference heterogeneity is unrelated to observable personal characteristics. This issue cannot be investigated using the traditional modelling tools.

This paper examines the distribution of preferences in a sample of patients who responded to a discrete choice experiment where they were asked to choose between different hypothetical general practitioner appointments. In addition to standard logit models, mixed and latent class logit models are used to analyse the data from the choice experiment. Mixed and latent class logit models are extensions of the standard logit model which make it possible, given certain assumptions, to estimate the distribution of preferences for the attributes in the experiment. Another advantage is that they account for the fact that each individual makes several choices which cannot be assumed to be independent. Although these properties have been recognised in the DCE literature for some time (Hanley et al., 2003), there have been few applications of either modelling technique to date.[1]

The analysis reveals significant preference heterogeneity for all the attributes in the experiment and both the mixed and latent class logit models lead to significant improvements in fit compared to the standard logit model. Moreover, the distribution of preferences implied by the preferred mixed and latent class models is similar for many attributes. These results underline the additional insights that can be made from accounting for preference het-

[1]See Johnson et al. (2000) and Borah (2006) for two health related applications of the mixed logit model. It should be noted that latent class models have been frequently applied within areas of health economics where the outcome is a count rather than a discrete variable (e.g. Bago d'Uva, 2006).

erogeneity when analysing data from discrete choice experiments.

Section 2 outlines the mixed and latent class logit models, section 3 describes the discrete choice experiment and section 4 reports the results of the analysis. Section 5 offers a discussion.

2 Methodology

Following Revelt and Train (1998) we assume a sample of N respondents with the choice of J alternatives on T choice occasions. The utility that individual n derives from choosing alternative j on choice occasion t is given by $U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt}$ where β_n is a vector of individual-specific coefficients, x_{njt} is a vector of observed attributes relating to individual n and alternative j on choice occasion t and ε_{njt} is a random term which is assumed to be distributed IID extreme value. The density for β is denoted as $f(\beta|\theta)$ where θ are the parameters of the distribution. Conditional on knowing β_n the probability of respondent n choosing alternative i on choice occasion t is given by:

$$L_{nit}(\beta_n) = \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} \tag{1}$$

which is the logit formula (McFadden, 1974). The probability of the observed sequence of choices conditional on knowing β_n is given by:

$$S_n(\beta_n) = \prod_{t=1}^{T} L_{ni(n,t)t}(\beta_n) \tag{2}$$

where $i(n,t)$ denotes the alternative chosen by individual n on choice occasion t. The *unconditional* probability of the observed sequence of choices is the conditional probability integrated over the distribution of β:

$$P_n(\theta) = \int S_n(\beta) f(\beta|\theta) d\beta \tag{3}$$

The unconditional probability is thus a weighted average of a product of logit formulas evaluated at different values of β, with the weights given by the density f.

The distribution of β can be either continuous or discrete. A model with continuously distributed coefficients is usually called a *mixed logit* (ML) model, although terms such as *random parameters* and *random coefficients logit* have also been used. Since the seminal contributions by Bhat (1998), Revelt and Train (1998) and Brownstone and Train (1999) the mixed logit model has been applied in several contexts in economics including environmental and transport economics (e.g. Train, 1998; Hensher, 2001; Greene and Hensher, 2003; Meijer and Rouwendal, 2006). A model in which the coefficients follow a discrete distribution, on the other hand, is called a *latent class logit* model. The latent class logit model has been frequently applied in marketing (see McLachlan and Peel, 2000, for a review) and, more recently, in environmental and transport economics (e.g. Greene and Hensher, 2003; Scarpa and Thiene, 2005; Meijer and Rouwendal, 2006).

The log likelihood for both models is given by $LL(\theta) = \sum_{n=1}^{N} \ln P_n(\theta)$. In the mixed logit case this expression cannot be solved analytically, and it is therefore approximated using simulation methods (see Train, 2003). The simulated log likelihood is given by:

$$SLL_{ML}(\theta) = \sum_{n=1}^{N} \ln \left[\frac{1}{R} \sum_{r=1}^{R} S_n(\beta^r) \right] \tag{4}$$

where R is the number of replications and β^r is the the r-th draw from $f(\beta|\theta)$. The log likelihood for the latent class logit model with Q latent classes is given by:

$$LL_{LC}(\theta) = \sum_{n=1}^{N} \ln \left[\sum_{q=1}^{Q} H_{nq} S_n(\beta_q) \right] \tag{5}$$

where H_{nq} is the probability that individual n belongs to class q and β_q is a vector of class-specific coefficients. Following Greene and Hensher (2003) H_{nq} is specified to have the multinomial logit form:

$$H_{nq} = \frac{\exp(\gamma_q' z_n)}{\sum_{q=1}^{Q} \exp(\gamma_q' z_n)} \tag{6}$$

where z_n is a vector of observed characteristics of individual n and γ_q are vectors of parameters to be estimated. The Qth parameter vector is normalised to zero for identification purposes.

Both the mixed and latent class logit models can be used to estimate respondent-specific taste parameters (Revelt and Train 2000; Greene and Hensher, 2003). Generally the respondent-specific taste parameters, β_n, are given by:

$$\beta_n = \frac{\int \beta S_n(\beta) f(\beta|\theta) d\beta}{\int S_n(\beta) f(\beta|\theta) d\beta} \tag{7}$$

Revelt and Train (2000) show how β_n can be estimated based on a mixed logit specification by simulating equation (7):

$$\hat{\beta}_n = \frac{\frac{1}{R}\sum_{r=1}^{R} \beta^r S_n(\beta^r)}{\frac{1}{R}\sum_{r=1}^{R} S_n(\beta^r)} \tag{8}$$

where β^r is the the r-th draw from $f(\beta|\hat{\theta})$. In the latent class logit case Greene and Hensher (2003) show that an estimate of β_n is given by:

$$\hat{\beta}_n = \frac{\sum_{q=1}^{Q} \hat{\beta}_q S_n(\hat{\beta}_q) \hat{H}_{nq}}{\sum_{q=1}^{Q} S_n(\hat{\beta}_q) \hat{H}_{nq}} \tag{9}$$

In the present paper we follow Hensher and Greene's approach of plotting of the estimated distributions of individual specific parameters as a means of comparing the results of the different models.

3 The choice experiment

Delivering primary care services that are acceptable to patients requires an understanding of patient preferences. Since little relevant revealed preference data is available a stated preference discrete choice experiment was developed at the National Primary Care Research and Development Centre with the aim of quantifying the relative strength of patients' preferences for key attributes of a primary care consultation. After extensive focus group and pilot testing the attributes in Table 1 were chosen for inclusion in the experiment. The inclusion of the cost attribute is controversial since the British health system is free at the point of care and could potentially increase non-response. On the other hand including cost has the substantial advantage of facilitating estimation of willingness to pay, and the pilot indicated that patients found it acceptable.

[Table 1 about here]

On the basis of the 256 combinations of attribute levels in the full factorial design, 16 choice sets with 2 alternatives were constructed using a D-optimality algorithm (Kuhfeld, 2005) with the attribute coefficients set to zero. The 16 choice sets were then randomly 'blocked' into two sets of 8 choices. A sample of patients was randomly selected from the lists of 6 practices in the Greater Manchester area, stratified by gender and 3 age bands (18-35, 36-59 and >60). Each patient received a questionnaire including 8 choice sets and a limited set of questions regarding socio-demographic characteristics. When completing the questionnaire the respondents were asked to imagine that the reason for their consultation was a minor skin problem[2]. See Cheragi-Sohi et al. (2006) for a detailed description of the questionnaire development.

The response rate was 55.8% which is comparable to other surveys of this kind. The estimation sample consists of 3242 usable responses by 409 respondents.

4 Results

4.1 Alternative specifications of the choice model

The modelling results using the standard logit model are presented in the third column of table 2[3]. It can be seen from the table that the attribute

[2] The questionnaire also included choice sets placed in alternative contexts which are not considered here.

[3] All the models presented in this paper are estimated in Stata using code written by the author with the exception of the logit model which is estimated using Stata's built-in command.

coefficients have the expected sign: on average patients prefer shorter waiting times, lower cost, a GP that knows them well and who is warm and friendly, a choice of appointment times and a thorough examination. All the coefficients are significant at conventional significance levels except the constant term. The constant term does not have a natural interpretation in this context as its significance would indicate a preference for 'alternative A' over 'alternative B' or vice versa net of the influence of the alternative attributes. Its insignificance indicates that patients do not prefer one consultation over the other when the difference in attributes are accounted for as would be expected (the respondents were explicitly instructed that the consultations were equal in all other respects than the information presented in the experiment). It is customary, however, to include a constant term in the model in DCE applications as a test for specification error (Scott, 2001). A random effects logit model was also estimated, but not reported, as the coefficient estimates were very similar to the logit coefficients and a likelihood ratio test concluded that the random effects model did not have better fit. Since the random effects logit can be thought of as a mixed logit model with a normally distributed constant term this finding is not surprising: if only the attributes are important for patients when making their choices both the mean and standard deviation of the constant term should be insignificantly different from zero.

It was also attempted to estimate logit models with interactions between the alternative attributes and the socio-demographic characteristics of the respondents, which is a common approach to accounting for preference heterogeneity in the analysis of DCEs (e.g. Scott, 2001; Hanson et al., 2005). The set of relevant socio-demographic characteristics in the data is limited to the respondents' gender, age, frequency of GP visits, self reported health and income, however, which limits the scope of this approach in the present application. Since different model specifications using one or more of these characteristics only led to minor improvements in fit compared to the model without interactions and few of the interaction terms were found to be significant these models are not reported.

A critical issue when specifying a mixed logit model is choosing the coefficients which are allowed to vary and the distribution they should take. The applications of the model to date use a combination of intuition and statistical tests (such as the likelihood ratio test) to decide on which coefficients to vary[4]. The random coefficients are usually specified to be normally distributed, probably due to the familiarity with the normal distribution in economics and the availability of estimation software capable of estimating mixed logit models with normally distributed coefficients. Columns 4 and 5 in table 2 present the results of two mixed logit models with normally distributed coefficients. The models are estimated by maximum simulated likelihood as described in section 2 using 500 Halton draws (Train, 1999). In the first model all the coefficients are specified to vary except the coefficient for cost and the constant term (model N1) while in the second model the cost coefficient is also normally distributed (model N2). Fixing the cost coefficient has several advantages as pointed out by Revelt and Train (1998) among others. In particular it ensures that the coefficient has the right sign: a normally distributed cost coefficient implies that some individuals may prefer an appointment with higher cost which is counter-intuitive. In addition a fixed cost coefficient implies that the distribution of willingness to pay for the remaining attributes follows the same distribution as the attribute coefficients - if the coefficients are normally distributed then so is willingness to pay. If the cost coefficient is also normally distributed the willingness to pay is the ratio of two normal distributions which does not have defined moments. Finally, fixing at least one of the coefficients in the model helps empirical identification, especially in applications using cross-sectional data (Ruud, 1996). On the other hand the possibility of significant preference heterogeneity in terms of cost cannot be ruled out. Meijer and Rouwendal (2006) find that models where the cost coefficient is allowed to vary fit the data better in their application and conclude that this specification should be considered despite the disadvantages identified by Revelt and Train (1998).

[Table 2 about here]

[4] McFadden and Train (2000) and Chesher and Santos-Silva (2002) describe tests for detecting preference heterogeneity based on the logit model.

Meijer and Rouwendal's result is confirmed in the present application: although both mixed logit models fit the data considerably better than the standard logit model the model in which the cost coefficient is allowed to vary (model N2) has markedly better fit than the model in which the cost coefficient is constrained to be fixed (model N1). Both models reveal the existence of substantial preference heterogeneity in the sample: all coefficients are found to have significant standard deviations, with the exception of the coefficients for the flexibility of appointment times and the doctor's interpersonal manner in model N1. The assumption of normally distributed coefficients may be inappropriate, however, as a further inspection of the results show. As mentioned earlier the normal distribution allows for the possibility that a proportion of the respondents have coefficients with counter-intuitive signs. The coefficient estimates of model N2 imply that about 17% of patients prefer longer to shorter waiting times, 8% higher to lower costs, 23% seeing a doctor that does not know them, 30% not having a choice of appointment times, 11% seeing a formal and businesslike doctor rather than a warm and friendly one and 16% receiving a not very thorough examination. It is likely that in the case of most of the attributes these findings are simply an artefact of the assumption of normally distributed coefficients, given that it is unlikely that any patient would prefer, for instance, to wait longer and pay more[5].

The log-normal distribution is an often-used alternative to the normal distribution in this context. Since the log-normal distribution has positive probabilities only for values greater than zero, specifying a coefficient to be log-normally distributed ensures that it has a positive sign for all individuals. If an attribute is expected to have a negative coefficient (such as waiting time and cost) the attribute is multiplied by minus one before entering the model and the estimated distribution interpreted as the mirror image of the actual distribution of the coefficient. Table 3a presents the results of two mixed logit models with log-normally distributed coefficients estimated by maxi-

[5] An analogous issue arises in the transportation literature where it is usually expected that all respondents prefer transport modes with shorter travel times and lower costs (Hess et al., 2005).

mum simulated likelihood using 500 Halton draws. In the first model all the coefficients are specified to be log-normally distributed except the coefficient for cost and the constant term (model LN1), while in the second model the cost coefficient is also log-normally distributed. Specifying the cost coefficient to be log-normally distributed avoids many of the problems related to a normally distributed cost coefficient. Apart from ensuring that the cost coefficient has the right sign the log-normal distribution has the additional desirable property that the ratio of two lognormally distributed variables is also lognormal, which implies that willingness to pay is log-normally distributed. Although the identification issue pointed out by Ruud (1996) remains, this is likely to be less critical in the present application since there are several observations per individual and the constant term is fixed (although it is found to be insignificantly different from zero). As in the case of the models with normally distributed parameters it is found that the model in which the cost coefficient is allowed to vary fits the data considerably better than the alternative model. It should be pointed out that the estimated parameters in models LN1 and LN2 are the means (b_k) and standard deviations (s_k) of the natural logarithm of the coefficients. The median, mean and standard deviation of the coefficients themselves are given by $\exp(b_k)$, $\exp(b_k + s_k^2/2)$ and $\exp(2b_k + s_k^2)\,[\exp(s_k^2) - 1]$, respectively (Train, 2003). Table 3b present the estimated means, medians and standard deviations of the coefficients in models LN1 and LN2 with t-statistics based on standard errors calculated using the delta method. As in Revelt and Train (1998) the median and the mean are in most cases found to bracket the means of the coefficients from the mixed logit models with normally distributed coefficients.

[Tables 3a and 3b about here]

The mixed logit models presented here assume that the coefficients are independently distributed. It is possible, however, that patients with a strong preference for a thorough examination also have a strong preference for having a choice of appointment times, for example, which would violate this assumption. This was investigated by re-estimating the models, allowing for a completely general covariance pattern across the coefficients[6]. This increase in flexibility comes at a cost, however: the number of parameters increases by $K(K-1)/2$, where K is the number of randomly distributed coefficients in the model. While the off-diagonal terms in the coefficient covariance matrix were found to be jointly insignificant in the models with log-normally distributed coefficients, the independence hypothesis was rejected in the models with normally distributed coefficients. On the whole, however, the willingness to pay estimates derived from the models allowing for a general correlation pattern are similar to those derived from the models with uncorrelated coefficients, and therefore only the latter, more parsimonious models are reported.

Table 4 presents the results of a latent class logit model with 3 latent classes. An advantage of the latent class model over the mixed logit model is that the choice of distributions for the random coefficients is not an issue. As Hensher and Greene (2003) point out the discrete distributions in the latent class model can be interpreted as nonparametric estimates of the continuous distributions in the mixed logit model. The difficulty of choosing the number of latent classes still remains, however, and must be determined prior to estimating the model. In practice it is often found that there is a trade-off between goodness of fit and the precision of the parameter estimates: while increasing the number of classes tends to increase the fit of the model it may lead to several coefficients having extremely large standard errors. In the present application it was found that a model with more than three latent classes suffered from this problem, and it was therefore decided that three latent classes was the preferred specification in spite of models with a higher number of latent classes having somewhat better fit. The estimated coefficients have the expected sign and are significant in most cases and the log-likelihood is comparable to the mixed logit models in which the cost coefficients are allowed to vary. In this model the class membership probability is a function of constants only, implying that the probability of belonging to each class is constant across individuals. This assumption can be relaxed by

[6] It should be noted that the parameters in the covariance matrix for the coefficients are not estimated directly. Following Train (2003) the estimated parameters are the elements in the lower-triangular matrix L and the covariance matrix is given by LL'.

including socio-demographic characteristics in the class membership model, but although the inclusion of characteristics such as age and the frequency of GP visits led to an increase in fit it had little impact on the willingness to pay estimates and therefore only the more parsimonious model with equal class probabilities across individuals is reported.

[Table 4 about here]

Table 5 presents a comparison of the goodness of fit of the models using the Akaike and Schwartz criteria. While model LN2 is the preferred specification according to both criteria there is disagreement in the rankings of the remaining models; the Schwarz criterion narrowly considers model LN1 to be second best, while the Akaike criterion which penalise a loss of degrees of freedom less heavily favours model N2 and the latent class model.

[Table 5 about here]

4.2 The distribution of willingness to pay

Tables 6 and 7 present the estimated mean and median willingness to pay (WTP) estimates derived from the various model specifications. 95% confidence intervals calculated using the Krinsky Robb method (Krinsky and Robb, 1986, 1990; Hole, 2007) are reported in parenthesis. Note that in the case of the logit model and model N1 the mean equals the median WTP and in the case of model N2 the mean WTP is not defined. The mean WTP estimates derived from the logit model are £1.71 for a 1-day reduction in waiting time, £4.48 to see a doctor that knows you, £2.53 to get a choice of appointment times, £4.13 to see a warm and friendly doctor and £13.82 to get a thorough examination. As in several other applications of the mixed logit model (Revelt and Train, 1998; Hensher and Greene, 2003) the mean/median WTP derived from the logit model is found to be similar to the estimates derived from the mixed logit models with normally distributed coefficients. Revelt and Train (1998) suggest that if this finding turns out to be an empirical regularity it is not necessary to estimate the much more computationally demanding mixed logit model if the main goal of the study is to estimate mean WTP. Although this result has been confirmed in many studies since Revelt and Train's study there are exceptions (Hensher, 2001; Hess et al., 2005), which suggest that this correspondence in WTP estimates cannot be taken for granted *a priori*. Further, the results from mixed logit models with non-normal distributions are sometimes found to be somewhat at odds with those derived from models with normally distributed coefficients (Meijer and Rouwendal, 2006). Both the models with log-normal distributions and the latent class model show evidence of a skewed distribution of WTP, which manifests itself in the mean WTP estimates being substantially higher than the median WTP estimates derived from these models. Hensher and Greene (2003) and Sillano and Ortúzar (2005) among others have critisised the log-normal distribution because of its long right tail, arguing that this property of the distribution can cause unrealistic WTP estimates. The fact that the latent class model leads to similarly skewed estimates of WTP, however, lends credibility to this finding being more than an artefact of the log-normal distribution. As with the parameter estimates the median and mean willingness to pay derived from the models with log-normally distributed coefficients bracket the mean/median willingness to pay derived from models N1, N2 and the logit model.

[Tables 6 and 7 about here]

Figures 1-5 presents kernel density plots of the distribution of the individual WTP estimates derived from models N2, LN2 and the latent class model using equations (8) and (9). Although there are noticeable differences, especially in the tails of the WTP distributions, the distributions are found to be relatively similar in many cases. It is interesting to note that like the individual WTP estimates derived from model LN2 and the latent class model the WTP estimates derived from model N2 are somewhat skewed even if the coefficients in the model are normally distributed. This finding suggests that if the goal of the study is to estimate the distribution of WTP in the sample this may be reasonably accurately approximated by a range of models with different assumptions regarding the underlying distribution of the coefficients. This is reassuring since the mixed and latent class models, by their greatly enhanced flexibility, make specification errors more likely. The concluding section offers some thoughts on the specification issue.

[Figures 1-5 about here]

5 Discussion

This paper studies the distribution of preferences in a sample of patients who responded to a discrete choice experiment where they were asked to choose between different hypothetical general practitioner appointments. Particular attention is paid to the distribution of willingness to pay for the attributes of the appointment. It is found that there is significant preference heterogeneity for all the attributes in the experiment and that both the mixed and latent class logit models lead to significant improvements in fit compared to the standard logit model. Moreover, the distribution of preferences implied by the preferred mixed and latent class models is similar for many attributes. The results demonstrate the additional insights that can be made from using choice models that allow the recovery of the *distribution* of preferences when analysing data from health related discrete choice experiments. While on balance the results in the present application suggest that if the goal is simply to analyse patients' mean preferences the logit model does a relatively good job, it fails to uncover the wide range in preferences among patients. Although preference heterogeneity has long been accounted for in the analysis of DCEs by interacting design attributes with socio-demographic characteristics, evidence from other fields suggests that this approach only partially accounts for the taste differences embodied in the data (Morey and Rossman, 2003; Iragüen and Ortúzar, 2004). This finding is confirmed in the present study: logit models in which the limited set of socio-demographic characteristics available in the data were interacted with the design attributes led to only modest improvements in fit compared to the model with no interactions and only a small proportion of the interaction terms were found to be significant. Even when the data include a very rich set of respondent characteristics the number of coefficients grow very quickly with the number of interactions, which tends to force researchers to use only the subset of characteristics believed to be the most relevant in their study. Mixed and latent class logit models offer a parsimonious alternative to this approach which is applicable even when the characteristics driving the preference heterogeneity are unknown.

Given that a wide range of software is now available to estimate both mixed and latent class models, the challenge that these models presented only a few years ago in terms of implementation is substantially diminished. As this paper shows the specification of the mixed and latent class models is less straightforward than a standard logit model since additional decisions need to be made regarding which coefficients to vary, which distribution they should follow, the number of latent classes etc. The relevant benchmark is not a logit model in which only the design attributes enter as explanatory variables, however, but a logit model in which preference heterogeneity is accounted for by interacting the attributes with socio-demographic characteristics. This approach also introduces the difficult questions of which characteristics to include, which attributes to be interacted, the choice of two- versus three-way interactions and so on. The conclusion is that modelling preference heterogeneity introduces specification challenges to the researcher whichever approach is adopted, and in the light of the very good record of the mixed and latent class logit models in other fields of economics as well as the evidence presented in the present paper these methods should be seriously considered for inclusion in the toolbox of the health related DCE analyst.

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Table 1. Attributes and levels in the discrete choice experiment

Attribute	Levels
Number of days wait for an appointment	Same day, next day, 2 days, 5 days
Cost of appointment to patient	£0, £8, £18, £28
Flexibility of appointment times	One appointment offered Choice of appointment times offered
Doctor's interpersonal manner	Warm and friendly Formal and businesslike
Doctor's knowledge of the patient	The doctor has access to your medical notes and knows you well The doctor has access to your medical notes but does not know you
Thoroughness of physical examination	The doctor gives you a thorough examination The doctor's examination is not very thorough

Table 2. Logit model and mixed logit models with normally distributed coefficients.

Variable	Parameter	Logit		N1		N2	
		Value	t-stat	Value	t-stat	Value	t-stat
Waiting time (days)	Mean coefficient	-0.131	-7.71	-0.209	-7.98	-0.382	-6.41
	Std. dev. of coefficient			0.187	4.77	0.393	5.61
Cost (pounds)	Mean coefficient	-0.077	-27.22	-0.115	-18.52	-0.238	-8.43
	Std. dev. of coefficient					0.167	7.61
Dr knows you well	Mean coefficient	0.344	6.49	0.610	7.16	1.342	6.41
	Std. dev. of coefficient			0.801	6.32	1.813	6.10
You get a choice of appointment times	Mean coefficient	0.194	3.60	0.270	3.82	0.492	3.51
	Std. dev. of coefficient			0.101	0.35	0.892	3.57
Dr is warm and friendly	Mean coefficient	0.317	6.13	0.397	5.02	0.710	4.79
	Std. dev. of coefficient			0.006	0.04	0.579	2.01
Dr gives you a thorough physical examination	Mean coefficient	1.061	18.24	1.580	11.98	3.069	7.65
	Std. dev. of coefficient			1.741	12.44	3.108	7.72
Constant	Mean coefficient	-0.023	-0.40	-0.047	-0.63	-0.066	-0.54
Number of responses		3243		3243		3243	
Number of respondents		409		409		409	
Log likelihood		-1397.74		-1275.74		-1145.53	

Table 3a. Mixed logit models with log-normally distributed coefficients.

Variable	Parameter	LN1		LN2	
		Value	**t-stat**	**Value**	**t-stat**
Waiting time (days)	Mean of ln(coefficient)	-2.512	-7.03	-1.651	-7.54
	Std. dev. of ln(coefficient)	1.720	8.14	1.053	7.18
Cost (pounds)	Mean coefficient	-0.145	-19.80		
Cost (pounds)	Mean of ln(coefficient)			-1.802	-19.93
	Std. dev. of ln(coefficient)			0.990	9.07
Dr knows you well	Mean of ln(coefficient)	-1.385	-3.53	-0.564	-2.59
	Std. dev. of ln(coefficient)	1.890	7.16	1.348	11.07
You get a choice of appointment times	Mean of ln(coefficient)	-1.782	-3.64	-1.503	-3.75
	Std. dev. of ln(coefficient)	1.461	5.64	1.325	6.12
Dr is warm and friendly	Mean of ln(coefficient)	-1.266	-3.57	-0.485	-2.29
	Std. dev. of ln(coefficient)	1.325	6.85	-0.590	-2.30
Dr gives you a thorough physical examination	Mean of ln(coefficient)	-0.043	-0.25	0.372	2.61
	Std. dev. of ln(coefficient)	1.613	10.85	1.351	11.68
Constant	Mean coefficient	-0.056	-0.59	-0.158	-1.52
Number of responses		3243		3243	
Number of respondents		409		409	
Log likelihood		-1148.78		-1098.11	

Table 3b. Means, medians and standard deviations of the log-normally distributed coefficients.

Variable	Statistic	LN1		LN2	
		Value	t-stat	Value	t-stat
Waiting time (days)	Mean	-0.356	5.98	-0.334	7.16
	Median	-0.081	2.80	-0.192	4.57
	Std. dev.	1.523	2.19	0.476	3.89
Cost (pounds)	Mean			-0.269	6.93
	Median			-0.165	11.06
	Std. dev.			0.347	3.34
Dr knows you well	Mean	1.494	4.89	1.412	7.34
	Median	0.250	2.55	0.569	4.60
	Std. dev.	8.790	1.50	3.205	4.27
You get a choice of appointment times	Mean	0.489	4.97	0.535	4.62
	Median	0.168	2.04	0.222	2.49
	Std. dev.	1.335	2.49	1.170	2.79
Dr is warm and friendly	Mean	0.679	6.25	0.733	6.31
	Median	0.282	2.82	0.615	4.71
	Std. dev.	1.485	3.53	0.473	1.82
Dr gives you a thorough physical examination	Mean	3.515	6.24	3.613	7.88
	Median	0.957	5.65	1.451	7.02
	Std. dev.	12.417	2.59	8.241	3.66

Table 4. Latent class logit model with 3 latent classes.

Variable	Class 1		Class 2		Class 3		Mean	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Waiting time (days)	-0.204	-2.33	-0.293	-7.00	-0.110	-2.21	-0.176	-5.53
Cost (pounds)	-0.048	-2.79	-0.037	-3.99	-0.161	-14.12	-0.106	-15.77
Dr knows you well	0.266	0.88	1.114	7.61	0.425	2.67	0.568	5.45
You get a choice of appointment times	0.045	0.19	0.386	3.30	0.544	3.09	0.402	3.90
Dr is warm and friendly	0.471	1.61	0.539	4.08	0.529	3.63	0.519	5.44
Dr gives you a thorough physical examination	3.758	9.57	0.647	4.38	0.678	3.94	1.299	9.88
Constant	-0.063	-0.17	-0.131	-0.91	-0.220	-1.19	-0.165	-1.37
Probability of belonging to (t-stat):								
Class 1	0.204 (8.71)							
Class 2	0.255 (5.59)							
Class 3	0.541 (12.76)							
Number of responses	3243							
Number of respondents	409							
Log likelihood	-1135.35							

Table 5. Goodness of fit measures.

	Akaike criterion	**Schwarts criterion**
Logit	2809.48	2852.07
N1	2575.48	2648.49
N2	2317.06	2396.16
LN1	2321.56	2394.57
LN2	2222.22	2301.32
Latent class	2316.70	2456.64

Table 6. Mean willingness to pay estimates.

	Logit	**N1**	**N2**	**LN1**	**LN2**	**Latent class**
Waiting time (days)	1.71 (1.29 – 2.13)	1.82 (1.41 – 2.23)	DNA	2.45 (1.86 – 3.44)	3.30 (2.41 – 4.84)	3.28 (2.23 – 5.60)
Dr knows you well	4.48 (3.08 – 5.92)	5.31 (3.92 – 6.72)	DNA	10.28 (7.49 – 16.77)	13.96 (10.09 – 20.59)	10.31 (6.55 – 19.40)
You get a choice of appointment times	2.53 (1.14 – 3.93)	2.35 (1.12 – 3.60)	DNA	3.37 (2.38 – 5.26)	5.29 (3.36 – 9.13)	4.70 (1.58 – 8.60)
Dr is warm and friendly	4.13 (2.80 – 5.50)	3.46 (2.12 – 4.76)	DNA	4.67 (3.61 – 6.49)	7.24 (5.23 – 11.04)	7.53 (4.47 – 13.79)
Dr gives you a thorough physical examination	13.82 (12.47 – 15.21)	13.75 (11.89 – 15.68)	DNA	24.19 (18.33 – 33.67)	35.73 (26.33 – 51.53)	22.83 (15.73 – 54.10)

Note: 95% confidence intervals calculated using the Krinsky Robb method in parentheses.
DNA = does not exist.

Table 7. Median willingness to pay estimates.

	Logit	N1	N2	LN1	LN2	Latent class
Waiting time (days)	1.71 (1.29 – 2.13)	1.82 (1.41 – 2.23)	1.61 (1.24 – 1.99)	0.56 (0.28 – 1.11)	1.16 (0.75 – 1.80)	0.68 (0.09 – 1.33)
Dr knows you well	4.48 (3.08 – 5.92)	5.31 (3.92 – 6.72)	5.65 (4.32 – 7.07)	1.72 (0.79 – 3.69)	3.45 (2.24 – 5.26)	2.63 (0.71 – 4.47)
You get a choice of appointment times	2.53 (1.14 – 3.93)	2.35 (1.12 – 3.60)	2.07 (0.97 – 3.21)	1.16 (0.44 – 3.07)	1.35 (0.60 – 3.02)	3.37 (1.23 – 5.58)
Dr is warm and friendly	4.13 (2.80 – 5.50)	3.46 (2.12 – 4.76)	2.99 (1.87 – 4.16)	1.94 (0.97 – 3.84)	3.73 (2.42 – 5.77)	3.27 (1.52 – 5.07)
Dr gives you a thorough physical examination	13.82 (12.47 – 15.21)	13.75 (11.89 – 15.68)	12.92 (11.10 – 14.86)	6.59 (4.76 – 9.20)	8.79 (6.66 – 11.61)	4.20 (2.10 – 6.50)

Note: 95% confidence intervals calculated using the Krinsky Robb method in parentheses.

Figure 1. Distribution of willingness to pay for a one day reduction in waiting time

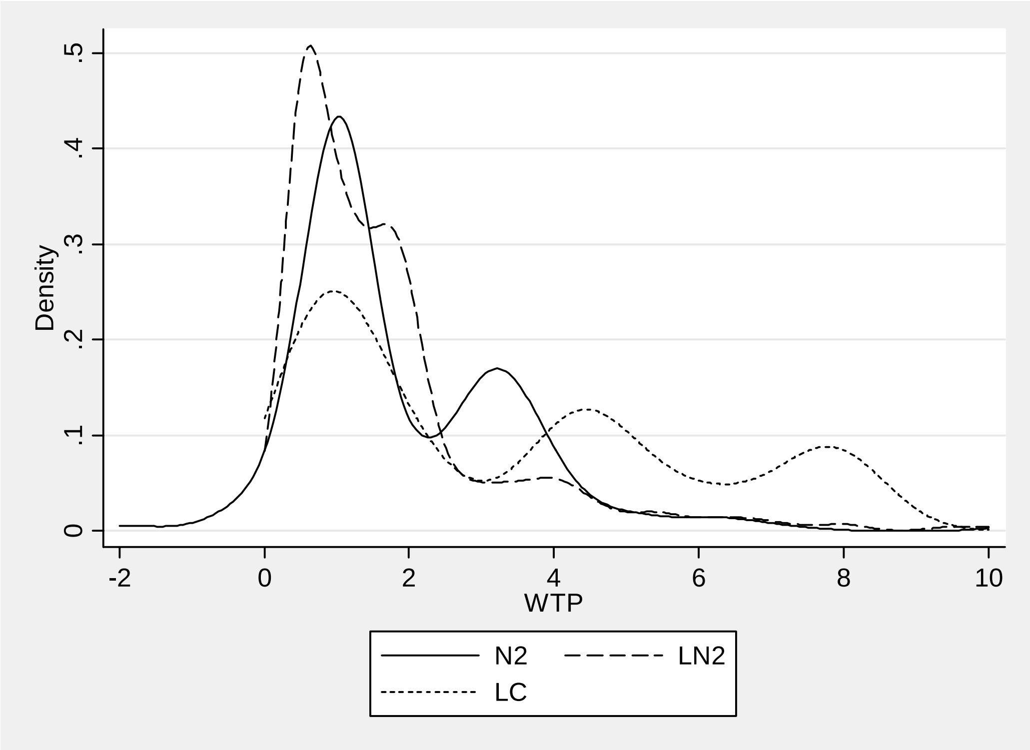

Figure 2. Distribution of willingness to pay for a choice of appointment times

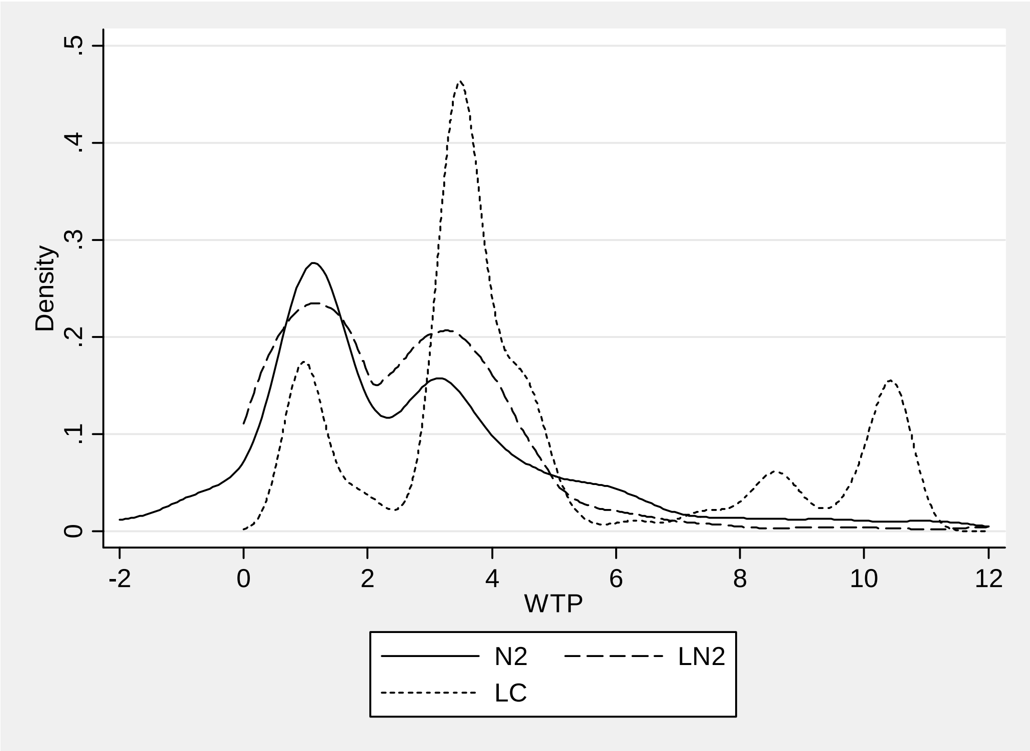

Figure 3. Distribution of willingness to pay to see a warm and friendly doctor

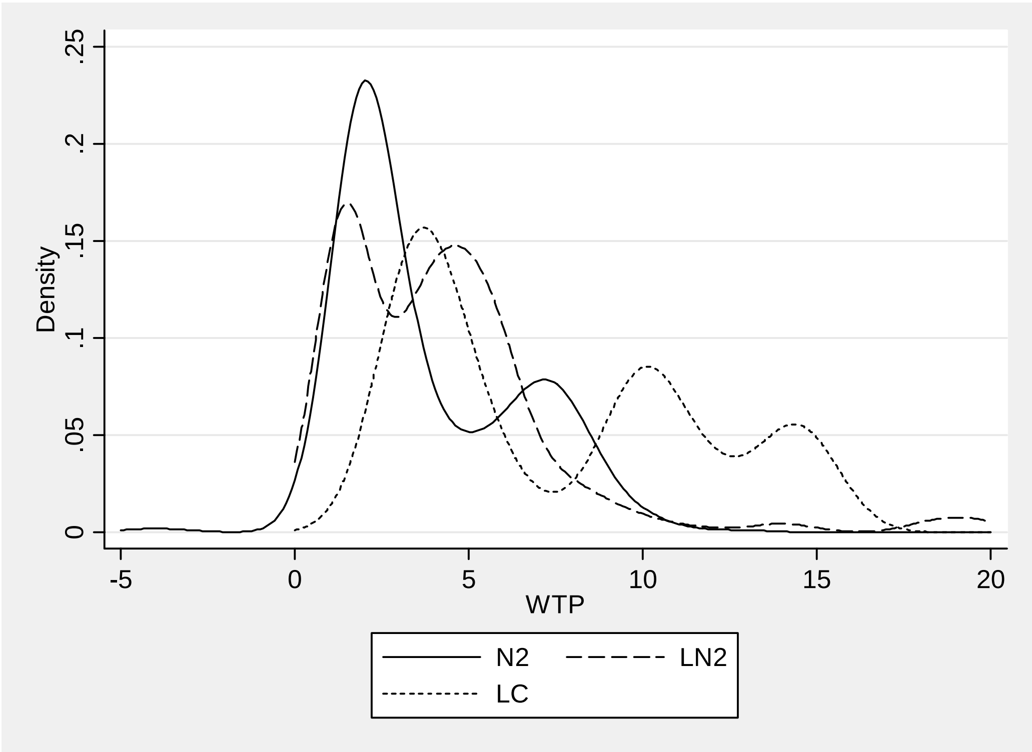

Figure 4. Distribution of willingness to pay to see a doctor that knows you

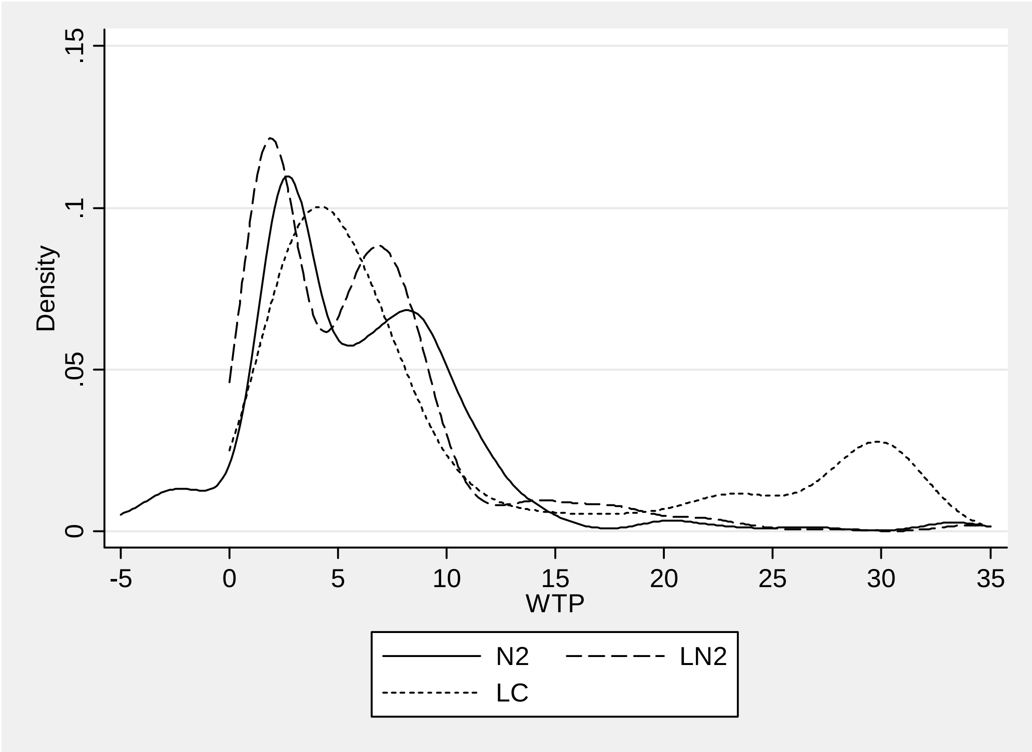

Figure 5. Distribution of willingness to pay for a thorough examination