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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 with different attribute processing strategies and allows the ANA probabilities 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 willingness to pay estimates derived from models which account for ANA are similar to the standard logit estimates.

Keywords: choice experiment, attribute non-attendance

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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 has 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.

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

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

[2] A third approach which is not pursued in this paper is to use a qualitative 'think aloud'

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. Cambell 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. Two contributions are made in this paper; firstly, building on the Endogenous Attribute Attendance (EAA) model described by Hole (2011a) we develop a more flexible 'full-attendance inflated' EAA (FAI-EAA) model which takes into account the possibility that respondents who are different in their attribute processing strategies may also have different preferences for the characteristics of the alternatives. The FAI-EAA model is found to fit the data better than both the standard logit and the EAA model. Secondly, we allow the probability of non-attendance to depend on the respondents' stated ANA. The fit of the EAA and FAI-EAA models in-

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.

creases when stated ANA is incorporated in the models, which suggests that the self-reported data contain useful information about the respondents' attribute processing strategy. On the other hand we find that the self-reported non-attenders have a positive probability of attendance, which illustrates the usefulness of the probabilistic approach as it avoids the sharp distinction between assigning an ANA probability of zero or one based on the self-reported data. Contrary to most papers in the literature we find that the willingness to pay estimates derived from the various models are similar. This suggests that failure to account for attribute non-attendance does not necessary lead to substantial bias in estimates of WTP.

The paper is structured as follows. Section 2 describes the Endogenous Attribute Attendance model and the more flexible 'full attendance inflated' 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; Ben-Akiva and Swait, 1987) and recent contributions to the literature on modelling heuristics include Hensher (2008) and Hess and Hensher (2011). 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 in the second stage is random. Conditional on the choice of attribute subset C_q the utility that individual n derives from choosing alternative i on choice occasion t is given by $U_{nit} = \sum_{k\epsilon C_q} x_{nit}^k \beta^k + \varepsilon_{nit}$ where x_{nit}^k represents the value of attribute k relating to alternative i on choice occasion t, β^k is the preference weight given to that attribute and ε_{nit} 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 $\exp(\gamma_k' z_n)/\left[1 + \exp(\gamma_k' z_n)\right]$, where z_n is a vector of individual-level observed characteristics and γ_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_n. 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:

$$H_{nC_q} = \prod\nolimits_{k\epsilon C_q} \frac{\exp(\gamma_k' z_n)}{1 + \exp(\gamma_k' z_n)} \prod\nolimits_{k\notin C_q} \frac{1}{1 + \exp(\gamma_k' z_n)} \tag{2}$$

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

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

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

The model is estimated by maximising the log-likelihood function:

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

It should be noted that it is not possible to identify γ_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.

2.2 The 'full attendance inflated' EAA model

In this subsection we propose an extension to the EAA model which has a more flexible structure for modelling the probability of taking all attributes into account in the choice process. We call this model the 'full attendance inflated' EAA model (FAI-EAA). In the full attendance inflated model the unconditional probability of the observed sequence of choices is given by

$$P_n^{FAI-EAA} = \left[\frac{\exp(\lambda)}{1+\exp(\lambda)}\right] P_n^{LOGIT} + \left[\frac{1}{1+\exp(\lambda)}\right] P_n^{EAA} \tag{5}$$

where λ is a parameter to be estimated, P_n^{EAA} is given in equation (3) and

$$P_n^{LOGIT} = \prod\nolimits_{t=1}^{T} \prod\nolimits_{j=1}^{J} \left[\frac{\exp(\sum_k x_{njt}^k \alpha^k)}{\sum_{j=1}^{J} \exp(\sum_k x_{njt}^k \alpha^k)}\right]^{y_{njt}}$$

In other words the FAI-EAA model is a mixture between a standard conditional logit model and the EAA model. The logit part of the model can be interpreted as representing respondents who attend to all the attributes, while the EAA part represents respondents who potentially ignore one or more of the attributes. As in the standard EAA model the probability of attribute attendance in the latter group is modelled as a function of a vector of observable characteristics z_n, which may include a dummy for stated non-attendance.

The λ parameter measures the degree of 'full attendance' inflation, or the degree to which respondents attend to all attributes in excess of the EAA probability of full attendance (H_{nC_Q}). Higher values of λ imply that more respondents belong to the logit part of the model, as the probability of belonging to this group is given by $\exp(\lambda)/(1+\exp(\lambda))$.

Respondents who are different in terms of their attribute processing strategies may also have different preferences for the characteristics of the alternatives. The FAI-EAA model can capture this type of preference heterogeneity as the attribute coefficients in the logit and EAA parts of the model, α^k and β^k, are allowed to differ. This is an 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., 2011). 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'.

The FAI-EAA model is estimated by maximising the log-likelihood function:

$$LL^{FAI-EAA} = \sum_{n=1}^{N} \ln P_n^{FAI-EAA} \tag{6}$$

Although the FAI-EAA model nests the 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).[3] For simplicity

[3] The FAI-EAA model becomes the logit model when $\lambda = \infty$ and the EAA model when $\lambda = -\infty$, in which case either the β^k ($\lambda = \infty$) or α^k ($\lambda = -\infty$) parameters are unidentified. Likewise, it can be seen from equation (2) that the EAA model becomes the logit model when $H_{nC_Q} = 1$ and $H_{nC_q} = 0 \; \forall \; q \neq Q$, which implies that $\gamma_k = \infty \; \forall \; k$.

we therefore base the comparison of the goodness of fit of the models on the Akaike and Schwarz 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 doctors were asked to indicate which of two alternative medicines they would prescribe for a hypothetical 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. (2011) 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.[4]

[4] 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.

Table 2 reports the self-reported attribute non-attendance frequencies for 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) and a 'full attendance inflated' EAA model (model 3). In the standard logit model the respondents are implicitly assumed to attend to all the attributes in the experiment, while the EAA and FAI-EAA models relax this assumption. The ANA probabilities are specified to be fixed across respondents ($z_n = 1$) 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 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 willingness to pay estimates derived from the different models.

[Table 3 around here]

It can be seen from the table that the goodness of fit of the EAA and FAI-EAA models is substantially better than that of the logit model. The

FAI-EAA model has the best fit, which reflects the more flexible structure of this model for modelling the probability of taking all attributes into account in the choice process. As explained in section 2 the FAI-EAA model also has the advantage that it can incorporate some degree of preference heterogeneity.

Table 4 reports the estimated ANA probabilities for each attribute based on models 2 and 3. The ANA probabilities based on model 2 are somewhat higher than those based on model 3 which are more in line with the stated ANA frequencies reported in table 2. 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 estimated ANA probabilities of 0.01 (EAA) and 0.11 (FAI-EAA). 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 as explanatory variables in the first-stage of the EAA and FAI-EAA models. The results are reported in table 5. By comparing models 4 and 5 with the benchmark models (2 and 3) we can see that the inclusion of the ANA dummies increases the goodness of fit of the models substantially. We also find that the FAI-EAA model continues to fit the data better than the EAA model.

[Table 5 around here]

Table 6 reports the predicted attribute non-attendance probabilities based on models 4 and 5 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 for all attributes in the FAI-EAA model[5]. 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. 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 FAI-EAA models with and without the stated ANA variables are 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.

4.3 Willingness to pay estimates

Tables 7 and 8 present the willingness to pay estimates derived from models 1-5. 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[6], as the doctors do not pay for the

[5] In the EAA model the difference is significant for all attributes except effectiveness and patient costs.

[6] See Carlsen et al. 2011 for a discussion of this issue. Carlsen et al. use the terminology 'willingness to impose societal costs'.

prescriptions out of their own budget. We use the more familiar WTP terminology here as our focus is on the difference between the estimation methods. Given the differences in model specification and underlying assumptions the WTP estimates are remarkably similar across models, although the EAA and FAI-EAA estimates are generally somewhat lower than those derived from the standard logit model. There is a big difference in WTP between the logit and EAA parts of the FAI-EAA models, which illustrates this model's capacity to capture preference heterogeneity in the data. The respondents belonging to the logit group ('the full attenders') are found to have much larger WTP than the respondents belonging to the EAA group, which in part reflects the greater sensitivity to cost in the latter group. The mean WTP estimates derived from the FAI-EAA models are very similar to the EAA estimates.

[Tables 7 and 8 around here]

The respondents are willing to pay the largest amount for an increase in effectiveness from 60% to 90%, with estimates ranging from 38,870 NOK (model 3) to 46,190 NOK (model 1)[7]. The second most highly valued attribute is patient preference, followed by the physician's experience with the medicine. Doctors are willing to pay the lowest amount 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.[8] There are no differences between the models in terms of the ranking of the attributes according to their WTP.

The finding that the WTP estimates are generally consistent across models is interesting since previous papers in this area have found large differences in WTP (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.

[7] 100 NOK $\approx$ 17 US dollars at the time of writing.

[8] 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.

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, the endogenous attribute attendance (EAA) model and a new model which we call the 'full-attendance inflated' EAA model (FAI-EAA).

We find that the fit of the EAA model is substantially better than that of the standard logit model, which suggests that a significant share of the respondents did not attend to all the attributes in the experiment. Furthermore, it is found that the FAI-EAA model which allows for a more flexible way of modelling attribute non-attendance (ANA) outperforms the EAA model in terms of goodness of fit. Including indicators for stated ANA in the EAA and FAI-EAA 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, which is also supported by the fact that the predicted probabilities of non-attendance derived from the FAI-EAA model are similar to the proportion of doctors reporting not having attended to the attributes. 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 do not find a substantial difference in the willingness to pay estimates across models. We suspect that this 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 good 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	**Model 3** FAI-EAA model	
			Logit	EAA
Total costs	-0.051	-0.113	-0.060	-0.218
	(-31.89)	(-25.10)	(-13.56)	(-9.53)
Effect 75%	0.998	1.930	1.302	2.558
	(17.92)	(16.56)	(12.18)	(8.63)
Effect 90%	2.349	4.556	3.001	6.032
	(32.55)	(20.34)	(17.98)	(10.96)
Patient costs 1000 NOK	-0.647	-0.936	-0.831	-1.251
	(-11.37)	(-7.48)	(-7.36)	(-3.23)
Patient costs 1800 NOK	-0.722	-1.127	-0.973	-1.683
	(-14.13)	(-7.98)	(-8.79)	(-4.29)
Preferred medicine	1.816	4.250	2.479	6.204
	(20.11)	(9.15)	(12.27)	(7.27)
Physician has good experience	1.014	2.155	1.195	4.133
with the medicine	(24.76)	(18.53)	(12.83)	(9.80)
Lambda			-0.021	
			(-0.12)	
Number of respondents	571	571	571	
Number of choices	6852	6852	6852	
Log-likelihood	-2693.54	-2441.51	-2390.01	
AIC	5401.08	4907.02	4820.02	
BIC	5431.51	4959.19	4906.97	

Notes: t-stats in parentheses

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

Attribute	EAA	FAI-EAA
Total costs	0.374	0.251
	(0.025)	(0.027)
Effect	0.224	0.146
	(0.025)	(0.022)
Patient costs	0.005	0.110
	(0.087)	(0.065)
Patient preference	0.246	0.161
	(0.054)	(0.035)
Physician's experience	0.268	0.234
	(0.035)	(0.026)

Notes: standard errors in parentheses.

Table 5. EAA and FAI-EAA models with ANA dummies

	Model 4	Model 5	
	EAA model	FAI-EAA model	
		Logit	EAA
Total costs	-0.112	-0.057	-0.181
	(-24.84)	(-13.39)	(-11.04)
Effect 75%	1.911	1.375	2.230
	(16.90)	(10.76)	(9.75)
Effect 90%	4.455	3.160	5.304
	(21.12)	(15.96)	(12.55)
Patient costs 1000 NOK	-0.983	-0.793	-1.474
	(-7.45)	(-5.96)	(-4.01)
Patient costs 1800 NOK	-1.196	-0.942	-1.794
	(-7.96)	(-7.63)	(-4.66)
Preferred medicine	4.405	2.472	5.663
	(9.06)	(10.28)	(8.28)
Physician has good experience	2.200	1.146	3.614
with the medicine	(18.80)	(11.29)	(10.29)
Lambda		-0.377	
		(-2.35)	
Number of respondents	571	571	
Number of choices	6852	6852	
Log-likelihood	-2367.93	-2319.90	
AIC	4769.86	4689.80	
BIC	4843.77	4798.48	

Notes: dummies for self reported non-attendance included in the first-stage model (not reported). t-stats in parentheses

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

	EAA			FAI-EAA		
Attribute	Att.	Non-att.	Diff.	Att.	Non-att.	Diff.
Total costs	0.279	0.693	0.414	0.175	0.513	0.339
	(0.027)	(0.047)	(0.053)	(0.027)	(0.040)	(0.039)
Effect	0.205	0.333	0.129	0.141	0.336	0.194
	(0.026)	(0.078)	(0.080)	(0.025)	(0.082)	(0.084)
Patient costs	0.002	0.243	0.240	0.098	0.326	0.228
	(0.082)	(0.145)	(0.124)	(0.066)	(0.106)	(0.095)
Patient preference	0.194	0.762	0.568	0.113	0.546	0.434
	(0.054)	(0.082)	(0.087)	(0.034)	(0.059)	(0.064)
Physician's experience	0.188	0.631	0.443	0.164	0.480	0.316
	(0.034)	(0.063)	(0.064)	(0.028)	(0.045)	(0.047)

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.

Table 7. Willingness to pay - benchmark models

	Model 1 Logit	**Model 2** EAA model	**Model 3** FAI-EAA model		
			Logit	EAA	Mean
Effect 75%	19.63	17.04	21.84	11.72	16.73
	(17.58, 21.67)	(15.26, 18.82)	(18.22, 26.05)	(9.50, 14.33)	(14.58, 18.87)
Effect 90%	46.19	40.23	50.34	27.64	38.87
	(43.88, 48.50)	(37.04, 43.42)	(44.02, 58.09)	(24.10, 32.04)	(34.79, 42.95)
Patient costs 1000 NOK	-12.73	-8.26	-13.93	-5.73	-9.79
	(-14.99, -10.47)	(-10.28, -6.24)	(-18.08, -10.19)	(-9.48, -2.29)	(-12.09, -7.48)
Patient costs 1800 NOK	-14.20	-9.95	-16.33	-7.71	-11.97
	(-16.27, -12.13)	(-12.18, -7.72)	(-20.32, -12.74)	(-11.15, -4.41)	(-14.23, -9.72)
Preferred medicine	35.69	37.53	41.58	28.43	34.94
	(32.14, 39.25)	(30.06, 45.00)	(34.70, 49.60)	(23.54, 33.25)	(30.65, 39.22)
Physician has good experience	19.93	19.03	20.04	18.94	19.48
with the medicine	(18.37, 21.49)	(17.42, 20.65)	(17.30, 23.16)	(16.33, 22.01)	(17.45, 21.52)

Notes: All figures are in thousands of Norwegian kroner. 95% confidence intervals calculated using the delta method in parentheses

Table 8. Willingness to pay - models with ANA dummies

	Model 4 EAA model	Model 5 FAI-EAA model		
		Logit	EAA	Mean
Effect 75%	17.10	24.21	12.35	17.18
	(15.30, 18.91)	(19.42, 29.01)	(10.05, 14.65)	(15.08, 19.27)
Effect 90%	39.87	55.64	29.38	40.06
	(36.69, 43.05)	(48.01, 63.28)	(25.93, 32.83)	(36.24, 43.89)
Patient costs 1000 NOK	-8.79	-13.97	-8.16	-10.52
	(-10.93, -6.66)	(-18.77, -9.17)	(-11.57, -4.75)	(-12.98, -8.07)
Patient costs 1800 NOK	-10.70	-16.58	-9.94	-12.64
	(-13.10, -8.31)	(-21.08, -12.08)	(-13.28, -6.59)	(-15.06, -10.23)
Preferred medicine	39.42	43.52	31.36	36.31
	(31.45, 47.39)	(34.79, 52.25)	(26.57, 36.16)	(31.94, 40.69)
Physician has good experience	19.69	20.17	20.02	20.08
with the medicine	(18.02, 21.36)	(16.86, 23.48)	(17.99, 22.04)	(18.29, 21.87)

Notes: All figures are in thousands of Norwegian kroner. 95% confidence intervals calculated using the delta method in parentheses