# Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation

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**Inattention and imperfect information bias behavior towards the salient and immediately visible. They drive individuals to lose sight of long-term goals, such as leading a sustainable and healthy life, and promote overindulgence and waste. We show that providing real-time feedback on a specific resource-intense behavior can be a powerful remedy for this bias: In a large-scale field experiment, participants receive real-time feedback on their resource use. We find that this approach reduced resource consumption by 22% - much larger conservation gains than conventional policy interventions achieve. Real-time feedback directly overcomes salience bias, and avoids the negative psychological pressure that has been observed with widely-used policy interventions. Providing real-time feedback has the potential for cost-effective policy inter-**

**ventions aimed at resource conservation, and could help individuals eliminate salience bias in other domains of life.**

# Introduction

Living up to our ideals can be challenging: Most people want to protect the environment, lead healthier lives, and purchase child-labor-free products - yet often fail to do so in their everyday lives. While often the contributions to one's ideals are elusive, the associated costs or forgone benefits are immediate and perceptible. This creates a bias in favor of the salient (*1–3*), in particular in the domain of resource consumption. For example, while the pleasant sensation of a warm shower is immediately felt, few individuals are aware of how much energy and water this action involves (*4, 5*). Thus, salience bias compounds far-reaching environmental (e.g., carbon emissions) and geopolitical (e.g., energy security and access to water) problems. Conventional policy interventions fail to address this bias. Households typically exhibit low sensitivity to price incentives in resource consumption (*6, 7*). Similarly, information campaigns (e.g., energy conservation tips) have proven largely ineffective to foster resource conservation (*8*). These results are puzzling, since the he vast majority of people indicate that they are willing to make sacrifices to protect the environment (*9*). Yet these attitudes are rather poor predictors of actual resource consumption (*10*): In many cases, individuals engage in ineffective conservation efforts while believing that they are doing their part (*4, 5, 11*).

Another widely-used policy is to provide feedback about one's past consumption, such as periodic "home energy reports." These reports contain historical electricity consumption data, convey social norms through comparisons with homes in the neighborhood, and provide energy conservation tips (*12–14*). Home energy reports lower electricity consumption by roughly 2% (*13*). Households reduce their electricity consumption in the time period right after the arrival of the report (*14*), but the saving effect tapers off within a month, as can be observed with

many other aspirational behaviors (*15*). Similar reports on household water use yield reductions in water use of roughly 5% (*16, 17*). Strikingly, despite a measurable reduction in water consumption, home reports showed no improvement in households' awareness of their water use (*17*). Past research also provides real-time feedback about aggregate electricity consumption through in-home displays or web portals. Recent electricity smart metering trials report treatment effects between 3 and 5% (*18*). In all cases, the feedback information is aggregated, blurring the link between the current action and its impact on resource consumption. Breaking electricity use down into six categories (lighting, HVAC, fridge, dishwasher, other kitchen, plug loads) already increases conservation effects to 8%, when combined with information about the environmental and health impact of energy consumption (*19*). All of these interventions appear to operate at least in part due to peer pressure or guilt (*11, 20, 21*), as has been found with other forms of prosocial behavior (*22–24*).

In our field study, we provide individuals with real-time feedback on the resource use of a specific behavior while they engage in it. Thus we make resource use salient while individuals can directly adapt their behavior in response to the real-time feedback. We chose showering as a highly energy-intensive activity: In the course of less than five minutes, a typical individual in our sample uses 44.8 liters of hot water, which requires on average 2.54 kWh to heat it up (see *SI* section 1.5). We measured, displayed, and recorded information on individual showers with the amphiro a1 smart shower meter that is mounted between the shower hose and the hand-held shower head. The device features a large LCD screen and the information displayed is easily visible to individuals while they shower (*25*) (see *SI* section 1.1 for a detailed description). The measurement data were supplemented by survey information collected before and after the field experiment (household characteristics, personality, attitudes, and (ex-post) experience with the shower meter).

We implemented three experimental conditions. In a control condition, we supplied no

feedback on energy and water consumption: The device displayed only water temperature. In the real-time condition, the device displayed water use in tenths of liters. Thus, it provided individuals with objective and easily understood feedback on their resource consumption during a shower. In a third condition, the display also showed the total amount of water used in the previous shower. In a two-person household, this may add an element of pressure, as one's own use can be seen by the other person. To measure all participants' baseline water use, both treatment conditions were preceded by a baseline period of ten showers when only water temperature was displayed, as in the control condition. The shower meters were deployed for two months and recorded water use, average water temperature, interruptions, and duration of each shower. All 697 participating households had access to the Internet, had completed an electricity smart metering study (*26*), and lived either alone or in a two-person household. Thus, our sample is significantly younger, more urban, and more educated than the general population, but also significantly less environmentally friendly ($p < 0.01$, see *SI* and (*9*)).

# Results

Figure 1 shows the effects of the three study conditions on resource use. Panel A shows roughly the same use of energy and water in all three study conditions during the baseline period. With the onset of the real-time feedback, resource use drops sharply in the two experimental groups: Energy used per shower is 0.59 kWh lower than in the control group and water use is 9.5 liters lower, amounting to a reduction of 22% both in energy and water consumption. These changes are statistically highly significant in each of the treatment groups (see *SI* Table S4).

Panel B displays the difference-in-difference estimates for each of the treatment effects in one-person and two-person households. The panel shows that real-time feedback has a strong effect on behavior, but that adding feedback on the past shower produces no extra effect ($p \geq 0.64$ in each of the cases, see *SI* Table S4). Panel B also shows that the effects are the same

both for the one- and two-person households. Importantly, as the visible impression from Panel A already suggests, the treatment effects are persistent throughout the two-month period of the study. If anything, multiple regressions point to a weak strengthening of the effect (see *SI* Table S5). Furthermore, while the treatments strongly reduced resource use per shower, the number of showers over the entire study period is not affected (see *SI* Table S7).

Providing real-time feedback also makes individuals measurably more aware of their resource use (see Figure 2). In a post-intervention survey, actual and estimated water use are more strongly correlated in the treatment groups than in the control group (also see *SI* Table S6 and Figure S2). Note that this result is in contrast to studies that provide aggregate feedback, which often does not lead to better awareness of resource use (*17*).

Overall, the intervention is highly effective and leads to a large change in behavior and awareness of resource use among the participants. While it is hard to pinpoint exactly the psychological mechanisms of the observed behavior change, we hypothesize that increasing the salience of resource use made it easier for individuals to act on their innate preferences towards resource conservation. In that case, the treatment effect should be moderated by the individuals' willingness to protect the environment, as measured before the intervention. It should also tap into individuals' tendency to quantify their behavior, a preference that is increasingly harnessed in other domains of behavior.[1] (see *SI* for details).

However, it is possible that the intervention generated negative psychological pressure to reduce water consumption, as has been observed in studies providing broader feedback (*20*) and for other types of prosocial behavior (*22*). If that were the case, individuals who are more susceptible to psychological pressure should respond more strongly. We measure this using the emotionality scale from the HEXACO (*28*). Conscientious individuals should also respond more strongly, since they are more meticulous in their efforts to meet goals (*29*).

[1]The 'Quantified Self' movement or the collection and use of metrics on aspects of one's own life and has been described as a major trend that has reached mainstream popularity (*27*).

We estimate a full regression model in which the treatment effect interacts with all these variables along with baseline use and basic demographics (see *SI* Table S1 and Table S8 for details). The results are displayed in Table 1, showing both the coefficient estimate of the interaction effect and the predicted effects for the top and bottom quintile in the distribution of each traits. We find no evidence of negative psychological pressure driving the treatment response. The interaction of the treatment with emotionality is small and far from being significant – the top and bottom quintile in emotionality show the same treatment response. Higher conscientiousness significantly reduces the treatment effect, which also goes against the psychological-pressure interpretation.

By contrast, the results support the salience hypothesis: Environmental attitude significantly moderates the treatment effect. The 20 percent with the weakest intent on preserving the environment display a conservation effect of 0.51 kWh per shower. The top quintile conserves 0.75 kWh per shower – an almost 50 percent stronger treatment effect. Similarly, our measures of an individual's tendency to quantify progress towards goals strongly moderates the treatment effect. Moving from the bottom to the top quintile in that trait increases the treatment effect by almost 0.21 kWh.

Finally, our data also shows that the effect of our intervention is stronger among individuals with high baseline consumption (Table 1). In addition, as Table 2 shows, the impact of personality on the conservation effect is larger in this case: High users with a strong environmental attitude and a tendency to quantify progress towards goals display a particularly pronounced treatment effect ($p < 0.05$ for each of the traits, see *SI* Table S9)[2].

[2]No other interactions with the treatment effect are significant. See *SI* for a more extensive discussion

# Discussion

Overall, these results strongly suggest that behavior-specific real-time feedback helps individuals make choices more in line with their innate preferences, leading to a large conservation effect. In the case of showering, extrapolated to one year, an individual (showering once a day) saves 215 kWh of energy, 3500 liters of water, and avoids 47 kg of carbon emissions [3] (see *SI* section 3.5). This is five times as much energy and eleven times as much carbon dioxide as with interventions providing broad feedback about electricity use to the same population of participants (see *SI* section 3.6 and (*26*)).

The current research suggests a novel strategy for behavioral interventions in resource conservation: The focus on a specific behavior and real-time feeldback can yield a greater effect than the provision of broader feedback (e.g., past household electricity or water usage). In part, this is due to a more persistent change in behavior in response to real-time feedback, as opposed to the tapering off observed with home-energy reports over similar or shorter time frames (*14*). Furthermore, real-time feedback taps into different and – we argue – more desirable psychological mechanisms. It allows individuals to align their behavior more closely with their deeply ingrained preferences and thus addresses the root cause of the salience bias, rather than creating psychological pressure and small conservation effects. Therefore, at a policy level, our intervention comes close to what has been suggested as a first-best policy to address biases arising from imperfect information and inattention (*30*).

This type of intervention may also hold promise for other domains of life where we aspire to long-term goals: New information systems enable the collection of fine-grained data over vast periods of time and to measure behaviors that so far have escaped us. This can be used to devise behavioral interventions that address salience bias in many domains: It could allow individuals

[3] C02 reduction calculated based on the Swiss energy mix for water heating. In the U.S., 90 kg of CO2 would be avoided per person per year due to a higher carbon intensity of electricity generation and a higher share of electric water heaters.

to better control their spending through real-time budgeting, help them follow through on exercise plans by measuring physical activity, or make dieting easier by immediately calculating calories and comparing them to their goals.

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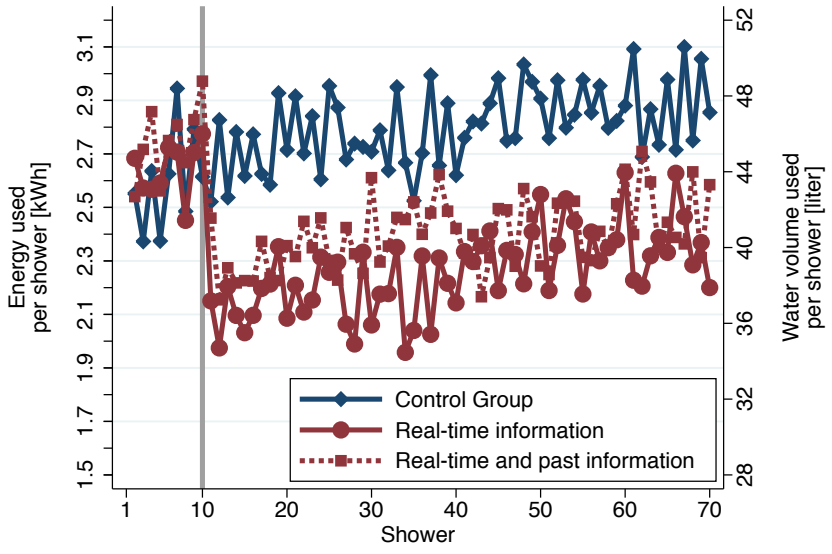
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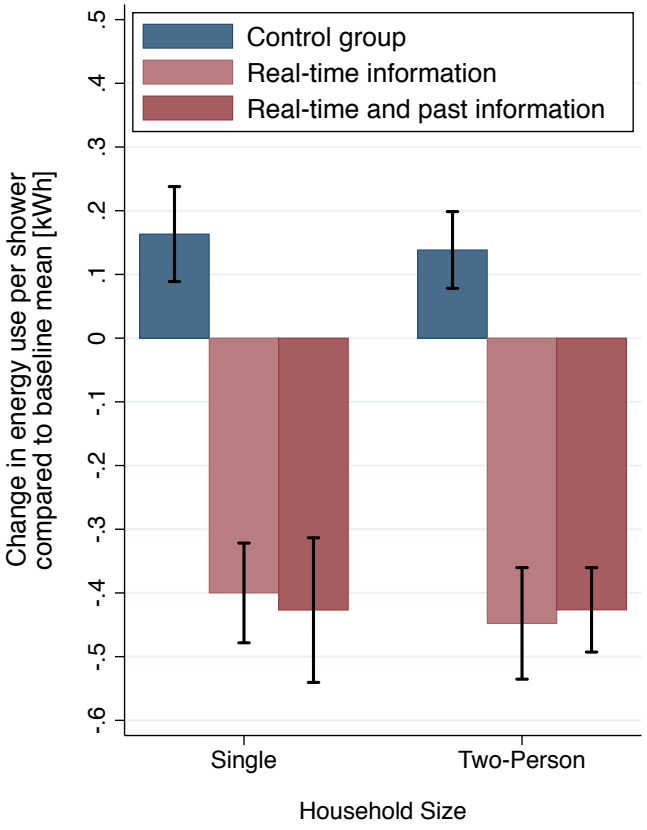
**Figure 1.** The Impact of Real-Time Information on energy consumption. (**A**) Average amount of energy used per shower in each experimental condition (left axis). The right axis reflects the corresponding approximate water use in liters. Resource use drops by 22% upon activation of the display, and this treatment effect remains stable throughout the study ($p < 0.01$, see *SI*).

(**B**) Difference-in-difference estimate of the treatments for one-person and two-person households. Each bar indicates the mean difference in energy use per shower during the intervention phase compared to energy use per shower during the baseline phase. The treatment effects are the same for one-person and two-person households. Adding feedback about the previous shower does not increase the treatment effect. Error bars, mean +/- SEM. See *SI* for details.

**Figure 2.** Association between estimated and actual water use after the intervention in the control (blue dots) and treatment conditions (red dots). The association improved significantly in the treatment groups ($p < 0.01$, see *SI* for details).


Energy used per shower [kWh]
1.5
1.7
1.9
2.1
2.3
2.5
2.7
2.9
3.1
Water volume used per shower [liter]
28
32
36
40
44
48
52
1
10
20
30
40
50
60
70
Shower
Control Group
Real-time information
Real-time and past information

A


Change in energy use per shower compared to baseline mean [kWh]
-.6
-.5
-.4
-.3
-.2
-.1
0
.1
.2
.3
.4
.5
Control group
Real-time information
Real-time and past information
Single
Two-Person
Household Size

B

**Figure 1**

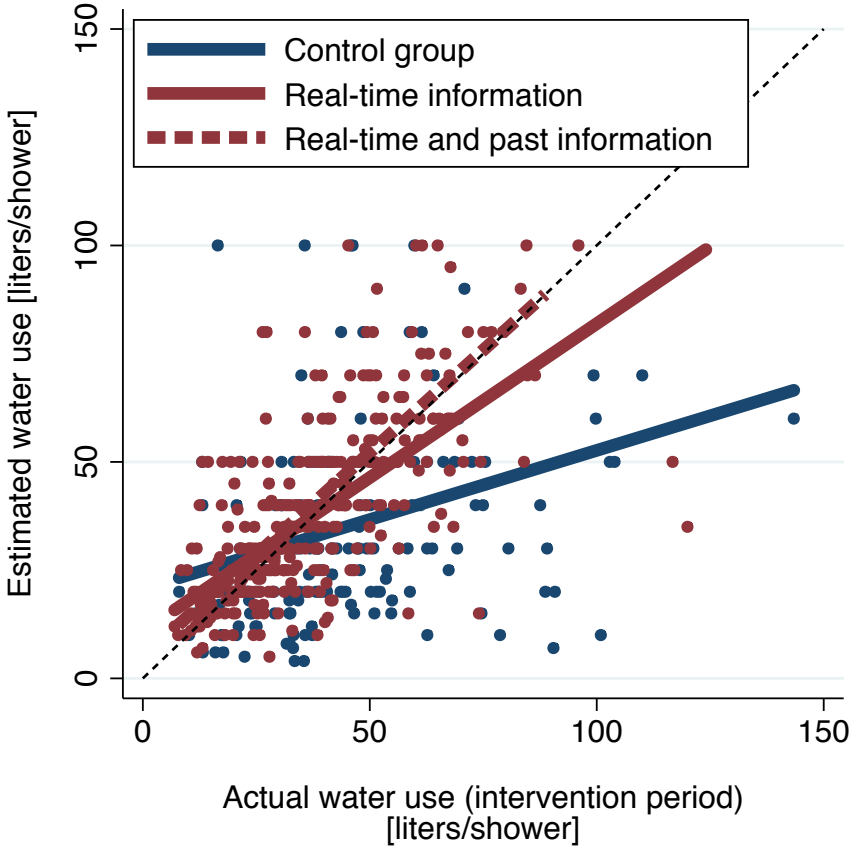

Control group
Real-time information
Real-time and past information
Estimated water use [liters/shower]
0
50
100
150
Actual water use (intervention period)
[liters/shower]

**Figure 2**

| **Behavioral mechanism** | **Susceptibility to psychological pressure** | | **Reducing salience bias** | | **Unspecific interactions** | | | |
|---|---|---|---|---|---|---|---|---|
| | Emotionality | Conscientiousness | Environmental att. | Quantifying goal progress | Baseline use | Age | Gender | Income |
| **Hypothesized impact on conservation effect** | + | + | + | + | + | | | |
| **Estimated interaction effect** | -0.015<br>(0.080) | -0.209*<br>(0.108) | 0.152**<br>(0.072) | 0.119**<br>(0.055) | 0.318***<br>(0.070) | -0.003<br>(0.052) | -0.249*<br>(0.138) | -0.016<br>(0.013) |
| **Treatment effects on** | | | | | | | | |
| bottom quintile of characteristic | 0.652 | 0.802 | 0.507 | 0.509 | 0.096 | 0.646 | 0.753 | 0.705 |
| top quintile of characteristic | 0.631 | 0.509 | 0.747 | 0.747 | 1.474 | 0.637 | 0.597 | 0.578 |

**Table 1.** Modulation of the treatment effect by various characteristics. The table displays the coefficient estimates of the interaction effects and their standard errors, clustered at the household level (in parentheses). The characteristics measuring susceptibility to psychological pressure do not interact with the treatment in the predicted way. A stronger environmental attitude and tendency to quantify predict a larger conservation effect, in line with a reduced salience bias through real-time feedback. *,** ,*** indicate significance at the 10, 5, and 1 percent level, respectively. See *SI* for details.

| | | Baseline consumption | Environmental attitude | Quantifying progress | Conscien-tiousness |
|---|---|---|---|---|---|
| Conservation effect (in kWh/shower) with average characteristic and baseline consumption | 0.630*** (0.073) | | | | |
| Modulation of conservation effect by baseline consumption | | 0.337*** (0.052) | | | |
| Modulation by characteristic at average consumption | | | 0.103* (0.058) | 0.133** (0.059) | -0.217** (0.094) |
| Change in modulation by a 1 kWh increase in baseline consumption | | | 0.179*** (0.066) | 0.125*** (0.046) | -0.088 (0.110) |
| F-test (t-test) of no modulation by characteristic | | $p < 0.01$ | $p = 0.02$ | $p = 0.03$ | $p = 0.05$ |

**Table 2.** Modulation of personality becomes stronger in high baseline uses. The table displays the coefficient estimates and standard errors, clustered at the household level (in parentheses) of the interaction effects between the treatment and various characteristics, and the baseline consumption. $^{*}$,$^{**}$ ,$^{***}$ indicate significance at the 10, 5, and 1 percent level, respectively. See *SI* for details.

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**Abstract**

This Supplementary Information provides the statistical background and the full set of empirical results referred to in the companion paper.

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## 1. Materials and Methods

### 1.1 Smart shower meter amphiro a1

Figure S1 shows the feedback device used in the study - the smart shower meter *amphiro a1*. The device measures and stores time series data on water and energy use and displays real-time feedback to users directly in the shower. Users install the device without any tools between the shower hose and the hand-held showerhead (which more than 95% of showers in Europe have). The smart shower meter was developed by Amphiro AG, a spinoff company from ETH Zurich, Switzerland.




Figure S1: On the left: a snapshot of the *amphiro a1* display - on the right: the device installed between the showerhead and shower hose

The smart shower meter is energy-autarkic, which eliminates the need for batteries and allows tracking behavior over extended periods of time (standard device: up to 507 showers): A built-in micro-generator harvests energy from the water flow, supplying the device with the power required for its processing unit and display. During each shower, the device continuously measures the generator speed and water temperature. Based on these data, water and energy consumption of the current shower are calculated. The standard device displays real-time feedback on water and energy consumption since the start of the shower and water temperature. Water consumption is displayed in tenths of liters, energy consumption in Wh (resp. kWh for values $> 999$ Wh), and temperature in degrees Celsius. Energy consumption is additionally visualized with a polar bear animation: Based on typical usage patterns collected in a previous study, an ice shell progressively shrinks as the amount of energy used increases. At

2.975 kWh, the animation disappears. Showers can be interrupted up to three minutes (e.g., for lathering up) to be stored as one coherent shower (after three minutes the device restarts counting from zero). Water extractions below five liters are not considered as showers and are not stored: The underlying assumption is that most of these occurrences serve other purposes (e.g., flower watering or bathtub cleaning). For the calculation of energy use please refer to section 1.5.

For the purpose of this study, memory allocation and display content of the device were modified. As for the memory, study devices also recorded the duration of each shower (in seconds) and interruptions (both their number and duration) of each shower. As a result, study devices could only record up to 205 showers, which was the reason why the duration of the study had to be limited to two months and the household size to one- and two-person households. The display content was modified depending on the feedback condition, as described in the paper. For the first ten showers, all study devices only displayed water temperature, yet recorded all shower data (baseline phase).

To retrieve the data stored on the study devices, participants were asked to temporarily ship their device back to the research lab. The data readout was carried out using a dedicated optical readout terminal with a webcam and a self-written readout application. A detailed description of the technical aspects and the data readout procedure is available in (*1*).

## 1.2 Recruitment of participants

The utility company ewz contacted 5919 households by mail; all of them had previously participated in an electricity smart metering study. The size of the study had been limited upfront to 700 households for cost and implementation reasons; among those registered who fulfilled the qualification criteria (the number of household members in particular), participants were chosen on a first-come-first-served basis. All others were invited to participate in a one-year (long-term) study instead.

A total of 1348 households filled out the online survey to register for the study (23%). Participants who did not have a hand-held shower at home, who planned to relocate to a new home during the study or who planned to travel for more than three weeks during the study were discarded. Moreover, survey respondents were asked to agree with the data privacy statements, with installing the device within a few days upon reception and to ship back the device at the end of the study for the data readout. Furthermore - and this was by far the most limiting constraint - participation had to be restricted to one- and two-person households for technical reasons: Due to a limited data storage capacity of the devices (205 showers), not all shower data might be recorded over the two-month duration of the study in larger households (assuming that the shower frequency is roughly one shower per day and person). An equal number of one- and two-person households was pursued to compare the effect on individuals in isolation with the effect on individuals sharing one roof (and shower). However, due to an under-representation of one-person households compared to the number of two-person house-

holds in the pool of households contacted, the number of participating one-person households ended up being slightly smaller (324 single- vs. 373 two-person households).

Out of the 697 initial participants, a complete and consistent shower dataset was retrieved from the devices of 640 households. Among the other 57 households, 20 had dropped out of the study for various reasons (incl. relocation, hospitalization), 24 devices had been affected by water damage and contained corrupt datasets and were therefore discarded, 2 participants said they never received the device and 11 households did not send their device back or respond to our reminder emails. Among the 640 households from which a complete and consistent shower dataset is available, 633 had filled out the final survey.

### 1.3 Descriptive Statistics

Table S1 provides some descriptive statistics on important demographics of our subjects. All participants live in the greater Zurich area. As can be seen, the study sample only consists of one- and two-person households (see section 1.2). None of the households included children or teenagers. This is a result of the limitation to one- and two-person households, not a restriction imposed by the study. The study sample is better educated than the average population of Switzerland: 52% of the study participants have a university degree, compared to 37% of the population of the greater Zurich area resp. (*2*). The share of dwelling owners, by contrast, is substantially smaller compared to the general population of Zurich (36%) (*3*)).

Table S1: Descriptive statistics: categorical variables

| Variable | Category | N | Fraction |
|---|---|---|---|
| Household size | 1 person | 318 | 47% |
| | 2 persons | 362 | 53% |
| | Total | 680 | 100% |
| Age | 0-19 years | 0 | 0% |
| | 20-29 years | 80 | 14% |
| | 30-39 years | 151 | 26% |
| | 40-49 years | 123 | 21% |
| | 50-64 years | 141 | 24% |
| | 65 years or more | 87 | 15% |
| | Total | 582 | 100% |
| Gender | Women | 47% | |
| | Men | 53% | |
| Housing situation | Rent | 91% | 580 |
| | Own | 9% | 58 |
| | Total | 100% | 638 |
| Income | Less than CHF 3,000 | 44 | 4% |
| | CHF 3,000 - 3,999 | 78 | 7% |
| | CHF 4,000 - 4,999 | 94 | 8% |
| | CHF 5,000 - 5,999 | 147 | 13% |
| | CHF 6,000 - 6,999 | 136 | 12% |
| | CHF 7,000 - 7,999 | 108 | 9% |
| | CHF 8,000 - 8,999 | 102 | 9% |
| | CHF 9,000 - 9,999 | 78 | 7% |
| | CHF10,000 - 11,999 | 114 | 10% |
| | CHF 12,000 - 14,999 | 114 | 10% |
| | More than CHF 15,000 | 68 | 6% |
| | Not disclosed | 72 | 6 % |
| | Total | 580 | 100% |
| Education | No schooling completed | 0 | 0% |
| | Compulsory school completed | 7 | 1% |
| | Specialized middle school (2-3 yrs) | 12 | 2% |
| | Trade/technical/vocational training | 129 | 22% |
| | Higher vocational school certificate | 15 | 3% |
| | Grammar school | 25 | 4% |
| | Specialized college of higher edu. | 74 | 13% |
| | University or univ. of applied sciences | 304 | 52% |
| | Other | 15 | 3% |
| | Total | 581 | 100% |
| Living space (in $m^2$) | Less than 15 | 1 | 0% |
| | 15 - 40 | 31 | 5% |
| | 41 - 65 | 158 | 27% |
| | 66 - 80 | 176 | 30% |
| | 81 - 115 | 167 | 29% |
| | More than 115 | 47 | 8 % |
| | Total | 580 | 100% |

Table S2: Descriptive statistics: Continuous variables - baseline shower data

| Variable | Mean | SD (between) | N |
|---|---|---|---|
| Number of showers in study period | 74.1 | 40.3 | 640 |
| Mean baseline water use per shower (l) | 44.8 | 26.5 | 640 |
| Mean baseline energy use (kWh) per shower | 2.54 | 1.71 | 640 |
| Mean baseline water temperature (°C) | 36.1 | 2.8 | 640 |
| Mean baseline water flow (l/min) | 11.0 | 2.3 | 640 |

## 1.4 Questionnaire items to assess household characteristics, personality traits, and attitudes

**Age**
Age of the study participants was collected in six age brackets (0-19 years, 20-29 years, 30-39 years, 40-49 years, 50-64 years, 65 and older).

**Income**
The participants were asked to indicate their monthly net income in 11 brackets ranging from "Up to 3,000 CHF" to "More than 15,000 CHF".

**Education**
The participants were asked to indicate their highest degree or level of school they had completed:
- No schooling completed
- Compulsory school completed
- 2-3 years of specialized middle school ("Diplommittelschule oder Fachmittelschule")
- Trade/technical/vocational training
- A higher vocational school leaving certificate ("Berufsmaturität")
- Grammar school
- Specialized college of higher education, university of applied sciences, college ("Höhere Fachschule")
- University or university of applied sciences
- Other

**Housing situation** The participants were asked whether they rent or own the space they live in.

**Emotionality**
Emotionality was assessed based on 10 items as one of the six dimensions of the HEXACO-PI-R scale (60 item version) (*4*). The dimension comprises four facets: fearfulness, anxiety, dependence, and sentimentality.

**Conscientiousness**
Conscientiousness was also assessed based on 10 items of the HEXACO-PI-R. This personality dimension comprises four facets: organization, diligence, perfectionism, and prudence.

**Quantifying progress towards goals**
An individual's tendency to monitor progress towards goals was measured with two survey items prior to the intervention. Both items were measured on a 5-point Likert scale (1 = Never, 5 = Often). The trait was calculated based on the mean of these two items:
"Do you often measure your performance against self-set goals?"
"Do you often evaluate your performance against the performance of your peers?"

**Environmental attitude**
An individual's environmental attitude was measured by an item originally formulated by (*5*) on a 5-point Likert scale (1 = "Strongly disagree", 5 "Strongly agree"). The participants were asked to rate their agreement with the following statement: "I act environmentally responsible, even if this is associated with higher costs and efforts".

### 1.5 Calculation of energy consumption

Energy consumption is primarily calculated based on the amount of water used and water temperature: $Q = m * c_p * \Delta T$, where $Q$ represents the thermal energy, $m$ the mass of water consumed, $c_p$ the heat capacity of water (4.184 kJ/(kg*K)), and $\Delta T$ the difference between the measured temperature and the typical cold water temperature in Switzerland (12 degrees Celsius (*6*)). The result, however, is only the lower bound of the actual energy use, as this formula assumes 100% boiler efficiency and does not consider any generation and storage losses. The actual energy use depends on the fuel type, boiler size and age, and distribution infrastructure. The average boiler efficiency for water heating in Swiss households is 65% (*7*) and distribution losses range between 24 and 36% (*8*). We use a more conservative estimate of 24% in all calculations. The average shower in the baseline period (44.8 liters, 36.1 degrees Celsius) thus requires 2.54 kWh of energy.

## 2. Randomization Checks

We verify that the randomization has successfully produced a balance on observable key characteristics between the three experimental conditions before the onset of the treatment. The following equation was estimated:

$$y_i = \alpha_i + \beta_1 T_{1i} + \beta_2 T_{2i} + d_t + \epsilon_i \quad (1)$$

where the dependent variable $y_i$ stands for the mean energy use during the baseline phase and various individual-level traits that are potentially important for this analysis. $T_1$ and $T_2$ are indicators for the *real-time information* and *real-time plus past information* conditions. A shower fixed effect $d_t$ was included to capture trends in the best possible way.

Table S3 shows the regression coefficients for the individual regressions along with the $p$-value of the (two-sided) hypothesis that the correlation is zero (in parenthesis). There are only minimal differences between the means of the three study conditions and one cannot reject $\beta_1 = 0$ and $\beta_2 = 0$ for any of the variables. Most importantly, there is no difference with respect to energy use per shower during the baseline phase. Thus, before the onset of the intervention, all groups had the same shower behavior. The constant term of each regression is also of interest, as it represents the mean value of the control group for each dependent variable.

| | Baseline use [kWh] | Age [years] | Fraction of women | Household size [persons] | Environm. attitude | Quantify goal progress | Emotio-nality | Conscien-tiousness |
|---|---|---|---|---|---|---|---|---|
| Real-time info | -0.002 | -0.107 | -0.017 | -0.030 | 0.079 | 0.019 | -0.107* | -0.034 |
| | (0.159) | (1.316) | (0.042) | (0.050) | (0.093) | (0.083) | (0.060) | (0.057) |
| Real-time & past info | 0.153 | -0.722 | 0.008 | -0.005 | 0.148 | 0.030 | -0.018 | -0.046 |
| | (0.179) | (1.303) | (0.040) | (0.050) | (0.092) | (0.084) | (0.057) | (0.055) |
| Constant | 2.613*** | 40.366*** | 0.683*** | 1.545*** | 3.411*** | 3.328*** | 2.881*** | 3.803*** |
| | (0.115) | (0.928) | (0.030) | (0.035) | (0.067) | (0.060) | (0.041) | (0.040) |
| $R^2$ | 0.002 | 0.001 | 0.001 | 0.001 | 0.004 | 0.000 | 0.007 | 0.001 |
| Obs | 596 | 581 | 535 | 596 | 579 | 565 | 505 | 506 |

* $p$ <0.10, ** $p$ <0.05, *** $p$ <0.01

Table S3: Randomization checks

## 3. Estimation of the treatment effects

This section provides details on the statistical methodology, and the detailed results, referred to in the main text of the paper. It details the unit of observations, the equations estimated and the corrections applied to the standard errors in the estimations.

### 3.1 The impact of real-time information on resource use

In Panels A and B of Figure 1 in the main text, we display treatment effects of the experimental intervention on resource use. This subsection details their estimation and reports the full results.

#### 3.1.1 The statistical model

The baseline model for our estimation is

$$y_{it} = \alpha_i + \beta_1 T_{1it} + \beta_2 T_{2it} + d_t + \epsilon_{it} \tag{2}$$

where $y_{it}$ is our dependent variable, either energy consumption (in kWh) or water use (in liters) in shower $t$. We include an individual fixed effect $\alpha_i$ for each household in order to eliminate all variance stemming from fixed differences in shower outcomes between households. The indicators $T_{1it}$ and $T_{2it}$ are all zero for the first 10 showers and then take on the value of 1 if household $i$ is assigned to the *real-time information* and *real-time plus past information* treatment, respectively. We also include a shower fixed effect $d_t$ to capture time trends in the best possible way. The error term $\epsilon$ captures any unmodeled effects.

We estimate equation 2 by ordinary least squares (OLS) and allow the residuals to be correlated within a household in arbitrary ways. We correct for this by reporting standard errors clustered at the household level.

We also estimate equation (2) separately for one-person and two-person households. These specifications also form the basis for the formal tests of equality of treatment effects, i.e. whether we can reject the hypothesis that $\beta_1 = \beta_2$ within each type of household. We then also test whether, across one-person and two-person households, the treatment effects are the same, i.e. whether we can reject the joint hypothesis that $\beta_1^1 = \beta_1^2$ $\beta_2^1 = \beta_2^2$, where the superscripts indicate the household size (one-person or two-person households).

In order to test the stability of the treatment effect over the study period, we augment equation (2) to include interactions of the treatment variables with the counting variables for the showers $t$, i.e., we estimate

$$y_{it} = \alpha_i + \beta_1 T_{1it} + \beta_2 T_{2it} + \beta_3 T_{1it} \cdot t + \beta_4 T_{2it} \cdot t + d_t + \epsilon_{it} \tag{3}$$

where we can test whether the initial treatment effects $\beta_1$ and $\beta_2$ are being offset over time by

$\beta_3$ and $\beta_4$.

### 3.1.2 The empirical results

Table S4 shows the results. The first two columns show the results on which the significance statements accompanying Figure 1, Panel A were based, exhibiting the main treatment effects on all of the households. As can be seen, both treatments have a statistically highly significant effect on energy use per shower and on the amount of water used per shower.

In the remaining four columns, we display the main treatment effects estimated separately for one-person and two-person households. In these specifications, we also conduct the tests of equality of treatment effects. As can be seen in the table, the treatment effects are estimated to be very similar in both of the specifications. For each of the four specifications, we never reject the hypothesis that adding the past information has no effect on the outcome variable (all $p > 0.63$, see Table S4), as cited in the discussion of Figure 1, Panel B in the main text. Similarly, we do not reject the hypothesis that each of the treatments had the same effect on one-person and two-person households ($p = 0.92$ for kWh and $p = 0.92$ for liters).

Table S5 displays the specifications testing the stability of the treatment effects, again estimated separately for each household type. As can be seen from the estimated coefficients of the interaction effects with the number of showers, there is no tendency of the treatment effects to fade over time. The estimated coefficients are small and far from significant, as referred to in the main text when discussing Panel A of Figure 1. In the case of one-person households, the treatment effects even become somewhat stronger over time, though this is only marginally significant. In order to quantify the treatment effects at the end of the study, we calculated the predicted treatment effects after 87 showers and 139 showers for one-person and two-person households, respectively. These represent the 90th percentile of the total number of showers over the study period for each household type, and thus convey an impression of how much the treatment effects varied. As can be seen, the treatment effects remain virtually constant over time and do not change in any significant way. If anything, for the group of one-person households, it appears that the treatment effects are becoming stronger.

Table S4: The main experimental outcomes

| **Dependent variable** | **All households** kWh | liters | **One-person households** kWh | liters | **Two-person households** kWh | liters |
|---|---|---|---|---|---|---|
| Real-time information (=1) | -0.586*** | -9.281*** | -0.597*** | -8.996*** | -0.577*** | -9.519*** |
| | (0.073) | (1.134) | (0.104) | (1.602) | (0.103) | (1.604) |
| Real-time and past information (=1) | -0.599*** | -9.663*** | -0.639*** | -10.040*** | -0.565*** | -9.341*** |
| | (0.080) | (1.251) | (0.141) | (2.196) | (0.090) | (1.424) |
| Constant | 2.625*** | 44.110*** | 2.649*** | 43.865*** | 2.617*** | 44.411*** |
| | (0.067) | (1.051) | (0.101) | (1.545) | (0.090) | (1.441) |
| t-test: both treatments have the same effect on the dependent variable | $p = 0.88$ | $p = 0.77$ | $p = 0.77$ | $p = 0.64$ | $p = 0.92$ | $p = 0.91$ |
| F-test: equality of treatment effects across household types | | | $p = 0.91$ | $p = 0.91$ | | |
| $R^2$ | 0.441 | 0.430 | 0.530 | 0.527 | 0.381 | 0.367 |
| Obs | 45036 | 45036 | 16068 | 16068 | 28968 | 28968 |

*Notes:* The table displays the main treatment effects on energy and water use, controlling for household and time fixed effects. Standard errors are in parentheses, adjusted for clustering at the household level. See equation 2 for a complete description of the statistical model. $^{*},^{**},^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

Table S5: Stability of the treatment effect over time (kWh)

| Household type | One-person | Two-person |
|---|---|---|
| Real-time info (=1) | -0.5501*** | -0.5724*** |
| | (0.1225) | (0.1079) |
| Real-time and past info (=1) | -0.4181** | -0.5336*** |
| | (0.1625) | (0.0963) |
| Real-time info × shower | -0.0009 | 0.0004 |
| | (0.0017) | (0.0011) |
| Real-time and past info × shower | -0.0040* | 0.0001 |
| | (0.0022) | (0.0010) |
| Constant | 2.0653*** | 1.8752*** |
| | (0.1034) | (0.0979) |
| Predicted treatment effect at 90th percentile of shower frequency | 87 showers | 139 showers |
| Real-time information | -0.6320*** | -0.5132*** |
| | (0.130) | (0.1426) |
| Real-time and past information | -0.7656*** | -0.5237*** |
| | (0.1684) | (0.1254) |
| $R^2$ | 0.526 | 0.378 |
| Obs | 16364 | 29298 |

Notes: The table displays the main treatment effects on energy use (kWh), controlling for household and time fixed effects. Standard errors are in parentheses, adjusted for clustering at the household level. See equation (3) for a complete description of the statistical model. $^{*}$,$^{**}$,$^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

### 3.2 The impact of real-time information on estimated water use

In Figure 2 in the main text, we show the correlations between the actual and estimated water use across the different experimental conditions. This subsection presents the statistical model and its estimation to support our assertions in the text.

#### 3.2.1 The statistical model

We estimate the following equation

$$\hat{E}(y_i) = \beta_0 + \beta_1 y_i + \beta_2 T_{1i} + +\beta_3 T_{2i} y_i + \beta_4 T_{1i} \cdot y_i + +\beta_5 T_{2i} \cdot y_i + \epsilon_i \tag{4}$$

where $\hat{E}(y_i)$ is household $i$'s estimate of its average water use per shower. The variable $y_i$ is the actual average water use of household $i$ per shower. As before, the variables $T_{1i}$ and $T_{2i}$ are binary variables indicating whether a household was exposed to the real-time information, or real-time and past information treatment, respectively. We also include interactions between the water use $y_i$ and the treatment groups in order to examine whether estimated water use becomes more closely aligned with actual water use in the different treatments. As usual, $\epsilon_i$ represents the error term.

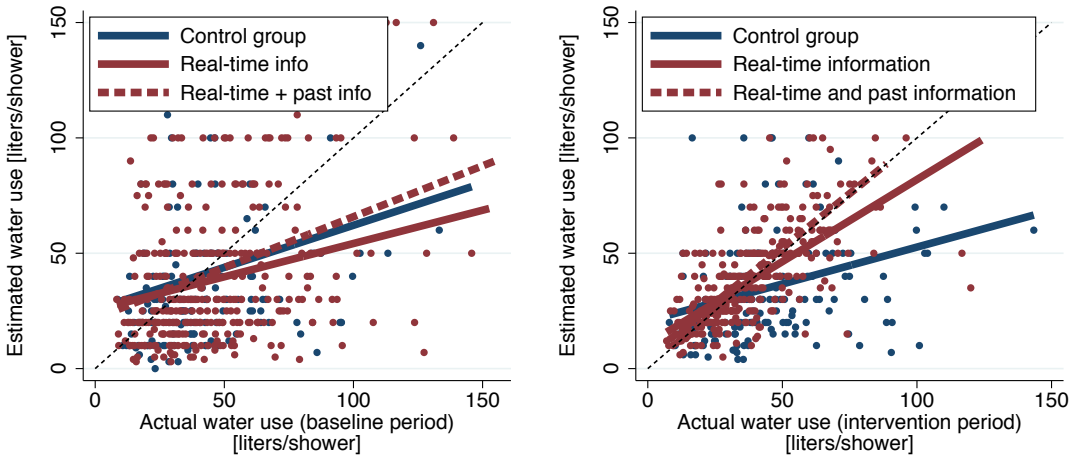
We obtained water use estimates before and after the intervention (initial survey resp. final survey). For each household, we compared the pre-intervention estimate with the actual mean water use per shower during the baseline phase and the post-intervention estimate with the actual use during the intervention phase. We thus estimated equation (4) for the baseline period and for the intervention period separately. For the baseline period, we take the average of the 9 observations during the baseline phase as actual water use. For the equation after the intervention, we take the average water use during the entire intervention phase (showers 11 to the end of the study) as our measure of actual water use. In both cases, we calculate robust standard errors.

#### 3.2.2 The empirical results

Figure S2 shows the scatterplots between the estimated and actual water use both for the baseline period (panel A) and the intervention period (panel B). As can be seen in Panel A, there is a somewhat positive relationship between the actual and estimated water use, indicating that users with higher baseline use also tend to estimate their usage higher. As should be expected, the slopes are roughly the same for each of the three treatments, since assignment to each of the conditions was random. The first column in Table S6 shows that, indeed, the slopes of the two experimental conditions are not different from that of the baseline condition: the coefficients on both interaction effects are small and not statistically significant.

Panel B of Figure S2 reproduces Figure 2 from the main text. It shows that there is now a much stronger association between the estimated and actual water use in the treatment groups than in the control groups. This can also be seen in the second column of Table S6. The interaction

Figure S2: Actual vs. estimated water use




**A.** Actual vs. estimated water use during the baseline period. **B.** Actual vs. estimated water use during the intervention period. Both graphs contain regression lines for each of the treatments, estimated based on the regression defined in equation (4).

terms of the treatment conditions with actual water use are significant and positive, and highly statistically significant. This is the result we referred to in discussing Figure 2 in the main text. Overall, this makes the association between the estimated and actual water use tighter in experimental conditions than in the control condition. In the control condition, the association between the estimated and actual water use remained roughly the same in the two periods, as can be seen by the similar magnitude of the main effect of actual water use in both regressions in Table S6.

Table S6: Estimated and actual water use

| measurement period | baseline | post-intervention |
|---|---|---|
| Actual water use | 0.406*** | 0.320*** |
| | (0.123) | (0.080) |
| Water use × real-time information | 0.024 | 0.625*** |
| | (0.185) | (0.110) |
| Water use × real-time and past information | -0.129 | 0.482*** |
| | (0.170) | (0.164) |
| Real-time information (=1) | -0.066 | -15.739*** |
| | (7.988) | (4.709) |
| Real-time and past information (=1) | 9.375 | -12.496** |
| | (8.225) | (6.046) |
| Constant | 22.261*** | 20.694*** |
| | (5.163) | (4.044) |
| $R^2$ | 0.051 | 0.340 |
| Obs | 522 | 516 |

Linear regressions between the estimated and actual water use in the three experimental conditions. Baseline estimated values were measured before the smart shower meter was deployed to households. Post-intervention estimated values were measured after the devices had been collected from the households. See discussion of equation (4) for more details. Heteroskedasticity-robust standard errors in parentheses. $^{*}$,$^{**}$ ,$^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

### 3.3 The impact of real-time information on the total number of showers

In the main text, we also refer to the total number of showers over the duration of the experiment. This subsection lays out the estimation and reports the full results.

#### 3.3.1 The statistical model

We estimate the following equation

$$y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + \epsilon_i \tag{5}$$

where the dependent variable $y_i$ in this case is the total number of showers of household $i$ during the study period, and $T_1$ and $T_2$ are binary variables indicating assignment to the real-time information, and real-time and past information treatment, respectively. We estimate equation (5) for one-person and two-person households separately, and report heteroskedasticity-robust standard errors.

#### 3.3.2 The empirical results

The results are displayed in Table S7. The first column displays the results for one-person households. As can be seen, there are only small differences in the number of showers between treatments, and none of these differences are significant, either individually or jointly. The same holds for the results for two-person households, displayed in the second column of Table S7: neither treatment condition had a total number of showers different from that in the control condition.

Table S7: The treatment effects on the total number of showers

| household type | one-person | two-person |
|---|---|---|
| Real-time information (=1) | 1.537 | 2.404 |
| | (3.700) | (5.716) |
| Real-time and past information (=1) | 5.709 | 1.816 |
| | (3.652) | (5.573) |
| Constant | 53.623*** | 96.689*** |
| | (5.172) | (8.110) |
| $R^2$ | 0.022 | 0.027 |
| Obs | 281 | 316 |
| F-test: no impact of the treatments on the number of showers | $p = 0.29$ | $p = 0.91$ |

Linear regressions of the total number of showers on the treatment conditions. See discussion of equation (4) for more details. Heteroskedasticity-robust standard errors in parentheses. $^{*}$,$^{**}$ ,$^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

### 3.4 Interaction effects of the treatment with household characteristics

In this subsection, we detail the specifications and estimation results that underlie Tables 1 and 2 in the main text.

#### 3.4.1 The statistical model

We estimate the following model

$$y_{it} = \alpha_i + \beta_1 T_{it} + \gamma_1' \mathbf{z}_i \cdot T_{it} + \gamma_2 \bar{y}_{i0} \cdot T_{it} + d_t + \epsilon_{it} \tag{6}$$

where $T_{it}$ is an indicator equal to 1 after shower 10 if household $i$ is in either the real-time or real-time and past information condition. As the previous section shows that the two treatments had the same effects on behavior, we collapse both treatments into one. For the same reason, we also do not distinguish between different households. We interact the treatment effect with a vector of personality traits $\mathbf{z}_i$ in order to test the different hypotheses formulated in the paper. Variable $\bar{y}_{i0}$ is the mean per-shower energy consumption of household $i$ during the baseline period (where none of the devices displayed any information about resource use). As before, we include household fixed effects $\alpha_i$ and shower fixed effects $d_t$. We adjust the standard errors for clustering at the household level.

As a robustness check we estimate equation (7), a second version of equation (6), in which we also include interactions between the personality traits $\mathbf{z}_i$ and a time trend.

$$y_{it} = \alpha_i + \beta_1 T_{it} + \gamma_1' \mathbf{z}_i \cdot T_{it} + \gamma_2 \bar{y}_{i0} \cdot T_{it} + \delta_1' \mathbf{z}_i \cdot t + d_t + \epsilon_{it} \tag{7}$$

We include these interaction terms in order to account for possible differences in Hawthorne effects that may be related to personality differences, and create personality-specific trends.

With this specification, the treatment effect depends on personality traits $\mathbf{z}$ and baseline consumption $\bar{y}_{i0}$, and is given by

$$E(y_{it}|T_{it} = 1, \mathbf{z}_i, \bar{y}_{i0}) - E(y_{it}|T_{it} = 0, \mathbf{z}_i, \bar{y}_{i0}) = \beta_1 + \gamma_1' \mathbf{z}_i + \gamma_2 \bar{y}_{i0} \tag{8}$$

Equation (8) is the equation that allows us to calculate the predicted treatment effects for the top and bottom quintiles of personality traits by inserting the mean of the personality trait $z_{ki}$ in the top or bottom quintile of $z_k$ into the equation, respectively.

For the specification in Table 2 of the main text, we estimate the following specification

$$y_{it} = \alpha_i + \beta_1 T_{it} + \gamma_1' \mathbf{z}_i \cdot T_{it} + \gamma_2 \bar{y}_{i0} \cdot T_{it} + \gamma_3' \mathbf{z}_i \cdot \bar{y}_{i0} \cdot T_{it} + d_t + \epsilon_{it} \tag{9}$$

Adding the triple interaction allows us to examine whether the personality traits become more important determinants of the treatment effects for households with high baseline consumption, i.e. where the possibility to reduce resource use was greater. It allows us to better explore the functional form of the interaction effects while still being nested in the earlier specifications and thus keeping the estimated coefficients directly comparable. Again, we estimate a second version of equation (9), including trait-specific time trends.

### 3.4.2 The empirical results

Table S8 presents the estimation results of equations (6) and (7). As can be seen in the two specifications, the conclusions with respect to the interaction effects of interest are robust to the details of the specification.

Table S9 presents the estimation results of equation (9) (in column 1), and the identical equation, augmented by the trait-specific time trends (in column 2).

Table S8: Interaction effects of the treatment with household characteristics

| | (1) | (2) |
|---|---|---|
| Treatment Effect ($T_{it}$) | -0.642*** | -0.642*** |
| | (0.070) | (0.069) |
| $T_{it} \times \bar{y}_0$ | -0.318*** | -0.307*** |
| | (0.070) | (0.071) |
| $T_{it} \times$ emotionality | 0.015 | 0.025 |
| | (0.080) | (0.083) |
| $T_{it} \times$ conscientiousness | 0.209* | 0.192* |
| | (0.108) | (0.108) |
| $T_{it} \times$ environmental attitude | -0.152** | -0.160** |
| | (0.072) | (0.077) |
| $T_{it} \times$ quantifying goal progress | -0.119** | -0.110* |
| | (0.055) | (0.058) |
| $T_{it} \times$ female | 0.249* | 0.164 |
| | (0.138) | (0.144) |
| $T_{it} \times$ age | 0.003 | 0.022 |
| | (0.052) | (0.052) |
| $T_{it} \times$ household income | 0.016 | 0.016 |
| | (0.013) | (0.013) |
| Constant | 2.497*** | 2.498*** |
| | (0.078) | (0.078) |
| F-test: Significance of interactions with environmental attitude and tendency to quantify. | $p = 0.02$ | $p = 0.02$ |
| $R^2$ | 0.446 | 0.447 |
| Obs | 29718 | 29718 |

The table displays the treatment effects on energy use (kWh) depending on a range of household characteristics. The regressions control for household and time fixed effects. Column (1) presents the baseline specification (equation (6)), column (2) presents the results controlling for characteristic-specific trends (equation (7)). Standard errors are in parentheses, adjusted for clustering at the household level. $^{*}$,$^{**}$,$^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

Table S9: Triple interaction effects of the treatment with household characteristics

| | kWh | kWh |
|---|---|---|
| Treatment Effect ($T_{it}$) | -0.630*** | -0.631*** |
| | (0.073) | (0.073) |
| $T_{it} \times \bar{y}_0$ | -0.337*** | -0.332*** |
| | (0.052) | (0.055) |
| $T_{it}$ $\times$ tendency to quantity | -0.134** | -0.127** |
| | (0.059) | (0.062) |
| $T_{it} \times \bar{y}_0 \times$ tendency to quantify | -0.125*** | -0.124*** |
| | (0.046) | (0.046) |
| $T_{it}$ $\times$ environmental attittude | -0.103* | -0.109* |
| | (0.058) | (0.061) |
| $T_{it} \times \bar{y}_0 \times$ environmental attitude | -0.179*** | -0.180*** |
| | (0.066) | (0.066) |
| $T_{it}$ $\times$ conscientiousness | 0.217** | 0.194** |
| | (0.094) | (0.095) |
| $T_{it} \times \bar{y}_0 \times$ conscientiousness | 0.088 | 0.088 |
| | (0.110) | (0.110) |
| F-test: joint significance of tendency to quantify | $p = 0.02$ | $p = 0.02$ |
| F-test: joint significance of environmental attitude | $p = 0.02$ | $p = 0.02$ |
| F-test: joint significance of conscientiousness | $p = 0.05$ | $p = 0.1$ |
| $R^2$ | 0.445 | 0.446 |
| Obs | 30604 | 30604 |

The table displays the treatment effects on energy use (kWh) depending on a range of households characteristics. The regressions control for household and time fixed effects. Column (1) presents the baseline specification (equation (9)), column (2) presents the results controlling for characteristic-specific trends. Standard errors are in parentheses, adjusted for clustering at the household level. $^{*}$,$^{**}$ ,$^{***}$ indicate significance at the 10, 5 and 1 percent level, respectively.

### 3.5 Carbon abatement

Carbon intensity of showering largely depends on the type of fuels used for water heating and varies from country to country. We calculate the impact of the shower feedback intervention on carbon emissions based on the fuel mix of Switzerland (where the intervention took place). Given the large variance between countries in the carbon intensity of water heating, we also calculate the figures for the U.S. for comparison (assuming the same baseline water use, water temperature, and treatment effect).

The majority of Swiss households rely on fossil fuels for water heating: 40% use fuel oil, 25% electricity, and 21% natural gas; renewable energy sources such as wood, solar thermal or ambient air only account for a relatively small fraction (*9*). In the U.S., water heating mainly relies on natural gas (51%) and electricity (42%); 3% use fuel oil (*10*).

In the case of electric water heaters, one must further take into account country-specific differences in the electricity generation. In Switzerland, electricity is mainly generated from fossil-free resources - hydro power (56%) (*11*) and nuclear power (39%) (*12*) - resulting in a carbon intensity of 102 g/kWh at the plug level (*13*). In the U.S., electricity production is primarily based on coal (39%), natural gas (27%), nuclear power (19%) and hydropower (6%), amounting to a carbon intensity of 648 g/kWh (*14*).

Table S10 shows the carbon intensity of water heating for Switzerland and the U.S.. Water heating in Switzerland results in a carbon intensity of 216 g of CO2/kWh, nearly twice as much as per kWh of electricity generated. Due to a higher share of fossil fuels, both electricity generation (648 g of CO2/kWh of electricity) and water heating (420 g of CO2/kWh of thermal energy) are substantially more carbon-intense in the U.S. Consequently, a 215 kWh reduction per person and year in water heating results in reduced carbon emissions of 47 kg and 90 kg in Switzerland and the U.S., respectively.

Table S10: Carbon intensity of water heating in Switzerland and in the U.S.

| Fuel type | Swiss share of fuel for res. water heating | Swiss carbon intensity of fuel [kg/kWh] | U.S. share of fuel for res. water heating | U.S. carbon intensity of fuel [kg/kWh] |
|---|---|---|---|---|
| Oil | 40%[1] | 0.299[2] | 3%[3] | 0.299[2] |
| Natural gas & LPG | 21%[1] | 0.252[2] | 55%[3] | 0.252[2] |
| Electric | 25%[1] | 0.102[4] | 42%[3] | 0.648[5] |
| Other (wood, district heating...) | 14%[1] | 0.125[2] | 0% | - |
| Weighted average | | 0.216 | | 0.420 |

References: [1] (*9*), [2] (*15*), [3] (*10*), [4] (*13*), [5] (*16*)

### 3.6 Comparison of the present study with a prior electricity smart metering study

When comparing the impact of the present study with other smart metering studies - mainly in the electricity sector - one must carefully consider the focus of each study (household electricity consumption vs. energy and water consumption in the shower) as well as the sample of participants / recruitment strategy.

All participants of this study had previously completed an electricity smart metering study (*17*). In order to opt into the present study, households had to fill out an online survey, which yielded a 30% response rate. A total of 697 households were finally selected for this study based on their shower type and household size (see section 1.3). Participants of the current study are thus a subset of the households who had previously completed an electricity smart metering study (opt-in design in both cases).

While the prior study investigated the impact of an in-home display on *aggregated household electricity use*, the study described in this article focuses on the *energy and water consumption in the shower*. We therefore distinguish between electric energy and thermal energy and take into account the different fuel mixes for the generation of one kWh in each domain. From an energy conservation perspective, the average treatment effect amounts to *thermal* energy savings of 215 kWh per person and year in the present study. By contrast, (*17*) report electricity savings of 86 kWh per household (*17*). Given the household size of 2.1 persons in the prior study, it results in *electricity* savings of 41 kWh per person and year. As section 3.5 shows, fuel mixes used for electricity and hot water generation are highly country-specific. Table S10 presents the figures both for Switzerland (where the interventions took place) and for the U.S. (assuming the same treatment effects).

Table S11 compares the resulting reductions in carbon emissions per person and year based on the fuel mix used for electricity generation and water heating in Switzerland, respectively. The table further gives the corresponding carbon abatement figures based on the U.S. fuel mix presented in table S10:

Table S11: Comparison of carbon reduction per person and year by electricity smart metering study (*17*) vs. shower feedback intervention

| Behavioral intervention | Energy savings per person and year | Carbon abatement in Switzerland per person (kg of CO2/yr) | Carbon abatement in the U.S. per person (kg of CO2/yr) |
|---|---|---|---|
| Electricity smart metering trial | 41 kWh (electric energy) | 4.2 | 26.6 |
| Present study (shower feedback) | 215 kWh (thermal energy) | 46.5 | 90.4 |

As table S11 shows, the impact on carbon abatement of the present study exceeds the impact of the prior electricity smart metering study in Switzerland by a factor of 11. In the U.S., both studies would yield a higher absolute impact on carbon abatement (assuming the same absolute numbers for energy conservation as in Switzerland), with the present study outperforming the electricity smart metering study by a factor of 3.4. Figures for energy savings of the two studies can only be directly compared to the 25% (resp. 42%) of Swiss (resp. U.S.) households that use electricity for water heating. In that case, the present study exceeds the energy conservation impact of the electricity smart metering study by a factor of 5.2. For all households that use a different fuel for water heating, the comparison would require more complex calculations on energy conversion, which is beyond the scope of this article.

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## Professional Appointments

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| 2015 to present | Full Professor, Department of Economics, University of Bonn |
| 2013 to present | Director of the Doctoral Program in Behavioral Economics and Experimental Research of the Conférence des universités de la suisse occidentale. |
| 2011 to 2014 | Department chair, Département d'économétrie et économie politique, Université de Lausanne. |
| 2009 to present | Full Professor, Département d'économétrie et économie politique, Université de Lausanne (on leave, 20015 to present). |
| 2009 to present | Associate member of the NCCR Affective Sciences. |
| 2009 | Full Professor, Département d'économie politique, Université de Genève. |
| 2007 - 2008 | Visiting Assistant Professor, Department of Economics, Massachusetts Institute of Technology. |
| 2006 - 2008 | Senior Economist, Federal Reserve Bank of Boston, Center for Behavioral Economics and Decision Making. |
| 2005 - | Research Affiliate, Centre for Economic Policy Research, London. |
| 2004 - | Research Fellow, Institute for the Study of Labor, Bonn. |
| 2003 - 2006 | Assistant Professor (Oberassistent), Institute for Empirical Research in Economics, University of Zurich. |
| 2001 - 2003 | Research Fellow at the University of California, Berkeley. Fellowship awarded by the *Swiss National Science Foundation* (Sponsors: Prof. George Akerlof, Prof. Matthew Rabin). |

## Education

| | |
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| July 2001 | Completion of graduate studies: Doctorate in Economics, *Summa Cum Laude,* University of Zurich<br>Primary Fields: Labor Economics and Behavioral Economics (Prof. Ernst Fehr)<br>Secondary Field: Macroeconomics (Prof. Robert G. King, Boston University) |
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## Grants

**Swiss National Science Foundation:** Stress and social economic decision-making: The impact of stress on confidence and other-regarding behavior CHF 395,383. Three-year grant 2013 – 2016.

**Swiss National Science Foundation:** Understanding Motivations to Donate Blood: Habits, Image and Social Networks. CHF 388,000. Three-year grant 2012 – 2015.

**Swiss National Science Foundation:** (co-PI with Alessandro Villa) NeurEcA: Does working memory training affect decision making? A neuroeconomic study of ADHD adults and healthy controls. CHF 500,000. Three-year grant 2012 – 2015.

**Swiss National Science Foundation:** Active Cognition and Organ Donation. CHF 380,000. Three-year grant 2012 – 2015.

**Swiss National Science Foundation:** Outcome-Based or Reference-Dependent Valuation? Understanding the Psychological Mechanisms of Valuation. CHF 550,000. Three-year grant 2012 – 2015.

**Swiss Federal Office of Energy:** (co-PI with Rafael Lalive). The role of information in electricity consumption, CHF 234,000. Three-year grant 2011 – 2014.

**Swiss National Science Foundation:** Cognitive Abilities and Economic Preferences. CHF 234,000. Two-year grant. 2009 – 2011.

**MacArthur Foundation:** Velo-Productivity: Team Production Experiments with Bicycle Messengers (with Steve Burks and Jeff Carpenter). USD 25,000.

**Russell Sage Foundation**, Small Grants in Behavioral Economics: Loss Aversion and Labor Supply. USD 3,500.

**Swiss National Science Foundation**, European Wages and Employment under Low Inflation, European Science Foundation Research Consortium with Per Lundborg, Hans Sacklén, Ernst Fehr, and Steinar Holden. CHF 21,000.

**Summer Scholar,** Center for Advanced Study in the Behavioral Sciences, Stanford, July – August 2004

## Editorial Boards

Associate Editor, *Management Science*, 2012 – present.

## Refereeing

*American Economic Review, B.E. Journal of Macroeconomics, Current Biology, Econometrica, Economic Inquiry, Economic Journal, Empirical Economics, European Journal of Social Psychology, European Economic Review, Finanzarchiv, Games and Economic Behavior, International Journal of the Economics of Business, Journal of Behavioral Decision Making, Journal of Labor Economics, Journal of Environmental Economics and Management, Journal of the European Economic Association, Journal of Monetary Economics, Journal of Population Economics, Journal of Economic Behavior and Organisation, Journal of Politics, Labour Economics, Management Science, Public Choice, Review of Economics and Statistics, Review of Economic Studies, Science, Swiss Journal of Economics and Statistics, Scandinavian Journal of Economics.*

**Teaching**

Personnel Economics (advanced undergraduate), *University of Zurich,* Summer term 2004.

Behavioral Economics (advanced undergraduate), *University of Zurich,* Winter term 2004 / 2005.

Personnel Economics (undergraduate), *University of Zurich*, Summer term 2005.

Behavioral Economics (graduate), *Central European University,* Spring 2005.

Behavioral Economics (advanced undergraduate), *University of Zurich,* Winter term 2005 / 2006.

Personnel Economics (undergraduate), *University of Zurich*, Summer term 2006.

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Intermediate Microeconomics (M.A. students), *MIT Department of Urban Studies and Planning,* Fall 2008.

Psychology and Economics (undergraduate), *University of Geneva,* Spring 2009

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Analyse économique: microéconomie (2nd year Bachelor), *HEC Université de Lausanne*, Spring 2010, Spring 2011, Spring 2012, Spring 2013.

Behavioral finance (2nd year Masters in Economics, Masters in Finance), *HEC Université de Lausanne*, Fall 2010, Fall 2011, Fall 2012.

Short course "Field experiments in economics" (Ph.D.-level), *BEER Doctoral Program* 2013, *University of Bern* 2012, *University of Zurich* 2013.

**Publications in refereed journals**

Stress pulls us apart: Anxiety leads to differences in competitive confidence under stress (with Samuel Bendahan, Carmen Sandi, Fiona Hollis and John Thoresen), forthcoming *Psychoneuroendocrenology.*

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**Working Papers**

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Randomizing endowments: is the reference point driven by expectations? (with Annette Harms and Charlie Sprenger)

Reference-dependent preferences and effort: evidence from a field experiment (with Ernst Fehr)

The Role of Information for Electricity Conservation: Evidence from a Large-Scale Field Experiment on its psychological mechanisms (With Kathrin Degen and Rafael Lalive)

If only they knew … : real-time user feedback dramatically reduces showering (with Kathrin Degen, Rafael Lalive, Verena Tiefenbeck and Thorsten Staake)

Call of Duty: The impact of randomized phone calls on blood donor motivation (with Adrian Bruhin, Beat Frey and Alexander Markovic)

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