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Opening the black box of demand response: Exploring the cognitive processes

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A R T I C L E I N F O

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A B S T R A C T

Evaluations of price-based demand response programs tend to focus on users' electricity use patterns and/or their practical experiences. Less is known about the effects that price-based demand response programs have on cognitive drivers and barriers to energy-using behaviors and habits, or how well these predict timing of households' electricity use. This study seeks to address this gap by evaluating the effects of a mandatory demand-based time-of-use distribution tariff, using electricity-meter and questionnaire data in an intervention and a reference area, and a structural equation model following the theory of planned behavior. Although no effect was found of the tariff on the actual proportion of peak-hour use, there were significant effects on users' intentions and motivations to shift electricity use to off-peak hours. The absence of effect on the proportion of peak-hour use seems explained by the facts that only a minority of consumers were aware of their tariffs, and by the (at least partially correct) beliefs that consumers used very little electricity and most of it was already used in off-peak hours. The relationships between intentions, drivers and the actual proportion of peak-hour use were stronger in the intervention area, compared to the reference area. Interestingly, this was true not only for the motivation targeted by the tariff, economic savings, but also for sustainability concerns and social norms. This suggests that effects of the tariff may partly run via other non-monetary motivators.

1. Introduction

Energy systems are conventionally dominated by large, well-established companies and characterized by centralized, high technology power generation. The transition to more energy-efficient, low fossil and climate smart economies, however, calls for more decentralized and open energy systems that involve all of society. The active and flexible energy user - who helps to optimize, alleviate bottlenecks and maintain balance in the system —is considered to be an important piece of the puzzle in realizing future energy systems [1].

Price-based demand response programs [2] have become popular tools in the quest for an increased demand side response (DSR) - that is, the use of time-varying rates to incentivize users to alter the timing of their electricity use. Various time-varying rates have been implemented and tested in many corners of the world and a many studies report their effects. Summarizing studies suggest that time-varying rates induce reductions in users' peak electricity demand [3]. In-depth investigations of what users actually do in response to time-varying rates suggest that they engage in several acts, such as altering the timing of when they use electrical appliances, changing how they achieve certain goals like keeping warm or cool, and automating certain functions/activities in their home [4–6].

There is, however, a large variability in the magnitude of reported peak demand reductions, both between and within different types of time-varying rates (see e.g. Refs. [3,7]). Attempts to explain why time-varying rates work the way they do usually focus on the impact of socio-demographic and intervention-related variables—such as the peak to off-peak price ratio and use of enabling technologies [3,8]. The psychological processes that govern peoples' decisions about whether and how to alter their electricity-related behaviors, habits, and routines in response to time-varying rates are not as frequently considered. Nor are the effects that time-varying rates may have beyond those which are visible in electricity use data.

Energy use patterns are largely the result of habits and routines governed by the social organization of users' everyday lives, such as when they go to and come home from work, pick up children at school, devote time to leisure activities etc. (e.g. Refs. [9,10]). To understand

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Abbreviations

DSR	demand side response
TOU	time-of-use
SS	Sample size
RR	response rate
TPB	Theory of planned behavior
SEM	structural equation modelling
kWh	kilowatt-hour

why and why not users choose to alter these habits and routines in response to time-varying rates, attention needs to be paid to psychological mediators involved in the "activation phase" - where users' habitual energy-using activities are brought into the cognitive realm, evaluated and possibly re-shaped before returning to a more habitual state [11].

The cognitive processes governing energy conservation behavior have been studied quite a bit (for reviews, see e.g. Refs. [12–14]). However, as saving energy and engaging in DSR are two different things and since there are not that many studies on the cognitive processes governing users' engagement in DSR, less is known about which cognitive processes are involved in users' decisions on whether and how to respond time-varying rates and how these processes affect their actual response. This currently limits understanding of how and why demand response programs work, and what can be done to increase their effectiveness.

1.1. Purpose

The purpose of this study is twofold: first, to explore how a mandatory demand-based time-of-use (TOU) distribution tariff has affected the timing of householders' electricity use and second, whether various cognitive mediators of relevance to users' engagement in DSR have been affected. This is done through a cross-sectional comparison of electricity use and questionnaire data collected from users who live in a Stockholm suburb where such a tariff was implemented at the end of the 1990s (henceforth the "intervention area") and users who live in a socio-demographically similar area without time-varying pricing (henceforth the "reference area"). In relating householders' actual electricity use to their beliefs surrounding DSR, and motivators to engage (or not) in DSR, we seek to understand how these cognitive mediators might drive or hinder a change in the timing of their electricity use. In relating householders' actual electricity use to their beliefs surrounding DSR, and motivators to engage (or not) in DSR, this study seeks to understand how these cognitive mediators might drive or hinder a change in the timing of their electricity use.

1.2. Cognitive processes underlying energy conservation and pro-environmental behavior

In this section, research covering cognitive processes involved in energy-related behavior is reviewed, including studies into re-configuration of habits and routines. While studies on the cognitive processes that mediate (or fail to mediate) between time-varying rates and actual behavior change is scarce, there are many studies on cognitive processes underlying energy conservation behavior (for reviews, see e.g. Refs. [12–14]). Hence, this review starts with a look at cognitive processes underlying energy conservation, as well as pro-environmental behavior in general, before moving on to studies that address the cognitive determinants of demand side response specifically.

Already three decades ago, Stern [15] reviewed what was then the state-of-the-art psychological research on households' energy use and conservation behavior, and concluded that the often used policies based on monetary incentives and information were not as straightforward in their effects as policymakers assumed. Nearly two decades later, in a paper focusing on climate change mitigation behavior, Stern [16] reiterated that financial incentives, although sometimes effective, often are not as efficient behavior changers as economic models would predict. External factors (physical, technological, economic etc.) need to be complemented by internal factors (knowledge, attitudes, etc.) in models of behavioral change. In his review, Stern describes how psychology has contributed to the field by suggesting (and testing) the role of internal factors such as attitudes, subjective norms, values, and normative influences.

Abrahamse and Steg [17] explored determinants of energy use among a sample of Dutch households and concluded that although socio-demographic variables can predict overall energy use, changes in energy use rather appear to be related to cognitive variables. The specific cognitive variables under scrutiny were the intention to perform an energy saving behavior, attitudes toward the behavior, subjective norms, and barriers to perform the behavior as well as a sense of moral obligation to perform that behavior. Similarly, Wang et al. [18] found that attitudes, subjective norms and perceived behavioral barriers affected electricity saving behavior. In a review covering 38 studies on energy-saving interventions, Abrahamse and colleagues [12] suggested that next to testing if an intervention is effective, one should evaluate the effects on changes in underlying cognitive processes that determine behavior, including causal relationships between such changes and actual behavior, and whether the effects are sustained over time. One of their conclusions was that providing people with information may not affect their behavior directly, but rather indirectly by changing levels of knowledge. A study by Ek and Söderholm [19] found that costs (savings), environmental attitudes and social interactions were determinants of (self-reported) energy savings.

Taking a step back from energy use specifically, there have been many studies looking at the determinants of so-called "pro-environmental behavior" in general. For example, Bamberg and Moser [20] combined data from 57 studies in a meta-analysis to see what could predict these kinds of behavior. Their results suggested that pro-environmental behaviors were best predicted by people's intentions to perform the behaviors—with intentions being predicted by perceived behavioral control, attitudes, and personal moral norms (here, a sense of responsibility). The meta-analysis by Klöckner [21] confirmed the findings of Bamberg and Moser [20] - i.e. that perceived behavioral control, attitudes, perceived social norms and personal norms were predictors of intentions to act pro-environmentally - while adding that habits are another important determinant of pro-environmental behavior.

The take-home message from the reviewed studies is that the active engagement in energy conservation and pro-environmental behaviors is, to a large extent, determined by psychological mediators, and that the effects of such mediators can be measured. Another take-home message is that concepts like attitudes, subjective norms, perceived barriers and intentions to act are recurring frequently in scientific literature, and thus candidates for possible behavioral determinants that may explain users' engagement in DSR.

1.3. Cognitive processes underlying demand side response

While there is an ample supply of studies focusing on the effects of time-varying rates on electricity use, there is less research on cognitive processes that mediate between time-varying rates and users' engagement in DSR. This section aims to provide an overview of studies on this topic.

Heberlein and Warriner [22] studied the effects of a TOU tariff with different price ratios on users' knowledge, attitudes and behavior. They found an effect of price on behavior (higher price ratios resulted in less on-peak electricity use), but a stronger effect of their moral commitment to shift their energy use in time—which in turn related to their knowledge of TOU tariffs and strategies on how to respond to them. Bradley, Coke and Leach [23] looked at the effects of incentive-based demand response programs [2]—where householders could receive a remuneration in the end of a trial by shifting their electricity use to off-peak hours—and the barriers to engage in DSR that householders perceived when subjected to such programs. They found both technological and psychological barriers, like competing values, limited knowledge and perceived loss of comfort or lifestyle changes.

Hall, Jeanneret and Rai [24] performed a survey to explore users' preferences regarding, and perceptions of, different time-varying rates. They found that about half of the respondents were willing to adopt a time-varying rate, although their understanding of peak electricity demand and its impact on electricity pricing was low. Some of the perceived barriers to engaging in DSR that were identified were: not being home during off-peak hours and a perceived difficulty breaking energy-using habits. They did not, however, evaluate whether any of the proposed rates affected user behavior or any other cognitive variable. A similar study on the willingness of people to switch to TOU tariffs was conducted by Nicolson, Huebner and Shipworth [25]. They found that over a third of their sample proved willing to shift to a TOU tariff, and that willingness was lower among participants who were loss averse and higher among those who owned flexible loads (electric vehicles and tumble dryers with timers).

What these examples suggest is that there are cognitive aspects mediating whether people adapt their electricity use to demand response programs. However, most studies fail to connect reported cognitive mediators to actual observable behavior (changes in electricity use), whereby there is still much to learn about the actual impact of these mediators. By doing so, this studycontributes to improvements in the design of demand response programs to increase user engagement in DSR.

2. Materials and methods

2.1. Empirical setting

The study compares households' electricity use patterns and attitudes toward DSR between two inner-city suburbs of Stockholm that have similar characteristics — an "intervention area" and a "reference area". A mandatory demand-based TOU distribution tariff was introduced in the intervention area at the end of the 1990s, whereas the reference area still has a traditional non-time-differentiated energy-based (i.e., volumetric) distribution tariff. The TOU tariff entails that users' distribution-related electricity costs[1] are based on the average of the three highest hourly meter readings (kWh/h) during peak hours in any one month, which are defined as the hours between 7:00 a.m. and 7:00 p.m. on weekdays. All other hours are defined as off-peak hours, during which the distribution of electricity is free of charge. The rate is lower in the summer season (defined as April–October) than in the winter season. The tariff in the reference area entails that the users' distribution-related costs are based on their total electricity use (kWh) during any one month, meaning that their costs are independent of when they use their electricity.

Since the deregulation of the Swedish electricity market in 1996, the supply of electricity (i.e., the retail business) is subjected to competition whereas the distribution of electricity is still a regulated monopoly. This means that, besides the costs associated with the distribution of electricity, the total electricity costs of users also encompass costs related to the supply of electricity, energy taxes, VAT and other fees. The relative distribution of costs between these categories depends on the individual users' distribution tariffs, supply contracts and use patterns. On average though, the fiscal, supply and distribution costs make up about 45, 30 and 25% respectively of the total costs that Swedish electricity users pay [26].

2.2. Sampling and data acquisition

Two stratified random samples were drawn by the distribution system operator in each area, consisting of 1500 households from each area with an equal distribution of single-family homes, condominiums and rental apartments. The areas were chosen based on their socio-demographic and infrastructural similarity, and the sampling was performed so that the households were equally divided between three different forms of housing: single-family homes, condominium, and rental apartments. Hourly electricity use data were extracted for each household, representing the period of the November 1, 2012 to the October 31, 2013. Though the intervention area was introduced to the TOU tariff already in the 1990s, the current study analyses whether there are differences between this area and a reference area at a later stage (i.e., the investigated timeframe). The aim was not to follow the changes from an implemented TOU over time, but to compare an area with to an area without TOU, after a period during which households can be expected to have adjusted to the new tariff.

Due to the unintentional inclusion of some non-residential users and summer houses, and a few incomplete electricity use time-series, the final number of households included in the analyses became somewhat smaller, and the distribution between the areas and forms of housing somewhat less even than initially anticipated (see Table 1).

A paper-based self-completion questionnaire, along with a cover letter including contact information, a prepaid return envelope and an appendix providing more information on the background and aim of the study, was sent to all households by mail. Two reminders were sent to those that had not replied by the given deadlines. As shown in Table 1, the overall response rate was 36.4 %, with a fairly even spread across the two areas, although with more respondents among single-family homes.

The questionnaire assessed the householders' perceived drivers and barriers to shifting their electricity use from peak to off-peak hours in response to a demand-based TOU tariff, if such a tariff would be in place. Although such a tariff was in place in the intervention area, the users were not told that it was, since one aim was to assess their awareness of the tariff and so that users in both areas could receive identical questions. The questionnaire included basic sociodemographic variables such as age, gender, income, educational level and number of family members, as well as a few questions on circumstances that may affect one's electricity use, such as the presence of major appliances and the occurrence of changes that might have had a significant effect on the electricity use pattern during the period in question (e.g. children moving out or exchange of the heating system). A detailed description of the questionnaire design is given under the heading "Questionnaire design".

2.3. The theory of planned behavior

Many of the psychological constructs revealed in this overview—such as user's attitudes, subjective norms, perceived barriers and intentions—are well-represented in the psychological field and are covered in various behavioral theories. One such theory is the widely used theory of planned behavior (TPB) [27,28], which stipulates that human behavior (in this case shifting the timing of electricity-using activities from peak to off-peak hours) is in many circumstances directed by an intention, which in turn is determined by attitudes, subjective norms (i.e. perceived social norms) and perceived behavioral control [29]. Attitudes refer to the expected consequences of any given behavior, such as that "*I expect to be saving money by doing the laundry during off-peak hours*". Subjective norms denote the extent to which the behavior at hand is perceived as being normal and/or expected in one's social environment, such as that "*my parents have always done the laundry during the day not to disturb the neighbors*". Perceived control refers to the degree to which one perceives being able to control a particular behavior, such as that "*I cannot do the laundry during off-peak hours in the evening, because I do not have time to hang it in the morning*". The basic

Table 1
Sample size (SS) and questionnaire response rates (RR, %) for the different areas and housing categories.

Housing categories	Single-family homes		Condominiums		Rental apartments		Total	
	SS	RR	SS	RR	SS	RR	SS	RR
Intervention area	451	48.0	494	36.7	497	25.8	1442	37.0
Reference area	512	44.0	487	35.6	414	27.7	1413	35.8
Total	963	46.2	981	36.1	911	26.8	2855	36.4

Table 2
Coefficients for the measurement equations of the structural equation model across the entire sample (both areas), linking the latent variables to the direct assessments of the TPB dimensions, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold.

	Latent variables (TPB constructs)				
Question[a]	Intention	Attitude	Subjective norm	Perceived behavioral control	R^2
15	**1.506** (0.095) 15.815				0.791
16	1.000				0.377
17		**0.964** (0.027) 36.021			0.798
18		1.000			0.810
19			**0.974** (0.046) 21.704		0.597
20			1.000		0.653
21				**1.011** (0.037) 27.242	0.861
22				1.000	0.853

[a] column refers to question numbers from questionnaire. The respective questionnaire items are: 15) The household intends to shift electricity use to off-peak hours in the future. 16) The household has shifted electricity use to off-peak hours during the last year. 17) The household perceives the consequences of shifting electricity use to off-peak hours as being... (very negative to very positive). 18) To shift electricity use to off-peak hours is perceived by the household as being... (very negative to very positive). 19) The [social] surrounding expects that the household shifts electricity use to off-peak hours. 20) Most [households] in the household's [social] surrounding are shifting their electricity use to off-peak hours. 21) It would be possible for the household to shift more of the electricity use to off-peak hours. 22) If the household wishes to, more of the electricity use can be shifted to off-peak hours.

structure of the TPB is summarized in Fig. 1.

2.4. Questionnaire design

The TPB is often used to structure self-completion questionnaires that tap into behavioral determinants (see e.g. Ref. [20]), and the current study followed that same approach, focusing on drivers of and barriers to householders' engagement in DSR in response to a demand-based TOU tariff.

According to the TPB, the behavior at hand is to be defined in terms of target, action, context and time [29]. In predicting a behavior, it is moreover essential that all questions relate to the particular behavior. The behavior of interest was defined as *shifting of electricity use to off-peak hours*, i.e., the target being electricity use and the action and time being shifting to off-peak hours. It is implicitly understood that the context is people's homes. This definition of the behavior in question was used throughout the questionnaire. In assessing the past and intended future performance of the behavior, the time frames "*during the last year*" and "*in the future*" were used respectively.

The questions that capture the different dimensions of the TPB should be specific, concrete and directly related to the behavior that is being studied, wherefore it is recommended that the questions are informed by qualitative explorations of the subject at hand [29]. To this end, two focus groups were conducted, one in the intervention area and another in a rural area, which had an almost identical demand-based TOU tariff. Both groups were comprised of about a dozen participants of different genders and various ages, with a slight under-representation of young adults and families with children. Based on the discussions, eighteen concrete factors were identified that were considered to motivate or impede householders to shift electricity use to off-peak hours, which formed the basis of the questionnaire.

The questionnaire was designed to capture both a direct assessment of their intention, attitude, subjective norm and perceived behavioral control, and an indirect assessment of their attitude, subjective norm and perceived behavioral control by measuring their behavioral, normative and control beliefs.

In conducting research according to the principles of the TPB, it has proven particularly fruitful to formulate questions in a value expectancy-like manner. That is, asking how important reaching any one "goal" is (e.g., lowering electricity costs) and how likely achieving the goal at hand is by performing a particular behavior (e.g., shifting electricity use to off-peak hours). Thus, the respondents were asked to evaluate the strength of concrete beliefs and motivators related to each of the TPB dimensions on a scale ranging from 1 (*very negative/not at all/not at all likely*, depending on the question) to 7 (*very positive/to a high degree/very likely,* depending on the question) for each belief and each motivator. The scores of each belief/motivator pair were then multiplied as a mathematical expected value. The product of each belief/motivator pair—which is henceforth referred to as a "belief component" to signify that these are the components that make up the TPB dimensions - thus amounted to a value between 1 and 49. By multiplying motivators and beliefs in this way, the interaction—which commonly exists between goal and means - is captured. If reaching a "goal" is unimportant, it will not matter whether the behavior is a good means of reaching it or not. A motivator will only become strong when the goal is important and the behavior is a sure means of reaching the goal.

Having the respondents assess motivators and beliefs separately onto two different scales also allowed us to get more reliable measures of the belief components and to use each of them as manifest indicators of latent variables (in this case, the TPB dimensions) in the structural equation model used for the analysis (described under the heading "Structural equation modelling").

The formulations of the motivators and beliefs within the perceived behavioral control-dimension had to be different, but the assessment scores were multiplied just as well. These belief/motivator pairs were composed of a question concerning the belief whether a certain barrier existed to shifting electricity to off-peak hours, and whether such a barrier is significant or weak. For two control beliefs, however, there were no questions on how strong of a barrier it was, because of the nature of these beliefs; they either are or are not a barrier. For example, "The household hardly uses any electricity", if true, is always a barrier to load-shifting. Therefore, the control beliefs that lacked a motivator counterpart were multiplied with the number 7 instead. The exact questionnaire as well as an English translation can be obtained from the corresponding author. Fig. 2 provides a schematic overview of how the questionnaire was structured in accordance with the TPB.

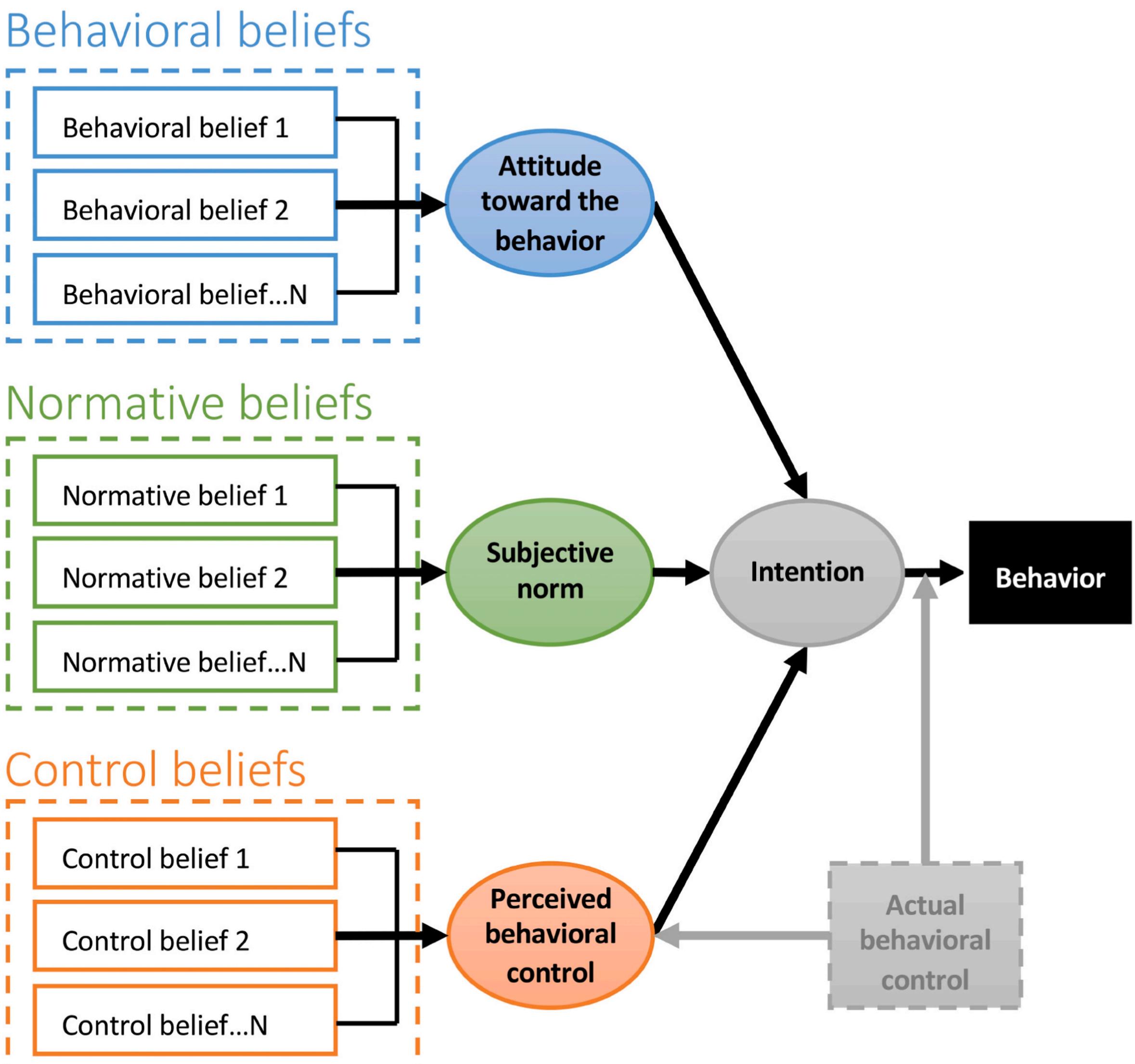

Fig. 1. Schematic representation of the theory of planned behavior, adapted from Ajzen [29].

2.5. Estimation of demand side response

The behavioral dimension of the TPB (to the far right in Figs. 1 and 2) was represented by data on the respondents' actual electricity use in the analysis. More specifically, the individual households' percentage of electricity use during peak hours, given by:

$$\frac{kWh\ between\ 7\ a.m.\ and\ 7\ p.m.\ on\ weekdays\ 1\ Nov\ 2012 - 31\ Oct\ 2013}{Total\ kWh\ 1\ Nov\ 2012 - 31\ Oct\ 2013} * 100(\%)$$

2.6. Structural equation modelling

To assess whether and how the respondents' intention, attitude, subjective norm and perceived behavioral control relates to their actual electricity use (percentage of electricity use during peak hours) structural equation modelling (SEM) was used. SEM, which is also known as covariance structure analysis or latent variable analysis, is a widely used statistical technique that can be used to assess the relationships among multiple interdependent variables, such as the ones at hand. A crucial difference between SEM and other multivariate techniques (such as multiple regression analysis) is that the relationships can be hierarchical, i.e., variables that are independent in one relationship can be dependent in another, which the variables of the TPB are. In simple terms, SEM combines factor analysis and multiple regression analysis to estimate a series of separate but interdependent multiple regression equations simultaneously while also accounting for measurement error [30].

In short, SEM is the most appropriate technique to use in a case like this, where one wants to assess complex interdependent relationships between a large number of variables while minimizing measurement error. An accessible introduction to SEM, including key terms and measures used to describe the fit and outcome SEM models, is given by Hair et al. [30]. The SEM analysis was carried out using the software LISREL [31].

3. Results

In the following, survey respondents' assessed strength of the eighteen beliefs are first presented. Thereafter, differences in intention and behavior between the users in the intervention and the reference area are presented. Finally, the degree to which the belief components predict the users' intention to shift electricity use to off-peak hours and their proportion of electricity use during peak hours is presented.

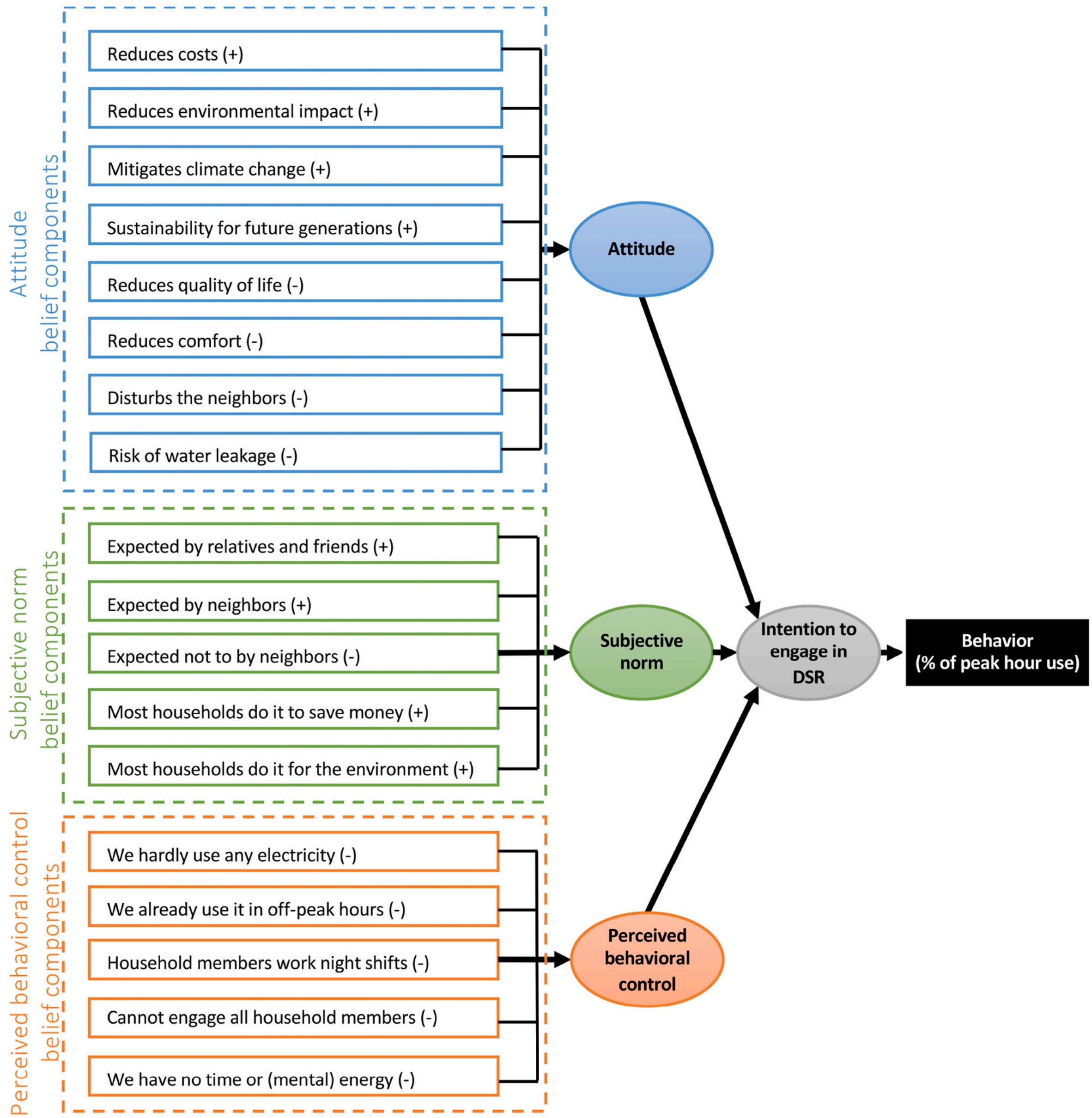

Fig. 2. Schematic representation of how the questionnaire was structured in accordance with the TPB. Each solid-line box in the diagram represents a belief component (i.e., the product of two questionnaire questions: the belief and motivator, except for the black box to the far right, which is represented by electricity use data.

3.1. *Drivers of and barriers to shifting of electricity use to off-peak hours*

As explained under the heading "Questionnaire design", the respondents were asked to assess the strength of eighteen pairs of motivators and beliefs related to the shifting of electricity use to off-peak hours. The mean scores of the belief components along with 95 % confidence intervals are presented in Fig. 3.

Differences in the mean assessed strength of each belief component between the reference and the intervention area are small with overlapping confidence intervals (see Fig. 3). The differences between the different belief components themselves within the respective areas are however large and significant in both areas. The strongest drivers to shift electricity use to off-peak hours (with mean scores of about 30) are the attitude belief components related to the will to contribute to a sustainable development for younger and future generations, reducing environmental impact and mitigating climate change. The strongest barriers to the same behavior were the perception that the household hardly uses any electricity (with mean scores of about 25) and the perception that the household's electricity use normally takes place mostly during off-peak hours (with mean scores of about 28). The subjective norm belief components were perceived as low motivators, whereas the belief targeted by the TOU tariff - that shifting electricity use to off-peak hours results in reduced electricity costs - turned out to be a moderately strong driver.

3.2. *Peak hour electricity use, intention to shift electricity use and tariff awareness*

The left panel of Fig. 4 presents the proportion of peak hour electricity use as a function of the area and housing category. It is evident that that there are no large or statistically significant differences in the proportion of peak hour electricity use in the two areas ($F(1, 961) = 1.43$; $p = .233$; $\eta^2 = 0.001$). Nominally the differences between the reference and the intervention area are well below one percentage unit in all three housing categories[2]. There is a statistically significant but small difference between the housing categories ($F(2, 961) = 44.97$; $p <$

Fig. 3. Mean assessed strength of the eighteen belief components (y-axis) on a scale from 1 to 49 (x-axis). The colors of the rows indicate which dimension of the TPB each belief component belongs to (attitude in blue, subjective norm in green, perceived behavioral control in orange). The black circles and blue crosses represent the mean score in the reference and intervention area respectively. Beliefs that increase and reduce motivation (i.e., drivers and barriers) are denoted with (+) and (−) respectively. The horizontal error bars represent 95 % confidence intervals. The eleven belief components in bold were the ones used in the SEM analyses (see the heading "Predictors of intention and behavior").

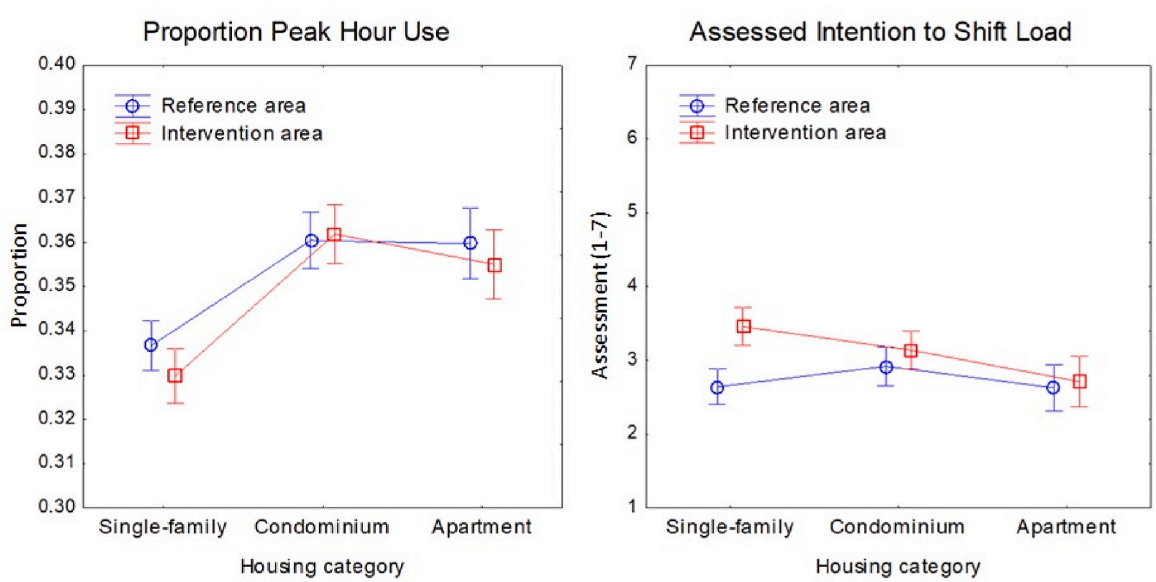

Fig. 4. Mean proportion of peak hour electricity use with 95 % confidence intervals as a function of area and housing category (left panel). Mean direct-assessed intention to shift electricity use to off-peak hours with 95 % confidence intervals as a function of area and housing category (right panel).

.001; $\eta^2 = 0.086$) in that the single-family homes have a slightly lower peak hour use than the other categories in both areas (app. 33 % vs. app. 36 %), but there is no statistically significant interaction ($F(1, 961) = 1.43$; $p = .233$; $\eta^2 = 0.001$).

In auxiliary analyses, several confounding factors that could conceal a difference between the reference and the intervention area were considered. The median household income was marginally higher in the reference area, but in the entire sample there was no large or statistically significant correlation between the household income and proportion of electricity use during peak hours ($r = -0.04$, $p = 212$), which means that there is no evidence for this alternative explanation. In the questionnaire, the households also indicated whether at least one member of the household was at home during daytime during the weeks, but these proportions were almost identical in the reference and intervention area (respectively 71 and 72 %, $p = .718$).

While there was no statistically significant difference between the areas in the households' proportion of electricity use during peak hours, there were significant differences in the householders' assessment of their intention to shift electricity use to off-peak hours (right panel, Fig. 4). There was a significant main effect of the area ($F(1, 1022) = 10.13$; $p = .002$; $\eta^2 = 0.010$) and the housing category ($F(2, 1022) = 3.78$; $p = .023$; $\eta^2 = 0.007$), and a significant interaction between the two ($F(2, 1022) = 3.99$; $p = .019$; $\eta^2 = 0.008$). In other words, while there is little difference in the assessed intention among condominiums and rental apartments, the single-family households in the intervention area assessed a significantly higher intention to shift their electricity use to off-peak hours than those in the reference area. In summary, although no difference can be seen in the proportion of electricity use during peak hours between the areas, there is a difference at the psychological level of intentions among the householders.

An absolute prerequisite for users to be able to adapt their electricity use to a price signal is that they are aware of its existence. However, the percentage share of households in the intervention area who (correctly) stated that they were charged according to a demand-based TOU tariff was only 33 % on average. The corresponding percentage share among single-family homes, condominiums and rental apartments was 48, 31 and 21% respectively. Four percent of the households in the reference area wrongly stated that they had a demand-based TOU tariff. These low rates of tariff awareness might help to explain the absence of a significant difference between the households' proportion of electricity use during peak hours in the two areas. The difference in rate awareness between the different types of households furthermore suggests that single-family homes are more aware of what they are paying for their use of electricity.

3.3. Predictors of intention and behavior

While Fig. 3 summarizes what the households themselves assessed to be the main drivers of and barriers to shifting the use of electricity to off-peak hours, the SEM-analyses reveal how well these belief components actually predict the householders' intentions and behavior—both as individual belief components and as constructs of the TPB. After inspection of the correlation matrix for all eighteen belief component scores (presented as means in Fig. 3), seven were removed before the SEM-analyses were run for one of two reasons: either they correlated too strongly with the other beliefs components and were thus redundant for prediction, or they did not correlate significantly with either the intention or the behavior. The eleven remaining belief components that were entered in the SEM-analyses are represented in bold in Fig. 3.

After list-wise deletion (i.e., removal of households that had not answered all the questions that were to be used in the SEM-analyses), the actual sample entered into the Multiple Indicators Multiple Causes (MIMIC) structural equation model was 707 households, of which 329 were from the intervention area (46 % single-family homes, 35 % condominiums and 19 % apartments) and 378 were from the reference area (43 % single-family homes, 35 % condominiums and 22 % apartments). Though this sample contained comparatively more single-family homes than the original sample (see Table 1), the proportions between areas are reasonably comparable. The matrix form of the model is given by

$$y = \Lambda_y \eta + \varepsilon, \eta = \Gamma x + \varsigma,$$

where $\boldsymbol{y}$ is an indicator vector including all the respondents' direct assessments of the TPB dimensions and their actual behavior (percentage of electricity use during peak hours). Vector $\boldsymbol{x}$ includes all the independent variables, which are the cause indicators of the latent variables (attitude, subjective norm and perceived behavioral control). $\boldsymbol{\eta}$ is the vector with the latent constructs of the TPB dimensions: intention, attitude, subjective norm, and perceived behavioral control. $\boldsymbol{\Lambda_y}$ is the factor loading matrix, $\boldsymbol{\Gamma}$ is the coefficient matrix. $\boldsymbol{\varepsilon}$ and $\boldsymbol{\varsigma}$ are errors terms. Fig. 5 provides a visual representation of the final structure of the model used for the SEM-analyses.

The parameters of the model were estimated using robust maximum likelihood estimation—first for the entire sample (Table 3), thereafter separately for the reference (Table 5) and the intervention (Table 6) area respectively. The resulting model provided satisfactory fit to the data for the entire sample ($\chi^2(109) = 193.506$; RMSEA = 0.0594; GFI = 0.950; CFI = 0.966; NFI = 0.951).

The factor loadings for the measurement equations presented in Table 2 suggest that all the direct assessments of the TPB dimensions are valid indicators of the latent variables (the TPB dimension constructs constructed from the belief components).

The coefficients indicating the causal relationships among the latent constructs shown in Table 3 demonstrate that across the entire sample, the householders' intention to shift their electricity use to off-peak hours significantly predicted their actual use of electricity in off-peak hours ($\beta = -0.717$; $se = 0.149$; $t = -4.797$; $R^2 = 0.042$). The intention to perform this behavior is in turn significantly predicted by the attitude and subjective norm, but not by perceived behavioral control—thus only partially confirming the original hypotheses of the TPB ($R^2 = 0.75$).

Our main interest in the SEM-analyses, however, lies in the differences between the reference area and the intervention area. To study the differences in the relationships among the latent TPB constructs between the two areas, a multi-group analysis (MGA) was performed. This analysis assumes that the measurement models are invariant over the groups. Hence, the factor loadings are constrained to be invariant for both areas (see Table 4 for these coefficients, which are similar to those for the entire sample presented in Table 2).

As Table 5 and 6 reveal, the coefficient from intention to behavior is significant in the intervention area ($\beta = -0.921$; $se = 0.208$; $t = -4.425$; $R^2 = 0.023$), but not in the reference area ($\beta = -0.457$; $se = 0.326$; $t = -1.402$; $R^2 = 0.004$). The results roughly correspond to the correlation between the householders' stated intention to shift their electricity use to off-peak hours and their actual percentage of electricity use in off-peak hours of 0.063 in the reference area and of 0.152 in the intervention area. These are by no means high correlations in absolute terms. Still, given the indirectness of the measurements, they nonetheless suggest that intentions are related to behavior, and more so in the intervention area where there is a demand-based TOU tariff. To verify the significance of the difference between the two areas, first a model was fitted assuming the same relations between the latent constructs in both areas, after which, in a second model, the relationship between intention and behavior was allowed to be different in the two areas. The χ^2 value reduced to 3.96, with the difference of one degree of freedom, which indicates that the second model provided a significantly better fit to the data, suggesting that the relationship between intention and behavior is indeed significantly stronger in the intervention area than in the reference area. In other words, the demand-based TOU tariff has affected the householders' intention to shift electricity use to off-peak hours.

As expected from the TPB, Table 5 shows that the intention is significantly predicted by the attitude, the subjective norm, and the

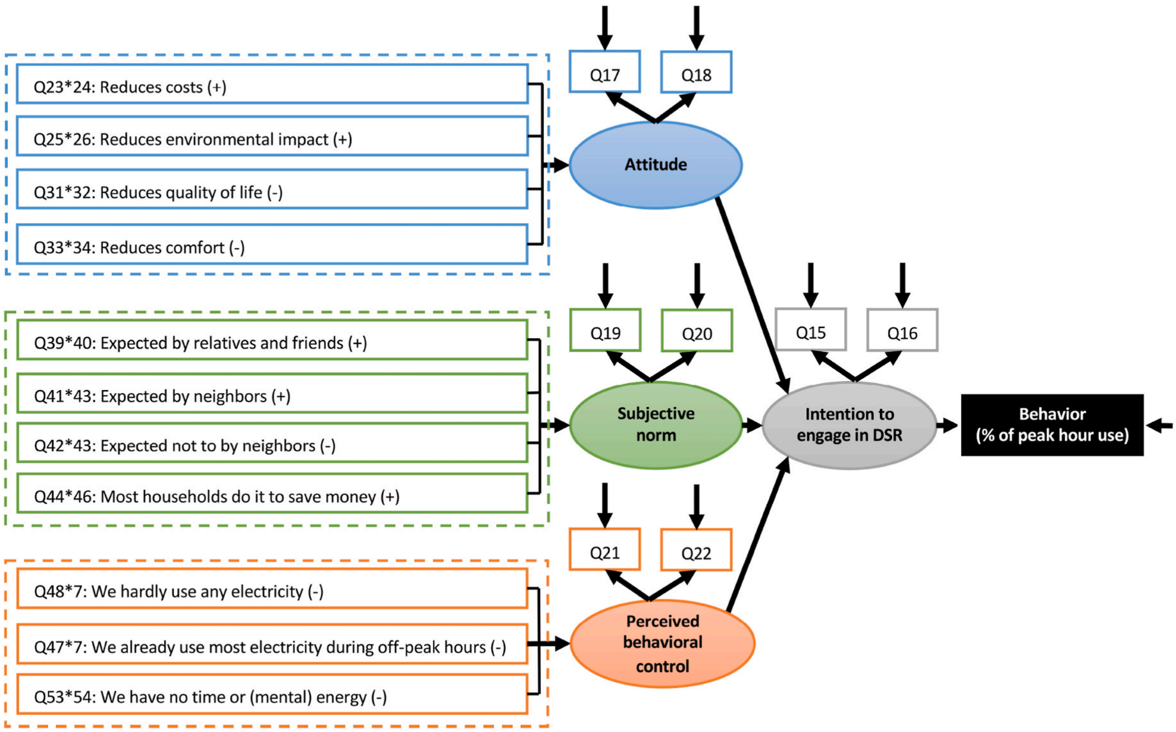

Fig. 5. The final structure of the model used for the SEM-analyses. The solid-line boxes in the left part of the diagram represent the eleven belief components used as independent variables in the model, and the ones above the oval-shaped TPB dimensions represent the direct assessments of each TPB dimension. Each square-shaped box contains a reference to the questionnaire question(s) they represent. The TPB dimensions intention, attitude, subjective norm and perceived behavioral control are oval-shaped to signify that they constitute latent variables in the model. The black box to the far right is represented by actual electricity use data (% of electricity use during peak hours).

Table 3
Coefficients for the structural equations of the structural equation model across the entire sample (both areas), linking the latent variables to the behavior, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold.

	Latent variables (TPB constructs)				
	Intention	Attitude	Subjective norm	Perceived behavioral control	R^2
Behavior (% of electricity use during peak hours)	**−0.717** (0.149) −4.797	-	-	–	0.0424
Intention		**0.503** (0.0623) 8.079	**0.241** (0.051) 4.752	0.0062 (0.0365) 0.169	0.750

Table 4
Coefficients for the measurement equations of the structural equation model used for the multigroup analysis reported in the main text of the article, linking the latent variables to the direct assessments of the TPB dimensions, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold.

	Latent variables (TPB constructs)				
Question[a]	Intention	Attitude	Subjective norm	Perceived behavioral control	R^2
15	**1.553** (0.127) 12.216				0.850
16	1.000				0.352
17		**0.986** (0.029) 33.525			0.821
18		1.000			0.789
19			**1.257** (0.078) 16.050		0.753
20			1.000		0.529
21				**0.958** (0.060) 15.850	0.837
22				1.000	0.946

[a] column refers to question numbers from questionnaire. See the tablenote in Table 2 for the exact questionnaire items.

perceived behavioral control in the reference area. However, the intention in turn is only weakly related to the behavior. While the intention significantly predicts the behavior in the intervention area (as shown in Table 6), the intention itself is only significantly predicted by the attitude and the subjective norm (and not the perceived behavioral control as in the reference area).

Additional exploratory analyses suggest that the non-significant effect of perceived behavioral control observed in the intervention area should be interpreted cautiously. Using a model fitted across both areas suggested that the effect of perceived behavioral control may not primarily be a main effect, but rather an interaction between perceived behavioral control and attitude on the intention This would suggest that the barriers (the perceived lack of behavioral control) do affect the intention to shift electricity use to off-peak hours, but only if the household has a positive attitude to perform the behavior in the first place. While this observation is potentially interesting, only the main effect models was reported (Table 5 and 6), as models incorporating interaction effects could not be reliably estimated, when analyzing the

Table 5
Coefficients for the structural equations of the structural equation model for the reference area, linking the latent variables to the behavior, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold.

	Latent variables (TPB constructs)				
	Intention	Attitude	Subjective norm	Perceived behavioral control	R^2
Behavior (% of electricity use during peak hours)	−0.457 (0.326) −1.402	–	–	–	0.004
Intention		**0.454** (0.041) 10.971	**0.249** (0.043) 5.826	**0.094** (0.023) 4.024	0.401

Table 6
Coefficients for the structural equations of the structural equation model for the intervention area, linking the latent variables to the behavior, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold.

	Latent variables (TPB constructs)				
	Intention	Attitude	Subjective norm	Perceived behavioral control	R^2
Behavior (% of electricity use during peak hours)	**−0.921** (0.208) −4.425				0.023
Intention		**0.526** (0.052) 10.123	**0.246** (0.048) 5.119	0.035 (0.026) 1.306	0.333

areas separately due to sample size constraints.

Table 7 reports on the structural equations of the model in reduced form, separately for the reference and the intervention area, with the direct path coefficients from each of the eleven belief components to the behavior. The coefficients associated with an absolute t-value larger than 2 were considered “statistically significant”, which corresponds to the 0.05 level for statistical significance used in conventional hypothesis testing. Comparing the columns for each area reveals a noteworthy difference: while there were no differences in regard to how the households themselves assessed the different belief components (Fig. 3), there is a difference between the areas in the degree to which the belief components predict the users’ proportion of electricity use during peak hours.

In the reference area, no belief component predicts the users’ proportion of electricity use during peak hours significantly. In the intervention area however, all four of the attitude belief components, and three out of the four subjective norm belief components, significantly predict the proportion of peak hour electricity use. Thus, in the intervention area, the degree to which a household perceived the consequences of engaging in, and social expectations to engage in, DSR predicted their actual proportion of electricity use during peak hours. It is worth noting that it is not only the motivation to reduce one’s electricity costs that predicts actual behavior. Households that are primarily driven by other motivations, such as environmental concerns, engage in DSR in response to the tariff just as well.

Although the households themselves assessed the perception that “we hardly use any electricity“ and “we already use it in off-peak hours” were strong barriers to engaging in DSR (see Fig. 3), the path coefficients from these belief components to the behavior are close to zero and not significant (see Table 6). As already noted, the effect of these barriers might have taken the form of an interaction with attitude (they operate only among respondents who see any point in shifting their electricity use in the first place), and these effects are not well captured by the current SEM-analysis. This suspicion is reinforced by further analyses of whether these beliefs may be correct. Investigating if households stating that they hardly use any electricity indeed use less electricity, and if households stating that the electricity use normally takes place mostly during off-peak hours indeed shows that this is the case. The correlation between the measured strength of the barrier “we hardly use any electricity” and the total amount of electricity used across users in both areas was $r_s(936) = -0.199$, 95 %, bias-corrected and accelerated confidence interval [-0.266, −0.135], $p < .001$. The correlation between the measured strength of the barrier “we already use it in off-peak hours” and the actual peak hour use of electricity was $r_s(945) = -0.253$, 95 %, bias-corrected and accelerated confidence interval [-0.311, −0.199], $p < .001$. The correlations are small in magnitude but suggest that there may be some degree of veracity in the respondents’ statements about these barriers.

In summary, although no evidence was found of a lower peak hour electricity use in the intervention area, there were clear and systematic differences between the areas at the level of intention to engage in DSR as well as in the strength of the underlying belief components, and the degree to which these predicted the proportion of peak hour electricity use. Interestingly, the motivation to save electricity costs is not the only, or even the strongest, motivator to respond to the tariff. A number of other motivators, that have little to do with the motive that the tariff is designed to appeal to, significantly predict the households’ time of use of electricity in the intervention area. Without an experimental design, there is no definitive way to attribute the observed differences between the areas to the fact that the intervention area has a demand-based TOU tariff, but it nonetheless remains the most compelling explanation.

The demand-based TOU distribution tariff does seem to have had an effect on the intervention area’s inhabitants, but for some reason, these effects have not translated into any noteworthy decrease in the households’ proportion of electricity use during peak hours (see Fig. 4, left panel). A clue as to the reasons for this weak effect might be that many of the households seem to believe—correctly or wrongly—that they consume very little electricity altogether or that they already use most of their electricity in off-peak hours. If these are your beliefs, then you likely will not care very much about a TOU tariff. Another possible explanation might be the low awareness of the tariff. Only 33 % of the respondents in the intervention area (correctly) stated that they had a demand-based tariff. In other words, most of the householders seemed unaware of the tariff, even though it had been in effect for decades.

4. Discussion

This study set out to explore how a mandatory demand-based TOU distribution tariff has affected the timing of householders’ electricity use, various psychological mediators of relevance to users’ engagement

Table 7

Coefficients for the structural equations of the structural equation model for the reference and intervention area, linking the eleven individual belief components to the latent variables and the behavior, together with the associated standard errors of measurement (within parentheses) and *t*-values (below the standard errors within parentheses). The statistically significant coefficients (with *t*-values with an absolute value larger than 2, corresponding to $p < .05$) are in bold. The colors of the rows indicate which dimension of the TPB that each belief component belongs to (attitude belief components in blue, subjective norm belief components in green, perceived behavioral control belief components in orange). Belief components that increase and reduce motivation (i.e., drivers and barriers) are denoted with (+) and (−) respectively.

	Latent variables (TPB constructs) and behavior							
	Reference area				Intervention area			
Belief components	Behavior	Attitude	Subjective norm	Perceived behavioral control	Behavior	Attitude	Subjective norm	Perceived behavioral control
Reduces costs (+)	−0.006	**0.028**			**−0.014**	**0.029**		
	(0.004)	(0.007)			(0.004)	(0.006)		
	−1.333	4.080			−3.118	4.866		
Reduces environmental impact (+)	−0.006	**0.030**			**−0.021**	**0.044**		
	(0.005)	(0.007)			(0.006)	(0.006)		
	−1.371	4.280			−3.739	7.246		
Reduces quality of life (−)	0.004	−0.020			**0.011**	**−0.022**		
	(0.004)	(0.010)			(0.004)	(0.008)		
	1.150	−1.993			2.432	−2.892		
Reduces comfort (−)	0.005	**−0.026**			**0.011**	**−0.023**		
	(0.004)	(0.009)			(0.004)	(0.007)		
	1.293	−2.837			2.671	−3.369		
Expected by relatives and friends (+)	−0.003		**0.029**		**−0.008**		**0.034**	
	(0.003)		(0.013)		(0.003)		(0.010)	
	−1.120		2.298		−2.437		3.262	
Expected by neighbors (+)	−0.007		**0.063**		**−0.008**		**0.034**	
	(0.005)		(0.014) 5.481		(0.003)		(0.011)	
	−1.368				−2.513		3.102	
Expected not to by neighbors (−)	0.002		**−0.021**		0.003		**−0.012**	
	(0.002)		(0.005)		(0.001)		(0.006)	
	1.312		−3.937		1.955		−2.226	
Most households do it to save money (+)	−0.002		0.017		**−0.006**		**0.026**	
	(0.002)		(0.006)		(0.002)		(0.007)	
	−1.265		2.743		−2.832		3.758	
We hardly use any electricity (−)	−0.00019			0.004	0.0003			−0.015
	(0.00037)			(0.007)	(0.0004)			(0.008)
	−0.514			0.575	0.990			−1.803
We already use it in off-peak hours (−)	−0.002			**0.044**	−0.001			**0.039**
	(0.001)			(0.007)	(0.001)			(0.008)
	−1.330			5.890	−1.126			4.797
We have no time or (mental) energy (−)	0.001			**−0.027**	0.0004			−0.013
	(0.001)			(0.009)	(0.001)			(0.018)
	1.398			−3.131	0.641			−0.753
R^2	0.037	0.437	0.408	0.159	0.028	0.534	0.348	0.087

in DSR and the connection between the two. In relating householders' actual electricity use patterns to their beliefs surrounding DSR, and motivators to shift or not to shift their use of electricity to off-peak hours, this study sought to understand how cognitive mediators might drive or hinder a change in the timing of householders' electricity use.

Our analyses revealed that there was no difference in the timing of the householders' electricity use between the area with a mandatory demand-based TOU tariff (the intervention area) and the area with a conventional energy-based volumetric tariff (the reference area). However, only 33 % of the households in the intervention area actually knew of the tariff, whereby the vast majority of users had no reason to respond to the tariff. This might help to explain the absence of a difference in the proportion of electricity use during peak hours between the areas. It also illustrates the importance of regularly informing users of the presence and purpose of demand response programs, and shows that rate awareness may be an important source of bias to consider in studies on the effects of time-varying rates. Despite the low awareness of the tariff, there were significant differences between the householders' beliefs surrounding DSR, and their motivators to engage (or not) in DSR.

The strongest identified drivers for householders to shift their electricity use to off-peak hours were their willingness to contribute to a sustainable development for younger and future generations, to reduce their environmental impact and to mitigate climate change, combined with their beliefs that shifting electricity use to off-peak hours helps them to achieve this. The strongest identified barriers to shifting electricity use to off-peak hours were their beliefs that they are hardly using any electricity and/or that they are already using their electricity mostly during off-peak hours.

Householders' perceived social norms, captured by the questionnaire, proved to be weaker motives to engage (or not) in DSR. As electricity use is an unnoticed and private activity by default, this is not entirely surprising. There were, however, several instances of significant relationships between different perceived social norms and intended as well as actual engagement in DSR—suggesting that these perceived social norms may become potential drivers of change if made visible, e.g., through feedback. Many studies have indeed shown that social norms can be successfully leveraged to induce changes in energy use (see e.g. Ref. [32] for an overview).

The potential for reduced electricity costs, which is really the motive that price-based demand response programs intend to convey, proved to be a less important driver for electricity users to engage in DSR than concerns about the environment and the sustainability for future generations. This highlights a potential mismatch between the type of instruments that are most often used to incentivize residential demand side response and the motives that householders hold, and might very well provide a clue as to why the demand-based TOU tariff had not induced any noteworthy shift in the timing of the householders' electricity use. So far, very little is known about the potential of demand response programs that target non-financial motives, but given the success of non-price interventions for energy conservation [32–35] and of a recent trial of a non-price demand response program [36], it is certainly worth exploring.

Coming back to the effects of the demand-based TOU tariff, households in the intervention area, and particularly those living in single-family homes, had a stronger intention to shift electricity use to off-peak hours than the households in the reference area. The reason why single-family homes had a slightly higher intention, and a slightly lower proportion of peak hour electricity use, might be explained by their higher tariff awareness—which may be a result of that they are more aware of and concerned about their electricity use and costs, e.g., because their overall use is higher. Hence, they might pay greater attention to the electricity rates to which they are subjected. Householders in single-family homes also have greater autonomy over home investments, and often greater economic freedom, whereby they can invest in technological solutions (such as major appliances with timers and smart thermostats) that can help them to shift more of their electricity use to off-peak hours.

The relationship between the householders' intention to engage in DSR and the corresponding measure of their actual behavior was significant in the intervention area, but not in the reference area. In the intervention area, the proportion of electricity use during peak hours was significantly predicted by: i) householders' beliefs that shifting electricity use to off-peak hours reduces electricity costs and their environmental impact, combined with their willingness to do so; ii) their beliefs that shifting electricity use to off-peak hours reduces their quality of life and comfort, combined with their willingness to maintain these; and iii) their beliefs that shifting electricity use to off-peak hours is expected by relatives, friends and neighbors and that most households shift their electricity use to off-peak hours to save money, combined with their willingness to conform to these norms. These motives did not predict householders' electricity use behavior in the reference area. Although householders' beliefs that they hardly use electricity and that they are already using their electricity mostly during off-peak hours were strong in absolute terms in both areas, these were not identified as significant predictors of their actual behavior.

The finding that the tariff has influenced users' motives and intention to engage in DSR, but not on their actual behavior, illustrates how conventional evaluations of the effects of demand response programs might overlook indirect, but nonetheless important, effects. Building a deeper understanding of why users respond to demand response programs (or not) is key to successful policymaking. Furthermore, if a demand response program has a positive impact on householders' beliefs and motives, this might lead to positive behavioral changes and spillover effects in the long run—for example, if some of the perceived barriers are removed by the introduction of technologies.

There are several possible and not mutually excluding explanations for the observed lack of an actual change in behavior, which will require further studies to disentangle. Firstly, only 33 % of the households in the intervention area knew about the tariff, which is obviously a major obstacle to the success of the tariff. Secondly, several barriers to shifting electricity use to off-peak hours were observed. If householders, rightly or not, perceive that they cannot shift electricity use to off-peak hours, as they are hardly using any electricity and/or are already using electricity during off-peak hours, then that is clearly a barrier towards behavioral change. Given what has been observed in qualitative studies of how and why (not) householders respond to demand side interventions (e.g. Refs. [6,37]), it is quite likely that the lack of perceived behavioral control among the householders, at least in part, reflects the fact that people are bound to daily rhythms and schedules—such as working hours, school hours, leisure activities etc.—that make it practically difficult to shift electricity use to off-peak hours. In other words, perceived barriers may be actual barriers as well, which limits how flexible electricity users can be.

Another explanation may be that the rationale behind the demand response program at hand is based on the notion that people are primarily motivated by the prospect of saving money—a motive which according to this study's findings is of relatively moderate importance compared to other motives such as a care for the environment and younger and future generations. In other words, the instrument itself may be of the wrong type or simply lack the features that are needed to engage the users in DSR. Another possibility might be that the monetary incentive is too weak to speak to the users' more moderate money-saving-motive. The magnitude of the price signal in this study is likely lower than in many other studies, such as those carried out in the U.S. (see e.g. Ref. [3]). This is due to the fact that the distribution and sales of electricity are separated in Sweden, which they usually are not elsewhere [38]. As electricity distribution costs only make up 25% of a Swedish electricity user's costs on average [26], the tariff under study may have had a fairly small impact on the householders' total electricity-related costs compared to what the same tariff could have had in a place where the distribution and sales of electricity are not separated. Given that the strength of the users' money-saving-motive was found to be moderate in comparison to other motives, price itself is unlikely to be able to explain the lack of a change in the proportion of electricity use during peak hours in response to the tariff, but it might explain part of it—particularly among households who were more motived by the prospect of saving money than others.

The fact that changes in people's motives and intentions do not always translate into the corresponding expected behavior is not unprecedented in psychological research. The value-action gap [39] is a long known phenomenon, and it is one worth calling attention to. In short, if one wants to learn about what people do, the actual behavior in question needs to be observed. Similarly, if one wants to understand why people do what they do, one needs to look at how their statements—such as their beliefs and motives—relate to their actual behavior. This study provides an illustrative example of how this can be done, which can hopefully contribute to expanding the scope of future studies on the effects of demand response programs and other demand side interventions.

5. Conclusions

The results of this study suggest that the demand-based TOU tariff has had an effect on householders' beliefs about the consequences of shifting their electricity use to off-peak hours, and on their intention to shift their electricity use to off-peak hours, but not on their actual behavior. This study suggests that there is reason to refine and complement future studies on the effects of demand response programs with measures that reach beyond those captured by electricity meters, such as the cognitive mediators of users' engagement in demand side response (or lack thereof). Building a deeper understanding of why (not) users may respond to demand side interventions by relating self-reports to actual behavior is a key contribution to successful policymaking, one that is not restricted to the area of study. For example, the finding that householders may hold intrinsic motives to engage in DSR, other and maybe stronger than the motive to save money, and which may predict actual behavior, suggests there might be large potential for demand side interventions that address and target such motives. Such avenues deserve to be explored.

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CRediT authorship contribution statement

Cajsa Bartusch: Conceptualization, Funding acquisition, Investigation, Data curation, Project administration, Resources, Writing – original draft, Writing – review & editing. **Peter Juslin:** Conceptualization, Funding acquisition, Project administration, Investigation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Britt Stikvoort:** Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Fan Yang-Wallentin:** Data curation, Formal analysis, Methodology. **Isak Öhrlund:** Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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