# Inferred vs stated attribute non-attendance in choice experiments: A study of doctors' prescription behaviour*

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**Abstract**

It is increasingly recognised that respondents to choice experiments employ heuristics such as attribute non-attendance (ANA) to simplify the choice tasks. This paper develops an econometric model which incorporates preference heterogeneity among respondents and allows the probability of non-attendance to depend on the respondents' stated non-attendance. We find evidence that stated ANA is a useful indicator of the prevalence of non-attendance in the data. Contrary to previous papers in the literature we find that estimates of marginal rates of substitution derived from models which account for ANA are similar to the standard logit estimates.

Keywords: choice experiment, attribute non-attendance

JEL codes: C25, I10

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# 1 Introduction

Over the past decades the Discrete Choice Experiment (DCE) has become a popular tool for non-market valuation in several fields of applied economics. The methodology behind choice experiments is rapidly evolving and substantial progress has been made in recent years in terms of both experimental design and data analysis. As part of these developments much effort has been devoted to studying the use of heuristics, or simplified decision rules, among respondents to choice experiments (see Hensher, 2010, for a review). One of the heuristics that have been identified in the literature is the tendency to ignore one or more of the attributes in the experiment, a phenomenon that has been labelled attribute non-attendance (ANA). Following the important contribution by Hensher et al. (2005) several papers have found evidence of ANA in a variety of fields including transportation (Hensher, 2006; Hensher and Greene, 2010), environment (Campbell et al., 2008; Carlsson et al., 2010) and health (Ryan et al., 2009; Hole 2011a). There is also a growing stock of evidence suggesting that attribute non-attendance may lead to biased coefficient estimates, and hence biased estimates of willingness to pay, if it is not taken account of at the data analysis stage (Scarpa et al. 2009; Hensher and Greene 2010; Hole 2011a).

Various methods have been proposed in the literature for identifying attribute non-attendance. One approach is to ask the respondents directly whether they ignored any of the attributes when making their choices and if so, which attributes ('Stated ANA'). This can either be done after the choice experiment has been completed, or after each individual choice to allow for the fact that the attribute processing rule may change over the choice sequence (Puckett and Hensher, 2008)[1]. Another approach is to use an econometric model which makes it possible to estimate the probability of attribute non-attendance without the use of supplementary data ('Inferred ANA'). The type of model used has typically been a form of latent class model, where the classes represent different attribute processing strategies

[1] It should be noted that asking after each choice could itself change the processing rule.

(Scarpa et al., 2009; Hensher and Greene, 2010; Campbell et al., 2011).[2]

The stated ANA approach has been criticised on the grounds that respondents may not be fully aware of the attribute processing rule they applied when making their choices, which would imply some degree of misreporting. Campbell and Lorimer (2009) and Hess and Hensher (2010) have found that when attribute coefficients are estimated separately for self-reported 'attenders' and 'non-attenders' the coefficients for the latter group tend to be significantly different from zero. Models in which the coefficients are forced to equal zero for the non-attenders, a common approach in the early literature on ANA, are therefore likely to be mis-specified. Moreover, it is potentially problematic to include the stated ANA variables as explanatory variables in the utility function as they may be endogenous. For example, a respondent with a stronger than average preference for a particular attribute may be more likely to report having ignored one or more of the other attributes in the choice set. Unless the preference heterogeneity is accounted for in the model the stated ANA variables will be correlated with the error term which may lead to bias. This suggests that modelling ANA probabilistically is preferable, but the question remains whether data on stated ANA can be used to improve the performance of the probabilistic model. That is the focus of the current paper.

We use DCE data on doctors' prescription choices where the respondents were asked to report which attributes they took into account after completing the experiment. The main contribution of this paper is to develop an econometric model which incorporates preference heterogeneity among respondents and allows the probability of non-attendance to depend on the respondents' stated non-attendance. Our main findings are; 1) the model fit increases when stated ANA is incorporated in the models, which suggests that the self-reported data contain useful information about the respondents' attribute processing strategy, 2) self-reported non-attenders have higher ANA probabilities than attenders, in general and 3) the extent of ANA decreases

[2] A third approach which is not pursued in this paper is to use a qualitative 'think aloud' procedure to identify non-attendance (Ryan et al., 2009). The advantage of this method is that several heuristics can be identified simultaneously. A potential disadvantage is that having to think aloud may influence the choice process.

markedly when preference heterogeneity is accounted for, which confirms recent findings in the literature (Hensher et al., 2012; Hess et al., 2013). Contrary to most papers in the literature we find that the estimates of marginal rates of substitution (MRS) derived from the various models are generally similar. This suggests that failure to account for attribute non-attendance does not necessarily lead to substantial bias in estimates of MRS, and that the importance of taking this heuristic into account in the analysis therefore needs to be assessed on a case-by-case basis.

The paper is structured as follows. Section 2 describes the Endogenous Attribute Attendance (EAA) model and the more flexible mixed EAA model. Section 3 describes the choice experiment and section 4 presents the modelling results. Finally, section 5 offers some concluding remarks.

# 2 Methodology

## 2.1 The endogenous attribute attendance model

The endogenous attribute attendance model (Hole, 2011a) is essentially a joint model of choice process and outcome. Such models have a long tradition in the discrete choice literature (e.g. Manski, 1977; Swait and Ben-Akiva, 1987) and recent contributions to the literature on modelling heuristics include Hensher (2008) and Hess and Hensher (2013). In the EAA model the joint probability of choosing an alternative using a particular attribute processing strategy (APS) can be broken down into the marginal probability of choosing the APS multiplied by the probability of choosing the alternative conditional on the choice of APS. To be more specific, the respondents are assumed to choose a subset $C_q$ from a total of $K$ attributes to consider when choosing an alternative. The total number of attribute subsets is given by $Q = 2^K$, which includes the set in which all attributes are included ($C_Q$) and the empty set in which the respondents discard all the information about the alternatives ($C_1$). The former corresponds to the conventional assumption that the decision-makers make use of all the available information on the alternatives when making a choice while the latter implies that the choice process is random. Conditional on the choice of attribute subset $C_q$ the utility that individual $n$ derives from choosing alternative $j$ on choice occasion $t$ is given by $U_{njt} = \sum_{k \epsilon C_q} x_{njt}^k \beta^k + \varepsilon_{njt}$ where $x_{njt}^k$ represents the value of attribute $k$ relating to alternative $j$ on choice occasion $t$, $\beta^k$ is the preference weight given to that attribute and $\varepsilon_{njt}$ is a random term which is assumed to be IID extreme value.

Given these assumptions the probability that decision-maker $n$ chooses alternative $j$ on choice occasion $t$ conditional on the choice of attribute subset $C_q$ is given by the logit formula (McFadden, 1974):

$$\Pr(choice_{nt} = j | C_q) = \frac{\exp(\sum_{k \epsilon C_q} x_{njt}^k \beta^k)}{\sum_{j=1}^{J} \exp(\sum_{k \epsilon C_q} x_{njt}^k \beta^k)} \tag{1}$$

The probability that decision-maker $n$ takes attribute $k$ into account is specified as $\exp(\gamma_k' z_{nk}) / \left[1 + \exp(\gamma_k' z_{nk})\right]$, where $z_{nk}$ is a vector of individual-level observed characteristics and $\gamma_k$ is a vector of parameters to be estimated. This probability can be specified to depend on the respondents' stated ANA by including a dummy variable for having reported to ignore attribute $k$ in $z_{nk}$. This approach makes it possible to incorporate the information on stated ANA in the model, but in a way that avoids the sharp distinction of assigning a non-attendance probability of one or zero which is inappropriate unless all respondents are fully aware of their attribute processing strategy. We can then test whether the modelled ANA probabilities are higher for the self-reported non-attenders, as would be expected if stated ANA carries useful information about the true probability of attending to an attribute.

Assuming that the ANA probabilities are independent over attributes the probability of choosing attribute subset $C_q$ is given by:

$$H_{nC_q} = \prod_{k \epsilon C_q} \frac{\exp(\gamma_k' z_{nk})}{1 + \exp(\gamma_k' z_{nk})} \prod_{k \notin C_q} \frac{1}{1 + \exp(\gamma_k' z_{nk})} \tag{2}$$

Combining equations (1) and (2) the unconditional probability of the observed sequence of choices is

$$P_n^{EAA} = \sum_{q=1}^{Q} H_{nC_q} \times \prod_{t=1}^{T} \prod_{j=1}^{J} \Pr(choice_{nt} = j | C_q)^{y_{njt}} \tag{3}$$

where $y_{njt}$ is equal to one if individual $n$ choses alternative $j$ on choice occasion $t$ and zero otherwise.

The $\beta$ and $\gamma$ parameters can then be estimated jointly by maximising the log-likelihood function:

$$LL^{EAA} = \sum\nolimits_{n=1}^{N} \ln P_n^{EAA} \tag{4}$$

The EAA model can be viewed as a variant of the equality-constrained latent class model (Scarpa et al., 2009), but while $H_{nC_q}$ takes the multinomial logit form in the latent class model it takes the form of a product of several binary logit probabilities in the EAA model (equation 2). The advantage of specifying the class-membership probabilities in this way is that it is possible to allow for all possible attribute processing strategies in the model without increasing the number of parameters dramatically. For example, with 5 attributes the total number of attribute processing strategies is $2^5 = 32$. This means that when the class-membership probabilities are fixed across respondents $H_{nC_q}$ would have $32 - 1 = 31$ parameters in the latent class model (one per APS minus one parameter normalised to zero for identification purposes). In the EAA model $H_{nC_q}$ has only 5 parameters (one per attribute) in this case. The drawback of the EAA specification is that it is necessary to assume that the non-attendance probabilities are independent, but it is important to point out that unless we make this assumption the estimation problem becomes impractical, especially when including stated ANA in the model and allowing for preference heterogeneity (see below).

It should be noted that it is not possible to identify $\gamma_k$ if $\beta^k = 0$. In other words, if the preference weight given to attribute $k$ is zero it is not possible to estimate the probability of attending to this attribute. This does not turn out to be an issue in the current application. While the structure of the EAA model is relatively simple Hole (2011b) found that it outperformed a very flexible parametric mixed logit model in terms of goodness of fit in a study of patients' choice of general practitioner appointment.[3]

[3]It should be noted that a potential drawback of the EAA model is that it does not allow for multiple heuristics. In the transportation literature, for example, it has been found that respondents in some cases treat two or more attributes (e.g. travel time

## 2.2 The mixed EAA model

In the EAA model the respondents who attend to an attribute are assumed to have identical preferences for that attribute. This assumption can be relaxed by allowing $\beta$ to vary across respondents, which leads us to the mixed EAA (MEAA) model.

In the MEAA model the utility that individual $n$ derives from choosing alternative $j$ on choice occasion $t$ is specified as $U_{njt} = \sum_{k\epsilon C_q} x^k_{njt}\beta^k_n + \varepsilon_{njt}$, where $\beta^k$ has been given an $n$ subscript to indicate that $\beta^k_n$ is an individual-specific coefficient for attribute $k$ ($x^k_{njt}$ and $\varepsilon_{njt}$ are defined as before). The density for $\beta_n = (\beta^1_n, ..., \beta^K_n)$ is denoted as $f(\beta_n|\theta)$ where $\theta$ are the parameters of the distribution. If $\beta_n$ is specified to be multivariate normally distributed, for example, $\theta$ represents the mean and covariance parameters. The probability that decision-maker $n$ chooses alternative $j$ on choice occasion $t$ conditional on the choice of attribute subset $C_q$ and $\beta_n$ is given by:

$$\Pr(choice_{nt} = j|C_q, \beta_n) = \frac{\exp(\sum_{k\epsilon C_q} x^k_{njt}\beta^k_n)}{\sum_{j=1}^{J} \exp(\sum_{k\epsilon C_q} x^k_{njt}\beta^k_n)} \tag{5}$$

This is identical to the corresponding probability in the EAA model (equation 1) with the exception that we are now conditioning on $\beta_n$ as well as $C_q$.

As in the standard EAA model the probability of choosing attribute subset $C_q$ is given by equation (2). Combining equations (5) and (2) the unconditional probability of the observed sequence of choices is

$$P_n^{MEAA} = \sum_{q=1}^{Q} H_{nC_q} \times \int S_n(C_q, \beta_n) f(\beta_n|\theta) d\beta_n \tag{6}$$

where $S_n(C_q, \beta_n) = \prod_{t=1}^{T} \prod_{j=1}^{J} \Pr(choice_{nt} = j|C_q, \beta_n)^{y_{njt}}$. This expression cannot be solved analytically, and it is therefore approximated using simulation methods (see Train, 2009). The MEAA model is estimated by maximising the simulated log likelihood function

under different conditions) as being identical and simply add them up. This heuristic has been labelled 'aggregation of common-metric attributes' (ACMA). ACMA is arguably less relevant in our application since the attributes in the experiment (see section 3 below) are less amenable to aggregation.

$$SLL^{MEAA} = \sum\nolimits_{n=1}^{N} \ln \left[ \sum\nolimits_{q=1}^{Q} H_{nC_q} \times \frac{1}{R} \sum\nolimits_{r=1}^{R} S_n(C_q, \beta^r) \right] \tag{7}$$

where $R$ is the number of replications and $\beta^r$ is the the $r$-th draw from $f(\beta_n|\theta)$. Hess et al. (2013) use a variant of this model to study travellers' choices between alternative trips in various contexts. We extend their methodology by allowing the ANA probabilities to depend on respondents' stated non-attendance.

Allowing $\beta$ to vary across respondents is a potentially important extension of the EAA model in light of the recent literature which suggests that models which fail to allow for preference heterogeneity among attenders may confound non-attendance with weak preferences (Alemu et al., 2011; Hess et al., 2013). In other words, it may be that some respondents have weaker preferences for an attribute than others, and unless this is captured in the model these respondents may be incorrectly categorised as non-attenders. We return to this issue in the Results section.

Although the MEAA model nests the logit, mixed logit and EAA models, the null hypotheses are at the boundary of the parameter space which complicates the use of likelihood ratio tests (McLachlan and Peel, 2000).[4] For simplicity we therefore base the comparison of the goodness of fit of the models on the Akaike and Bayesian information criteria.

# 3 The choice experiment

A randomly drawn sample of Norwegian general practitioners and hospital consultants were electronically invited to participate in a choice experiment designed to establish the relative importance of different criteria when prescribing medicines. Out of the 2172 invited participants 571 responded, implying a response rate of 26%. In the experiment, the respondents were presented with the following patient description:

[4]The MEAA model becomes the mixed logit model when $H_{nC_Q} = 1$ and $H_{nC_q} = 0 \ \forall \ q \neq Q$, which implies that $\gamma_k = \infty \ \forall \ k$. The $\gamma_k$ parameters are therefore at the boundary of the parameter space under the null. If the further restriction is imposed that $\beta_n = \beta$ the MEAA model reduces to the standard logit model.

*"Imagine a patient, Mrs Howes*[5]*, 50 years of age, who has just been diagnosed with a chronic condition, which requires preventive medication. Mrs Howes has, with the right medication, a good prognosis for continuing in full employment. However, she currently feels that she has reduced quality of life with her condition."*

The doctors were then asked to indicate which of two alternative medicines they would prescribe for this patient. An example choice task is given in figure 1.

[Figure 1 around here]

The medicines were constructed as bundles of five attributes with between two and four levels. The attributes and their corresponding levels are presented in table 1.

[Table 1 around here]

The identification of the attributes in the design and their levels was based on interviews with doctors and medical researchers; see Carlsen et al. (2012) for more details about the survey development. Twenty four choice sets were constructed using a D-optimality algorithm based on a standard logit model with the coefficients set to zero (Carlsson and Martinsson, 2003). To avoid exhausting the respondents the 24 choice sets were randomly divided into two blocks so that each doctor made 12 choices. Considering that it takes around 10 minutes to answer the whole questionnaire and that the respondents to a pilot study did not find the task too burdensome, it was concluded that 12 was a manageable number of choices.

After completing the choice experiment the doctors were asked to state whether they ignored one or more attributes when making their choices.[6] Table 2 presents the self-reported attribute non-attendance frequencies for

[5] In Norwegian, this common name was translated to 'Fru Hansen'.

[6] The wording of the question was 'When you made your choices, were there any factors/attributes you chose not to take account of?'. The attributes were listed in the same order as in the choice experiment.

the 571 respondents in the sample. Only 9% of the doctors reported not attending to the effectiveness of the medication when making their choices while 16% reported that they did not take the preferences of the patients into account. A somewhat larger proportion (23-25%) reported that they ignored the information regarding costs (overall/patient costs) and 26% ignored the 'Physician's experience' attribute.

[Table 2 around here]

# 4 Results

## 4.1 Benchmark models

Table 3 presents the results of a standard logit model (model 1), an endogenous attribute attendance model (model 2), a mixed logit model with log-normally distributed attribute coefficients (model 3) and a mixed EAA model with log-normally distributed attribute coefficients (model 4)[7] [8]. In the standard logit model and mixed logit model the respondents are implicitly assumed to attend to all the attributes in the experiment, while the EAA and MEAA models relax this assumption. The ANA probabilities are specified to be fixed across respondents ($z_{nk} = 1$) but this assumption will be relaxed in the next section. The attribute coefficients in all the models are found to be significant and have the expected signs. In particular we find that higher costs (for both the patients and society) reduce the likelihood of a doctor prescribing a medicine, while a medicine with higher efficacy is more likely to be chosen. Doctors are also more likely to prescribe medicines

[7] We also estimated mixed logit and MEAA models with normally distributed coefficients (available on request), but these were found to have lower goodness of fit. The log-normal distribution implies that the coefficients are positive for all respondents, which is reasonable for the non-monetary attributes. In the case of total/patient costs the *negative* of the coefficients are specified to be log-normally distributed since doctors are expected to dislike an increase in those attributes.

[8] The models are estimated with Stata's built-in routines for maximum likelihood estimation and code written by the authors. The mixed logit and MEAA models are estimated using 500 Halton draws. Increasing the number of draws to 1,000 did not have a marked impact on the results.

with which they have a positive experience (in terms of patient outcomes) and those which the patients prefer. We will discuss the relative importance of the attributes in section 4.3 which presents the estimates of marginal rates of substitution derived from the different models.

[Table 3 around here]

The goodness of fit of the models is measured by the Akaike (AIC) and Bayesian (BIC) information criteria, which both have penalty terms for the number of parameters in the model[9]. The MEAA model is found to have the best fit overall, followed by the mixed logit model. The fact that the MEAA and mixed logit models have better fit than the EAA and logit models suggests that there is evidence of preference heterogeneity in the data. On the other hand, the finding that the MEAA model fits the data better than the mixed logit model can be taken as evidence of attribute non-attendance. This highlights the ability of the MEAA model to reflect two characteristics of respondents' behaviour which are both found to be important in the present application.

Table 4 reports the estimated ANA probabilities for each attribute based on models 2 and 4[10]. The ANA probabilities based on model 2 are substantially higher than those based on model 4. This confirms previous evidence in the literature that allowing for preference heterogeneity reduces the influence of ANA (Hensher et al., 2012; Hess et al. 2013), since allowing for a range of preferences makes it possible to better distinguish the non-attenders from respondents with small (but non-zero) coefficients. Despite the reduction in the ANA probabilities the probability of ignoring the 'effect' and 'patient preference' attributes are still significantly different from zero in model 4, however, and there is weak evidence of non-attendance to total costs (significant at the 10% level). This suggests that while allowing for preference

[9] The BIC criterion penalises additional parameters more heavily.

[10] In model 4 the ANA probability for the patient cost attribute is constrained to 0. This is a consequence of the fact that models in which this parameter was left unconstrained did not converge. After inspecting the iteration log we realised that the reason for the non-convergence was that the algorithm was trying to set the ANA probability as close to zero as possible, which implies that the underlying gamma parameter goes to infinity.

heterogeneity reduces the influence of ANA it does not necessarily remove it altogether.

Generally speaking the stated ANA probabilities are lower (greater) than the inferred probabilities from the EAA (MEAA) models, but there are some exceptions. The biggest difference between the stated and inferred probabilities is for the 'patient costs' attribute which a quarter of respondents reported to have ignored compared to an estimated ANA probability of 0.01 according to the EAA model[11]. While we cannot be certain about the reason for this discrepancy, one possible explanation is that the doctors in their stated ANA response want to signal that patient costs are not the main concern when choosing which medicine to prescribe. When they make their choices, however, it seems like most doctors do in fact take this attribute into account. While this may be taken as evidence that stated ANA should be viewed with caution we will see in the next section that the stated and inferred ANA approaches are complementary.

[Table 4 around here]

## 4.2 Models with stated ANA dummies

In this section we relax the assumption that the attribute attendance probabilities are fixed across respondents by including stated ANA dummies in the EAA and MEAA models. To be specific, we now specify that $z_{nk} = (1, d_{nk})'$, where $d_{nk} = 1$ if respondent $n$ reported to ignore attribute $k$ and 0 otherwise. The results are reported in table 5. By comparing models 5 and 6 with the benchmark models (2 and 4) we can see that the inclusion of the ANA dummies increases the goodness of fit of the models substantially. We also find that the MEAA model continues to fit the data better than the EAA model.

[Table 5 around here]

[11] As explained above the ANA probability for this attribute was constrained to 0 in the MEAA model.

Table 6 reports the predicted attribute non-attendance probabilities based on models 5 and 6 for self-reported attribute attenders and non-attenders, respectively. It can be seen that the ANA probability is consistently higher for the self-reported non-attenders and that the difference is significant at the 1% level for all attributes except effectiveness and patient costs[12]. This suggests that the doctors are aware of their attribute processing strategies, at least to a certain extent, and that the stated ANA contains some useful information. This impression is reinforced by the fact that, with the exception of effectiveness, the ANA probabilities for the self-reported attenders are insignificantly different from zero according to model 6. On the other hand, while the difference in probabilities is marked, there is still a positive probability of attribute attendance among the self-reported non-attenders, which suggests that there is some misreporting in the data. This confirms previous suspicions in the literature that data on stated ANA should be used with some caution.

[Table 6 around here]

It should be acknowledged that including the stated ANA dummies in the models may be problematic if these variables are endogenous, i.e. related to unobservable factors that determine the outcome. The fact that the attribute coefficients in the EAA and MEAA models with and without the stated ANA variables are generally very similar can be taken as evidence that endogeneity bias is not an issue in the present study. Moreover, including the stated ANA dummies allows us to model the relationship between stated and inferred ANA. This is a unique feature of our study which would not have been possible otherwise.

[12] As pointed out by a referee these are the most important and least important attributes in terms of MRS (see section 4.3).

## 4.3 Estimates of marginal rates of substitution

Table 7 presents the estimates of marginal rates of substitution derived from models 1-6[13]. These are estimates of how large increases in societal costs the doctors are willing to accept in exchange for an improvement in an attribute rather than willingness to pay in the usual sense[14], as the doctors do not pay for the prescriptions out of their own budget. Given the differences in model specification and underlying assumptions the MRS estimates are fairly similar across models. Having said that, the MRS estimates from the EAA models are generally somewhat lower than those derived from the standard logit model, while the reverse is true for the estimates derived from the mixed logit model and the MEAA models. Table A1 in the appendix reports the results of tests for equality between the MRS estimates using the method of convolutions (Poe et al., 2005). It is worth noting that there are no significant differences between the MRS estimates derived from the models which allow for preference heterogeneity (models 3, 4 and 6). While we do find evidence of statistically significant differences between the MRS estimates from some of the other models, on the whole the differences are relatively small from a practical point of view.

The biggest difference in MRS across the models is for the ‘patient preference’ attribute, with estimates ranging from 35,690 NOK (model 1) to 56,060 NOK (model 4)[15]. This is also the attribute which has the largest prevalence of non-attendance in the MEAA models, which helps explain the difference in the estimates. As discussed by Hess et al. (2013) in the context of willingness to pay (WTP) estimates it is expected that the WTP for an attribute will be higher in a model that accounts for ANA if some respondents ignore the attribute, since the estimate will reflect the WTP of the attenders while ignoring the zero WTP of the non-attenders. Non-attendance to the cost attribute will have the opposite effect, as respondents who ignore cost

[13] The figures reported for the mixed logit and MEAA models represent the median of the MRS distributions.

[14] See Carlsen et al. (2012) for a discussion of this issue. Carlsen et al. use the terminology ‘willingness to impose societal costs’.

[15] 100 NOK $\approx$ 17 US dollars at the time of writing.

implicitly have an infinitely high WTP. Since the estimated proportion of respondents who ignore cost is small according to the MEAA models, this latter effect is likely to be relatively unimportant in the present application.

[Tables 7 and 8 around here]

The respondents are willing to accept the largest increase in costs for an increase in effectiveness from 60% to 90% or to accommodate the patient's preference, depending on the model. Doctors are willing to accept the lowest increase for a reduction in patient costs, which may reflect the fact that the co-payments generally constitute a relatively small share of the total cost of the medicines in the experiment[16].

The finding that the MRS estimates are generally similar across models is interesting since previous papers in this area have found large differences (Scarpa et al. 2009, Hensher and Greene 2010, Hole 2011a). This suggests that the magnitude of the bias that arises due to failure to allow for ANA in the model is context dependent. In the concluding remarks we offer some thoughts on this issue.

# 5 Concluding remarks

In this paper we have presented a set of models estimated using data from a Discrete Choice Experiment on doctors' choice of medication. The models include a standard logit model, an endogenous attribute attendance (EAA) model, a mixed logit model and a mixed EAA (MEAA) model which allows for preference heterogeneity among attribute 'attenders'.

We find that the fit of the EAA model is substantially better than that of the standard logit model, which suggests that some respondents did not attend to all the attributes in the experiment. Furthermore, it is found that the MEAA model which allows for preference heterogeneity outperforms the EAA model in terms of goodness of fit. The estimated ANA probabilities are

[16] The range of patient costs was chosen to be as realistic as possible so we consider this a positive feature rather than a weakness of the experimental design.

lower in the MEAA model than in the EAA model, which may imply that respondents with weak preferences are incorrectly classified as 'non-attenders' in the simpler model. There is evidence of non-attendance in the more flexible MEAA models as well, however, so it is not the case that allowing for heterogeneity implies that all respondents are classified as attenders. This suggests that the MEAA model, which allows for both non-attendance and preference heterogeneity simultaneously, provides a richer picture of respondents' decision-making behaviour than either the EAA model or the standard mixed logit.

Including indicators for stated ANA in the EAA and MEAA models further improves the fit of these models, and we find that the self-reported non-attenders have higher ANA probabilities than the attenders. This suggests that self-reported ANA conveys useful information about the respondents' attribute processing strategies. On the other hand we find that self-reported non-attenders have a positive probability of attending to an attribute, which illustrates the advantage of modelling non-attendance probabilistically.

Contrary to previous papers in the literature we generally do not find a substantial difference in the estimates of marginal rates of substitution across models. It's worth re-emphasising that our estimates are of doctors' willingness to use public funds, not their own, which may limit their generalisability to other contexts. Having said that, we suspect that the similarity in the estimates is due to the fact that the prevalence of ANA is lower in our sample than in many other applications. Our sample consists of professionals (doctors) who are used to making choices similar to those in the experiment (prescribing medicines) on a regular basis. It is not surprising that the prevalence of simplifying 'shortcuts' is less common in this group than among patients choosing between doctors, for example, which was the setting in Hole (2011a). The importance of taking attribute non-attendance into account in the analysis should therefore be assessed on a case-by-case basis. The results presented in this paper suggest that self-reported ANA provides a useful indicator of the prevalence of non-attendance and, consequently, of whether adjustments to the modelling procedure are required.

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Figure 1 – Example of a choice situation

| | **Medicine A** | **Medicine B** |
|---|---|---|
| Benefit/effect | • The best on the market, 90% normally respond to this medicine | • 60% normally respond to this medicine |
| Patient costs per year | • 1000 NOK | • 1800 NOK |
| Total costs per year | • 50 000 NOK | • 10 000 NOK |
| Patient's own wishes about medication | • prefers this (rather than the other) | • does not prefer this (to the other) |
| Your experience with this medication | • little or none | • good |
| **Which medicine will you choose? (please tick)** | | |

Table 1 – Attributes and levels

| Attributes & levels | Total costs | Effect | Patient costs | Patient preference | Physician's experience |
|---|---|---|---|---|---|
| Level 1 | 5000 NOK | 60% normally respond to this medicine | Free | Does not prefer this medicine | Little or none |
| Level 2 | 10 000 NOK | 75% normally respond to this medicine | 1000 NOK | Prefers this medicine | Good |
| Level 3 | 25 000 NOK | The best on the market; 90% normally respond to this medicine | 1800 NOK | | |
| Level 4 | 50 000 NOK | | | | |

Table 2. Self-reported attribute non-attendance

| Attribute | ANA percentage |
|---|---|
| Total costs | 23% |
| Effect | 9% |
| Patient costs | 25% |
| Patient preference | 16% |
| Physician’s experience | 26% |

Table 3. Benchmark models

| | Model1 Logit | Model 2 EAA | Model 3 Mixed logit | | Model 4 MEAA | |
|---|---|---|---|---|---|---|
| | | | Mean | SD | Mean | SD |
| Total costs | -0.051*** | -0.113*** | -0.096*** | 0.099*** | -0.108*** | 0.093*** |
| | (0.002) | (0.005) | (0.006) | (0.013) | (0.008) | (0.013) |
| Effect 75% | 0.998*** | 1.930*** | 1.666*** | 0.084 | 1.963*** | 0.144 |
| | (0.056) | (0.117) | (0.093) | (0.230) | (0.133) | (0.582) |
| Effect 90% | 2.349*** | 4.556*** | 3.881*** | 1.650*** | 4.496*** | 1.467*** |
| | (0.072) | (0.224) | (0.186) | (0.203) | (0.268) | (0.209) |
| Patient costs 1000 NOK | -0.647*** | -0.936*** | -0.856*** | 0.542*** | -0.926*** | 0.644*** |
| | (0.057) | (0.125) | (0.087) | (0.132) | (0.102) | (0.143) |
| Patient costs 1800 NOK | -0.722*** | -1.127*** | -1.174*** | 0.308 | -1.234*** | 0.323 |
| | (0.051) | (0.141) | (0.084) | (0.198) | (0.100) | (0.234) |
| Preferred medicine | 1.816*** | 4.250*** | 5.033*** | 6.427 | 4.734*** | 1.203 |
| | (0.090) | (0.465) | (1.561) | (4.754) | (0.641) | (2.239) |
| Physician has good experience | 1.014*** | 2.155*** | 1.726*** | 1.308*** | 1.928*** | 1.397*** |
| with the medicine | (0.041) | (0.116) | (0.099) | (0.146) | (0.168) | (0.179) |
| Number of respondents | 571 | 571 | 571 | | 571 | |
| Number of choices | 6852 | 6852 | 6852 | | 6852 | |
| Number of parameters | 7 | 12 | 14 | | 18 | |
| Log-likelihood | -2693.54 | -2441.51 | -2379.89 | | -2364.80 | |
| AIC | 5401.08 | 4907.02 | 4787.78 | | 4765.60 | |
| BIC | 5431.51 | 4959.19 | 4848.64 | | 4843.85 | |

Notes: standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5% and 1%, respectively.

Table 4. Estimated ANA probabilities based on EAA and MEAA benchmark models

| | **Model 2** | **Model 4** |
|---|---|---|
| Attribute | EAA | MEAA |
| Total costs | 0.374*** | 0.079* |
| | (0.025) | (0.047) |
| Effect | 0.224*** | 0.076*** |
| | (0.025) | (0.025) |
| Patient costs | 0.005 | 0 |
| | (0.087) | |
| Patient preference | 0.246*** | 0.201** |
| | (0.054) | (0.080) |
| Physician's experience | 0.268*** | 0.034 |
| | (0.035) | (0.058) |

Notes: standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5% and 1%, respectively. In model 4 the ANA probability for the patient cost attribute is constrained to zero.

Table 5. EAA and MEAA models with ANA dummies

| | Model 5 EAA | Model 6 MEAA Mean | SD |
|---|---|---|---|
| Total costs | -0.112*** | -0.114*** | 0.089*** |
| | (0.004) | (0.008) | (0.012) |
| Effect 75% | 1.911*** | 1.997*** | 0.052 |
| | (0.113) | (0.127) | (0.446) |
| Effect 90% | 4.455*** | 4.534*** | 1.431*** |
| | (0.211) | (0.254) | (0.211) |
| Patient costs 1000 NOK | -0.983*** | -1.025*** | 0.702*** |
| | (0.132) | (0.109) | (0.162) |
| Patient costs 1800 NOK | -1.196*** | -1.342*** | 0.405* |
| | (0.150) | (0.106) | (0.209) |
| Preferred medicine | 4.405*** | 5.529*** | 2.630 |
| | (0.486) | (0.959) | (2.301) |
| Physician has good experience with the medicine | 2.200*** | 2.154*** | 1.286*** |
| | (0.117) | (0.169) | (0.193) |
| Number of respondents | 571 | 571 | |
| Number of choices | 6852 | 6852 | |
| Number of parameters | 17 | 23 | |
| Log-likelihood | -2367.93 | -2298.79 | |
| AIC | 4769.86 | 4643.58 | |
| BIC | 4843.77 | 4743.57 | |

Notes: dummies for self-reported non-attendance included in the model (not reported). Standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5% and 1%, respectively.

Table 6. Estimated attribute non-attendance probabilities based on EAA and MEAA models with ANA dummies

| | | **Model 5** EAA | | | **Model 6** MEAA | |
|---|---|---|---|---|---|---|
| Attribute | Att. | Non-att. | Diff. | Att. | Non-att. | Diff. |
| Total costs | 0.279*** | 0.693*** | 0.414*** | 0.032 | 0.504*** | 0.472*** |
| | (0.027) | (0.047) | (0.053) | (0.035) | (0.073) | (0.071) |
| Effect | 0.205*** | 0.333*** | 0.129 | 0.061** | 0.215*** | 0.154* |
| | (0.026) | (0.078) | (0.080) | (0.024) | (0.083) | (0.084) |
| Patient costs | 0.002 | 0.243* | 0.240* | 0 | 0.185 | 0.185 |
| | (0.082) | (0.145) | (0.124) | | (0.126) | (0.126) |
| Patient preference | 0.194*** | 0.762*** | 0.568*** | 0.128 | 0.786*** | 0.658*** |
| | (0.054) | (0.082) | (0.087) | (0.079) | (0.091) | (0.105) |
| Physician's experience | 0.188*** | 0.631*** | 0.443*** | 0.028 | 0.526*** | 0.498*** |
| | (0.034) | (0.063) | (0.064) | (0.045) | (0.084) | (0.081) |

Notes: Att. = self-reported attribute attenders, Non-att. = self-reported attribute non-attenders, Diff. = difference in ANA probability between the two groups. Standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5% and 1%, respectively. In model 6 the ANA probability for the patient cost attribute is constrained to zero for self-reported attribute attenders.

Table 7. Estimates of marginal rates of substitution between total costs and the remaining attributes

| | **Model 1**<br>Logit | **Model 2**<br>EAA | **Model 3**<br>Mixed logit | **Model 4**<br>MEAA | **Model 5**<br>EAA | **Model 6**<br>MEAA |
|---|---|---|---|---|---|---|
| Effect 75% | 19.63 | 17.04 | 25.01 | 23.92 | 17.10 | 22.34 |
| | (17.60, 21.70) | (15.29, 18.84) | (22.12, 28.16) | (19.83, 28.79) | (15.31, 18.89) | (19.04, 26.11) |
| Effect 90% | 46.19 | 40.23 | 53.69 | 52.22 | 39.87 | 48.39 |
| | (43.90, 48.59) | (37.11, 43.49) | (48.32, 59.62) | (43.83, 62.10) | (36.75, 43.10) | (41.75, 56.00) |
| Patient costs 1000 NOK | -12.73 | -8.26 | -10.88 | -9.29 | -8.79 | -9.47 |
| | (-14.99, -10.59) | (-10.27, -6.27) | (-14.39, -8.20) | (-12.42, -6.90) | (-10.91, -6.65) | (-12.53, -7.13) |
| Patient costs 1800 NOK | -14.20 | -9.95 | -17.07 | -14.58 | -10.70 | -14.38 |
| | (-16.30, -12.16) | (-12.19, -7.70) | (-20.39, -14.31) | (-18.09, -11.68) | (-13.09, -8.28) | (-17.66, -11.66) |
| Preferred medicine | 35.69 | 37.53 | 46.64 | 56.06 | 39.42 | 55.88 |
| | (32.31, 39.25) | (30.10, 45.01) | (38.72, 56.42) | (42.22, 74.89) | (31.31, 47.08) | (41.87, 75.24) |
| Physician has good experience | 19.93 | 19.03 | 20.68 | 19.07 | 19.69 | 20.70 |
| with the medicine | (18.42, 21.54) | (17.46, 20.67) | (17.92, 23.85) | (14.72, 24.80) | (18.04, 21.34) | (16.73, 25.72) |

Notes: All figures are in thousands of Norwegian kroner. 95% confidence intervals calculated using the Krinsky Robb (1986, 1990) method in parentheses. The CIs are based on 10,000 replications.

# Appendix

Table A1. Tests for equality between the MRS estimates

| | Model 1 vs. | | | | | Model 2 vs. | | | | Model 3 vs. | | | Model 4 vs. | | Model 5 vs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M2 | M3 | M4 | M5 | M6 | M3 | M4 | M5 | M6 | M4 | M5 | M6 | M5 | M6 | M6 |
| Effect 75% | ** | *** | ** | ** | * | *** | *** | | *** | | *** | | *** | | *** |
| Effect 90% | *** | *** | * | *** | | *** | *** | | ** | | *** | | *** | | ** |
| Patient costs 1000 NOK | *** | | ** | *** | ** | * | | | | | | | | | |
| Patient costs 1800 NOK | *** | * | | ** | | *** | *** | | *** | | *** | | ** | | ** |
| Preferred medicine | | *** | *** | | *** | * | *** | | ** | | | | ** | | ** |
| Physician has good experience with the medicine | | | | | | | | | | | | | | | |

Notes: M2-M6 refer to Models 2-6. *, **, and *** indicate a significant difference at the 10%, 5% and 1% level, respectively. The tests are carried out using the using the complete combinatorial approach described in Poe et al. (2005).