Better Get Focused: How Feedback on a Specific Behavior Can Reduce Energy Consumption

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Abstract

Behavioral interventions are increasingly considered a politically feasible instrument to promote resource conservation and to increase energy efficiency quickly, at scale, and in addition to technological efficiency gains. In particular, programs providing households with feedback on their utility consumption have lately received a lot of attention. High hopes have been placed on smart meters as a key technology enabling the provision of timely feedback on web portals or in-home displays. In smart meter-enabled feedback programs, individuals generally have access to information on their household's aggregate electricity (also, gas or water) consumption, with conservation effects ranging between 2 and 5%.

We chose a different strategy: instead of getting feedback on their household's aggregate utility consumption, individuals received feedback on a single, energy-intensive behavior while they engaged in it. In a randomized controlled trial with 697 households, we gave individuals feedback on their energy and water consumption in the shower. We used smart shower meters that display the feedback on a little LCD screen; the devices stored measurement data on every shower.

We found that the narrow focus on a specific behavior induced large savings: the treatment group who received feedback in real time reduced their energy and water consumption in the shower by 22% over the control group. The effects were stable throughout the two-month study, resulting in average savings of 1.2 kWh per day and household. The savings are equivalent to the energy consumption of two modern European refrigerators.

Introduction

Residential energy use represents 27% of the final energy used in the member countries of the European Union (EU28) (European Environment Agency, 2015). Many citizens are motivated to reduce their energy consumption both to keep their utility bills low and to protect the environment. In fact, 95% of EU citizens feel that protecting the environment is important to them personally and 58% consider it to be very important (Eurobarometer, 2011). In the same vein, the majority of U.S. citizens say that environmental protection should be given priority, even at the risk of curbing economic growth (Gallup, 2014). Given the large share of citizens with pro-environmental attitudes, many policymakers and researchers have raised the question why citizens do not take more action to effectively reduce their use of energy, water and their carbon footprint. Aside from institutional (e.g., split incentives between landlords and tenants) (Bird and Hernández, 2012) or financial barriers (e.g., liquidity constraints to finance energy efficiency upgrades) (Baden et al., 2006), many individuals simply lack the necessary knowledge to act (Gardner and Stern, 2008) or have fundamental misperceptions about effective means to reduce their environmental impact (Attari et al., 2010; Attari, 2014). As (Inskeep and Attari, 2014) stated, *"Many households may […] be motivated to conserve, but lack the knowledge, time, or resources necessary to take meaningful action to curb use."* Likewise, (Gardner and Stern, 2008) argue that *"When strategies are proposed for households, they often appear in laundry list* *format, giving little or no priority to effectiveness. It is easy for households that want to cope with rising gasoline prices and heating and cooling bills to respond by taking small actions under the impression they are saving energy, while they are actually making a negligible dent in their personal energy consumption."* In other words, what households lack is personalized feedback on concrete actions that would make a meaningful difference to their environmental impact or utility bills.

An increasing number of studies with large sample sizes have shown that behavioral interventions that provide feedback to households on their electricity, gas or water use can help them conserve these resources (e.g., Ferraro et al., 2011; Allcott and Rogers, 2014; Asensio and Delmas, 2015). The most widespread type of intervention sends periodic "Home Energy Reports" (enhanced utility bills on paper) to millions of households. Another feedback technology that has been tested in thousands of households are in-home displays that provide consumers with more timely feedback on their household electricity use or with information on current electricity rates, for instance. While Home Energy Reports have proven to be a cost-effective means to curb electricity use by 2% on average (Allcott and Rogers, 2014), in-home displays typically achieve electricity savings of 2-5%, at substantially higher program costs (McKerracher and Torriti, 2013; Buchanan et al., 2015). In all cases, consumers receive feedback on their household's aggregated use of electricity, gas, or water. While a number of programs provide conservation tips to households, most programs leave the burden of identifying effective conservation strategies with the consumers.

Instead of providing abstract feedback on a household's aggregate utility consumption over an extended period of time, we implemented a measure that directly showed individuals the environmental impact of one concrete, resource-intensive behavior in real time: showering. Water heating accounts for 14-18% of the final energy use in households both in Europe and in the U.S. (Eia, 2013; BAFU, 2013). In urban areas with a higher fraction of multi-family buildings (and less detached single-family homes) or in well-insulated homes, water heating represents an even larger fraction of residential energy use.

Showering, in turn, accounts for a large fraction of residential hot water use. For that reason, we provided smart shower meters to 697 households in Zurich, Switzerland. The devices measured and recorded data on every shower taken and displayed feedback on energy and water use in real time on a LCD-screen (56mm by 38mm, or 2.2in by 1.5in) at eye level. The methodology section provides a more detailed description of the device.

Our intervention reduced the focus to a single behavior, and quantified and displayed the impact of the target behavior which the consumer could directly influence. Thus, our intervention raised awareness for the environmental impact of a concrete behavior, measured its impact in terms of resource consumption, and quantified the outcomes of individual conservation efforts.

Prior Work on This Study

Note that the study outlined in this article is also described more in detail in the working paper "Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation" that is currently in the second round of review in a journal. The current article takes a somewhat different perspective more from a general-practical program evaluation point of view and has been adapted to the format of this conference. Nevertheless, given that both articles share the same study as database and results, some parts of this article are very similar to the more detailed journal article.

Study Design and Methodology

The goal of our study is to investigate how individuals respond to feedback in real time on a specific behavior, more precisely to feedback on their energy and water consumption in the shower.

We hypothesize that the effect size of this kind of concrete feedback that is given during the action is substantial and larger than the average treatment effect achieved in programs that provide feedback on aggregated household consumption. This section gives an overview of the study and introduces the feedback device used, the study design, and the sample of participants.

Feedback Device. As a measurement and feedback device, we used an adapted version of the commercially available smart shower meter *amphiro a1*. In its standard operation mode, the device displays feedback on water consumption (in liters), energy consumption (in kWh), water temperature (in °C), an energy efficiency class (every shower starts in class A (for very energy-efficient showers); the subsequent classes B-G were defined based on the per-shower distribution collected in a pilot study) and a polar bear animation whose state (size of the ice floe) changes as a function of the energy efficiency class. Although the study was framed as an energy efficiency study, the screen also displays water use quite prominently. This is due to the fact that most consumers are very familiar with the unit liters (or gallons in the U.S.) from their daily lives, while the majority of people have difficulties in relating to the energy unit kilowatt hours (kWh).

The device does not contain a battery: it contains a little generator that uses the water flow to power the device while someone takes a shower. As soon as a user turns on the water, the device switches on; a capacitor stores excess energy to power the device during short interruptions of the water flow, e.g., if someone turns off the water while soaping three minutes after every shower, it stores the final data of the shower (water volume, duration, average temperature etc.) and switches off again. We modified the standard device in two ways: first, our study devices recorded more detailed data; and second, we aligned the information displayed with our study design (see next paragraph). The participants installed the device themselves in their shower by screwing it between the shower hose and the shower head[1]. The installation did not require any tools and could be carried out in a minute or two. Figure 1 shows a screenshot of the device display along with an illustration of the position of the device in the shower.

Figure 1. The smart shower meter displays feedback on energy and water use in real time in the shower, toggling different display elements (e.g., temperature and energy efficiency class). The image on the left shows a snapshot of the feedback displayed; the drawing on the right illustrates the position of the device in the shower.

[1] Note that in contrast to the typical wall-mount showerheads in the U.S., more than 95% of showers in Europe have handheld showerheads.

The smart shower meter continuously measures water volume (based on the rotational speed of the generator) and the water temperature. Based on these two values, it is possible to integrate the lower bound of the energy consumed using the caloric formula $E=c_p*m*(T-T_o)$, with c_p the heat capacity, m the mass (or volume) of water, T the water temperature measured by the device (per time interval or the average for the stored value) and T_o the cold water temperature. This value, however, represents the minimum amount of energy used (100% efficiency) and does not take into account any heating and distribution losses, which largely depend on the type and age of the heating system. As Prognos (2013) shows, 40% of Swiss homes heat their water with oil, 25% with electric heating, and 21% with gas. Boiler efficiency depends upon boiler size, fuel type, and age; boiler efficiency averages 65% in Swiss households (Prognos AG, 2013) and we take a rather conservative estimate for distribution losses of 20% (Tschui and Stadelmann, 2006).

Study Design. We implemented the study as a randomized controlled trial, randomly assigning a third of the participants to the control group. We performed the randomization separately by household size (one- and two-person household) and by age bracket, assuring a balance in the number and age of participants across treatment and control groups. We performed detailed randomization checks on the key variables of interest and found no significant difference in any of those dimensions[2]. For the first ten showers, all devices displayed only the water temperature, hence not providing any indicator on time or resource use (baseline phase). After that, the devices of the treatment group automatically entered the intervention mode, displaying real-time on the individual's current shower metrics (energy and water consumption etc.). Control group devices, on the other hand, continued to display only the water temperature. Displaying the water temperature instead of a blank screen indicates to the participants of the control group (or of the treatment group during baseline) that the device is functional and measuring data.

Implementation and Sample. The study was implemented in collaboration with ewz, the municipal utility company of Zurich, and with the support of the Swiss Federal Office of Energy (SFOE). The utility company gave the smart shower meters as a thank you gift to the 5,919 participants of a prior smart metering study (Degen et al., 2013). In their announcement of those thank-you gifts, the utility company informed the households about the possibility to voluntarily participate in another study with that device. The study was framed as an energy efficiency study: water conservation is not much of an issue in water-rich Switzerland. The materials provided to the study participants (leaflets, user manual etc.) explained the important role of water heating in residential energy consumption as the second-largest energy end use in a typical Swiss household. In order to opt into the study, households had to fill out a survey.

A total of 1,354 households completed the pre-study survey. Given the level of logistics involved in the study and data readout, we limited the number of participants upfront to a maximum of 700 households. We did not admit households with more than two members: as the study devices could only store the data of 202 showers, not all shower data might have been recorded in larger households. Households who met the other eligibility criteria (in particular: no wall-mount or rain shower, no extended period of absence during the study, no relocation, and consent to install the device in due time and to temporarily ship it back (for free) for the data readout) were admitted on a first-come first-served basis.

Studies with opt-in design always give rise to the question whether the recruitment strategy may induce self-selection biases. To minimize these concerns, we collected an extensive list of socio-demographics, attitudes etc. to evaluate to what extent our sample is representative for the local

[2] For the detailed analysis of the randomization checks (and all other analysis), please contact the authors for a copy of our working paper "Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation."

population. Compared to the average Swiss household, our sample consists only of one- and two-person households. Thus, our sample does not contain any children and teenagers, it is more urban, slightly younger and more educated, and – this is noteworthy – is slightly *less* environmentally friendly than the average Swiss population (Diekmann and Meyer, 2010) Diekmann et al., 2008). Hence, we can exclude a self-selection bias towards a particularly "green" mindset. Nevertheless, we cannot be sure whether our participants differ from the overall population on other, unobserved characteristics; for instance, one could conceive that they might be more curious, more eager to fill out surveys, or more keen to try out new gadgets than the average citizen. Yet, no matter how many survey questions participants answer, a possibility for biases on unobserved characteristics will always remain in an opt-in study. On the other hand, the only way to mitigate that issue would be a roll-out with opt-out or compulsory participation.

Data Collection and Cleaning. In order to collect the data, the participants had to ship back their smart shower meter at the end of the study for the data readout (the new version of the smart shower meter that is able to transfer the data via a mobile phone app was not available at that point). For that purpose, the participants had received a stamped and addressed stuffed return envelope along with the device. In the pre-study survey, they had committed to shipping back the device for the data readout on our request after two months.

In order to extract the data from the devices, a member of the research team placed each device separately into a dedicated readout terminal for optical readout using a webcam. For a comprehensive description of the readout process, we refer readers to a more detailed article (Tiefenbeck et al., 2013). All datasets underwent a data sanity check to ensure that all devices had been read out properly and that devices that had been compromised by water damage or sensor issues (which could clearly be identified in the dataset by their absurdly high flow rates and temperature values) were removed from the dataset. Overall, shower data from 640 households are available, resulting in a dataset of 45,664 showers. Almost all of the participants (N=633) had also filled out the online surveys. Among the 57 households whose shower data are not available, 33 did not send the device back or had dropped out of the study for various reasons (including unrelated events like hospitalization or breakup of partnerships), and 24 datasets from defective devices could not be used.

Results

For the data analysis, we took advantage of the randomized assignment of the households to treatment and control groups. As a first step, we analyzed whether the two groups used the same amount of energy per shower during the baseline phase.

Energy Consumption During the Baseline Phase. The average shower during the baseline phase used 2.67 kWh of heat energy and 44.9 liters of water and lasted 247 seconds. Both groups used roughly the same amount of energy: the difference between the treatment (M_T=2.70 kWh, S_T=1.74 kWh, N_T=419) and the control (M_C=2.61 kWh, S_C=1.64 kWh, N_C=207) group mean was not significant (p=0.54).

Main Treatment Effect. We used a difference-in-differences strategy to estimate the main treatment effect: for each household, we calculated the energy use per shower a) during the baseline period (up to shower number 10) and b) during the intervention period (after shower 10). We then compared the group means in the treatment period to the group means in the baseline period, as shown in Figure 2. While the groups did not (significantly) differ in the energy they used per shower during the baseline period, they differed significantly in their use during the intervention phase. The overall treatment effect was 0.6 kWh – a 22% reduction in the energy use for showering.

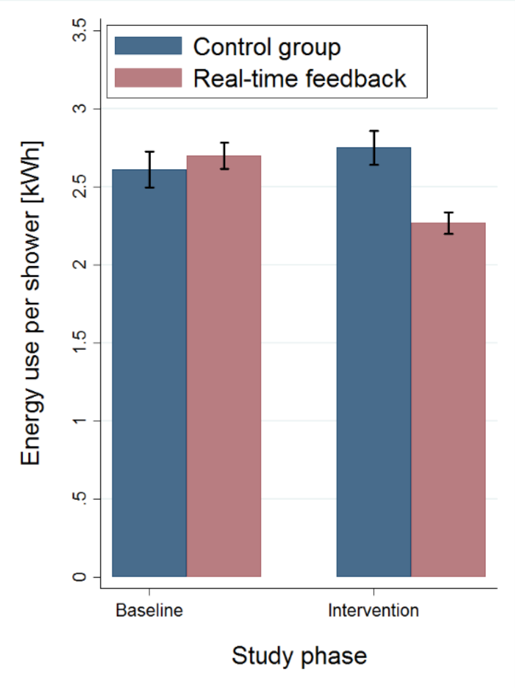

Figure 2. The difference-in-difference analysis of the treatment effect shows a large conservation effect for the treatment group. Black bars indicate standard errors of the mean.

Stability of the Effects. A central question for the study was whether the treatment effects would remain stable over time or whether they would decay during the two-month duration of the study. For that purpose, we spilt the intervention phase of every household into two halves. As Figure 3 shows, we found no evidence for decay from the first to the second half of the study.

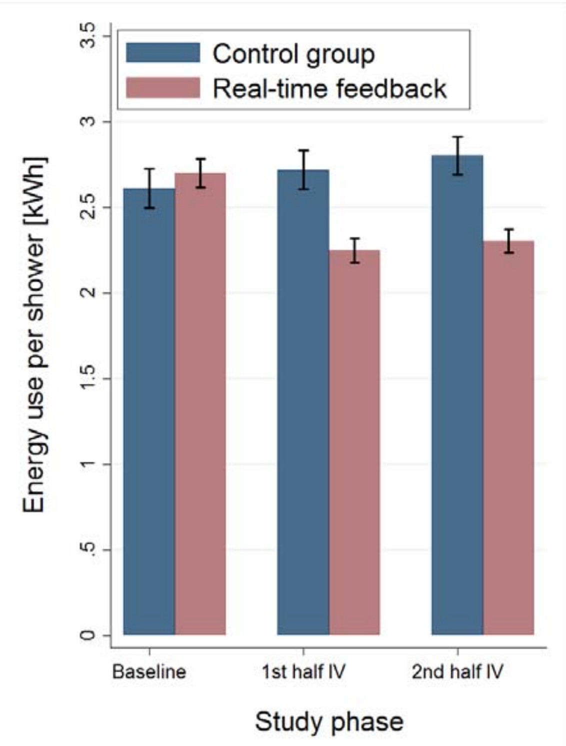

Figure 3. Group means during baseline phase (first ten showers) and the first and second half of the study (IV=intervention). The entire study lasted two months and the baseline period was completed after one week on average. Black bars indicate standard errors of the mean.

Discussion

Overall, the results of our study showed that real-time feedback on a specific behavior can induce large energy savings. Our treatment reduced the energy use per shower by 22%. This means a reduction of 1.2 kWh per day or 452 kWh per year for the average Swiss household (2.1-persons, one shower per person per day). The savings are equivalent to the daily energy consumption of two modern refrigerators in Europe (Michel et al., 2015). For our metropolitan study sample, this translated into a reduction of 5% of their energy use (ecospeed, 2012).

During the two-month study, the effects showed no sign of decay. Additional studies are currently ongoing or under review that evaluate whether the treatment effects are also stable over longer periods of time. So far, the results look encouraging, indicating effect stability also far beyond the two-month horizon measured in this study.

While our study primarily focused on energy use as outcome variable, the intervention also reduced the annual water consumption by 7,300 liters per household. While water-rich Switzerland may not have water conservation on the top of their political agenda, our intervention could simultaneously address two pressing problems in more water-stressed regions in the world.

Outlook: More Complex Analysis and Future Research. While the difference-in-difference approach is relatively simple to conduct and to understand, it does not control for unobserved, time-invariant household characteristics (e.g., geometry of the showerhead) and it collapses the richness of the dataset with their within-household variance to a single data point for every period. For that reason, in our working paper, we also estimate a fixed-effects model (using ordinary least squares). The fixed-effects model has the additional advantage in that it allows testing the stability of the treatment effects more formally. Furthermore, a fixed-effects model makes it possible to evaluate the Who and How more in detail. First, are there specific subgroups of the sample who are more responsive to the feedback than others? Second, how did the treatment group achieve the reduction in energy use? In theory, participants could have recurred to different strategies: take shorter showers, take colder showers, takes less showers, reduce the flow rate, or turn off the water while they are shampooing, for instance.

Another question we will seek to answer (based on survey data) is which metrics participants pay most attention to. As for now, we know that the combination of the different elements (feedback on water and energy consumption, energy efficiency class, polar bear animation, and water temperature) induced considerable behavior change among the treatment group; future work will evaluate which components – or combination thereof – were the main drivers of the treatment effect.

More research is also needed to understand to what extent the findings can also be applied to other domains like space heating, cooling, driving behavior, and others. In this context, the key questions is what exactly drives the large effects size: is it the fact that the information is given in real time, or on a one and only behavior, or the fact that the feedback is concrete and actionable, or merely a particular feature of the shower context? We are currently conducting a series of follow-up studies to investigate those questions more in detail.

References

Allcott, H. and T. Rogers 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." *American Economic Review* 104, October: 3003-3037.

Asensio, O. and M. Delmas 2015. "Nonprice Incentives and Energy Conservation". *Proceedings of the National Academy of Sciences* 112 (6), Feburary: E510–E515

Attari, S. Z. 2014. "Perceptions of Water Use." *Proceedings of the National Academy of Sciences* 111 (14), 5129-5134.

Attari, S. Z., M. L. DeKay, C. I. Davidson and W. de Bruin 2010. "Public Perceptions of Energy Consumption and Savings." *Proceedings of the National Academy of Sciences 107* (37), 16054-16059.

Baden, S., P. Fairey, P. Waide and Jens Laustse 2006. "Hurdling Financial Barriers to Low Energy Buildings: Experiences From the USA and Europe on Financial Incentives and Monetizing Building Energy Savings in Private Investment Decisions". *Proceedings of the 2006 ACEEE Summer Study on Energy Efficiency in Buildings*, August.

BAFU 2013. "Charts and Evaluations: Households and Consumption." Available at: http://www.bafu.admin.ch/umwelt/ 10822/12896/index.html?lang=en (visited on 29/07/2014)

Bird, S. and D. Hernández 2012. "Policy Options for the Split Incentive: Increasing Energy Efficiency for Low-Income Renters." *Energy Policy* 48, September: 506-514

Buchanan, K., R. Russo and B. Anderson 2015. "The Question of Energy Reduction: The Problem(s) with Feedback." *Energy Policy* 77, February: 89-96.

Degen, K., C. Efferson, F. Frei, L. Goette and R. Lalive 2013. "Smart Metering, Beratung oder sozialer Vergleich: Was beeinflusst den Elektrizitätsverbrauch? ewz-Studie Smart Metering: Zusammenfassung der Resultate." Available at: http://www.bfe.admin.ch/forschungewg/02544/02807/index.html?lang=de&dossier_id=05892

Diekmann, A., R. Meyer, C. Mühlemann and A. Diem 2008. "Schweizer Umweltsurvey 2007: Analysen und Ergebnisse." Zürich. Available at: http://www.socio.ethz.ch/forschung/umweltsurvey/umweltsurvey2007.html

Ecospeed 2012. "Städtevergleich Schweiz-Deutschland zu Energieverbrauch und Treibhausgasemissionen pro Person." Available at: https://www.stadt-zuerich.ch/gud/de/index/umwelt/energie/energiestatistik/2000-Watt-Indikatoren/Staedtevergleich.html (visited on 22/02/2016)

Eia 2013. "Today in Energy - Heating and Cooling no Longer Majority of U.S. Home Energy Use." URL: https://www.eia.gov/todayinenergy/detail.cfm?id=10271 (visited on 01/02/2016)

Eurobarometer 2011. "Special Eurobarometer 365 - Attitudes of European Citizens towards the Environment." European Commission 295. Available at: http://www.socioilogico.com/Attitudes_Europeans_MD_2007.pdf

European Environment Agency 2015. “Final Energy Consumption by Sector and Fuel.” URL: http://www.eea.europa.eu/data-and-maps/indicators/final-energy-consumption-by-sector-9/assessment (visited on 15/02/2016)

Ferraro, P. and M. Price 2011. “Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-Scale Field Experiment.” *Review of Economics and Statistics* 95 (1), March: 64-73.

Gallup 2014. “Americans Again Pick Environment over Economic Growth.” Washington, DC, USA.

Gardner, G. T. and P. C. Stern 2008. “The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change.” *Environment* 50, December: 12-23.

Inskeep, B. D. and S. Z. Attari 2014. “The Water Short List: The Most Effective Actions US Households Can Take to Curb Water Use.” *Environment: Science and Policy for Sustainable Development* 56 (4), July: 4-15.

McKerracher, C. and J. Torriti 2013. “Energy Consumption Feedback in Perspective: Integrating Australian Data to Meta-Analyses on in-Home Displays.” *Energy Efficiency* 6 (2), May: 387-405.

Michel, A., S. Attali and E. Bush 2015. “Energy Efficiency of White Goods in Europe: Monitoring the Market with Sales Data.” URL: http://www.topten.eu/uploads/File/WhiteGoods_in_Europe_June15.pdf

Prognos AG 2013. “Der Energieverbrauch Der Privaten Haushalte 2000 - 2012. Ex-Post-Analyse nach Verwendungszwecken und Ursachen der Veränderungen.” Report to the Swiss Federal Office of Energy. URL:

Tiefenbeck, V., V. Tasic, S. Schoeb and T. Staake 2013. “Mechatronics to Drive Environmental Sustainability: Measuring, Visualizing and Transforming Consumer Patterns on a Large Scale.” *Energy Informatics* 2013. IEEE.

Tschui, A. and B. Stadelmann 2006. “Studie Warmwasserverteilung - Kurzstudie über die Energieverluste der verschiedenen Verteilsituationen von Warmwasser im Mehrfamilienhaus.” URL: http://www.awel.zh.ch/internet/baudirektion/awel/de/energie_radioaktive_abfaelle/veroeffentlichungen/_jcr_content/contentPar/publication_0/publicationitems/warmwasserverteilung/download.spooler.download.1297157668166.pdf/Warmwasserverteilung_HTA.pdf