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Abstract

In a European perspective, the electricity markets have been experiencing major changes via deregulation, new technologies and changes in the production mix. Together with the daily and seasonal peak hours on the demand side, the changing markets put pressure on increased flexibility to handle and sustain balance in the grid systems. This paper focuses on the demand side and analyzes preferences related to demand management of Swedish households energy use. Preferences are analyzed within the framework of choice experiments and people are faced with hypothetical electricity contracts. The respondents reveal their preferences for attributes related to external control of heating, household electricity and information dissemination (integrity). The results show that people put a substantial value on not being controlled, illustrated by compensations up to thousands of SEK for accepting a contract characterized by external control of energy use in various dimensions. In addition, the results show that household composition, age, gender and income play a role for the perceived discomfort from the external control and information dissemination.

Keywords: *choice experiment; demand side management; electricity market; energy policy; demand flexibility; smart grids*

1. Introduction

It is fair to say that climate change and energy security are high on the political agenda, in particular in the EU. The European council recently decided on a climate and energy policy framework reaching for 2030 and although the new framework put the climate on a pedestal, the targets for renewable energy and energy efficiency remain central pieces of the EU structural plans. In light of this, large-scale investments in renewable energy, back-up power and transmission capacity are needed to accomplish the targets and aims. As the share of renewables increases the degree of intermittent production increases and investments in local power grids are typically needed for a well functioning power system. Both the internal market in electricity directive (2009/72/EG) and the renewable energy directive (2009/28/EG) suggest that demand response (or demand flexibility) is likely to ease the transition of power markets by improving the interplay between local power demand and supply, and by stimulating energy efficiency. It is clear that a development characterized by demand flexibility would reduce the need for new investments in the power grid and back-up capacity.

This paper elaborates on the economics and potential of smart grids and demand flexibility, which have become keywords in energy policies worldwide (see Joskow, 2012 for a U.S. context). Smart grids are often discussed in a context focusing on the possibilities of new technology, often ignoring the consumers' willingness to accept and use this technology. From an economic perspective cost and benefits of power market reforms are not limited to the energy systems, but will also include end-users in several dimensions. Ignoring the demand-side will severely bias cost-benefit analysis and policy-making. The main objective with the paper is to study potential utility loss, or discomfort, associated with consumer flexibility and demand management. By the use of a so-called choice experiment, households are faced with hypothetical electricity contracts and their choices reveal preferences for different attributes of the contracts. By statistical methods it is then possible to explicitly estimate the compensations needed to be "flexible" in different dimensions at the household level. The dimensions of flexibility considered in the contracts are related to types of electricity use (heating and domestic electricity), time of day and the provision of private information regarding household energy use. As for the latter, one may recall that there is a growing literature suggesting that peer comparisons of electricity use as such is potentially an effective policy instrument for energy saving (see e.g., Allcott, 2011 and Dolan and Metcalf, 2013). In any case of behavioral control related to electricity use, it possibly affects and reduce household daily comfort. Given the idea of reduced comfort it is also reasonable to think that this is related to socioeconomic factors such as e.g., age, income, time spent at home, etc. Therefore, in addition to the "main-effects" the paper elaborates on the importance of socioeconomic factors for preferences and flexibility.

The method of choice experiments is commonly used in the field of environmental economics and for purpose of non-market valuation. There are also choice experiment studies related to the electricity market via e.g. load shifting, tariff choice and outages.[1] The method makes it possible to estimate the value of separate attributes of goods opposed to only measuring the value of a specific good (a bundle of attributes). In the present study, it is possible to estimate a value on the discomfort a household experience from, say, not being able to use the dishwasher, or from a lower indoor temperature during the peak hours and the utility/disutility associated with peer comparisons of electricity use. These values are highly policy relevant by revealing how much money households need to, for example, move electricity use from hours of peak demand.

[1] See e.g., Buryk et al., 2015; Pepermans, 2011; Carlsson and Martinsson, 2008; Abdullah and Mariel, 2010; and Goett et al., 2000.

The paper is structured such that section 2 gives a background to the discussion on smart grids and demand response. Section 3 explains the method of choice experiment and presents the survey and the experimental design together with descriptive statistics and the empirical specification. Section 4 continues with the results, while the paper is closed with a summary and discussion in section 5.

2. Smart grids and demand response

Measures to stimulate demand flexibility are commonly referred to as enabling policies empowering the end-consumers' role in the energy markets. Demand flexibility rests on the idea that end-consumers react (respond) to economic incentives like prices or other forms of compensation. This type of flexibility is desirable in unregulated markets where the electricity price changes by the hour, as is the case on the Nordic power market, Nordpool. Given todays advanced electricity meters, it is possible to measure household level electricity use by the hour and charge prices based on the real time spot price on the wholesale market. This type of pricing scheme is referred to as "real time pricing". More generally, when the price facing end-consumers changes at least once per 24 hours, it is referred to as dynamic pricing.

Dynamic pricing in general, and real time pricing in particular, is rather uncommon today although the interest is growing with the technology development and with the change in the production mix towards more intermittent sources. Since October 2012, the Swedish electricity suppliers have to, upon request by consumers, offer real-time contracts. So far however, the interest in these contracts has been limited among customers. By the spring of 2014, only 8 600 households (about 0.2 percent of all households) had signed real-time contracts (Swedish Energy Markets Inspectorate, 2014).[2] To have more consumers opting for real-time contracts, the incentives for such contracts need to increase. It is not known, however, to what degree increased price volatility will affect demand flexibility, which is ultimately an empirical question. In all cases, it is urgent to examine how households are likely to act under various circumstances. To some degree, the high hopes of an untapped potential of demand-side flexibility is contradicted by the vast literature on the so called energy efficiency gap arguing that consumers are rather price-insensitive and may react inefficiently to price signals due to informational, organizational and behavioral failures (for an overview, see Broberg and Kazukauskas, 2014). With this in mind, empowering end-consumers by enabling dynamic pricing (or other compensation mechanisms) and the provision of detailed information about their energy use may turn out to be ineffective. Still, a number of studies have shown that dynamic pricing affects households' electricity consumption (Faruqui and Sergici, 2013). In a field experiment on electricity customers in the US it was found that real-time pricing does not primarily lead to load shifting, but rather decreases electricity consumption in peak price hours, amounting to an energy saving of approximately two percent of a households total electricity use (Allcott, 2011a). A potential problem in such studies is that the consumers participate on a voluntary basis, which may cause a selection-bias (see e.g. Pankhurst et al., 2014). For example, Torriti (2012) found that when Italian households were involuntarily exposed to dynamic pricing (time of use) total electricity use actually increased by approximately 13 percent. The study also found that the introduction of time of use pricing succeed in, to some degree, lowering the morning peak, while worsening the evening peak problem.

A different way to have households reschedule their use of electricity is to use a demand side management (DSM) approach through direct load control at the household level. Given peak demand in time, both through the year but also through the day, intermediaries on the electricity market

[2] Critics may argue that there is a substantial status quo, or default, bias in electricity contracts and, for example, in a US pilot with dynamic tariffs as default it was found that only 10% opted out (Herter, 2007).

(aggregators) may curb and control consumption by simply performing effect-control on given households. The direct and exact control of the demand side is very attractive from a practical perspective, although potentially imposing disutility and discomfort at the household level. DSM makes it simpler to optimize the available capacity, as the power demand is more predictable compared to the case with active price response through real time pricing. The idea of DSM is however not new, although typically practiced in warmer climate countries, such as Australia, and relating to air conditioning etc. (see e.g. Strengers, 2008).

In addition to paving the way for demand flexibility, smart grids increase the opportunities for monitoring and evaluating household electricity use via e.g. so-called energy service companies. The improved flow of information via smart metering potentially enables energy system operators and energy service companies to improve their businesses and end consumers to lower their costs for energy. Moreover, alluding to social norms may be an effective way to induce behavioral changes leading to energy conservation (see e.g. Delmas and Lessem, 2014). A resent large-scaled field experiment on American households found that informing households about how their electricity use relates to that of similar households (peers) decreased actual electricity use (Allcott, 2011b). However, the increased amount of information sharing among households may give rise to issues related to integrity and ethics. It is reasonable to believe that individuals expect compensation when giving away personal information.

Although there are potential benefits from employment of detailed metering and dynamic pricing, there is a tendency in the public debate to focus on the technology as such. Demand response not only requires smart meters and potentially other capital investments, but also requires that the cost of changing behavior is relatively low. In developed economies, the cost for energy constitutes a rather small share of total household expenditures. In addition, habits and norms typically reflects the structure of the society and rescheduling energy use is by no means a costless task as it may impose significant disutility on households and firms in the form of transaction costs and everyday discomfort. In other words, the consumer surplus from most of our electricity consumption is large, meaning that electricity demand is expected to be rather inelastic.

3. Method

Direct management of consumers can be seen as a more extreme alternative to the idea of demand response through dynamic pricing. Unlike real-time pricing influencing energy demand through active response, DSM works through passive response and electricity contracts designed to remotely control electricity use (Babar et al., 2014). For example, consumers may sign a contract specifying that they disclaim any right to control part of their electricity use at certain hours of the day, or at certain occasions. In practice, a market player may adjust the domestic heating system during cold periods, or block the dishwasher during dinnertime, to smoothen daily energy use over time.

To analyze household attitudes to DSM inspired contracts, the choice experiment method is applied. The method is typically used to estimate monetary values for non-market goods (or bads) and makes it possible to value product specific attributes such as e.g. a car's safety or comfort, as opposed to an evaluation of the whole product (the car). For example, Carlsson and Martinsson (2008) use a choice experiments approach to estimate the value of avoiding blackouts with different durations at different times of the week and year. Their results point at a WTP for reducing the risk of blackouts ranging from SEK9 to SEK123. The WTP was found to increase with the duration, being higher in weekends and during wintertime. In the specific context of the present paper, the choice experiment method allows for an assessment of how and when to expect household compliance in the power market.

People are supposed to choose between hypothetical contracts characterized by constraints in their daily comfort related to domestic electricity (appliances and installations) and whether they are part of peer comparisons (information sharing). A monetary compensation is included and makes it possible to interpret preferences in terms of a monetary measure. By choosing among the contracts, the respondents make trade-offs and implicitly reveal their preferences for the attributes (constraints) characterizing the contracts. Along the real world relevance, it is crucial that the hypothetical contracts are realistic and reasonable from a cognitive perspective.

It is reasonable to believe that DSM substantially affects people's everyday life and comfort. From other studies it is known that the consumption of (demand for) electricity follows a pattern over time (for the case of Sweden see Vesterberg et al., 2014). Besides the seasonal patterns, there are peaks in the morning and in the evening. Realistic scenarios of DSM would then mean turning off the dishwasher, domestic heating, etc. during certain hours, which, in turn, would affect people's utility and comfort. In addition to the above-mentioned control of heating and household appliances, the integrity aspect is reflected in an attribute related to information sharing and peer comparisons regarding energy use. Although there exists a literature related to electricity markets, smart meters, information and DSM, it tends to focus on efficiency on the supply side ignoring the demand side and hence lacks explicit valuation of utility change from the consumer perspective. From a welfare perspective, it is crucial to know more about the compensation people require to reschedule their power consumption regardless of whether the context is dynamic pricing or DSM.

3.1 The choice experiment

The starting point is the hypothetical contracts specified such that the possibilities to use energy are limited with respect to time of day (morning and evening) and type of usage (heating or household electricity). The contracts (alternatives) presented in the survey are characterized by five attributes, of which three relate to external (remote) control, one to information sharing and one to annual monetary compensation. As for external control, focus is on time, usage and randomness. The contracts specify restrictions to energy use 7-10am (morning) and 5-8pm (evening) weekdays, which are typical peak hours in Sweden (Vesterberg et al., 2014). The external control during these hours refers to heating and household electricity. Notice that the reference level is "no control".

The power situation in the electricity system is occasionally affected by more or less unpredictable events such as production disruptions, as well as sudden changes in the demand. These events affect the market and may lead to large price fluctuations and price spikes in the wholesale market which may be mitigated by household response. To capture such events, an attribute described as random external control is included in the contracts. The attribute is defined in terms of maximum number of days that households may be restricted in their energy use (both heating and electricity from 7am to 8pm).

Smart grids are expected to pave the way for load shifting and energy conservation, which in turn is important for the phase-out of conventional electricity in exchange for renewables. Smart meters collect and communicate a considerable amount of information related to household electricity use, which allows for greater predictability in the electrical system as well as for new energy services. In the Swedish context, it is not clear who "owns" the information – the household or the "grid owner" (EiR2012:12). In all cases, any information sharing may give rise to integrity issues and one attribute is designed to capture this.

Table 1 summarizes the attributes and the respective levels. In the questionnaire the respondents faced the exact same information ahead of the choice sets (although the original text in Swedish).

Table 1. Attributes and the respective levels.

Attribute	Levels
External control of heating, monday-friday	A firm, e.g. a utility company, controls your heating system every day, Monday to Friday during certain hours. The heating will be turned off but the temperature never decreases more than two degrees (Celsius) and never below 18 degrees (Celsius). The control will take place **• 7am to 10am • 5pm to 8pm • Never (as today)**
External control of domestic electricity, monday-friday	A firm, e.g. a utility company, controls your domestic electricity use every day, Monday to Friday during certain hours. During these hours it is not possible to use the dishwasher, the laundry machine and dryer. In addition, the electricity for towel warmers and comfort floor heating will be cut off. The control will take place **• 7am to 10am • 5pm to 8pm • Never (as today)**
External control in extreme cases	During certain days there are extreme situations on the energy market due to e.g. extreme cold or low production. You will be notified one day ahead that the heating system and domestic electricity will be turned off the coming day between 7am and 8pm (including weekends). The control implies the same restrictions as in the attributes above. Extreme situations are more or less random and will be limited to a certain number of days per year. **• 3 days per year • 7 days per year • 10 days per year • Never (as today)**
Distribution of information	Information from your electricity meter and similar can be communicated to companies and compared to neighboring and similar households. Each household is kept anonymous in the comparisons. •**Yes** – It is okay to spread information about my household consumption and use it in anonymous comparisons across e.g. the neighborhood. • **No** – It is not okay to spread information about my household consumption and use it in anonymous comparisons across e.g. the neighborhood.
Compensation[3]	A new contract is related to an annual monetary compensation. **• SEK300 • SEK750 • SEK1500 • SEK2,500**

3.2 Experimental design and data

The choice experiment constituted the second part of a three-section questionnaire. The first section contained questions related to energy issues in general and implicitly worked to give background information within the relevant context. The respondents were asked to state their general opinions, experience, etc. in relation to energy issues and the electricity market. The final part of the questionnaire collected mainly socioeconomic information. Given a web-panel consisting of approximately 90,000 randomly phone-recruited Swedish citizens, a sample of 918 respondents was collected in June 2014.[4] The respondents were collected according to age, gender and place of residence to be representative for the Swedish population. Ahead of the final survey a pilot study with 100 respondents was conducted to test questions, layout, etc. In addition, the pilot study helped to develop a statistically more efficient design of the experiment (more on this below).

Internet-based surveys have their pros and cons, but are in general less costly, more flexible and imply faster data collection than traditional mail surveys. Today, and especially in Sweden, the argument that

[3] €1=SEK9 at the time of the survey.

[4] In total, 5907 panelists were invited to answer the survey. The order was for 900 respondents and the survey was closed within a week and the final number of respondents turned out to be 918.

Internet-based surveys are less representative of the population does not seem valid. It is clear that the vast majority has Internet access although the access to computers and Internet may vary across countries and population groups. For example, the experience from previous studies is that respondents from web-panels are slightly older and more educated than the average.[5] Given the panel-type of respondents there is a potential risk of "panel conditioning", meaning that experience from previous surveys may affect answers in the present study. The experience may however also lead to more correct and truthful answers (see e.g. Dillman et al., 2009). Irrespectively of sampling method, dropouts are a potential issue in surveys given that they are statistically different from the rest of the panel.

In addition to the construction and formulation of attributes and the corresponding levels, the design of a choice experiment also considers the variation of attribute levels across and within choice sets. The respondents were faced with a choice between three generic contracts for electricity, each contract characterized by the above-mentioned attributes. A respondent is supposed to choose her preferred contract, which implicitly means a trade-off between the attributes associated with each contract. The impact from each attribute on the choice of contract is then measured by altering the level of each attribute for the contracts. In the choice literature it is highlighted that respondents must not be forced to make choices, which motivates the inclusion of a "status-quo", or opt-out, alternative.[6] All choice sets therefore included one contract denoted "as today", with predetermined and fixed attribute levels mimicking the current situation.

Finally, the variation in attribute levels is of vital importance to estimate statistical relationships in an efficient way. The design of choice sets and the explicit attribute "levels" follow a process related to "efficient design". Given the results from the pilot study and methods inspired by related literature, the design was made in the software Ngene. In total, twelve choice sets were used in the final experiment. To reduce the burden of each respondent the choice sets were divided in two blocks - each respondent facing six randomly ordered choice situations.[7] An example of a choice set is found in the Appendix.

Table 2 presents relevant descriptive statistics and there are, in our view, no crucial and significant deviation from the Swedish population. Still, one may notice that the sample is slightly older and includes somewhat more men. The reason for this observation is not known, but one possible explanation could be a relatively large interest in energy issues within this group. Similar patterns have been found in other studies such as e.g., Ek and Söderholm (2010).

Table 2. Descriptive statistics

Variable	Mean/Share	Variable	Share
Age	54.79	Children 0-12 year (share)	0.13
Retirees	0.40	Apartment	0.42
Men	0.55	Direct electric heating	0.07
Household income	SEK40,000 - 45,000	District heating	0.10
Household size	2.21	Environmental organization	0.11
Single households	0.26	Politically active	0.08

5 See e.g. Ek and Persson (2014) for a discussion on the representativity of web-panelists.

6 Forced choices may cause the respondents to protest by choosing contracts not considering the trade-offs.

7 There is a literature discussing the "optimal" number of choice sets, and six seems to be a reasonable number, see e.g. Carlsson and Martinsson (2008) and Hensher et al. (2001).

3.3 Empirical specification

Each choice question implies a discrete choice between three hypothetical contracts characterized by the attributes presented above. It is assumed that each alternative contract corresponds to a specific utility level, and that the respondent chooses the alternative that provides the highest expected level of utility. From an econometric point of view, this can be interpreted as the probability of choosing a specific contract, given the attribute levels characterizing the contracts. The analysis of this type of data is typically done within the logit framework. The multinomial logit model (MNL) assumes that unobserved factors affecting the choice of alternatives are strictly independent of each other, which often is a strong assumption. Unobserved factors affecting the utility of each respective contract may be correlated with observable factors included as attributes in the experiment. Given this shortcoming of the MNL model it has become common practice to analyze the responses in the random parameter logit (RPL) framework[8]. The RPL model is a more general version of the MNL and allows unobserved factors underlying choices to be random and to follow a pre-specified distribution; see e.g Train (2009). To increase the ability to interpret and discuss the results, the following gives the basics (although not any formal derivation).

In general, individual *q*'s utility from choosing contract *j* in choice situation *t* can be defined as:

$$U_{qtj} = \beta'_q X_{qtj} + \varepsilon_{qtj} \quad (1)$$

where X_{qtj} is a vector of observable variables related to the alternative and the respondent. The unobserved parts of equation (1) are β_q, which is a vector of coefficients corresponding to the variables (including alternative specific constants, ASC), and ε_{jtq}, which is the error component. Given this specification, β_q represents individual taste among the respondents. In the behavioral process, the respondent knows the utility and the true value of his/her own β_q and ε_{qtj} for all j and chooses the contract with the highest utility. In the RPL framework taste is allowed to vary across individuals and the coefficients are characterized by a distribution $f(\beta)$, which is assumed to depend on underlying parameters captured by θ. These underlying parameters could be the mean and the covariance of the distribution. Note that the researcher observes only the variables X_{qtj} in equation (1). Hence, assuming that β_q is observable and that ε_{qtj} is independent and identically distributed (IID) extreme value type 1, the choice probability would be of a standard logit type. That is, given the values of β_q the probability is defined by:

$$L_{qj}(\beta_q) = \exp(\beta'_q X_{qj}) / \sum_k \exp(\beta'_q X_{kq}) \quad (2)$$

However, since β_q is unknown (follows a random distribution) it is not possible to use this probability. Instead, the unconditional probability is defined as the integral of $L_{jq}(\beta_q)$ for all possible values of the coefficients,

$$P_{qj} = \int \left(\frac{\exp(\beta' X_{qj})}{\sum_k \exp(\beta' X_{kq})} \right) f(\beta|\theta) d\beta \quad (3)$$

Given a specified distribution for the coefficients, the parameters, θ, of the distribution for the coefficients, $f(\beta)$, can be estimated through a simulated maximum likelihood estimator using Halton

[8] Also known as the mixed logit model in the literature.

draws.[9] As for the choice of distribution, it can take on any distributional form such as normal, lognormal, triangular, etc. In the present study, there is no prior information suggesting any other distribution than the normal, or similar, which will be the starting point in the estimations.

The output of the RPL model described above gives (i) estimates of the coefficients with corresponding standard errors and (ii) the standard deviation of each random coefficient reflecting preference heterogeneity. In general, the interpretation of the coefficients as such is analogous to the standard logit and measures the effect on the probability of choosing an alternative (although the absolute numbers requires a transformation to be directly comparable). A statistically significant standard deviation is interpreted such that the coefficient actually varies across individuals and preference heterogeneity is present. This is in contrast to the MNL where the coefficients are assumed to be the same for all individuals in the population and no heterogeneity is accounted for. In the actual choice experiment, one of the contracts will represent a status quo situation where the attributes are supposed to represent the "before" situation on the electricity market. In a context of contracts on the electricity market, it is important to allow households to express preferences for, or against, the status quo. In the estimation, this is captured by including a particular coefficient (alternative specific constant) for the status quo alternative to represent the role of unobserved sources of utility.

4. Results

4.1 The MNL, RPL and willingness to accept

For the purpose of comparison and robustness, Table 3 presents results from estimation of both the MNL and RPL specifications. All variables (attribute levels), except extreme occasions and annual compensation, are dummy coded to reflect possible non-linear effects on the probability of choosing a contract. The number of days of external control due to extreme occasions and the annual compensation are, instead, assumed to have a linear effect on the choice of contract. In general, the MNL and RPL specifications produce similar results with a few exceptions. In the MNL, the parameters for all attributes, except for information sharing, are statistically significant and have the expected signs. "Heating 7-10am" is not significant in the RPL model, while the information attribute is by comparison to the MNL specification. Turning to the heterogeneity across respondents, the standard deviations for the random parameters in the RPL are all statistically significant. Furthermore, all standard deviations, but for the extreme occasions, are assumed to be normally distributed. The elaboration on the standard deviations revealed that a triangular distribution better represents the preferences for the extreme occasions attribute.[10] Given the log likelihood value and the AIC measure, it is clear that the RPL specification is preferred to the MNL from a statistical perspective. Therefore, most of the discussion and analysis of results are based on the RPL estimations. Finally, by normalizing the coefficients with the one for compensation, a monetary value is derived for each of the attribute levels. The values reflect the mean marginal willingness to accept for each respective attribute level. Note that a positive value means that the respondent needs a compensation corresponding to that value to accept a change from the case of no external control.

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[9] Halton draws are more efficient than standard random draws. Still, although as few as 25 draws may produce stability and 100 draws produce good coverage, larger numbers such as 1000 are typically found in the literature (see e.g. Bhat (2001) and Train (2003) for a more thorough discussion on this topic).

[10] In alternative specifications, i.e. the interaction-models, significant heterogeneity was found. Given no prior knowledge on preference heterogeneity, the triangular distribution turned out to work better than the normal distribution.

In Table 3 it can be seen that all significant attributes of the contracts relating to systematic control of the households energy use and information sharing contribute negatively to utility (i.e. the choice of contract). The negative impact on utility is expected as external control prevents people from using energy when they want to. The compensation needed to accept the respective restriction lies in the range between SEK44 to SEK1,409. The control of domestic heating 7-10am does not significantly affect respondents utility and one possible explanation may be that people go to work during these hours and the decrease in indoor temperature happens with a delay and reach its lowest level at 10am or later. People are normally at home in the evening and may therefore experience discomfort by temperature fluctuations during those hours. On average, people require SEK643 to accept external control of their heating system during the evening peak hours.

The results show that more disutility is placed on not being able to use certain electrical appliances and installations at all times of the day compared to not having full control over the heating system. Again, most discomfort is attached to constraints during the evening peak hours. The control of household electricity during the evening peak requires SEK1409, while the morning hours require SEK833. Turning to the attribute related to accepting external control during extreme occasions, the respondents show preferences for a compensation corresponding to SEK44 per day of "extreme occasions". Still, it is important to recall that the interval of possible number of days is up to ten in the choice design, meaning that that any extrapolation beyond that may give questionable predictions.

The attribute reflecting peoples preferences for sharing information about their electricity consumption and the comparing with their peers has a significant and negative effect on the probability of choosing a contract. The discomfort from sharing information, and perhaps revealing relatively wasteful behavior, corresponds to a compensation of SEK243. Finally, turning to the alternative specific constant (ASC) it is specified such that it reflects any preference for the status quo alternative relative to the other two generic alternatives. The results show that this effect is significant and also constitutes a substantial amount of money corresponding to about SEK3,000. Although the simple interpretation is that people in general need a monetary compensation of this amount to even consider anything else than the status quo, this result will be further elaborated on in the next subsection.

Tabell 3. Parameter estimates and willingness to accept – main effects model.

Attributes	MNL	RPL		Willingness to accept, SEK [a]	
	Coeff (s.e.)	Coeff (s.e.)	Std dev	MNL	RPL
Heating, 7-10 am	-0.1971***	-0.015	0.687***	597**	24
	(0.0723)	(0.124)	(0.173)	(248)	(204)
Heating, 5-8pm	-0.2749***	-0.405***	0.424***	833***	643***
	(0.0500)	(0.091)	(0.216)	(208)	(157)
Domestic electricity, 7-10am	-0.2280***	-0.524***	0.486**	691***	833***
	(0.0667)	(0.101)	(0.221)	(189)	(141)
Domestic electricity, 5-8pm	-0.3464***	-0.887***	1.058***	1049***	1409***
	(0.0594)	(0.105)	(0.137)	(194)	(161)
Extreme occasions/day	-0.0203***	-0.274***	1.085**	61***	44***
	(0.0064)	(0.099)	(0.574)	(21)	(17)
Information, yes	-0.0297	-0.153**	1.071***	90	243**
	(0.0487)	(0.079)	(0.108)	(150)	(123)
ASC (status quo)	0.3301***	1.754***	4.927***	-2701***	-2788***
	(0.0307)	(0.217)	(0.258)	(250)	(336)
Annual compensation	0.8917***	0.629***			
	(0.0750)	(0.049)			

Log-likelihood	-5351,657	-3782.749
Restricted Log-likelihood		-6051.156
McFadden Pseudo R^2	0,018	0.375
AIC	1,946	1.379
BIC	1,956	1.397
No. of respondents	918	918
No. of observations	5508	5508
No. of Halton draws		1000

***, **, *: Significant at 1, 5 and 10%-level, respectively.
[a] Estimated by the Wald command (Limdep), Krinsky-Robb method with 1000 draws. SEK/€≈9.

Although the results in Table 3 are interesting and policy relevant as such, it also gives rise to additional and new relevant questions and research topics. From the results of the RPL, it is obvious that there exist preference heterogeneity around the mean of the random parameters, which can be further elaborated on. In the next two sub-sections the focus is on possible interaction effects related to socio-economic factors.

4.2 Preference heterogeneity and the status quo contract

There are many potential reasons to why some respondents choose the status quo (SQ) contract. The most straightforward reason is perhaps that it is the most preferred alternative in the choice set. For some, the compensation offered may simply be too small relative to the disutility (discomfort) from being restricted in energy use or the potential information sharing. In addition, the literature on behavioral economics suggests that people are generally inclined to retain SQ when faced with complicated and/or risky options. The underlying reason could be related to risk- and loss aversion, regrets, omission bias or psychological commitment in some form. Furthermore, the SQ-contract may also be seen as the easy way out of the choice situation. Finally, it may also be that the SQ-contract is a protest against the choice experiment or research question as such.[11]

To better understand, and possibly explain, the SQ-responses Table 4 shows the results from a model including interactions between the ASC for the SQ and socioeconomic factors. The socioeconomic factors in this specification relates to age, income, gender, family type, type of residence, type of heating system, current indoor temperature, education and weather being at home during typical peak hours. In addition, potential correlation between the choices of SQ and if the respondent has stated "green" preferences, or being politically active, is tested for.

In line with related literature (see e.g. Moon, 2004; Boxall et al., 2009), the results suggest that age is positively correlated with the choice of SQ. The positive correlation is also found for household income and people living in apartments. Perhaps, people living in apartments may find the choice of electricity contract more challenging and potentially irrelevant. For example, people living in apartments may, to a less extent, have a dishwasher, a washing machine or floor heating, making it more difficult to relate to the hypothetical contracts. There may also be other reasons, e.g., lifestyle issues or that those who live in the apartment buildings may have less control over the indoor temperature to begin with.

The results also show that respondents with children (0-12 years old) college education, members of environmental organizations and those who are politically active are less likely to opt for the SQ-

[11] See a more thorough discussion on status quo bias in Boxall et al., 2009.

option. The result for children is perhaps surprising given that external control may increase the discomfort of not being able to clean clothes or dishes at all times. The result concerning educational level is in line with previous studies that explicitly analyze SQ-bias (Moon, 2004; Boxall et al., 2009). An explanation for this result may be that well-educated people may find it easier to make trade-offs between different attributes and realize the benefits of opting for an alternative contract. When it comes to "green" people and politicians, the results mean that these people are more inclined than the representative respondent to opt for something else than SQ. Perhaps such respondents see a wider value for the society via e.g., increased opportunities for renewable energy or reduced dependence on fossil fuels.

Table 4. The status quo effect and socioeconomics.

Attributes	Main effects RPL		Status quo interactions	
	Coeff (s.e.)	Std dev (s.e.)	Interactions*SQ	Coeff (s.e.)
Heating, 7-10 am	-0.056 (0.129)	0.700*** (0.169)	Age	0.023* (0.014)
Heating, 5-8pm	-0.402*** (0.094)	0.434* (0.227)	Gender	-0.245 (0.388)
Domestic electricity, 7-10am	-0.534*** (0.106)	0.562*** (0.207)	Household income	0.135* (0.069)
Domestic electricity, 5-8pm	-0.863*** (0.109)	1.055*** (0.145)	Adults	0.300 (0.509)
Extreme occasions	-0.307*** (0.101)	0.744 (0.794)	Children, 0-12 years	-0.437 (0.631)
Information, yes	-0.132*** (0.081)	1.052*** (0.112)	Apartment	1.128** (0.451)
ASC (status quo)	-0.540 (1.035)	4.785*** (0.258)	Electric heating	0.252 (0.789)
Annual compensation	0.627*** (0.050)		High indoor temperature	0.011 (0.457)
			High education	-0.916** (0.399)
Log-likelihood	-3519.596		Home, 7-10am	0.499 (0.450)
Restricted Log-likelihood	-5635.881		Green preferences	-0.973*** (0.419)
McFadden Pseudo R^2	0.376		Politically active	-1.963*** (0.663)
AIC	1.383			
BIC	1.417			
No. of respondents	855			
No. of observations	5130			
No. of Halton draws	1000			

***, **, *: Significant at 1, 5 and 10%-level, respectively.

4.3 Preference heterogeneity within attributes

It is reasonable to believe that observable socioeconomic factors partly help explain the heterogeneity around the means of the random attribute parameters. To decide which interaction terms to include, the basic model (Table 3) was tested for preference heterogeneity around the mean of one attribute at the time. A model including all significant (or close to significant) interaction terms were then estimated

(Table 5).[12] It should be noted that each attribute level has been interacted with a unique set of interaction terms although all sets included age, gender, household income, adults, children and apartment. The attributes related to heating have been controlled for indoor temperature and whether the household use electric heating. While almost all respondents stated that someone in their household usually is at home 5-8pm this is not the case for 7-10am. If people are in their homes when the energy use is controlled, more discomfort is to be expected.

The first part of the results is the main effects from the respective attribute level. The reduced explanatory power is, in general, more or less expected given that the interaction effects capture much of attribute significance. The more extensive and potentially interesting part of Table 5 relates to how socioeconomic factors explain preference heterogeneity. The interaction coefficients reported in Table 5 are not exclusively significant at the ten percent level. All reported coefficients did however show a tendency to vary systematically with respondents' preferences for attribute levels in the estimations underlying the final interaction model. As can be seen in Table 5 there is no general preference heterogeneity related to the socioeconomic factors (such as a general age or income effect).

The socioeconomic variables cannot help explain, at any reasonable statistical significance, the heterogeneity underlying the preferences related to control of heating 7-10am. Turning to the preferences for control of heating 5-8pm, the household income and indoor temperatures of more than 22 degrees Celsius seem to have a negative impact. On the other hand, if there is more than one adult in the household it has a positive effect on the preferences for the control of heating 5-8pm. Turning to the control of domestic electricity use it is found that age, gender and being at home are significant factors underlying the preferences. Specifically, older people are less negative to being controlled with respect to household electricity during all times, while women and households where someone is at home 7-10am are more reluctant to being controlled 7-10am. The latter two findings are to some extent expected given basic intuition and that women to a larger extent do household related work. It is also found that richer people experience more discomfort from control due to random extreme occasions. Finally, the results show that heterogeneous preferences concerning information sharing with the purpose of peer comparisons are negatively correlated to age, if there are more than one adult in the household and if the respondent lives in an apartment. The underlying reasons for these results are not obvious although older people perhaps are less used to sharing personal information in general. In addition, people living in apartment buildings may be more exposed to peer comparisons in the neighborhood since physical and technical conditions in the apartments are identical or very similar.

[12] It should be emphasized that signs and significance levels remain stable moving from the individual attribute variable models to the final model.

Table 5. Attributes and socioeconomics

Attributes	Main effects RPL		Attribute-to-socioeconomic interactions RPL	
	Coeff (s.e.)	Std dev	Interactions	Coeff (s.e.)
Heating, 7-10 am	-0.323* (0.187)	***	Heat, 7-10am*Adults	0.316 (0.208)
Heating, 5-8pm	-0.318 (0.194)	*	Heat, 7-10am*Children (0-12y)	0.328 (0.240)
Domestic electricity, 7-10am	-1.518*** (0.308)	**	Heat, 5-8pm*Household income	-0.046** (0.023)
Domestic electricity, 5-8pm	-1.563*** (0.340)	***	Heat, 5-8pm*Adults	0.535*** (0.197)
Extreme occasions	0.234 (0.224)	*	Heat, 5-8pm*Electric heating	-0.433 (0.297)
Information, yes	0.962*** (0.351)	***	Heat, 5-8pm*High indoor temp	-0.295* (0.177)
ASC (status quo)	1.681*** (0.222)	***	Dom. el., 7-10am*Age	0.021*** (0.005)
Annual compensation	0.628*** (0.051)		Dom. el., 7-10am*Gender	0.262* (0.157)
			Dom. el., 7-10am*Home, 7-10am	-0.457** (0.178)
Log-likelihood	-3508.233		Dom. el., 5-8pm*Age	0.015*** (0.005)
Restricted Log-likelihood	-5635.881		Dom. el., 5-8pm*Apartment	-0.182 (0.176)
McFadden Pseudo R^2	0.378		Ext. occ.*Household income	-0.056** (0.022)
AIC	1.380		Ext. occ. *Apartment	-0.209 (0.162)
BIC	1.421		Information*Age	-0.011** (0.005)
No. of respondents	855		Information*Adults	-0.495*** (0.180)
No. of observations	5130		Information*Apartment	-0.328* (0.177)
No. of Halton draws	1000		Information*Electric heating	-0.487 (0.321)

***, **, *: Significant at 1, 5 and 10%-level, respectively.

5. Summary and discussion

Considering the topical discussion within the EU regarding balancing production- and consumption of electrical power, it is easy to see merits in policy measures stimulating consumer flexibility. In this paper we have estimate the disutility people experience from being systematically controlled with respect to their daily energy use. Specifically, a choice experiment has been applied to analyze the case of direct management of consumer energy use during certain time periods such as daily peak hours and cold periods. The choice questions included hypothetical contracts characterized by attributes related to restrictions regarding energy use and information dissemination. By choosing among contracts the respondents implicitly revealed their stated preferences for not adjusting their energy use according to the stipulated restrictions. Besides the control of heating and household appliances, the hypothetical contracts included an attribute regarding information on household electricity use for purpose of peer comparisons. A monetary annual compensation was included, which also made it possible to express preferences in terms of monetary measures.

From other studies it is known that the consumption of (demand for) electricity follows a pattern over time. Besides the seasonal patterns, there are demand peaks in the morning when people get up and make breakfast, and in the evening when people turn on their stove, dishwasher, washing machine etc. Realistic scenarios of demand management would therefore imply turning off the dishwasher, domestic heating, etc. during certain hours, which, in turn, would affect people's utility and comfort.

The results are in general rater expected and overall predict that consumer flexibility is associated with high costs. Turning to the explicit monetary compensations for each attribute level, it is interesting to find rather substantial values. Most types of external control correspond to monetary values of several hundreds SEK, which should be contrasted to the margins and potential efficiency gains at the market level. It is more or less unrealistic to imagine these amounts of monetary compensations in a real world policy implementation. Nevertheless, the results give that any future reform, or expectations related to price response, needs to consider the potentially high cost of creating flexibility.

In line with the results in Torriti (2012) it is found that people are less flexible in their evening energy use and thus requires relatively higher compensations to reschedule their energy use than for the morning hours. The results also show that people ask for more compensation to accept restrictions in their use of domestic electricity, compared to having their heating system controlled. On average people require a relatively small compensation (SEK44 per day) for accepting external control at random extreme occasions. Given that this estimate can be interpreted as the willingness to accept a controlled, and limited, blackout, it is comparable to the willingness to pay for reduced risk of blackouts estimated by Carlsson and Martinsson (2008).

Turning to the socioeconomic factors explaining preference heterogeneity, it is not easy to find a general pattern. Still, the respective attribute level and the corresponding socioeconomic factors illustrate interesting and important preferences among the Swedish population. It is found that the control of domestic electricity use concerns older people less than younger. The explicit reason for this result is of course unknown, although a speculation is that older people are less dependent on, or less used to, household electricity use in terms of dishwashers, washing machines, towel dryers etc. On the other hand, older people seem to experience relatively more disutility from sharing personal information about their energy use with other households. An explanation for the latter may be that younger people are more used to having private information spread on the Internet etc. Another potentially interesting result is that households with more than one adult in the household are less concerned about the control of heating 5-8pm, while more concerned about the information attribute. People living in apartments are also more concerned about the information attribute and a possible explanation for this fact is that such respondents may live closer to the people with whom they compare themselves to, and hence experience a higher social cost.

To conclude, the future power market is challenged by deregulations, new technologies and changes in the production mix via e.g. intermittent production, and a key to manage such challenges is demand side flexibility. This study finds that the compensation needed to systematically "reschedule" and control the household electricity use is considerable and measures to hundreds and thousands of SEK annually. Moreover, the "price" for demand flexibility largely depends on when, how and about what households we think of. Finally, it is important to keep in mind that the results are found in a somewhat stylized framework focusing on demand management on the Swedish market, and any conclusions about consumer flexibility and preferences under different circumstances must be made with this in mind.

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8. Appendix – an example of a choice question

Question XX

Which contract, A, B or C, would be your choice? Everything not given by the suggested contracts are as it is today, e.g. with respect to price and type of contract. Mark one of the contracts.

	Contract A	**Contract B**	**Contract C – as today**
EXTERNAL CONTROL OF HEATING, MONDAY-FRIDAY	5pm-8pm	7am-10am	No
EXTERNAL CONTROL OF DOMESTIC ELECTRICITY, MONDAY-FRIDAY	7am-10am	No	No
EXTERNAL CONTROL IN EXTREME CASES	No	Max 10 days	No
DISTRIBUTION OF INFORMATION	Yes	No	No
COMPENSATION (SEK PER YEAR)	1 500	750	0
My choice (mark)	[ ]	[ ]	[ ]