Effects of Feedback on Residential Electricity Demand – Results from a field trial in Austria

Joachim Schleich, Fraunhofer Institute for Systems and Innovation Research (ISI), Karlsruhe, Germany and Grenoble Ecole de Management, Grenoble, France
Marian Klobasa, Fraunhofer Institute for Systems and Innovation Research (ISI), Karlsruhe, Germany
Sebastian Gölz, Fraunhofer Institute for Solar Energy Systems (ISE), Freiburg, Germany

Abstract

This paper analyzes the effects of providing feedback on electricity consumption in a field trial with more than 1500 households in Linz, Austria. Participation in the pilot group was random, but households could choose between two feedback types: access to a web portal or written feedback by post. Results from cross section OLS regression suggest that feedback provided to the pilot group results in electricity savings of around 4.5% for the average household. Results from quantile regressions imply that for households in the 30th to the 70th percentile, feedback on electricity consumption is statistically significant and effects are highest in absolute terms and as a share of electricity consumption. For percentiles below or above this range, feedback appears to have no effect. Finally, controlling for a potential endogeneity bias induced by non random participation in the feedback type groups, we find no difference in the effects of feedback provided via the web portal and by post.

1 Introduction

According to directive 2006/32/EC, smart meters should be installed in EU Member States when an existing meter is replaced, when a new building is connected to the grid, or when an existing building undergoes major renovations as far as this is technically feasible and economically reasonable. Final customers also need to receive information on actual energy consumption and costs. EU regulation requires the roll-out of smart meters to 80 % of consumers in EU Member States by 2020, but Member States may decide on their own implementation strategies. Consequently, Member States have taken different routes in terms of timing and technology regulation. In Austria, only few utilities have installed smart meters so far, awaiting details on future federal regulation.

For most customers current metering and billing practices mean that they receive only limited information about their energy consumption - typically once a year. More frequent and timely feedback is expected to raise awareness, to improve information about energy use patterns and energy costs and to help overcome information-related barriers and lead to lower energy use. Recent reviews focusing on programs in the US and Canada report electricity savings in the ranges of 5-15% (Darby 2006; Fischer 2008; Ehrhardt-Martinez, Donnelly & Laitner 2010). Lower effects are estimated by Matsukawa (2006) for Japan (1.5%) and by Gleerup et al. (2010) for Denmark (3%).

In this paper, we estimate the effects of feedback on household electricity consumption in a recent field trial carried out in the city of Linz in Austria, where more than 1500 house-holds were randomly selected into a pilot and a control group. Participants in the pilot group could choose between two types of feedback information: access to a web portal and written feedback via post. We also explore whether feedback effects depend on consumption levels. Finally, we test whether web-based feedback and written feedback are equally effective.

The remainder of this paper is organised as follows. Section II describes the field trial and the feedback provided. The methodology is developed in Section III. Data and variables are described in section IV. Section V presents the results and the final section concludes.

2 Field Trial

An initial pool of more than 1500 potential participants in the Austrian city of Linz was identified by the utility and these were then randomly assigned to a pilot group and a control group of about equal sizes. The actual field phase started in December 2009 and ended in November 2010. During the field phase the electricity consumption of households in the pilot group and the control group was recorded on an hourly basis. Computer-assisted telephone interviews were conducted with households in both groups, relying on standardized questionnaires about household appliance stock and socio-demographic characteristics.

Based on the findings from 76 qualitative interviews with household customers two types of feedback on energy consumption were developed between which households in the pilot group could choose: access to a web-portal and written feedback information via post. The web portal was designed to help households reduce their electricity consumption and costs by providing information on electricity consumption patterns and on practical measures to save electricity. The user may compare energy consumption over time (months, days, hours) and identify consumption patterns by load types. Users can choose their favorite charts for a year (comparison of the months), half a year (comparison of the weeks), a month (comparison of the days), or a day (hours). Users can also choose between graphs (bar charts) and a combination of tables and charts and switch between the display of energy use (in kWh) and energy costs (in Euro). Finally, intermittent loads and (estimated) base loads (refrigerators and freezers) are displayed as shares of the total electricity consumption (see Figure 1).

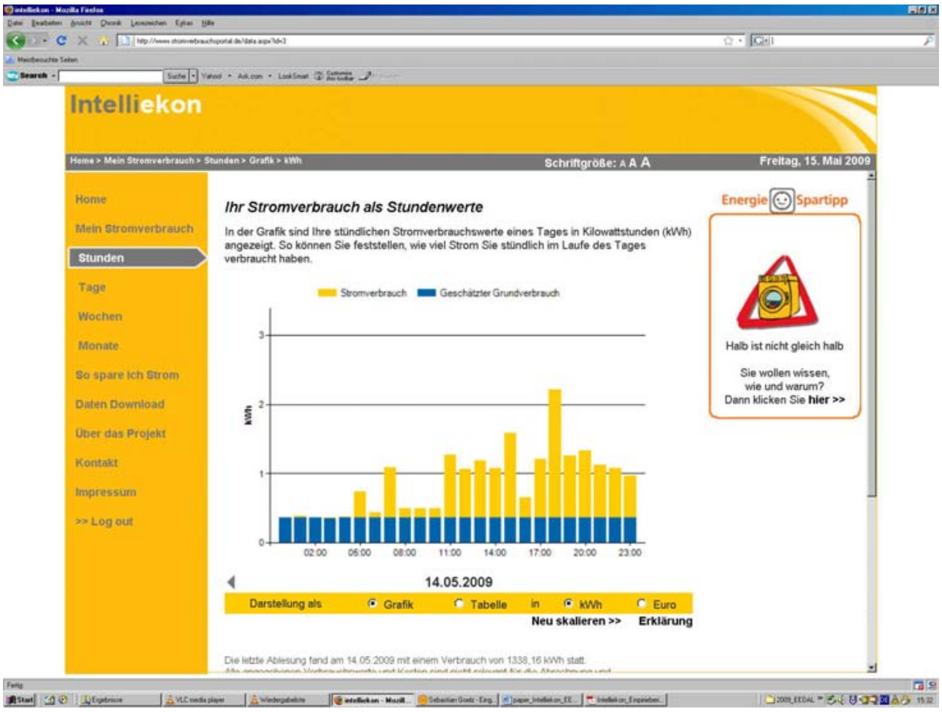

Figure 1. Screenshot of the web portal feedback instrument

Web-portal usage was highest during the first month and then declined steadily. For example, web-portal use dropped by bout 50% between the first and the second month. More than a third of the users visited the portal only during the first month and less than 10% of households visited the web-portal at least once in every month of the field trial. Users were most interested in information on hourly and daily electricity consumption (see Gölz et al. 2011). The written feedback option consisted of two pages including colour-printed information on daily, weekly and monthly household electricity consumption in the form of graphs and tables and energy saving recommendations which were taken from the web portal. Written feedback was sent to participants by post once a month.

Consequently, possible feed-back impacts can only be expected from the second month onwards, i.e. between the eleven month span of January and November 2010. Table 1 provides descriptive statistics of the variables used in the subsequent econometric analyses. The figures in Table 1 confirm that as the outcome of the random assignment characteristics of households in the pilot group and the control group are quite similar.

Table 1: Descriptive statistics

		Full sample				Pilot	Control
Variable	Unit	Mean	Std. Dev.	Min.	Max.	Mean	Mean
Electricity	kWh/year	3288	1452	703	7963	3267	3314
Smart	0/1 dummy	0.56	0.50	0	1	1	0
Age5	number	0.18	0.48	0	3	0.16	0.22
Age17	number	0.41	0.75	0	4	0.40	0.42
Age30	number	0.41	0.67	0	4	0.38	0.45
Age45	number	0.66	0.80	0	3	0.68	0.63
Age60	number	0.51	0.73	0	3	0.47	0.57
Age60plus	number	0.35	0.68	0	3	0.40	0.28
Floorsize	m^2	105	46	25	538	107	102
Income	1/2/3 dummy	2.16	0.77	1	3	2.16	2.16
Education	0/1 dummy	0.54	0.50	0	1	0.51	0.57
Fridge	number	1.22	0.47	0	4	1.25	1.18
Dryer	number	0.39	0.49	0	1	0.40	0.38
Freezer	number	0.74	0.56	0	3	0.75	0.72
Dishwash	number	0.88	0.36	0	2	0.90	0.87
Boiler	number	0.39	0.57	0	3	0.38	0.40
TV	number	0.83	0.80	0	5	0.87	0.79
Computertime	number	2.63	3.61	0	24	2.63	2.62
Appliances	number	6.67	2.77	1	27	6.73	6.59

3 Methodology

Our empirical analyses involve estimating a reduced form household electricity consumption equation relying on cross sectional data. As is standard in evaluations based on cross-sectional data, we assume that our regression analyses sufficiently control for differences in characteristics between the pilot and the control group such that the outcome that would result in absence of the feedback is the same in both cases.[1] In the evaluation literature, this assumption is also termed “conditional independence” or “unconfoundedness” (Mills & Schleich 2009). We employ two types of models. The feedback model estimates the effect of receiving feedback on energy consumption and is also used to analyze whether feedback effects differ by consumption level. The feedback type model assesses differences by feedback type controlling for pilot group households’ possible non-random choice of feedback type.

1 If data on historic electricity consumption was available, a before-after estimator (e.g. difference-in-difference approach) to assessing the effects of feedback on electricity consumption were feasible as applied in Gleerup et al. (2010), hence controlling for time-constant unobserved heterogeneity across households.

3.1 Feedback Model

Suppressing subscripts for individual households, observed household electricity consumption may be expressed as:

$$Y = X\beta + I_p\delta + \varepsilon \qquad (1)$$

where X is a row vector of variables influencing household electricity consumption, β is a vector of parameters to be estimated, and ε is an error component. The dummy variable I_P indicates whether a household belongs to the pilot group. Since participation in the pilot group is random, (1) may be estimated via simple OLS regression. Least squares estimation involves estimating the conditional mean of electricity consumption, typically relying on normality of the underlying conditional distribution. Also, OLS implies that parameters are constant across consumption levels. In particular, the effects of providing feedback are assumed to be the same for all consumption levels. To explore whether feedback effects differ by electricity consumption, we employ nonparametric quantile regression (Koenker 2005), which involves estimating conditional quantiles as functions of X. Hence, δ (as well as β) may differ across quantiles.

3.2 Feedback types model

To explore differences by feedback type, the reduced form consumption equation is only estimated for households in the pilot group. Since households' choice of feedback type may not be random we employ a treatment model where the treatment condition (choice of feedback type) is directly entered into the electricity consumption equation.

$$Y = X\beta + I_W\delta + \varepsilon \qquad (2)$$

The dummy variable I_W indicates whether a household chooses to receive feedback on energy consumption via access to a web account or via post. This choice is modeled as a standard treatment equation.

$I_W^* = \gamma Z + \mu$, with

$I_W = 1$ if $I_W^* \geq 0$ (web feedback) (3)

$I_W = 0$ if $I_W^* < 0$ (post feedback),

and where Z is a row vector of variables affecting the choice of feedback type, γ is a vector of parameters to be estimated, and μ is the error component. Typically, the error components are assumed to be bivariate normal with mean zero and covariance ρ). Since I_W may be endogenous in (2), estimating the model requires controlling for a potential endogeneity bias induced by non random choice of feedback type (unless ρ=0). The model may be estimated by a standard Heckman-type (Heckman 1979) two step estimator, employing appropriate instruments.

4 Data

Data on socio-economic and technical characteristics were taken from the survey. Correcting for households which moved or which encountered technical problems data was available for 1525 households, of which 775 were in the pilot group.

4.1 Dependent variable

The dependent variable used in the econometric analysis is annual household electricity consumption (*electricity*). Rather than working with data for the eleven-month framework of the trial period, average daily electricity consumption was scaled up proportionally to employ more familiar annual figures.

4.2 Explanatory variables

The set of explanatory variables includes variables characterizing the household, the residence and the appliance stock which are assumed to affect household electricity consumption and participation in the control group (see Table 1). Household *income* is categorized in three groups and takes on the values of 1, 2, and 3 if household disposable monthly income (including transfer payments) is below 1500 €, between 1500 € and 2500 € and above 2500 €. The indicator variable *education* takes on the value of 1 if the survey respondent experienced at least 10 years of education. We include variables for the number of household members for the following six age groups: 0-5, 6-17, 18-30, 31-45, 46-60, > 60. *Floorsize* is supposed to capture the impact of the size of the residence on electricity consumption. Separate count variables indicate the number of the following electrical appliances in the household: boiler, dishwasher, dryer, freezer, refrigerator and TV. For parsimony, we included a variable which sums up the number of other *appliances* in the household such as air conditioners, espresso machines, microwaves, or play stations. Unlike for other household appliances, data is available on the intensity computers are used in the household. Hence, the reported daily running time of the first (i.e. most intensively used) computer (*computertime*) is also included. Finally, the electricity consumption equation includes a dummy variable titled "*smart*" reflecting participation in the pilot group. Hence, *smart* captures the effect of feedback from the smart metering programme on electricity consumption. Data on all the explanatory variables were available for 1070 households, of which 601 (or 56 %) belong to the pilot group. Of those 276 (i.e. 46 %) chose to receive feedback via access to the internet portal. The set of explanatory variables for estimating the household electricity consumptions (1) and (2) is the same in both models. For the feedback type model, the number of computers in a household (*computer*) is used as the identifying restriction. That is, *computer* is included in the Probit specification (3) but not in (2).

5 Results

All variables entered the analyses in levels, but results are virtually the same of the logarithm of electricity consumption is regressed on the set of explanatory variables instead.

5.1 Feedback model: effects of feedback in general

Results from estimating (1) via OLS suggest that *smart* is statistically significant at p=0.05. The associated point estimate suggests that the feedback provided under the smart metering programme results in electricity savings of around 154 kWh, which translates into savings of 4.51% of total annual electricity consumption of the mean household in the pilot group. Further, electricity consumption positively depends on the number of household members in each but the youngest *age* group (at p=0.01) and tends to increase with age. Larger residences are associated with higher electricity consumption of just below 6 kWh per year and m^2 (p=0.01). Higher *income* is associated with higher electricity consumption (p=0.05). Parameter estimates of appliances typically exhibit the expected positive sign, are statistically significant (at p=0.01) and take on reasonable values. Higher *education* is associated with lower electricity consumption, but is not statistically significant at conventional levels.

5.2 Feedback model: effects of feedback by consumption level

Our findings from the quantile regressions suggest that feedback is statistically significant and effects are highest in absolute terms and as a share of electricity consumption for the 30th to 70th percentiles. The calculated saving rates range from just below 6% for households in the 30th and 40th percentiles to around 3% for the 60th and 70th percentiles. In contrast, for households outside of these percentiles, feedback appears to have no statistically significant effect. While the point estimates differ across the 30th to the 70th percentile, from a statistical point the parameters cannot be distinguished. In general, the point estimates tend to be higher for higher deciles, reflecting – for example in the case of household appliances - higher intensity of use or lower efficiency.

5.3 Feedback type model

Estimating a Heckman-type two stage model we fail to reject the null hypothesis that $\rho=0$. Hence, we may treat feedback choice as random conditional on observed characteristics and therefore estimate (2) employing propensity scores as weights (abandoning the restrictive assumption of joint normality on the error components) [9]. Specifically, the propensity scores from the Probit specification in (3) may be used to calculate weights for each observation. The electricity consumption (2) may then be estimated by OLS employing these observation weights to obtain an unbiased estimate of differences in the effects of feedback types (e.g. Mills & Schleich 2009; Price 2005). Since we find that the parameter estimate associated with the indicator variable for web-based feedback *web* is not statistically significant, our results do not provide support for the hypothesis that there are differences in the impact of feedback by type. The parameter estimates associated with the other control variables for the pilot group households are generally similar to those found for the full sample.

6 Conclusions

Our findings from the OLS regressions suggest that providing feedback information on electricity consumption leads to electricity savings of about 4.5% for the average household in our sample. This figure is rather at the lower end of savings rates found in the literature. While the corresponding annual electricity cost savings of around 30 € are rather modest, our findings entail that more frequent metering (and billing) – the latest proposal by the EU commission for the new directive on energy efficiency requires monthly billing – effectively reduces electricity consumption. Further, based on additional quantile regressions, we find statistically significant feedback effects on electricity consumption for about half the households, i.e. those in the 30th to 70th percentile of electricity consumption. Low consumption households may already have exhausted (short term) potentials to reduce electricity use. High consumption households may have little motivation to save electricity because of attitudes or individual and social norms, or because electricity costs are a small share of household income. Additional research would have to be carried out to corroborate these conjectures. Nevertheless, our findings cast doubt on the effectiveness and efficiency of regulation rendering smart meters mandatory for all households or for households with very high electricity consumption such as in the German Energy Law. Finally, controlling for observed heterogeneity of households choosing between web-based and written feedback, we found no evidence for differences in the effectiveness of feedback types.

When interpreting the results it should be kept in mind that we have no indication of whether the calculated savings made in response to feed-back will persist over time, since no data was collected beyond the field trial period. Thus, future research could take into account that the impact of feedback effects may change over time. Also, our econometric analysis does not take into account how households use the information provided by the web-portal or by postal mail. Hence, rather than using dummies to capture feedback on electricity consumption, more sophisticated indicators could be employed. Such indicators may reflect the intensity of use (e.g. frequency of clicks on web-portal), the types of information acquired (on the web-portal) or recipients' assessment of the usefulness and quality of the information provided. Finally, evaluating the full impact of the regulation on smart metering should include a comprehensive analysis of the effects of information feedback and of changes in the tariff structure on the load pattern, as well as associated system-wide benefits, including reduced meter reading costs, faster outage detection, enabling of “smart homes” and improved load management, or reductions in infrastructure needs (e.g. Hackbarth & Madlener 2008; Faruqui, Harris & Hledik 2010).

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