D3.4 | Report on economic factors impacting individual short-term energy choices

Report Information

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The project in brief

The Energy Union Framework Strategy laid out on 25 February 2015 aims at fostering a cost-efficient energy transition able to deliver secure, sustainable and affordable energy to all European consumers. It has embraced a citizen-oriented energy transition based on a low-carbon transformation of the energy system. At the end of the day, the successful implementation of the Energy Union will materialise in a change in energy production and energy consumption choices. Such choices are heavily shaped by particular economic prerequisites, value systems, gender-based preferences, efficiency of governance and the maturity of civil society.

The ENABLE.EU project attempts to understand the key drivers of individual and collective energy choices, including in the shift to prosumption (when energy consumers start to become also energy producers). The project will develop participatory-driven scenarios for the development of energy choices until 2050 by including the findings from the comparative sociological research. As differences between European countries remain salient, ENABLE.EU will have a strong comparative component.

The final aim of this project is to contribute to more enlightened, evidence-based policy decisions, to make it easier to find the right incentives to reach the twin goals of successful implementation of the Energy Union and Europe's transition towards a decarbonised energy system. To reach this final aim, ENABLE.EU will seek to provide an excellent understanding of the social and economic drivers of individual and collective energy choices with a focus on understanding changes in energy choice patterns. Results will be disseminated to relevant national and EU-level actors as well as to the research community and a wider public.

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1. Executive summary

The European Union's 2020 and 2030 strategies, which constitute a set of binding legislation, aims to increase energy efficiency by 20% by 2020 and by 32.5% by 2030. Further, the 2020 strategy aims at a share of 20% renewables in final energy consumption by 2020 and a share of 32% renewables by 2030. These strategies put a strong focus on households' short-term energy demand[1]. By employing energy saving measures, energy services are consumed more efficiently. A more flexible energy demand avoids grid overloads, as it can be adapted to the supply-dependent feed-in of renewable energies. However, these demand side opportunities for more efficient and low-carbon energy use go hand in hand with the question: "Which factors influence the short-term energy consumption choices of households?". This case study deals with the demand for energy services by private households. By understanding the drivers of energy consumption, policy can directly target these drivers and implement corresponding policies. Therefore, we aim to identify the causal effect of different policy interventions on energy consumed in four distinct country case studies, conducted in Bulgaria, Germany, Serbia and the United Kingdom. From a methodical point of view, the country case studies are implemented in the form of randomized controlled trials (RCTs). RCTs are economic experiments, which aim at identifying the causal effect of an intervention on an outcome variable by instrumenting randomized exposure to the intervention.

As an analysis of the ENABLE.EU households survey[2] shows, Bulgarian households provide less accurate estimates of appliances' energy costs compared to households in Germany, Serbia and the United Kingdom. By receiving an energy consumption and cost break-down by different appliances, households are able to understand and to learn about their consumption. Thus, the research question of the Bulgarian case study was: "What is the effect of energy cost break-downs by appliance on energy consumption?" To answer the question an RCT was conducted with 405 households over a duration of four months, including both heating and non-heating seasons. Results show that, although households in the treatment group received monthly energy cost break-downs by appliance, their energy consumption is not significantly different to the control group, which did not receive the information. However, a within-analysis of the treatment group for specific appliances shows that the treatment group significantly decreases utilization of both the electric water heater and the washing machine over time. Still, the lacking significance in the comparison with the control group indicates very limited potential for detailed cost break-downs to decrease energy consumption. A possible reason might be the high share of energy poor households in Bulgaria, who might already consume energy most efficiently.

The results of the German case study provide important insights into one driver of households' energy consumption: intermittent billing. For Germany, the lag between consumption of energy and payment of the bill is particularly severe as meter readings only occur on a yearly basis. Thus, the researchers designed an RCT to focus on the discounting effects associated with such intermittent billing. The research question is, whether there is evidence of hyperbolic-discounting in energy consumption. Hyperbolic discounting gives rise to time-inconsistent choices, such that overconsumption of energy occurs from both a social and an individual perspective. The RCT was conducted as a lab experiment with 171 students to investigate the effect of more frequent energy billing on energy consumption, holding saliency and information effects constant. The control scenario is billing one week after consumption has taken place, the treatment scenario is billing

[1] The terms "energy" and "electricity" are used as synonyms throughout this report.
[2] ENABLE.EU conducted a nationally representative survey in the 11 project's partner countries from October 2017 to February 2018 (see D 4.1 for more information).

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immediately after consumption. The main result is that immediate billing decreases light consumption on average by around 10-12% compared to delayed billing. Further, these results are consistent with (quasi-) hyperbolic but not with exponential discounting. The results provide important insights to understand qualitatively the consequences of intermittent billing. From a practical perspective, holding information and saliency effects constant, more frequent billing will decrease energy consumption. From a conceptual perspective, first causal evidence of hyperbolic discounting under intermittent billing is provided.

Because energy prices of households in Serbia are the lowest in Europe, information provision, rather than financial incentives, was selected as a potential policy intervention in the Serbian case study. In particular, the research aims to shed light on whether energy saving instructions are a fruitful strategy to promote reduction in energy consumption. In cooperation with the national electricity supplier EPS Supply, a total of 330 participants were recruited to participate in an RCT, where the treatment group received a brochure of energy-saving instructions. Such intervention was used to increase consumer's awareness, and observe if the adoption of new consumption patterns has an actual impact on consumption reduction. The results show that in a country where the electricity price is very low, energy-saving instructions do not affect consumer behavior. Households may be not interested to pursue the instructions, as their expected monetary savings are too low.

The single most important domestic energy policy initiative ongoing in the UK is the Smart Meter Implementation Programme (SMIP). This programme provides the legal framework to install smart electricity and gas meters in every household in the UK by 2020. Smart metering may allow consumers to save energy and money, but of greater social benefit is their potential to pave a path toward a more flexible energy system, allowing optimisation of generation and storage. Indeed, smart meters can be considered a key enabling technology of a sustainable energy system. However, consumer resistance has severely inhibited rollout thus far. This research provides new evidence on this important topic. Information treatments are provided to households to assess the impact of anchoring in willingness-to-accept elicitation for this unusual but important context, where subjects are essentially asked to place a value on the compensation necessary to provide a public good. From these responses, the study infers the optimal subsidy level policymakers may need to provide to incentivise households to adopt smart meters and comment on the sensitivity of that inference to the methodology deployed.

Taking the different country case studies together, this report demonstrates a limited potential for information and feedback policies in decreasing energy consumption. This is particularly the case when the countries either exhibit a high share of energy poverty, as seen in Bulgaria, or have a very low energy price, as seen in Serbia. Households living in energy poverty might not demand information as they already gathered knowledge themselves on how to save as much as possible. Households facing low energy costs may simply value the effort costs of following through energy saving behaviours higher than expected savings. Once taking information as given, the German case study points to the role of discounting in recurring billing cycles. Because consumption and payment of energy are separated in time, the payment will be (quasi-)hyperbolically discounted leading to an overconsumption of energy. A change in the billing system, such as more frequent billing or prepaid metering, would decrease this overconsumption. The UK case study complements the three other case studies by focusing on adoption of a potentially energy saving technology. The results suggest that, in contrast to the previous RCTs focusing on consumption, information treatments, combined with subsidies has a significant impact on household behaviour regarding adoption of energy saving technologies

The following report is structured as follows: Section 2 provides a common introduction and

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motivation to the national case studies. It mainly relies on a comparison between the energy literacy levels in the different countries as elicited in the ENABLE.EU household survey. Further, the RCT methodology is explained. Sections 3 to 6 give the country case study reports. Section 3 describes the Bulgarian case study, as conducted by the researchers of the Center for the Study of Democracy (CSD). Section 4 comprises the German case study, conducted by researchers of the University of Münster (WWU). The Serbian case study, conducted by researchers of the Economics Institute (EI), is covered in Section 5. Finally, Section 6 refers to the UK case study conducted by researchers at the Grantham Research Institute at the London School of Economics (GRI-LSE). Each of the country case study reports can be read independently.

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2. Introduction

The European Union's 2020 and 2030 strategies, which constitute a set of binding legislation, aims to increase energy efficiency by 20% by 2020 and by 32.5% by 2030. Further, the 2020 strategy aims at a share of 20% renewables in final energy consumption by 2020 and a share of 32% renewables by 2030. These strategies put a strong focus on households' short-term energy demand. By employing energy saving measures, energy services are consumed more efficiently. In order to avoid overloading the grid with the advancing energy transition, the supply of electricity must always correspond to the demand for electricity. Fluctuating generation and grid feed-in from renewable energies with relatively rigid demand at the same time presents problems that can be addressed with various flexibility options. A more flexible energy demand avoids grid overloads, as it can be adapted to the supply-dependent feed-in of renewable energies. However, these demand side opportunities for more efficient and low-carbon energy use go hand in hand with the question: "Which factors influence the short-term energy consumption choices of households?". This report deals with the demand for energy services by private households. By understanding the drivers of energy consumption, policy can directly target these drivers and implement corresponding policies. Therefore, we aim to identify the causal effect of different policy interventions on electricity consumed in four distinct country case studies, conducted in Bulgaria, Germany, Serbia and the United Kingdom.

2.1 Motivation

An economic determinant of short-term energy consumption, which joints the four country case studies, is the acknowledgement of households' being uncertain on their energy costs and needing more information on how to save energy. This acknowledgement is considered in survey questions included in the ENABLE.EU household survey. The household survey included some questions eliciting participant's energy literacy just for the participating case study countries. Following Blasch, Boogen, Filippini, & Kumar (2017), energy literacy is used to gather participant's knowledge about energy. Therefore, we measure in three questions the degree to which households know energy prices, how much the consumption of certain energy services costs and which energy services consume more than others. Specifically the three energy literacy questions are the following:

E1. How much do you think 1 kWh of electricity currently costs in [COUNTRY] on average? Please indicate your best guess without checking your bill or other resources.
1. ………………… (amount in [cents] [pense])
99. Don't know

E2. Please <u>estimate</u>, how much electricity costs occur for an average household in [COUNTRY] when running:
ONE answer per row

		0-19 [cents] [pense]	20-39 [cents] [pense]	40-59 [cents] [pense]	60-79 [cents] [pense]	80-100 [cents] [pense]	More than 100 [cents] [pense]	Don't know
A.	A TV set for an hour	1	2	3	4	5	6	99
B.	A washing machine (load of 5kg at 60°C) for an hour	1	2	3	4	5	6	99

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E3A. Assuming an average household in [COUNTRY], which of the following two activities consumes more electricity?
Only ONE answer
1. Bringing 1 litre of water to a boil in an average pot with lid
3. Running a washing machine with a load of 5kg at 60°C
3. Both consume about the same
99. Don't know

E3B. Assuming an average household in [COUNTRY], which of the following two activities consumes more electricity?
Only ONE answer
1. Bringing 1 litre of water to a boil in an average pot with lid
2. Bringing 1 litre of water to a boil in an electric kettle
3. Both consume about the same
99. Don't know

E3C. Assuming an average household in [COUNTRY], which of the following two activities consumes more electricity?
Only ONE answer
1. Running a tube TV for 1 hour
2. Running a flat screen TV for 1 hour
3. Both consume about the same
99. Don't know

From these questions, we gather an energy literacy index (Blasch, Boogen, Filippini, & Kumar, 2017), by giving points to each correct answer. The maximum energy literacy index is 11, indicating maximum sophistication about energy consumption and costs. The graphics below depict the energy literacy indexes for the four case study countries.

Figure 1: Average energy literacy indexes by country

The average energy literacy score for Bulgaria and the UK is 3. Germany and Serbia do slightly better by an average energy literacy score of 4. However, given the maximum score of 11, all countries exhibit a rather low energy literacy. In the UK, not a single participant achieved the full

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11 points. Looking in detail at the questions blocks allows understanding where exactly the

Figure 2: Average share of correct answers to E1 by country

misperception stems from.

Figure 2 gives the average share of correct answers on E1. Whereas in Germany and in Serbia almost 50% of participants know the correct average price of energy, in the UK only 15% knew the correct average price. For Bulgaria, 27% gave the correct answer. Also in Figure 3, giving the share of correct answers to E2, and in Figure 4, giving the share of correct answers to E3, both

Figure 3: Average share of correct answers to E2 by country

Germany and Serbia do comparably well. An interesting reverse emerges for Bulgaria and the UK. The share of correct answers for the costs of particular energy services (E2) is particularly low for

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Bulgaria. In contrast, the UK outperforms both Serbia and Germany on E2. It seems that although

Figure 4: Average share of correct answers to E3 by country

the knowledge on the correct average energy price is lower in the UK, the knowledge on the cost of particular services is higher in the UK. However, again the reverse is true for the knowledge on the costs of services in comparison to each other (E3). In Bulgaria the share of correct answers is comparable to Germany and Serbia, but in the UK knowledge on E3 is the lowest.

Based on these statistics, the four countries involved in this study focus on different fields to examine economic factors influencing household's short-term energy choices in more detail.

2.2 The country case studies

As shown in section 2.1, Bulgarian households have a comparative lack in giving cost estimates of the energy consumption of particular appliances or services. Similarly, utility bills are often difficult to understand and consumption is only presented as an aggregated measure. Thus, the research question of the Bulgarian case study is: "What is the effect of energy cost break-downs by appliance on electricity consumption?". By providing cost break-downs to different appliances, households should be able to understand and to learn about their consumption. As a consequence, consumers should be empowered to conduct energy saving measures. The RCT is designed such that over a total duration of four months, including both heating and non-heating seasons, 405 households report their electricity consumption. Treatment group households received detailed break-downs by appliance for each month, giving them the energy consumption and energy cost for each appliance. As the control group did not receive this detailed feedback, the treatment group is hypothesized at the very least to decrease utilization of the most consuming appliances and thus to decrease energy consumption.

The payment of electricity consumption usually occurs some time after consumption has taken place. In Germany, the time lag is particularly severe: consumption is immediate, whereas billing occurs only once a year. This lag has two consequences: future costs are discounted when making decisions and information on consumption behaviour is just given once a year. However, as the comparison of energy literacy across countries shows, the energy literacy in Germany is already

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rather high. Thus, the German case study focuses on the discounting effects and examines the existence of hyperbolic discounting by increasing the billing frequency while holding informational and saliency effect constant. The RCT was conducted as a lab experiment with 171 students. The control scenario is billing one week after consumption has taken place, the treatment scenario is billing immediately after consumption. This change in billing induces a change in discounting the bill, while information is held constant across both groups. In case of hyperbolic discounting, the control group consumes significantly more energy than the treatment group.

Because the Serbian energy market is not liberalized and energy prices are the lowest in Europe, information provision, rather than financial incentives, was selected as a potential policy intervention in the Serbian case study. In particular, the researches aim to shed light on whether energy saving instructions are a fruitful strategy to promote reduction in electricity consumption. In cooperation with the national electricity supplier EPS Supply, 330 participants were recruited to participate in an RCT, where the treatment group received a brochure of energy-saving instructions. Such intervention was used to increase consumer's awareness, and observe if the adoption of new consumption patterns has an actual impact on consumption reduction.

The single most important domestic energy policy initiative ongoing in the UK is the Smart Meter Implementation Programme (SMIP). This programme provides the legal framework to install smart electricity and gas meters in every household in the UK by 2020. The UK case study presents an incentive-compatible RCT to elicit the willingness to accept of a representative panel of UK households for smart meter installation. Given the relatively low energy literacy level in the UK, information treatments are provided to households to assess the impact of anchoring in willingness-to-accept elicitation for this unusual but important context, where subjects are essentially asked to place a value on the compensation necessary to provide a public good. From these responses, the study infers the optimal subsidy level policymakers may need to provide to incentivise households to adopt smart meters and comment on the sensitivity of that inference to the methodology deployed. The results demonstrate that information treatments can be effective in lowering household resistance to smart meter adoption. The results also reveal a wide range of willingness-to-accept valuations. Despite this fact, the range is largely within the range of values that would be considered cost-effective for society to subsidise.

2.3 Methodology

From a method point of view, the country case studies are implemented in the form of randomized controlled trials (RCTs). RCTs are economic experiments, which aim at identifying the causal effect of an intervention on an outcome variable by instrumenting randomized exposure to the intervention. For this case study, the relevant outcome variable is energy consumption in the Bulgarian, German and Serbian case studies, and smart meter adoption for the UK case study. The interventions are described in section 2.2.

The difficulty in identifying causal effects stems from finding the correct counterfactual situation: how would the same individual behave if she would not have been exposed to the intervention. Naturally, such a counterfactual does not exist: Either an individual experiences the intervention or not. Comparing the same individual before and after exposure to the intervention, is contaminated by time effects, as e.g. weather, institutional background, etc. might have changed as well. Comparing individuals who are exposed to the intervention and individuals who are not exposed, gives rise to selection bias. Individuals might have selected into experiencing the intervention, thus are systematically different to individuals not experiencing the intervention. Thus, for econometric analysis of natural occurring data stricter assumptions are necessary to

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identify the correct counterfactual (Harrison & List, 2004).

Controlled experiments provide the most robust method of creating a counterfactual by instrumenting randomisation. Thereby, self-selection into experiencing the intervention is prohibited by researchers randomizing participants into either a treatment or a control group. Only the treatment group has access to the intervention. Because of randomization the participants in both groups are in expectation equal in all observable and unobservable characteristics, except of the intervention. Thus, a comparison of average energy consumption in treatment and control group reveals the causal effect of the intervention without contamination of any other characteristics (Harrison & List, 2004). Thereby, RCTs can provide apples-to-apples comparisons of different interventions and policies, and inform policy makers about robust causal effects and channels influencing behaviour.

2.4 References

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3. Country case study: Bulgaria

In Bulgaria, smart metering in the residential sector is not yet implemented and all customers receive monthly bills for their electricity consumption. The bills include information on the total amount to be paid and the sub-amounts for transmission and access to the different type of grids, as well as the single price, paid by the customer for a kWh. However, the bills do not include information on the cost of electricity consumption by separate appliances, as there is no technical possibility for this consumption to be measured. Respectively, the main assumption in constructing the RCT experiment was that people are not aware of the amount of energy consumed by separate appliances and respectively – about the related costs, even for appliances with known electricity consumption per hour (e.g. indicated in the technical characteristic of the respective appliance).

The main research hypothesis, tested with the current RCT is that detailed information on electricity consumption and respective cost per separate appliance will impact the consumption patterns of the customers, leading to lower consumption in general and higher energy savings. The experiment's design focuses only on voluntarily behaviour change through increasing the knowledge and awareness of people for their energy consumption, and do not aim at changing contextual factors (e.g. introducing more energy efficient devices or better insulation). The RCT experiment was designed to test the effect of feedback information about electricity consumption and related costs of particular household's appliances on the experimental group. The sample design includes a total number of 405 households, selected on a random base, following several quota criteria. The experiment last for four months (September to December 2018) and covered periods of both non-heating and heating seasons in the country.

The analysis found that there is no statistically significant difference between the energy bills of the control and experimental groups with the exception of December, where surprisingly the bill of the experimental group was significantly higher than the average bill for the control group. This pattern does not confirm the main research hypothesis that the experimental intervention would lead to a decrease in bills of the experimental group, as compared to the control one. However, a possible reason for the December's result could be also the much lower response rate for December among the participants in the experimental group as compared to the two previous months and the response rate of the control group for December.

A more thorough multivariate regression model was used to delve deeper into these results with the monthly electricity bill as a dependent variable and the group type (experimental vs. control) as an independent variable, while various demographic factors were added as control variables in order to isolate better the effect of main independent variable. The regression models for each of the three months, when a feedback information was delivered to the experimental group (i.e. the intervention was performed) prove again that there is not any significant difference between the control and experimental groups.

While the main dependent variable "monthly electricity bill" did not show any effects of the intervention, we tested whether the intervention (i.e. receiving feedback information) has any effect on energy consumption behavioural patterns within the experimental group only. The assumption was that the intervention might have influenced the way households utilized their most energy consuming appliances at least a little, even if there is not difference in comparison to

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the control group. The analysis explored whether the feedback information on the share of a particular appliance consumption in the individual monthly report influenced individual time usage for this appliance. The results show statistically significant differences for electric water heater and washing machine (two out of four appliances with highest share of cost in the electricity bills, see details in the following sections) which at least partially confirms that the intervention (received feedback information) have influenced the energy-related behaviour of the participants in the experimental group.

While providing detailed feedback for the monthly energy consumption did not yield the desired effect of decreasing the energy bills for the experimental as compared to the control group, the intervention proved successful in certain cases (for two of the most energy consuming households' appliances: the electric water heater and the washing machine). The personalized feedback managed to influence even slightly the individual behaviour in the planned direction, but only for a very limited number of appliances and not after each feedback. This result could be interpreted as partial success of the RCT experiment and that detailed feedback could potentially influence in a positive way the energy usage, especially in the long term. This provides some support for the main research hypothesis. The lack of statistically significant results in the desired direction for the rest of the high-energy consuming electric appliances and the lack of significant difference between the control and treatment groups in the monthly energy bills might be caused by other factors that have stronger influence on the consumption patterns of households. Such a factor could be the fact that according to different estimations, energy poor households represent between 40% and 63% of the households in the country and most – or even all of them, have already optimized their energy consumption as much as possible.

3.1 Research hypotheses and research questions

In Bulgaria, smart metering in residential sector is not yet implemented and all customers receive monthly bills for their electricity consumption.[3] The bills include information on the total amount to be paid and the sub-amounts for "transmission via and access to high-voltage network", "transmission via low-voltage network" and "access to low-voltage network". In addition, depending on the metering device of the customer, the bill includes also price of a "daily tariff" and/or "night tariff" (in BGN/kWh). There is no technical possibility to measure the consumption of separate appliances and to report their individual consumption to the customer. Respectively, the main assumption in constructing the RCT experiment was that people are not aware of energy consumed by separate appliances and about the related costs, even for appliances with known electricity consumption per hour (e.g. indicated in the technical characteristic of the respective appliance).

Having this in mind, the main research hypothesis, tested with the current RCT is the following:

[3] There are three District System Operators (DSOs) in the country that are distributing power to the residential customers. In addition, after the introduction of liberalization measures in 2016, residential customers are able to change their supplier, leaving the regulated market. In this case, they can choose each of the licensed "power traders", operating in their region, which is then responsible for billing activity, incl. the structure and the information, provided by the bill. However, according to the legislation, the Regulatory Commission on Electricity and Water provides minimum requirements for information, provided by the bill, which must include the elements as described above in the text. As for the moment, there is no information about a "power trader" who requires the use of smart metering systems, which can provide detailed feedback information to the customer.

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Detailed information on electricity consumption and respective cost per separate appliance could impact the consumption patterns of the customers, leading to lower consumption in general and higher energy savings. Respectively, the major research questions are:

- Does detailed information on electricity consumption and respective price per separate appliance impact the consumption patterns of the customers?
- Does the provision of detailed information impact the consumption patterns towards lowering the consumption in general?
- Does the provision of detailed information impact the consumption patterns in the same direction regarding different groups of appliances (e.g. appliances with high- and low-energy consumption or appliances used on every day or ad-hoc basis, etc.).

The design of the current RCT experiment focuses only on voluntarily behavioural change through increasing the knowledge and awareness of people for their energy consumption, and does not aim at changing contextual factors (e.g. introducing more energy efficient devices or better insulation) which is expected to influence the households' behavioural decisions. As a result, the realization of the planned RCT does not expect to provoke so called re-bound effect, which is observed mainly in cases when contextual factors are changed[4]. In general, the current RCT is planned as belonging to approaches that focus on testing the effectiveness of intervention strategies aiming to change end-user behaviour regarding the use of energy at home (Abrahamse et al., 2005). Based on theoretical and methodological framework of this set of approaches, the current experiment targets a limited number of determinants of energy use and energy savings, i.e. attitudes and knowledge in a very specific and narrow scope and namely – awareness of and knowledge about the cost of electricity consumption by a separate appliance. In addition, using the fact that the price of electricity for residential end-customers in Bulgaria have not changed in the period when the experiment was performed[5] , the RCT was designed as a non-price intervention (Allcott, 2011).

3.2 Experimental design

The randomized controlled trial was designed to test the effect of feedback information about electricity consumption and related costs of particular household's appliances on the experimental group. The sample design includes two groups, with a total number of 405 households, selected on a random base[6], following several quota criteria: type and size of settlement, age and sex of the respondent. The respondents were recruited from a larger group of households, participating in an online panel, managed by a survey company. All respondents were granted additional but equal payment for their participation in four consecutive "surveys" according to the company's rules. The final sampling was done using automatically generated list of random numbers, matching the ID of the respondents, ordered by the date of their inclusion in the panel, which was considered as being naturally randomized ordering. The distribution of the sample according to these criteria is given in the tables below. In addition, both groups were observed to include also families with and without kids, however an equal distribution according

[4] See for example Herring & Roy (2007), Sorrell (2007), Greening et al. (2000), Gillingham et al. (2015), Abrahamse et al. (2005).
[5] All households included into the sample, buy electricity on regulated market.
[6] The households were selected among those, using internet, in order to allow the use of an online survey tool for collection of data and provision of information feedback to the experimental group.

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to this factor between the groups was not sought.

Table 1: Sample distribution by groups and sex

	Female	Male	Total
Experimental group	108	95	203
Control group	108	94	202
Total	216	189	405

Table 2: Sample distribution by groups and age

	18-34	35-59	60+	Total
Experimental group	35	109	59	203
Control group	35	111	56	202
Total	70	220	115	405

Table 3: Sample distribution by groups and type of location

	Sofia (capital)	Big city (Plovdiv, Varna, Bourgas, Ruse, Stara Zagora)	Other city/town	Village	Total
Experimental group	58	56	75	14	203
Control group	43	68	85	6	202
Total	101	124	160	20	405

Table 4: Sample distribution by groups and kids in the family

	0	1+	Total
Experimental group	152	51	203

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Control group	137	65	202
Total	289	116	405

The experiment last for four months (September to December 2018) and covered periods of both non-heating and heating seasons in the country[7]. The distribution of households per main energy sources used for heating of the dwellings is given below (see Figure 1). The collection of data and the information feedback to the experimental group were done through an online survey tool. The initial questionnaire, filled in by all households in the sample, includes the following blocks of questions:

- Socio-demographic data
- Description of dwellings, incl. main heating sources and technologies
- Cost of electricity consumption (monthly bill)
- Number, types and age[8] of appliances in the household (19 major type of appliances were included)
- Usage of appliances (average number of hours in the last week)

Each round of data collection was held in the beginning of the respective month (i.e. about 10th day), just shortly after the dates, when the monthly electricity bills have been received by the households. The second and the next rounds included a shorter version of the initial questionnaire, covering only usage of appliances for the previous month. After the initial round, and up to ten days after filling in the questionnaire, each household in the experimental group received a feedback information on their personal electricity consumption per separate appliance[9] and related cost of consumed electricity per separate appliance for the previous month. The calculations were based on external reference data about the electricity consumption (in kWh) of different appliances and the usage data (in average hours per week) – the latter collected through the households' responses to the online questionnaire. The feedback information did not pretend to reflect the actual consumption and its cost per appliance(s), but to be only tentative result, based on approximations and calculations according to external reference data and data reported by the household. Both control and experimental group were not aware of the existence of the reciprocal group and each of them has been informed that it participates in a standalone study. Respectively, the control group has been told that the study aims at collecting information on the usage of electricity appliances in the households in small-scale empirical research. The experimental group was told that the study is a small-scale pilot research and aims at collecting data about the future usability of such kind of detailed information on consumption and respective

[7] The heating season started officially in mid-October, when the district heating was turned on.
[8] The age of appliances was pre-defined in three sub-categories – up to three years, four to ten years, and above ten years.
[9] In fact, the consumption and the related costs were calculated for each type of appliances and not for each separated appliance (e.g. when the household reported to have more than one appliance per given type such as two or more air-conditioning units or two or more electric cookers, it received information about calculated electricity consumption and related cost for all air-conditioning units or electric cookers in the household).

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costs in the consumer bills.

3.3 Research limitations

The initial design and the execution of the RCT experiment have several limitations that possibly affect the results.

- Although initially the experiment's design envisaged the use of technical devices to measure the actual electricity consumption of major appliances in selected households, this approach was abandoned due to budget restrictions and the fact that it was not possible to ensure random selection of households that are both willing to participate in such an experiment and are able to use such measuring devices (both because of lack of knowledge and lack of technical ability)[10]. As a result, the research team decided to construct an experiment, based on calculated data about the usage of electricity as described above.
- An online survey using a panel of households was the only feasible option due to budget limitations and the fact that a personalized feedback information needed to be provided to each household in a timely manner. This possibly led to relatively lower motivation among participants since the RCT is not a typical online survey but rather an experiment, which steps upon the assumption of participants' personal motivation to participate in longitudinal 4-in-a-row consecutive surveys. However, in the current experiment, this limitation was assessed as of low importance due to the requirement of the experiment's design, the participant not to be informed who is part of the experimental group and who belongs to the control group.
- The period when the RCT experiment took place was between seasons and the average monthly temperatures decreased from about 20 °C to 0 °C.[11] This introduced additional factors that possibly influenced the usage of electricity - shorter days with more use of lightening, continuously lowering temperatures which increase the use of heating appliances, and last but not least – the very beginning of the heating season usually starts with more extensive use of electricity for many households because the district heating is turned on later (when the temperature for 3 consecutive days is below 12 °C). While in theory these factors were the same for all participants, individual trajectories caused by some of these factors could possibly introduced additional noise to the results.

3.4 Analysis of the results and major findings of the RCT experiment

The majority of the selected sample (70.4%) lives in apartments in a multi-family residential building with less than one third (28.1%) living in a single-family building or a separate storey of multi-family building. One-tenth (10.4%) of the studied households are single-person and 28.6% of all households have one or more children younger than 14 years. The majority of the households (63.0%) are using electricity as heating source and about one third (35.3%) of these

[10] An initial screening of dozens of households shows for example that major high-consumption appliances are directly connected to the electricity cable network in the dwellings and not through a power plug (e.g. cookers, water heaters (boiler), dishwashers, washing machines, etc.). The latter was required in order to introduce the planned metering devices.

[11] For example, the average monthly temperatures for Sofia were: 17.1 °C in September, 12.7 °C in October, 6.1 °C in November and 0.2 °C in December.

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households are combining electricity with one or more sources of heating. The other major heating sources are solid fuels (mainly wood and coal). About half of the households (47.4%) declared that they have not heated all rooms in their dwellings during the last heating season (2017/2018).

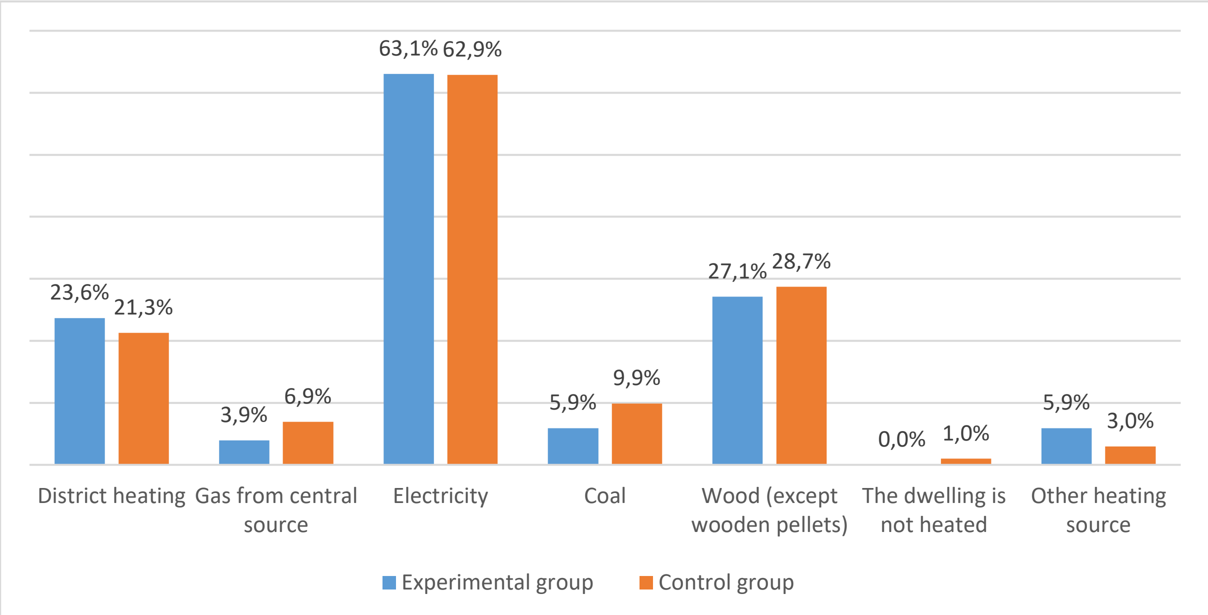

Figure 1: Use of heating sources by sample groups (multiple responses, % of cases). Source: Online survey of households, September 2019, number of observations: 405.

In terms of usage and respective cost of electricity, there is a stable trend of increase in the studied months, which could be explained by the use of more power for heating in colder months and the fact that the first reported month (i.e. September) did not include outside temperatures that required cooling of the dwellings.

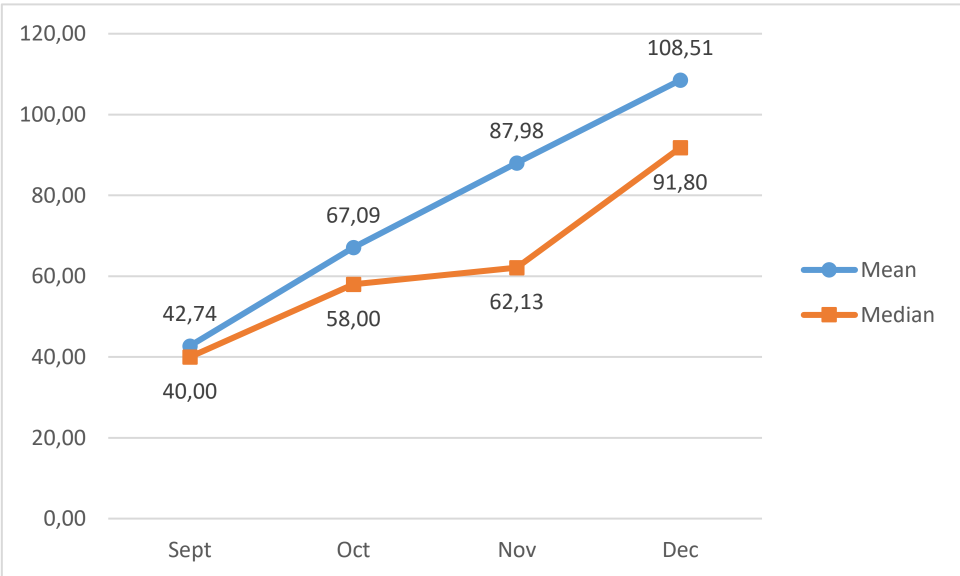

Figure 2: Cost of electricity, paid by households (in BGN). Source: Online survey of households, September – December 2019, number of answers in the respective months: 380, 364, 385, 330.

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The information about households' habits of using electricity and implementing measures towards higher energy efficiency shows that more than half of them have been trying to be more effective and to lower their respective costs. The majority (81.7%) of all studied households reported to use energy efficient bulbs (e.g. LED, compact fluorescent bulbs or halogen bulbs) and more than half of all (58.8%) – to adjust the temperature inside the dwellings dynamically either manually or automatically.

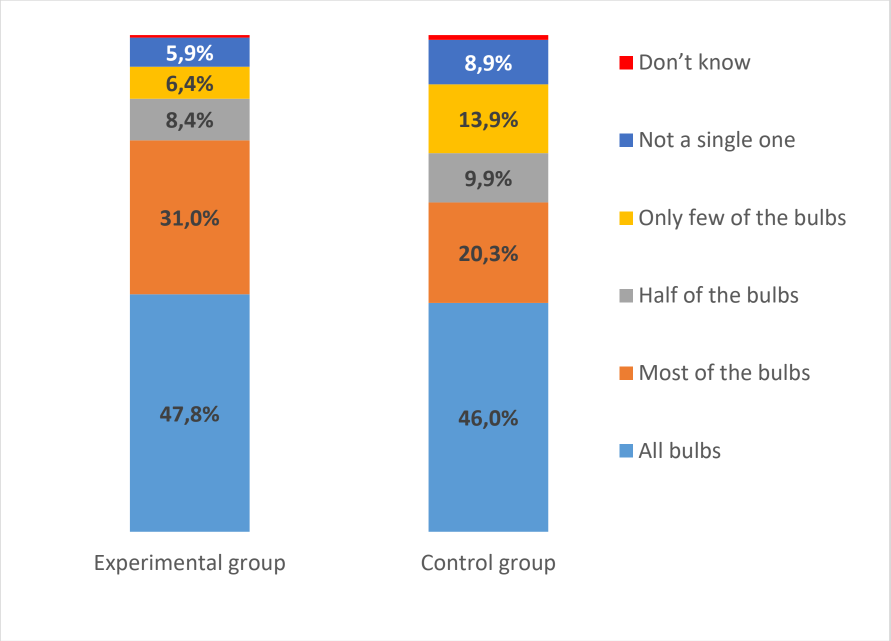

Figure 3: Share of energy efficient bulbs in the dwellings (% of cases). Source: Online survey of households, September 2019, base 405.

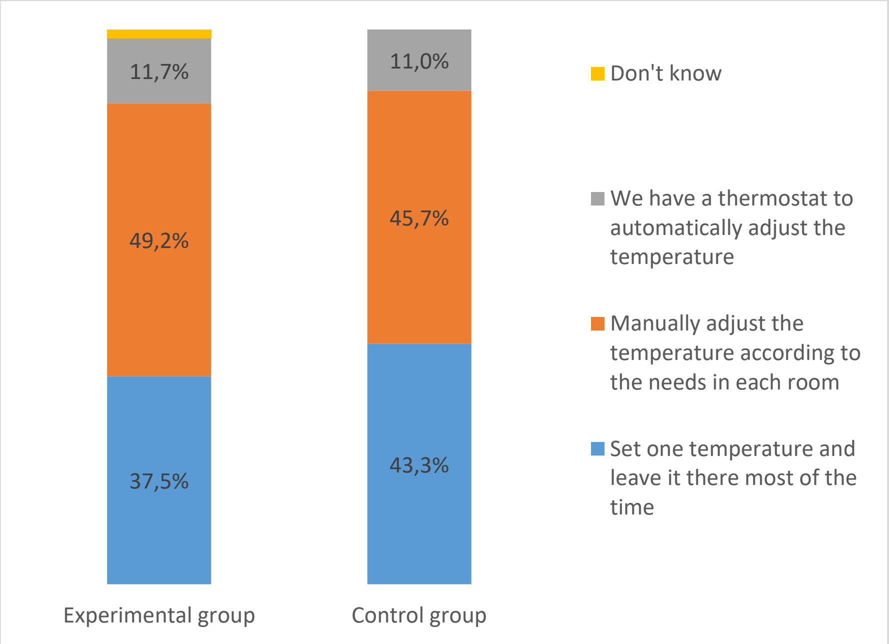

Figure 4: Which of the following best describes how your household controls your heating equipment? (% of cases). Source: Online survey of households, September 2019, number of answers: 255.

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3.4.1 Major findings of the RCT experiment

The analysis found that there is not any statistically significant difference between the energy bills of the control and experimental groups (see graph below) with the exception of December, where surprisingly the bill of the experimental group was significantly higher than the average bill for the control group. This pattern does not confirm the main research hypothesis that the experimental intervention would lead to a decrease in bills of the experimental group, as compared to the control one. However, a possible reason for the December's result could be also the much lower response rate for December among the participants in the experimental group as compared to both previous months and the response rate of the control group for December: 67% vs 96% response rate respectively for the experimental and the control group. The reasons for lower response rate could be numerous and it is difficult to speculate which combination of factors have affected the experimental group.

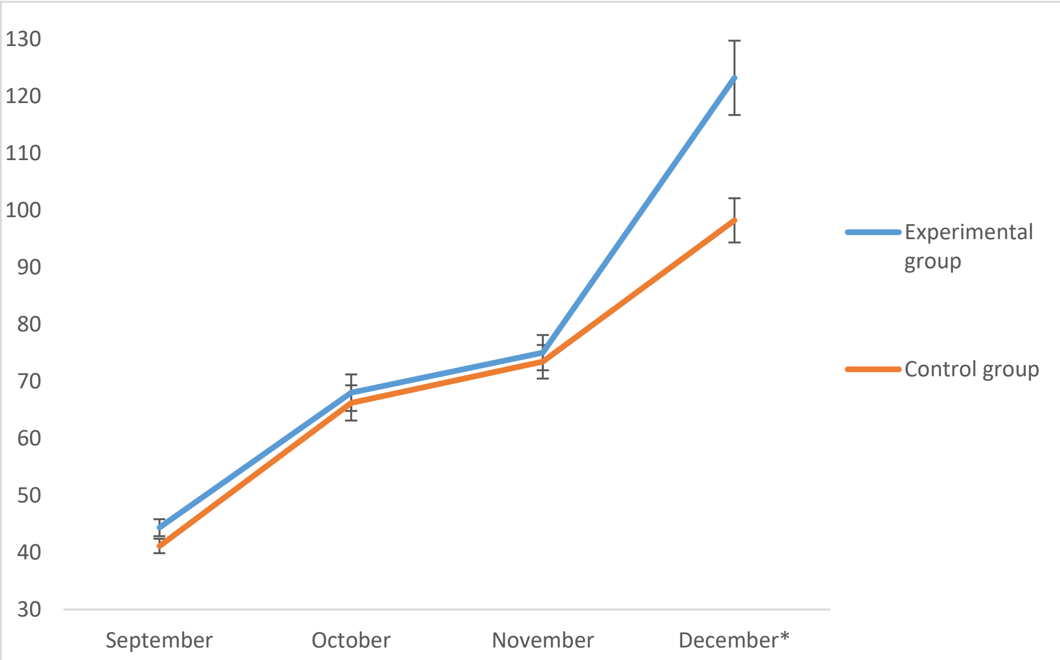

*Figure 5: Electricity bills, paid by households (in BGN, statistical mean). Source: Online survey of households, September – December 2019, bases: 380, 364, 385, 330. * vertical bars denote standard errors.*

A more thorough multivariate regression model was used to delve deeper into these results: the monthly electricity bill was used as a dependent variable, the type of group (experimental vs. control) was used as an independent variable and various demographic factors (e.g. gender, age, settlement type, dwelling type, number of rooms in the dwelling, number of people living there and number of children) were added as control variables in order to isolate better the effect of main independent variable.

The full model for September is presented in table 5 below. Since this is the beginning of the period (before the experimental intervention – providing feedback to the experimental group), no effect of the type of group was expected for this month since the control and experimental groups were carefully matched through the sampling procedure.

The results for September showed a small but statistically significant difference in the average

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monthly bill between the control and experimental groups. This result shows that despite all the efforts to match perfectly the experimental with the control groups, the control group started the RCT with slightly lower monthly bills for electricity when all control variables were accounted for.

The control variables had predictable effects: a) the higher the number of rooms in the dwelling, the larger the electricity bill and b) the higher the number of household members, the higher the bill. Other control variables failed to reach significance in influencing the average electricity bill. Surprisingly, no effect of income could be found, showing that electricity consumption was not determined by economic status at least in the current sample.

Table 5: Bill for September and different factors influencing it

Dependent and independent variables in the model	**Standardized Beta Coefficients**	**t**	**Sig.**
(Constant)		5.155	.000
Type of group (control vs. experimental)	**-.111**	**-2.146**	**.033***
Control variables:			
Gender of the participant	-.101	-1.918	.056
Age	-.079	-1.464	.144
Size of the settlement	-.004	-.083	.934
Number of rooms in the dwelling	.152	2.734	.007**
Number of permanent members of the household	.331	5.824	.000**
Education	-.037	-.689	.491
Average income of the household	-.019	-.330	.742

*Notes: * denotes p < 0.05; ** denotes p<0.01. Two variables (number of children below 12 and type of dwelling: apartment/house) were also tested, but ultimately excluded from the model because of issues with multi-collinearity: number of children is correlated with number of household members (r=0.63), and the type of dwelling is correlated with the number of rooms (r=0.53).*

The October electricity bill is the first one after the experimental group received feedback, so any confirmation in the hypothesis should be observed as a statistically significant positive beta. Such effect, however, was not observed in the regression model with October's bill as a dependent variable. The results followed the same pattern as in September with the only difference that the significantly lower electricity bill in the control group disappeared in October. While null results cannot be interpreted, this could be possibly connected with the experimental intervention.

Table 6: Bill for October and different factors influencing it

Dependent and independent variables in the model	**Standardized Beta Coefficients**	**t**	**Sig.**

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(Constant)		1.615	.107
Type of group (control vs. experimental)	**-.058**	**-1.136**	**.257**
Control variables:			
Gender of the participant	-.079	-1.525	.128
Age	-.055	-1.034	.302
Size of the settlement	.022	.412	.680
Number of rooms in the dwelling	.201	3.677	.000**
Number of permanent members of the household	.357	6.391	.000**
Education	.000	-.003	.997
Average income of the household	.033	.593	.553

Notes: * denotes $p < 0.05$; ** denotes $p<0.01$

The November bill mirrored the same pattern of results, again there wasn't any significant difference between the control and experimental groups once all the control factors were accounted for.

Table 7: Bill for November and different factors influencing it

Dependent and independent variables in the model	**Standardized Beta Coefficients**	**t**	**Sig.**
(Constant)		2.285	.023
Type of group (control vs. experimental)	**-.055**	**-1.068**	**.286**
Control variables:			

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Gender of the participant	-.069	-1.323	.187
Age	-.056	-1.047	.296
Size of the settlement	.049	.919	.359
Number of rooms in the dwelling	.176	3.203	.001**
Number of permanent members of the household	.327	5.875	.000**
Education	.013	.238	.812
Average income of the household	.006	.101	.919

*Notes: * denotes p < 0.05; ** denotes p<0.01*

Finally, the electricity bill for December showed once again as in September that when all factors are accounted for, the control group has lower bill than the experimental one.

Table 8: Bill for December and different factors influencing it

Dependent and independent variables in the model	**Standardized Beta Coefficients**	**t**	**Sig.**
(Constant)		5.501	.000
Type of group (control vs. experimental)	**-.230**	**-4.001**	**.000****
Control variables:			
Gender of the participant	-.055	-.923	.357
Age	-.078	-1.281	.201
Size of the settlement	-.046	-.754	.452
Number of rooms in the dwelling	.064	1.025	.306

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Number of permanent members of the household	.230	3.613	.000**
Education	-.063	-1.046	.296
Average income of the household	-.063	-1.016	.310

*Notes: * denotes p < 0.05; ** denotes p<0.01*

The four regression models above were tested with different subgroups to explore interactions of the experimental intervention with different socio-demographic strata. The group of respondents without children (296 cases) replicated the same results with regard to the independent variable (type of group). The same pattern was replicated for the group using electricity for heating (255 cases). The effect of the group type in the four models remained very similar for the participants living in apartments (285 cases) as well as for the higher education subgroup (279).

Finally, the lower income subgroup (< 1100 BGN monthly per household) which consisted of 130 participants, once again showed no statistically significant difference between the control and experimental groups for September, October, and November. Only for December, the electricity bill for the control group was significantly lower than the average bill for the experimental group in the low-income subgroup case.

While the main dependent variable "monthly electricity bill" did not show any effects of the experimental intervention, there are other variables which could show in more direct way whether the experiment had any effect on changing energy consumption behavioral patterns.

Since the experimental group received detailed information about their energy consumption, unlike the control group, this information might have influenced them at least a little. Naturally, this given information is much less reliable than the information provided by actual smart meters since it was estimated based on previous answers in the survey. Still, this does not change the fact that participants received certain feedback, which among other things (e.g. serving as a reminder) showed to what degree different appliances contributed to the overall energy bill.

On the average, the electricity consumption for some of the most energy consuming appliances (e.g. electrical water heater, washing machine) has declined for the experimental group, which at least partially could verify the main hypothesis. The table below shows the average share of the appliances' consumption in the bill, as reported by the participants from the experimental group, based on their replies for the corresponding month. The table shows signs of a declining trend in the share of some of the largest contributors to the energy bill: the share of the electric water heater in the bill declines from 31% in September to 26% in November and the share of the washing machine decreases from 10% to 7% in October (albeit the control group usage also dropped from 11% to 9%).

Table 9: Average contribution to the cost of electricity for different electrical appliances: Experimental group

Electrical appliance	**September**	**October**	**November**	**Average for the three months**
Electrical water heater (boiler)	**31%**	**30%**	**26%**	**29%**

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Electric cooker (with an oven and cooktops)	**12%**	**13%**	**13%**	**13%**
Air conditioning unit	**9%**	**10%**	**12%**	**10%**
Washing machine	**10%**	**7%**	**8%**	**8%**
Electric heater (e.g. oil or convector)	2%	7%	8%	6%
Standalone freezer	6%	6%	5%	6%
Micro oven	5%	4%	5%	5%
Refrigerator with inbuilt freezer	4%	5%	3%	4%
Electric heating stove (e.g. a stove with heating resistors)	3%	2%	5%	3%
Personal computer	3%	3%	2%	3%
Dishwasher	3%	2%	3%	3%
Laptop / Notebook	2%	2%	2%	2%
Standalone cooktops	2%	2%	2%	2%
TV set or home theater system	2%	2%	2%	2%
Combined cooker on electricity and gas (with an oven and cooktops)	1%	1%	1%	1%
Standalone clothes dryer	2%	1%	1%	1%
Refrigerator (without an inbuilt freezer)	1%	1%	1%	1%
Audio set	1%	1%	0%	0%
Printer, multi-functional device or scanner	0%	0%	1%	0%

The same average share of different appliances is presented in the table below for the control group, which, however, did not receive this information as feedback.

Table 10: Average contribution to the cost of electricity for different electrical appliances: Control group

Electrical appliance	**Septe mber**	**Octo ber**	**Nove mber**	**Average for the three months**
Electrical water heater (boiler)	**26%**	**26%**	**25%**	**26%**
Electric cooker (with an oven and cooktops)	**14%**	**14%**	**14%**	**14%**
Air conditioning unit	**8%**	**9%**	**9%**	**8%**
Washing machine	**11%**	**9%**	**10%**	**10%**
Electric heater (e.g. oil or convector)	2%	6%	6%	5%
Standalone freezer	7%	6%	5%	6%
Micro oven	4%	4%	5%	4%
Refrigerator with inbuilt freezer	5%	6%	4%	5%
Electric heating stove (e.g. a stove with heating resistors)	3%	3%	7%	4%
Personal computer	4%	4%	3%	3%
Dishwasher	2%	2%	2%	2%
Laptop / Notebook	2%	2%	2%	2%
Standalone cooktops	2%	2%	2%	2%
TV set or home theater system	2%	2%	2%	2%
Combined cooker on electricity and gas	3%	2%	2%	3%

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(with an oven and cooktops)				
Standalone clothes dryer	2%	2%	2%	2%
Refrigerator (without an inbuilt freezer)	1%	1%	1%	1%
Audio set	0%	0%	0%	0%
Printer, multi-functional device or scanner	0%	0%	1%	1%

In order to test directly the hypothesis that the feedback for two particular high-consuming electric appliances (a water heater and a washing machine) influenced participants' behavior, analysis of covariance (ANCOVA) was used with the share of the appliance cost as a covariate and the experimental group (control vs. experimental) as an independent variable.

This analysis explored whether the feedback information on the share of a particular appliance consumption in the individual monthly report influenced individual time usage for this appliance. The change in how long the appliance was used in a week-period (as estimated by the respondents) was used as a dependent variable, while the percentage of the overall cost (computed and sent as a feedback only in the case of the experimental group) was used as an independent variable.

If the usage (in reported hours) decreased during the month after feedback was received, then the dependent variable "change in usage of the appliance" would have negative values (i.e. the difference between a lower usage number for month X and higher usage in the previous month X-1 is a negative number) and if the usage increased – then the dependent variable will be positive; if the usage of the appliance remains exactly the same (the same number of hours as reported in the previous month), then the difference is 0.

Hence, if the experimental intervention was successful, there should be a main effect of the group type on the change in usage, or interaction between group type and share of the appliance cost in the electric bill. A potential main effect of the share of cost on the change in usage would mean that the higher the share of the cost, the lower the usage in the next month (negative change) and the opposite. Such main effect could be difficult to explain in the current context – it could be due to fluctuations in usage/reporting (lower usage tends to become higher in the next month and higher tends to become lower) as well as self-provided feedback, since even participants from the control group are more or less aware which appliances are more energy consuming and this knowledge could serve as a sort of internal feedback for them as well (such hypothesis could provide one possible explanation for the failure in confirming the main hypothesis). Still, a main effect of the group type or an interaction could partially confirm the hypothesis for a particular appliance.

The four appliances with highest average share of cost in the electricity bill were tested with the procedure explained above. In almost all of the models, there was main effect of the covariate (share of the cost in percentage). The meaning of this main effect is discussed above. Only main effects of the group type and interactions are discussed in the sections below.

3.4.2 Water heater

There is not any statistically significant effect in the ANCOVA model for October (change in usage of water heaters between October and September). Similarly, for November there were no significant main effects of the group type and only a marginally significant interaction ($p=0.094$).

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Finally, for December there was a significant main effect of the group type (p<0.01) as well as an interaction (p<0.01) between the group type and the covariate (share of cost, %). The post-hoc comparison between the means for the two groups, however, did not reach significance.

Table 11 shows the results from post-hoc comparison with Bonferroni adjustment for all months. Estimated marginal means of the average change for the two groups are presented in the table together with the significance of the difference between the two groups (*p*).

Table 11: Results from post-hoc comparison with Bonferroni adjustment for all months for Water Heater

Electric water heater, change in usage between:	**Mean, Experimental group**	**Mean, Control group**	**Sig**
October and September	-.046	.030	0.272
November and October	.359	.455	0.592
December and November	-.536	-.285	0.355

The interaction between the two factors is reflected in the steeper line for the experimental group in the graph below. It demonstrates the stronger connection between the share of the cost and the decrease in usage for December in the case of the experimental group, which received feedback. Positive values on the Y-axis show increase in usage, negative show decrease and 0 shows the same usage in December as in November.

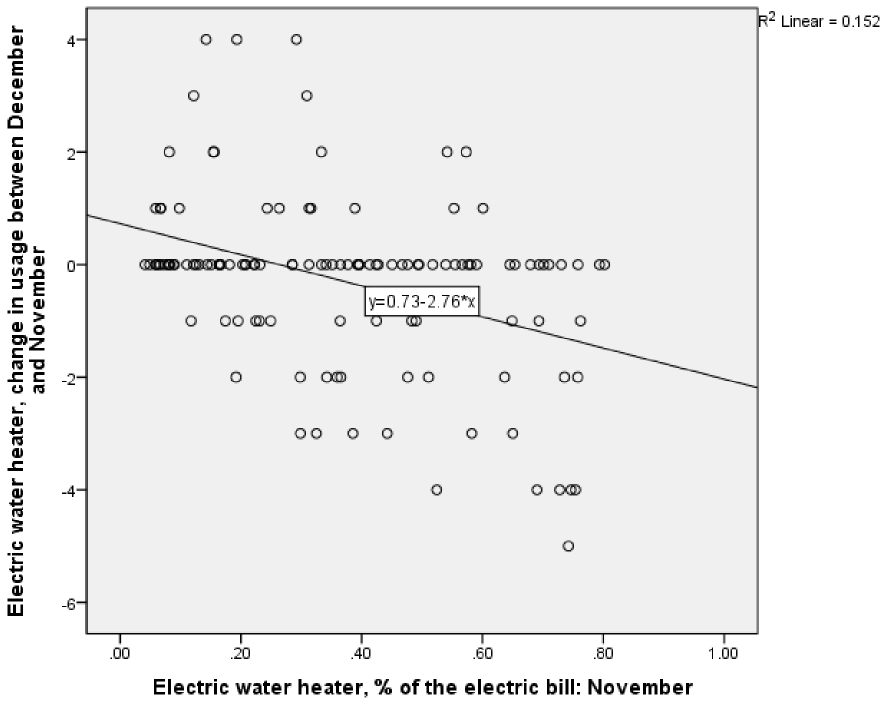

Figure 6: Electric Water heater: Change in Usage between December and November vs share of electric bill; control group

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Figure 6 and 7 show the visible difference between the pattern of the control group which in many cases shows no difference (0 on the Y axis) and the experimental group, where there is strong link between the share of the cost for water heaters and the change in usage – when the share is low, the usage rather tends to increase, while when it is high, it tends to decrease.

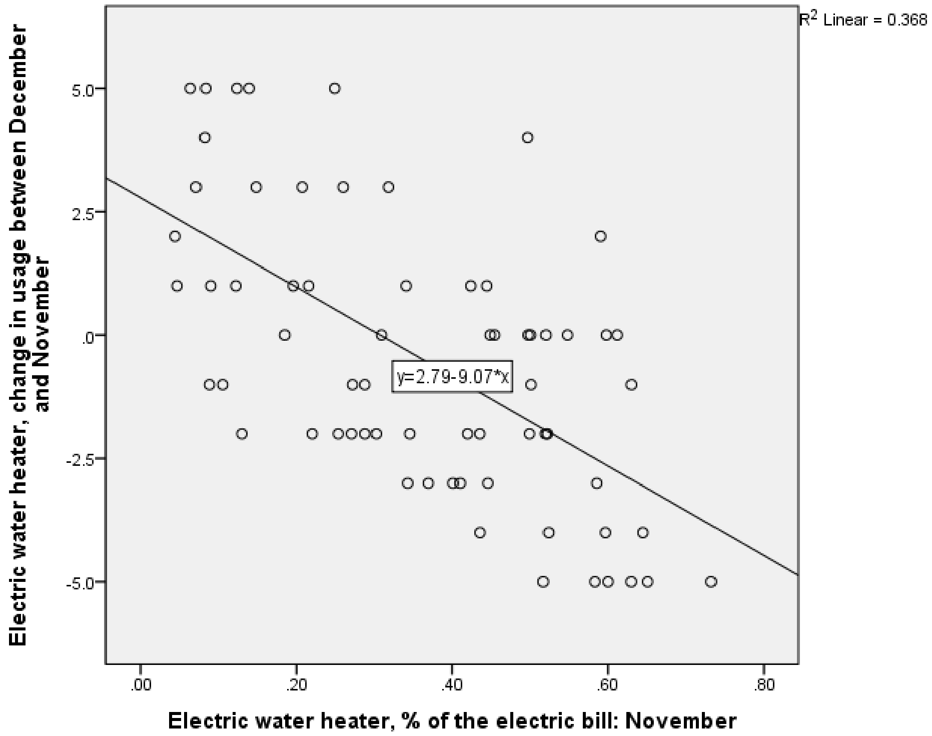

Figure 7: Electric Water heater: Change in Usage between December and November vs share of electric bill; experimental group

3.4.3 Electric cooker

The same ANCOVA models were tested for the second most energy consuming appliance – the electric cooker. Data for the change between October and September is not available for this appliance. The November and December models showed no significant main effects of the type of group or significant interactions. The estimated marginal means are again presented in the table below.

Table 12: Results from post-hoc comparison with Bonferroni adjustment for all months for Electric Cooker

Electric Cooker, change in usage between:	**Mean, Experimental group**	**Mean, Control group**	**Sig**
October and September	NA	NA	NA
November and October	.391	.362	.783
December and November	-.275	-.146	.345

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3.4.4 Air conditioning unit

Air conditioning unit showed similar results to the electric cooker – no significant main effects were observed for this appliance for the type of group independent variable in any of the three tested months (means presented below).

Table 13: Results from post-hoc comparison with Bonferroni adjustment for all months for Air Conditioning Unit

Air conditioning unit, change in usage between:	**Mean, Experimental group**	**Mean, Control group**	**Sig**
October and September	.598	.567	0.884
November and October	.615	.620	0.983
December and November	.122	-.366	0.250

3.4.5 Washing machine

Finally, the fourth most energy consuming appliance (on the average) – the washing machine was tested in the same way as the other three appliances. There was significant interaction between type of group and share of the electricity cost ($p<0.05$) which is combined with a main effect of the share of the cost and shows a pattern similar to the presented above for the electric water heater. The post-hoc comparison of the means showed a tendency for usage of this appliance in October to decrease slightly more in the experimental group than the control one (marginally significant, $p = 0.09$). The model for November revealed no significant effects. Finally, the model for December showed significant main effect of the group type ($p<0.05$) which also led to a significant difference ($p<0.01$) in the post-hoc comparison of the means. The washing machine usage in the case of the experimental group decreased (-0.54) significantly more in December than the average usage of this appliance in the control group (-0.12) for the same month.

Table 14: Results from post-hoc comparison with Bonferroni adjustment for all months for Washing Machine

Washing Machine, change in usage between:	**Mean, Experimental group**	**Mean, Control group**	**Sig**
October and September	-.496	-.361	0.089
November and October	.505a	.539a	0.752
December and November	-.540	-.115	0.001

3.5 Conclusions

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While providing detailed feedback for the monthly energy consumption did not yield the desired effect of decreasing the energy bills for the experimental group in general, the feedback proved successful in limited cases: for two of the most energy consuming households' appliances: the electric water heater and the washing machine. The personalized feedback managed to influence individual behavior in the planned direction, but only for a very limited number of appliances and months. This result could be interpreted as providing partial support for the main hypothesis that detailed feedback could potentially influence in a positive way the energy usage, especially in the long term. The lack of significant difference in the energy bills between the experimental and control groups as well as the lack of statistically significant effects for other appliances like air conditioners and cookers fail to support the main hypothesis.

It could be that there are other factors that have stronger influence on the consumption patterns of households in Bulgaria. Such a factor could be the fact that according to different estimations, the energy poor households represent between 40% and 63% of households in the country and most – or even all of them, have already optimized their energy consumption as much as possible.

3.6 References

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4. Country case study: Germany

The energy consumption of households accounts for a quarter of total energy consumption in Germany (Arbeitsgemeinschaft Energiebilanzen e.V., 2018). Due to associated externalities from energy production, the German government particularly promotes reductions in households' energy consumption to achieve its national climate targets (BMWi, 2018). The results of the German case study provide important insights into one driver of households' energy consumption: intermittent billing. One particular feature of energy consumption, in distinction to other consumption goods, is that consumption and payment are separated in time. For Germany, the lag between consumption and payment is particularly severe as meter readings only occur on a yearly basis. Existing literature supports (quasi-)hyperbolic discounting in such settings[12]. Hyperbolic discounting gives rise to time-inconsistent choices, such that overconsumption of energy occurs from both a social and an individual perspective.

In this case study, we designed an RCT to focus on the discounting effects associated with such intermittent billing. The research question we seek to answer is, whether there is evidence of hyperbolic discounting in energy consumption. The RCT was conducted as a lab experiment with 171 students to investigate the effect of more frequent energy billing on energy consumption, holding saliency and information effects constant. Through consuming 'light', participants can increase their productivity to finish a given amount of real effort tasks. However, light consumption is charged through an 'energy bill'. The control scenario is billing one week after consumption has taken place[13], the treatment scenario is billing immediately after consumption.

The main result is that immediate billing decreases light consumption on average by around 10-12% compared to delayed billing. This result is significant and stable across specifications. Additionally to affecting energy consumption itself, we observe strong substitution patterns in terms of time spent at solving the tasks. As light increases participants' productivity, light can be substituted by spending more time on the task. Time spent increases with immediate billing on average by around 15-19%, which remains significant at the 1%-level across specifications. This provides evidence that participants not only decrease light consumption because of immediate billing, but also test and exert substitution behavior, which costs participants even more time. This somewhat compares to real-life energy savings: Most measures of decreasing consumption are time consuming (e.g. switching of stand-by, using the longer eco-washing programs) but save just a few kilowatt-hours. By running a back-of-the-envelope calibration, we show that these results are consistent with (quasi-)hyperbolic but not with exponential discounting. The results provide important insights to understand qualitatively the consequences of intermittent billing. From a practical perspective, holding information and saliency effects constant, more frequent billing will decrease energy consumption. From a conceptual perspective, we provide first causal evidence of

[12] Quasi-hyperbolic and hyperbolic discounting occur with dynamically inconsistent, present-focused preferences (Ericson & Laibson, 2018). Present-focused preferences are defined as "agents are more likely in the present to choose an action that generates immediate experienced utility, then they would be if all the consequences of the actions in their choice set were delayed by the same amount of time." (Ericson & Laibson, 2018, p. 5). Such present-focused preferences are also dynamically or time- inconsistent, if these inconsistent choices occur while the state of decision-making (e.g. environment, information) is held constant (Ericson & Laibson, 2018).

[13] In fact, under yearly billing effects should be much stronger than observed with weekly billing. However, only with weekly billing payment uncertainty is plausibly constant between the control and treatment scenario. Further, only with weekly billing hyperbolic discounting can be distinguished from exponential discounting (see Section 4.4).

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hyperbolic discounting under intermittent billing.

A typical instrument to account for hyperbolic discounting is a commitment device (Laibson, 2015). However, first, to demand commitment households must be aware of their own time-inconsistent decisions and second, commitment comes at either monetary or non-monetary costs. As the source of hyperbolic discounting in energy consumption stems from the billing structure, another policy recommendation is to change the billing structure. The lab experiment conducted in this case study provides one possible change in billing, by introducing real-time billing. An alternative would be pre-paid billing as currently discussed in some countries. Additionally, more frequent energy billing, e.g. from yearly to monthly billing, would reduce the extent to which the energy costs are discounted. However, existing empirical studies investigating the effect of receiving an energy bill find rather mixed results due to differential interactions with informational and saliency effects (Gilbert & Zivin, 2014, Wichmann, 2017, Sexton, 2015). Relatedly, our results provide insights on the sensitivity to energy price policies: If energy costs are devaluated due to hyperbolic discounting, households may exhibit a low price elasticity of demand.

4.1 Motivation and research question

The energy consumption of households accounts for a quarter of total energy consumption in Germany (Arbeitsgemeinschaft Energiebilanzen e.V., 2018). Due to associated externalities from energy production, the German government particularly promotes reductions in households' energy consumption to achieve its national climate targets (BMWi, 2018). However, energy reductions are way behind their targets. The national targets of 10% reductions in gross electricity consumption and 20% reductions in total primary energy consumption until 2020 will be most likely not achieved (Löschel et al., 2018). To define and implement effective policies a greater understanding of the drivers of households' energy consumption is needed.

One particular feature of energy consumption, in distinction to other consumption goods, is that consumption and payment are separated in time. Whereas consumption is immediate, the costs are only experienced intermittently. For Germany, the lag between consumption and payment is particularly severe as meter readings only occur on a yearly basis. An extensive behavioral economics literature has shown that households engage in (quasi-)hyperbolic discounting when dynamic trade-offs are involved[14]. If individuals discount future costs (quasi-)hyperbolically, they overvalue present benefits compared to an ex ante valuation, i.e. they are biased towards the present. This inconsistency in valuation induces a reversal of choices. The consequence is an overconsumption of the respective good. For energy this means an overconsumption, not only with respect to the social costs of energy but also with respect to own ex ante plans. Next to an externality, there is an internality from energy consumption.

The literature has however not experimentally validated hyperbolic discounting in trade-offs involving goods which are only intermittently billed, such as water, gas or electricity. The research question we seek to answer is, whether there is evidence of hyperbolic discounting in energy consumption. Support of such evidence stems from the literature on credit card consumption. Credit card consumption faces the same dynamic trade-off as energy consumption. Quasi-hyperbolic discounting has been shown to correlate with credit card debt (Meier & Sprenger, 2010) and to explain credit card choice (Shui & Ausubel, 2005). Further, Harding & Hsiaw (2014)

[14] See Ericson & Laibson (2018) for an overview.

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provide evidence in favor of present biased energy consumption by motivating energy saving goals as commitment device to follow through ex ante plans.

However, intermittent billing of energy has more consequences than hyperbolic discounting of costs. Existing literature focused on information and saliency effects of receiving a bill. Wichmann (2017) finds an increase in water consumption by 3.5-5% after the billing frequency has been increased from bimonthly to monthly billing. The author explains such an increase by households expecting water costs to be higher than they actually are. Information provided by the bill induces a decrease in cost expectations. By analyzing high-frequency smart meter data, Gilbert & Zivin (2014) argues that an energy bill reminds households of their energy costs. After being reminded through the bill, households reduce their consumption by 0.6-1%, but return to usual consumption habits one week later. Similarly, Sexton (2015) shows that automatic bill payment programs increase residential electricity consumption by 4-6%. Because of automated transactions, households pay less attention to energy costs. Jack & Smith (2016) exploits a switch from pay-later-billing to pay-ahead-billing in South Africa. Households responded with a persistent decrease in electricity consumption of 13%. Considering these studies, the effect of an increase in billing frequency on energy consumption is not clear because of competing channels.

To identify hyperbolic discounting in energy consumption, we need to abstract from the competing channels. Therefore, we experimentally vary only the timing of receiving an energy bill, holding information on and saliency of costs constant. In a laboratory environment with 171 students, we adapt the setting of immediate real effort costs and delayed wage payment (Augenblick & Rabin, 2018, Kaur et al., 2015) to a setting of immediate benefits and delayed costs. Through consuming 'light', participants can increase their productivity to finish an exogenous amount of real effort tasks. However, light consumption is charged through an 'energy bill'. The control scenario is billing one week after consumption has taken place, the treatment scenario is billing immediately after consumption. Importantly, as the distance between consumption and billing is only one week, an exponentially discounting participant would not act substantially different in both scenarios[15]. Because of hyperbolic discounting, we hypothesize light consumption to be lower with immediate billing compared to delayed billing. Further, there is an indirect effect of the change in billing on the time spent on solving the task. As light increases participants' productivity, light can be substituted by spending more time on the task. With more light, less time for solving the fixed number of tasks is needed. Hence, the time spent on solving the tasks will be higher in the scenario with immediate billing compared to delayed billing.

4.2 Description of experimental design[16]

4.2.1 Sample

[15] This would imply exponential discount rates not in line with literature (cf. Section 4.4).

[16]This trial was pre-registered at the AEA RCT Registry under trail number AEARCTR-0003503 (https://www.socialscienceregistry.org/trials/3503/history/36623). In addition to the between-design described in this section, we also employed a within-design. Therefore, the identical experiment was repeated with the same participants. However, in the repetition, participants being before on real-time billing experienced now delayed billing and vice versa. The main motivation of adding the within-design was the fear of dropouts in the between-design, which would have endangered the assumption of random exposure to billing scenarios. In fact, we only observe a single dropout from date 1 to date 2, but 11% dropouts to the repetition. Due to this loss of sample size and between-designs having less strong assumptions than within-designs, this report only relies on the between-design.

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The reason for using students as study sample is that a change in billing will only affect energy consumption if the energy bill affects participant's disposable income. This is particularly the case for low-income households, whose consumption possibilities are affected most by energy bills. Similarly, existing research has found scarcity in money to increase discounting and impatience (Carvalho et al., 2016, Haushofer & Fehr, 2014). This implies that low-income households are particularly sensitive to overconsumption under delayed billing. Further, corresponding policy implications, such as pre-paid billing, are particularly discussed for low-income households.

Among low-income households, students are the most appropriate. First, students have a relatively high cost-effectiveness. The costs to run a lab experiment with non-students are substantial because compensation rates are higher. Second, students tend to understand the rather complicated instructions of laboratory experiments, which could be problematic with low-educated households.

4.2.2 Organization

To be able to control for information or saliency effects from more frequent billing, the experiment was conducted as longitudinal lab experiment. That means the experiment was organized across two sequential dates with one-week distance. The first date was conducted in the computer pool of the economic department of the University of Münster. On the second date, only a payment needed to be collected. For convenience, we offered a grace period of one day for that second date. Students were recruited via the online recruitment tool ORSEE (Greiner, 2015). Upon registration participants agreed to participate on the sequential dates. We offered 10 sessions, with five sessions being on Tuesdays and five on Wednesdays. In particular, the experiment started on either Tuesday, 30th October or Wednesday, 31st October, with the second date being either 6th November (+/- 1 day) or 7th November (+/- 1 day). We reminded participants of the dates on the evening before via e-mail. For the second date, we sent up to four reminders if the payment was not collected. On the first date, participants received a letter, reminding them about the dates and of general experimental instructions. That letter also contained a unique ID consisting of four letters. That ID was used as identification across the experiment, such that we can match participant's decisions across dates.

Each session allowed for 25 participants, such that we were able to recruit 250 participants. Assuming a treatment effect of 10%, as comparable to Augenblick & Rabin (2018) and Kaur et al. (2015), and using the standard deviation in outcome as measured in non-incentivized pilots, the required sample size for a between-subjects analysis is 200 subjects[17]. In total 213 students registered for the experiment, but only 171 students appeared at the computer pool. Participants could earn between 10 and 20 Euros depending on their decisions in the experiment if they participated on both dates. All payments were made in cash at the Chair of Microeconomics, esp. Energy and Resource Economics.

[17] We further assumed a power of 80% and an alpha-value of 0.05.

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4.2.3 Experimental design

The first date in the computer pool started by participants' log in to the computer program using their ID. Upon log in, the computer randomized the participant with equal probabilities into a group with real-time billing (RTB) or with delayed billing (DB). Figure 1 gives the procedure for

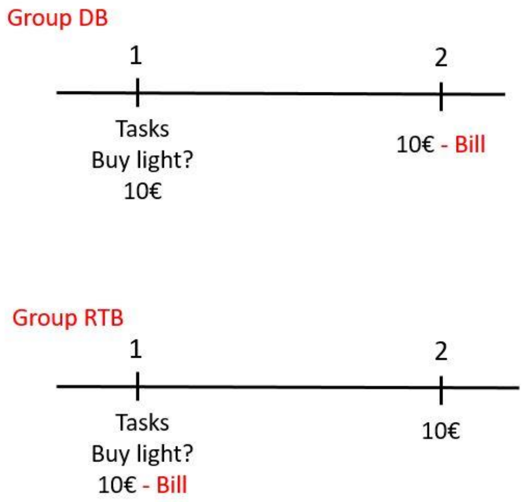

Figure 1: Experimental design

both groups. On the first date, participants do a real effort task. The real effort task is designed to reproduce the energy consumption decision, e.g. when being at work and doing a desk-based task. The task is to find a certain letter in a table full of 100 letters. The number of tasks is exogenously fixed at solving 25 tables. The letters are shown with weak contrast (i.e. black letters on a grey background). For each task, participants can decide the amount of "light" they want to consume. Light increases the contrast and therefore eases the task. By pressing the light switch, the contrast changes. Per second of light switched on a price of 0.5 Eurocents is charged. We count the seconds

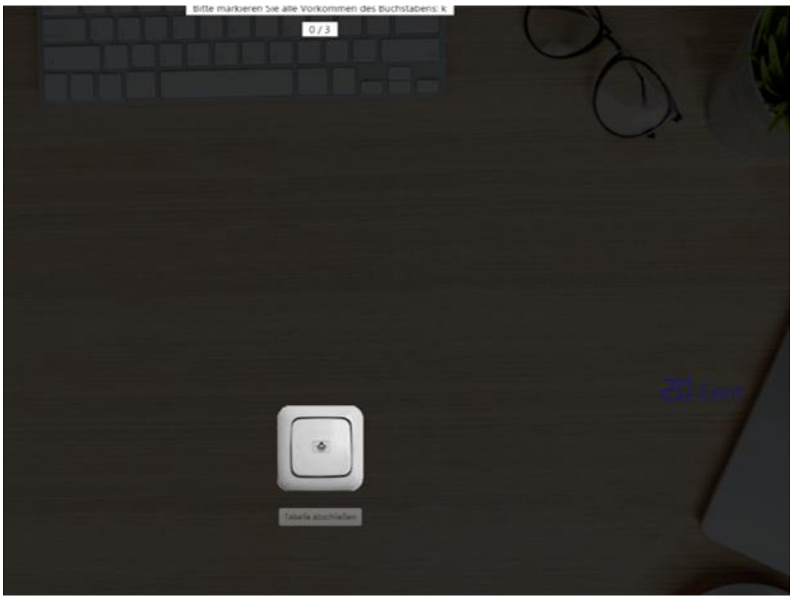

Figure 2: Task with light switched off

light is switched on and the total time spent on solving the tasks. Figure 2 and figure 3 show

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screenshots of the tasks, with light off or on.

Figure 3: Task with light switched on

To ensure that there is full information and attention about costs for both groups, a "meter" shows subjects their light costs in real-time while solving the tasks. Consequently, the only difference between groups is the timing of when light costs are subtracted. In the instructions, this trade-off is highlighted by saying: "Every second you switch on lights **today**, decreases your payment in **one week/today** by 0.5 Eurocent.". To make participants familiar with the task, we started with three introduction rounds, which were not payoff relevant. After the tasks were finished, participants answered a short survey. The survey includes socio-demographic questions, such as gender, age and income brackets. Further, we ask for the subject of study, the desired degree and begin of study. We code the subject of study in a binary measure, indicating whether the participant visited any economics classes ('economics=1') or not ('economics=0').

The first date ends with all participants picking up a first payment at the Chair of Microeconomics, esp. Energy and Resource Economics, which is about three walking minutes from the computer pool. In RTB, light costs are subtracted from that first payment received on the first date, i.e. immediately after consumption. On the second date, all participants picked up a second payment at the Chair of Microeconomics, esp. Energy and Resource Economics. In DB, light costs are subtracted from that second payment received on the second date, i.e. one week after consumption. Whenever participants paid their light costs, they received an 'energy bill', telling them the seconds of light consumed, the price per second and the total costs. We required participants to pick up all payments at the Chair of Microeconomics, esp. Energy and Resource Economics, to have transaction costs and uncertainty constant across groups. Both the first and the second payment equals 10 Euros. Hence, if no light is consumed, the maximum payment is 20 Euros, as all participants, irrespective of their group, receive two payments. The minimum payment is 10 Euros because light costs are subtracted on only one of the two dates. The average payment is 18.29 Euros.

4.3 Descriptive and analytical results

4.3.1 Summary statistics of sample and outcome variables

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Table 1 gives the summary statistics of the outcome variables. Total light gives the sum of seconds the light was switched on over the 25 tasks. Total time gives the seconds spent on solving the 25 tasks. On average 342 seconds of light (i.e. 5.7 minutes) are consumed and the average time spent is 826 seconds (i.e. 13.77 minutes). As the average of total light is slightly smaller than the median of 367 seconds, the average is downward adjusted by some participants consuming only very few or none light seconds. The number of observations reflects the 171 students participating.

Table 1: Summary statistics of total light and total time

Variable	Average [Std. Dev.]	Percentile					N
		10th	25th	50th	75th	90th	
Total light	341.73 [166.70]	100.03	209.30	367.21	454.83	533.23	171
Total time	825.85 [293.82]	488.62	578.52	786.87	1000.57	1250.92	171

To give an indication of how light consumed and time spent relate to each other, we introduce the

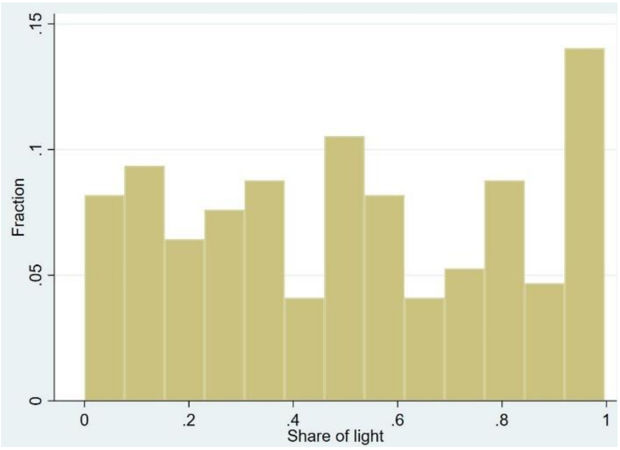

Figure 4: Fraction of share of light

measure 'share of light'. Share of light gives the proportion of light seconds to the time spent on solving all tasks. A share of light of one indicates that light was always switched on, a share of light of zero indicates that light was never switched on. Figure 4 plots the fraction of participants across their share of light. The largest fraction had the light always switched on, but there is an almost equal distribution across all shares of light.

To give an overview on the sample characteristics, table 2 gives the average sociodemographic and study characteristics as elicited in the survey. There is almost a gender split, with males being only slightly overrepresented (44% females). The average age is 23 years, which is consistent with the average degree being a master degree and an average begin of study in 2016. Around half of

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our sample studies economics or has attend economics introductory courses. The average income category refers to an average monthly net income of 1.300-1.499 Euro[18].

Table 2: Summary of sample characteristics

Variable	Average [Std. Dev.]
Female	0.44 [0.50]
Age	22.82 [2.87]
Income	7.01 [3.38]
Economics	0.45 [0.50]
Degree	1.87 [1.28]
Begin of study	2016.05 [1.67]

4.3.2 Descriptive statistics of outcomes by treatment

Table 3 gives the average light consumed and the average time spent on the tasks both for participants in the RTB and the DB group. The standard deviations are in brackets. There are 85 participants in the RTB group and 86 participants in the DB group. The last column gives the differences between group means for both outcome variables, as well as the significance levels of t-tests on equal means. Both for light consumed and time spent, the hypothesis of equal means can be rejected at the 10%- and the 5%-level, respectively. Light consumption is significantly lower in the RTB group than in the DB group. On average, the reduction is around 44 seconds or 12%. In turn, the RTB group spent significantly more time on solving the tasks than the DB group. On average, RTB spent 145 seconds more, which is about 19%. These results are also supported by non-parametric Mann-Whitney tests. The hypotheses of equal medians can be rejected both for light and for time at the 10%- and 5%-level.

Table 3: Average light and time by group

	RTB	DB	Difference
Average light [Std. Dev.]	319.66 [169.26]	363.54 [162.15]	-43.89 [25.35]*
Average time [Std. Dev.]	883.68 [303.97]	768.69 [273.32]	144.99 [44.20]**
Observations	85	86	

*Notes: Standard errors for difference in parenthesis. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.*

[18] This question was refused to answer by 33 participants.

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Figure 5 displays these first results graphically. When comparing the average light consumption

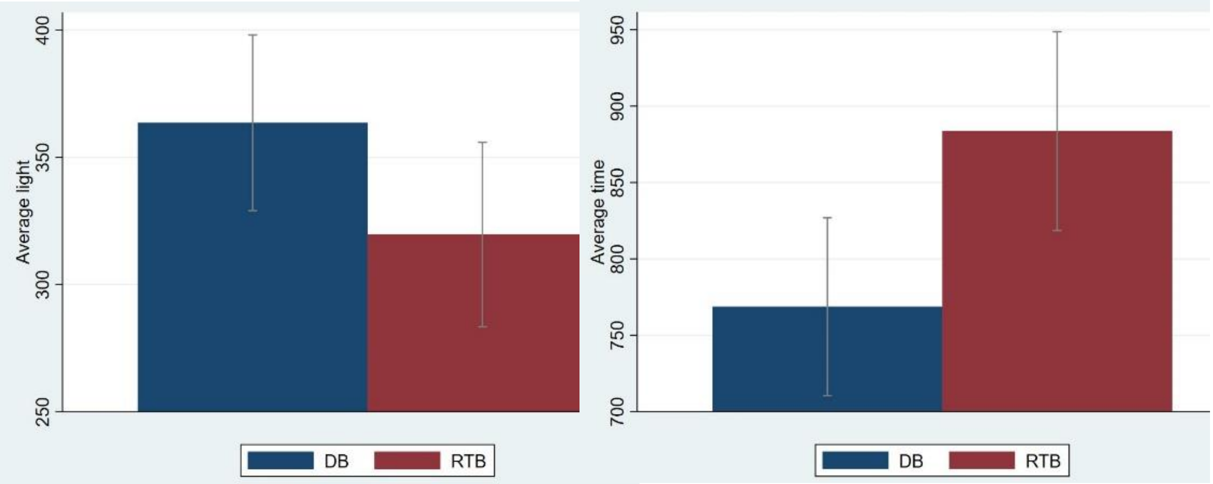

Figure 5: Average light (left) and average time (right) by DB and RTB. The vertical lines indicate 95% confidence intervals of the means.

in the RTB and the DB group, consumption of the DB group is significantly higher. The contrary holds when comparing the average time spent on solving the tasks: the DB group spent significantly less time. This gives first evidence, that we can confirm our initial hypotheses.

4.3.3 Regression results

To further investigate our research question, we run OLS regressions with first, the total light consumed and second, the total time spent on solving the tasks as outcome variables. The two specifications are:

$$Total\_light_i = \gamma_0 + \gamma_1 RTB_i + \boldsymbol{\gamma_2 X_i} + \varepsilon_i$$

$$Total\_time_i = \gamma_0 + \gamma_1 RTB_i + \boldsymbol{\gamma_2 X_i} + \varepsilon_{i,}$$

where the subscript i denotes the individual observation and the coefficients are given by the γ - values. RTB is a dummy indicating whether the participant was in the RTB group (*RTB=1*) or in the DB group (*RTB=0*). **X** is a vector of control variables, which will be subsequently added to the regressions. Control variables compromise the session, study characteristics, gender and age[19]. Finally, ε is the error term. Table 4 gives the regression results for total light and table 5 for total time.

Table 4: Regression results of total light on RTB

	(1) Total_light	(2) Total_light	(3) Total_light	(4) Total_light
RTB	-43.89* (25.35)	-42.37 (25.67)	-59.13** (28.49)	-61.82** (29.59)

[19] We do not include income as control variable, as the corresponding decrease in number of observations offsets the gains in explanatory power.

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Session		X	X	X
Study characteristics			X	X
Gender and age				X
N	171	171	147	140

*Notes: Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.*

Column (1) of table 4 replicates the graphical and descriptive results from above. Participants in the RTB group consumed on average 44 seconds less light than the DB group. Once controlling for the session in column (2), the results turn marginally insignificant: the p-value is 0.10 and the t-statistic is 1.65. Particularly, the last sessions on both dates led to less light consumption. Probably, because the light contrast in the laboratory itself became easier once it was dark outside. However, when controlling for study characteristics in column (3) and for age and gender in column (4), the effects of RTB on light consumption become significant at the 5%-level. RTB reduces light consumption by around one minute in comparison to DB.

Table 5: Regression results of total time on RTB

	(1) **Total_time**	**(2)** **Total_time**	**(3)** **Total_time**	**(4)** **Total_time**
RTB	114.99** (44.22)	121.76*** (43.02)	126.15*** (45.38)	133.63*** (46.45)
Session		X	X	X
Study characteristics			X	X
Gender and age				X
N	171	171	147	140

*Notes: Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.*

Compared to the effects on total light, the effect of RTB on total time is much stronger. Across all four specifications, i.e. column (1)-(4), the effect of RTB on total time is highly significant. Participants in RTB spent on average two minutes more to finish the 25 tasks. As a side remark, particularly economics students spent more time on solving the tasks.

For a more detailed analysis, we modify the regressions above by using the light consumed per task and the time spent per task as outcome variables. With j being the task, i.e. j=1, …, 25, the regressions change to:

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$$Light\_per\_task_{ij} = \gamma_0 + \gamma_1 RTB_{ij} + \boldsymbol{\gamma_4 X_{ij}} + \varepsilon_{ij}$$

$$Time\_per\_task_{ij} = \gamma_0 + \gamma_1 RTB_{ij} + \boldsymbol{\gamma_4 X_{ij}} + \varepsilon_{ij.}$$

The set of control variables **X**, does now compromise the session, the task number and the study characteristics. We refrain from using gender and age, as these did not add explanatory power in the regressions on total light and total time. The results of the two task-based specifications are displayed in table 6 and table 7.

Table 6: Regression results of light per task on RTB

	(1) **Light_per_task**	**(2)** **Light_per_task**	**(3)** **Light_per_task**	**(4)** **Light_per_task**
RTB	-1.76* (1.01)	-1.69* (1.00)	-1.69* (1.00)	-2.37** (1.08)
Session		X	X	X
Task number			X	X
Study characteristics				X
N	4,275	4,275	4,275	3,675

*Notes: On individual level clustered standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.*

Across all four specifications of table 6, RTB significantly decreases the amount of light consumed per task compared to DB. The average effect is about two seconds less per task, which is about 10%. This matches our results on the aggregate level: When doing 25 tasks with on average 2 seconds less, the average effect on total light is 50 seconds less. Also, the coefficient on tasks is highly significantly negative. The subjects seem to learn and improve as the tasks proceed, making them consuming less light.

Table 7: Regression results of time per task on RTB

	(1) **Time_per_task**	**(2)** **Time_per_task**	**(3)** **Time_per_task**	**(4)** **Time_per_task**
RTB	4.60***	4.87***	4.87***	5.05***

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	(1.76)	(1.67)	(1.67)	(1.72)
Session		X	X	X
Task number			X	X
Study characteristics				X
N	4,275	4,275	4,275	3,675

*Notes: On individual level clustered standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.*

Table 7 reproduces the aggregate results of table 5. Participants in RTB spent significantly more time on solving the tasks compared to participants in DB. The results remain robust and significant at the 1%-level across all specification. The average effect is about five seconds per task more in RTB, which is about 15%. Among the control variables, the coefficient of the task number is significantly negative, supporting the learning argument stated above.

4.4 Discussion of results

Our main results are that, first, RTB significantly decreases light consumption by 10-12%, and second, RTB significantly increases the time spent on solving the tasks by 15-19%. Thus, we can confirm our initial hypotheses. Importantly, the laboratory environment allowed us to keep information on and saliency of light costs constant. The only difference between RTB and DB, is that DB pays for the light costs with one week delay. This also means that the effects of RTB on time spent are only attributable to the change in billing. Because of differential discounting, RTB participants consumed less light, which they substituted with spending more time. However, as the effect is stronger for time than for light, we conclude that RTB participants mainly *tried* to substitute time for light. Trying to substitute time for light, costs the RTB participants even more time. Moreover, we may observe only marginally significant differences in light consumption because the task was too difficult to solve without light[20]. This result somehow reflects real energy conservation behaviour: when increasing the billing frequency, more effort is used for decreasing energy consumption as suggested by our treatment effects. Most attempts of decreasing consumption are however time consuming (e.g. searching on how to save, switching of stand-by, using the longer eco-washing programs) but save just a few kilowatt-hours.

The results further support the literature on hyperbolic discounting of future payments (Augenblick & Rabin, 2018, Kaur et al., 2015). Most related to our design, Kaur et al. (2015) compare the number of real-effort tasks conducted when corresponding payments are received immediately and when payments are received with delay. Similar to Kaur et al. (2015), we can do some back-of-the-envelope calculations, to get the exponential discount factor implied by our treatment effects. To do so, we assume participants to produce the fixed amount of tasks using a

[20] To determine a 'good' amount of darkness, we run two pilots, however the appropriate amount of contrast seems to depend strongly on the hour-of-day as the session specific effects suggest.

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Cobb-Douglas production function. The participant can decide between two technologies for production, either she uses her time while having light switched on or she uses her time while having lights switched off. The two inputs she thus chooses to produce the tasks are either time with light on (*light_on*) or time with light off (*light_off*). Together these two inputs determine the total time spent on solving the tasks: *Total_time = light_on + light_off*. The production function is given by:

$$\overline{Task} = \frac{1}{\alpha} light\_on^{\alpha} light\_off^{1-\alpha}.$$

As the number of tasks is fixed, participants choose *light_on* and *light_off* according to a cost-minimization problem. For participants in RTB this is

$$min\ \ (p_L + p_T) light\_on_{RTB} + p_T light\_off_{RTB}\ s.t.\ \overline{Task} = \frac{1}{\alpha} light\_on_{RTB}^{\alpha} light\_off_{RTB}^{1-\alpha}.$$

By deriving the first order conditions, the optimal amount of light switched on and off, $light\_on^*_{RTB}$ and $light\_off^*_{RTB}$, can be calculated as a function of p_L, p_T, $\overline{Task}$, and α. The price for each second of light was experimentally determined at p_L=0.5. Further, the participant experiences opportunity costs p_T for spending her time. As she spends her time on the tasks, both when light is switched on and off, p_T is charged on both inputs. We assume opportunity costs to equal the minimum wage in Germany, which was 8.84 Euros per hour in 2018. On a per second basis this means p_T=0.002. Further, we fixed $\overline{Task}$=25. By using the average time with light on and average time with light off in the RTB group as $light\_on^*_{RTB}$ and $light\_off^*_{RTB}$, we can back-up the missing parameter α, which is α=0.993.

The parameter α gives the elasticity of production with light switched on, i.e. with 1% more seconds having lights switched on the number of solved tasks increases by 0.993%. Contrary, 1% more seconds having light switched off increases the number of solved tasks by only 0.007%. This reflects the above discussed necessity of having light switched on to solve the tasks.

Turning to the DB group, the relevant cost minimization problem is

$$min\ \ (\delta^w p_L + p_T)\ light\_on_{DB} + p_T light\_off_{DB}\ s.t.\ \overline{Task} = \frac{1}{\alpha} light\_on_{DB}^{\alpha} light\_off_{DB}^{1-\alpha}.$$

In contrast to the minimization problem of the RTB group, the DB group discounts the light costs p_L as these costs occur with a week delay. The opportunity costs p_T occur immediately, while sitting in the computer pool, just as before. We first only introduce a time-consistent, exponential discounting parameter δ^w, for one week discounting. Existing literature suggests a yearly exponential discounting parameter close to one (Ericson & Laibson, 2018, Augenblick et al., 2015, Kaur et al., 2015). Using the imputed α-Parameter and the observed time with lights on and off by the average DB group participant, we calibrate the discounting parameter consistent with our data and assumptions. The result is an average exponential discounting parameter δ^w=0.6273. This parameter is comparable to the daily discounting parameter calibrated by Kaur et al. (2015) of δ^d=0.9615, which equals a weekly discounting parameter of δ^w=0.7599.

The yearly exponential discounting parameter implied by our results is much smaller than the exponential discounting parameters observed in the literature. Further, as argued by O'Donoghue

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& Rabin (2015): "Any Noticeable Short-Term Discounting is Evidence of Present Bias" (p. 274). In line with the results of Kaur et al. (2015), our results are inconsistent with exponential discounting of future costs, but consistent with (quasi-)hyperbolic discounting. Under the assumption of quasi-hyperbolic discounting according to the $\beta\delta$-framework (Laibson, 1997) and an exponential discounting parameter of δ=1, the average present bias parameter consistent with our data is β=0.6273. Such an estimate is much more in line with the literature, e.g. Augenblick & Rabin (2018) estimate $\beta \epsilon [0.81;0.84]$ and Augenblick et al. (2015) estimate $\beta \epsilon [0.88;0.90]$. Although our experiment does not allow for distinguishing between quasi-hyperbolic and hyperbolic discounting, our results provide evidence against time-consistent, exponential discounting as this calibration exercise shows.

As the experiment was conducted in a lab environment with students, our results might not hold quantitatively if implemented in the field. However, qualitatively our results provide important and novel insights on the importance of billing frequency. First, holding information and saliency effects constant, more frequent billing will decrease energy consumption. Second, we provide causal evidence that the underlying reason for overconsumption under intermittent billing is (quasi-)hyperbolic discounting.

4.5 Conclusion and policy implications

The results of the German case study provide important insights into one driver of households' energy consumption: intermittent billing. One particular feature of energy consumption, in distinction to other consumption goods, is that consumption and payment are separated in time. Whereas consumption is immediate, the costs are only experienced intermittently. For Germany, the lag between consumption and payment is particularly severe as meter readings only occur on a yearly basis. Existing literature supports (quasi-)hyperbolic discounting in such settings. Hyperbolic discounting gives rise to time-inconsistent choices, such that overconsumption of energy occurs from both a social and an individual perspective. The literature has however not experimentally validated hyperbolic discounting in trade-offs involving goods which are only intermittently billed, such as water, gas or electricity.

In this case study, we designed an RCT to focus on the discounting effects associated with such intermittent billing. The research question we seek to answer is, whether there is evidence of hyperbolic discounting in energy consumption. The RCT was conducted as lab experiment to investigate the effect of more frequent energy billing on energy consumption, holding saliency and information effects constant. Through consuming 'light', participants can increase their productivity to finish an exogenous amount of real effort tasks. However, light consumption is charged through an 'energy bill'. The control scenario is billing one week after consumption has taken place, the treatment scenario is billing immediately after consumption.

Our main result is that in our lab environment immediate billing decreases light consumption on average by 10-12% compared to delayed billing. This result is significant and stable across specifications. Additionally, we observe strong substitution patterns in terms of time spent on solving the tasks. The time spent increases with immediate billing on average by 15-19%, which remains significant at the 1%-level across specifications. This provides evidence that participants not only decrease light consumption because of immediate billing, but also test and exert substitution behavior, which costs participants even more time. This somewhat compares to real-life energy savings: Most measures of decreasing consumption are time consuming (e.g. switching

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of stand-by, using the longer eco-washing programs) but save just a few kilowatt-hours. By running a back-of-the-envelope calibration, we show that these results are consistent with (quasi-)hyperbolic but not with exponential discounting.

We acknowledge that our results may not hold quantitatively when implementing real-time billing in the field. However, our results provide important insights to understand qualitatively the consequences of intermittent billing. From a practical perspective, we provide evidence, that holding information and saliency effects constant, more frequent billing will decrease energy consumption. From a conceptual perspective, we provide first causal evidence of hyperbolic discounting under intermittent billing.

A typical instrument to account for hyperbolic discounting is a commitment device (Laibson, 2015). If households are sophisticated about their inconsistent choices, they demand commitment to stick to their ex ante plans. For energy or water, studies have investigated the role of energy saving goals (Harding & Hsiaw, 2014, Agarwal et al., 2015, Loock et al., 2013), which could be a commitment device, and find large effects between 4-20%. However, first, to demand commitment households have to be aware about their own time-inconsistency and second, commitment comes at either monetary or non-monetary costs. As the source of hyperbolic discounting in energy consumption stems from the billing structure, another policy recommendation is to change the billing structure. The lab experiment conducted in this case study provides one possible change in billing by introducing real-time billing. An alternative would be pre-paid billing as currently discussed in some countries. With pre-paid billing, the intertemporal trade-off changes to immediate costs of charging the meter and delayed benefits of consumption. An empirical study, investigating the introduction of prepaid meters finds prepaid meters to decrease electricity consumption by 13% compared to traditional, delayed billing (Jack & Smith, 2016). Additionally, more frequent energy billing, e.g. from yearly to monthly billing, would reduce the extent to which the energy costs are discounted. However, existing empirical studies investigating the effect of receiving an energy bill find rather mixed results due to differential interactions with informational and saliency effects (Gilbert & Zivin, 2014, Wichmann, 2017, Sexton, 2015). Furthermore, hyperbolic discounting of energy costs may explain why existing studies observe only a low price elasticity (e.g. Wolak (2011), Allcott (2011), Jessoe & Rapson (2014)). If energy costs are devaluated due to discounting, households may be less sensitive to changes in prices. Thus, price-based policies may not prove effective.

Future experimental research should examine the different consequences resulting from intermittent billing more closely. In particular, disentangling and estimating the effect sizes of discounting, saliency and informational effects both in the lab and in the field, can be fruitful to understand the overlaying mechanisms of receiving an energy bill. Moreover, more research is needed on the relationship between hyperbolic discounting and price insensitivity.

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5. Country case study: Serbia

Serbian households have a share of 51% in total electricity consumption in Serbia. Households' electricity consumption is not efficient due to electricity being mostly used for heating. Eurostat data indicates that 2.5 million households in Serbia spend almost five times more electricity per unit of GDP than the EU-28 average. Since Serbian electricity production is mainly based on lignite-fired thermal power plants (thermal power plants account for 73% of total electricity production), there is a high level of CO2 emissions. The level of CO2 emissions per capita is at the EU-28 average, but the emission per unit of GDP is almost six times higher in Serbia.

Having in mind that electricity prices in Serbia are the lowest in Europe, the preliminary hypothesis of this research was that the low electricity price of households in Serbia is the main reason why electricity is inefficiently used. Starting from this assumption, the research question is whether the energy saving information can change electricity consumption behavior in Serbia. The research hypothesis is that energy saving information represents an effective means for affecting the energy consumption behavior of households in Serbia and for reducing electricity consumption.

The research was designed with the aim to determine the effect of energy saving instructions on household's electricity consumption. The research sample consisted of 3528 households in Belgrade, which demonstrate similar average levels of electricity consumption. In order to have equal representation of households with different heating solutions, the total sample in Belgrade was divided into three strata depending is it electricity the main heating source or one of sources (when households have district heating or use energy mix). For each stratum, households were randomly chosen and informed about the study and asked for participation in RCT research. Those who agreed to participate were randomly divided in treatment and control group (50:50). Participants in the treatment group received a brochure with energy-saving instructions. Such intervention was used to increase consumer's awareness, and observe if the adoption of new consumption patterns has an actual impact on consumption reduction. The control group was not exposed to the "treatment" and this group was used for making a comparison with the experimental group.

The research results showed that in a situation where the electricity price is very low, energy saving information does not lead to changes in consumer behavior. Based on the analysis of statistical data and field research, it could be concluded that energy efficiency, as well as energy efficiency awareness, is still at low level in Serbia.

Serbia has undertaken commitments to increase the share of renewable energy under the Energy Community Treaty to 27% by 2020. However, in 2015 it managed only 21% of renewable energy – mostly wood used for space heating. As of May 2018 wind power construction has been finally speeding up somewhat and in its energy strategy implementation plan, Serbia has committed to bring online more than 500 MW of wind power by the end of 2020.

5.1 Motivation and research question

The research in Serbia will be based on the examination of the impact of information provision on consumers' behavior in household's electricity consumption. The research question in this study is:

RQ: What is the effect of energy saving instructions on household's electricity consumption?

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With regard to factors of individual short-term energy choices, the impact of non-price factor will be analyzed, in particular, the impact of energy saving-related information on the increase in consumers' knowledge and behavioral patterns. Energy saving information will be provided within the experimental material to the participants in the research, in order to determine if the adoption of new consumption patterns actually impacts the reduction of consumption.

The set research question is especially interesting for Serbia due to certain country characteristics. Even though electricity consumption per capita in Serbia is bellow EU-28 average (4.54 MWh/capita in Serbia in comparison with 5.97 MWh/capita in the EU-28), electricity consumption in Serbian households is not efficient due to the fact that electricity is significantly used for heating. Having in mind that Serbian households represent 51% of total electricity consumption, there is a huge space for improving efficiency in electricity consumption. Secondly, Serbian electricity production is mainly based on lignite-fired thermal power plants (thermal power plants account for 73% of total electricity production).[21] Therefore, the negative consequence of inefficient electricity consumption is a high level of CO_2 emissions. Table 1 shows the latest available data (2015) for electricity consumption and CO_2 emissions in the 11 project countries.

Table 1. Electricity consumption and CO2 emission in all partner countries

Country	**Electricity consumption / population** (MWh/capita)	**Electricity consumption / GDP** (MWh/2010 USD)	**CO_2/ population** (t CO2/capita)	**CO_2/GDP** (kgCO_2/2010 USD)
EU-28	5.97	169.99	6.28	0.18
Serbia	**4.54**	**801.64**	**6.27**	**1.11**
Bulgaria	4.86	638.17	6.10	0.8
France	7.04	168.00	4.37	0.1
Germany	7.01	155.00	8.93	0,2
Hungary	4.10	282,20	4.32	0.3
Italy	5.10	150.35	5.45	0.16
Norway	23.40	261.24	7.07	0.08
Poland	4.01	277.03	7.34	0.51
Spain	5.48	179.79	5.32	0.17
Ukraine	3.21	1196.74	4.20	1.56
United Kingdom	5.08	123.74	5.99	0.15

Source: http://www.iea.org/statistics/statisticssearch/report/?country=EU28&product=indicators&year=2015

While electricity consumption per capita in Serbia is below the EU-28 average, the available data indicate that 2.5 million households in Serbia spend almost five times more electricity per unit of GDP than the EU-28 average. The level of CO_2 emission per capita is at the EU-28 average, but the emissions per unit of GDP is almost six times higher in Serbia. Analysis based on 11 ENABLE.EU project countries shows that only Ukraine has higher electricity consumption per unit of GDP. Ukraine is at the same time the country where CO2 emissions per GDP is 8.66 times higher than the EU-28 average.

[21] Energy Balance of Republic Serbia, retrieved on 4 June 2018 from http://www.mre.gov.rs/doc/efikasnost-izvori/EN%20BILANS%20ZA%202017%2012.12.2016.pdf

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The fact is that every household can influence the improvement of energy efficiency and achieve noticeable savings. Although monthly savings at the individual level may appear small and not so important, this amount may become significantly high at the annual level. Furthermore, a reduction of consumption by just a few percent in individual households will contribute to the achievement of global and national goals of reduction of energy consumption and environmental protection.

Electricity prices in Serbia are the lowest in Europe. For comparison, given the latest Eurostat data[22], at the end of 2017 the average electricity price in the EU-28 including taxes and levies for medium size household consumers (Consumption Band Dc with annual consumption between 2500 and 5000 kWh[23]) was 20.52 Eurocent, while household electricity price in Serbia was 6.41 Eurocent.

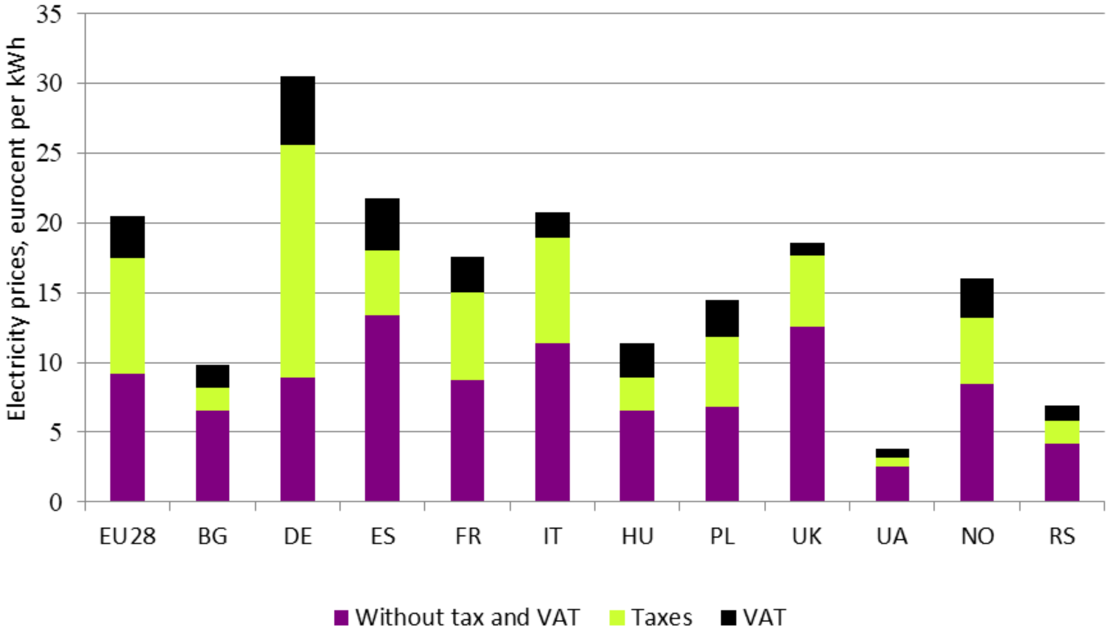

Figure 1. Residential electricity prices in the EU-28 and partner countries, the second semester 2017, in Eurocent per kWh. Source: http://ec.europa.eu/eurostat/data/database

It is interesting to analyze the share of taxes in the final electricity price. The relative share of taxes in 2017 at the EU-28 level was on average 40%. Analyzing the project countries, the lowest share of taxes in final electricity price were found in Serbia (9.7%), Bulgaria (16.7%) and Ukraine (17%), while the highest levels were observed in Germany (54.6%), Italy (36.3%) and France (36.3%). According to the Eurostat data for the second semester of 2017, the highest electricity prices were recorded in Germany (30.48 Eurocent), while the lowest prices were achieved in Ukraine (3.83 Eurocent), Serbia (6.93 Eurocent) and Bulgaria (9.83 Eurocent). Having these facts in mind, the preliminary hypothesis of this research was that low electricity price for households in Serbia is the main reason why electricity is inefficiently used. Starting from this assumption, the idea of this research was to analyze whether energy saving information can change electricity consumption behavior in Serbia.

[22]http://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=ten00117&language=en

[23] Methodology for classification and calculation https://ec.europa.eu/eurostat/cache/metadata/en/nrg_pc_204_esms.htm

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Field experiments have become a useful and commonly used method in consumer behavior studies in different areas, as well as in the area of electricity consumption. It usually includes the existence of experimental and control groups and demand implementation of precise experimental design. Burchell et al. (2016) implemented experimental design in exploration of the impact of two factors: community action and monitoring of energy consumption on the behavior change in the area of energy consumption. The field experiment was conducted as a part of the two-year project that took place in London and included a sample of 400 households. Participating households were exposed to experimental stimuli in the form of advices on seasonal energy saving and information about different local and national events and programs dedicated to energy saving. As a result of this field experiment, statistically significant differences in knowledge between experimental and control group were obtained. Actually, households that participated in the project and were engaged in monitoring and providing feedback demonstrated change in energy consumption behavior in relation to households that were the control group (that did not join the project).

Abrahamse et al. (2007) conducted the field experiment in Groningen, Netherlands by using two experimental groups (314 households) and one control group. The goal was to determine the effectiveness of experimental interventions from the aspect of changes in direct and indirect energy use, energy-related behaviors and behavioral antecedents over the period of five months. In order to determine the impact of these interventions, participants filled out online questionnaires three times in the course of the study. After five months, those households that were exposed to the combinations of interventions saved more energy (5.1%), while households that were in control group consumed slightly more energy. Furthermore, households in experimental groups accepted more energy-saving behaviors and demonstrated more knowledge of energy conservation during the study in comparison to the households in control group.

Alcott (2011) conducted randomized natural field experiment in order to determine the influence of information feedback on energy consumption. The data was collected during a specialized program that included about 600,000 households in the USA, as participants in treatment and control groups. The treatment included sending letters to households where they could see the comparison between the level of electricity consumed by them and neighboring households, which had been provided by energy supplying company. Since the program reduced energy consumption by 2%, the results clearly provided the evidence that non-price interventions are proper way to substantially and cost-effectively induce the change in consumer behavior.

In other research, authors Carrico & Riemer (2011) had a goal to determine the way and the extent to which peer education and feedback represent significant factors in reducing energy consumption. They conducted a cluster-randomized field experiment with a 2 x 2 (feedback x peer education) factorial design. There were 24 buildings used as clusters within one private university in the United States, where 2,300 people were employed. All clusters were exposed to the same basic information campaign aimed to educate people about energy consumption and conservation. The control group consisted of one-fourth of the buildings that received only information from public information campaign. Experimental groups consisted of buildings that received a peer education intervention, a feedback intervention and combination of all three interventions (one-fourth of buildings for each intervention). Interventions were conducted simultaneously during four months and data were collected through online survey. Results indicated the statistically significant decrease of consumption of feedback and combined experimental groups (by 7% and 8%) and the slight decrease in case of peer education (but not statistically significant), while consumption during the intervention phase increased within the control group (by approximately 4%).

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Taking into account literature review as well as key characteristic for household's electricity consumption in Serbia, the research was designed with the aim to determine the effect of energy saving instructions on household's electricity consumption. The following research hypothesis was developed:

H0: Energy saving information represents an effective means for affecting the energy behavior of households in Serbia and reduction of electricity consumption.

5.2 Description of experimental design

The research in Serbia was conducted in cooperation with national electricity supplier – Elektroprivreda Srbije (Power Industry of Serbia, EPS). EPS has a dominant position and owns all large generation capacities and supplies most consumers.

Experimental design was adapted to the national characteristics, so the RCT methodology was developed by considering the following facts:

- The Serbian electricity market has not been totally liberalized yet and electricity prices are regulated on the national level;
- Households can choose among several electricity suppliers, but every one of them is EPS's customer due to low electricity price;
- There is no smart metering in households in Serbia, and electricity consumption is still recorded by field operators employed by EPS who visit houses and buildings on monthly basis and make records of the consumption, based on which monthly bills are later sent by the company;
- EPS is interested to provide support as a segment of its socially responsible business, which includes education of consumers.

Therefore, the support of EPS in this research was crucial mainly for choosing a sample of households that are suitable for participation in the research and following their monthly electricity consumption.

The sample consists of 3528 households in Belgrade, which demonstrate similar average levels of electricity consumption in order to enable comparison of the obtained results upon terminating the experiment. EPS performed the selection of the sample by observing their consumption during the previous year.

In order to have equal representation of households with different heating solutions, the total sample in Belgrade was divided into three strata:

1. Households in buildings with district heating (the new part of Belgrade),
2. Households in smaller and older buildings without district heating, so electricity is mainly used for heating (the old Belgrade city center,) and
3. Households in Belgrade suburb, mainly houses, where various energy sources are used for heating (electricity, wood, etc.).

This division is important since heating appliances are often consuming the largest amount of energy, and, therefore, may affect the overall possibility of households to apply energy-saving instructions. Since the target population was split into three strata, stratified random sampling was used since households from each stratum must be included in both, experimental and control group. When each stratum was defined, simple random sampling was performed to choose

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elements from each stratum.

Randomization was performed in order to randomly choose experimental participants. For this purpose, simple random sampling was used, where participants were assigned random numbers and then drawn randomly from a sample where everyone has an even probability of being part of experiment. Then, by using software tools, the assigned numbers were shuffled and randomly assigned either to treatment or control group.

By respecting the protocol for implementation of this kind of methodology, the randomization was performed by EPS (assigned employees in IT sector). Randomization in case of this experiment was performed in order to avoid bias. In this way, selection bias (where some groups are underrepresented) is eliminated and accidental bias (where chance imbalances happen) is minimized. Furthermore, if your sample is random it enables later running of a variety of statistical tests on the obtained data to test the hypotheses. For each stratum, 300 households were randomly chosen by assigning numbers to all households in the sample and choosing random numbers (the 'participants'). Every household in the sample has the same probability to be chosen.

In the next research phase, fieldwork was organized. These randomly selected households were contacted and informed about the study and asked for participation in RCT research. Those who agreed to participate – the participants were randomly divided in treatment and control group (50:50). The control group was not exposed to the "treatment", unlike the treatment group. The control group was used for making a comparison with the experimental group regarding the consumption during the experiment. In this way, the subjects of the total sample of 330 households living on the territory of Belgrade were randomly assigned to control group (165 households) and treatment (or experimental) group (165 households). Therefore, the proportion between treatment and control group was 50:50.

Participants in the treatment group received brochure with energy-saving instructions. As already mentioned, the type of introduced intervention was the provision of information about energy-saving options. The expected impact of such intervention reflects households' adoption and implementation of given instructions during the experiment. Such intervention was used to increase consumer's awareness, and observe if the adoption of new consumption patterns has an actual impact on consumption reduction.

Such interventions were also used by other authors. As it was noted by Abrahamse et al. (2005), we used the "antecedent interventions", which include "providing households with information about energy-saving options" that "may result in energy savings, because people have acquired (more) knowledge." In this article, different strategies to influence consumer behavior, i.e. their consumption, are mentioned, so we choose to use the information strategy, which is described as follows: "Information is a commonly used strategy to promote energy conservation behaviors. This may be general information about energy-related problems, or specific information about possible solutions, such as information about various energy-saving measures households can adopt." As for the "treatment", which the experimental group was exposed to, in our case, it consisted of written energy-saving tips/instructions on the possibility to reduce energy consumption (forms of behavior that members of households should adopt and implement during the experiment). Something similar was described in the paper of author Alcott (2011), who used letters with instructions that were sent to consumers, and conducted measurements after a certain period of time and compared results with control group.

The Economics Institute team prepared experimental material, and further distributed it to

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households through face-to-face contact. Household members assigned to the treatment group were asked to follow provided instructions. The households assigned to the control group just received notification that they will be participating in the research and that their monthly consumption will be observed (at the level of the entire group). Monthly consumption of consumers in the treatment group was compared with the households in the control group on a monthly basis. Such comparison of the electricity consumption between treatment and control group allows us to determine the effect of information on behavioral change, and consequently, electricity consumption.

Intended duration of the experiment is three months, starting from February, 1st 2018 and lasting until April, 31st 2018. This duration was agreed with EPS Supply since this company provided us with the information on the electricity consumption of households during the experiment.

The electricity consumption was measured by monthly billing. Consumption of individual households was monitored on a monthly basis and data were provided by EPS Supply. Upon receiving information regarding electricity consumption, the analysis of households' data within treatment group were performed by taking into account different variables (household characteristics, previous energy behavior, etc.), as well as comparison of data between treatment and control group.

According to our hypothesis, households in the treatment group should adopt and implement simple energy-saving instructions given in the brochure. Those instructions for saving energy in households refer to more efficient use of home appliances for everyday use. The household appliances that use significant amount of electricity, besides heating stoves, are: boiler, washing machine, cooker, fridge and lighting in the apartments. By optimizing the use of appliances, it would be possible for households to reduce consumption, which is intended to be demonstrated with this research.

On the other hand, consumers from the control group did not receive these energy-saving instructions (this is the only distinction between these two groups). The participants in both groups were informed about the research and both groups were asked at the beginning to participate in the research. Furthermore, the participants were informed that their consumption will be monitored for three months for the research purposes. Due to previous experience with similar research, it was necessary to offer some kind of stimulation at the beginning, in order to make households willing to initially accept to participate. The reason for that can be found in lower level of environmental awareness that currently exist in Serbian market. Consumers in Serbian market are not very "open" to such surveys and field experiments, especially if they last several months, and are often reluctant to provide researchers with any personal data and data regarding behavioral patterns.

For these reasons, we considered giving a small gift at the very beginning (a voucher for supermarket - approximate cost of 3-4 EUR) in order to encourage households to accept the invitation and to fully cooperate. The initial reward was given to participants from both experimental and control group, in order not to make this incentive to be a contaminating factor.

At the end of the research, the participants who had been randomly assigned to experimental and control groups were asked to fill in a short questionnaire regarding their current energy consumption. All the participants who were able to fill in the questionnaire received a small tip (as a reward for their time).

Since the experimental material included multiple instructions for several house appliances, the

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influence of each instruction on the reduction of the consumption could not be properly observed. Only the aggregate results of application of some or all of the instructions by some or all household members can be observed and analyzed. Since we cannot know for certain whether all household members implemented instructions during the entire experiment, nor can we rely on their self-reporting, we will perform the analysis solely based on the data on consumption received by EPS and data collected in the questionnaire.

5.3 Descriptive and analytical results

EPS prepared the sample of 3528 households, which demonstrate similar monthly average levels of electricity consumption. Households were divided into three strata representing different types of energy mix used for heating (electricity, district heating, and energy mix). In order to reach a total number of 330 participants in the survey, 1605 households were contacted, out of which 899 households did not provide access (interviewer could not enter the building or nobody was at home), 368 did not accept to participate in the survey, 8 were incapable to participate in the research (Table 2).

Table 2. Total number of contacted persons and number of the participants in the research

Contact	Contact	Number	Type of contact	
Interview was not done	Without response	899	The interviewer could not enter the building	669
			Respondent is not at home (after 2 attempts)	230
	Refusal	368	Refusal by the whole household	212
			Refusal by respondent	153
			Refusal during the interview (interruption of the interview, the respondent refuses to complete the interview)	3
	Other	8	Respondent is physically or mentally incapable to participate in the research	8
Interview	Done	330	Successful interviews	330

The analysis of the entire sample or the number of participants in the research was difficult for several reasons:

- Inability to access potential respondents (they were not at home or would not open the door, etc.);
- Lack of respondents' interest or engagement;
- The topic of the research was not interesting for participants
- Lack of trust in the research or lack of credibility of the process;
- Concerns about anonymity and how personal information can be used;
- Lack of time for respondents or unwillingness to participate due to duration of the research;
- Preventing the interviewer to reach the place.

In order to achieve the desired number of research participants, the following measures were taken:

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- The interview was done by Economics Institute team after joint training and interviews with professional interviewers;
- Participants in the project / survey (experimental and control group) were rewarded by vouchers;
- A contact line for interviewers and respondents was provided so that at any time a response or clarification could be obtained, which at the same time created an image that the research is serious which reassured households to participate;
- Conducting an interviewer's Log containing the necessary information about respondents, who were not included in the questionnaire;
- The interviewers wore a badge that pointed out that ESOMAR standards were met, which directly implied compliance with the confidentiality test requirements.

A group of 330 participants was selected based on RCT. As the request was to form a 50:50 control and treatment group, it was much harder to find 165 participants willing to participate in the experimental group. Therefore, 368 respondents refused to participate when they heard that they were expected to follow certain instructions and that they would be contacted on a monthly basis.

The difference between the two groups is only in the fact that the experimental group received instructions, and the control group did not receive instructions on measures for more efficient use of electricity in the household. All households were informed about the research and all 330 households accepted to participate in the research.

5.3.1 Analysis of electricity consumption

Depending on the type of energy used for heating (district heating, electricity and mix), the research was carried out on three strata. For each stratum, the change in consumption in the control and experimental group was analyzed for the period January-April, where the impact of instruction can be analyzed only for the period February – April. Using RCT based on the control and experimental group, the seasonal effects were eliminated (temperature and other weather effects).

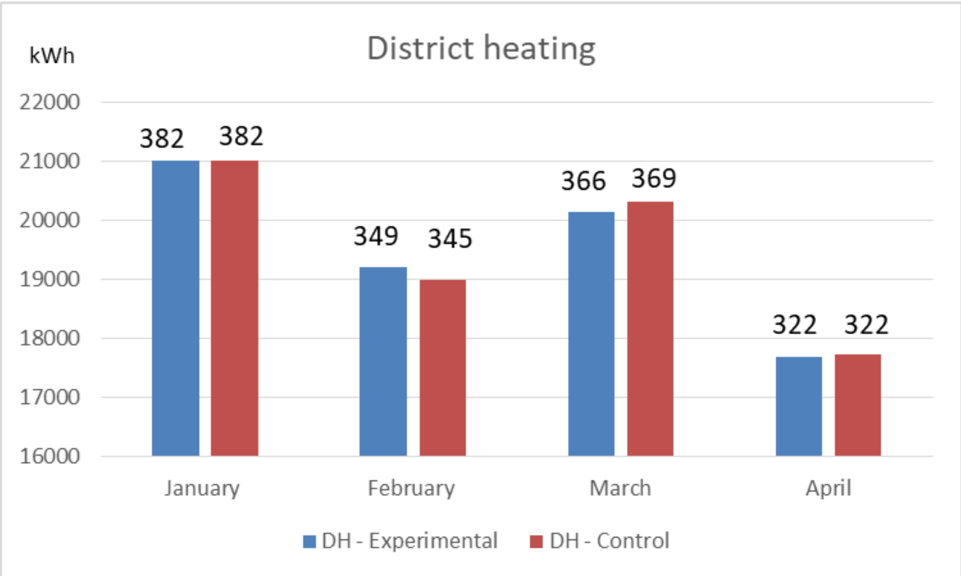

Figure 2. Comparison of electricity consumption in the sample of 110 households (55 in each group) with district heating

Strata of households having access to district heating (the lowest level of electricity consumption)

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recorded the lowest level of changes in electricity consumption considering the observed period February-April. Consequently, consumption in January (when the research has not started yet) at the experimental and control group level was almost identical (average consumption of 382kWh). In February, the experimental group recorded an increase in consumption relative to the control group. This trend contradicted expectations that the group that received energy saving instructions will reduce consumption. In February, the average household consumption in the experimental group and control group was 349kWh and 345kWh, respectively. In March, the control group recorded a decrease in consumption (average electricity consumption of households in the experimental group was 366kWh in comparison to 369kWh in the control group), while in April the level of consumption in both groups was at the same level (322kWh). It can be concluded that in this strata, electricity consumption is comparable throughout time in both groups.

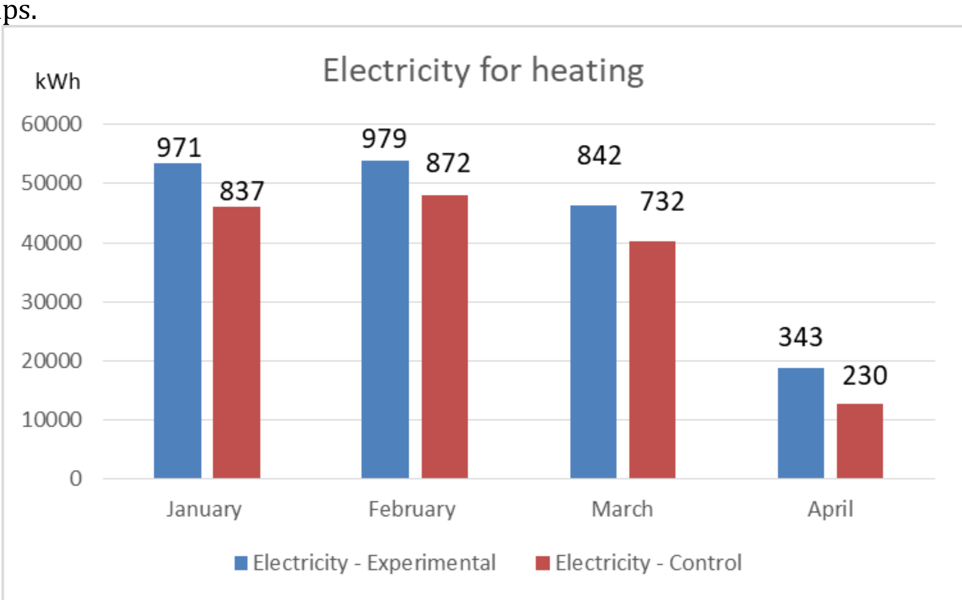

Figure 3. Comparison of electricity consumption in the sample of 110 households (55 in each group) which dominantly use electricity for heating

In the strata of households that dominantly use electricity for heating, average electricity consumption is the highest. Observing the control group in January, the average monthly consumption is 2.5 times higher in this stratum than in households with district heating. In this stratum, experimental group during the whole experimental period recorded the level of electricity consumption higher than in the control group. These data indicates that the instructions were not followed by households that normally have the highest average electricity consumption. Likewise, throughout the observed period, the difference in average monthly consumption at the household level was maintained - in February the difference in the average monthly household consumption was 107kWh, in March 110 kWh, and in the last month the difference was 113kWh.

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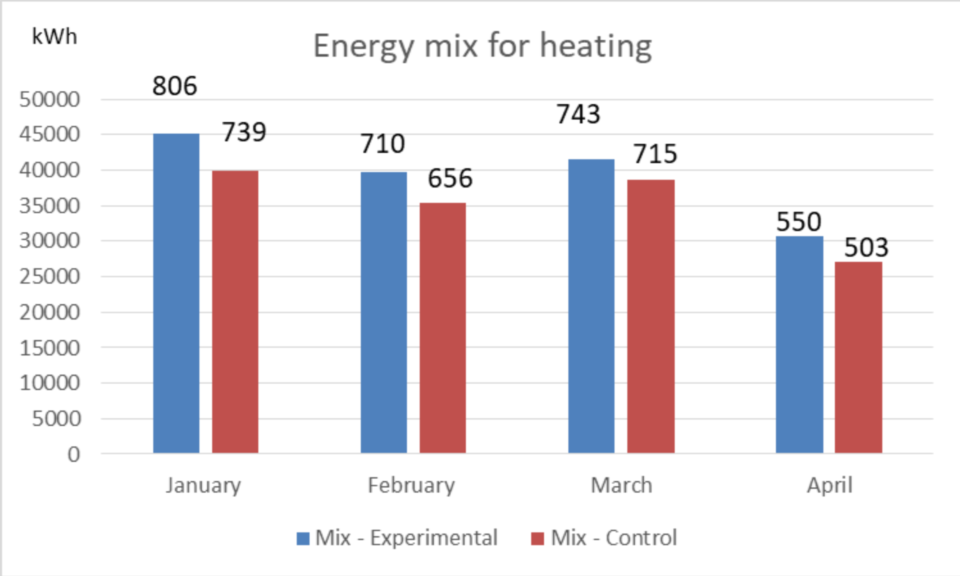

Figure 4. Comparison of electricity consumption in the sample of 110 households (55 in each group) which use energy mix for heating

In the strata of households that use different energy sources for heating, the experimental group recorded a higher level of electricity consumption than the average household consumption in the control group during the whole observed period. Furthermore, the level of electricity consumption in the experimental group was higher than in the control group during the whole experimental period.

Although the criterion for equal number of participants in the control and experimental group was met, at the beginning of the research the level of average consumption was the same only in the first case (households with district heating). In the two other cases, the experimental group had a higher average electricity consumption and kept that trend until the end of the research.

5.3.2 Socio-economic analysis – post experimental survey

Analysis of socio-economic factors was based on face to face interview on the sample of 330 participants in the research. The study was carried out on population aged 19 years and over, and women (54.8%) showed higher interest in the research than men (45.2%). The elderly population aged 60 to 69 years was the most open to participate in the study (Figure 5).

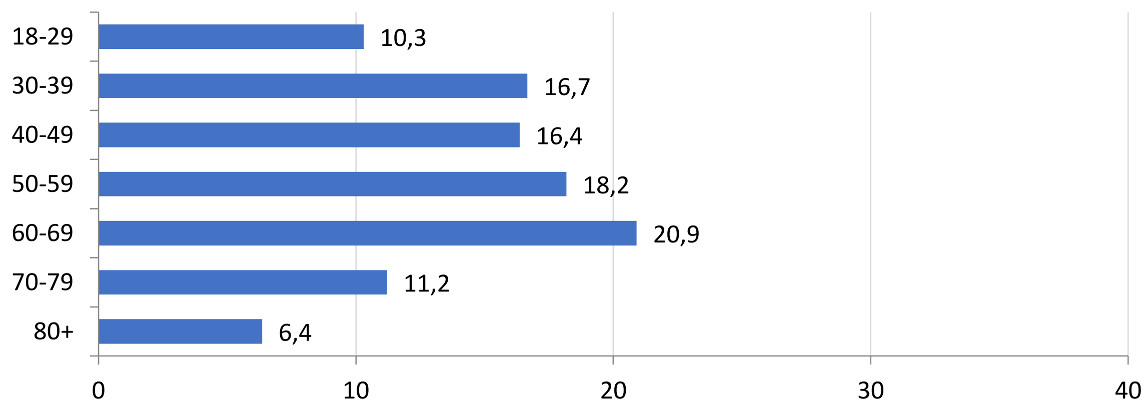

Figure 5. Age structure of respondents, in %

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Given the educational structure (Figure 6), people with secondary education (64.2%) were dominant participants in the research.

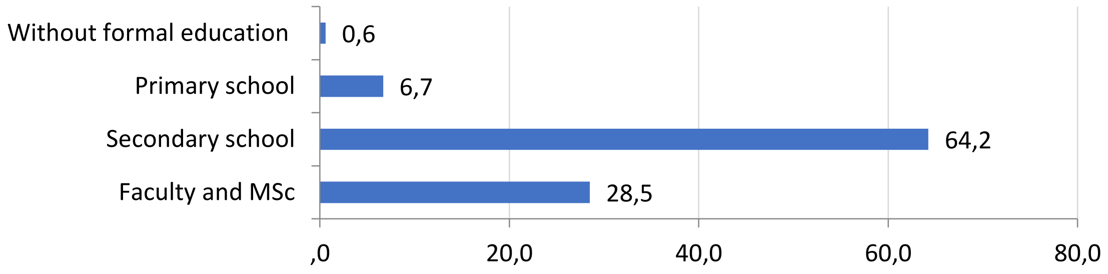

Figure 6. Education of respondents, in %

The majority of participants (70%) were full time employed (Figure 7).

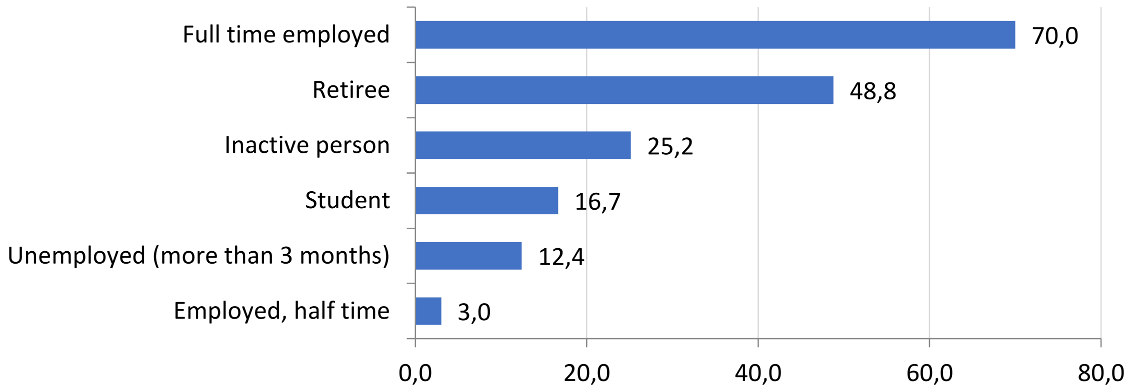

Figure 7. Employment, in %

In terms of housing type, 70.6% of participants live in apartments, and 29.4% live in houses. Considering the size of living space, the highest share of participants lives in flats/houses of 43-63m² (Figure 8).

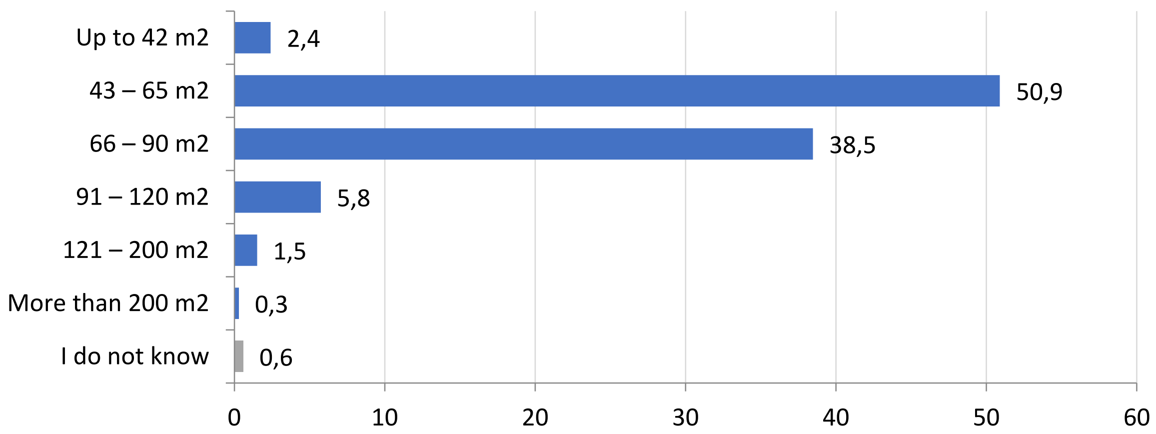

Figure 8. Size of living space, in m2

Respondents were asked about their personal monthly income. Although the survey was completely anonymous, as many as half of respondents refused to provide answers (Figure 9).

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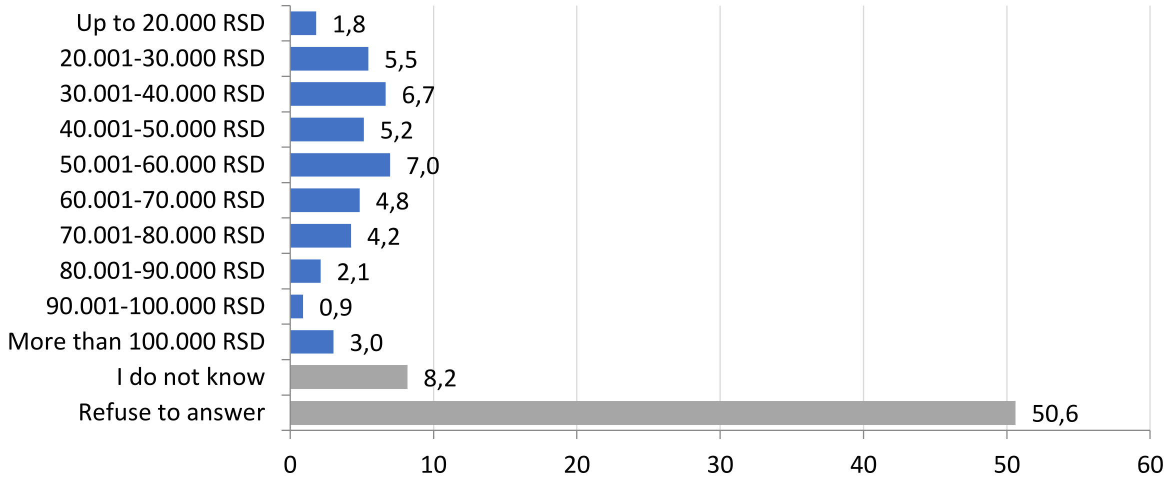

Figure 9. Personal earnings, and RSD (currency 1EUR = 120RSD)

The largest number of participants in the research is connected to district heating (46.1%), while 37% use electricity for heating (Figure 10).

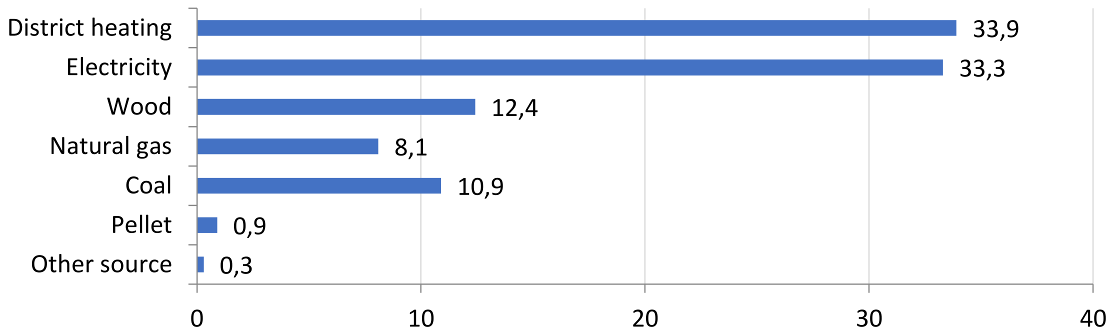

Figure 10. Structure of respondents by type of energy sources used for heating, in %

Out of the total number of respondents (330) who use storage heaters, as many as 92% responded that they let heaters store thermal energy at night when electricity is cheaper (Figure 11).

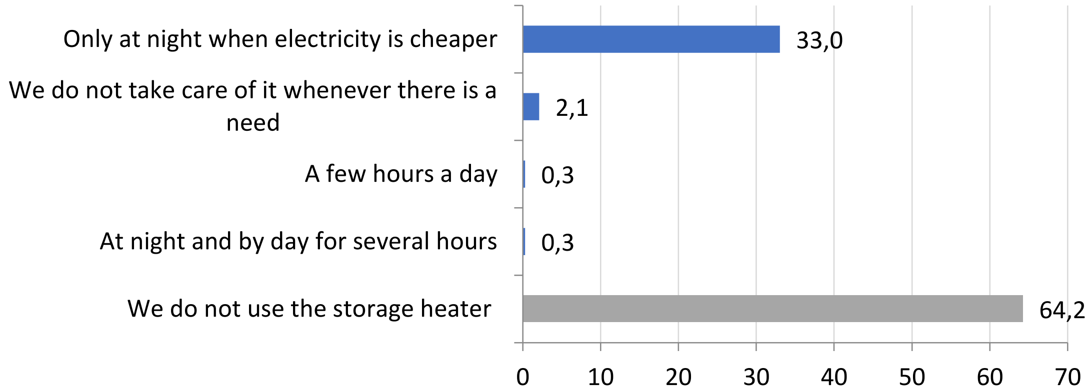

Figure 11. When do households charge their storage heaters, in %

The most commonly used electric appliance is the TV, as 97% of respondents confirmed to be watching TV on a daily basis. The second most frequently used household electrical appliance is the stove – (87% of respondents said they use the stove on a daily basis), while water heater is on

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the third place, with 77% of respondents stating they use this appliance on a daily basis (Figure 12).

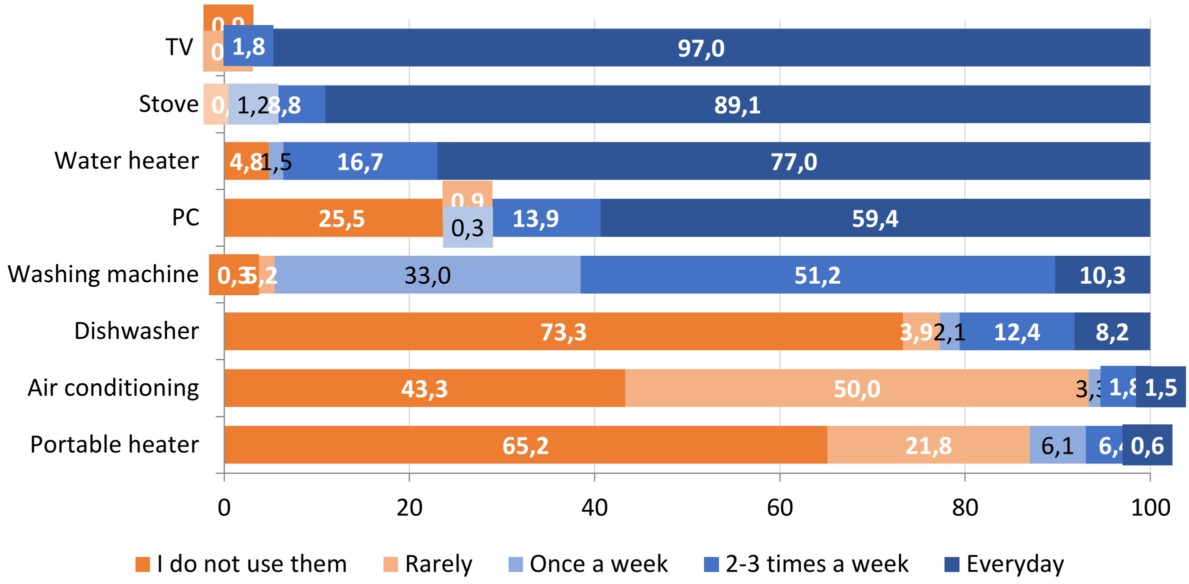

Figure 12. How often do you use the following electrical appliances in your household?

Most respondents have only ordinary light bulbs in their household (36.7%), while only 11.2% of the respondents use only energy-efficient light bulbs (Figure 13).

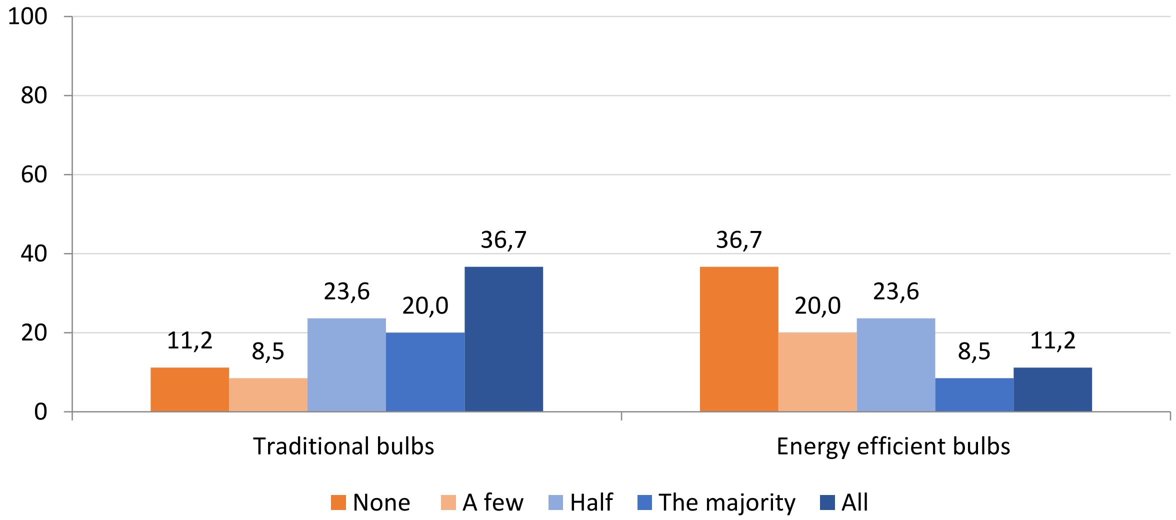

Figure 13. Type of bulbs in the living space, in %

In order to examine how much respondents are informed about CO2 emissions, the following question was raised: "In your opinion, what is the percentage of the total amount of CO2 emitted, released from combustion of fossil fuels during the production of heat and electricity?" The highest percentage of respondents (41.2%) replied that out of the total amount of CO2 emitted, about 50% emits on the basis of combustion of fossil fuels during the production of heat and electricity (Figure 14).

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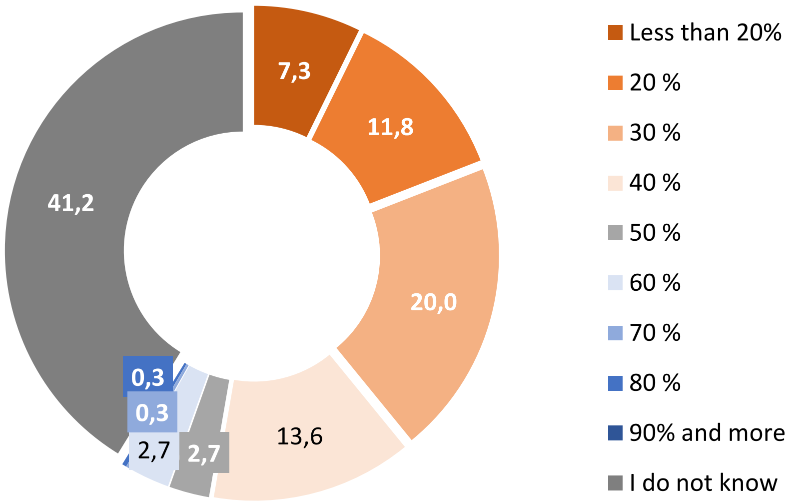

Figure 14. Respondents' answers to the question on the percentage of the total amount of CO2 emitted, released from combustion of fossil fuels during the production of heat and electricity?

The majority of respondents believe that the most effective energy saving is through the installation of thermal insulation (50.6%) and the replacement of windows 37% (Figure 15).

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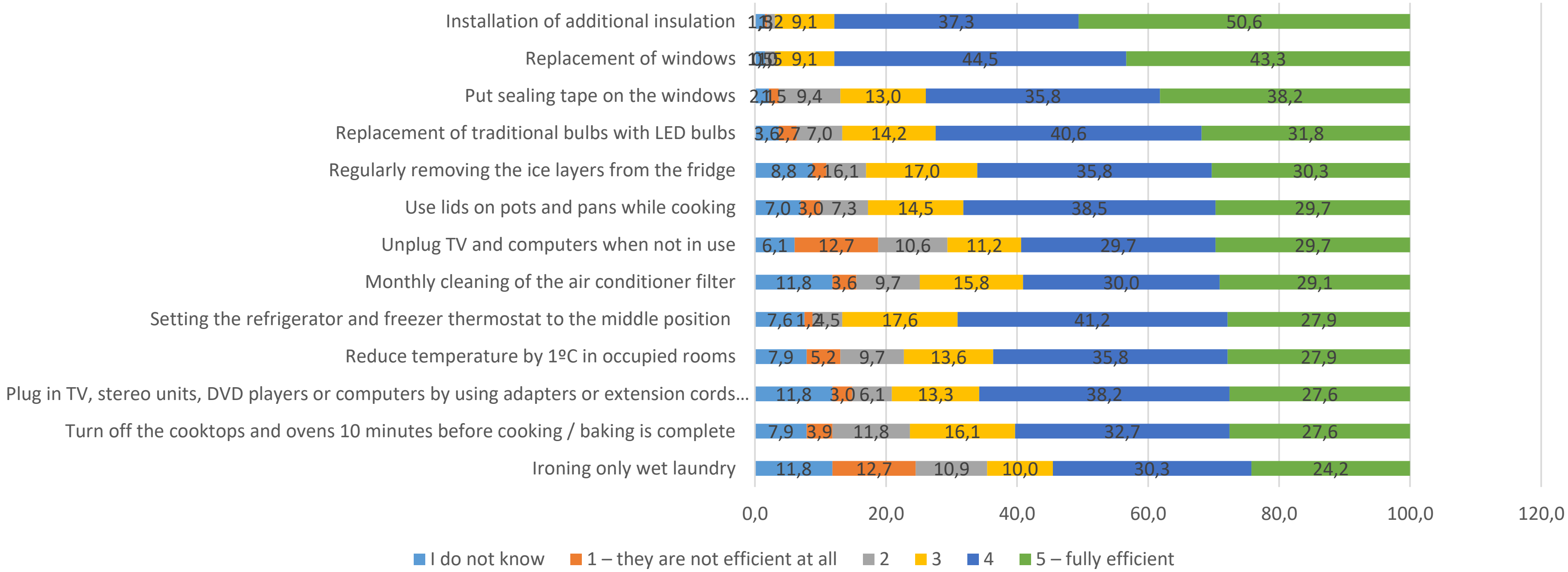

Figure 15. Respondents' opinions on the most efficient measures in reducing the consumption of electricity in the household?

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A large share of respondents (43.9%) answered that they were informed on how to save electricity on TV, which confirms that TV is the most prominent medium.

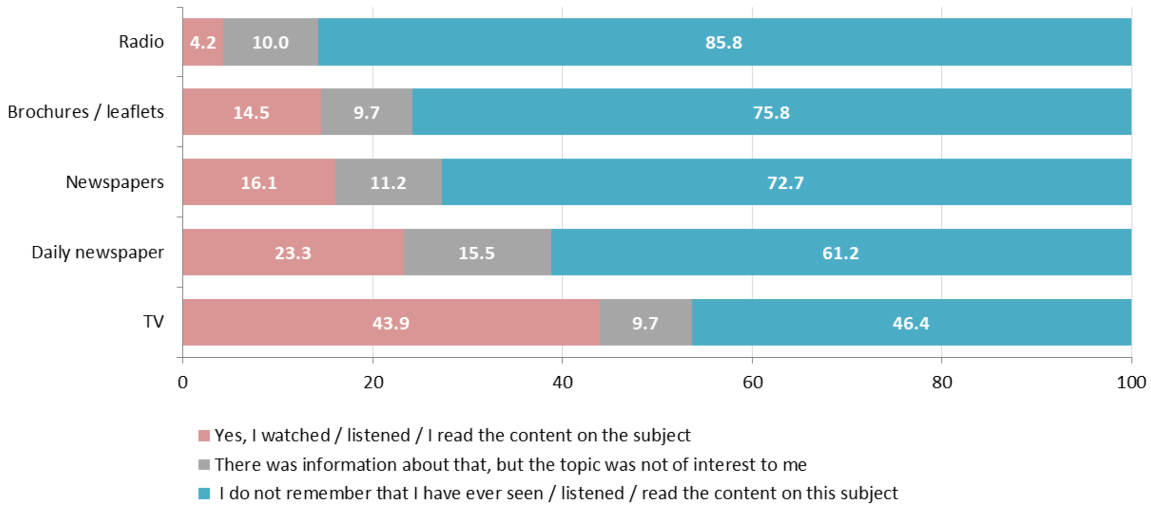

Figure 16. Have you ever had an opportunity to get information about ways to save electricity through the following sources?

An extremely high percentage (43.6%) of respondents stated they were not interested in seeking information on possible ways of saving electricity on the Internet (Figure 17).

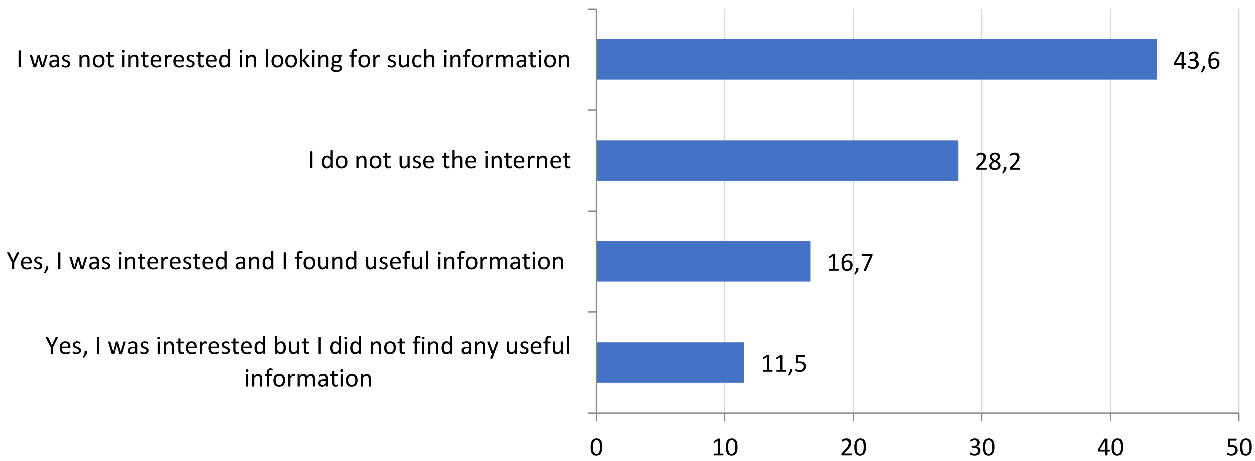

Figure 17. Have you ever tried to find information on the Internet about the possible ways to save electricity?

In order to gain an impression of how much research participants were informed about the possibilities of saving household electricity, the participants were asked whether they were familiar with some methods of saving electricity (Figure 18). It is interesting to note that the highest percentage of respondents (51%) said that they were informed that energy-efficient light bulbs last up to six times longer than ordinary bulbs, but they were not motivated to change bulbs in their household. Out of the information provided in the instructions, the largest percentage of respondents (66%) said they heard for the first time that TV consumes electricity even when it is turned off. Likewise, as many as 52% of respondents did not know that plugged in mobile phone charger consumes energy although the mobile phone is not being charged.

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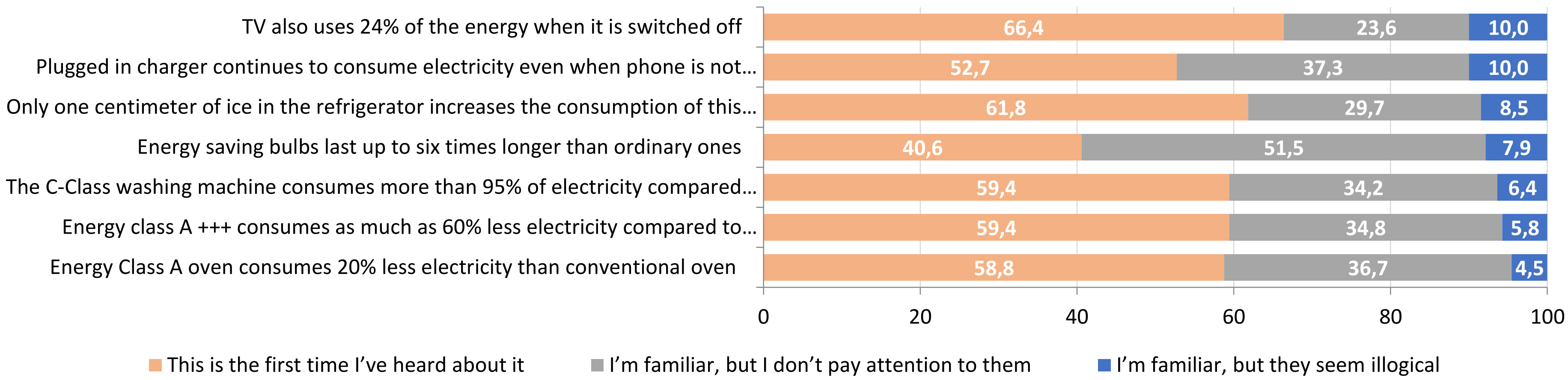

Figure 18. Are you familiar with the following facts?

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5.4 Discussion of results

At the beginning of our research, we started from the preliminary assumption that price incentives would not be effective in our case due to the fact that electricity price in Serbia is the lowest in Europe. We suppose that the low electricity price is the key reason for high and inefficient electricity consumption in households. Instead of choosing price incentives, we set the research hypothesis that energy saving information represents an effective means for changing the energy behavior of households in Serbia and reduction of electricity consumption.

However, the research results did not confirm this hypothesis. Moreover, this research showed that in situation when electricity price is very low, energy saving information does not affect changes in consumer behavior. Since this trend contradicted the research hypothesis, Difference in Difference (DnD) analysis was implemented. Data used for DnD analysis, where:

- y is electricity consumption;
- x - 0 for control group, 1 for experimental group
- t - 0 for January, 1 for later months;
- xt - 1 for experimental group after instructions, 0 for all others.

Table 3: Explanation of Regression Variables

	Y	X	T	XT
Electricity for heating	837	0	0	0
Electricity for heating	971	1	0	0
Electricity for heating	611	0	1	0
Electricity for heating	721	1	1	1
District heating	382	0	0	0
District heating	382	1	0	0
District heating	346	0	1	0
District heating	346	1	1	1
Energy mix	739	0	0	0
Energy mix	806	1	0	0
Energy mix	625	0	1	0
Energy mix	668	1	1	1

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Source	SS	df	MS		
Model	63968.3333	3	21322.7778	Number of obs =	12
Residual	431126.667	8	53890.8333	F(3, 8) =	0.40
				Prob > F =	0.7598
Total	495095	11	45008.6364	R-squared =	0.1292
				Adj R-squared =	-0.1973
				Root MSE =	232.14

y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
x	67	189.5448	0.35	0.733	-370.091	504.091
t	-125.3333	189.5448	-0.66	0.527	-562.4244	311.7577
xt	-16	268.0568	-0.06	0.954	-634.1401	602.1401
_cons	652.6667	134.0284	4.87	0.001	343.5966	961.7367

Figure 19: Estimation Results

Interpretation of the coefficient value:

- The average consumption of the control group in January was 652.6667kWh;
- The difference between the average consumption of the experimental and control group in January was 67kWh;
- The difference between the average consumption of the control group in the later period (February-April average) and January was -125.333;
- The difference in the change in average consumption between the experimental and the control group in the observed period was -16.

Considering the p-value, it could be noticed that coefficients are greater than 0.05. This means that these higher coefficients are not statistically significant. In particular, these differences in the change in consumption of either group cannot be explained by the criterion applied in the research (whether they were given instructions or not).

Coefficients are not significant. In addition, the coefficient is negative, which means that electricity consumption is more reduced in the control group than in the experimental group. Changes in the electricity consumption that occurred could not be explained by the above used factors (whether they received instructions or not). R-square indicates that only 12.92% of the change in consumption can be explained by these variables, and besides it is insignificant (p value 0.7598 and less than 0.05 or 0.10).

Socio-economic analysis of participants showed the following:

- In order to reach the number of 330 households that will participate in the survey, 1605 households were contacted, out of which even 368 refused to participate in the research for various reasons (they were not interested in the subject, long research period, not ready to follow the instructions, concerns for anonymity, etc.);
- Women (54.8%) were more interested in the research than men (45.2%);
- The most commonly used electric appliances on daily basis are TV, stove and water heater;
- Most respondents have traditional light bulbs in their households (36.7%), while only 11.2% of the respondents use only energy-efficient light bulbs. Most households in Serbia use incandescent bulbs. There are no tax incentives for using more efficient but more expensive fluorescent bulbs;
- In more than 90% of households in Serbia, water is heated by immersing a water heater. Most of the tanks are domestically produced, with poor or damaged insulation and inadequate controls;

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- The majority of respondents believe that the most effective energy saving is through the installation of thermal insulation and the replacement of windows;
- TV is still the most influential medium for disseminating energy efficiency information;
- An extremely high percentage of participants stated they were not interested in seeking information on possible ways of saving electricity on the Internet;
- Since 51% of participants said they were informed that energy-efficient light bulbs last up to six times longer than usual bulbs, but they were not motivated to change bulbs in their households, it could be concluded that people are not very interested in changing their consumption behavior even though large material investment is not required;
- Analyzing other answers on being informed on how to improve energy efficiency in the household without significant material investments (e.g., unplug chargers when not used), it can be concluded that the level of information is at a rather low level.

The biggest limitation of this study was at the very beginning, prior to conducting the survey, to ensure that the experimental and control group have the same average electricity consumption on the basis of RCT. Despite the fact that EPS created a household base that has a fairly uniform consumption at the level of the strata, it was almost impossible to divide the experimental and control group on the basis of RCT so to have the same level of consumption before the start of the research. Since this criterion was fulfilled only in the first case (households with district heating), it seems that these data are the most reliable. In the other two groups, the use of RCT for the distribution of respondents to the control and experimental group at the very beginning of the study showed that the experimental group had a higher level of consumption before the start of the study. Despite the fact that they received instructions and were called each month on the phone and reminded of the measures for more efficient use of household electricity, the research participants did not manage to reduce their spending in any month compared to the control group.

The research showed that the respondents' greatest concern was anonymity. As the questionnaire also included questions of a personal nature (monthly income), we had to make additional efforts to get the requested information. First of all, it was necessary to convince respondents that the interview is anonymous and that their identity will remain anonymous. In order to ensure the anonymity of the research, our team adopted the following control measures:

- There will be no identification data needed to complete the survey, and
- There will be no identifiable information displayed in the questionnaire,
- The information of all respondents will be written in a separate document, the "Log"

5.5 Conclusion and policy implications

This research yields some important conclusions that could influence the energy policy design and future research relevant to household's electricity consumption patterns in Serbia.

The case study showed that in a situation where electricity price is very low, energy saving information does not have an influence on consumer behavior. Based on the analysis of statistical data and field research, it could be concluded that energy efficiency, as well as energy efficiency awareness, is still at low level in Serbia. Lack of adequate knowledge about energy use and available devices reduces the quality of energy services. The fact is that a majority of Serbian households use electricity for heating, since the price of electricity is still more attractive than prices of other energy sources (e.g. gas). The other reason why electricity is used for heating is the fact that infrastructure for district heating is still not developed enough in Serbia. The lack of alternative energy sources and energy-using devices severely constrains household consumption patterns and their ability to save electricity.

Consequently, households adopted inefficient electricity practices. Standards on the thermal characteristics of buildings especially in older buildings have rarely been enforced, and residents complain about dampness, leaking roofs and inadequate walls and floors. Residential buildings

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connected to the district heating grid are considered to be of better quality, since in many cases they were constructed by builders who were able to enforce technical standards.

Although electricity prices in Serbia are the lowest in Europe, it is important to note that expenditures related to housing, water, electricity, gas, etc. have a very high share (17.4%) in the individual consumption expenditures of the Serbian households[24]. It is the second largest share after expenditures for food and non-alcoholic beverages (34%).

Lack of information means that most households are not able to predict the long-term consequences of their current electricity consumption patterns. Both district heating and electricity services are billed after consumption, with considerable flexibility in fee collection. The combination of district heating systems and electricity is considered a good package of energy services and costs. Households connected to district heating systems rarely consume quantities of electricity large enough to be placed in the higher tariff zones. Electricity consumption is likely to depend on the sufficiency or the lack of district heating service and is inelastic with respect to the price of electricity. The surveys indicate that knowledge of electricity prices is very limited.

Retail price of electricity for households is not realistic (for example CO2 costs are not included into the final price), which is the only reason why energy suppliers and traders do not compete with EPS in supplying electricity to households. The current price of 6.4 Eurocents/kWh is even below EPS' production price, but the Government builds its social policy on the price of electricity, which is significantly lower compared to other countries in the region. However, EPS sells electricity to traders in Serbia and region at market prices, thus covering the losses made in supplying households.

The electricity market in Serbia is still dominated by state-owned public companies and is mainly characterized by incomplete liberalization, as well as the low level of participation of private companies. Since February 2008, the qualified buyers could have opted for new electricity to be supplied either at market prices or at regulated tariffs. Since regulated tariffs are currently lower than the market prices, consumers have generally chosen the supply at regulated tariffs.

Although the electricity market in Serbia has been liberalized for more than three years, state-owned power utility EPS is the main supplier of electricity to Serbian households. EPS currently holds 97.25 % of electricity market in Serbia, which includes the supply of households, small and medium-sized enterprises, public institution and large industrial consumers.

Serbian households have the right to choose their own supplier, but that right has not been exercised so far, because EPS offers electricity at prices far below market prices, which means that independent suppliers would suffer losses if they offered prices competitive with EPS's prices. Independent suppliers will have the motivation to participate in the supply of Serbian households only if the price rises above 7 Eurocents/kWh, plus VAT and other excise duties.

Electricity price, which the consumers will finally pay, is affected by electricity tariffs and contracts structure, which usually implies many factors, such as established charges and unit prices that differ in relation to the electricity consumed and period of its consumption. An empirical analysis shows that electricity bills received by residential consumers can serve as a basis for division of taxation components into taxes that are connected to energy policies and value added tax (VAT), and other taxation instruments that can be recovered. It is also noticed that these electricity bills might be impacted by energy efficiency policies, renewable energy policies, emissions trading schemes, and investment in infrastructure. Financing that is related to policy priorities in the member states is done in two ways, i.e. through taxes or levies and as an element of energy production price or network costs. However, generally speaking, VAT is considered as the general tax applied to every business activity

[24] Household Budget Survey, data available at http://www.stat.gov.rs/en-us/vesti/20180615-prihodi-u-novcu-i-u-naturi/?s=0101

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regarding manufacture and delivery of goods and service.

The analysis showed that the lowest share of taxes in final electricity price were found in Serbia (9.7%), Bulgaria (16.7%) and Ukraine (17%), while the highest levels were observed in Germany (54.6%), Italy (36.3%) and France (36.3%). At the same time, Serbia, Bulgaria and Ukraine are the countries with the lowest electricity prices and the highest emissions of CO2. This implies that electricity price policy should be changed and the other model, which brings together economy, energy and environmental policy (3E policy), should be implemented.

As Serbia intends to join the EU, it should also aim at reducing emissions by 80-95% by 2050, in line with the EU policy. However, Serbian government and EPS plan to remain locked-in to a carbon-intensive energy system, most notably through the construction of the 350 MW Kostolac B3 lignite power plant and the expansion of the associated mine from 9 to 12 million tons annually. Although Kostolac B3 is the only plant expected to be built before 2025, the Serbian Energy Strategy also puts forward several more fossil fuel power plants for construction.

With its traditional forms of generation not proving resilient to climate change, Serbia would do well to diversify its energy mix and work more on energy efficiency. Serbia has a promising potential for renewable energy, but as with all the countries in the region, different sources put the exact figures at quite different levels, depending among other things on whether they use sustainability criteria.

Serbia has a significant potential for energy efficiency and has a target to increase energy efficiency by 20% by 2020 under the Energy Community Treaty. Inefficient use of energy represents a major concern in the country. It has the second-highest energy intensity in the region, nearly four times as much as the EU average. Incentives to save energy are limited due to artificially low electricity prices but this is going to have to change in the coming years as Serbia integrates into the European electricity market.

Generally, the results of this research imply the following policy recommendations:

- Creating the conditions for education and information of citizens and the youth about the importance of efficient electricity use and benefits of renewable energy sources;
- Preparation of the Guide for citizens about the importance of energy efficiency and possibilities of their investments in energy efficiency home appliances as well as home RES projects;
- Encourage a variety of institutions (companies, NGOs, professional organizations, government-owned institutions, financial institutions) to enter the energy efficiency field by providing innovative services and investments;
- Analysis of incentive models for citizens and small projects in the area of RES (feed-in tariffs, energy cooperatives, net metering, green certificates, etc.) based on the international practice with the assessment of optimal economic incentive model for domestic conditions;
- Establishment of a work group with the task to investigate the possibility, validity and limitations of tax incentives or other financial models for citizens so that they would use energy efficient boilers/furnaces/stoves and to develop a proposal of concrete measures;
- Consideration of the possibility to introduce incentives for the innovation and promotional energy efficiency projects in the production and use of renewable energy sources, etc.

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6. Country case study: United Kingdom

6.1 Introduction and Motivation

The single most important domestic energy policy initiative ongoing in the UK is the Smart Meter Implementation Programme (SMIP). This programme provides the legal framework to install smart electricity and gas meters in every household in the UK by 2020. It has been described as the most expensive and complex smart meter rollout in the world and the largest UK Government run IT project in history (Lewis and Kerr, 2014). Successful implementation of the SMIP hinges on consumers' voluntary agreement to install meters in their homes. However, a number of parties—including the UK's National Audit Office, the media, and interest groups—have expressed several concerns relating to the technical performance of the meters, data security and privacy, consumer vulnerability, and consumer resistance and ambivalence, amongst others (Sovacool et al, 2014). In addition, concerns have been raised over the SMIP's lack of clarity of purpose and transparent communication of benefits to consumers (House of Commons STC, 2016).

Smart metering may allow consumers to save energy and money, but of greater social benefit is their potential to pave a path toward a more flexible energy system, allowing optimisation of generation and storage. Enhanced demand flexibility would enable more efficient management of the energy system, allow for a greater proportion of intermittent renewables in the UK's energy mix, and potentially reduce system costs.

Consumer resistance due to a range of factors has clearly inhibited rollout. In deciding whether or not to adopt a smart meter, a household must weigh up a range of costs and benefits. Both costs and benefits have private, social, and intertemporal dimensions. The costs are generally more immediate while a greater proportion of the benefits will accrue in the future. The present value of the net benefits to a given household is idiosyncratic, i.e. it may vary depending on the individual's preferences and behaviour, and may be positive or negative.

Of key policy interest is to what level consumers will need to be incentivised in order to adopt smart meters? And would this incentive level be justified based on the net present value of the estimated social benefit? Moreover, of academic interest is the extent to which framing of information can anchor people's responses in behavioural interventions.

This research develops an incentive-compatible online experiment to elicit the willingness-to-accept (WTA) of a representative panel of UK households for smart meter installation. Various treatments are provided to households to assess the impact of anchoring in WTA elicitation for this unusual but important context, where subjects are essentially asked to place a value on the compensation necessary to provide a public good. From these responses, we will aim to infer the optimal subsidy level policymakers may need to provide to incentivise households to adopt smart meters and comment on the sensitivity of that inference to the methodology deployed.

6.2 Background

The UK government has obliged energy companies to offer every household in the UK a smart electricity and gas meter by 2020 as part of its commitment to meet European energy reduction and climate change targets. Nearly seven million smart meters had been installed to date, with approximately 46 million traditional meters remaining to be replaced.

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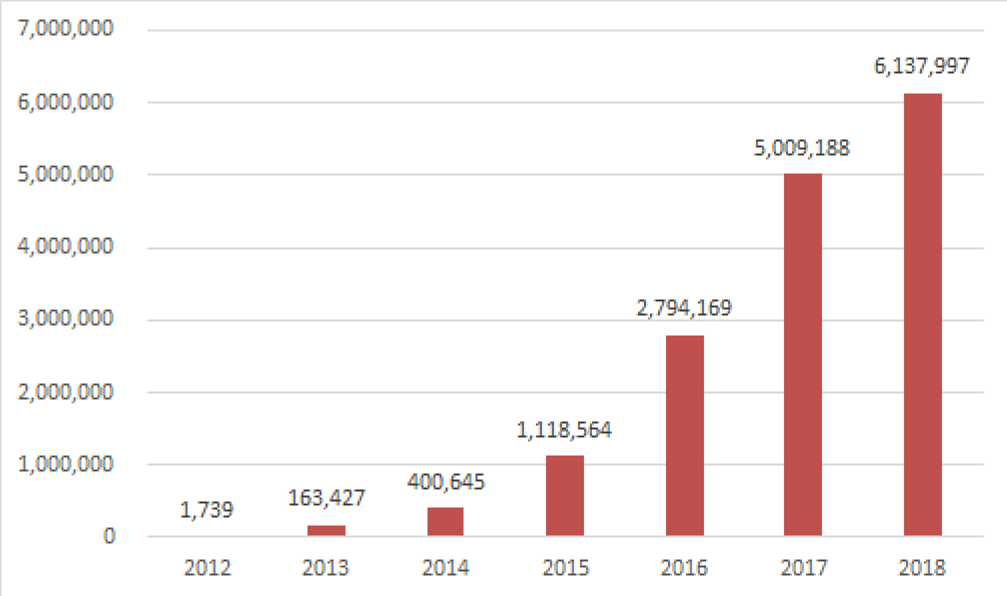

Figure 1: Smart meter rollout in the UK. Source: https://www.gov.uk/government/collections/smart-meters-statistics

A major aim of smart metering is to allow households to better control their energy consumption through increased information on their usage and costs. That is, by providing real-time information on consumption, smart meters can help to reduce overall consumption and time-shift demand if the right incentives are in place. However, not only may some households be unaware of the potential benefits of smart meter installation, they may be reluctant to adopt for a number of reasons such as privacy (McKenna et al., 2011), financial costs (Ozkan et al., 2013), hidden costs (Gillingham and Palmer 2014), or general disengagement with their energy utility (CMA, 2016). In addition, energy utilities may have difficulty in accessing certain customers, there may be physical and structural constraints associated with dwellings that make installation of smart meters impossible, or misaligned incentives and communication channels between landlords and tenants may constrain adoption in the private rented sector.

More generally, a broad literature exists that examines the so-called "energy efficiency gap", a well-evidenced phenomenon suggesting that consumers do not invest in energy-saving technologies (such as insulation or replacement boilers) that may be privately beneficial for them. This gap is often attributed to imperfect information or inattention on the part of consumers (McKinsey, 2009; Allcott and Greenstone, 2012). Gillingham and Palmer (2014) provide an extensive overview of reasons why the gap may be smaller than perceived, and of both market failures and behavioural anomalies that may be contributing the gap that exists.

Importantly, the non-monetary costs of energy efficiency upgrades have been shown to deter households from installing free measures, even once households have become aware of the potential private benefits and made an application for a home upgrade (Fowlie et al., 2015). Such hidden costs can be substantial and are difficult to account for in estimating the size of the energy efficiency gap. While these non-monetary costs are significantly smaller for smart meter installation, hidden costs such as making an appointment and sticking to it may be an issue for some households, and the appointments require that the householder is in the home for several hours for the appointment. Thus, in the current UK context where householders are perhaps unaware, uncertain, or untrusting of information regarding the benefits of smart meter installation, and with alarmist media exacerbating energy consumers' confusion and resistance, consumers may require considerable compensation before agreeing to install a meter in their homes. Our study takes a first step at quantifying this resistance with careful attention

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paid to the influence of the survey methodology on consumers' valuations.

6.3 Methods

6.3.1 Survey methodology for eliciting willingness-to-accept compensation

Environmental economics aims to incorporate the social costs of any project or policy into the decision making of social planners using cost-benefit analysis. If all of the costs and benefits of a given project or policy are aggregated and the outcome suggests a positive net present value (NPV) that outweighs the NPVs of all other alternatives, then economists would recommend implementation on the grounds of maximizing social efficiency. However, valuing environmental goods and bads is not straightforward given the lack of markets governing their exchange. While some environmental goods may have an implicit market price—e.g., the value that the public places on green space may be inferred from housing prices with varying distances to parks—others lack convenient market proxies. Take, for instance, the value that society places on the existence of Antarctic wildlife. While there are few to no direct market benefits of the continued existence of the polar bear, individuals may still garner utility from their survival as a species. This 'existence value' is one of several 'non-use' or 'passive use' values that is not encapsulated in any market exchange.

In recent decades, economists have identified a number of methods for eliciting the *total* valuation of non-market goods or goods with non-market attributes (Carson, 1996). Early surveys in environmental economics tended to ask hypothetical and open-ended questions, thereby suffering from a number of biases and shortcomings. More refined stated preference methods following from the NOAA Panel of 1993 (see Arrow et al., 1993) arguably improve upon these surveys using additions such as cheap talk (Cummings and Taylor, 1999) and consequentiality (Cummings and Taylor, 1998; Landry and List, 2007), though many still use hypothetical payouts, such that the veracity of respondents in specifying their valuations remains in question.

A number of survey methods overcome this hypothetical bias by using incentive-compatible survey methods. One simple method—the 'take-it-or-leave-it' (TIOLI)—simply asks respondents whether they will buy or sell a good or service at a given price, where the researchers generally vary the price to back out an implicit demand curve. TIOLI boasts an obvious benefit of comprehensibility. Its resemblance to familiar and routine market exchanges consumers make in their daily lives all but ensures that researchers will elicit a true and unbiased response from their subjects. Yet, unless followed up with several (theoretically infinite) subsequent questions, the method suffers from imprecision: we do not obtain an exact data point for a given respondent to reflect his/her true WTA using the TIOLI method.

To overcome the issue of relatively limited information provided by each respondent (which demands a very large sample size to flesh out a demand curve), the Becker-DeGroot-Marschak (BDM) method circumvents the requisite iterative process of the TIOLI method by directly eliciting an exact WTA—i.e. a single selling price—using a second-price auction against an unknown bidder. In accordance with the theory set out in Becker, DeGroot, and Marschak (1964), surveyors can elicit a true and exact WTA (or 'selling price') from respondents by offering to pay them an unknown (and, in our case, double blind) amount *b*--the researcher's buying price--in the event that the latter exceeds the former. Since sellers (i.e. survey respondents) do not know the value of *b* in advance, they essentially cognitively engage in an iterative TIOLI process, asking themselves whether they would be willing to accept *b* in exchange for the service for every possible value that *b* could take, thereby ultimately identifying and stating their true selling prices.

In addition to the precision of the method—and the resulting implications for requisite sample size and budget to infer a demand curve—Berry et al. (2015) point out that the BDM mechanism offers additional practical advantages over TIOLI. If there is a wide range of prices over which the researcher is eager to understand WTA, then TIOLI can be quite impractical. In our case, consumers' WTA compensation for installing a smart meter is highly uncertain and the private costs associated with installation vary

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immensely across individuals, so the variance of true WTAs is potentially substantial. Moreover, it is possible that there is an interaction effect between one's true WTA and potential treatment effects. In other words, if a researcher is interested in the impact of various treatments on one's WTA and only one or two prices are offered as part of a TIOLI survey, then the researcher can only identify the treatment effect at that/those price level(s). Therefore, without the assumption of a constant treatment effect, TIOLI could preclude identification of a treatment effect when one indeed exists for some individuals. Finally, if compensation received could be a predictor of subsequent behaviours--e.g., in our case, actual smart meter installation--then BDM offers the variation in compensation necessary to tease out such an effect.

The contextual features of the service we aim to value more closely reflect those that favour BDM rather than TIOLI. As mentioned, the range of individuals' true WTA is likely wide, and lack of a well-established market for provision of this service means that individuals will have little prior experience of prices to anchor their valuations. Moreover, we are indeed interested in heterogeneous treatment effects, so BDM provides us with the nuance necessary to tease out these effects with a fairly limited sample size.

However, aside from its lower comprehensibility relative to TIOLI, some methodological difficulties are worth mentioning. Foremost, and particularly when the market for such a service is missing or unfamiliar, the appropriate buying price range is both difficult to identify and could even influence survey responses if mentioned explicitly. Simultaneously, without such a range to anchor respondents' selling price, the surveyor risks extracting valuations that are perhaps unreasonable or, at the very least, infeasible to pay out.

To understand the implications of various solutions to this issue for the valuation of a familiar commodity—here, subjects are endowed with a voucher for gasoline—Bohm et al. (1997) conduct an experiment in which they compare mean selling prices elicited using the BDM to those in a real market setting. In addition to sensitivity of responses to varying levels of the upper bound of the buying price, they find that an upper bound on the buying price equal to either the actual market price of the good or an unspecified value described as 'the maximum price we believe any real buyer would be willing to pay' leads to valuations no different from the experimental market price; when this text is omitted, or when the upper bound is set above the market price, the selling price significantly exceeds the market price. Similarly, Vassilopolous et al. (2018) find an anchoring effect of the buying price range when selling mugs, and Sugden et al. (2013) find an anchoring effect of both the buying and selling price range for several goods whose market value is £5.

In the absence of a market price on which to anchor our subjects—or on which subjects' prior experience may anchor their valuations in the absence of a researcher-induced anchor—we test whether such an anchoring effect exists in the BDM when subjects are asked their WTA to adopt technology in their homes. The technology--the smart meter--has been widely promoted by the UK Government and therefore respondents may perceive compensation as a type of subsidy for providing a public good. While various supplier incentives have been trialled with small customer samples in the UK, most energy decision-makers will be unaware of these offers, and offers may have varied both within and across suppliers. Moreover, most of these trials are commercially sensitive, so the incentives offered remain unknown; a published trial performed in partnership with British Gas reveals that £5 and £10 incentives have been trialled at the low end, though we are aware of some suppliers having offered £30 incentives.

6.3.2 Experimental design

In line with the above description, the BDM works by allowing individuals who do not wish to accept a free meter to select a value that they would be willing to accept (WTA) as compensation for having a

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smart meter installed in their homes. The researchers then randomly draw a value within a delineated range, and if the value equals or exceeds the stated WTA, then the transaction takes place; that is, the researchers will pay the individual the randomly drawn offer (which acts as a subsidy for adoption in this case), and the individual's name will be added to the waitlist for smart meter installation with their energy supplier. If the number drawn is below their WTA, no such transaction takes place.
By using this method, the research team aims to elicit a monetary value for consumers' WTA smart meter installations in their homes. However, a major methodological question remains regarding the extent to which the range of possible buying prices—i.e., the subsidy that individuals could potentially receive—influences these responses. To glean insight into the importance of this survey design decision randomly expose respondents to identical surveys that vary along this dimension alone.

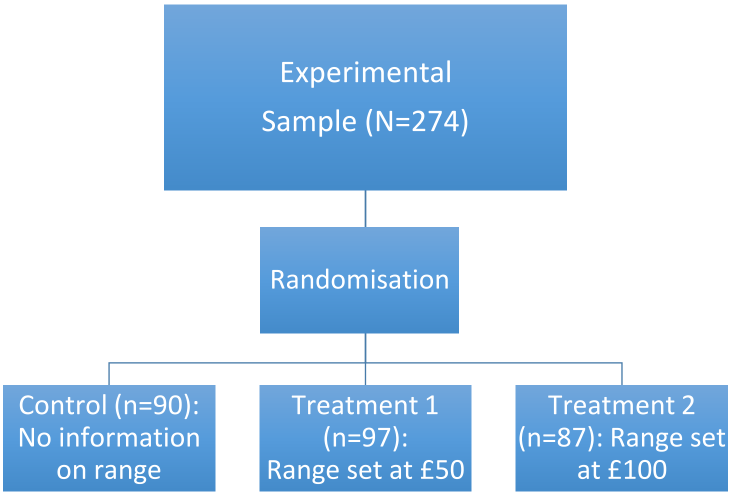

Figure 2: Experimental design

Specifically, in delimiting the potential buying price, we test three designs. First, given the purported monetary savings of £50 in energy costs per customer who adopts a smart meter, we test an explicitly denoted range of £0 to £50, which simply guarantees the customer will reap the monetary benefits promised by the smart meter rollout campaign. Additionally, all values used for our comprehension tests lie in this range, further reinforcing the possible range of the buying price and conveying expectations on the respondent's WTA. Secondly, we test whether setting an upper bound of £100 increases valuations and, if so, whether this change is proportional to the doubling of the range. Since compensation of £100 captures the opportunity cost of time for approximately 90% of the population—assuming installation time of 4 hours per household—this treatment represents our preferred range. Finally, since explicitly mentioning the range may signal either some 'objective' value for the good or the experimenter's expectation of what constitutes a reasonable price, an otherwise identical treatment simply does not mention the maximum buying price that may be drawn, though all random values used for the comprehension tests remain below £100.

Figure 2 summarises. In total the sample consists of 274 households. The control group of 90 households do not receive any information of the range of WTA acceptable WTA values; Treatment 1 consists of 97 households who have been instructed that the range of values lies between 0 and £50; Treatment 2 consists of 87 households who have been instructed that the range lies between 0 and £100.

Note that, due to budget constraints, we do not pay out all participants who 'win' the BDM exercise but instead inform participants that they have a 1 in 10 chance of being selected for payout should our offer exceed their bid price. Since this level of incentive compatibility is constant across treatments, we should still identify an effect of anchoring if one, in fact, exists.

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6.3.3 The sample

The sample was chosen to be nationally representative of the UK in terms of age, gender, income and region. Participants were recruited through an online panel on Qualtrics. Households who had previously been contacted by their energy supplier regarding having a smart meter installed were screened out. Additionally, any households who were not customers of the 11 largest suppliers, who represent about 90% market share in the UK, were also screened out.[25]

6.3.4 Survey overview

The survey first screens for a number of variables, including: (i) age, gender, region, and income (to ensure we meet quotas for representativeness); (ii) whether the individual is listed on the household's electricity bill; (iii) whether the individual's supplier is one of the 11 largest in the UK; and (iv) whether the household has already been asked to have a smart meter installed. To simulate the 'control' group of a follow-on survey (for which the results of this report will inform the design), the participants are then exposed to some very basic information regarding the energy grid, after which they are asked whether they would like to sign up to adopt a smart meter in their homes (without compensation).

Individuals who answer this question in the affirmative move on to a series of attitudinal questions that assess their sentiments toward renewable energy, energy suppliers in the UK, science and technology, and the UK Government; additionally, they report on their electronic appliance ownership, their energy-saving behaviour, and their tolerance for risk. Subsequently, they provide further demographic information, including education level, household members of various age groups, government benefits receipt, employment status, and whether they own or rent their home. Finally, individuals are asked to provide their electricity account information so that we may sign them up to get a smart meter on their behalves. If the individual has further comments, they may share them in an open-ended comment box at the end of the survey.

[25] This was purely for practical reasons as the research team will need to follow up by contacting the suppliers of any households interested in having a smart meter installed.

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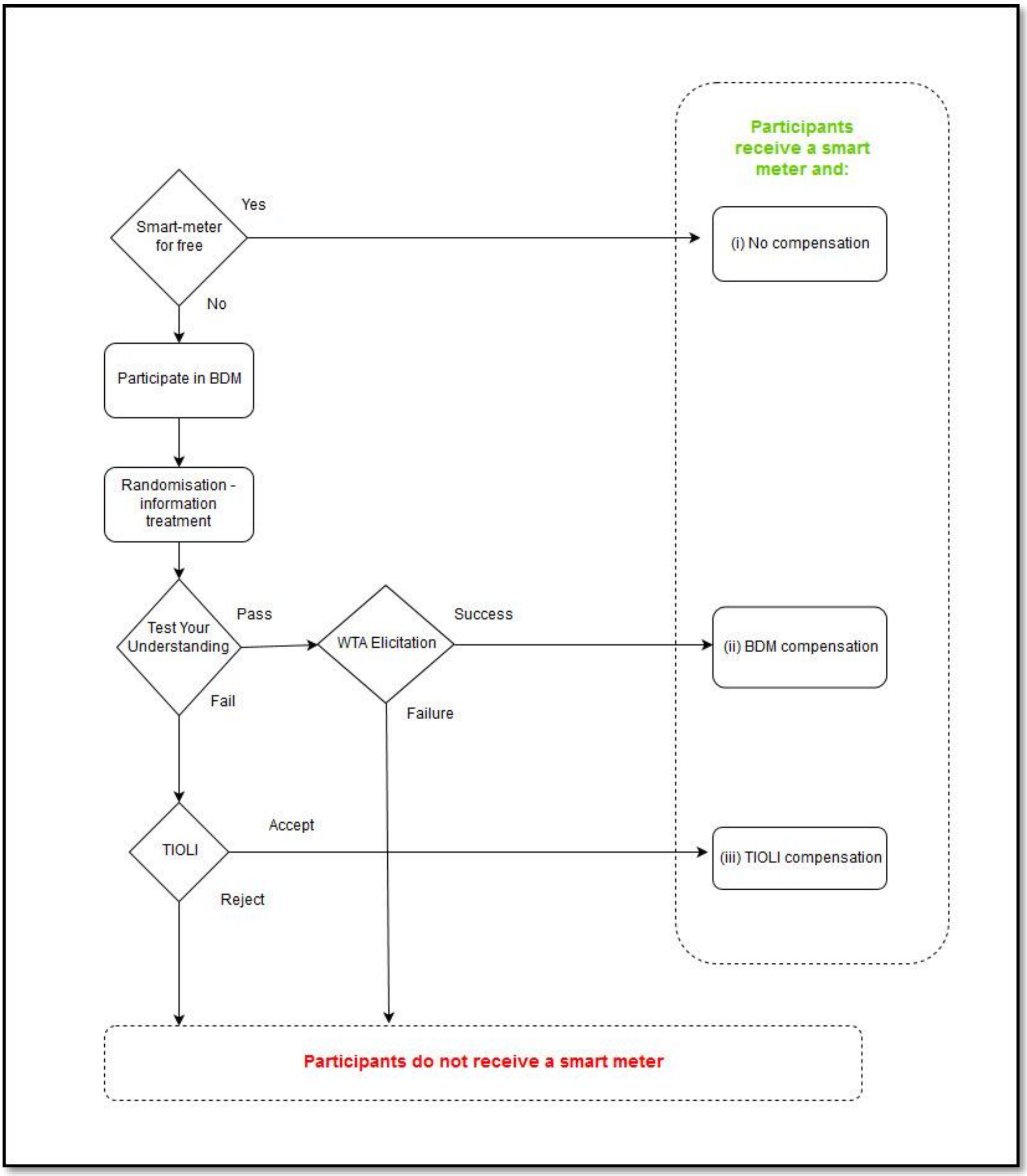

Figure 3: Overview of survey logic

Individuals who turn down the offer to sign up for a free meter branch to a different survey path that ultimately leads to their provision of information on their willingness to accept compensation for signing up to get a meter installed (see Figure 3). These individuals view five screens in total that provide background explanation and instructions for the exercise. The second and third screens both allude to the randomly selected buying price, and we specify a range of potential values for this buying price in Treatments 1 and 2 while we do not specify any such range for the control group (see Figure 4). Individuals indicate whether they are confident they understand the exercise and are offered to review the instructions and keep them open in a separate tab while undertaking the subsequent

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comprehension test.
To pass the comprehension test, individuals must correctly answer three questions wherein we specify the seller's (respondent's) *bid price* and the buyer's (researcher's) *offer* and the participant must select the correct answer as to what happens next from three multiple choice options. If the participant fails to answer one question correctly, she sees a screen explaining the correct answer to any questions she missed and then tries again on a second screen. If she fails both her second and third attempts, she fails the comprehension test and is screened out of the BDM component of the survey; instead, she answers a TIOLI question that offers her £10 in return for signing up to get a smart meter installed and moves on to the attitudinal questions, as above.

The comprehension test reinforces the possible buying price range for each of the three treatments. That is, for Treatment 1, all randomly selected values for the bid price and offer fall between 0 and 50, and for Control and Treatment 2 all randomly selected values fall between 0 and 100. To ensure individuals are exposed to both higher and lower ends of the possible range, we programmed the questions to randomly select values both above and below the midpoint of the range.

Once a participant passes this comprehension test, she then views a screen that asks her to state her personal bid price, with a final reminder that if our randomly selected offer is above her bid price, she will receive it and we will sign her up to start the smart meter installation process. If she would not accept a smart meter for any price, she should leave the response blank. Regardless of her valuation, she is asked next why she did not want a free smart meter in the first place in a multiple response format, where the possible responses are: (i) privacy/security concerns; (ii) too much hassle; (iii) health concerns; (iv) I do not think I will save energy/money; (v) I do not trust my energy supplier; and (vi) Other (please specify), the latter of which contains a box for text entry. We then display the offer, let her know the outcome of the BDM, and then let her know whether she was in the 10% of respondents selected for payout. Similar to above, she then answers the attitudinal and sociodemographic questions, then provides her account details if she is selected for payout, then she may provide additional comments prior to survey close.

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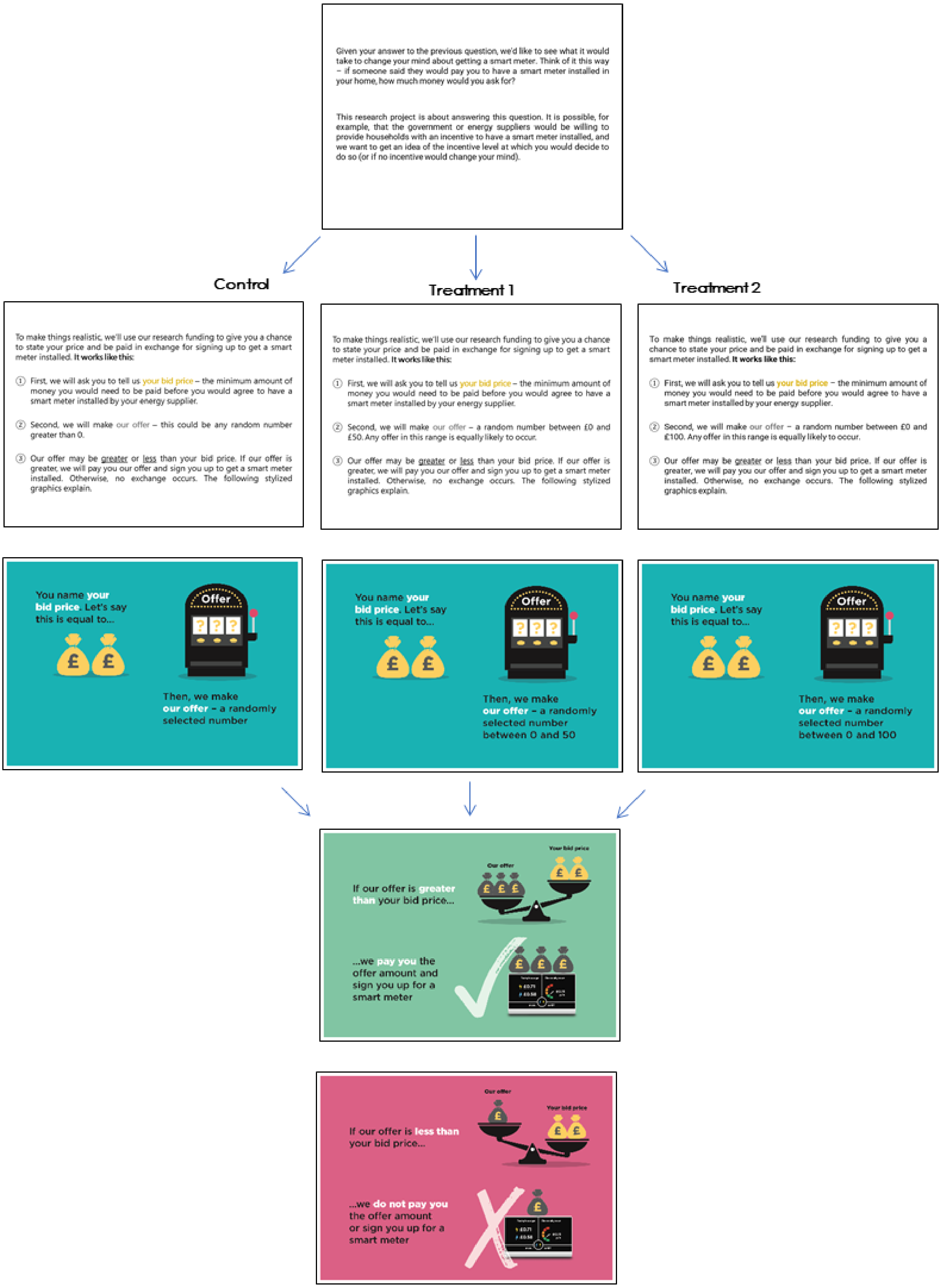

Figure 4: Instructions for the BDM Exercise, by treatment

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6.4 Descriptive and analytical results

6.4.1 Descriptive statistics of explanatory variables

To first demonstrate balance on covariates in the randomisation, in Table 1 we present descriptive statistics of the demographic observables before progressing onto a more detailed analysis.

Table 1: Descriptive statistics by group

Variable	National population	Control	Treatment 1: Range 50	Treatment 2: Range 100
Total Observations	-	90	97	87
Sex				
Female	51%	50%	52%	56%
Male	49%	50%	48%	44%
Age				
18-24	12%	10%	12%	13%
25-34	19%	18%	21%	21%
35-44	18%	19%	17%	17%
45-54	20%	20%	19%	22%
55-64	17%	20%	16%	11%
65-74	14%	13%	15%	16%
Household Income				
Gross earnings less than 27K GBP annually	20%	19%	20%	22%
Gross earnings between 27K GBP and 40K GBP annually	60%	53%	58%	56%
Gross earnings between 41K and 55K GBP annually	10%	11%	11%	11%
Gross earnings in excess of 55K GBP annually	10%	17%	11%	11%
Region				
East Midlands (UK)	7%	10%	7%	8%
East Of England	10%	10%	10%	8%
London	14%	13%	15%	16%
North East (UK)	5%	4%	5%	7%
North West (UK)	11%	11%	10%	12%
South East (UK)	14%	14%	14%	16%
South West (UK)	9%	9%	9%	6%
West Midlands (UK)	9%	10%	11%	10%
Yorkshire And The Humber	8%	4%	8%	9%
Scotland	8%	8%	9%	9%
Wales	5%	6%	5%	1%

6.4.2 Summary statistics of outcome variable

The following section presents summary statistics for the primary outcome variable, participants'

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Willingness-to-Accept (WTA) smart meters. As described in the previous section, this value is the minimum financial compensation (in GBP) that participants would need to be paid in order to prefer signing up with their energy supplier to have a smart meter installed and receiving payment to the alternative. Table 2 presents summary statistics of the WTA elicited for each group. It is worth noting that the number of observations differs across each group as not all participants made it through the test of comprehension and undertook the BDM exercise. The mean of the control group is £671, considerably larger than the mean of both treatment groups, which are broadly comparable at £109 and £133, respectively. Some respondents reported extremely large values, £10,000 in one case. It is questionable whether or not responses of this magnitude are credible, or whether they are due to protest votes or a lack of comprehension of the exercise.

Table 2: Range of WTA, willingness-to-accept, by treatment.

Survey taken	Obs	Mean	Std. Dev.	Min	Max
Control	46	670.54	2036.70	1	10000
Treatment 1: Range 50	53	109.04	279.23	1	2000
Treatment 2: Range 100	42	133.15	215.97	0.5	1000

To further examine the range of outcomes, Table 3 presents similar results; however, in this case, WTA values are winsorized (i.e. censored) at £500 (i.e. extreme values over £500 are taken out). The mean of all groups converge due to the removal of outliers. The value of £500 was chosen based on an examination of percentiles of the distribution.

Table 3: Range of WTA, willingness-to-accept, by treatment. Range capped at £500

Survey taken	Obs	Mean	Std. Dev.	Min	Max
Control	38	128.84	95.36	1	300
Treatment 1: Range 50	51	64.29	66.90	1	350
Treatment 2: Range 100	39	79.29	65.27	0.5	300

Figure 5 presents this result graphically using a kernel density function of the entire distribution on WTA values elicited. A kernel density estimation is a non-parametric way to estimate the probability density function for a random variable. Figure 5 suggests that much of the distribution of values falls in the £0-200 range, with some additional mass from £200-500.

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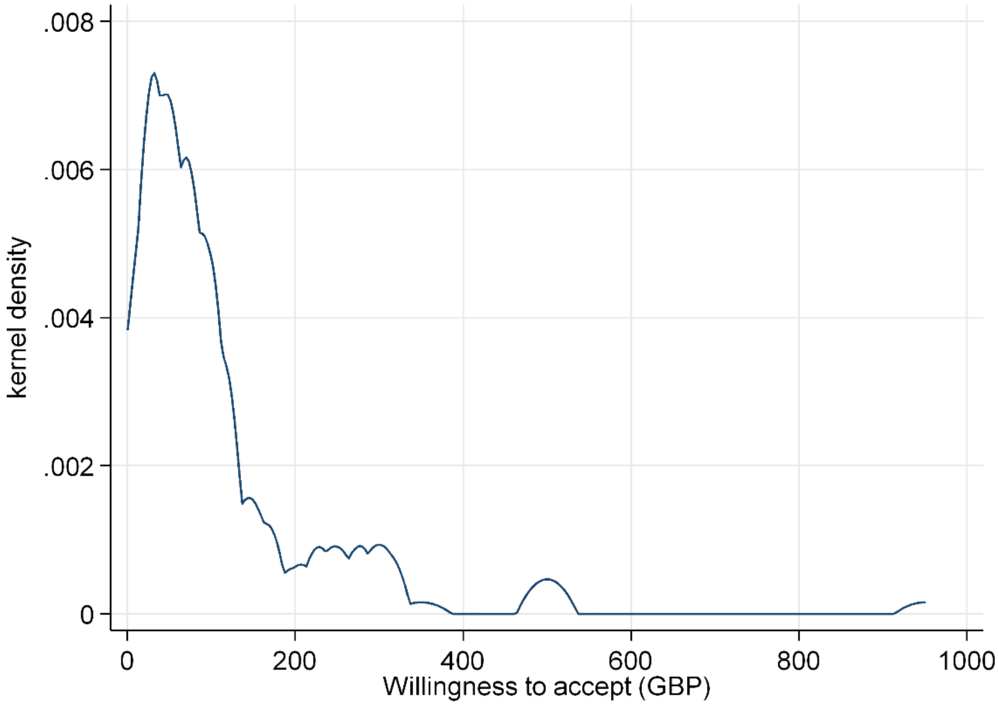

Figure 5: Kernel density plot for willingness-to-accept, all groups

As an initial examination of the effect of the information treatments, Figure 6 presents the WTA values elicited in each treatment group. An initial inspection of the results suggests that information may have had an effect on the range of WTA values. Examining the histograms of each WTA separately in Figures 6 and 7 would also indicate evidence of anchoring for each of the treatment groups. Treatment 1 demonstrates significant mass at £50, Treatment 2 at £100, while the range of the control group is considerably more evenly dispersed.

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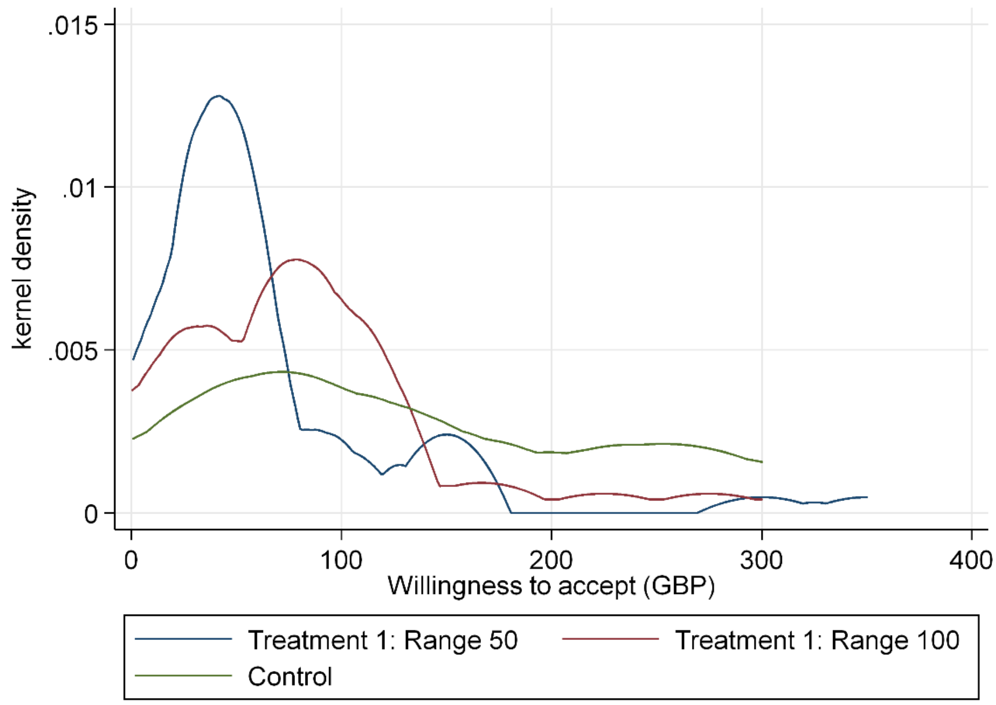

Figure 6: Kernel density plot for willingness-to-accept, by treatment, winsorized at £500

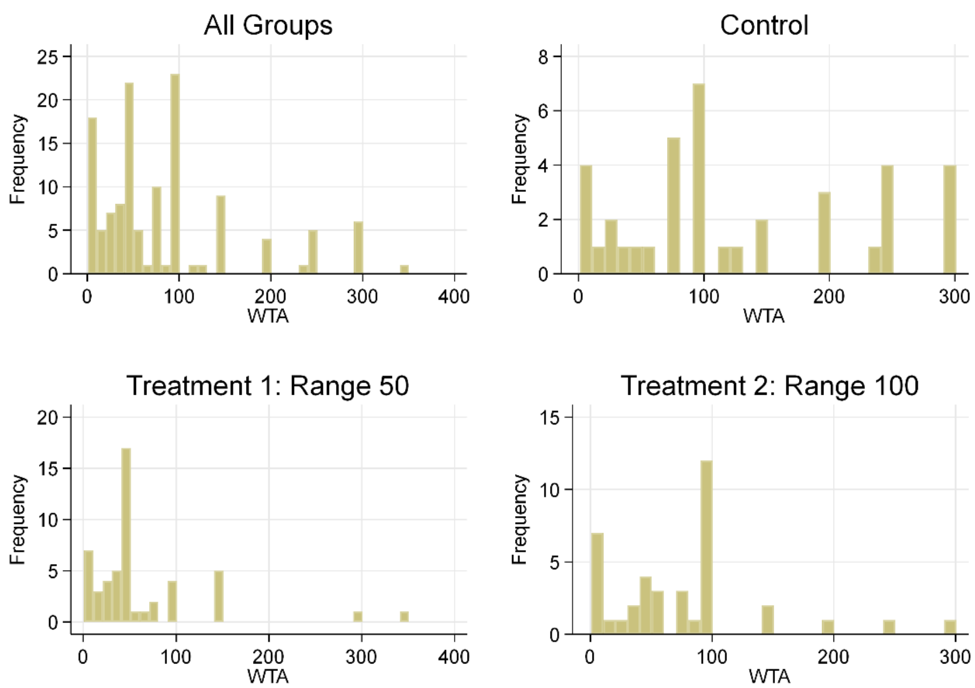

Figure 7: Histogram of willingness-to-accept (bin size=10), by treatment, winsorized at £500

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6.4.3 Analytical results

Table 4: Effect of information treatment on Willingness-to-Accept

Treatments	(1)	(2)	(3)	(4)
Treatment 1: Range 50	-561.5**	-495.7*	-64.55***	-58.31***
	(238.1)	(268.7)	(16.29)	(17.96)
Treatment 2: Range 100	-537.4**	-467.2	-49.55***	-38.88*
	(252.2)	(293.4)	(17.32)	(19.65)
Constant	670.5***	923.2	128.8***	74.55*
	(174.2)	(650.0)	(12.33)	(41.82)
Observations	141	139	128	127
R-squared	0.047	0.28	0.116	0.397
Control Variables	NO	YES	NO	YES
Constrained at 500	NO	NO	YES	YES

Notes: The table shows the outputs of an OLS regression of WTA on treatment, where the control survey acts as the reference category. The outputs represent the effect of the two treatment ranges on respondents' WTA, with and without constraints and winsorisation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The regression outputs in Table 4 indicate that reported WTA depends causally on the range of bid price provided in the survey. Due to the existence of large outliers, we focus our discussion on the winsorized sample (columns 3 and 4). Ignoring large outliers, Treatment 1—which explicitly constrained offers at £50 and provided examples in the comprehension tests within this range—appears to have suppressed stated WTA by about £65 relative to an unconstrained offer range. The picture is slightly less clear for Treatment 2, which matched the Control group's survey in terms of the actual range of offers provided and the examples shown in the comprehension test (i.e. the only difference is that the range was specified). Here we see about a £50 decrease in the WTA for individuals in Treatment 1 compared to Control, but most of this effect can be accounted for by other observable variables in our vector of controls, which indicates that there is some imbalance in the samples.

Table 5: Effect of information treatment on percentiles of reported WTA distribution

WTA (GBP)	Control	Treatment 2: Range 100	Treatment 1: Range 50	Comparison
50	20	36	68	1
100	48	81	83	2
1000	93	100	98	

Were there no anchoring effect, we would expect no difference in the percentiles of the distribution for each of the groups. For example, we would expect a similar proportion in each group to have reported £50 or less and £100 or less. Table 5 demonstrates that this is not the case. Compared to the control group, a greater proportion of both treatment groups report WTA values of £50 or less (comparison 1). While compared to the control group a greater proportion of Treatment 2 report WTA of £100 or less (Comparison 2).

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6.4.4 Demand for smart meters

Based on the reported range of WTA values elicited, it is possible to construct a demand curve for smart meters. Figure 8 graphically depicts the relationship between participant's willingness to accept (or the price they would need to be paid) and the cumulative quantity demanded at each price. In this instance, prices are displayed as negative values as it is the price someone would need to be paid. Again, outliers are removed by winsorizing the range at -£500. Based on a sample size of 273 this curve suggests that about one third of households would adopt for a subsidy level of £100. However, a considerable proportion report significantly higher values and other policy levers may be required to encourage these people to adopt.

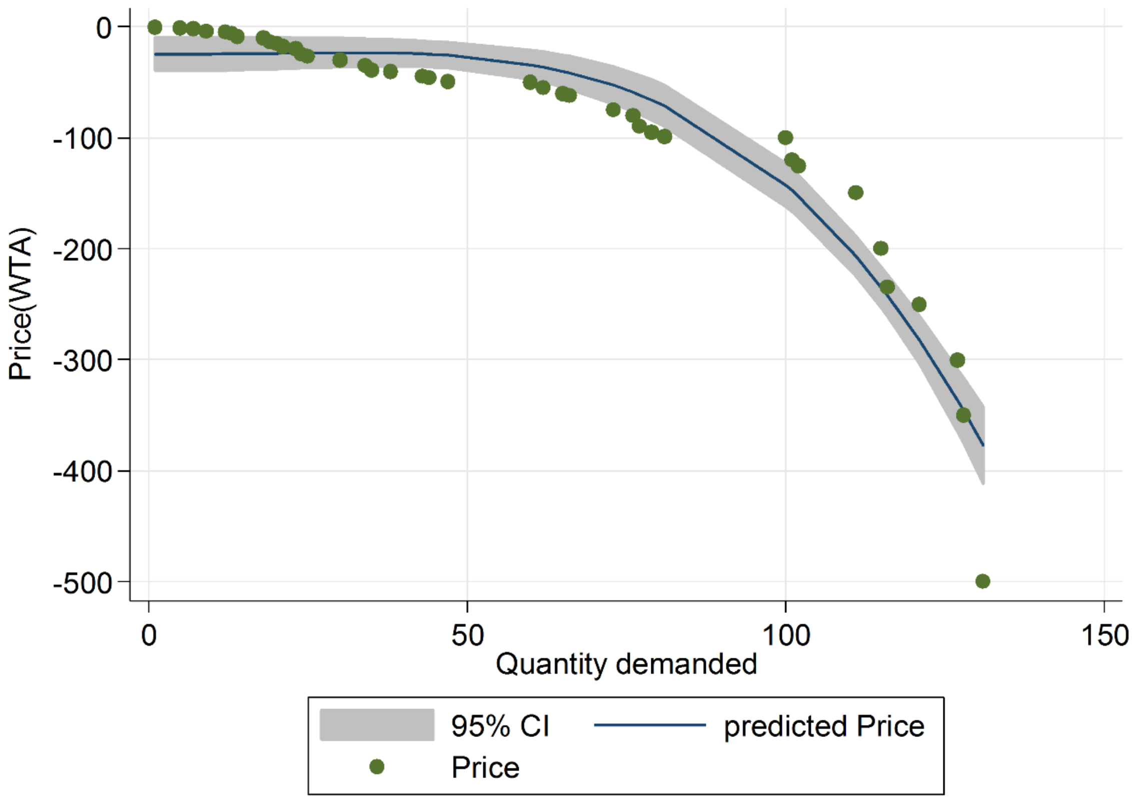

Figure 8: Demand curve for smart meters among participants not willing to accept one for £0

6.5 Conclusion

This research presented an incentive-compatible online experiment to elicit the WTA of a representative panel of UK households for smart meter installation. Various treatments were provided to households to assess the impact of anchoring in willingness-to-accept elicitation for this unusual but important context, where subjects are essentially asked to place a value on the compensation necessary to provide a public good. From these responses, we provided evidence on the subsidy level policymakers may need to provide to incentivise households to adopt smart meters and comment on the sensitivity of that inference to the methodology deployed.

Results suggest that significant barriers to adoption exist, as evidence by the high WTA values elicited. The results from the information treatments suggest that anchoring does exist in participant's valuations of smart meter adoption. Despite the fact that participants report high WTA values, the range is largely within the range of values that would be considered cost-effective for society to subsidise.

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