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Key elements and attributes affecting prosumers' behavior

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Preface

This report was done as a part of the Finnish national research project "Flexible Energy Systems" FLEXe, and it was funded by Tekes, the Finnish Funding Agency for Technology and Innovation, and the project partners. The report was written in the Finnish Environment Institute (SYKE).

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Summary

Many aspects of households' motivation to participate to the energy market are not yet well understood. Hence, the mechanisms to promote flexibility among households are still inadequate. This report provides an ex ante evaluation of households' acceptance for hypothetical flexibility contracts and services in Finland. We use a survey-based method referred to as the Choice Experiment (CE) to analyze individuals' preferences for different characteristics of demand side flexibility.

This study has several objectives. First, it provides detailed information on household preferences toward demand side flexibility. We investigate households' willingness to offer flexibility via timing their electricity usage and heating. Moreover, we study if households are interested in flexible contracts such as real-time pricing, two-rate tariffs or power based tariffs. Second, our aim is to explain taste variation among individuals. Different socio-demographic and behavioral characteristics of the respondents are expected to have significant role in explaining their choices. Third, we explore individuals' actual choices regarding e.g. electricity sales contracts and other energy-related behavior. Lastly, we examine households' level of knowledge and thoughts what comes to different energy-related issues.

In this report, we summarize findings from a pilot survey, which preserves as a first step of a larger study going to be conduct during autumn 2016. Our preliminary results from the pilot CE study indicate that respondents' sensitivity to restrictions in household electricity usage is greater than sensitivity to restrictions in heating. The results also imply that fluctuating real-time pricing contracts are perceived as something negative, and that individuals therefore want to be compensated in order to accept them. Moreover, the findings suggest that there is likely some room for new flexible distribution contracts, such as power based pricing scheme, in the market. There exists also some other value creating elements how to increase demand side flexibility than just reductions in annual energy payments as possible system level reduction in CO_2 emissions is valued among households. Finally, our analyses illustrate the importance of careful planning of flexibility services, as several socio-demographic characteristics clearly affect individuals' decisions.

Overall, demand side flexibility is expected to take an increasing role in the future power systems. Households should adjust their electricity consumption based on price signals and other incentives in order to facilitate efficient use of generation and network infrastructure and functioning of overall electricity market. By investigating carefully the determinants of demand side flexibility, we can support the development of future energy system to meet households' needs.

Helsinki, June 2016

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1 INTRODUCTION

Electricity and energy markets are currently facing complex challenges. As the levels of variable renewable energy sources increase, flexibility is a key element for reliable operation of energy system. In general, flexibility refers to energy system's ability to maintain continuous service during rapid and large changes in energy supply and demand. Demand side flexibility is an essential part of the overall system level flexibility. In turn, it is necessary that also households take an active role in the energy market. However, in order to make households active, the market has to offer incentives (monetary or other value creating incentives) and opportunities regarding flexible energy usage.

In general, the term "prosumer" refers to private households that both produce and consume energy. In this report, we further develop the use of this term to consider households who participate to the electricity market by changing their behavioral patterns in a way that is beneficial for the electricity market as a whole.

Many aspects of households' motivation to participate to the energy market are not yet well understood. Hence, the mechanisms to promote flexibility among households are still inadequate. This report provides an ex ante evaluation of households' acceptance for hypothetical flexibility contracts and services in Finland.

Knowing the households' preferences eases the implementation of new flexible services and contracts. In this study, we use choice experiment (CE) method (see, Hensher et al., 2015) to examine individuals' preferences for characteristics of demand side flexibility. CE is a stated preference method which is a widely applied quantitative statistical method to analyze individual's discrete choices (see, e.g., Achtnicht, 2011; Islam and Meade, 2013; Huh et al., 2015; Ruokamo, 2016). The main goal of this method is to determine how individuals construct their preferences for services and goods, and what are the trade-offs between different characteristics describing them.

This report summarizes the first findings based on a pilot survey which preserves as a first step of a larger study going to be conduct during autumn 2016. The pilot survey is available on request from the authors (in Finnish only). The study as a whole has several objectives. First, it provides detailed information on household preferences toward demand side flexibility. We investigate households' willingness to offer flexibility via timing their electricity usage and heating. Moreover, we study if households are interested in flexible contracts such as real-time pricing, two-rate tariffs or power based tariffs. Second, our aim is to explain preference heterogeneity among individuals. Different socio-demographic and behavioral characteristics of the respondents are expected to have significant role in explaining their choices. Third, we study individuals' actual electricity sales contract choices and reasons for choosing them. Lastly, we also examine households' level of knowledge and thoughts what comes to different energy-related issues.

The remaining sections of this report are organized as follows. Section 2 presents briefly previous studies and gives a short discussion on demand side flexibility. In Section 3, we first show the theoretical framework of choice experiments and then focus on the survey design. Preliminary results are presented and discussed in Section 4. Section 5 concludes with future research plans.

2 ELECTRICITY MARKET IN TRANSITION

2.1 PREVIOUS STUDIES

Although household preferences play a key role in creating demand side flexibility, the previous literature has focused either on the possibilities and potential of demand response (see e.g. Darby and McKenna, 2012) or on different technologies enabling demand response (see e.g. Hargreaves et al., 2010; Kobus et al., 2015) leaving the thorough investigation of individuals' needs on the background (see Annala, 2015; Broberg et al., 2014; Ek et al., 2010).

First, we list few reviewing papers that have explored different aspects of demand side flexibility, after what we present some case-specific studies. Darby and McKenna (2012) reviewed what is known about user response from a range of residential demand response programmes. For an interesting review focusing on uptake and usage of cost-reflective electricity pricing from behavioral economics point of view see a paper from Hobman et al. (2016). Furthermore, for a comprehensive literature review concentrating on socio-economic, dwelling and appliance related factors affecting households' electricity consumption see Jones et al. (2015).

Kobus et al. (2015) explored the electricity demand shift of households and the role of smart appliances to enable this shift. They focused on smart washing machines combined with solar panels, and used real behavioral data. Their result revealed that households shifted the use of their washing machines to hours when electricity was locally produced, and this in turn reduced peak demand. Hargreaves et al. (2010) studied how UK households interacted with feedback on their energy consumption. They conducted interviews with households that were trialling smart energy monitors. Results suggested that monitors do affect household behavior to some extent, however, several limitations were found. Ek et al. (2010) investigated Swedish households' electricity saving behavior and the role of information in it. Their results indicated that costs, environmental attitudes and social interactions are all important contributors of electricity saving activities.

Broberg et al. (2014) studied Swedish household behavior on the electricity market while focusing on the possibilities and incentives for changing current consumption patterns. They used CE method to investigate household views of different flexibility aspects. Examined attributes in their study were: remote control of heating, remote control of electricity use, remote control of heating and electricity during extreme conditions, dissemination of information regarding household energy usage, and annual compensation. Their findings suggested that demand side flexibility is fairly limited, and requires better compensation that is currently offered. Annala (2015) examined in her dissertation the potential of demand side flexibility in Finland. She investigated households' motives to participate in demand response, and further, experiences of households with electricity consumption monitoring systems were discussed. Results indicated that households seem ready to allow remote control of electric appliances that does not require changes in their everyday routines. It was also found that households were worried whether the control system functions always in the agreed manner. Additionally, the compensations required to engage in demand response activities were relatively high.

2.2 DEMAND SIDE FLEXIBILITY

The key drivers behind demand side flexibility in future energy system are the increasing share of variable (intermittent) production and the new type of smart technology. In the future, a significant part of the new generation capacity will be based on solar and wind power. This type of variable production creates potential problems related to correlation among demand and variable production profiles. Weak correlation of demand and supply in turns creates so called profile costs. Lots of research effort is devoted into the suitability of power system's supply side to meet the residual load, i.e. load less intermittently generated power. By comparison, the demand side has received less attention. Instead of focusing purely on matching the load with the suitable supply technology mix, systemically efficient solutions can be achieved by including demand into the optimization decision as well. In short, handling the system demand as reactive consumption instead of passive load.

On the system efficiency point of view electricity prices should be based on their system level marginal costs. However, until recently there has not been technological possibilities to measure real time electricity consumption such a manner that marginal costs reflective price contracts could be offered. Technology (i.e. smart house technology, automatic meters) makes it also possible to optimize consumers' electricity consumption such that no direct every day action from customer side are needed.

Programs that aim to alter the timing and level of electricity consumption are not a new concept. In the 1970s demand side management (DSM) programs took their first steps in the US in response to growing concerns about dependence on foreign energy sources and environmental consequences of electricity. However, DSM programs did not start to grew rapidly before late 1980s (Eto, 1995). Generally speaking, DSM refers to the planning, implementation, and monitoring of activities that aim to change the shape of the utility load by influencing customers' electricity use (see Gellings, 1985). As DSM encompasses a variety of utility activities, we present next the division by Nadel (1993) regarding DSM programs. These activities consist of the following: (1) general information to increase customer awareness of energy use and opportunities to save energy; (2) technical information including energy audits, which identify specific recommendations for improvements in energy use; (3)

financial assistance or direct payments to lower the cost of energy efficient technologies; (4) direct or free installation of energy efficient technologies; (5) performance contracting, in which a third party contracts with both the utility (e.g. energy company) and a customer and guarantees energy performance; (6) load control and load shifting, in which the utility offers financial payments or bill reductions for controlling a customer's use of certain energy-using devices; (7) innovative tariffs, such as time-of-day and real-time pricing, price signals that can enhance the effectiveness of DSM programs

The objectives of DSM programs cover e.g. reducing electricity demand during peak times, increasing off-peak consumption, and/or changing the time of use from high-cost periods to low-cost periods (Barakat & Chamberlin, 1993). Furthermore, the aim is to encompass better reliability, lower costs and electricity bills, and a reduced need for generation investments (Barakat & Chamberlin, 1993).

DSM can be said to cover both demand response and energy efficiency. Thus, measures to permanently reduce electricity consumption are not considered a part of demand response (Annala, 2015). It is, however, important to keep in mind that the use of demand response comes with a risk of conflict of interest between different parties at the electricity market.

Recently new type of electricity price contracts, especially related to energy price, have emerged into the market. There is also expectations that larger variety of distribution (network) price contracts will appear in near future. As electricity pricing is a complex tasks and final electricity price is constructed from many different parts, there is clear threat that price contracts may give contradictory consumption signals to individual consumers. Consequently, it would be of great importance that the whole electricity system and value chain would be optimized simultaneously. In order to fulfill this task, new knowledge related to consumers values, attitudes and general understanding towards new types of contracts is needed.

3 METHOD AND MATERIAL

In this section, we first present the theoretical framework of choice experiments. Then we focus on the survey design. We give a detailed description of both data collection and development of the choice tasks.

3.1 THEORETICAL FRAMEWORK OF CHOICE EXPERIMENT

Choice experiments (CE) utilize a multi-criteria approach to inform prioritization of decisions from a broader context. It involves decomposing flexible energy service alternatives into their important characteristics. Viewing these services as bundles of characteristics (or attributes) allows us to study trade-offs between them. CE involves asking individuals their preferred alternative in a predetermined choice set. This generates outputs to weight and compare competing service scenarios and acceptability from the public's perspective.

The CE technique is an application of the characteristics-based theory of value (Lancaster, 1966) combined with random utility theory (Thurstone, 1927). According to random utility theory, individuals make choices based on the presence of good characteristics and based on a small degree of randomness. Assume now that a decision maker *n* can choose among *J* alternatives in each *T* choice situation. Levels of utility relating to each alternative *j*, as evaluated by each individual *n* in the choice situation *t*, is represented in the following general form

$$U_{njt} = \beta' x_{njt} + C_j + \varepsilon_{njt}, \tag{1}$$

where x_{njt} is a vector of attributes, β is a vector of estimated parameters and ε_{njt} is an idiosyncratic error. C_j is an alternative specific constant (ASC) that allows for an intrinsic preference for the status quo alternative describing the current situation. Note that the deterministic utility is assumed to be linear in parameters.

McFadden (1974) related the theoretical random utility model to statistical discrete choice models and to the Conditional Logit (CL) model in particular. Within the CL context, it is assumed that the idiosyncratic error ε_{njt} is independently and identically distributed (IID) and extreme value one (EV1) type across individuals, alternatives and choice situations. The conditional probability of choice *j* in choice situation *t* for individual *n* is

$$P_{njt} = \exp\left(\beta' x_{njt} + C_j\right) \Big/ \sum_{k=1}^{J} \exp\left(\beta' x_{nkt} + C_k\right). \tag{2}$$

The CL model is limited in that it makes strong assumptions regarding respondent behavior. The CL model assumes that utility functions are identical across respondents. This independence suggests that the unobserved portion of utility for one alternative is unrelated to the unobserved portion of utility for another alternative (Train, 2009). Thus, the CL model generates homogeneous average taste parameter estimates, β. Moreover, the CL model only makes sense under the independence of irrelevant alternatives (IIA) property, denoting that the ratio of probabilities for any two alternatives remains the same whether or not other alternatives are available.

The Mixed Logit (MXL) model has become a frequently used specification (see Ben-Akiva et al., 1997; Revelt and Train, 1998), as it avoids the IIA property while taking into account preference heterogeneity. The MXL model is flexible and can approximate any random utility model (Train, 2009). In the MXL model, the utility relating to each choice alternative *j*, as evaluated by each individual *n* (ignoring the *t* subscript), is represented as the following

$$U_{nj} = \beta'_n x_{nj} + C_{nj} + \gamma_{nj} + \varepsilon_{nj}. \quad (3)$$

As in the CL model, the idiosyncratic error ε_{nj} is IID and EV1 in type. In the MXL framework, however, a vector x_{nj} that contains attributes of choice alternatives can contain other explanatory variables, such as individual characteristics. Moreover, the ASC can also be interacted with individual characteristics. In the above equation, γ_{nj} is a random term whose distribution over individuals and alternatives depends on underlying parameters and observed data related to each alternative and individual. Several distributions can be used for random parameters (e.g., normal, lognormal, gamma, uniform or triangular). By denoting the density of γ by $f(\gamma|\Omega)$, where Ω are fixed parameters of the true parameters of the distribution, unconditional MXL probabilities are the integrals of standard logit probabilities over density parameters. Thus, the unconditional probability for choice *j* is

$$P_{nj} = \int_{\beta_n} \left(\exp\left(\beta'_n x_{nj} + C_{nj} + \gamma_{nj}\right) \Big/ \sum_{k=1}^{J} \exp\left(\beta'_n x_{nk} + C_{nk} + \gamma_{nk}\right) \right) f(\gamma_n|\Omega) d\gamma_n. \quad (4)$$

The choice probability value of equation (4) cannot be calculated exactly, as the integral does not take a closed form. This integral is approximated using a simulated maximum likelihood estimator calculated with Halton draws. Halton procedure involves taking intelligent draws from the distribution rather than random ones. Train (2009) showed that, on average, one can generate the same estimates using 100 Halton draws as 1000 random draws.

In our preliminary analysis, we use the CL model as a starting point and then utilize the MXL model to account for taste variations among respondents. We treated all other parameters as random except the monetary one and assigned normal distributions to them.

3.2 SURVEY DESIGN

3.2.1 DATA COLLECTION AND SAMPLE

The survey instrument was carefully developed and tested. Testing the survey instrument is important for many reasons. First, focus groups and pilot studies are needed to identify relevant issues and suitable wording of questions. Second, they are essential in order to design the choice experiment in such way that investigated attributes become reasonable, understandable and relevant for respondents.

The design of our survey instrument started by identifying relevant factors relating to flexibility services. This was based on discussions with experts and on previous literature (Annala, 2015; Broberg et al., 2014; Ek and Söderholm, 2010; Goulden et al., 2014; Partanen et al., 2012). Generally speaking, the amount of examined alternatives and attributes is rather limited in CE studies, as individuals cannot consider too many of them at the same time. Hence, it is important to determine the most important attributes with what we can describe the demand side flexibility possibilities in a realistic way.

We have had two pilot rounds in order to make the upcoming final survey as good as possible. First, we used focus groups by interviewing ten individuals in fall of 2015. These interviews were important in deciding the most relevant attributes and corresponding attribute levels (see Section 3.2.2.). At this point, we were also able to test how to present the investigated attributes in a meaningful and understandable way. The second and broader pilot study was conducted via web-based questionnaire in Webropol. In general, the objective of this study is to examine preferences of individuals who could potentially offer flexibility to the electricity market. Correspondingly, the relevant population for this kind of investigation covers all Finns. Hence, the sample of second pilot survey was drawn from the Population Information System of Finland, and it included 600 randomly selected Finnish households. We mailed the invitations to participate to the web-based survey in January of 2016, and received 35 responses yielding a response rate of 6 percent. The number of received responses was too low for the data analysis, and hence, we had to expand our data collection. In turn, we sent e-mail invitations to Oulu Business School faculty members and to employees in the Finnish Environment Institute in Oulu. In addition to this, a survey link was available online allowing all willing to participate. In the end, we received 92 responses to the second pilot.

The final survey is going to take place in August of 2016 and it is going to be executed via both mailed questionnaire and web survey. Three thousand Finns are going to be selected from the Population Information System of Finland. This sample will be randomly drawn from a group of homeowners, as the response rate in the second pilot survey was clearly higher among homeowners than among individuals who were living in rental flats or houses.

Note that the second pilot survey is going to be critical when we implement experimental designs to reduce the number of choice profiles shown to respondents in the final study. For the final survey, we are going to create the choice tasks with the help of Ngene 1.1.1. We are going to use the Bayesian efficient D-optimal designs. Generally speaking, efficient designs are intended to identify designs that are statistically as efficient as possible in terms of predicted standard errors and parameter estimates (Carlsson and Martinsson, 2003). In efficient designs, parameter prior values are assumed to be known and fixed. However, there is always some uncertainty surrounding true parameter values. To take this uncertainty into consideration, we use Bayesian efficient designs, which make use of random priors rather than fixed priors (see Ferrini and Scarpa, 2007). Thus, when we employ the Bayesian efficient design for the final survey, prior parameter values are going to be based on the priors obtained through the second pilot survey.

3.2.2 CHOICE TASKS

In the pilot survey, the hypothetical CE setting covered several important aspects of demand side flexibility. The CE was employed using six hypothetical choice tasks (see the example in Figure 1) presented to each respondent. Respondents were provided with three choice alternatives and asked to choose their preferred alternative among them. One of the alternatives corresponded to the present situation (i.e. status quo) without flexibility characteristics, whereas the two other alternatives presented possible choice scenarios with flexibility characteristics. The choice alternatives were described by six attributes: electricity distribution contract, electricity sales contract, remote control of heating, remote control of electricity use, system level emission reduction and annual savings. Table 2 shows a summary of the levels of the attributes used in the choice experiment.

Figure 1. Example of a choice task

CHOICE TASK 1	**Alternative 1**	**Alternative 2**	**Status Quo**
Electricity distribution contract	Two-rate tariff	Power based pricing scheme	Fixed rate tariff
Electricity sales contract	Real time pricing	Fixed price	Fixed price
Remote control of heating	7 am – 10 am	5 pm – 8 pm	No control
Remote control of electricity use	No control	5 pm – 8 pm	No control
System level emission reduction (CO_2)	–10%	–10%	0%
Annual savings (€)	30€	80€	0€
My choice:	☐	☐	☐

Electricity sales contract had two possible levels: fixed price contract and real-time pricing contract. Both of these contracts are currently available for households in Finland. For fixed price contract, the price of electric power consists of a fixed monthly charge and a consumption charge that depends on how much electricity the customer has used. There is only one consumption charge for general electricity (cents/kWh). Electricity companies determine the fixed basic charge and the fixed consumption charges themselves. For real-time pricing contracts, the price consists of the base fee, the seller's margin and the energy price. Here, the energy price varies according to Finland's regional price in Nord Pool.

Electricity distribution contract had three possible levels: fixed price tariff, two-rate tariff and power based pricing scheme. The fixed price tariff comprises of a fixed standing charge (€/month), which depends on the size of the main fuse, and an energy rate (cents/kWh), which is constant regardless of the time of use. The two-rate tariff similarly comprises of a fixed standing charge and an energy rate. Now, however, the energy rate is lower during the night-time (usually from 10 pm to 7 am). The incentive effects of two-tariff is different compared to fixed rate tariff as it includes an incentive to schedule the electricity use to the night-time whenever possible. In practice, this tariff type is often used among households with electric storage heating. Fixed price and two-rate tariffs are currently available for households, whereas power based pricing scheme is only available for large-scale customers. In the case of power-based pricing scheme a small-scale customer (i.e. household) would subscribe to desired electricity distribution capacity. In turn, customer's power band would be determined based on the highest metered hourly mean power of the year. Put in other words, power band would be determined according to the customer's hourly peak power and this would lead customer paying a fixed monthly charge for the power band every month of the year (€/month). If power based pricing would be available also for households, these contracts would encourage them to optimize their energy consumption into a direction that is optimal from the viewpoint of the overall energy system.

The remote control of heating and remote control of electricity usage were defined in terms of time. As the load on the electricity system appears to be highest during the morning and early evening, we assigned these attributes to have three possible levels: no remote control, control between 7 am and 10 am and control between 5 pm and 8 pm. System level emission reduction in CO_2 emissions had three possible levels: 0%, –10% and –30%. Generally speaking, electricity markets can be made more efficient by matching better the demand and supply. An essential factor in this is the flexibility offered by households. If households start to adjust and time their electricity usage that in turn reduces the load during traditional peak-hours, it will decrease the need of running conventional power plants utilizing fossil fuels to meet the demand during peak-hours. Finally, the annual saving in electricity bill was varying between 0€ – 500€ for individuals living in detached and semi-detached houses, whereas individuals living in smaller flats, e.g. in terraced houses and apartment buildings, were facing lower annual savings varying between 0€ – 250€.

Table 1. Attributes and levels.

ATTRIBUTE	DESCRIPTION	LEVELS
Electricity distribution contract	Electricity distribution contract includes two already existing alternatives (fixed price and two-rate tariffs) and one alternative under consideration (power based).	1. Fixed price tariff 2. Two-rate tariff 3. Power based pricing scheme
Electricity sales contract	Electricity sales contract describes two alternatives that are currently available in the market.	1. Fixed price 2. Real-time pricing
Remote control of heating	A service provider will be controlling your heating system remotely every day during certain hours. The heating will be turned off, but in such way that the temperature will never drop by more than 2 degrees and never below 18 degrees.	1. No control 2. 7am – 10 am 3. 5pm – 8pm
Remote control of electricity use	A service provider will be limiting parts of your household's electricity use every day during certain hours. At those times, you are not able to use dishwasher, washing machine or tumble dryer. Additionally, you are not able to use comfort underfloor heating in your bathroom.	1. No control 2. 7am – 10 am 3. 5pm – 8pm
System level emission reduction	This describes the possible system level reduction in CO2 emissions, if supply and demand of electricity would meet more efficiently.	1. 0% 2. – 10% 3. – 30%
Annual savings (€)	By changing your electricity contract type and/or adjusting your heating/electricity use you will save in your annual energy bill.	*Detached and semi-detached houses:* 0€, 30€, 80€, 150€, 300€, 500€ *Terraced houses and apartment buildings:* 0€, 30€, 70€, 120€, 180€, 250€

4 PRELIMINARY RESULTS

We begin this section by shortly presenting descriptive statistics of the pilot data. We also present few preliminary observations regarding households' preferences for different energy related issues. Then, the results of the pilot CE study shown and discussed.

Table 2 presents the descriptive statistics of the collected sample. Note that the results of this pilot are not generalizable for all Finns, as we were not able to collect enough responses via random sampling. Nevertheless, the findings are suggestive to some extent.

Table 2. Descriptive statistics of the respondents.

Sample size	92
Socio-demographic characteristics	
	Average
Age (years)	46.7
Household size	2.4
	Percent
Gender	
Female	43.5
Male	56.5
Household's income (gross, €/month)	
<4000	21.7
4000-5999	29.3
6000-7999	20.7
8000-9999	13.0
>10000	14.2
Not available	1.1
Education	
Basic education	4.3
Matriculation examination or/and vocational degree	13.0
Polytechnic degree	28.3
University degree	50.0
Other	4.4
Living environment	
Sparsely populated area or small population center	13.0
Town or city	87.0

In the pilot survey, respondents were presented with general energy-related questions and claims. When asked about their actual electricity sales contracts 76 % of the respondents had a fixed price contract, whereas only 15 % had a real-time pricing contract. Remaining 9 % did not know their contract type. Further, when asked the reason for choosing fixed price contract the two most common explanations were that: (1) fixed price contract is the cheapest alternative, and (2) the need to avoid fluctuations in the electricity price. Note that 26 % of respondents, however, reported they had considered real-time pricing contracts but had not yet got one. Interestingly, 85 % of the respondents stated that they would like to have more possibilities how to affect to their electricity bills, and further, 66 % of the respondents claimed that they would be willing to adopt services offering remote control of electricity. Additionally, 75 % of respondents stated that the cost of electricity distribution contract is too high compared to the cost of actual electricity. When asked about willingness to pay for renewable energy compared to one generated with fossil fuels, 42 % stated they would be willing to pay more for renewable energy. Finally, about 80 % of the respondents would like to get more information about their energy consumption in general.

Next we focus on the result from the pilot CE study. By analyzing individuals' choices between presented alternatives in the choice tasks, we can estimate individuals' valuation for different attributes and attribute levels. A full list of determinants of the respondents' choices is presented in Table 3. The dataset was composed of 552 choices for 92 respondents. Status quo levels worked as reference categories in the analysis.

Table 3. Definition of explanatory variables.

Variable	**Notation**	**Type**
Electricity distribution contract		
Two-rate tariff	DIS_TT	dummy-coded
Power base pricing scheme	DIS_PB	dummy-coded
Electricity sales contract		
Real-time pricing	RTP	dummy-coded
Remote control of heating		
7 am – 10 am	HEAT_M	dummy-coded
5 pm – 8 pm	HEAT_E	dummy-coded
Remote control of electricity use		
7 am – 10 am	ELE_M	dummy-coded
5 pm – 8 pm	ELE_E	dummy-coded
System level emission reduction	CPOL	continuous
Annual savings	SAVE	continuous
Status quo	ASC_SQ	dummy-coded

We also identified respondents with attribute non-attendance (A-NA) based on information gathered from follow-up questions. We accommodated A-NA by excluding those attributes from the analysis that were stated being ignored by the respondent in the follow-up question. There are many studies that make use of this kid of de-briefing questions to identify and classify attribute non-attendance (see e.g., Campbell et al., 2008; Scarpa et al., 2010). Failing to account for A-NA is likely to rise to inappropriate model selection, poorer goodness-of-fit in discrete choice models and biased willingness-to-pay estimates. According to Colombo et al. (2013) it is better to assume the parameters of the ignored attribute equal zero, and hence, we followed this suggestion. In our data, the frequency of A-NA varied greatly across the attributes. Respondents were most likely to ignore the electricity distribution contracts (21.7%), followed by electricity sales contracts (15.2%), remote control of heating (9.8%), system level pollution reduction (7.6%) and remote control of electricity use (6.5%). Only one respondent stated ignoring the annual savings attribute.

The CL and MXL models were estimated using Nlogit5. The results are presented in Table 4, where the CL model is shown in the two middle columns, and the MXL model is presented in the last three columns. The CL model did not have very good fit (0.09) measured as McFadden's Pseudo R2. However, using the MXL model improved the model fit resulting in relatively good level of 0.30. The estimated MXL model was based on 1000 Halton intelligent draws.

Table 4. Results of the CL and MXL models.

	CL		MXL		
Variable name	**Coefficient (St.Err)**	WTA	**Coefficient (St.Err)**	*St.Dev.*	WTA
DIS_TT	**-0.32036* (0.17365)**	141,51	**-0.55241 (0.43507)**	*1.33134****	(86,70)
DIS_PB	**-0.18236 (0.17977)**	(80,55)	**-0.18657 (0.39833)**	*1.01459***	(29,28)
RTP	**-0.51816*** (0.13056)**	228,88	**-0.97564*** (0.32454)**	*1.22211****	153,12
HEAT_M	**-0.01730 (0.18221)**	(7,64)	**-0.39818 (0.41121)**	*0.85357*	(62,49)
HEAT_E	**-0.52849*** (0.18142)**	233,44	**-1.24566*** (0.40141)**	*0.08781*	195,50
ELE_M	**-0.27380 (0.16834)**	(120,94)	**-0.74902** (0.37522)**	*1.28556****	117,55
ELE_E	**-0.88939*** (0.17723)**	392,86	**-1.93577*** (0.45845)**	*1.52782****	303,81
CPOL	**0.14557*** (0.05231)**	-64,30	**0.29440*** (0.11344)**	*0.41652****	-46,20
ASC_SQ	**-0.84605** (0.34985)**	373,71	**-3.15742*** (1.10988)**	*5.0053****	495,53
SAVE	**0.22639** (0.05213)**	-	**0.63717*** (0.12179)**	-	-
LL(0)	-606.4		-606.4		
LL	-550.8		-423.0		
AIC	1121.6		883.9		
Mc Fadden Pseudo R^2	0.092		0.303		
Note: ***,**,* → Significance at 1%, 5%, 10% level WTA values reported in the parantheses are not statistically different from zero when one takes into account the standard errors.					

Note that based on both model fit as well as avoidance of making strong assumption about context independence (see Section 3.1.), we focus on the results of the MXL model. Marginal willingness-to-accept (WTA) values were calculated from $\beta_k / -\beta_€$, where β_k and $\beta_€$ are the parameters for the non-cost and annual saving attributes, respectively. Note that in order to obtain meaningful marginal WTA measures, both attributes used in the calculation must be statistically significant (Hensher et al., 2015). Moreover, the WTA values gained should be interpreted with caution (i.e. not straightforward in terms of absolute values). One should also keep in mind that the WTA values apply for the representative, average individual, so the exact amounts do not apply for everyone.

The results show that fluctuating real-time pricing contracts (RTP) and limitations in possible energy use (HEAT_E, ELE_M, ELE_E) were perceived as something negative, and that individuals therefore wanted to be compensated in order to accept them. Our results imply that households required, on average, around 153€ compensation in their annual electricity bill in order to choose real-time pricing contracts over fixed price contracts. This is a clear indication that uncertainty in the monthly energy bill created disutility among respondents. Furthermore, regarding electricity distribution contracts both coefficients were not statistically different from zero. This indicates that, on average, individuals were indifferent between the presented contract alternatives. In turn, there is likely some room for new flexible distribution contracts, such as power based pricing scheme, in the market.

In general, respondents' sensitivity to restrictions in household electricity usage was greater than sensitivity to restrictions in heating. There was also considerable differences in respondents' perceptions between electricity control in the morning and in the evening. Control during the evening resulted in higher WTA values than control during the morning (304€ vs. 118€). One possible explanation for this finding is that everyday household tasks (doing laundry etc.) usually take place in the evening. Concerning remote control of heating in the morning, the coefficient is not statistically different from zero. This may be due to a fact that individuals usually spend daytime hours outside their homes, and hence, they might not notice the ambient temperature adjustment. Our results regarding control of heating and electricity use are in line with Broberg et al. (2014).

Moreover, coefficients for annual savings (SAVE) and system level emission reduction (CPOL) presented expected signs. As annual savings and system level emission reduction increased, the probability of choosing respective alternatives increased among respondents. Respondents were on average willing to pay 46€ annually for system level emission reductions. This shows that there existed also some other value creating elements how to increase demand side flexibility than just reductions in annual energy payments.

Additionally, high levels of heterogeneity was found among the respondents with respect to investigated attributes, as the magnitudes of coefficients for standard deviations were greater than the corresponding mean coefficients. To explain this heterogeneity between respondents, we introduced interactions between random variables and other covariates. Note that we have not reported these results, as we could not add them all to the same model due to relatively small amount of observations. The following findings are results of individual models, and hence, they should be interpreted with caution. Nevertheless, they give some interesting insights of possible sources of preference heterogeneity in this sample. The interaction between household's gross income and choosing the status quo was statistically significant, denoting that the choice probability of status quo was greater among high-income households. The interaction between respondent having an electric heating system and remote control of heating was found to be significant, further implying that existence of electric heating system increased the probability of remote control of heating selection. The negative interaction between the household size and remote control of electricity usage in the morning suggests that bigger households are less likely to opt for remote control of electricity use than smaller households. In addition, men were more likely to choose power-based pricing contracts.

5 CONCLUSION

Demand side flexibility is expected to take an increasing role in the future power systems. Households should adjust their electricity consumption based on price signals and other incentives in order to facilitate efficient use of generation and network infrastructure and functioning of overall electricity market. By investigating carefully the determinants of demand side flexibility, we can support the development of future energy system to meet households' needs. In order to offer better electricity services for households, their preferences and willingness to pay for these services should be clearly understood.

Our preliminary results from the pilot CE study indicate that electricity usage restrictions are perceived more negatively than heating restrictions. The results also imply that individuals are sensitive for fluctuating real-time pricing contracts. In addition, the findings suggest that there is likely some room for new flexible distribution contracts in the market. Furthermore, possible system level reductions in CO_2 emissions are valued among households.

As this report presents only preliminary analysis, our plan is to execute the final survey later this year, and then address thoroughly the research objectives which were listed at the end of Section 1. Additionally, it would be interesting to investigate how homeowners' actual choices are reflected in their hypothetical choices. From methodological viewpoint in choice experiments, modelling attribute non-attendance explicitly is an important task for future research.

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