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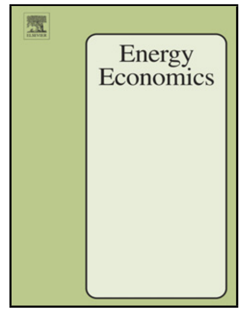

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PII: S0140-9883(19)30311-1

DOI: https://doi.org/10.1016/j.eneco.2019.104522

Reference: ENEECO 104522

To appear in:

Received Date: 21 November 2018

Revised Date: 29 August 2019

Accepted Date: 7 September 2019

Please cite this article as: Ruokamo E, Kopsakangas-Savolainen M, Meriläinen T, Svento R, Towards flexible energy demand – Preferences for dynamic contracts, services and emissions reductions, *Energy Economics* (2019), doi: https://doi.org/10.1016/j.eneco.2019.104522

Towards flexible energy demand – Preferences for dynamic contracts, services and emissions reductions

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Abstract

Households' preferences for attributes of flexible energy demand are not well understood. This paper evaluates Finnish households' acceptance of hypothetical contracts and services aimed at increasing demand side flexibility. We conduct a Choice Experiment to analyze households' willingness to offer flexibility through timing their electricity usage and heating; their interest in dynamic pricing contracts such as real-time pricing, two-rate tariffs, or power-based tariffs; and how emissions reductions affect their choices. The results indicate that households' sensitivity to restrictions in electricity usage is much stronger than their sensitivity to restrictions in heating. Households also require considerable compensation to choose real-time pricing over fixed fees. Furthermore, other value-creating elements besides monetary compensation could incentivize households to offer demand side flexibility because they value reductions in CO_2 emissions at the power system level.

Keywords: choice experiment, consumer, demand response, demand side management, direct load control, electricity, power-based tariff, real-time price, two-rate tariff, willingness to pay

JEL classification: D12, Q40, Q48, Q51

1 Introduction

Electricity and energy markets currently face complex challenges. As the levels of variable renewable energy sources increase, flexibility has become a key element for the reliable operation of an energy system (Paterakis et al., 2017). Generally, flexibility as a term refers to an energy system's ability to maintain continuous service during rapid and significant changes in energy supply and demand. Demand side flexibility is an essential part of the overall system-level flexibility.

The European Commission has high expectations for demand side flexibility (e.g., significant savings from reduced backup capacity and network and fuel costs) and has stipulated a number of proposals dealing with demand side participation (see the Electricity Directive (2009/72/EC) and the Energy Efficiency Directive (2012/27/EU)). Regardless of the targets and attempts, to date, European energy markets have often failed to offer incentives (monetary or other value-creating incentives) and opportunities for households to become more flexible in their energy usage (Bertoldi et al., 2016).

One possible explanation for this lack of incentives is that many aspects of households' motivation to participate in demand side flexibility are not thoroughly understood; therefore, the mechanisms for promoting flexibility among households are still inadequate. This study contributes to addressing this gap by providing an evaluation of households' acceptance of flexibility characteristics, that is, dynamic electricity pricing contracts and automated load control services.

We use the Choice Experiment method (CE) (Hensher et al., 2015; Johnston et al., 2017) to analyze individuals' preferences for characteristics of demand side flexibility. In particular, we survey Finnish homeowners' flexibility-related choices. CE is a stated preference method that is widely applied to analyzing an individual's discrete choices (Johnston et al., 2017) and is also being increasingly used in energy economics (Achtnicht, 2011; Alberini et al., 2013; Bartczak et al., 2017; Broberg and Persson, 2016; Hidrue et al., 2011; Huh et al., 2015; Kubli et al., 2018; Ruokamo, 2016; Tabi et al., 2014). CE allows assessing preferences for hypothetical, yet realistic, flexibility characteristics.

The main goal of this study is to determine how individuals construct their preferences for demand side flexibility by identifying the characteristics i.e. attributes that are significant for an individual's choice, the ranking of these attributes, and the marginal willingness to pay (WTP) for a change in a specific attribute. In particular, we investigate households' willingness to participate in direct load control of electricity consumption and space heating, whether they are interested in dynamic pricing contracts such as real-time pricing, two-rate tariffs, or power-based tariffs, and how different levels of emissions reductions affect their participation in flexibility. Furthermore, we study households' opinions on energy conservation, pro-environmental actions, and electricity pricing that are linked with demand side flexibility.

The remaining sections of this paper are organized as follows. Section 2 discusses barriers related to demand side flexibility and presents a summary of previous studies. Section 3 focuses in detail on the survey design. Section 4 describes the modeling approach. The results are presented and discussed in Section 5. Section 6 concludes the paper.

2 Demand side flexibility

2.1 Existing barriers

Demand side flexibility is an important resource for energy systems and simultaneously highly underutilized. Several barriers in the market slow down the efficient utilization of this flexibility (for a review of the challenges and barriers to demand response, see Nolan and O'Malley (2015) and Kowalska-Pyzalska (2018)). These barriers are related to pricing, available services, technology, and incomplete incentives to participate in demand response.

Electricity pricing schemes vary from fixed rate to fully dynamic, with retail prices changing within short time intervals[1]. Alternatively, dynamic pricing can be categorized as time-varying and load-based programs (Dütschke and Paetz, 2013). In time-varying programs, the rate depends on the point in time at which electricity is demanded, whereas the rate in load-based programs is determined by the household's current power load level. Real-time pricing (RTP) is the most dynamic program and has significant potential to increase flexibility. RTP reflects the scarcity in the power system and, typically, prices vary from hour to hour. Several studies have shown that dynamic pricing affects households' consumption behavior (Allcott, 2011; Faruqui and Sergici, 2013). Nevertheless, RTP has proven to be an unattractive contract alternative among households. For instance, only seven percent of households had an RTP contract in Finland in 2016 (Energy Authority, 2017), and the corresponding share in Sweden in 2014 was even lower at less than a one-percent share (Broberg and Persson, 2016). According to Joskow (2012), current knowledge of household behavior is not comprehensive enough to achieve universal deployment of dynamic pricing. Moreover, predicting to what degree the dynamic prices affect demand flexibility is difficult (Allcott, 2011). Thus, to enhance the attractiveness of dynamic contracts, household preferences should be better understood and the incentives designed appropriately.

In many deregulated electricity markets, customers pay separately for energy to an electricity retailer and for distribution to an electricity distributor. For example, in Finland, the retail side is a

[1] The roll-out of smart meters enables the provision of more complex and sophisticated pricing structures to households (Pepermans, 2014). Finland has already completed a full roll-out of smart meters (Annala, 2015).

competitive market, whereas distribution companies are regulated local monopolies. Usually, distribution and transmission tariffs do not reflect the value of demand flexibility. Distribution network operators in Finland typically have three types of distribution tariffs[2] that are all widely used: general fixed-rate tariff, two-rate (i.e., time-of-day) tariff, and seasonal tariff. All of these tariffs have a basic monthly charge (€/month) and an energy rate (cents/kWh). Under the fixed-rate tariff, the energy rate is the same for every hour of the year. In the two-rate tariff, two different energy rates exist—for days and for nights—where the lower nighttime load is reflected by lower charges at night. For the seasonal tariff, the energy rate is higher during winter workdays when loads are higher and cheaper at other times. Both the two-rate and seasonal tariffs are so-called time-of-use tariffs, which encourage customers to use electricity during certain times but do not necessarily encourage customers to provide flexibility (e.g., decrease peak power) to the market when the power system requires it (Partanen et al., 2012). As a solution to this problem, a new dynamic load-based tariff alternative called a power-based tariff (PBT) has been proposed[3]. PBT is better at accounting for the costs caused by an individual as part of the distribution bill, which is collected by charging customers based on their utilized peak power capacity (Haapaniemi et al., 2017). Generally, the introduction of PBTs would create an incentive for households to limit their peak power usage and smooth their consumption profile.

On top of different pricing schemes, realizing the full potential of demand side flexibility also requires automated and/or third-party load control services of energy for households (Annala, 2015; Dütschke and Paetz, 2013; Kobus et al., 2015). The clear advantage of a direct load control service is that an individual household does not need to be particularly active, although control measures can create some discomfort for the household. Despite offering a range of potential benefits, such as financial incentives and ongoing technological advances of load control devices, widespread consumer uptake and usage of direct load control remains low (Stenner et al., 2017). Furthermore, having many households interested in signing up for load control services creates new business opportunities in the market. For a flexibility service provider, such as an aggregator (Campaigne and Oren, 2016), these new business opportunities mean that it can utilize the fragmented demand flexibility of individual households and design products that can be sold, for example in the balancing market. However,

[2] From now on, we use the word "tariff" for distribution pricing schemes.
[3] For a description of different power-based tariffs, see Partanen et al. (2012).

currently, only a limited number of services exist for households that allow an external actor to remotely control parts of their electricity consumption and/or heating. Another finding is that, even if such services are available, households may be unwilling to participate for several reasons, such as a perceived lack of control, resulting discomfort in everyday life, limited knowledge, and a sense of distrust (Fell et al., 2015; Stenner et al., 2017).

Another important barrier to slow down the adoption of demand side flexibility relates to financial issues. Savings on a household's electricity bills may not be sufficient enough to warrant, for example, investment in equipment or to compensate for the experienced discomfort. Frequently, the demand flexibility program provider imposes the entire investment costs of the technology on the customer, which in turn results in minimal participation in the program. This behavior may be partly explained by missing or limited competition in the current flexibility service markets. Furthermore, for individual households to trade their flexibility in current market environments is not possible. For example, in the Nord Pool's balancing markets in which flexibility is typically valued, the minimum bid level is 5 MWs, which requires the joint contribution of a large number of households. Broadly speaking, if the energy market's current monetary rewards for flexibility by households are insufficient to cover even the initial investments—and given that households may also require compensation from other things—engagement in demand side flexibility programs will be low.

To overcome these barriers, end-user behavior and preferences should be appropriately analyzed and accounted for in the successful implementation of demand side flexibility. Furthermore, because financial incentives may be inadequate, other possible value-creating elements should be determined and examined in detail. After the preferences and possible compensation levels for households are determined, different types of new business models could be considered.

2.2 Insights into household preferences for flexibility

The literature on households' motivations to participate in demand side flexibility is growing. Annala (2015) examined the potential of demand side flexibility in Finland. The results indicated that households seem ready to allow remote control of electric appliances, which does not require changes in their everyday routines. Households were also found to be worried about whether the control system always functions in the agreed-on manner. Additionally, the compensations required to engage in demand response activities were relatively high. Hobman et al. (2016) identified several common cognitive biases and psychological influences that may affect consumer decision making and behavior regarding dynamic pricing. They highlight the importance of simplicity, framing (i.e., describe how cost-reflective pricing may help customers avoid losses, reduce costs, or minimize risks), and fairness (i.e., explain how cost-reflective pricing restores fairness in the power system) when presenting dynamic pricing alternatives to households. Qiu et al. (2017) studied consumers' willingness to participate in voluntary time-of-use programs in Arizona and California. They found that risk-averse consumers are less likely to participate in the studied time-of-use programs, as are those households that consume limited energy during peak hours. Stenner et al. (2017) surveyed homeowners' willingness to participate in a direct load control program in Australia. They focused on self-reported distrust and how it affected participation. The results suggested that individuals' distrust in the utility was associated with a significantly lower willingness to register for a direct load control program.

Several studies also exist on the characteristics of demand side flexibility utilizing the CE methodology (Broberg and Persson, 2016; Buryk et al., 2015; Dütschke and Paetz, 2013; Kubli et al., 2018; Pepermans, 2014; Richter and Pollitt, 2018). Dynamic pricing has been one important topic of the executed studies. Dütschke and Paetz (2013) investigated the type of pricing programs that consumers are most likely to choose. Their results show that some consumers are open to dynamic pricing but prefer simple programs (i.e., time-of-use) to complex and highly dynamic ones (such as RTP). Buryk et al. (2015) studied whether expressing the environmental and system benefits of dynamic pricing to consumers can increase adoption. The results indicate that consumers may be more receptive to dynamic pricing if the environmental and system benefits are highlighted.

Other papers focus on the technology that enables demand response and flexibility. Pepermans (2014) examined whether and to what extent consumers are willing to pay for smart metering with varying characteristics. The results show that a significant portion of households might be reluctant to voluntarily switch to a smart meter, especially if the cost of the device is charged to the household. Kubli et al. (2018) studied preferences of potential flexibility providers who were prosumers. The CE was targeted to owners of (1) solar power systems and storage, (2) electric vehicles, and (3) heat pumps and executed with technology-specific flexibility characteristics. Their results suggest that electric car and solar power system owners exhibit a stronger willingness to cocreate flexibility relative to heat pump users.

Regarding flexibility services, Broberg and Persson (2016) studied Swedish households' preferences for direct load control and information dissemination. Their findings imply that the acceptability of electricity load control is lower compared to respective control in heating and that individuals experienced discomfort from sharing information on their electricity consumption. In a recent study, Richter and Pollitt (2018) examined the flexibility program that British consumers would choose if they were offered a menu of contracts bundling a variety of components, such as electricity usage monitoring, load control of electrical devices, technical support, privacy aspects, and compensations. The results suggest that households require compensation to accept remote load control of electrical devices, monitoring of real-time electricity usage with alerts, and sharing of information on their electricity usage. In contrast, households seem to value technical support.

Whereas demand side flexibility is increasingly being studied, according to our knowledge, no studies exist on a household's willingness to participate in demand response such that they have simultaneously considered the effects of alternative pricing schemes, direct load control, required compensations, and potential emissions reductions. Furthermore, this study is one of the first to provide information on household preferences for PBTs and to determine a household's WTP for power system level emissions reduction that results from increased demand flexibility.

3 Survey design

3.1 Choice experiment

The CE survey covered several important aspects of demand side flexibility. Previous research was used to identify candidate attributes for the CE (Broberg et al., 2014; Goulden et al., 2014; Partanen et al., 2012; Pepermans, 2014), and the descriptions of the attributes were subsequently designed with several energy industry experts. Generally, the amount of examined alternatives and attributes is rather limited in CE studies because individuals cannot consider choice scenarios that are too complex (Johnston et al., 2017; Swait and Adamowicz, 2001a; Swait and Adamowicz, 2001b). Hence, determining a few important attributes that describe the flexibility possibilities in a realistic manner is important.

In the survey, the CE was employed using six hypothetical choice tasks (see the example in Figure 1). In each choice task, the respondent was provided with three choice alternatives and was asked to choose the best alternative among them. One of the alternatives corresponded to the benchmark situation, that is, the status quo, without flexibility characteristics. The two other alternatives presented possible 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 emissions reduction, and annual monetary savings (i.e., reduction in annual energy bill). Table 1 shows a summary of these attributes.

The starting point for the design of the distribution and sales attributes was the Finnish case in which consumers pay separately for electric power and transmission and distribution service. Both distribution and sales sides offer/can potentially offer contracts that enable different flexibility levels. The electricity sales attribute consisted of an inflexible fixed price contract and a flexible RTP contract[4].

[4] This is often referred as spot price contract in Finland.

Both contracts are currently available for Finns; however, the share of RTP contracts is rather low in practice. The fixed price contract was described to respondents as the most common electricity sales contract in which consumers are charged a fixed fee (cents/kWh) for the consumed electricity. The RTP contract was described as a relatively new contract alternative in which the energy price varies hourly according to Nord Pool's spot price. The RTP contract was also mentioned as enabling the household to decrease its electricity payments by shifting consumption to hours with lower spot prices.

The electricity distribution attribute included three possible contract types: fixed-rate tariff[5], two-rate tariff (also known as a time-of-day tariff), and power-based tariff (PBT). The inflexible fixed-rate tariff was described as being comprised of a fixed basic charge (€/month) that depends on the size of the main fuse and an energy rate (cents/kWh) that is constant regardless of the time of use. The two-rate tariff was similarly described to include a fixed basic charge and an energy rate. Now, however, the energy rate is lower during the night (from 10 p.m. to 7 a.m.) than during the day. Generally, the flexibility potential of the two-rate tariff is different from the fixed-rate tariff because it includes an incentive to schedule electricity use at night whenever possible. In practice, this tariff type is popular among households with electric heating.

When the survey was executed, fixed-rate and two-rate tariffs were available for households, whereas PBT was only available for large-scale customers. However, at the moment of this writing, some electricity companies have also introduced PBTs to small-scale customers. The PBT was described in the survey such that the household would subscribe to a certain power band determined according to the highest hourly metered mean power. Subsequently, this subscription would lead the household to pay a fixed monthly charge for the power band (€/month) plus an energy rate (cents/kWh). Respondents were reminded that the existing tariff alternatives (fixed- or two-rate tariff) do not account for the actual power band needed and that households with lower peak power demand are paying oversized distribution tariffs relative to households with higher peak power demand[6]. Respondents were told that PBT would create an incentive for the households to limit their peak power usage and smooth out their consumption profile. If PBT is available for households, these contracts

[5] Currently, fixed-rate tariffs comprise the majority of the distribution contracts among households in Finland.
[6] In practice the power band is never restricted in Finland.

could encourage them to optimize their electricity consumption in a direction that is optimal from the viewpoint of the power network.

The idea for the load control attributes originated from a Swedish CE study (Broberg et al., 2014; Broberg and Persson, 2016). Load control in heating was presented to the respondents such that a service provider is remotely controlling their space heating every day during certain hours. The heating is turned off, but in such a way that the temperature never drops by more than 2 degrees and never below 18 degrees. The load control in electricity was described such that a service provider is limiting parts of a household's everyday electricity use during certain hours. At those times, the household cannot use the dishwasher, washing machine, tumble dryer, or comfort underfloor heating in the bathroom. Remote control of heating and electricity usage attributes were defined in terms of time. Because a household's energy consumption load appears highest during the morning and early evening (Vesterberg and Krishnamurthy, 2016), we assigned three possible levels to these attributes: no load control, control between 7 a.m. and 10 a.m., and control between 5 p.m. and 8 p.m. Daytime control was omitted because of the need to limit the number of attribute levels and because daytime demand does not represent the most significant potential for smoothing consumption peaks among households.

The power system level CO_2 emissions reduction attribute was created to investigate whether households are willing to pay for environmental improvements and whether environmental improvements can decrease the experienced discomfort from participating in demand side flexibility. In the CE, emissions reduction had three possible levels: 0%, –10%, and –30%. In the description of this attribute, the respondent was reminded that the efficiency of the power system can be enhanced by better matching demand and supply, which further results in emissions reductions. Respondents were told that if households[7] participate in load control (with remote control of electricity use and/or heating) and/or utilize flexible distribution and sales contract alternatives, the load during traditional

[7] The motivation to use collective system level CO_2 emissions reductions instead of household specific ones was that the effects of one household on system level changes in load, electricity prices and emissions are very limited. However, the relative value and effect of a single household increases when households are pooled, and the pooled consumption is optimized based on the need of the electricity system. Optimizing the electricity consumption of a pool of households may not lead only to system-level changes in load and electricity prices but also in significant CO_2 emissions reductions (Karhinen et al., 2018; Kopsakangas-Savolainen et al., 2017). Thus, the collective emissions reduction attribute describes the linkage between demand side flexibility and emissions in a realistic manner in the Finnish electricity market environment. The collective emissions reduction attribute was also found to be meaningful and understandable for the respondents in the pilot studies.

peak hours and the need for running conventional fossil-fueled power plants to meet the demand during peak-hours are decreased.

The monetary attribute was the reduction in the annual electricity bill given that it was expected to affect participation in demand flexibility. Savings potential varied between 0€ and 350€ for individuals living in detached or semidetached houses, whereas individuals living in smaller flats—terraced houses or apartment buildings—faced lower annual savings potential that varied between 0€ and 200€. The savings were calculated using reasonable potential savings given some heating and electricity usage shifting, prices from Nord Pool, and typical electricity consumption of Finnish households.

The CE design was generated using Ngene software. We conducted a Bayesian D-efficient design consisting of 36 choice situations that were further divided into six blocks to minimize the burden of the respondent. 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, prior parameter values are assumed to be known and fixed. To account for some uncertainty, we used a Bayesian efficient design in the Multinomial Logit framework, which assumes random rather than fixed priors (Ferrini and Scarpa, 2007). The prior parameter values were obtained from the second pilot survey (see Section 3.2).

In addition to the choice tasks, the survey collected information on respondents' living conditions and attitudes toward different energy-related issues. Through the survey, also respondents' current electricity contracts and services and demographic details were recorded and studied.

3.2 Pretesting and data

Careful design of the survey instrument is crucial to accomplishing reliable results (Johnston et al., 2017). We conducted two thorough pilot studies in 2015 and 2016 to ensure that the survey is both understandable and credible to respondents. The first pilot round was qualitative and entailed pretesting the survey by interviewing a small group of Finns in the fall of 2015. This pretest focused on how to present the survey questions to the respondents in the most understandable manner. The second and broader pilot study was quantitative and carried out through an Internet survey in

Webropol[8]. With this pilot, we were able to assess the potential response rate and target population, the refinement of the experimental design and compensation levels for the CE, and conduct the preliminary analysis.

The final survey occurred in October 2016 and was done by sending a mail invitation with instructions on how to respond to the Internet survey. Because the objective of this study is to examine preferences of individuals who could potentially offer flexibility to the electricity market, the survey targeted Finnish homeowners, of whom 4000 were randomly drawn from the civil registry, that is, the Population Information System of Finland[9]. First, 4000 owner-occupied homes were randomly selected to assure that each owner-occupied home, regardless of the household size, has the same probability of being chosen. Then, one adult from each home was randomly picked for whom the survey invitation was sent to[10]. The age range of the target population was limited to 24–75 years. Younger individuals were excluded because of the low number of eligible participants and the presumably short period of ownership. In addition, selecting young people still living with their parents could have introduced a problem because they have limited control over the actual decision making in the household. In the final survey, respondents were incentivized to participate by offering a chance to win a prize in a lottery: a smart plug or a tablet computer.

We received 380 responses to the final survey, resulting in a response rate of 9.5%. Given time and strict budgetary constraints of the study, sending a further reminder letter was not possible even though doing so could have positively affected the overall response rate. We acknowledge that the response rate is rather low and, thus, the collected sample may suffer from nonresponse bias. However, a clear advantage of the collected sample is that we had access to a representative sample frame of homeowners from which our target population was randomly drawn. One possible reason for the low

[8] The survey design and the results of the second pilot study are reported in Ruokamo and Kopsakangas-Savolainen (2016). The pilot study was conducted as part of the Tekes-funded Finnish national research project “Flexible Energy Systems,” FLEXe.
[9] The decision to target homeowners was based on the response rate observed in the second pilot. The response rate was clearly higher among homeowners than among individuals living in rental flats or houses. One possible explanation for this difference is that rentees cannot make decisions for all of the energy-related issues in their homes, such as heating or type of distribution contract, which in turn is reflected in low interest toward the survey topic and the survey.
[10] Even though the survey invitation was assigned to one household member, we cannot be entirely sure that the responses were made by single respondent and not jointly at household level. We acknowledge that joint decision-making concerning household level issues might have a role.

response rate could be the selected survey mode (i.e., here, Internet survey)[11]. We also checked whether respondents who started to answer the survey dropped out at some point. The response rate is, however, only partly explained by dropouts because approximately 80% of those who started the survey finished it. Thus, the low response rate is likely a result of something else, such as the difficulty of the subject matter and that, generally, energy issues are less interesting for households. To track possible selection bias, we asked respondents whether their work had any links to the energy industry or electricity markets, and no significant bias existed toward having more than expected "experts" in the respondents.

Table 2 presents the descriptive statistics of the respondents. Significance tests for equality of means and proportions were carried out on the variables with available corresponding data. The collected sample was representative regarding living environment, dwelling type, and electric space heating. However, the households were slightly larger, and the sample consisted of homeowners that were somewhat older on average than the Finnish homeowners. Additionally, the men were slightly overrepresented in the data. Interestingly, similar patterns concerning age and sex were observed in two Swedish energy-related studies (Broberg and Persson, 2016; Ek and Söderholm, 2010). These patterns could be explained by an increased interest in energy issues within this group. The sample is more highly educated than the average Finn aged 20-74, but there is no data available for testing on the education levels of corresponding population of over 24-year-old homeowners.

[11] Furthermore, Internet surveys have been linked to concerns over representativeness given varying levels of computer literacy and access to the Internet or the extent to which respondents take care when responding to the survey (Börger, 2016; Lindhjem and Navrud, 2011; Sandorf et al., 2016). However, only minor differences in value estimates have been observed when comparisons between the Internet and other survey formats have been made (for a review, see Lindhjem and Navrud, 2011).

4 Modeling approach

The CE technique is an application of the characteristics-based theory of value (Lancaster, 1966) combined with random utility theory (Thurstone, 1927). CE involves decomposing flexible energy demand into its important characteristics. According to random utility theory, individuals make choices based on the presence of good characteristics and some degree of randomness. The utility for individual *n* related to alternative *j* is specified as:

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \qquad (1)$$

where V_{nj} is a deterministic part of the utility and ε_{nj} is a random component.

The Mixed Logit (MXL) model has become a frequently used specification (Ben-Akiva et al., 1997; Revelt and Train, 1998) as it avoids the independence of irrelevant alternatives (IIA) property and accounts for preference heterogeneity. The MXL model is very flexible and can approximate any random utility model (Train, 2009). In the MXL model, the utility related to each choice alternative *j*, as evaluated by each individual *n*, is represented as the following:

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj}, \qquad (2)$$

where x_{nj} is a vector of attributes (including also an alternative specific constant for the status quo) and β_n is the corresponding vector of estimated parameters. The idiosyncratic error ε_{nj} is independently and identically distributed (IID) and an extreme value one (EV1) type. The idiosyncratic error has a variance (or scale) that is normalized to achieve identification.

In the MXL framework, each individual also has random taste parameters in β_n, with values that depend on the values of the population mean b and covariance matrix Ω of an underlying distribution $\varphi(\beta|\mathrm{b}, \Omega)$. Several distributions can be used for random parameters (e.g., normal, lognormal, gamma, uniform, or triangular). Because β_n is now unknown, the unconditional probability for choice j is:

$$P_{nj} = \int_{\beta_n} \frac{\exp(\beta'_n x_{nj})}{\sum_{k=1}^{J} \exp(\beta'_n x_{nk})} \varphi(\beta|\mathrm{b}, \Omega) d\beta. \qquad (3)$$

The choice probability value of Equation (3) cannot be precisely calculated because the integral does not take a closed form. This integral is approximated using a simulated maximum likelihood estimator calculated using scrambled Sobol draws.

The utility specification in Equation (2) is presented in the preference space, but often economic investigations focus on willingness to pay (WTP) estimations. Thus, we reparametrize the utility to the WTP space in which the utility coefficients can be immediately interpreted as marginal WTP values (Scarpa and Willis, 2010; Train and Weeks, 2005). In the WTP space, the utility for the respondent n takes the following generic form:

$$U_{nj} = \sigma(\alpha_n m_{nj} + \beta_n' x_{nj}) + \varepsilon_{nj} = \sigma\alpha_n(m_{nj} + \beta'_n x_{nj}/\alpha_n) + \varepsilon_{nj}$$
$$= \lambda_n(m_{nj} + \upsilon'_n x_{nj}) + \varepsilon_{nj}. \qquad (4)$$

Now m_{nj} is the monetary attribute, x_{nj} are all other attributes, α_n is the parameter for the monetary attribute, and β_n is the vector of parameters for the nonmonetary attributes. When we manipulate the original Equation in (4), we have $\upsilon_n = \beta_n/\alpha_n$, a vector of marginal WTP for each nonmonetary attribute (where a vector β_n is divided by a scalar α_n). The scale parameter σ does not directly impact the WTPs but remains in λ_n, i.e. in the monetary parameter[12]. The λ_n can be linked with scale-covariates as follows: $\lambda_n = \exp(\theta' h_n)\alpha_n$, where h_n is a vector of scale-related covariates of individual n and θ is the corresponding coefficient vector (Faccioli et al., 2018). Generally, the WTP space specification enables convenient distributions for WTP because it avoids the need to consider the distribution of inverse coefficients (Daly et al., 2012; Train and Weeks, 2005). Moreover, the estimated coefficients are interpretable in the money metric, as are the estimated standard errors that need not be derived using simulation or closed form approximations (e.g., via the Delta method). Models in the WTP space may provide more reasonable distributions of WTP with fewer individuals having large WTPs than models in the preference space (Train and Weeks, 2005).

In the analysis, we use the MXL model in the WTP space. We allow for a correlation between random coefficients because it is likely that the unobserved effects between different attribute levels are correlated in the choice sets. Correlation reflects individuals' preferences for one attribute being related to their preferences for another attribute[13]. Generally, an MXL model that allows all parameters to be randomly distributed and estimates a full covariance matrix among them is the most general form

[12] The assumption regarding the variance of the error term may be expressed by scaling the utility function. Note that given the ordinal nature of utility, the specification in Equation (4) represents the same preferences as in Equation (2).
[13] This may also control for possible endogeneity between certain attributes. For example, the RTP contract may be correlated with the monetary attribute.

possible (Hess and Train, 2017). Furthermore, we control for possible scale differences because the respondents were presented with two different bid vectors (for the monetary attribute) in the choice tasks.

5 Results and discussion

5.1 Opinions on energy conservation, pro-environmental actions, and electricity pricing

In the survey, the respondents were asked to evaluate several energy-related claims measured on a 5-point Likert scale to obtain a better understanding of their attitudes (see Figure 2). When respondents were asked about energy conservation, they viewed it as necessary mostly for monetary reasons; however, according to the results, preventing climate change also proved to be important. Another interesting finding was that more than two-thirds of the respondents (71%) wanted households to have more decision-making power over energy production in Finland. Furthermore, most respondents (70%) exhibited a positive attitude toward increasing the share of renewable energy even if it added costs to society. In contrast, nearly a quarter of the respondents (22%) thought that the effect of energy production on emissions and climate change is generally exaggerated. Based on these answers, we conclude that respondents seem to exhibit a relatively high interest in energy conservation and renewable energy. However, a difference of opinion exists in terms of the energy sector's influence on climate change.

Respondents were also asked questions about electricity pricing. Regarding their current electricity sales contract (see Figure 3), a clear majority (72%) had a fixed price contract, whereas only a few (5%) had an RTP contract. Despite the low adoption of RTP contracts, 11% of respondents reported that they had considered RTP contracts but had not yet signed one. Surprisingly, many (14%) did not know their contract type. Furthermore, when asked about the reason for choosing the fixed price contract, the most popular explanation was related to the ease of understanding this contract type (36%), followed by the need to avoid fluctuations in the electricity price (19%) and the idea of the fixed price being the most affordable alternative (16%).

Figure 4 shows that a large share of respondents (60%) believed that the price of electricity would increase significantly in the near future. Moreover, nearly 90% of respondents stated that the distribution fee for electricity is too high relative to the price of electric energy. This finding suggests that households are quite unsatisfied with their current possibilities to affect the size of their electricity distribution bills. Interestingly, 79% of respondents wanted more possibilities to influence their electricity bill through their actions. The tolerance for uncertainty, however, proved to be quite low given that 84% of respondents disliked variations in their monthly electricity bill. Moreover, a clear majority (80%) of respondents would have liked to receive more information on their energy consumption in general.

Choice experiment and determinants of flexibility

In the survey, 56 respondents (14.7%) chose the status quo alternative in *every* choice task. In the debriefing question, 22 respondents out of the 56 stated that the status quo was truly the best alternative in every choice task. From the remaining status quo respondents, 15 stated that they did not have enough knowledge on the research topic, 4 stated they did not consider the topic important, 4 stated that the questions were too difficult, and 12 respondents had some other reason. Only those respondents were included in the final analyses who indicated that the status quo was truly the best alternative (we interpret that these are true 0 WTP responses)[14]. The resulting subsample (after removing 34 protest respondents and one respondent that did not answer all choice tasks, i.e., 9% of the full sample) is composed of 2070 choices of the 345 respondents.

The extent of stated attribute non-attendance (A-NA) was quite modest in this CE. Thus, we neither explicitly accounted for a possible impact of stated A-NA on the value estimates nor explored inferred A-NA. The stated A-NA was highest for the electricity distribution contract attribute (10.5%), followed by the electricity sales contract (10%), remote control of heating (9.7%), emissions reduction (9.5%), remote control of electricity use (8.2%), and reduction in energy bill (4.5%) attributes.

[14] We acknowledge that the exclusion criteria used for protest responses is based on subjective judgement, and that protest responses should be handled with care in the valuation analysis. Although the literature is clear that protest responses of various types may be a concern, there is no agreement on a single set of practices how to identify protest responses (Johnston et al., 2017; Meyerhoff et al., 2012). No clear-cut decision rules or criteria for such identifications yet exist and the identification of protest responses often requires the analyst to use subjective judgement. Suggested approaches to handle this issue include: dropping observations, conducting analyses with and without the protest responses, and developing models that attempt to control for protest responses (Johnston et al., 2017; Krishnamurthy and Kriström, 2016). We conducted sensitivity analyses to be transparent in the identification and treatment of our suspected protest responses. In the sensitivity analyses, we included all or some of the possible protest responses to our analyses. The sensitivity analyses indicate that the relative importance of the attributes is very robust. However, the WTP values are slightly lower when some of the suggested protest responses are included in the analysis.

The definitions of the explanatory variables are presented in Table 3. Status quo levels (fixed-rate tariff, fixed price, no load control, no emissions reduction, and no reduction in annual energy bill) worked as reference categories in the analysis. The estimations were done in MATLAB[15]. We estimated several models starting from a Multinomial Logit (MNL) model to a simple attributes-only MXL model to different models that include interactions with explanatory variables, such as socio-demographics. Note that the MXL model always outperformed the MNL model, indicating that unobserved heterogeneity is significant in this data (see Table 4). In addition, the MXL model with correlation performed better than the MXL model without correlation (see the Appendix A and Table A.1) based on all information criteria (LL, McFadden R2, Ben-Akiva R2, AIC, and BIC)[16].

In the MXL model, all utility parameters were treated as random with normal distributions assigned to nonmonetary parameters and lognormal distribution assigned to monetary parameter. The model was executed with 1000 Sobol draws using random linear scramble and random digital shift. The gradients were derived analytically, and multiple starting values were used to assure convergence to the global optimum.

5.1.1 Preferences for dynamic pricing, remote load control, and emissions reductions

The results of the CE are presented in Table 4. Based on both model fit and allowing for the most flexible model structure, we focus on the results of the MXL model. The results reveal that all of the variables had their expected signs. RTP and load control (HEAT_M, HEAT_E, ELE_M, ELE_E) alternatives were associated with significant disutility, whereas emissions reductions (EMIS_10 and EMIS_30) and increases in annual energy bill savings (SAVE) were associated with significant increases in utility. Note that the coefficients can be interpreted in money metrics (WTP coefficients are in 100€ per year).

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[15] The models were estimated using a DCE package, which is available at https://github.com/czaj/DCE.

[16] The likelihood ratio test also showed that we must reject the null hypothesis that the unrestricted model (MXL with correlation) is no better than the restricted model (MXL without correlation). This finding demonstrates that not accounting for the correlation between random parameters may significantly affect the WTP estimates.

Respondents required, on average, a 78€ [±14€] compensation (i.e., a reduction) in their annual electricity bill to choose RTP over fixed price. This result indicates that factors such as uncertainty and complexity in the monthly energy bill are likely linked to considerable discomfort (see also, Dütschke and Paetz, 2013). This finding may also reflect the degree to which individuals are, on average, willing to adjust their electricity consumption in response to changes in electricity spot prices[17].

Regarding electricity distribution contracts, the TT was associated with a close to significant 33€ [±21€] compensation requirement. The WTP for PBT was not significantly different from zero. Many possible reasons exist for this finding. One possible explanation is that respondents may have had problems understanding this new contract type. The result may also be linked to the overall dissatisfaction of the current distribution tariff offering (see Figure 4) and households may be willing to consider any new alternatives. Alternatively, the result may reflect that some respondents are indifferent between fixed-rate tariffs and PBTs. We cannot conduct comparisons between our findings and previous research because household preferences for PBTs have yet to be studied.

The results reveal that respondents' sensitivity to restrictions in electricity usage was greater than that for comparable restrictions in heating. Considerable differences also existed in their perceptions between load control in the morning and the evening. The greatest disutility was attached to constraints imposed on both heating and electricity load controls in the evening. The required compensation from electricity load control was 199€ [±26€] in the evening and 54€ [±17€] in the morning. One possible explanation for this finding is that everyday household tasks (e.g., doing laundry and dishes) usually take place in the evening. The required compensation for accepting load control in heating was 80€ [±21€] in the evening and 58€ [±17€] in the morning. This result indicates that the load control in heating is acceptable in principle for many households, at least within tight bounds (Fell et al., 2015). Load control in heating offers flexibility by sacrificing only a little comfort of living. These results are in line with Broberg and Persson (2016).

The results show that, as the levels of emissions reductions (EMIS_10, EMIS_30) and annual savings (SAVE) increased, the probability of choosing respective alternatives increased among the respondents. The respondents were willing to pay on average 79€ [±27€] annually for a 10% emissions

[17] Note that the RTP contract was described to respondents in a way that it enables individuals to decrease their electricity costs by shifting electricity consumption to hours with lower spot prices.

reduction and 133€ [±15€] for a 30% emissions reduction. This result demonstrates that, in addition to monetary savings, other value-creating elements exist to increase demand side flexibility. The evidence from the previous literature is somewhat missing regarding simultaneous accounting for flexibility and environmental aspects (although, see Buryk et al., 2015). Nevertheless, households have been shown to be willing to pay both significant and low premiums for green electricity (Krishnamurthy and Kriström, 2016; Sundt and Rehdanz, 2015). Moreover, thresholds might exist before possible willingness is activated (Rowlands et al., 2003; Tabi et al., 2014).

We also controlled for possible differences in scale in the estimations because the respondents were presented with low and high bid vectors for the monetary attribute[18]. As the results demonstrate, this induced a statistically significant covariate for SAVE_LOW.

5.1.2 Choice between flexible and inflexible alternatives

The results show that the alternative specific constant (ASC) is statistically significant and has a negative sign, suggesting that, on average, moving away from the inflexible benchmark situation increased respondents' utility. Additionally, this result indicates that the status quo bias may not be a significant problem in this data[19].

High levels of heterogeneity exist among respondents with respect to ASC values. To investigate possible reasons, we introduced interactions between the status quo (ASC) and other variables (see Table 4). This enabled us to examine the respondent characteristics that affect the choice between inflexible and flexible alternatives. From the socio-demographic covariates, the statistically significant negative interaction between a household's education level (HEDU) and the ASC denotes that the choice probability of the status quo was higher among low-educated households. This finding suggests that high-educated households are more willing than low-educated households to participate in flexibility. A similar observation has been presented by Broberg and Persson (2016). The explanation for this result could be related to a better understanding of the decision context among well-educated people. Additionally, making an active decision requires physical effort and involves transactions costs

[18] Reductions in annual energy bills varied between 0€ and 350€ for individuals living in detached or semi-detached houses, whereas individuals living in smaller flats, such as terraced houses or apartment buildings, faced a lower annual savings potential that varied between 0€ and 200€.

[19] Note that we have excluded from the analysis 35 protest responses (see the beginning of Section 5.2).

(Samuelson and Zeckhauser, 1988). Surprisingly, respondents over the age of 60 (OLD) were more likely to choose flexibility alternatives. The opposite was found by Broberg and Persson (2016). From other characteristics, we found that POS_RTP (i.e., the respondent either had RTP or had considered such contract) was associated with a higher probability for choosing flexibility alternatives. This finding indicates that understanding the potential benefits of dynamic pricing is likely linked with a higher willingness to participate in demand side flexibility. It has also been found that dynamic contracts appear to attract individuals with a higher ability to respond to varying prices, that is, a higher potential for demand side flexibility (Ericson, 2011).

We also tested several other intuitively relevant factors that were not included in the presented model because the associated coefficients were not found to be significant. The findings imply that respondents' gender or income level did not explain their choices. In addition, a respondent's living environment and heating mode did not have explanatory power[20].

5.1.3 Correlation of flexibility characteristics

The correlation matrix related to unobserved heterogeneity is reported in Table 5. The matrix shows a strong correlation within dynamic pricing contract alternatives and within load control alternatives. Emissions reduction alternatives have weak correlations with dynamic pricing and load control alternatives. In general, a positive correlation indicates that larger parameter estimates for respondents along the distribution of one attribute are generally associated with larger parameter estimates for that same respondent in the parameter space for the second attribute (Hensher et al., 2015). For example, positive correlations between RTP and ELE_M (0.67), as well as ELE_E (0.62), imply that respondents with higher compensation requirements for RTP are expected to also have higher compensation requirements for the remote load control of electricity. Moreover, the correlation of 0.77 between HEAT_M and HEAT_E suggests that people who are more willing to choose heating control in the morning are also more likely to choose control in the evening.

[20] Unfortunately, the survey did not include questions on home size, home age or conducted renovations which would have been interesting and relevant explanatory variables.

6 Conclusion

This paper studies households' preferences for different electricity pricing programs, automated load control services, and emissions reductions. Using a sophisticated Choice Experiment method, we obtain several interesting results that are relevant to smart electricity market development and policy objectives.

There is a clear need in the market for automated smart home technologies[21] that can optimize consumers' heating or electricity consumption in such a way that no direct action from the user side is needed. Our results suggest that households are willing to participate in smart load control services; however, at the same time, they require compensation for the associated discomfort. According to our findings, the load control of heating is likely to be the low hanging fruit because the required compensations were moderate and distinctly lower relative to the respective compensations for the load control of electricity usage. Space heating also corresponds to a considerable share (approximately 70%) of the total residential energy consumption (Official Statistics of Finland, 2016b) and, hence, has the highest potential for demand side flexibility.

Regardless of the potential interest in direct load control services and smart meter infrastructure, the market penetration of smart home technologies has been rather low in practice. Arguably, the lack of reasonably priced automated home technologies is closely linked to the slow adoption of demand response programs (Nolan and O'Malley, 2015). Given that demand side flexibility brings clear system-level benefits, such as a higher utilization rate of existing capacity and more efficient use of variable renewable energy, it would be important to consider whether the costs of these technologies should also be covered by energy companies or even society.

This study, among others, demonstrates that dynamic RTP contracts have not gained considerable market share even though they have been available for residential customers for some years. Many possible reasons exist for this phenomenon. One reason is the fact that electricity spot prices in the Nordic power market area have been rather low in the past and, thus, the potential savings from shifting the timing of electricity use have been quite modest. Our results also suggest that risk aversion and

[21] For a study on smart home technologies, see Wilson et al. (2017).

difficulties in understanding the contracts may explain the low participation in RTP schemes (Hobman et al., 2016). This suggestion indicates that energy companies should make dynamic RTP contracts even simpler and more customer friendly. The price-related risks can be at least partly reduced by utilizing smart automated home technology, which manages the price information and load (Dütschke and Paetz, 2013).

As previously explained, the financial benefits from RTP contracts for individual households are quite modest given low spot prices. In the future, however, new service providers, such as aggregators or virtual utilities, might combine several households and offer their flexibility to, for example, the balancing market in which the potential financial benefits are higher. Part of the revenue can then be shared with flexible households through new types of contracts. The increasing share of variable renewable energy requires more variable demand to maintain the balance. Clearly, a two-rate or a seasonal tariff cannot provide this type of flexibility. Consequently, contracts that provide incentives for (at the minimum) hourly-based flexibility are needed.

According to our results, households think that the share of the distribution price in the total electricity bill is too high. This perception may be realized for example as a willingness to accept new types of distribution contracts. In this study, we accounted for three types of distribution contracts of which the PBT is a new alternative. Distribution companies have argued that power-based contracts are needed to provide incentives to reduce peak demand and smooth the load curve. Such changes would result in a better load factor because the networks are better utilized under PBTs. Generally, both PBT and RTP aim to decrease the peak-hour consumption by shifting the consumption to non-peak hours that results in smoother load profiles. However, an occasional contradiction may exist between PBT and RTP pricing. When the spot price for electricity (i.e. RTP) is very low, the local distribution network can get congested. Thus, electricity retail and distribution companies are incentivized to give contradictory consumption signals. Whereas the low spot price from retail side incentives the household to consume as much as possible (use e.g. flexibility compatible consumption), the PBT from distribution side may penalize the household for the momentary peaking demand. On the system level, the requirement is to balance between the goals of efficient network control (which requires a smooth load) and efficient electricity production (which requires greater variability).

Increasing understanding of how households could be motivated to become active members in the electricity market is important. Such a better understanding seems to require a combination of technological, monetary, and other value-based incentives. Environmental aspects have become increasingly important as individuals carry greater concerns over climate change. However, currently, almost no contract types provide real incentives to change consumption patterns based on environmental information (such as real-time emissions; see Karhinen et al. 2018; Kopsakangas-Savolainen et al., 2017). Our results highlight that system-level emissions reductions are highly valued among households and may activate households to participate in demand side flexibility.

Finally, although our study yielded some important findings on household preferences for demand side flexibility, it was limited to homeowners in Finland. Additionally, our CE included a stylized set of flexibility services and dynamic contracts. Future research areas consist of an investigation of household preferences in broader contexts and real-life experiments.

Declarations of interest: none

Acknowledgments

The paper has previously been presented in the PhD dissertation of Enni Ruokamo. The authors acknowledge comments from two anonymous referees, Anna Alberini, Wiktor Adamowicz, Artti Juutinen, and the research assistance of Otto Appelgren. The authors also thank participants at the 41st IAEE International Conference in Groningnen, the 25th Ulvön Conference on Environmental Economics in Ulvön, and the 6th World Congress of Environmental and Resource Economists in Gothenburg. This work was supported by the Academy of Finland Strategic Research Council project BC-DC (AKA292854); the Academy of Finland project on regulation and dynamic pricing for energy systems REDYFLEX (288957); the Tauno Tönning Foundation; and the Maj and Tor Nessling Foundation.

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Fig 1 Example of a choice card.

CHOICE TASK 1	**Alternative 1**	**Alternative 2**	**Status Quo**
Electricity distribution contract	Power-based tariff	Two-rate tariff	Fixed rate tariff
Electricity sales contract	Fixed price	Real-time price	Fixed price
Remote control of heating	7 am – 10 am	5 pm – 8 pm	No load control
Remote control of electricity use	No load control	5 pm – 8 pm	No load control
System level emissions reduction (CO_2)	-10%	-30%	0%
Reduction in energy bill (€/year)	50€	180€	0€
My choice:	☐	☐	☐

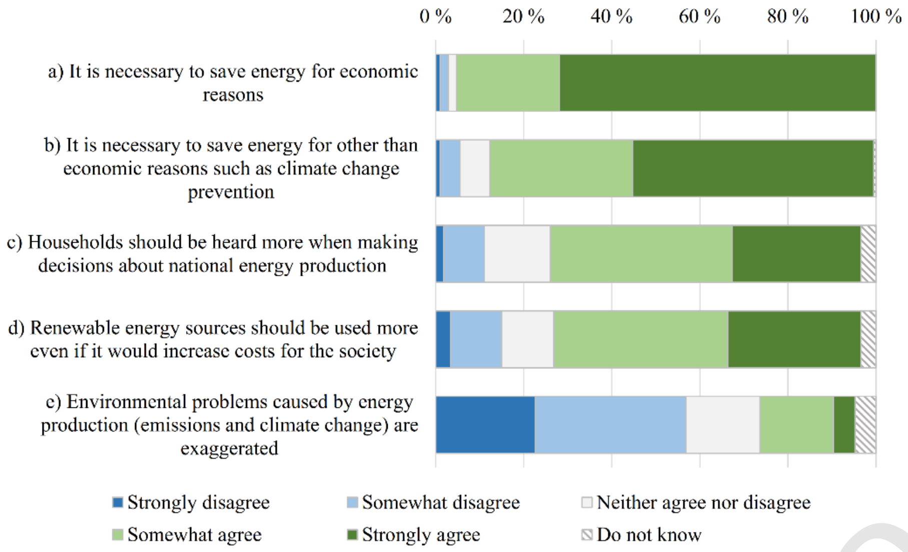

fig 2 Opinions on energy conservation and production (N=380).

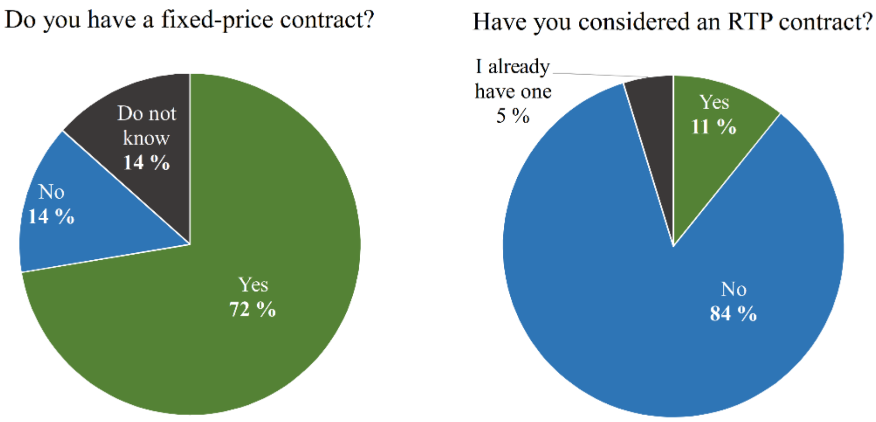

fig 3 Electricity sales contracts of respondents (N=380).

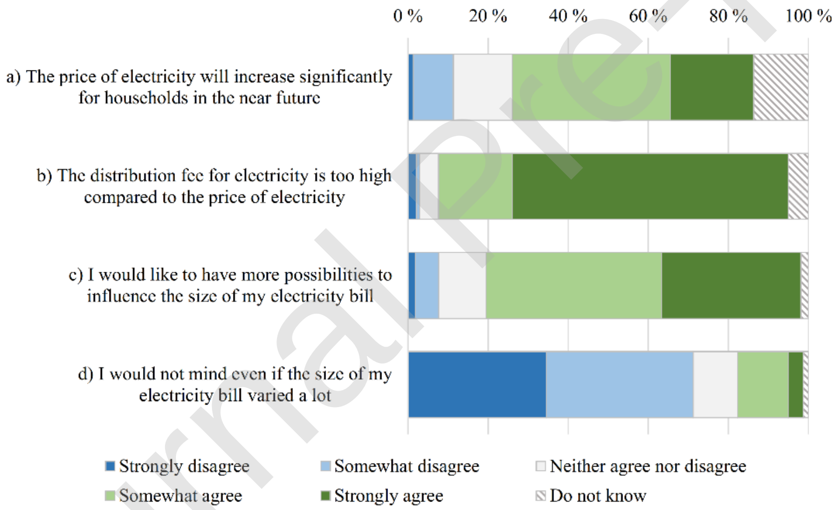

fig 4 Opinions on electricity pricing (N=380).

Table 1. Attributes and levels.

Attribute	Description	Levels
Electricity distribution contract	Electricity distribution contract includes two already existing alternatives (fixed-rate and two-rate tariffs) and one alternative under consideration (power-based tariff).	Fixed-rate tariff Two-rate tariff Power-based tariff
Electricity sales contract	Electricity sales contract describes two alternatives that are currently available in the market.	Fixed price Real-time price
Remote control of heating	A service provider will be remotely controlling your heating system every day during certain hours. The heating will be turned off, but in such a way that the temperature will never drop by more than 2 degrees and never below 18 degrees.	No load control 7 a.m.–10 a.m. 5 p.m.–8 p.m.
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 the dishwasher, washing machine, or tumble dryer. Additionally, you are not able to use comfort underfloor heating in your bathroom.	No load control 7 a.m.–10 a.m. 5 p.m.–8 p.m.
System-level emissions reduction	This describes the possible system-level reduction in CO_2 emissions if supply of and demand for electricity would meet more efficiently.	0% -10% -30%
Reduction in energy bill (€/year)	By changing your electricity contract type and/or adjusting your heating/electricity use, you will see a reduction in your annual energy bill.	Detached and semidetached houses: 0€, 40€, 90€, 150€, 230€, 350€ Terraced houses and apartment buildings: 0€, 20€, 50€, 90€, 140€, 200€

Table 2. Descriptive statistics of the respondents.

	Respondents	Corresponding statistics
Socio-demographic characteristics		
	Average	**Average**
Age (years)*	56.4	52.1[a]
Household size*	2.4	2.2[b]
	Percent	**Percent**
Gender*		
Female	43.2	50.0[a]
Male	56.8	50.0[a]
Household's income (gross, €/month)		
<4000	31.3	NA
4000–5999	30.5	NA
6000–7999	18.2	NA
8000–9999	9.2	NA
>10000	10.8	NA
Education		
Polytechnic or university degree	56.1	24.0[c]
Living environment		
Urban areas and local centers	75.3	75.4[d]
Rural areas	24.7	23.2[d]
Dwelling type		
Detached or semidetached house	67.4	64.5[a]
Terraced house	11.8	13.3[a]
Apartment building	20.8	22.2[a]
Electric space heating		
Yes	38.5	38.6[e]
No	61.5	61.4[e]
Work related to energy sector		
Yes	6.8	NA
No	89.7	NA
No answer	3.4	NA

NA: Not available

a: Corresponding statistics of the original sample of 4000 homeowners.

b: Corresponding statistics of Finnish homeowners (Official Statistics of Finland, 2016c).

c: Corresponding statistics of Finnish population aged 20–74 (Official Statistics of Finland, 2016a).

d: Corresponding statistics of Finnish population (Official Statistics of Finland, 2019).

e: Corresponding statistics of Finnish dwellings (Official Statistics of Finland, 2017).

* The means or proportions are not equal at the 5% level according to the t-test or chi-squared test.

Table 3. Definition of explanatory variables.

Variable	**Notation**	**Type**
ASC status quo	**ASC**	dummy-coded
Electricity distribution contract		
two-rate tariff	**TT**	dummy-coded
power-based tariff	**PBT**	dummy-coded
Electricity sales contract		
real-time pricing	**RTP**	dummy-coded
Remote control of heating		
7 a.m.–10 a.m.	**HEAT_M**	dummy-coded
5 p.m.–8 p.m.	**HEAT_E**	dummy-coded
Remote control of electricity use		
7 a.m.–10 a.m.	**ELE_M**	dummy-coded
5 p.m.–8 p.m.	**ELE_E**	dummy-coded
Emissions reduction		
–10%	**EMIS_10**	dummy-coded
–30%	**EMIS_30**	dummy-coded
Reduction in energy bill (€/year)	**SAVE**	continuous
Interactions with the ASC		
old (over 60 years)	**OLD**	dummy-coded
high education (university or polytechnic degree)	**HEDU**	dummy-coded
either has RTP or has considered it	**POS_RTP**	dummy-coded
Covariates of scale		
SAVE-attribute with low bid vector (0€-200€)	**SAVE_LOW**	dummy-coded

Table 4. Results of Multinomial Logit and Mixed Logit models.

MNL in WTP space					**MXL in WTP space**						
	Means					Means			Standard Deviations		
Variables	*Coeff.*	*St.Err.*	*P-value*		*Variables*	*Coeff.*	*St.Err.*	*P-value*	*Coeff.*	*St.Err.*	*P-value*
ASC	-0.5017	0.5881	0.3936		**ASC**	-1.9479***	0.5052	0.0001	2.2275***	0.5767	0.0001
TT	-0.3036	0.2873	0.2907		**TT**	-0.3287	0.2110	0.1192	1.4287***	0.2108	0.0000
PBT	0.0122	0.2352	0.9585		**PBT**	-0.1269	0.1739	0.4655	1.7463***	0.1965	0.0000
RTP	-0.5237***	0.1772	0.0031		**RTP**	-0.7798***	0.1447	0.0000	1.9634***	0.2155	0.0000
HEAT_M	-0.2527	0.2197	0.2501		**HEAT_M**	-0.5755***	0.1736	0.0009	1.9655***	0.2677	0.0000
HEAT_E	-0.3293	0.2883	0.2534		**HEAT_E**	-0.8033***	0.2055	0.0001	2.2127***	0.3015	0.0000
ELE_M	-0.2735	0.2038	0.1797		**ELE_M**	-0.5378***	0.1666	0.0012	1.6305***	0.1967	0.0000
ELE_E	-1.1768***	0.3056	0.0001		**ELE_E**	-1.9920***	0.2563	0.0000	3.3648***	0.4141	0.0000
EMIS_10	0.7924***	0.2660	0.0029		**EMIS_10**	0.7892***	0.2727	0.0038	1.9109***	0.2917	0.0000
EMIS_30	1.1404***	0.1633	0.0000		**EMIS_30**	1.3255***	0.1523	0.0000	1.7968***	0.2188	0.0000
SAVE	0.4126***	0.0402	0.0000		**SAVE**	5.9015**	2.4789	0.0173	5.5121	1.5637	0.1543
						Interactions with ASC					
						Coeff,	*St.Err.*	*P-value*			
					OLD	-0.7080*	0.4059	0.0811			
					HEDU	-1.4284***	0.3986	0.0003			
					POS_RTP	-1.7885***	0.5081	0.0004			
	Covariates of scale					Covariates of scale					
	Coeff.	*St.Err.*	*P-value*			*Coeff,*	*St.Err.*	*P-value*			
SAVE_LOW	0.3405**	0.1375	0.0133		**SAVE_LOW**	-3.8341**	1.6989	0.0240			
Model characteristics					*Model characteristics*						
LL	-2102.36				LL	-1588.53					
LL(constants only)	-2196.64				LL(constants only)	-2196.64					
McFadden's pseudo-R²	0.0429				McFadden's pseudo-R²	0.2768					
Ben-Akiva-Lerman's pseudo-R²	0.3742				Ben-Akiva-Lerman's pseudo-R²	0.4825					
AIC/n	2.0429				AIC/n	1.1631					
BIC/n	2.0755				BIC/n	1.8336					
n (observations)	2070				n (observations)	2070					
r (respondents)	345				r (respondents)	345					
k (parameters)	12				k (parameters	81					

*, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 5. Correlation matrix of random parameters in the Mixed Logit model.

	ASC	TT	PBT	RTP	HEAT_M	HEAT_E	ELE_M	ELE_E	EMIS_10	EMIS_30	SAVE
ASC	**1.0000**	-0.3237	-0.4215	-0.3362	-0.9265	-0.8699	-0.2899	-0.6268	-0.2742	-0.3092	-0.6251
TT		**1.0000**	0.4946	0.6378	-0.0493	0.4114	0.0753	0.3962	0.1076	0.2050	0.0824
PBT			**1.0000**	0.5254	0.2539	0.5284	0.2664	0.3921	-0.1422	-0.0030	0.3604
RTP				**1.0000**	0.1556	0.6439	0.6659	0.6183	-0.3540	0.2448	0.0360
HEAT_M					**1.0000**	0.7740	0.3279	0.5444	0.2159	0.2663	0.6154
HEAT_E						**1.0000**	0.6396	0.6266	0.1035	0.3821	0.4779
ELE_M							**1.0000**	0.5743	-0.1947	0.4342	0.1802
ELE_E								**1.0000**	-0.0297	0.3832	0.5494
EMIS_10									**1.0000**	0.5453	0.1452
EMIS_30										**1.0000**	0.1107
SAVE											**1.0000**

Appendix A

Table A1. Results of the MXL model without correlation in WTP space.

	Means			Standard Deviations		
Variables	*Coeff.*	*St.Err.*	*P-value*	*Coeff.*	*St.Err.*	*P-value*
ASC	-1.1424*	0.6264	0.0682	4.8820***	0.5695	0.0000
TT	-0.4570**	0.2280	0.0450	0.7349***	0.1474	0.0000
PBT	-0.0701	0.1824	0.7006	0.9417***	0.1614	0.0000
RTP	-0.7646***	0.1396	0.0000	1.1713***	0.1353	0.0000
HEAT_M	-0.4833***	0.1719	0.0049	1.3150***	0.1951	0.0000
HEAT_E	-0.6098***	0.2177	0.0051	1.0815***	0.1662	0.0000
ELE_M	-0.6424***	0.1599	0.0001	0.7576***	0.1551	0.0000
ELE_E	-1.5457***	0.2553	0.0000	1.8911***	0.2137	0.0000
EMIS_10	0.3560	0.2392	0.1366	1.3787***	0.3180	0.0000
EMIS_30	1.2063***	0.1290	0.0000	1.3708***	0.1477	0.0000
SAVE	0.9338***	0.3334	0.0051	1.6740***	0.3829	0.0000
	Interactions with ASC					
	Coeff.	*St.Err.*	*P-value*			
OLD	-1.8316***	0.4543	0.0001			
HEDU	-1.9166***	0.4464	0.0000			
POS_RTP	-1.3497**	0.6390	0.0347			
	Covariates of scale					
	Coeff.	*St.Err.*	*P-value*			
SAVE_LOW	-0.4218	0.3647	0.2475			
Model characteristics						
LL	-1688.64					
LL(constants only)	-2196.64					
McFadden's pseudo-R^2	0.2313					
Ben-Akiva-Lerman's pseudo-R^2	0.4607					
AIC/n	1.6567					
BIC/n	1.7274					
n (observations)	2070					
r (respondents)	345					
k (parameters	26					
*, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.						