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Getting the signal – Do electricity users meet the preconditions for making informed decisions on demand response?

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ABSTRACT

Demand response refers to changes in power consumption by electricity users in response to certain conditions on the electricity market. Anticipated to play a major role in the energy transition, demand response is conventionally exercised through network tariffs, which serve as a medium for price signals intended to incentivize and guide electricity users on how to best behave. Considerable attention has been devoted to the unresolved question of whether users are *willing* to respond to these signals, a question premised on the implicit assumption of cognizant users making informed decisions. Less attention has been dedicated to evaluating the validity of this assumption, and the extent to which users actually *internalize* these signals prior to making any decision on how to respond. This study posits that prior to making an informed decision on how to act, an electricity user must first "qualify" through meeting a set of preconditions. These preconditions are captured by a proposed three-stage framework that involves i) receiving the price signal (being aware of the tariff), ii) processing the price signal (comprehending its features) and iii) assimilating the price signal (understanding how behavior influences costs). Evaluating this framework using a survey, the study finds that only 3.8–8.5 % of respondents clear all three stages. This minority is substantially more likely to contain older villa-residents, who are comparatively more concerned with their costs and read their bills more frequently. The findings of this study demonstrate that the "audience" of tariff-based price signals are a small fraction of what is commonly supposed, and that research and policy should shift from a dominant focus on the magnitude of these price signals, towards alternative or improved strategies for communication and engagement.

1. Introduction

1.1. Background

The energy transition is a project that entails the decarbonization of the global energy system, which in turn requires the rapid uptake of renewable energy sources and the increasing electrification of end-use sectors (like heat and transport) [1]. This transformation imposes a considerable set of challenges on power systems. Tasked with increasing the uptake of renewables, ensuring grid stability and mitigating the growing risks of capacity shortages [2], electricity grids face a growing number of constraints in meeting public policy goals. One of these goals has been to compensate for the increasing rigidity of the supply-side (brought about by a growing uptake of intermittent energy sources) through improving the grid's demand-side flexibility. Demand-side flexibility refers to measures that would reduce, increase or shift electricity consumption during certain periods of time [1]. One common approach to improving this flexibility relies on demand response (DR) measures, which refer to actions taken by electricity users "in response to certain conditions within the electricity system" [3]. Typically, these actions take the form of a reduction or a temporal shift in electricity consumption. While DR measures have been long-established, they have generally been applied to large-scale industrial and commercial users. Exploring the prospects of adopting similar measures in the residential sector is a relatively recent phenomena, though one that has garnered a considerable amount of attention. Increasing demand-side flexibility

Abbreviations: CEER, Council of European Energy Regulators; DR, Demand Response; DSO, Distribution System Operator; dTOU, Dynamic Time-of-use; IHD, In-home Display; NordREG, Nordic Energy Regulators.

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would benefit the electricity system through improving frequency regulation (maintaining a balance of electricity supply and demand at the time frame of seconds), reducing the risk of a power deficit, reducing price volatility and generating a more efficient allocation of resources that would reduce losses and delay the need for infrastructure investments [4]. Tapping into these benefits requires a task that has been described as "activating" passive consumers, a project made challenging by the need to "translate the need of the system" into something that they may find "valuable and motivating" [5]. The standard interface for this translation has been the electricity user's tariff.

Network tariffs concern how distributors of electricity charge customers for their consumption. They convey the different components of electricity bills, detailing how costs are incurred. Tariffs widely vary in their form and complexity. On the simplest end of the scale, one finds fixed-rate tariffs which charge a customer a fixed amount, irrespective of their usage (say, €30 a month). Slightly more sophisticated, volumetric charges price users according to the total volume (namely, amount) of electricity they consume in kilowatt-hours (kWh). A customer charged at a volumetric rate of 1€/kWh who uses 50 kWh will pay half as much (€50) as a customer who is charged according to the same rate but uses 100 kWh (€100). These volumetric charges can also be time-differentiated, so that a customer pays two different rates according to the time of day that they are using electricity – for example, 1€/kWh between 7 p.m.-7 a.m. and 2€/kWh between 7 a.m.-7 p.m. There has been a growing tendency to transition away from these conventional fixed-rate or volumetric tariffs and towards the adoption of more intricate tariffs that reflect the costs consumers "inflict on the grid" [6]. While volumetric rates charge users according to their total energy consumption, most network costs are actually driven by peak demand – periods of time when the *rate* of electricity consumption is at its highest - and are "largely independent of the actual energy delivered" [7]. Consequently, regulators have pushed for adopting cost-reflectivity as a "key principle" with tariffs adequately reflecting "the relevant costs of the service" through the introduction of new features, an example of which may be a "power component" [8]. This power component commonly takes the form of a demand charge, which is based on peak electricity consumption, either "measured at the time of system-wide peak" (time at which a distribution system's electricity consumption is at its highest) or taken to be an "individual customer's maximum demand" (time at which an individual customer's electricity consumption is at its highest) [9]. Benefits of these residential demand charges range from a "better alignment of prices and costs" to "improving utility cost recovery" and "reducing intra-class cross-subsidies" [10].

Aside from being cost-reflective, these tariffs provide the arguably more important function of serving as a medium for "price signals", which would "directly influence behavior by providing an economic stimulus", with high prices reflecting periods of high demand and low supply, and vice versa [11]. This conception of price signals as an incentive and a basis for DR is pervasive. Eurelectric, the sector association representing the European electric industry, has recommended that tariffs be used to "incentivize demand response and energy-efficient behaviour" [7], a sentiment echoed by the organization for Nordic energy regulators (NordREG) which also advocates using tariffs to change consumption behavior in ways that would reduce peak load and level the distribution of their electricity use [6]. The Council of European Energy Regulators (CEER) also recognizes tariffs as a channel for price signals which would "convey information" and "in principle" allow users to respond "by either increasing or decreasing the quantity (energy or capacity) demanded" [8].

Accordingly, price-based DR presumably solves the problem of individualizing the system need of demand-side flexibility through "exposing" residential end-users to "forward-looking price signals" [8] and providing them with "options that allow them to actively participate in the energy system" [6]. A common conceptualization of this process begins with price-sensitive users observing "the shape of their electricity usage profile", realizing "the effect this profile has on expenditures" and consequently changing their behavior through "actively shifting usage to lower-cost time periods" [12]. This ideal scenario is perhaps best captured in one study of a dynamic time-of-use (dTOU) trial in the UK [13]. Participants were notified of rate changes a day in advance through an In-home Display (IHD) equipped with a "traffic light indicator" of their energy usage. Detailed interviews shed light on the extent to which participants would adjust their behavior in response to the rates. Adaptations varied from avoiding laundry to more committed measures like keeping lists of what they "should and shouldn't do" during peak hours, timing their vacuuming, as well as changing when and what they eat so that they could use the gas cooker and microwave instead of the oven. Such individuals represent the idealized archetype that is central to DR policy.

Reviews of various trials have provided evidence of DR achieving some measure of success, with users shifting demand in response to incentives [14–17]. A critical and largely ignored caveat however, is that a vast majority of these trials are pilot studies where participants have opted into the studies. While reviewers of these trials recognize that customers who opt-in are not representative and are typically "more conscious of their energy usage" and more "conservation minded" [16], some still conclude that priced based DR can be relied on by utilities and system operators, and that the evidence "supports the case" for a "rollout of dynamic pricing wherever advanced metering infrastructure is in place" [15]. Other reviews of DR trials and programmes suggest that assumptions concerning DR may be "overly optimistic" and that its "wider applicability" remains uncertain [18–20]. Despite the fact that "customer participation in trials and existing programmes is often 10% or less of the target population", modelling studies used to forecast the performance of DR programs make "highly optimistic assumptions about residential consumer engagement", assuming participation rates as high as 70–100 %.

The disparity between pilot studies and wide-scale adoption is well exemplified by the French "Tempo" tariff. This tariff split the year into 300 "blue days", 43 "white days" and 22 "red days", the third of which are the most critical for the grid and therefore the most expensive. Each of these days were further divided into peak and off-peak hours. A pilot study provided 800 customers with "various energy control systems", devices that provide notifications, brochures, guidebooks as well as "anniversary reports" [21]. The pilot was deemed successful, with reductions in daily consumption that ranged from 15 % on low-peak days to 45 % on high-peak days. A vast majority of customers expressed satisfaction with the tariff and achieved an average reduction on their electricity bill of 10 %, but a study reviewing the roll-out of the Tempo tariff concluded that customers who opted for it had "very particular" profiles, with managerial tendencies and a willingness to "constrain their life and family to make little in the way of savings compared with their standard of living". This reality limited the uptake of the tariff, which despite offering a "highly attractive price" ultimately "remained confined to less than 2% of the customers". Some posit that uptake could perhaps be increased by switching to an opt-out scheme [19], but a higher uptake does not necessarily lead to more engagement or a higher response. Participants of opt-out designs are likely to "exhibit lower average responses" than those enrolled in opt-in schemes such that both variants may ultimately "give rise to similar aggregate responses overall" [18]. The evidence seems to suggest that regardless of how electricity users are recruited into DR studies and programmes, only a small minority of users exhibit active engagement.

The diagnosis of this outcome quite commonly locates the problem in the incentive. If DR is thought of as a process with a price signal as the input and a response in demand as the output, then a poor response must necessarily stem from an issue with the signal, supposedly its strength. Indeed, a commonly professed remedy is to strengthen the price signal (through increasing peak to off-peak price ratios for example) in order to improve DR outcomes [16]. This assessment however, makes the implicit assumption that price signals are unimpeded in their transmission, and that they are received and processed by their subjects, who then decide whether or not to respond. Concretely, users are assumed to be perfectly cognizant of their tariffs, acquainted with their technicalities and knowledgeable of the appropriate curtailment actions and their effects. They then decide whether or not to "act" on this knowledge, and so when the level of response is either marginal or negligible the problem is frequently attributed to inadequate incentives, barriers to behavioral change, or an overall lack of motivation. These assumptions arguably may have held in small-scale pilot studies with highly self-selected samples of exceptionally interested participants. Whether they continue to hold when DR programmes and tariffs are rolled out at a larger scale remains to be assessed.

The assumptions above lead to an interpretation of poor DR outcomes as a consequence of electricity users *choosing* not to respond, but this overlooks a set of preconditions that must be met by electricity users *prior* to any choice being made. Reexamining the model of price-based DR, where an input signal leads to a response in demand, it becomes clear that the first prerequisite to the process would be the *reception* of the signal, namely that a given electricity user is made *aware* of the price signal. This may have been self-evident in opt-in pilot studies where users have already taken an active decision to participate, but may not hold with opt-out designs or when tariffs are mandatorily set. In a large-scale rollout, it is likely that the distribution system operator (DSO) would be responsible for providing electricity users with information regarding their tariff, and it is possible that this information may be entirely overlooked. The more "general" electricity user may not share the pilot study participant's enthusiasm for energy concerns, and some may not even be aware of their contract type [22]. This lack of interest suggests that users may heed little attention to the provided information, "missing" the price signal entirely. DSOs may insert information regarding the tariff into electricity bills which they assume will be read. Even users who do "read" the bill may instead gloss over what they deem to be irrelevant information and only visit the total cost. Evidence for this was provided by a "Bill Click Tracking Study" which explored "consumers' reading habits with regards to their electricity bill" and made attempts to "identify the regions of the bills that are most salient, overlooked, or misunderstood by consumers". The authors found that recall of the bills' terms and usage information was poor, and that "the most attended to region of the bill was the total price" [23].

Supposing electricity users do in fact meet this first prerequisite and "receive" the signal (read the information provided), a second precondition is that this signal be correctly "processed". Before users can respond to a tariff through a change in behavior, they must first decipher their tariffs, understand the different components and how they determine their costs. Users with volumetric charges should understand that their costs are driven by their total energy usage, and those with demand charges must understand that their costs are driven by "peak usage". If users are subject to time-differentiated tariffs, they need to understand how the cost of their electricity varies according to the hour of the day. Again, this is commonly taken as self-evident in pilot studies, but the wider population may have "only a basic understanding" of concepts like "peak usage" and may fail to discern what causes peaks [24]. Providing more elaborate forms of feedback as suggested by [25] may not be a sufficient alleviation of the problem. A detailed field study provided participants with "web-based time series visualization of their recorded electricity data" but found that after the course of 3 months their understanding of home electricity consumption had "hardly changed", and that they were "unable to reliably identify specific events in the data visualization" [26].

Supposing electricity users also meet this second prerequisite and "process" the signal, responding to the tariff would require a final precondition where users "assimilate" the signal to some degree. They may have discerned the details of their tariff with a basic understanding of the drivers of their electricity costs (peaks or total usage), but responding to the signal requires an ability to correctly link these drivers with the appropriate behaviors that generate and can therefore influence their respective costs. A user with a volumetric charge may understand that their total energy usage is what drives their costs, but they cannot adequately respond to their tariff if they are oblivious to the appliances and behaviors that are associated with high energy use. Users may resort to turning off unused lights as an energy conservation measure for example, despite its small share of a household's energy expenditure [23,27]. Correspondingly, users facing demand charges would need to understand that their costs are driven not by total energy consumption but by their maximum demand, which in turn depends on their propensity to run appliances and carry out energy-intensive activities during the same span of time. Users may struggle in understanding how this "range of curtailment behaviors" influences their costs [27].

Only after "clearing" these three hurdles of signal awareness, signal processing and signal assimilation, can a user be considered "ready" to respond to their tariff. Only at this point, may a user weigh the inconveniences of the appropriate curtailment actions against the savings expected from the tariff and make an *informed* choice. Even at this stage, some would argue that expectations of price-sensitive and cost-minimizing users, despite being widespread, stem from a conception of "humans as a distinctly economically rational breed" and have been "poorly anchored in empirical data" [28]. The emphasis on the role played by financial incentives, perhaps appropriate in the industrial and commercial sectors [29], may not carry over to the residential sector. One review investigating price unresponsiveness provides an example where a "striking skewed distribution of household electricity price elasticities" was composed of a "small fraction of households" accounting for a large share of the price elasticity, with the majority of respondents exhibiting "near-zero elasticity" [20]. That only a small proportion of users may in fact be "responsive" to prices, with a majority of indifferent or disinterested users, suggests that the instruments designed by policymakers are appropriate only to an active minority. The highly responsive interviewees from the dTOU study in the UK were mostly wealthy, and despite the extensive lifestyle adjustments made, they expressed reluctance in maintaining these adaptations, citing the "difficulty in shifting certain practices". Others argue that even when users respond, the price signal itself "does not have that much influence on householders' willingness to engage in demand response" and that their response may perhaps be driven by other motives [30]. Recent studies come to similar conclusions, finding that factors like "personal environmental motivations" [31] or convenience [32] may be more important than financial motivations.

As argued above, it is common to conceptually place the target population of a DR intervention on the same foundation, drawing a distinction between those who ultimately *choose* to respond and those who do not. This study attempts to demonstrate that in fact, this distinction may only apply to a subgroup of the target population, those who meet a set of preconditions necessary to a price signal response. The "audience" of a DR program may therefore be considerably smaller than imagined, with only a minority making an active and informed choice regarding the flexibility-cost tradeoff they are offered. Identifying this minority and their characteristics may help address the question of where and why price signals fail. Policy-makers would benefit from an ability to distinguish between users who overlook the signal completely, receive it but fail to understand, or receive it and understand it but lack a strong enough incentive to act on it.

1.2. Aim

Prior to making an informed decision on whether or not to respond to a signal, this study assumes that electricity users must first meet a set of preconditions for DR engagement. The term "engagement" denotes a change in behavior *in response* and *in accordance* to a given tariff. In other words, any behavioral response must be guided by the specific and distinct "requirements" of a given tariff and its associated price signal, not an indiscriminate, arbitrary reduction in general energy usage. The preconditions for engagement proposed in this study can be consolidated into the simple three-stage framework shown in Fig. 1. A given user must i) receive the price signal (be aware of the tariff/tariff change) ii) process the price signal (comprehend the tariff and its features) and iii) assimilate the signal by understanding the behavioral implications and respective curtailment actions through which they can respond to the tariff. Each stage is contingent on the one that precedes it. A user cannot identify the appropriate curtailment actions if they do not understand how their behavior influences their costs. They cannot understand how their behavior influences their costs if they have failed to correctly interpret the tariff, and they cannot interpret a tariff that they are entirely unaware of. This sequence may be represented as a three-stage funnel, where users must meet the three preconditions *before* they can choose if and how to respond. Applying this framework, this study attempts to answer the following question: - *Who meets the preconditions for demand response engagement?*

One aspect to this question is a simple assessment concerning the proportion of a target population that meets each and all of the preconditions. A second aspect is a deeper understanding of the *types* of individuals who meet each precondition, in terms of their demographic, economic and social characteristics. Both aspects are important to understanding the prospects and limitations of price-based DR, and may guide future improvements on how DR policies are designed and implemented.

2. Data and methods

2.1. Study design

This study relies on data collected in a previous investigation, the results of which concerned a comparison between electricity users subject to energy-based tariffs (volumetric pricing) with those subject to demand-based tariffs [33]. In that study, the two groups were compared in terms of their conceptual understanding of energy and power, and their general ability to comprehend different tariffs. Using the same survey data, this study develops a framework for predicting and understanding which electricity users are sufficiently interested in their tariffs, process them correctly and ultimately qualify for DR engagement, while also investigating what factors may lay behind their qualification. The survey was administered to a set of web panel respondents (by the company Norstat) across a range of municipalities in Sweden. Open between the 26th of January - 14th of February 2021, the survey was answered by 1393 respondents. The selection of the municipalities and a more exhaustive overview of the empirical setting can be found in Section 2.1 of the previous study [33]. The strength of the empirical setting lies in the fact that electricity users in Sweden have no choice regarding their DSO or the network tariffs they are subject to. This means that when a DSO changes a tariff (introducing a demand charge, for example), the tariff mandatorily applies to all the users connected to the distribution system. In other words, these tariffs are neither opt-in nor opt-out, but obligatory. Respondents may participate in taking the survey, but they are not participants who are opting into a pilot study, and are therefore more representative of a general population of electricity users. The survey begins by demographically profiling respondents through gathering a set of background variables (age, gender, education, etc.). It also asks respondents questions regarding the frequency at which they read their electricity bills and the extent to which they are concerned with their electricity costs. The survey then proceeds sequentially, each section corresponding to one of the preconditions in the three-stage funnel (Fig. 1).

2.1.1. Stage I – signal reception: will a user detect a change in tariff?

The first precondition, signal reception, refers to a basic recognition of a tariff change. When a DSO introduces a new tariff, information is usually sent out to communicate the change. If a user misses this signal, they may still be able to detect it through their electricity bills, which would continue to communicate the terms of the new tariff. The motivation of this first stage is to distinguish between electricity users who would be conscious of the change (receive the signal) but may or may not understand the information, and users who may remain completely unaware of the tariff (miss the signal). While the former move on to the next precondition, the latter can be ruled out from DR engagement. Attempting to isolate this group is important, since it would be inaccurate to classify them as users who fail to understand the tariff, or users who lack an incentive to respond. This is a group that has neither misunderstood the tariff nor declined the DR “offer” of flexibility for savings, but is entirely oblivious to the offer itself.

Measuring whether or not a signal has been received retrospectively is considerably difficult. The respondents come from a wide range of municipalities represented by a variety of DSOs, each of which may have had its own unique communication strategy and been rolled out at different times. If and when a respondent became aware of the last tariff change cannot be definitively ascertained. The aim however, is to make an informed presumption regarding which respondents are likely to notice a change and examine the provided information. Essentially, the precondition of signal reception can be phrased as the following question: If a DSO rolls out a new tariff, will a given respondent recognize the change? As mentioned, respondents have likely been exposed to different tariffs through different mediums of communication at different times. The one constant however, is the DSO itself, which is always the entity responsible for the tariff change and its communication (at least in the Swedish setting). Whether the medium of communication is a paper letter, an app or a website, its provision through the

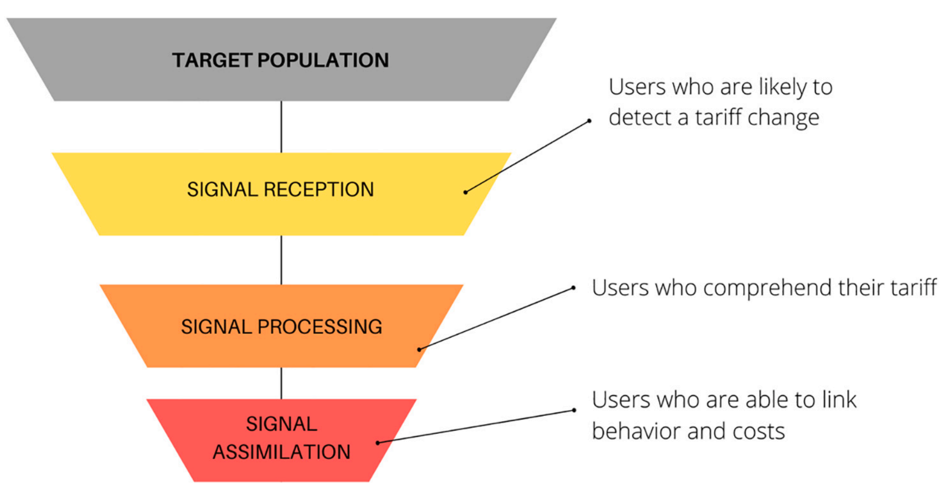

Fig. 1. Depiction of three-stage framework that filters out users who do not “qualify” for DR engagement.

DSO virtually ensures that their name and/or logo will also be displayed. Given that the DSO is the "emitter" of the price signal, one may expect that a respondent who receives the signal would at the very least be able to identify its carrier. Conversely, a respondent unfamiliar with their domestic energy matters to the point that they cannot even identify their DSO (an entity which bills them on a monthly basis), is unlikely to heed much attention to a tariff change notification and the contained price signal.

With these considerations in mind, the measure selected as an indicator of signal awareness is whether or not a respondent can identify their DSO. Respondents are asked whether they know their DSO (yes/no) and are subsequently asked to select it from a list of options. Unavoidably, some respondents may falsely claim to know their DSO, and while it is not possible to match each respondent to their exact DSO (since multiple DSOs operate in each municipality), a respondent who has selected a DSO that does not operate in their municipality can be confidently classified as incorrect. It is highly likely that respondents classified as correct may be overestimated, but this would then represent an upper-bound estimate. Additionally, false positives are highly unlikely to meet the subsequent preconditions and will likely be "filtered out" during the next stages of the funnel.

DSO identification, one must concede, is an arguable and crude measure of signal awareness. The ideal way to measure signal awareness would be to actually check whether respondents have received information from their DSO directly after a tariff change. This is considerably difficult in an empirical setting where respondents are served by a variety of different DSOs, not all of which roll out new tariffs at the same time. Nevertheless, while crude it is still considered a relevant measure that makes an attempt at separating those who might fail to process the signal from those who would miss the signal entirely. The first case points to problems with comprehension while the second implies that users are too apathetic and uninvolved to even entertain the thought of reading and comprehending network tariffs. A user's ability to identify their own DSO is reflective of a very basic and minimal level of familiarity with domestic energy matters, and is therefore a reasonable indicator of whether or not a respondent is likely to recognize a change in tariff.

2.1.2. Stage II – signal processing: will a user comprehend their tariff?

The second precondition, signal processing, refers to the accurate comprehension of a tariff. The survey's respondents are either subject to an energy-based tariff, based on a user's volumetric consumption (in kWh), or a demand-based tariff based on a user's maximum monthly demand (in kW). To reiterate, those with energy-based tariffs incur costs in accordance to the total volume of energy they consume in a given month, measured in kWh, whereas those with demand-based tariffs incur costs based on the highest (or sometimes average of top three highest) hourly energy consumption they consume in a given month, measured in kWh/h). The costs of those with energy-based tariffs are directly linked to the volume of energy consumption while costs associated with demand-based tariffs are linked to the highest rate of energy consumption. These tariffs are either time-differentiated (prices depend on the time of day and the day of the week) or time-invariant (prices are constant). Correctly identifying these two components, the classification of a tariff (energy or demand) and the time-differentiation (varied or constant), is what determines whether a user has correctly processed the signal. A failure to recognize either of these components would mean that a user cannot respond to the tariff with any precision and would be entirely oblivious to what is required for a reduction in costs. It is possible that users who fail on the above criteria may still react to a tariff in some way, perhaps through an indiscriminate reduction in energy usage. As previously mentioned, this cannot be considered a form of engagement, as any alignment between a user's behavior and the "goals" of the tariff would be entirely coincidental, and obviates the point of a price signal.

Determining whether a user has selected the correct tariff type and time-differentiation is straightforward. Conditional on having answered yes to the question of whether or not they know their DSO, and having selected their DSO from a list, one is able to verify that the tariff type and time-differentiation selections made by respondents match those stipulated by the DSO (publicly available online). In some cases, DSOs have different tariffs for those living in apartments and those living in villas, but respondents also indicate their residence type which allow these differences to be incorporated into the results. One potential issue is that respondents may select an incorrect DSO but correct tariff types and time-differentiation, and would then be marked as incorrect since their choice does not match the DSO they selected. While it is unlikely that this will affect the results in any important way, additional checks will be performed to ensure that this is indeed that case.

2.1.3. Stage III – signal assimilation: will a user understand the link between behavior and costs?

The final precondition is an understanding of the behavioral implications associated with a given tariff – how certain electricity consumption or load-shifting behaviors may influence costs. A user may be able to vaguely distinguish whether their tariff is energy or demand based, and whether or not it is time-differentiated. Nevertheless, their ability to respond to a given tariff hinges on understanding how behaviors are linked to their associated costs. Those with a time-differentiated energy-based tariff for example, would need to understand that to reduce their costs they need to load-shift away from high-peak times to low-peak times. Those with a time-invariant demand-based tariff would need to understand that reducing costs corresponds to reducing peaks, which in turn requires that they "spread" their loads across time. The final section of the survey evaluates this understanding.

Given that the focus of this precondition is on the link between behavior and costs, the final section assesses respondents' abilities to recognize whether certain actions would increase, decrease or have no effect on costs. Respondents are presented with four different tariffs, all of which are currently in use by one or more DSOs in Sweden and cover the possible range of tariffs a respondent may have. These include the traditional, energy-based volumetric tariff, and the less prominent but increasingly discussed demand-based tariff (based on the individuals single highest monthly peak). Both these tariffs come in time-differentiated (cost depends on the hour of the day) and time-invariant (cost does not depend on the hour of the day) forms resulting in the combination of four tariffs shown in Table 1.

It is true that in the context of the funnel framework, a user need only understand the link between behavior and action for *their* respective tariff, but assessing respondents on the four different tariffs allows for an evaluation of their *general* interpretative abilities. It is important to recall that the intention of this precondition is not to determine whether users have retrospectively learned about their tariff from past exposure, but to gauge their general capacity to assimilate price signals.

Each tariff is accompanied by an explanation of how it functions, a hypothetical load curve and a set of different load-shifting scenarios, an example of which is shown in Fig. 2. The presentation of the graphics and the information is intended to closely mirror how Swedish DSOs present their own tariffs to their customers. DSOs' communication formats vary, ranging from a basic verbal summary of the tariff to more intricate diagrams containing explanations and examples, with the latter being selected as the more appropriate model for this survey. The reason being that this section is more interested in evaluating general cognitive capacities than appraising DSOs' communication capabilities, and so the

Table 1
2×2 within-subjects factorial design used to test respondents' understanding of curtailment actions and how this understanding varies across tariffs.

	Time-invariant	Time-differentiated
Demand-based	Tariff A	Tariff B
Energy-based	Tariff C	Tariff D

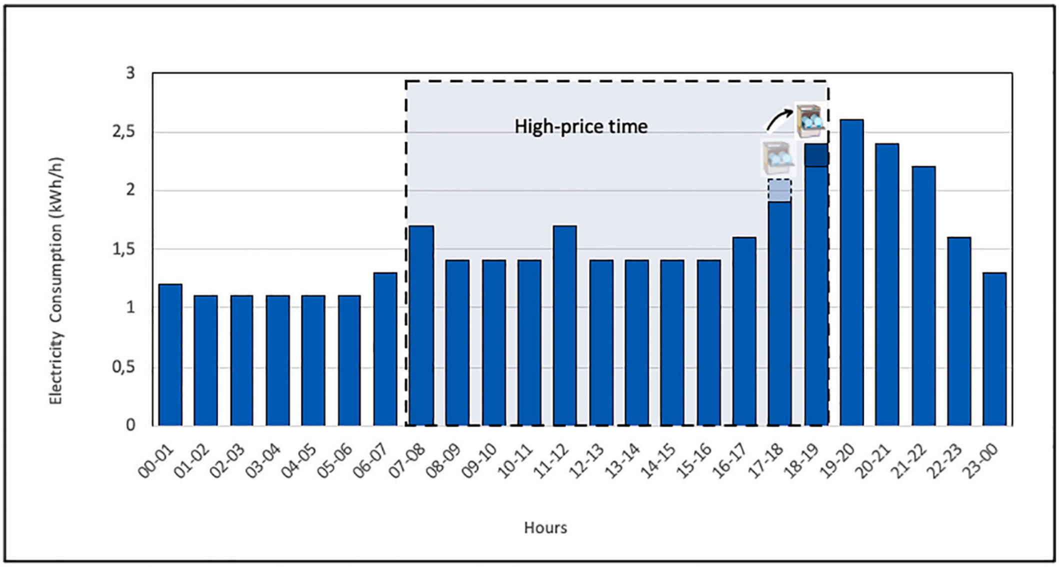

Fig. 2. Example of load-shifting diagram (translated to English) showing the dishwasher being load-shifted from 17 to 18 to 18–19 and its effect on the load profile. Respondents would then be asked if monthly costs would increase, decrease or remain the same considering this action and given the tariff in question.

aim was to provide respondents with a "best case" scenario of what they could expect to receive in a natural setting. Respondents are asked to assume that the hypothetical daily load curve repeats each day for the course of a month, and that while loads can be shifted in time, they cannot be eliminated (energy usage cannot be reduced, only shifted). Given this constraint, they are asked if something (some load-shift) can be done to reduce the hypothetical costs under the given tariff (yes/no). They are then presented with three different load-shifting scenarios, and asked whether the result of each is an increase, decrease or no effect on the monthly cost. The load curve and the scenarios are the same for each tariff, but the effect of each scenario on the hypothetical costs vary. The example shown in Fig. 2 would see an increase in costs under a time-differentiated demand-based tariff, but there would be no effect if the tariff was instead energy-based, or if it remained demand-based but was time-invariant (high-price time area disappears).

Each of the four different tariffs were accompanied by a total of four questions, resulting in sixteen questions in total. The order in which the tariffs were presented was randomized for each respondent to minimize any effects the presentation sequence may have. Each respondent receives an average score for each tariff and an average total score for the combined tariffs. Each binary score (correct/incorrect) is combined with Likert confidence scores (that range from complete uncertainty to complete certainty) respondents provided on each answer and converted to a point-scale system that varied from 0 to 100 points. This score allows one to distinguish between responses that reflect mere indifference or uncertainty as opposed to strongly held convictions, and therefore provide a more sensitive pseudo-continuous measure of their performance. The method and motivation for this conversion can be found in Appendix B. A respondent's point score characterizes their general ability to assimilate price signals.

2.2. Analysis plan

The first aspect of the research question involves a basic quantitative understanding of the proportion of survey respondents who meet each of the preconditions. For the first stage, this is the share of respondents who correctly identify their DSO. For the second stage, it is the share of respondents who correctly identify their tariff type (including the energy/demand classification *and* the correct time-differentiation). For the final stage (signal assimilation) the outcome variable is no longer binary, but is a point score (from 0 to 100), requiring a threshold to be set, above which respondents "pass" and below which respondents "fail". Two different thresholds are examined, the first of which is 50 points, representing a level of understanding that is quite low but slightly higher than a sequence of random guesses. The second threshold is set at 70 points, which represents a moderate level of understanding and is indicative of a respondent largely able to link load-shifting behaviors with their impact on costs. One could experiment with various thresholds, but these two are deemed sufficient in covering a reasonable range for the purposes of this analysis.

The second aspect involves exploring the socio-economic composition of the "qualifiers". Doing so sheds light on who one can and cannot expect to be a part of the audience for DR engagement. For each of the preconditions described above, an attempt is made to understand the characteristics and attributes of respondents who "qualify" to the next stage. This is carried out by running a set of regression models, regressing the outcome variable of each stage on a selection of socio-economic background variables. Logistic regression models are used for the first two preconditions (binary outcome variables) and a linear regression model is used for the final precondition (continuous outcome variable). The variables selected for the models include gender, age, education and residence type (villa or apartment). Respondents' municipalities were used as control variables to account for geographical differences. In a second regression for each stage in the funnel, the frequency at which respondents read their electricity bills and how important they consider electricity costs to be are also added as variables in order to test whether individuals who read their bills and are cost-conscious are more likely to be knowledgeable about electricity bills and tariffs, and the extent to which these variables mediate the effects of the socioeconomic variables.

The aim is to understand which of the predictor variables play an important role in a respondent qualifying (or not) through the designated stage. In other words, which characteristics are associated with higher propensities to meeting each and all of the pre-conditions. To that end, the average marginal effects were calculated and interpreted for each model.

3. Results

Descriptive statistics for each of the variables included in the analysis are summarized in Appendix C. Two logistic regression models were run for each stage of the funnel. The first containing the set of sociodemographic variables (columns 1,3,5) while the second supplements the former with the Likert-scale measures of bill-reading frequency and cost importance (columns 2,4,6). The results are summarized in Table 2 below, and will be examined sequentially in accordance to the three stages.

3.1. Stage I - signal reception

Around 82 % of respondents *claimed* to know their own DSO, with around 18 % stating that they were unaware. Reviewing these claims, the proportion of respondents who actually selected a DSO operational in their municipality falls to 69 %, which means that in addition to the 18 % who acknowledged their unawareness, 13 % of respondents made an incorrect choice despite claiming to know their DSO. As previously mentioned, it is possible that respondents who selected a "correct" DSO may have mistakenly selected a DSO operational in the municipality but which might not necessarily be *their* DSO. DSOs are not uniformly distributed among municipalities however, and there is usually one "dominant" DSO that owns most of the grid, with a few others owning considerably smaller shares. This means that a randomly selected respondent (from a given municipality) is most likely to fall under the jurisdiction of this "dominant" DSO, and the fact that most respondents do select this DSO suggests informed responses, and not arbitrary guesses. Nevertheless, only one deduction can be made with any confidence, and that is that *at least* 31 % of respondents cannot identify their own DSO.

The first column in Table 2 summarizes a logistic regression model where the dependent variable is whether or not a respondent could correctly identify their DSO (indicator variable) regressed against a set of background variables. In addition, a full set of indicator variables for the municipalities are also included. The table displays the average marginal effects for each variable with associated standard errors in parenthesis.[1] The two continuous variables, age and years of education, have been standardized to have a standard deviation of one in order to facilitate a simpler interpretation.

The results indicate that age is a strong predictor of correct DSO identification, with older individuals being more knowledgeable. An increase of one standard deviation in age is associated with an average increase in the probability of correct DSO identification of 7.3 percentage points. Education is also positively associated with the outcome variable, but the association is less strong than that of age: an increase of one standard deviation in education is associated with an average increase of 3.1 percentage points in the probability of correct DSO identification. On the other hand, gender does not seem to have a strong effect on the outcome, with women and men being similarly knowledgeable. Finally, the housing classification is of particular importance - compared to individuals living in houses, those living in apartments they own or rent are on average 11–13 percentage points less likely to be able to correctly identify their DSO.

In the second column of Table 2, two variables that are likely to have a direct impact on DSO knowledge are added - bill-reading frequency and cost importance. Both are measured on a seven-point Likert scale, where they are standardized to have a standard deviation of one. As one might expect, bill-reading frequency has a positive relationship with DSO knowledge - an increase of one standard deviation in bill-reading frequency is associated with an average increase in the probability of correctly identifying the DSO of around 8.5 percentage points. On the other hand, there is no significant evidence that individuals who are cost-conscience are more knowledgeable about their DSO.

It is relevant to study what happens with the background characteristics when bill-reading frequency and cost importance are added. For instance, the difference between those who live in houses and apartments decreases by around a quarter, suggesting that individuals living in houses are more knowledgeable about their DSO partly because they read their bills more often. The average marginal effect of age also sees a drop when the new variables are added, whereas the effects of education and gender are virtually unchanged.

3.2. Stage II - signal processing

At this stage there is a drastic drop in the proportion of respondents who meet the precondition. Only around 39 % of respondents are able to correctly classify their tariff (between being energy or demand-based), and only 27 % are able to correctly identify their time-differentiation. The proportion of respondents who correctly identify their tariff by meeting *both* these previous conditions is around 14 %.

158 respondents selected an incorrect DSO and might conceivably have correctly classified their tariff (false negatives). Of those who correctly classified their DSO however, only 17 % also correctly identify their tariff. It seems highly unlikely that the individuals who did not know their DSO should have a greater knowledge of their tariff than those who did know their DSO. If that presumption is correct, then the proportion who correctly identify their tariff can be bounded to be between 14 % and 17 % in the sample, a rather small difference. Therefore, the fact that tariff knowledge may be incorrectly classified for a small subgroup is a minor concern.

Column 3 in Table 2 above summarizes the outcome of correct tariff identification regressed on the socio-economic background variables. Age is again positively related to knowledge, although the effect is smaller compared to DSO knowledge. Education has virtually no effect, whereas women are substantially less likely to be able to identify their tariff. House owners are once again more knowledgeable, although the relationship is less strong, especially compared to individuals who own their apartment. As for bill-reading frequency and cost importance (column 4), bill-reading frequency remains the variable with the strongest impact on knowledge, but cost importance also reveals a substantial positive effect. Adding bill-reading frequency and cost importance to the background characteristics has a similar effect as was the case in the first stage - the difference between individuals living in houses compared to apartments is smaller and there is also a drop in the estimated effect of age.

3.3. Stage III – signal assimilation

The final precondition is based on the points respondents scored on the tariff scenario questions. The scores range from 0 to 100 points, and so linear multiple regression is used to model the relationship between the scores and the predictor variables. Depending on the level of understanding sought, different thresholds can be set to distinguish those who may be deemed knowledgeable enough to participate in DR. Only 54 % of respondents manage to clear a threshold at 50 points while the share drops to 24 % if the threshold is increased to 70 points. One concern is that respondents had to read, understand and answer questions on four different tariffs, instead of the single tariff that they would face in a more natural setting. This higher cognitive load could lead to survey response fatigue, impacting how respondents answered the questions. As mentioned, one countermeasure taken to address this risk was randomizing the order of tariffs presented to the respondents. If in fact they systematically perform better on tariffs presented earlier rather

[1] These have been calculated using the "margins" package in R. The estimated marginal effect is found by calculating the change in predicted value of the outcome variable for a given individual for an increase in the respective independent variable, while holding all other variables fixed. The estimate of the average marginal effect is the average of the estimated marginal effects for all individuals in the sample. Essentially, the average marginal effect is the estimated average change in the probability for an increase in the given variable (holding all other variables constant). For the case of linear regression (columns 5–6) this is equivalent to the estimated regression coefficients. The interested reader may consult [34] where average marginal effects are discussed in detail.

Table 2
The table displays the average marginal effects from the different models. Standard errors, shown in parenthesis, have been calculated using the Delta method. The outcome variable in the first two columns is an indicator (i.e., a binary or dichotomous variable) for whether the respondents could correctly identify their DSO, in columns 3 and 4, it is an indicator for whether respondents correctly identified their tariff, and in the final two columns,the outcome is the tariff comprehension variable which is standardized to have a standard deviation of one. The age, years of education, bill reading frequency and cost importance variables are all standardized to have standard deviation of one, whereas the other independent variables are indicator variables. A full set of indicator variables for the different municipalities are included in all models. R2/Pseudo-R2 refer to McFadden's pseudo-R2 in the first four columns and the standard R-squared for linear regression in the last two columns.

	(1)	(2)	(3)	(4)	(5)	(6)
	Stage I: DSO correct		Stage II: Tariff correct		Stage III:Tariff comprehension	
Age	0.073***	0.059***	0.034***	0.023*	−0.057*	−0.065*
	(0.012)	(0.012)	(0.010)	(0.010)	(0.026)	(0.027)
Years of education	0.031*	0.031*	0.004	0.005	0.253***	0.252***
	(0.012)	(0.012)	(0.009)	(0.009)	(0.026)	(0.026)
Woman	−0.006	0.008	−0.066***	−0.058**	−0.331***	−0.320***
	(0.025)	(0.024)	(0.018)	(0.018)	(0.051)	(0.052)
Own apartment	−0.128***	−0.087**	−0.027	−0.001	−0.321***	−0.307***
	(0.027)	(0.027)	(0.021)	(0.021)	(0.059)	(0.060)
Rent apartment	−0.115**	−0.068	−0.080*	−0.055	−0.478***	−0.460***
	(0.036)	(0.036)	(0.033)	(0.033)	(0.078)	(0.079)
Bill reading frequency		0.085***		0.056***		0.057*
		(0.012)		(0.012)		(0.028)
Cost importance		0.024		0.030***		−0.013
		(0.013)		(0.009)		(0.027)
Model	Logistic	Logistic	Logistic	Logistic	Linear	Linear
R2/Pseudo-R2	0.057	0.095	0.070	0.115	0.146	0.149
Nr. observations	1336	1336	1336	1336	1336	1336

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

than later, then this effect would at least be cancelled out by randomizing the presentation order. Looking more closely at the responses however, no systematic difference was detected between tariffs presented earlier or later in the survey, which suggests that response fatigue was unlikely.

The regression results are summarized in columns 5 and 6 of Table 2. Tariff comprehension, the outcome variable is a continuous variable standardized to have a standard deviation of one. Age is now negatively related to tariff comprehension, with an increase in one standard deviation of age leading to a drop in tariff comprehension by 0.06 standard deviations. On the other hand, education exhibits a much stronger relationship than in the previous stages, whereas women have a significantly lower comprehension compared to men. Finally, once again, individuals living in houses are more knowledgeable compared to those living in apartments.

Comparing the size of the effects to the previous regressions is not a straightforward matter, as the outcome variable in this stage is measured on a different scale, but one can note that the standard deviations of DSO correct and Tariff correct are 0.46 and 0.35, respectively. This means, for instance, that the standardized differences for individuals who rent their apartment compared to those living in houses are 0.115/0.46 = 0.25 standard deviations for DSO knowledge and 0.08/0.35 = 0.23 standard deviations for tariff knowledge, as compared to 0.46 standard deviations for tariff comprehension.

Finally, this stage is where the bill-reading frequency and cost importance variables have their weakest effect on the outcome variables, with the estimate even being negative (although not statistically significant) for the latter. Consequently, the change in the estimates for the background variables are generally small as one goes from column 5 to column 6.

3.4. Funnel overview

In the first stage of signal reception, 82 % of respondents claimed to know their DSO and 69 % selected a DSO that was active in their municipality. In the second stage of signal processing, only 14 % of respondents were able to correctly identify their tariff. In the final stage of signal assimilation, depending on the threshold set (with 50 points reflecting a basic level of understanding and 70 points reflecting a moderate level of understanding), between 24 %–54 % of respondents demonstrated some capacity to link curtailment actions with costs. The funnel framework is designed such that only respondents who clear *all* three stages are deemed ready for DR engagement. Retaining only those who meet all three preconditions and depending on the selected threshold for the tariff scenario questions, the result is that only 3.8 % (70-point threshold) to 8.5 % (50-point threshold) of the entire sample remain. The funnel framework shown earlier is updated accordingly and re-displayed below in Fig. 3.

4. Discussion

4.1. Stage I - signal reception

It may seem unwarranted to question the idea that electricity users would receive a signal sent by their own DSO. Those who use electricity pay for it, and it is perhaps reasonable to suppose that they would therefore be aware of any change in the terms of payment. Reality is more complicated however, and to grasp the fallibility of this assumption, it is important to first scrutinize the link between the users and the payers. An important consideration is that electricity is used by multiple individuals living in a household, but is likely paid for by a single individual who is responsible for the bill. If one of these non-paying individuals was a survey respondent, it would not be surprising that they may be entirely oblivious to their DSO, and would not notice a tariff change. If the channel of communication between a DSO and a household is confined to one person (conceivably the case), then only this individual can receive the signal, and if this individual does not relay the signal to other household members, then only they can eventually engage in any form of demand response.

A second consideration is the case of tenants in rental units, which also provides a justification as to why DSO identification was used as a proxy for signal reception. If tenants are forwarded the entire bill from their landlords, exactly as it has been received, they should then be able recognize their DSO and would hypothetically be able to notice a tariff

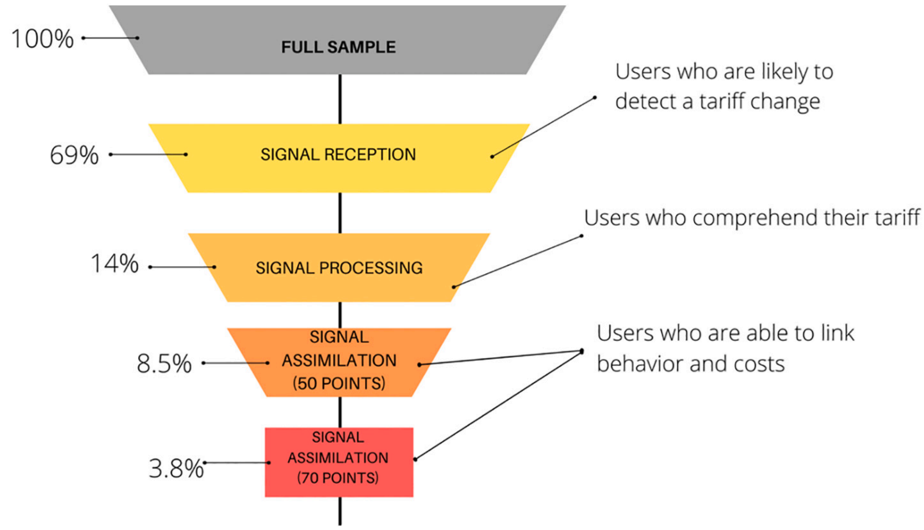

Fig. 3. Three-stage funnel framework depicting the pre-conditions of demand response, with the respective proportions of the sample that meet each precondition.

change and receive the price signal. If, however, the cost of their electricity consumption is included in their rent, or they are just forwarded the cost that they owe (without the entire bill) then they are likely to have no knowledge of their DSO, lack any insight to the design or details of the tariff and fail to receive a price signal. This may explain findings like the youngest demographic being the worst performing segment at this stage. Only 7 % of respondents living in villas were under the age of 30, whereas this proportion triples to 21 % in rental apartments, the largest share claimed by any age group.

The main split however, seems to lie between respondents living in villas and respondents living in apartments, both rented *and* owned. While 89 % of the former group receive the signal, only 76 % of the latter group do the same. This share is almost identical between owned and rented apartments, which suggests that there may be more factors to consider than the landlord-tenant dynamic. One culprit may be variations in the importance placed on electricity costs by respondents living in the different types of residence. Villa owners, the group most aware of their DSO are also the group that seems to be the most concerned with their electricity costs. Both types of apartment dwellers seem substantially less concerned with their costs, and so even if they do receive information from their DSO, it is possible that they disregard it entirely, or subscribe to automatic billing without heeding any attention to new information. Villa owners, although wealthier on average, likely face a larger electricity expenditure, and consequently may be more interested in tracking their usage and minimizing their costs. Conversely, for those living in apartments electricity likely makes up a modest share of their monthly expenditure, and may not be worth the trouble of bothering with complex letters from electricity providers. It is then feasible that some of these residents may fail to recall their DSO, and may fail to receive a price signal.

A final but important note is that if one were to remove the first stage of the funnel entirely, and replace the framework with a two-stage funnel looking only at the signal processing and signal assimilation, there would be virtually no change in the final outcome. The proportion of those who make it through the two-stage funnel would increase from 8.5 % to 9.5 % (50-point threshold) and from 3.8 % to 4 % (70-point threshold). This means that while DSO identification may be an imperfect proxy, the occurrence of respondents who do not know their DSO but perfectly understand their tariffs and the link to costs (false negatives) is close to negligible. It is also abundantly clear that critical stage where the largest reduction in the sample takes place, is the second stage of signal processing (see Fig. 3).

4.2. *Stage II - signal processing*

Many of the associations discussed in the previous section carry over to the next stage. Respondents more concerned with costs and respondents living in villas are more likely to meet the precondition and process the signal, for reasons discussed above. The emergence of a statistically significant gender gap may possibly be attributed to gender roles that see males as more likely to be the "managers" of domestic energy matters, and therefore more likely to be the ones receiving the tariffs and reading the bills. The most important factors however, were cost importance and bill-reading frequency. It is perhaps unsurprising that those who are more concerned with costs and read their bills more frequently were better able to process the signal. It may also not be very surprising that these frequent "bill-readers" were more likely to be male, older and living in villas. What is noteworthy, is that even among respondents who claimed to "always" read their bill (39 % of the total sample), the highest performing group, <22 % managed to correctly identify their tariff (last column in Fig. 5). This seems to indicate that the problems of signal transmission go beyond just having people read their electricity bills. One possibility is that what has been described as "reading bills" in this study really just amounts to a superficial glance with much of a reader's attention span directed to the total cost, as suggested by the Bill-Click tracking study [23]. Another possibility is that respondents may have actually carried out a more in-depth reading of their bills and tariffs, but simply failed to understand what they mean. One can only speculatively reason as to why there is sharp drop in respondents clearing the signal processing stage. Nevertheless, it is difficult to dispute the fact that a large majority of respondents have, for one reason or another, failed to recognize their own tariffs.

4.3. *Stage III - signal assimilation*

At this stage there is a shift in the role played by different variables. Education, which did not play a major role in the previous stages is now a very strong predictor of meeting the final precondition. Factors like bill-reading frequency and cost importance no longer play a major role. This likely has to do with the fact that the tariff scenario questions were designed to test for respondents' general interpretive capacities, not an understanding of their own tariffs which they may have accumulated over time. This would explain why reading bills more frequently doesn't seem to improve one's ability to link load-shifting scenarios to different types of tariffs. Finally, the proportion of respondents who meet this precondition (24 %–54 %) likely leads to an overestimate in the actual share of the final sample of "qualifiers". While these respondents have cleared the thresholds required to meet the precondition, it is important to note that they were primed by the survey and aided by a set of instructional diagrams which may not be available to them when they consider or carry out load-shifting activities in their day. The signal assimilation stage evaluates respondents understanding on information they are immediately confronted with. In reality, they may never ponder these questions and so the real proportion of those who qualify may be even lower.

4.4. Limitations

To avoid a misinterpretation or a mischaracterization of the above results, it is important to outline some of the study's limitations. While one of the posited strengths of the study is that it avoids a small sample of enthusiastic pilot study participants, reaching a wider sample of respondents subject to mandatory network pricing, the sample is still selected and therefore not perfectly representative of the general Swedish population. Respondents have not volunteered to be part of a pilot study on electricity pricing, but they have agreed to respond to the survey, which may reflect a curiosity concerning energy-related matters that systematically differs from the Swedish population at large. Given a curiosity and willingness to open and complete the survey, one may cautiously presume that respondents may be more knowledgeable concerning the topic of electricity pricing compared to the general population. In summary, despite being more representative than the more usual case of pilot study participants, the sample's characteristics are still not fully representative of the general population.

Another important set of limitations concerns how the different stages were operationalized. As discussed in previous sections, whether or not a respondent could identify their DSO is not a rigorous measure of signal awareness, but it was retained for lack of a better indicator given the empirical context. If future studies could time the rollout of their instrument (survey or other) so that it coincides with (or shortly after) the rollout of a new tariff, they could employ more valid indicators of signal awareness, though this approach would also come with its own set of limitations. The operationalization of the latter two stages, while more valid, likely leads to an overestimation of respondent's knowledge and capacities. When it comes to selecting one's own tariff, respondents are provided with a multiple-choice list, making their task much easier than if they were to try and describe their tariff with no hints or cues provided. The tariff descriptions may have induced a cued recall that would have otherwise been absent. Similarly, the final set of questions concerning signal assimilation provided respondents with a high quality (in comparison to other Swedish DSOs) visual description of the tariff and the cost impacts of various actions. The visual aids, the wording of the questions and the fact that the questions were single-answer multiple choice drastically narrowed down the problem, reducing the cognitive demands of “responding to a price signal”. In a “real” setting, an electricity user may never contemplate thinking in these terms, and may perhaps never succeed (or decide to) reduce the problem of demand response into a simple set of load-shifting actions. These limitations are more difficult to address. It is challenging to try and devise a measure of knowledge for a complex and multi-faceted problem (responding to a price signal) without breaking down the problem into constituent parts. At the same time, disaggregating a problem will inevitably influence how respondents perceive it, framing it in one of many possible forms. The limitations discussed thus far point to a likely overestimation in those who “qualify” through the preconditions. This conjecture suggests that if these limitations were to be adequately addressed, one may expect that the proportion of people who qualify through the three stages would be even smaller.

In addition to the above discussion, there are also the usual limitations that are inherent to survey research. Response fatigue, random response bias, a dependence on respondent's memory and willingness to seriously engage with the questions. Measures were taken to counterbalance some of these issues, like randomizing the presentation order and inserting the confidence scale. Nevertheless, the surveys can only capture certain aspects of a complex phenomenon, and are therefore rarely fully representative of a real-world setting.

5. Conclusion

The results of this study suggest that price signals, which are central to price-based DR, are unlikely to be internalized by their targets in large-scale roll-outs. While a majority of respondents could identify their DSO, a small minority were able to correctly process the price signals embedded in their tariffs. The fraction of respondents who could not identify their own tariff is indicative of a severe communication problem that could either be due to shortcomings in the current communication strategies employed by DSOs, the outright indifference of disinterested users, or some combination of both. By prioritizing the magnitude of incentives and the role of willingness to respond, various diagnoses of demand response failure overlook the scarcity of users who meet the preconditions for DR engagement. In turn, faulty diagnoses for why DR fails may lead to inappropriately designed policies and interventions. In the current model of price-based DR, users need to be aware of changes to their tariff, read their bills, understand their tariffs and then deduce what behavioral actions would lead to an increase/decrease in their costs. They would then presumably decide on whether or not to “trade” flexibility for savings. It is therefore imperative to reach a clearer understanding of these stages and where respondents are siphoned off. While the funnel framework proposed above is elementary, future research should advance the task of attempting to disaggregate the DR process into its constituent components, and analyze these components separately in order to gain more clarity on *how* and *why* DR may lead to underwhelming results.

On the psychological front, there is a crucial need to identify the mechanisms behind decision-making and behavioral change in the field of energy use, which have thus far primarily focused on price signals as the prime determinants of behavioral change. As this study has shown however, users cannot make decisions on “offers” they are not aware of, and so aside from the usual questions of “how can we encourage users to respond to signals”, policymakers might also be interested in answering questions that relate to getting users sufficiently interested in domestic energy usage to carefully read their bills and recognize changes in their tariffs. The ambivalence of users identified in this study suggests that DSOs and network operators need to work on improving their engagement strategies, which includes the pedagogical presentation of bills and tariffs but perhaps more importantly, should also include general outreach efforts with public communication and campaigns on awareness. Future research could build on previous work that has investigated these strategies in other market settings [35]. Finally, researchers and policymakers should seriously consider the prospects of circumventing the funnel entirely. If only a small minority of users are sufficiently active and informed to “respond” to a price signal, it is important to reflect on whether society's goal should be to convert the more general “passive” users into their active counterparts (the dominant policy goal today), or instead identify ways that passive users could perhaps contribute to demand flexibility without the need to become active, domestic energy experts.

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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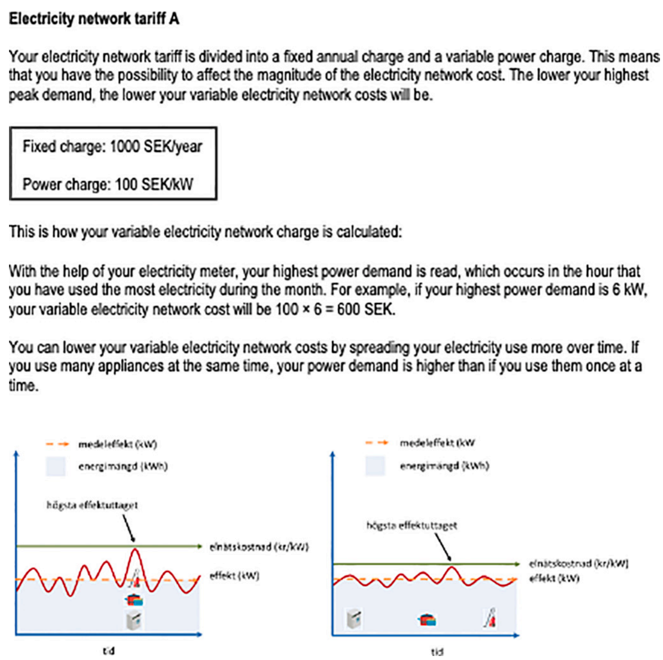
Appendix A. Stage III tariffs and questions

This section presents the four different tariffs respondents were shown with regards to stage III of the funnel, followed by the tariff scenario questions they received. Note that Swedish was the original language of the survey, and that some wording issues might potentially stem from an imperfect translation. Also note that for the sake of brevity, this section shows all four tariffs followed by the set of questions (which were the same for each tariff). In the survey, respondents were instead shown each tariff followed by its respective set of questions (so that they could focus on one tariff at a time).

Tariff A was the time-invariant, demand-based tariff and was presented as follows:


Electricity network tariff A

Your electricity network tariff is divided into a fixed annual charge and a variable power charge. This means that you have the possibility to affect the magnitude of the electricity network cost. The lower your highest peak demand, the lower your variable electricity network costs will be.

Fixed charge: 1000 SEK/year

Power charge: 100 SEK/kW

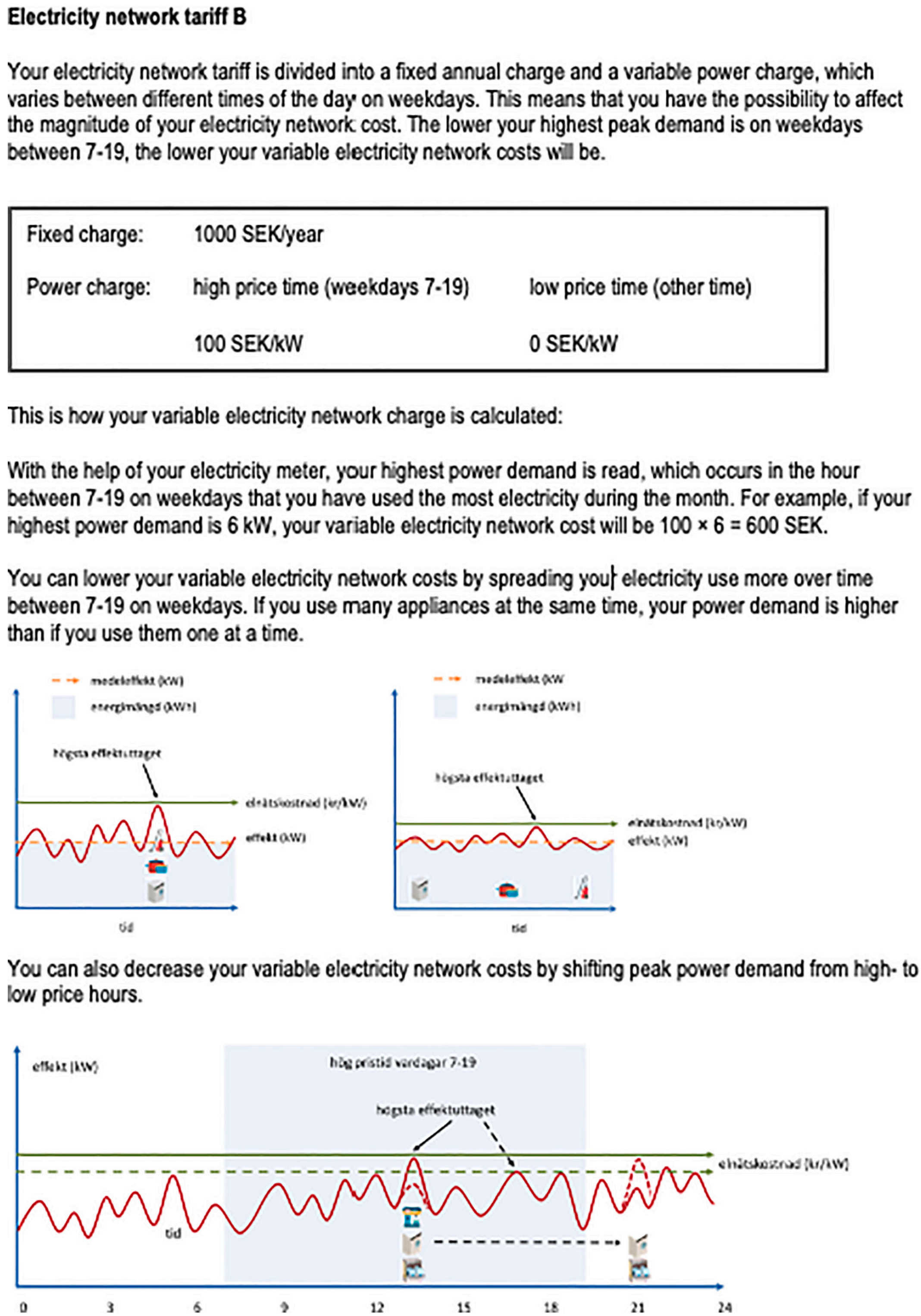
This is how your variable electricity network charge is calculated:

With the help of your electricity meter, your highest power demand is read, which occurs in the hour that you have used the most electricity during the month. For example, if your highest power demand is 6 kW, your variable electricity network cost will be 100 × 6 = 600 SEK.

You can lower your variable electricity network costs by spreading your electricity use more over time. If you use many appliances at the same time, your power demand is higher than if you use them once at a time.

Fig. 4. Presentation of Tariff A to survey respondents.

Tariff B was the time-differentiated, demand-based tariff and was presented as follows:



Electricity network tariff B

Your electricity network tariff is divided into a fixed annual charge and a variable power charge, which varies between different times of the day on weekdays. This means that you have the possibility to affect the magnitude of your electricity network cost. The lower your highest peak demand is on weekdays between 7-19, the lower your variable electricity network costs will be.

Fixed charge:	1000 SEK/year	
Power charge:	high price time (weekdays 7-19)	low price time (other time)
	100 SEK/kW	0 SEK/kW

This is how your variable electricity network charge is calculated:

With the help of your electricity meter, your highest power demand is read, which occurs in the hour between 7-19 on weekdays that you have used the most electricity during the month. For example, if your highest power demand is 6 kW, your variable electricity network cost will be 100 × 6 = 600 SEK.

You can lower your variable electricity network costs by spreading your electricity use more over time between 7-19 on weekdays. If you use many appliances at the same time, your power demand is higher than if you use them one at a time.

You can also decrease your variable electricity network costs by shifting peak power demand from high- to low price hours.

Fig. 5. Presentation of Tariff B to survey respondents.

Tariff C was the time-invariant, energy-based tariff and was presented as follows:

Electricity network tariff C

Your electricity network tariff is divided into a fixed annual charge and a variable energy charge. This means that you have the possibility to affect the magnitude of the electricity network cost. The less electricity you use, the lower your variable electricity network costs will be.

Fixed charge: 1000 SEK/year	
Energy charge: 0.4 SEK/kWh	

This is how your variable electricity network charge is calculated:

With the help of your electricity meter, your electricity use during the month is read. For example, if your electricity use is 1,500 kW, your variable electricity network cost will be 0.4 × 1,500 = 600 SEK.

You can reduce your variable electricity costs by using less electricity.

Fig. 6. Presentation of Tariff C to survey respondents.

Tariff D was the time-differentiated, energy-based tariff and was presented as follows:

Electricity network tariff D

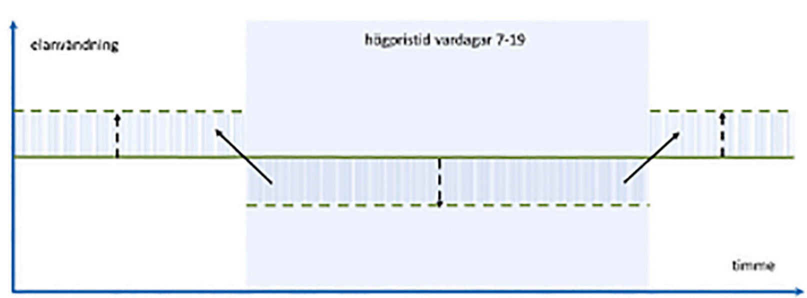
Your electricity network tariff is divided into a fixed annual charge and a variable energy charge, which varies between different times of the day on weekdays. This means that you have the possibility to affect the magnitude of the electricity network cost. The less electricity you use on weekdays between 7-19, the lower your variable electricity network costs will be.

Fixed charge:	1000 SEK/year	
Energy charge:	high price hours (weekdays 7-19)	low price hours (other times)
	0.6 SEK/kWh	0.3 SEK/kWh

This is how your variable electricity network charge is calculated:

With the help of your electricity meter, your electricity use in high- and low price hours during the month is read. For example, if your electricity use in high- and low-price hours is 500 and 1,000 kWh respectively, your variable electricity network cost will be (500 × 0.6) + (1,000 × 0.3) = 600 SEK.

You can reduce your variable electricity costs by shifting electricity use from high- to low price hours.



You can also reduce your electricity network costs by reducing your electricity use.

Fig. 7. Presentation of Tariff D to survey respondents.

For each tariff, respondents received the same exact set of questions, to which the correct answers would differ according to the tariff. These questions, along with the confidence level ratings, are shown below. The first question is a basic recognition question, where respondents are asked whether there is anything they can do to reduce costs given the tariff that they have.

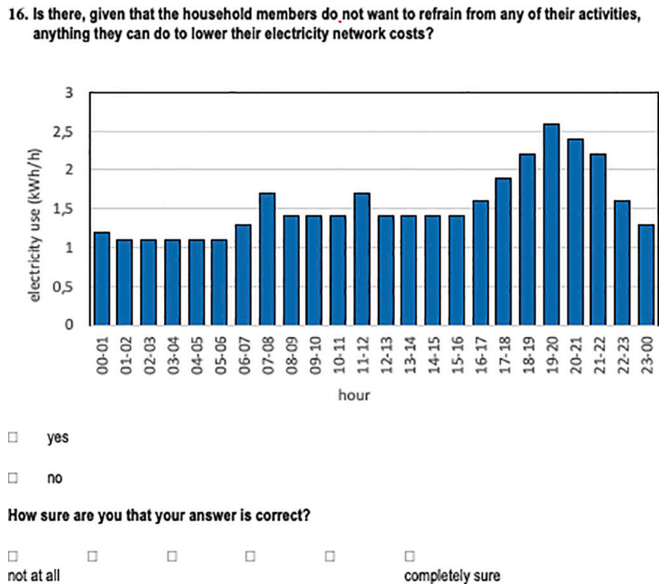


Fig. 8. Presentation of first tariff scenario question to respondents.

The remaining questions involved actual load-shifting scenarios. An example of the second question shown to survey respondents is presented below:

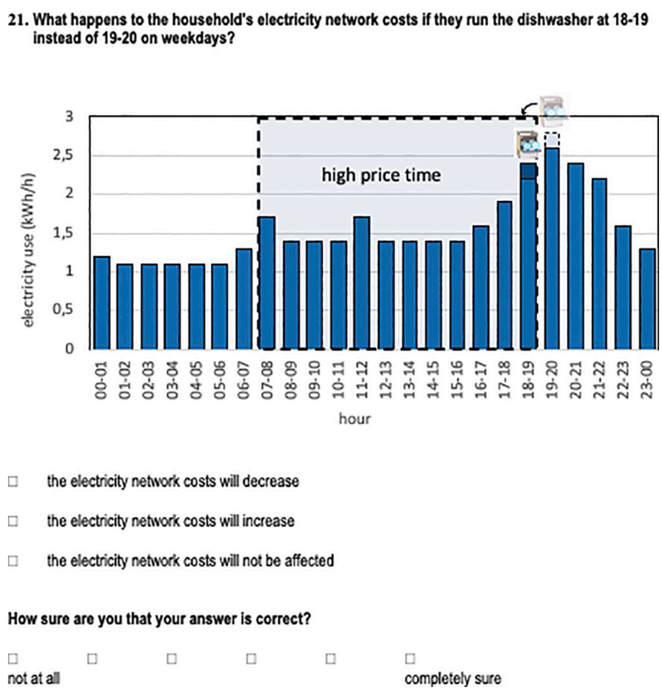


Fig. 9. Presentation of second tariff scenario question to respondents.

An important note is that the shaded band designating "high price time" is only shown when the question concerns a time-differentiated tariff. In cases where the tariff is time-invariant, the band is erased, as shown below in the case of the third question for a time-invariant tariff:

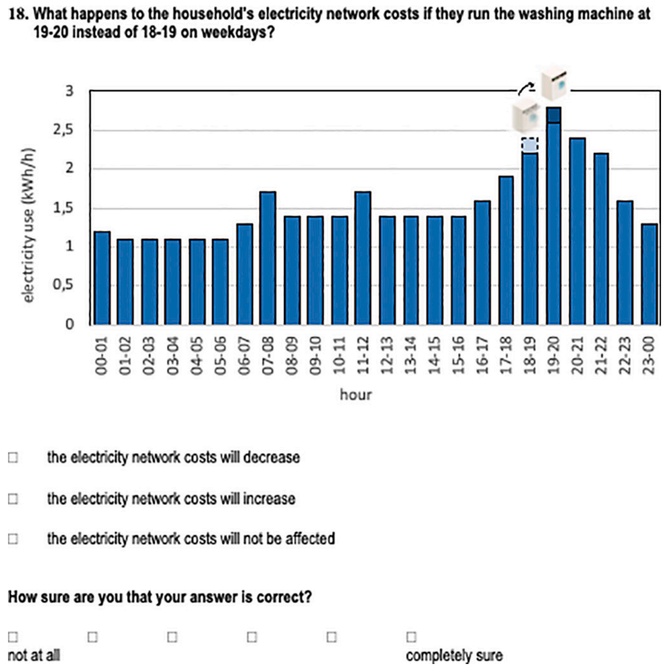


Fig. 10. Presentation of third tariff scenario question to respondents.

The fourth and final tariff scenario question is shown below, with the high-band returned, indicating that it now concerns a time-differentiated tariff:

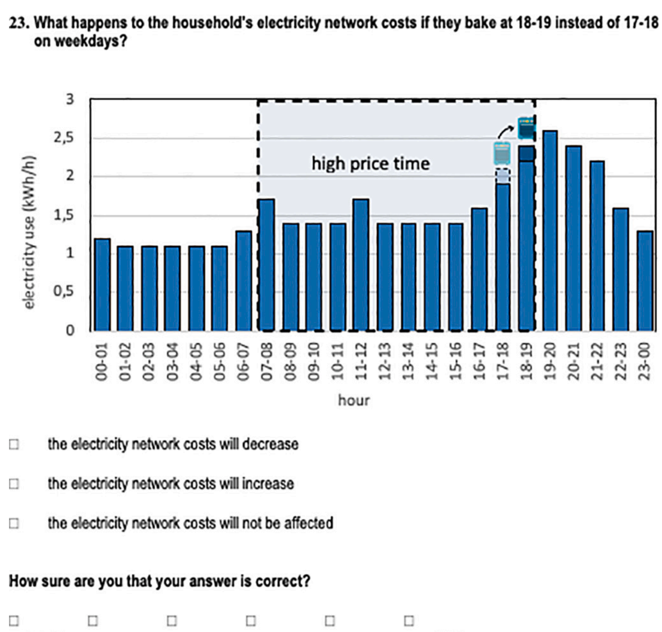


Fig. 11. Presentation of fourth tariff scenario question to respondents.

Appendix B. Point conversion

This section, copied from Appendix E in [33] outlines how the confidence scales are incorporated with a respondent's answer to generate a score on a point scale. For questions with 2 possible answers the following equations were used to convert the response and confidence level (C) to a score.

Correct Answer→Score $= 40 + 10C$

Incorrect Answer→Score $= 60 - 10C$

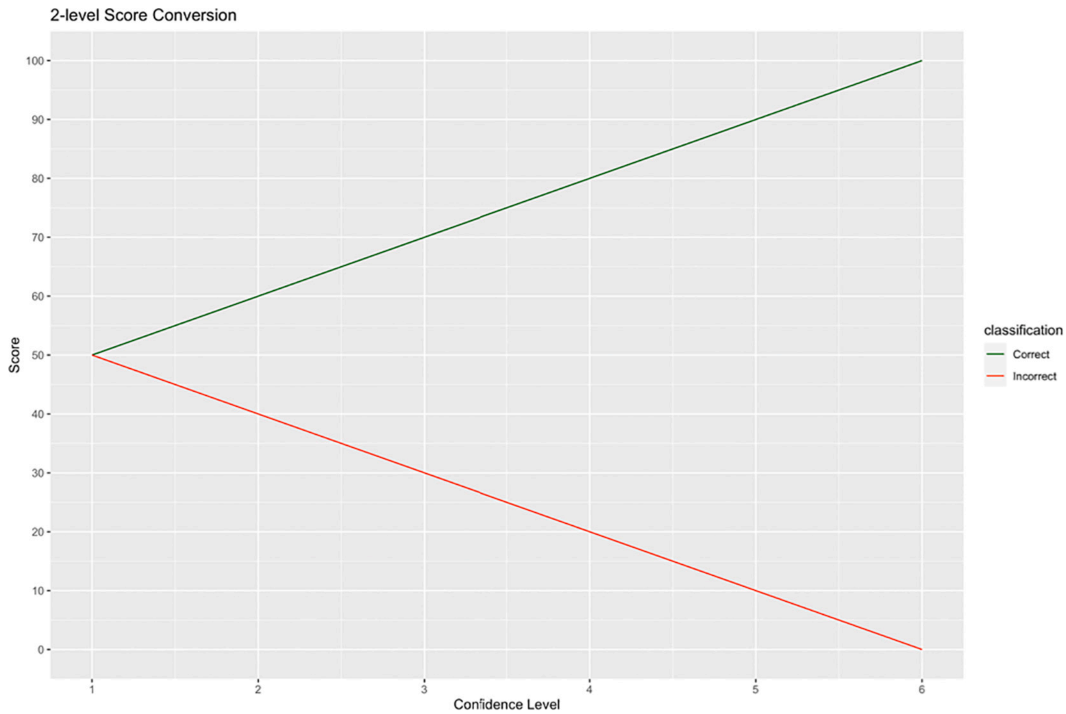


Fig. 12. Converting 2-level responses to a score that ranges from 0 to 100.

A respondent who answers a question correctly with a confidence level of 2/6 would receive a score of 40 + 10(2) = 60. If the respondent had the same confidence level but scored incorrectly, they would instead receive a score of 60–10(2) = 40. For questions with 3 possible answers the following equations were used to convert the response and confidence level (C) to a score.

$$\text{Correct Answer}\rightarrow\text{Score} = 20 + \frac{40}{3}\text{C}$$

$$\text{Incorrect Answer}\rightarrow\text{Score} = 40 - \frac{20}{3}\text{C}$$

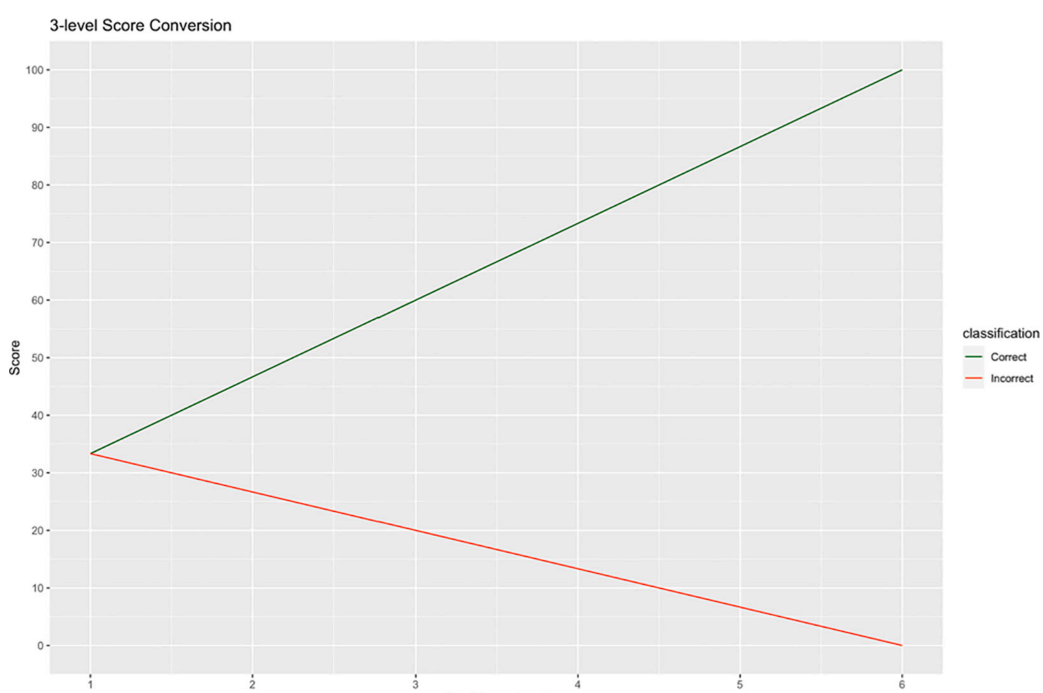


Fig. 13. Converting 3-level responses to a score that ranges from 0 to 100

Appendix C. Descriptive statistics of variables

Table 3
The table provides descriptive statistics. The first column displays the number of individuals belonging to each category with the second being the share (out of 1336 observations). The third columns show 95 % confidence intervals for the share, while the fourth column displays how each variable is coded. That is, for education, the code roughly translates into how many years of schooling an individual with the given category will have. For age, the linear coding is an approximation for the average age in each bracket. The two Likert-scale measured variables (bill-reading frequency and cost importance are answers to the questions 7 and 11. These have also been coded linearly for simplicity.Each municipality receive its own indicator variable (i.e., either taking the value 0 or 1, with one the indicators omitted in the regressions to avoid the "dummy variable trap") and the variables in Panel F and G are also indicator variables. In the regressions, all variables which are not indicator variables have been standardized to have a mean of zero and standard deviation of one to facilitate easier interpretation.

	(1)	(2)	(3)	(4)
	Count	Share	95 % CI	Code
Panel A. Education categories				
Not finished elementary school	6	0.004	0.002–0.010	7
Elementary school	58	0.043	0.033–0.056	9
Not finished upper secondary school	114	0.085	0.071–0.102	11
Upper secondary school	238	0.178	0.158–0.200	12
Tertiary education, not university	165	0.124	0.107–0.143	13
University studies	189	0.141	0.123–0.162	14
University degree	539	0.403	0.377–0.430	16
PhD studies	27	0.020	0.014–0.030	19
Panel B. Age categories				
−29	185	0.138	0.121–0.158	1
30–39	197	0.147	0.129–0.168	2
40–49	206	0.154	0.135–0.175	3
50–59	266	0.199	0.178–0.222	4
60–69	199	0.149	0.131–0.169	5
70+	283	0.212	0.190–0.235	6
Panel C. Bill-reading frequency				
1 never	187	0.140	0.122–0.160	1
2	106	0.079	0.066–0.095	2
3	121	0.091	0.076–0.108	3
4	137	0.103	0.087–0.120	4
5	155	0.116	0.100–0.135	5
6	110	0.082	0.068–0.099	6
7 always	520	0.389	0.363–0.416	7
Panel D. Cost importance				
1 no, not at all	410	0.307	0.282 – 0.333	1
	172	0.129	0.111 – 0.148	2
	178	0.133	0.116 – 0.153	3
	241	0.180	0.160 – 0.202	4
	171	0.128	0.111 – 0.147	5
	62	0.046	0.036 – 0.059	6
7 yes, to a large extent	102	0.076	0.063 – 0.092	7
Panel E. Municipalities				
Enköping	143	0.107	0.091–0.125	Indicator
Hedemora	37	0.028	0.020–0.038	Indicator
Nacka	347	0.260	0.237–0.284	Indicator
Partille	109	0.082	0.068–0.098	Indicator
Ragunda	17	0.013	0.008–0.021	Indicator
Sala	57	0.043	0.033–0.055	Indicator
Sollentuna	261	0.195	0.175–0.218	Indicator
Sundbyberg	114	0.085	0.071–0.102	Indicator
Täby	251	0.188	0.167–0.210	Indicator
Panel F. Other independent variables				
Female	677	0.507	0.480–0.534	Indicator
Own apartment	476	0.356	0.331–0.383	Indicator
Rent apartment	212	0.159	0.140–0.180	Indicator
Panel G. Knowledge variables				
DSO correct	933	0.698	0.673 – 0.723	Indicator
Tariff correct	518	0.388	0.362–0.415	Indicator

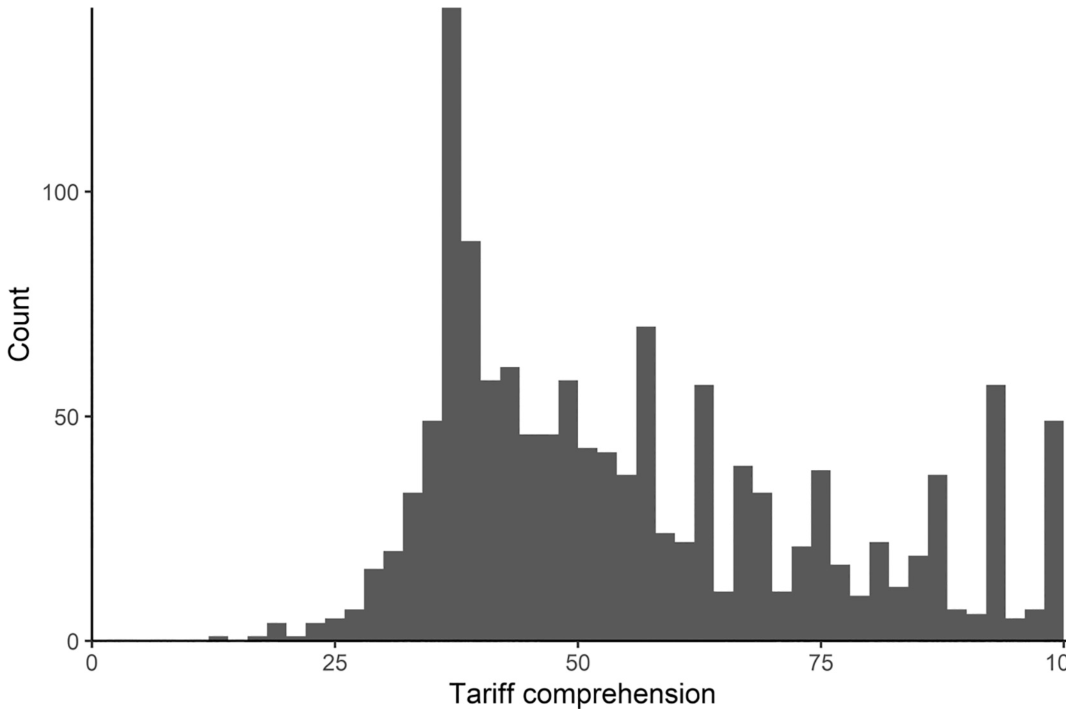


Fig. 14. Distribution of Tariff comprehension score. See Appendix B for how this variable is coded.

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