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Abstract: We report on a discrete choice experiment aimed at eliciting Swedish households' willingness-to-accept a compensation for restrictions on household electricity and heating use during peak hours. When analyzing data from discrete choice experiments, we typically assume that people make rational utility maximizing decisions, i.e., that they consider all of the attribute information and compare all alternatives. However, mounting evidence shows that people use a wide range of simplifying strategies that are inconsistent with utility maximization. We use a flexible model capturing a two-stage decision process. In the first stage, respondents are allowed to eliminate from their choice set alternatives that contain an unacceptable level, i.e., restrictions on the use of heating and electricity. In the second stage, respondents choose in a compensatory manner between the remaining alternatives. Our results show that about half of our respondents choose according to an elimination-by-aspects strategy, and that, on average, they are unwilling to accept any restrictions on heating in the evening or electricity use, irrespective of time-of-day. Furthermore, we find that considering elimination-by-aspects behavior leads to a downward shift in elicited willingness-to-accept. We discuss implications for policy.

JEL codes: C25, Q41, Q51, R21

Keywords: Choice experiment; Electricity contract; Willingness-to-accept; Household electricity; Elimination-by-aspects; Two-stage decision

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1. Introduction

Over the past century demand for electricity has increased dramatically, and population growth and greater reliance on appliances that use electricity is likely to increase demand even more. During recent years, the Swedish electricity market has been deregulated and integrated with the larger European market. Although Sweden is self-supporting in electricity partly via the large share of hydropower, the integration of markets and intermittent renewable energy sources to the grid, for example, wind power, put high pressure on the system[1]. Given the limited ability to effectively store electricity, supply may be disrupted when extreme weather conditions prevent constant balance between demand and supply; or when demand for electricity exceeds the grid capacity - leading to disruptions and black-outs. The demand for household energy follows a cyclical pattern with peaks in the morning and afternoon, and it is possible that in the near future this can lead to a situation where the demand for energy exceeds the capacity during those morning and afternoon hours. The high cost of grid expansion and backup power can thus spell trouble for the security of energy supply in the short term. The critical question is how to induce households to shift their use of electricity from peak to off-peak hours. The theory of supply and demand gives that the market clearing price is established where supply meets demand. It follows that during peak hours, i.e., when demand is high, the price should be higher than during off-peak hours. In this case, we would expect people to respond to the higher price by shifting their consumption patterns. The majority of Swedish households are however on fixed-term electricity contracts and do not face hourly price variations. As such they have no incentive to shift consumption away from peak hours. In 2015, about 1% of Swedish households were on real-time pricing contracts, and Vesterberg and Krishnamurthy (2016) showed that the cost savings of shifting consumption for up to five hours led to a meager saving of 2-4% of daily costs.

Where price-based demand management policies do not succeed, one possibility is to design energy contracts that induce demand flexibility through direct load control, i.e., a restriction on energy use. The idea is that households might be willing to change their demand for energy during certain hours of the day for monetary compensation. However, designing such contracts require information on household's preferences. In this paper, we report on a discrete choice experiment (DCE) aimed at eliciting Swedish households' willingness-to-accept (WTA) compensation for restrictions on household electricity and heating use during peak hours. A DCE is a multi-criteria approach tailored to inform policymakers about how people value, and make trade-offs, between attributes of different experimentally designed options (Alpizar et al., 2001), here electricity contracts. In the DCE, respondents were faced with hypothetical experimentally designed contracts that included some of the key aspects of such a contract. The hypothetical contracts included in

[1] The share of electricity generated by wind power in Sweden rose from 2.6% in 2010 to 12.2% in 2015 (IEA, 2015).

the choice experiment were designed to reflect and capture the potential of direct load control in energy use during morning and evening peak hours. The control was limited to consider the restriction on use of heating and specific electric appliances during morning and evening peak hours (7-10 am and 5-8 pm), anonymous distribution of metering information, restriction on use during situations of low production or extreme demand, and compensation for accepting the contract.

Every day people make countless more or less complex decisions ranging from what to have for breakfast to what electricity contract your household should have, and most, if not all, involve trade-offs between different competing options. According to standard economic theory, when a decision maker is faced with such a choice, he will choose the option that gives the highest utility. This implies that he is indeed willing and able to make trade-offs between the desirable and undesirable aspects of each option. While appealing in theory, this assumption is questionable in real life. When analyzing data from DCEs, we assume that people make rational utility maximizing decisions, i.e., that they consider all of the attribute information and compare all alternatives. However, mounting evidence shows that people use a wide range of simplifying strategies that are inconsistent with utility maximization (see e.g. Campbell et al., 2006; Erdem et al., 2015; Hensher et al., 2005; Hess et al., 2012; Sandorf et al., 2016; Scarpa et al., 2009). Of particular interest is the theory of elimination-by-aspects (EBA), which involves eliminating from the choice set any alternative that includes an undesirable aspect or does not include a desirable one (see e.g. Batley and Daly, 2006; Erdem et al., 2014; Hess et al., 2012; Tversky, 1972)[2].

In general, there are many reasons why people restrict their choice set to form a smaller consideration set. For example, as shown by Campbell et al. (2014) people might eliminate alternatives that are too expensive. In the present study, we consider restrictions formed on the basis of two of the included attributes: electricity and heating. In Broberg and Persson (2016), using the same data, they show that people required high compensation for any restriction in these two aspects, irrespective of time-of-day, which indicates that people place much emphasis on these two aspects. Furthermore, both heating and electricity may be considered "essential" goods and people might not be willing to accept any restriction in their use of it, at least not within the compensation levels offered. If people did not make trade-offs with respect to these attributes but excluded merely alternatives containing them from the choice set, this indicates that demand flexibility depends crucially on these two aspects, and our model needs to consider such behavior. Indeed, failing to consider the actual decision process might lead to wrong inferences with respect to preferences, and hence the applicability of the results for prediction and policy recommendation

[2]Other simplification strategies that are not discussed in this paper include attribute non-attendance (see e.g. Campbell et al., 2011; Erdem et al., 2015; Hensher et al., 2005; Sandorf et al., 2016; Scarpa et al., 2009), lexicographic choice rules (see e.g. Campbell et al., 2006; Hess et al., 2012) and random regret minimization (see e.g. Chorus, 2010; Chorus et al., 2008; Hess et al., 2012).

can be limited. To allow for such a decision-making strategy, we use a version of the model developed by Erdem et al. (2014) in the context of health service innovations, which enable us to consider EBA type behavior. This model allows modelling the decision-making process in two stages. In the first stage, an individual eliminates all alternatives from the choice set that includes an undesirable attribute (or level). In the second stage, the same individual chooses according to a random utility model among the remaining alternatives in the consideration set (Campbell et al., 2014; Erdem et al., 2014). Our approach represents the first application of elimination-by-aspect type behavior in electricity contract choice and the first application in a WTA context. We also address the importance of considering such simplifying strategies when making policy recommendations.

Our results show that about half of the respondents choose according to an EBA strategy and that, on average, they are unwilling to accept any restrictions on heating in the evening or electricity use at any time of the day. This result reflects a typical weekday. People use electricity in the morning, but do not necessarily need additional heating because they will not be at home during the day, but when they come home in the afternoon, they use both electricity and heating. Interestingly, when we consider preference heterogeneity in a latent class framework, we see that respondents tend to be characterized by two distinct behaviors, those that are willing to make trade-offs and those that are not. Importantly, we see that those who are willing to make trade-offs tend to make choices in which heating in the morning is restricted. One possibility is that this, combined with a positive compensation, is perceived as "free money". If true, it indicates that a policy aimed at compensating people for restrictions on heating in the morning might lead to a situation where you pay something for nothing.

The rest of the paper is organized as follows. In Section 2 we provide information on the design and implementation of the survey, in Section 3 we outline the modelling framework, in Section 4 we show and discuss the results of the model, and finally, in Section 5 we give some concluding remarks.

2. Survey design and data

This study makes use of data from a discrete choice experiment aimed at eliciting Swedish households' willingness-to-accept a compensation for external control of heating and electricity use during peak demand hours and situations with extreme shifts in either supply or demand for energy. The general result of this discrete choice experiment is published in Broberg and Persson (2016) and we refer the interested reader to this paper for a fuller discussion of the data. The data was gathered in 2014, and respondents were sampled from a probability-based internet panel using stratified random sampling. In total, 918 respondents provided 5508 choice observations. In the DCE, respondents were asked to choose between two experimentally designed hypothetical electricity contracts described by five attributes and their current contract. We list the attributes, descriptions of these and levels that they could take in Table 1 and show a sample choice card in Figure 1. The attributes and levels were decided based on a review of the literature and discussions with experts. The choice cards were generated using an efficient experimental design and updated based on priors obtained from a pilot study of 100 respondents. The final design consisted of twelve choice sets divided into two blocks of six choice sets each. Recruited respondents were randomly allocated to one of the blocks, and the order of the choice sets was randomized across respondents.

Table 1 - Attributes and attribute levels

Attributes	Description	Levels
Control of heating (Monday-Friday)	The electricity provider turns off your heating system but temperature never decreases by more than 2°C and never falls below 18°C.	Heat-morning(7-10am), Heat-evening(5-8pm) & never (as today)
Control of domestic electricity (Monday-Friday)	The electricity provider controls your domestic electricity and it is not possible to use the dishwasher, laundry machine and dryer, towel warmers and comfort floor heating during certain hours in weekdays.	Electricity-morning(7-10am), Electricity- evening(5-8pm) & never (as today)
Control in extreme conditions per year (7am - 8pm)	During extreme situations in the electricity market due for e.g., to extreme cold or underproduction, your heating system and domestic electricity will be cut between 7am and 8pm. You will be notified one day a head when this control will take place.	3 days , 7 days, 10 days & 0 (as today)
Distribution of information	It is okay to spread my electricity consumption information and use it anonymously (e.g. for comparisons across the neighborhood)	Yes, No (as today)
Annual compensation	A new contract is related to an annual compensation.	SEK300 , SEK750, SEK1500 , SEK2500 & SEK0 (as today)

In Table 2, we show some key socio-demographic characteristics of our sample. In general, there are no important deviations from the Swedish population (Broberg and Persson, 2016). We do however acknowledge that our sample is slightly older, includes more men and have a larger proportion of people with higher education. This result is not uncommon for internet panels (see e.g. Lindhjem and Navrud (2012)). Of particular interest is the fact that 45% live in detached houses, 10% have district heating and 34% state that environmental damage is the main reason for trying to reduce their energy consumption. About 32% have received more than three years of college or university education, while 66% of the sample reported that a family member is staying at home during 7-10am.

Which of the following A, B or C contracts would you choose if offered to you? Unless otherwise stated in the agreement, everything else works as today. For example, what electricity or district heating price you pay and how often it changes.

Attributes	**Alternative A**	**Alternative B**	**Alternative C /as today/**
Control of heating (Monday-Friday)	07-10 a.m.	7-10 a.m.	No
Control of electricity (Monday-Friday)	17-20 p.m.	7-10 a.m.	No
Control in extreme situations per year (7 a.m. -8 p.m.)	Maximum 5 days	Maximum 5 days	No
Distribution of information	Yes	No	No
Compensation (SEK)	1500	750	0
Your choice	[ ]	[ ]	[ ]

Figure 1 - Sample choice set

Table 2 - Sample characteristics

Variable		**Variable**	
Age (mean)	55	Apartment (share)	0.42
Men (share)	0.55	Household size (mean)	2.21
Children 0-12 years (share)	0.13	Home7-10am (share)	0.66
Retirees (share)	0.4	Detached house (share)	0.45
Household income (mean category)	SEK40,000-45,000	Single households(share)	0.26
Environment (share)	0.34	College/University >3 years (share)	0.32

3. Modeling approach

To introduce notation, let us write the utility that respondent n experiences from alternative i in choice situation t as:

$$U_{nit} = \beta x_{nit} + \varepsilon_{nit} \tag{1}$$

where β is a vector of parameters to be estimated, x_{nit} the levels of the attributes and ε an *i.i.d.* type-I extreme value distributed error term with a constant variance of $\pi^2/6$. Given these assumptions, the probability of choosing alternative i in choice situation t can be defined as:

$$Pr(i_{nt}|\beta, x_n) = \frac{\exp(\beta x_{nit})}{\sum_{j=1}^{J} \exp(\beta x_{njt})} \tag{2}$$

To consider the repeated nature of the data, i.e., each respondent makes a sequence of choices, we take the product over all choice tasks faced by respondent n such that

$$Pr(y_n|\beta, x_n) = \prod_{t=1}^{T} Pr(i_{nt}|\beta, x_n), \tag{3}$$

where y_n is the sequence of choices $y_n = [i_{n1}, i_{n2}, ..., i_{nT}]$. This is the multinomial logit model (MNL) and it is the workhorse in discrete choice analysis. Importantly, it recovers parameters based on the assumption that respondents consider all alternatives and attributes in a compensatory manner (Leong and Hensher, 2012). Moreover, the MNL model assumes that people choose in a utility maximizing manner and that all have the same preferences.

3.1. Accounting for EBA type choice behavior

Elimination-by-aspects is a simplifying strategy first proposed by (Tversky, 1972). The idea is that people simplify their choices by sequentially eliminating alternatives from their choice set based on the level of one or a few attributes until a single alternative remains. This implies a complete order and ranking of attributes and levels. For an example of this type of model in a discrete choice experiment context see e.g., Hess et al. (2012). Instead of considering only a RUM model or an EBA model, it is possible that EBA is part of a hybrid decision strategy, i.e., people start by eliminating undesirable alternatives from their choice set to form a smaller consideration set, and then choose between the remaining alternatives in a compensatory manner (Swait, 2001). This is the approach taken by Campbell et al. (2014) and Erdem et al. (2014), and also the approach we take here. Importantly, if people eliminate alternatives from the choice set and our model fails to capture such behavior, we risk underestimating the probability of the chosen alternative. For example, with three alternatives in the choice set, the probability of choosing any alternative is allocated across all three. However, if an alternative has been eliminated based on an EBA rule, then the probability of choosing this alternative should be zero, and the probability of choice should be allocated across the remaining alternatives. Here we develop a two-stage model where the first stage is described by an elimination-by-aspect process and the second stage a compensatory random utility model.

Both stages are considered simultaneously in the log-likelihood function. Considering every possible EBA rule is outside the scope of this paper, and we restrict ourselves to look at a subset of rules presented in Table 3. These rules are based on restrictions placed on the heating and electricity attributes during morning and afternoon peak hours. We consider four different rules separately and one rule that is a combination of the four. The strategies are restrictions on: *i*) heating, *ii*) electricity, *iii*) heating and electricity in the morning, and *iv*) heating and electricity in the evening. Recall that all restrictions regard weekdays.

Table 3 - Attribute levels used as decision rule to eliminate an alternative in the different EBA-models

	Models				
Attribute levels	EBA-Heating	EBA-Electricity	EBA-Morning	EBA-Evening	EBA-Full
Heat-morning	✓		✓		✓
Electric-morning		✓	✓		✓
Heat-morning or Electric-morning			✓		✓
Heat-evening	✓			✓	✓
Electric-evening		✓		✓	✓
Heat-evening or Electric-evening				✓	✓
Heat-morning or evening	✓				✓
Electric-morning or evening		✓			✓

Individuals may of course differ with respect to decision rule strategies, meaning that heterogeneity in alternative processing strategies is introduced. The actual decision rule used by any given individual is unobservable, but we estimate the use of each rule up to a probability using a latent class formulation where each class pertains to a specific decision rule, i.e., RUM or one of the five EBA rules considered. We estimate this probability using constants only multinomial logit model (see e.g. Campbell et al., 2014; Greene and Hensher, 2003) such that:

$$\pi_q = \frac{\exp(\theta_q)}{\sum_{q \in Q} \exp(\theta_q)}, \tag{4a}$$

where θ_q is a constant corresponding to class q, with one class constant set to zero for identification. We then write the probability of choice under an EBA rule as:

$$Pr(y_n|\beta, x_n, \pi) = \sum_{q=1}^{Q} \pi_q \prod_{t=1}^{T} Pr(i_{nt}|\beta, x_n)(1 - I_{x_{knit}|q}), \tag{4b}$$

where $I_{x_{knit}|q}$ is an indicator taking on a value of 1 if the attribute level restriction x_k, as given by the rule in class q, is present in the alternative i. For example, if we consider the EBA-heating model, then $Q = 4$, i.e., 3 EBA classes (morning, evening, and morning or evening) and 1 RUM class. Importantly, this approach restricts the probability of alternatives that are eliminated to zero and ensures that the

EBA rule holds for the entire sequence of choices. It is the specification of the indicator variable that varies across classes and for the RUM class it is considered equal to 0 for all attribute levels, meaning that no alternatives are eliminated.

3.2. Accounting for preference heterogeneity

Using a multinomial logit model to describe the underlying preference structure is restrictive in that it implies that people have the same preferences. It is likely that people do differ with respect to their preferences for electricity contract attributes and we accommodate this preference heterogeneity using a latent class model.[3] One of the benefits of the latent class approach is that we avoid the need to specify distributions for the preferences. Instead, we assume that preferences can be described by a finite number of preference vectors and estimate the probability that any given vector describes preferences. We estimate the probability that a given individual is in a preference class using constants only MNL model with one constant set to zero for identification. Let the probability of being in a preference class be given by:

$$\omega_r = \frac{\exp(\lambda_r)}{\sum_{r \in R} \exp(\lambda_r)}, \tag{5a}$$

where λ_r is a constant corresponding to preference class r.

We then write the probability of the sequence of choices as:

$$Pr(y_n|\beta, x_n, \omega, \pi) = \sum_{r=1}^{R} \omega_r \sum_{q=1}^{Q} \pi_q \prod_{t=1}^{T} Pr(i_{nt}|\beta_r, x_n)(1 - I_{x_{knit|q}}) \tag{5b}$$

where β_r is the vector of parameters pertaining to class r. Notice that we consider all the EBA rules for each of the preference classes and that if $R = 1$ the model collapses into Equation 4b.

3.3. Conditional estimates and willingness-to-accept

By using Bayes' theorem, the conditional, i.e. individual specific, class probabilities can be derived (Train, 2009). The conditional estimates are conditional on the sequence of choices made by a respondent.

$$\omega_{r|n} = \frac{\omega_r Pr(y_n|\beta_r, x_n, \omega)}{\sum_{r=1}^{R} \omega_r Pr(y_n|\beta_r, x_n, \omega)} \tag{4}$$

[3]Note that this is in addition to the already introduced alternative processing heterogeneity.

The conditional willingness-to-accept is then calculated by weighting the willingness-to-accept measures with the conditional probabilities. That is,

$$\text{WTA}_{kn} = \sum_{r=1}^{R} \omega_{r|n} \frac{\beta_{kr}}{-\beta_{cr}}, \forall k \neq c \tag{5}$$

where β_k and β_c refer to the non-compensation and compensation attributes respectively.

4. Results

All the models presented in Section 3 were coded in the open source software R. To check for convergence to local optima, each model was run multiple times with random starting values. In the first part of this section, we report the estimation results from a basic MNL model (Equation 3) and models that account for EBA-type behavior with fixed parameters (Equation 4b), i.e., homogenous preferences within each class of alternative processing strategies. Preference heterogeneity is then introduced based on finitely distributed parameters (two latent classes). Finally we present results on variations in the use of choice strategies across respondents, and comparisons of conditional marginal WTA distributions from the different models.

4.1. Homogeneous preferences

Table 4 presents the results of the basic MNL model, which serves as a reference for comparison, and five other models incorporating various elimination-by-aspect strategies. For the MNL model, all parameters are of the expected sign (i.e., positive for compensation and negative for any restriction on use and sharing of electricity consumption information) and significant except for the information attribute. We note that the sign on the alternative specific constant for the status quo (ASC-SQ) alternative is positive and significant which can be interpreted as, on average, respondents are not willing to change from their current contract to one that involves one or more restrictions for a given compensation.

We are aware that any direct comparison of models is inappropriate since each model is subject to different scaling. Still, it is possible to make some cross-model observations. First, there is a sign-change on the attribute levels used as elimination criteria. This somewhat counter-intuitive result is likely an artifact of the model setup. Remember that the choice probability of an alternative is restricted to zero when the elimination criteria is present in that alternative, and the probability of the sequence of choices for a choice maker is non-zero only if the EBA strategy is not implemented for the entire sequence. Hence, the parameter for the attribute level used as elimination criteria just shows the preferences of respondents that do not implement the specific EBA strategy. This result is however mitigated to some degree when we consider preference heterogeneity. Further, note that the parameter estimates on the remaining attributes are of the expected sign.

Comparing the fit of the basic MNL model with models that account for EBA behavior directly is somewhat misleading since the former does not consider the panel structure of the data, but we can make comparisons across the EBA models. First, we see that irrespective of specification, the unconditional average probability of choosing according to a RUM is between 44% (EBA-Evening) and 53 % (EBA-Heating). This is a relatively stable result. Second, the models with the best fit, as measured by the AIC and BIC statistics, are the ones considering only electricity as elimination criteria or the "full" specification. Notably, these two models also predict low shares of respondents choosing according to a RUM process. This suggests that a considerable number of respondents are unlikely to accept reductions in their use of electricity for a compensation, a result that proves to be quite robust across specifications.

Turning to elimination rules based on heating and electricity separately, the models suggest that both were used as elimination criteria and the model considering only electricity vastly outperforms the model using heating only. This could further suggest that restrictions in electricity are more problematic than heating. Moving on to consider whether restrictions in the morning or evening might be the drivers behind the results, we observe a slightly lower probability of using EBA strategy for morning than evening restrictions (50% compared to 56%). Only a minority are predicted to be in a class where heating attribute level is used as the elimination criteria in "EBA-Morning" and "EBA-Evening" models, which again suggests that EBA strategy is more likely to be adopted when the control is for electricity rather than heating. This result is strengthened, yet moderated, when we consider all four EBA strategies jointly in the final model. In fact, the classes "electricity-morning", "electricity-evening", "electricity-evening × heating-evening" and "electricity-morning × electricity-evening" are all significant with the latter comprising the majority of respondents eliminating by aspects. This suggests that while electricity is dominating, a significant share of respondents are predicted to not accept any restriction in either heating or electricity in the evening.

From a behavioral perspective, this result is intuitive. People use electricity in the morning for making breakfast, while it is not important to consider the indoor temperature when at work. Consequently, when turning home in the afternoon households need electricity to cook, watch TV, do laundry etc., and they might want to turn up the heat to stay nice and cozy.[4] This result reflects the typical weekday consumption pattern of the average household.

[4]The Swedish climate makes the heating system and indoor temperature a relevant aspect in this context.

Table 4 - Multinomial logit model and elimination-by-aspects specifications

	MNL		EBA - Heating		EBA - Electricity		EBA - Morning		EBA - Evening		EBA - Full	
	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
$\beta_{\text{Compensation}}$	0.3301***	0.0272	0.5001***	0.0340	0.3361***	0.0417	0.3516***	0.0363	0.4463***	0.0386	0.3538***	0.0445
$\beta_{\text{Heat - morning}}$	−0.1971***	0.0768	1.2297***	0.0994	−0.2880***	0.0850	0.3468***	0.0831	−0.0503	0.0871	−0.2464*	0.1350
$\beta_{\text{Heat - evening}}$	−0.2749***	0.0485	0.9573***	0.0832	−0.4526***	0.0647	−0.4258***	0.0571	0.6059***	0.0822	−0.3929***	0.1263
$\beta_{\text{Electric - morning}}$	−0.2280***	0.0560	−0.6007***	0.0707	1.2056***	0.0962	0.7783***	0.0844	−0.3857***	0.0635	1.1967***	0.1035
$\beta_{\text{Electric - evening}}$	−0.3464***	0.0580	−0.5909***	0.0702	0.9554***	0.0892	−0.3601***	0.0624	0.6558***	0.0873	0.9577***	0.0918
$\beta_{\text{Extreme event}}$	−0.0203***	0.0061	−0.0022	0.0064	−0.0352***	0.0073	−0.0291***	0.0067	−0.0124*	0.0072	−0.0336***	0.0076
$\beta_{\text{Info - yes}}$	−0.0297	0.0484	−0.0096	0.0554	−0.1650***	0.0610	0.0381	0.0558	−0.1312**	0.0581	−0.1614**	0.0660
$\beta_{\text{ASC - SQ}}$	0.8917***	0.0840	0.9959***	0.0872	0.6408***	0.0999	0.7036***	0.0864	0.9208***	0.0987	0.6772***	0.1101
Unconditional class prob.												
$\Pr(RUM)$	1.0000		0.5335***	0.0204	0.4631***	0.0184	0.5023***	0.0189	0.4393***	0.0198	0.4533***	0.0194
$\Pr(Heat-morning)$			0.0081	0.0084			0.0208**	0.0087			0.0051	0.0210
$\Pr(Electric-morning)$					0.0182**	0.0072	0.0441***	0.0107			0.0174**	0.0079
$\Pr(Heat-morning \times Electric-morning)$							0.4328***	0.0184			0.0018	0.0074
$\Pr(Heat-evening)$			0.0149	0.0130					0.0308***	0.0103	0.0007	0.0021
$\Pr(Electric-evening)$					0.0535***	0.0113			0.0761***	0.0125	0.0332***	0.0105
$\Pr(Heat-evening \times Electric-evening)$									0.4538***	0.0177	0.0313***	0.0212
$\Pr(Heat-morning \times Heat-evening)$			0.4436***	0.0169							0.0009	0.0041
$\Pr(Electric-morning \times Electric-evening)$					0.4652***	0.0167					0.4567***	0.0179
LL	-5351.657		4766.606		4382.466		4800.098		4858.057		4375.981	
$\bar{\rho}^2$	0.11		0.09		0.12		0.11		0.10		0.14	
AIC	10719.31		9555.21		8786.93		9622.2		9738.11		8783.96	
BIC	10772.23		9627.97		8859.69		9694.95		9810.87		8889.79	
K	8		11		11		11		11		16	
N	5508		5508		5508		5508		5580		5508	

'***' - 1 % level, '**' - 5 % level, '*' - 10 % level
Adjusted robust standard errors

4.2. Heterogenous preferences

Instead of assuming homogeneous preferences within each class of alternative processing strategies, we now introduce heterogeneity using a latent class model with two preference classes. The results of these models are presented in Table 5. The first model is a standard latent class model where class probabilities are estimated using a constant only logit model, and the next five models consider the same EBA strategies as above. Given the risk of confounding between heterogeneity in preference and processing strategies, the individual behavioral rules were the same for the two preference classes (see also Erdem et al. (2014)).

Inspecting the latent class models, the models fit the data better relative to the models with fixed parameters. Allowing for discrete preference heterogeneity reveals an interesting grouping of respondents. Respondents in preference class one are more likely to accept compensation for a restriction on their use of heating and electricity. This is evident from the positive and significant compensation parameter and the negative and significant alternative specific constant. Respondents in class two have a weaker preference for the compensation and a strong positive preference for the status quo. Hence, the second class constitutes respondents with a tendency to implement different elimination criterion instead of making trade-offs between attributes. This is also supported by the result that the average unconditional probability of choosing based on a RUM process is more than double in preference class one compared to the respective probabilities and model in preference class two for the models considering EBA behavior.

Turning to more attribute specific observations, for heating in the morning in class one (where trade-offs are more likely to be made) the estimate is positive albeit not significant. This indicates that people in this class tend to choose contracts where heating in the morning is restricted. This result is in line with the EBA models that do not consider preference heterogeneity. People tend to eliminate alternatives (contracts) with restrictions on electricity and heating in the evening relative to heating in the morning. If it is the case that people do not mind restrictions on heating in the morning because they, for example, do not use heating in the morning, then choosing a contract with this restriction and a positive compensation is "free" money. Indeed, restriction in morning heating was shown to cause less disutility in the background paper by Broberg and Persson (2016) .

The five models considering the EBA strategies describe the data better relative to the latent class model as evident by the log-likelihood value and the AIC statistic[5]. The results are however more ambiguous considering the BIC statistic, which penalizes number of parameters harder. We note that the story is similar to models under homogeneous preferences - the attributes used as elimination criteria tend to

[5]Comparisons based on the ρ^2 are somewhat misleading since the log-likelihood value at 0 for all parameters differ across models given that the number of alternatives considered varies across models.

have a sign-change in the utility functions. However, this is most prevalent for those predicted to be in preference class two, which is a class describing respondents more likely to choose anything but the status quo after eliminating alternatives with restrictions. Furthermore, we observe that respondents predicted to use an EBA strategy, across all model specifications, are significantly more likely to be in this class. This indicates that respondents using an EBA type strategy end up with substantially more status quo choices. If this result holds in a general context, it suggests that status quo choosers may choose the status quo as a result of an EBA strategy. Given the good under consideration, this is not surprising. If they are not willing to accept any restriction in their use of electricity and eliminate all alternatives where such attribute level is present, choosing the status quo will then always be available. Another point of interest relative to the fixed parameter based models is that respondents eliminating based on one level of the aspect in question are more likely to be in preference class one whereas if they eliminate based on multiple aspects they are more likely to be in preference class two. This is particularly true for combined aspects that are chiefly used as elimination criteria. Again, this result makes intuitive sense. If you only eliminate based on the level of one of the attributes, you are still willing to make trade-offs with respect to the remaining attribute levels.

If we consider the information contained in all the models and in particular the "EBA-Full" model, the story mirrors that of the MNL models. On average, people are unwilling to accept limitations on electricity use irrespective of time of day, but they are willing to accept a restriction in heating in the morning. Even now, it is possible to see the potential benefits of this type of model concerning policy. It provides important information regarding what attributes people are indeed willing to trade off or accept limitations on and which attributes they are not. Furthermore, it suggests what attributes to focus on for policymakers to avoid paying something for nothing. In Section 4.4 we take a closer look at what this means for the welfare estimates derived.

Table 5 - Latent class model and elimination-by-aspects specifications

	Latent class		EBA - Heating		EBA - Electricity		EBA - Morning		EBA - Evening		EBA - Full	
	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
$\beta_{\text{Compensation—Class 1}}$	0.5695***	0.0491	0.5873***	0.0523	0.6011***	0.0561	0.5767***	0.0518	0.6016***	0.0539	0.6294***	0.0568
$\beta_{\text{Heat - morning—Class 1}}$	0.1739	0.1105	0.1805	0.1163	0.3231**	0.1281	0.2258*	0.1199	0.2460**	0.1193	0.3737***	0.1275
$\beta_{\text{Heat - evening—Class 1}}$	−0.1989**	0.0833	−0.1196	0.0862	−0.1083	0.0959	−0.1819**	0.0891	−0.0438	0.0887	0.0109	0.0955
$\beta_{\text{Electric - morning—Class 1}}$	−0.2098**	0.0995	−0.2189**	0.1062	−0.2801**	0.1109	−0.1996*	0.1047	−0.2945***	0.1067	−0.3266***	0.1137
$\beta_{\text{Electric - evening—Class 1}}$	−0.3936***	0.0882	−0.3812***	0.0902	−0.2321**	0.0890	−0.3635***	0.0916	−0.2130**	0.0914	−0.2470***	0.0917
$\beta_{\text{Extreme event—Class 1}}$	−0.0062	0.0074	−0.0040	0.0077	0.0011	0.0079	−0.0040	0.0078	−0.0019	0.0078	0.0029	0.0082
$\beta_{\text{Info - yes—Class 1}}$	−0.1012	0.0639	−0.0934	0.0662	−0.0595	0.0721	−0.0893	0.0665	−0.0964	0.0688	−0.0687	0.0745
$\beta_{\text{ASC - SQ—Class 1}}$	−0.7928***	0.1123	−0.8675***	0.1214	−0.9618***	0.1357	−0.8989***	0.1241	−0.8165***	0.1227	−0.9255***	0.1444
$\beta_{\text{Compensation—Class 2}}$	0.1330	0.1118	0.1963	0.1198	0.2549**	0.1230	0.1910	0.1174	0.2914*	0.1529	0.2641**	0.1292
$\beta_{\text{Heat - morning—Class 2}}$	−0.8960**	0.2521	0.9449***	0.3487	−0.8230***	0.2265	0.0472	0.4708	−0.7559***	0.2827	−0.8239***	0.2420
$\beta_{\text{Heat - evening—Class 2}}$	−0.8108***	0.2213	0.8711***	0.2820	−1.0561***	0.2192	−0.8911***	0.2221	0.2390	0.2700	−0.9080***	0.2269
$\beta_{\text{Electric - morning—Class 2}}$	−1.5233***	0.2023	−1.5544***	0.2136	0.9387***	0.3385	0.4894	0.3401	−1.6149***	0.2375	0.9821***	0.3599
$\beta_{\text{Electric - evening—Class 2}}$	−2.0329***	0.2222	−2.1518***	0.2287	−0.0321	0.2869	−2.0174***	0.2210	−1.1045***	0.2576	0.0407	0.2986
$\beta_{\text{Extreme event—Class 2}}$	−0.0871***	0.0234	−0.0899***	0.0240	−0.0931***	0.0228	−0.0835***	0.0209	−0.0979***	0.0282	−0.1016***	0.0257
$\beta_{\text{Info - yes—Class 2}}$	−0.0234	0.1776	−0.0273	0.1874	−0.2020	0.1803	−0.0137	0.1797	−0.0271	0.1938	−0.0903	0.2049
$\beta_{\text{ASC - SQ—Class 2}}$	1.6019***	0.2455	1.6154***	0.2469	1.6386***	0.2510	1.5521***	0.2343	1.8476***	0.2575	1.8071***	0.2633
$\Pr(RUM\|Class1)$	0.4635***	0.0175	0.4334***	0.0186	0.3990***	0.0179	0.4358***	0.0239	0.4041***	0.0179	0.3859***	0.0180
$\Pr(Heat-morning\|Class1)$			0.0000	0.0000			0.0049	0.0047			0.0016	0.0046
$\Pr(Electric-morning\|Class1)$					0.0046	0.0040	0.0047	0.0044			0.0042	0.0036
$\Pr(Heat-morning \times Electric-morning\|Class1)$							0.0000	0.0001			0.0008	0.0022
$\Pr(Heat-evening\|Class1)$			0.0156	0.0079					0.0164**	0.0066	0.0124*	0.0065
$\Pr(Electric-evening\|Class1)$					0.0338***	0.0084			0.0340***	0.0085	0.0275***	0.0077
$\Pr(Heat-evening \times Electric-evening\|Class1)$									0.0169***	0.0064	0.0135**	0.0062
$\Pr(Heat-morning \times Heat-evening\|Class1)$			0.0039	0.0040							0.0018	0.0029
$\Pr(Electric-morning \times Electric-evening\|Class1)$					0.0085*	0.0046					0.0082**	0.0041
$\Pr(RUM\|Class2)$	0.5365***	0.0175	0.1561***	0.0235	0.1183***	0.0254	0.0924***	0.0245	0.1907***	0.0404	0.1117***	0.0248
$\Pr(Heat-morning\|Class2)$			0.0001	0.0002			0.0170	0.0251			0.0000**	0.0000
$\Pr(Electric-morning\|Class2)$					0.0250	0.0362	0.1262**	0.0613			0.0257	0.0346
$\Pr(Heat-morning \times Electric-morning\|Class2)$							0.3189***	0.0533			0.0000	0.0000
$\Pr(Heat-evening\|Class2)$			0.0000	0.0001					0.0000	0.0000	0.0000*	0.0000
$\Pr(Electric-evening\|Class2)$					0.0005	0.0005			0.0017	0.0028	0.0000	0.0000
$\Pr(Heat-evening \times Electric-evening\|Class2)$									0.3362***	0.0430	0.0000	0.0000
$\Pr(Heat-morning \times Heat-evening\|Class2)$			0.3909***	0.0254							0.0000**	0.0000
$\Pr(Electric-morning \times Electric-evening\|Class2)$					0.4101***	0.0282					0.4067***	0.0291
$\text{LL}(\hat{\beta})$	-3829.947		-3808.866		-3790.541		-3814.117		-3790.815		-3779.067	
$\bar{\rho}^2$	0.36		0.27		0.24		0.29		0.3		0.26	
AIC	7693.89		7663.73		7627.08		7674.23		7627.63		7624.13	
BIC	7806.33		7815.85		7779.2		7826.36		7779.75		7842.39	
K	17		23		23		23		23		33	
N	5508		5508		5508		5508		5508		5508	

'***' - 1 % level, '**' - 5 % level, '*' - 10 % level
Adjusted robust standard errors

4.3. Respondent characteristics and use of decision rules

In this section, we take a look at how socio-demographic characteristics of our respondents relates to the average conditional probabilities of choosing according to a random utility model or elimination-by-aspects model. The conditional probabilities are individual specific and conditional on the sequence of choices made by respondents. This can provide insights on who is more likely to use this particular simplifying strategy. In Figure 2 we report this for the "EBA-Full" model only.

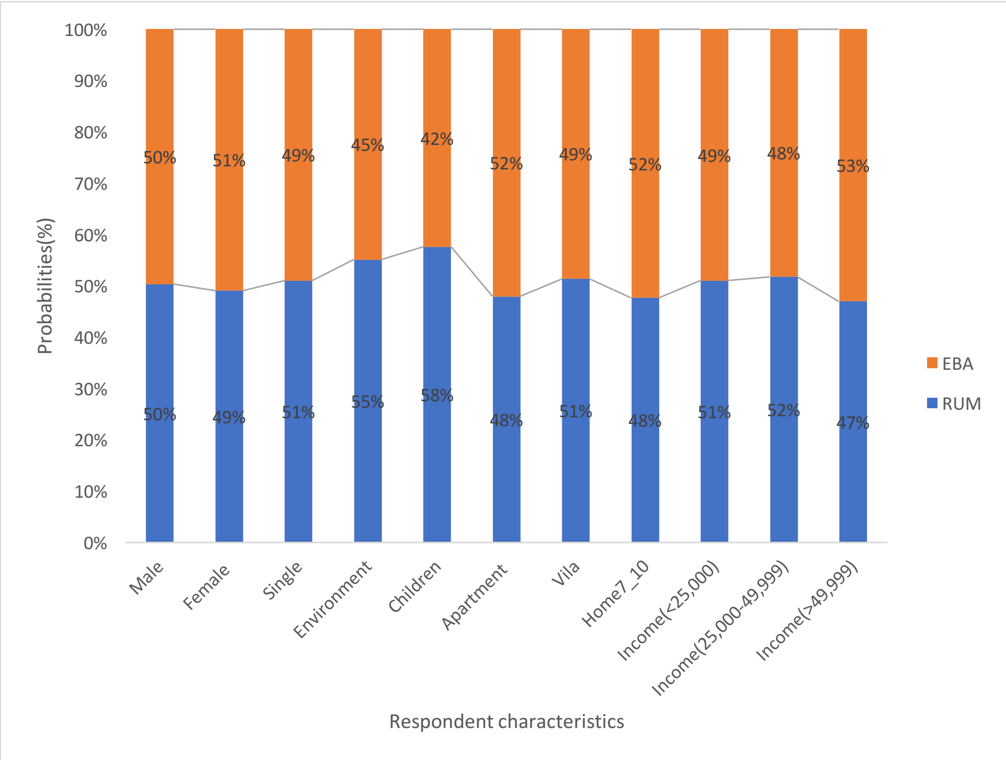

Figure 2 - Average conditional probailities of using decision rules

Across the socio-demographic characteristics we consider, the average conditional probability of using an EBA strategy is about 50% - with a few notable exceptions. For example, respondents who reported that they would reduce energy consumption for the sake of the environment are slightly more likely to choose according to a RUM. This makes intuitive sense. If you care about the environment, you are more likely to consider electricity contracts that reflect demand flexibility. We also note that this seems to hold true for households with children, but our data do not provide any insights into what drives this result. Respondents who live in apartment buildings, have family members staying home during the morning peak hours (7-10am) and those whose monthly family income is at least SEK 50,000 have a slightly higher probability of using an EBA strategy. The fact that the two decision rules do not vary a lot across the respondent characteristics indicates that observed characteristics are not able to fully explain respondents' use of such rules.

4.4. Marginal willingness to accept estimates

It is evident that allowing for EBA strategies improves model fit. From a practical policy perspective, however, it is interesting to look at the marginal willingness-to-accept measures. Given the apparent evidence of preference heterogeneity in our sample, in Table 6, we report the conditional WTA estimates based on the latent class model and the "EBA-Full' model reported in Table 5. The conditional willingness-to-accept estimates are the class-specific estimates weighted by the conditional (i.e., individual specific) class probabilities.

At first glance, three things are immediately clear: i) people ask a substantial compensation to accept restrictions on their use of energy, ii) considering EBA leads to lower WTA measures, and iii) the median is higher than the mean. For example, we see that people require SEK6314 and SEK8520 in compensation to accept restrictions on the use of electricity in the morning and evening, respectively. Remember from Table 1, that this attribute specifically listed restrictions on the use of the dishwasher, laundry machine and dryer, towel warmers and floor heating during these hours. Notice that the compensation required for restrictions during extreme periods of demand or limited supply is relatively low. This can reflect the possibility that such disruptions are unavoidable regardless of contract type. Next, we compare these WTA estimates with those derived from the EBA model. We see that there is a substantial reduction in the mean WTA. This is again not surprising since the estimates for attribute levels used as elimination criteria only effectively apply to those who do not use such elimination strategies. The reduction in WTA is more pronounced to control of domestic electricity attribute levels. This substantial fall in WTA values for morning and evening electricity attribute levels could be due to the large proportion of respondents eliminating alternatives based on these two attribute levels. The negative WTA value for restrictions on electricity in the morning does indeed seem extreme, although this is also a result of the already discussed sign change in parameters corresponding to the respective EBA strategy. Another interesting thing to note is that preferences for the status quo alternative (ASC-SQ) relative to the two generic alternatives decreases when accounting for EBA behavior. This is reflected by a reduction in the amount they require to even consider the hypothetical alternatives from SEK5815 to SEK3053 per year. The rather large difference between mean and median estimates is likely caused by a right skew of the distribution, i.e., we have many observations in the tail of the lower end of the distribution.

Table 6 - Conditional marginal WTA estimates(in SEK)

Levels	Model	2.5%	Median	Mean	97.5%
Heat - morning	LC	- 305.4	6517.8	3472.6	6734.3
	EBA	-593.6	2765.2	1426.6	3118.8
Heat -evening	LC	349.2	5918.8	3432.3	6095.5
	EBA	- 17.1	3108.2	1862.6	3437.2
Electric-morning	LC	368.5	11109.4	6314.3	11450.2
	EBA	-3718	-3314.2	-1787.9	518.7
Electric-evening	LC	691.1	14833.9	8520.1	15282.5
	EBA	-154	-102	95.6	392.5
Extreme-event	LC	11.0	635.4	356.6	655.2
	EBA	- 4.6	347.4	207.1	384.4
Information-yes	LC	175.5	175.6	177.3	177.7
	EBA	109.2	319.6	235.7	341.7
ASC-SQ	LC	-12040.3	-11627	-5815	1392.1
	EBA	-6841.2	-6050	-3053	1470.5

5. Conclusion

In this paper, we report on a discrete choice experiment aimed at eliciting Swedish households' willingness-to-accept a compensation for restrictions on household electricity- and heating use during peak hours. Following Erdem et al. (2014), we implement a flexible modeling approach that allows us to consider non-utility maximizing behavior. Specifically, we use a model that captures a two-stage decision process, whereby respondents in the first stage eliminate from their choice set alternatives that contain an unacceptable level, i.e., restrictions on the use of heating and electricity, and in the second stage choose in a compensatory manner between the remaining options.

First, we find that people do indeed eliminate alternatives that include attributes they find undesirable from their choice set. Most notably, people tend to eliminate alternatives that include restrictions on the use of electricity in general and restrictions on the use of heating in the evening. This result is robust across models that do and do not consider preference heterogeneity. The result is intuitive and reflects a typical weekday in the average Swedish household. People use electricity in the morning for making breakfast, while it is not essential to consider the indoor temperature when at work. Consequently, when coming home in the afternoon they need electricity to cook, watch TV, do laundry, etc., and they might want to turn up the heat. Second, in the models that do consider preference heterogeneity, we observe that respondents are predicted to be in one of two groups of people: those who are willing to make trade-offs and those who tend to stay with the status quo. Importantly, and in support of our initial findings, we see that the people who are willing to make trade-offs tend to choose alternatives in which heating in the morning is restricted. This suggests that restrictions on heating in the morning does not inconvenience respondents as much - a result which is in line with the findings of Broberg and Persson (2016). One possible explanation could be that, combined with a positive compensation, a restriction on heating in the morning is perceived as “free money”. If true, it indicates that a policy aimed at compensating people for restrictions on heating in the morning might lead to a situation where you pay something for nothing. Third, we find that willingness-to-accept estimates are sensitive to whether we consider elimination-by-aspects behavior. Specifically, considering such behavior leads to a downward shift in willingness-to-accept. Intuitively, by considering a respondent’s actual consideration set, we restrict the calculation of willingness-to-accept only to consider alternatives that were indeed considered. This information is important for any policymaker, and it helps identify households that are willing-to-accept reduction in energy use, what type of reductions and how much they need to be compensated.

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