Effects of feedback on residential electricity demand

Joachim Schleich

Grenoble Ecole de Management, Grenoble, France

Fraunhofer ISI, Karlsruhe, Germany

e-mail: joachim.schleich@grenoble-em.com;

Marian Klobasa, Fraunhofer ISI, Karlsruhe, Germany;

Sebastian Gölz, Fraunhofer 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. About half of these households received feedback together with information about electricity-saving measures (pilot group), while the remaining households served as a control group. 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, which is at the lower end of the savings typically found in the literature. Our 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. Last but not least, 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.

Keywords: Smart metering, feedback, household electricity consumption

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 EU Member States may decide on their own implementation strategies. Consequently, Member States have taken different routes in terms of timing and technology regulation. For example, Sweden has already almost completed the roll-out, while in Austria implementation of smart meters has started only recently. In 2010 a roadmap for Smart Grids in Austria has been published by major stakeholders (Lugmaier et al. 2010). Furthermore a cost-benefit analysis suggests that penetration rates of up to 95 % are cost effective in Austria (PWC, 2010). So far however, only few utilities have installed smart meters in Austria, postponing further action until federal regulation is in place.

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. EU and subsequent national regulations also require electricity providers to offer optional tariff structures, where tariffs vary either by time or by load since late 2010. Time of use tariff structures which result in higher marginal costs for electricity consumption during peak periods compared to off-peak periods are expected to shift consumption to off-peak periods.

Since so far only few programs involving feedback on electricity consumptions have been implemented and evaluated in Europe, the literature has largely focussed on applications in the US and Canada. Recent reviews report electricity savings in the ranges of 5-15% (Darby 2006, Fischer 2008, Ehrhardt-Martinez et al. 2010), but these estimates tend to be based on studies with small sample sizes. Lower effects are estimated by Matsukawa (2004) for Japan (1.5%) and by Gleerup et al. (2010) for Denmark (3%). This wide range of estimated effects may, among other things, be explained by different evaluation methodologies (e.g. ex-ante versus ex-post evaluation, controlled experiment versus before-after comparison of participants' electricity consumption, definition of control and treatment groups, estimation procedure), by different time frames (long-run versus short run-effects), or to which extent the analyses account for moderating factors and covariates such as energy prices, household socio-economic characteristics, or the appliance stock. The effectiveness of feedback information also depends on the type of feedback provided (Fischer 2008, Darby 2010, Ehrhardt-Martinez et al. 2010). Accordingly, successful feedback schemes allow the user to choose from several options, involve interactive elements, provide feedback over a long time and comparative information on past electricity consumption (benchmarking), at frequent intervals (more often than monthly), at an appliance-specific level, and in real time rather than after consumption occurs. Abrahamse and Steg (2005) point out that feedback is more effective when combined with other strategies, such as providing information on energy-efficient measures.

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 households 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. For example, in Germany implementation of smart meters will only be mandatory for households whose annual electricity consumption exceeds 6000 kWh (EnWG 2011). Finally, we test whether web-based feedback and written feedback are equally effective. To do so, household electricity consumption is estimated econometrically, controlling for a wide range of socio-economic factors as well as the household appliance stock. Our estimation procedure on the effectiveness of feedback type allows for nonrandomized treatment and for observed heterogeneity which otherwise may bias parameter estimates.

The remainder of this paper is organised as follows. Section 2 describes the field trial in detail and the feedback provided. The statistical framework is developed in Section 3. Data and variables are described in section 4. Section 5 presents the results of the econometric analyses. The concluding section summarizes and discusses the main findings and also indicates further research needs.

2. DESIGN OF THE FIELD TRIAL

Recruiting the participating households for the field trial took place in three steps. In a first step, an initial pool of potential participants was identified by the utility and these were then randomly assigned to a pilot group and a control group. In a second step, written invitations and information about the experiment were sent out to the pilot group households. Control group households also received a written invitation to take part in a study about energy consumption, but were not informed that they were part of a feedback experiment. In the third step, all the households were contacted once again by phone to invite them to take part and to record their binding participation and acceptance of a privacy agreement.

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. Computer-assisted telephone interviews were conducted with households in both groups, relying on standardized questionnaires about household appliance stock and socio-demographic characteristics.

2.1 Feedback

The research concept recognizes that smart metering technology is part of a socio-technical system (Emery and Trist 1965). As a consequence, the information provided and specifically displayed by feedback systems only leads to action by households if it can be socially and cognitively integrated into the everyday routines of the feedback recipients. Following Kempton and Layne (1994), households are assumed to best diagnose energy use and decide on energy saving measures if the feedback information is tailored appropriately to their abilities and needs. In order to better integrate the perspectives of the consumers in designing appropriate feedback options, 76 qualitative interviews were conducted prior to the field phase. The findings of these interviews suggest that it may not be useful to provide information about real-time electricity consumption because individuals are unable to adequately process and interpret the data. Electricity consumption information should be based on manageable time intervals, instead. Likewise, the presentation of information such as electricity consumption over time in the form of graphs can help to induce practical changes in consumers' habits. Providing only a few but carefully selected and well-designed data illustrations is considered to be most effective. As a result of these qualitative interviews, two types of feedback instruments 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 transparent information on electricity consumption patterns and on practical measures to save electricity. It does so by providing information on energy consumption and energy costs using temporally aggregated data and allows the user to compare energy consumption over time (months, days, hours) and to identify consumption patterns by load types. Users could choose their favourite 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 could 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 €). Finally, intermittent loads and (estimated) base loads (i.e. refrigerators and freezers) were displayed as shares of the total electricity consumption.

Several components have been introduced to increase the motivation for and practical knowledge of energy saving measures. The screen in the web portal was divided into several areas for navigation, presenting consumption data and to provide a link to the energy saving recommendations. A graphical teaser was used to attract attention to practical information, relying on adapted traffic signs to provoke surprise and curiosity. To increase motivation for energy savings, users were also able to participate in a game and eventually become "energy saving king/queen”. Hints on how to save energy were presented by room type (kitchen, living room...) and according to the typical household appliances. Curious individuals were given the chance to browse additional information on energy-saving options under the category “Did you know …?. Finally, the web portal offered a function to download data and provided contact information for further inquiries.

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.

The wide range of possibilities of analysing household energy consumption patterns, however, does not allow changes in energy use to be traced back to individual behavioural or investment decisions. Also, it was not feasible to involve energy experts in the field trial, which could have offered advice to help consumers understand the information on energy use and energy saving measures.

2.2 Technical implementation

The technical metering system provided hourly consumption data, which could be read at the end of each day by a remote system. Since the meters were usually installed in a cellar room, the display was not visible to the consumer without additional effort. Data on electricity consumption was stored in the meter and transferred once a day to a data concentrator via a narrow band power line communication. The data concentrator collected the data from several meters and transferred them twice a day to the data server of the utility. These data were then transported via automated data export to the project server platform. A server platform was set up, which hosted the web portal and generated the monthly printed feedback information as PDF-documents from the portal. The utility sent these documents to those pilot households which had chosen to receive feedback by post.

All the participants in the pilot group who chose the web portal option received log-in and access information by post. Participants who chose the written feedback option received feedback information by post after the first month of the trial. Consequently, possible feedback impacts can only be expected from the second month onwards, i.e. between the eleven month span of January and November 2010.

3. STATISTICAL MODELS

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] 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.

We employ two types of models. The *feedback model* estimates the effect of receiving feedback on energy consumption and is also used to analyse 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.

3.1 Feedback model

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

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

1 In the evaluation literature, this assumption is also termed "conditional independence" or "unconfoundedness" (see Imbens 2004). It allows any difference between the treatment and the control group to be attributed to the feedback provided.

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, equation (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 quantile regression (Koenker 2005), which is nonparametric and involves estimating conditional quantiles as functions of X. That is δ (as well as β) may differ across quantiles.

3.2 Feedback type 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.

$$Y = X\beta + I_W\delta + \varepsilon \, , \tag{2}$$

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

$$\begin{aligned} &I_W^* = \gamma Z + \mu \text{, with} \\ &I_W = 1 \text{ if } I_W^* \geq 0 \text{ (web feedback))} \\ &I_W = 0 \text{ if } I_W^* < 0 \text{ (post feedback),} \end{aligned} \tag{3}$$

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. According to the conventional assumptions $P(I_W = 1) = \Phi(\gamma Z)$ and $P(I_W = 0) = 1 - \Phi(\gamma Z)$, where $\Phi(\bullet)$ denotes the normal cumulative density function. Typically, the error components are assumed to be bivariate normal with mean zero and covariance matrix $\Sigma = \begin{bmatrix} \sigma_\varepsilon^2 & \rho \\ \rho & 1 \end{bmatrix}$.

Estimating equation (2) yields an estimate of the parameter δ, i.e. the effect of receiving feedback on electricity consumption via web access rather than by post.[2] Since I_W may be endogenous in equation (2), estimating the model requires controlling for a potential endogeneity bias induced by non random choice of feedback type.[3] In other words, unless ε and μ are independent (ρ = 0), the conditional mean of ε in equation (2) is not zero. The model may be estimated by a standard Heckman-type two step estimator, employing appropriate instruments. In the first step the endogenous treatment equation (3) is estimated first via a Probit model and results are used to predict the probability of each household being in the group with web-based feedback. In the second step, a transformation of this probability – the estimated inverse Mill's ratio – is included as an additional explanatory variable in equation (2) to correct for a potential (omitted variable) bias. Hence, in the second stage household electricity consumption is estimated as

$$Y = X\beta + I_W\delta + \rho\hat{\lambda} + \varepsilon \ , \qquad (4)$$

where $\hat{\lambda}$ is the estimated inverse Mills ratio, defined as

$$\hat{\lambda} = \frac{\hat{\phi}(\gamma Z)}{1 - \hat{\Phi}(\gamma Z)}, \qquad (4)$$

2 Note that equation (2) is essentially a switching regression equation with separate outcome models for households receiving feedback via web access and by post.

3 Unlike in typical selection models, where the dependent variable is only observed for a restricted sample, the dependent variable is available for all observations in our treatment model.

and where $\phi(\bullet)$ is the density function of the normal probability distribution. Failure to reject the null hypothesis that ρ is statistically zero presents evidence that household participation in the web group satisfies the conditional exogeneity assumption.[4] Hence, it is plausible to consider web group participation as random, conditional on observed characteristics. The model may then be estimated without the assumption of joint normality on the error components by applying propensity scores (Rosenbaum and Rubin, 1983). Specifically, the propensity scores from the Probit specification in (3) may be used to calculate weights for each observation

$$\varpi = \frac{I_W}{\hat{e}(Z)} + \frac{1-I_W}{1-\hat{e}(Z)}, \qquad (5)$$

with $e(Z) = P(I_W = 0 \mid Z)$. Thus, a household receives a larger weight if it is less likely to be in the web group conditional on observables. The electricity consumption equation (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. Price, 2005).[5]

4. DATA AND VARIABLES

Data on socio-economic and technical characteristics, which are used in the econometric estimations, were taken from the survey at the beginning of the field phase. Eventually, after correcting for households which moved during the time or which encountered insurmountable technical problems data was available for 1525 households, of which 775 were pilot group households and 750 control group households.

4 This condition has also been referred to as selection on observables (Imbens, 2004) and is analogous to the standard “conditional independence” or “unconfoundedness” assumption (Rosenbaum and Rubin 1983) in the evaluation literature.

5 Alternatively the joint distribution of the Probit model capturing participation in the web access group (equation (3)) and the electricity consumption equation (2) could be estimated via maximum likelihood methods. In this case though, identification hinges alone on the assumption of normality.

4.1 Dependent variable

The dependent variable used in the econometric analysis is annual household electricity consumption (*electricity*). That is, 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.

Variables reflecting household characteristics include income, education level and the number of persons in the household by age groups. Household income groups were categorized in three groups. The variable *income* 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 €, respectively. The level of education is represented by an indicator variable which takes on the value of 1 if the survey respondent experienced at least 10 years of education. Since electricity consumption may differ by a person's age 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*) also enters the set of explanatory variables.

Last, but not least, 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.

Using cross-section rather panel data does not allow analysing the effects of temperature on electricity consumption. While controlling for climate-related variables is relevant for analysing electricity consumption in countries with a high heating or cooling demand satisfied by electricity such as in Sweden, Norway or France (for heating) or Southern European countries or large parts of the US (for cooling), electricity is hardly used for heating or cooling purposes in Austria. In fact, no households using electricity for heating are included in our sample, and the existence of air conditioners is controlled for.

Data on all the explanatory variables were available for 1070 households, of which 601 (or 56%) belong to the pilot group. Table 1 provides descriptive statistics of the variables used in our econometric analyses.[6] 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.

6 For example, about 16% of households failed to report information on income and had to be excluded from the econometric analysis. To abstract from "unreasonable" consumption levels in our final sample, annual electricity consumption was trimmed to the range of 700 kWh to 8000 kWh, resulting in a loss of about 3% of observations.

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

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 feedback choice equation (i.e. endogenous treatment equation 3) but not in the electricity consumption equation (2).

4. RESULTS

We first present the results for the feedback model, starting with the findings from the ordinary least squares (OLS) regressions. Then results from the quantile regressions are presented, allowing parameters do differ across electricity consumption levels.

4.1 Feedback effects

Results from estimating the electricity consumption equation (1) via OLS are displayed in Table 2. 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. Robust standard errors appear in parentheses.

The (corrected) R^2 of 42.23% suggests that the model explains a fairly large share of the variation in household electricity consumption. Most notably, the parameter estimate associated with *smart* is significant at p=0.05. The point estimate suggests that the feedback provided under the smart metering programme results in electricity savings of around 154 kWh (the 90% confidence interval for δ ranges from -39 kWh to -270 kWh), which translates into savings of 4.51% of total annual electricity consumption of the mean household in the pilot group[7]. Electricity consumption positively depends on the number of household members in each *age* group, is statistically significant for all age groups but *age5*, and tends to increase with age[8]. Larger residences are associated with higher electricity consumption of just below 6 kWh per year and m^2. Higher *income* is associated with higher electricity consumption (p=0.05). Arguably, the effects of income on electricity consumption are to a large extent also reflected in the size of the residence and the appliance stock.[9] Parameter estimates of appliances exhibit the expected positive sign, are statistically significant (except for *dishwasher*) and take on reasonable values. Higher *education* is associated with lower electricity consumption, but is not statistically significant at conventional levels.

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7 Here, average electricity consumption of a pilot household was calculated as the average level of the observed consumption levels (3267 kWh) corrected for the effects of feedback (154 kWh).

8 Note that even though the point estimates differ across age groups, they cannot all be distinguished from a statistical perspective. Additional analysis using an aggregate variable for the number of household members rather than six different age groups produced very similar results as the ones presented in Table 2. The point estimate for the electricity consumption of an average household member in this case is 291 kWh.

9 Tests for collinearity based on variance-inflation factors (VIFs) suggest, though, that the explanatory variables are not highly inter-correlated. All VIFs are below 3.

Table 2. OLS results of electricity consumption equation

Smart	-154.47	**
	(69.90)	
Age6	118.05	
	(77.99)	
Age17	276.95	***
	(63.08)	
Age30	356.76	***
	(71.59)	
Age45	531.02	***
	(82.75)	
Age60	506.49	***
	(79.82)	
Age60plus	557.04	***
	(74.27)	
Floorsize	5.81	***
	(1.04)	
Income	103.19	**
	(52.11)	
Education	-89.11	
	(72.22)	
Fridge	328.14	***
	(101.90)	
Dryer	434.89	***
	(75.56)	
Freezer	217.57	***
	(68.42)	
Dishwash	44.74	
	(105.29)	
Boiler	304.14	***
	(61.79)	
TV	159.20	***
	(49.06)	
Computertime	39.00	***
	(11.40)	
Appliances	65.29	***
	(19.35)	
Constant	-53.17	
	(164.55)	
R^2 (adjusted)	0.4330	
Sample size	1070	
Smart in % of consumption	4.51%	

Note: *** indicates significance at the p=0.01 level, ** indicates significance at the p=0.05 level and * indicates significance at the p=0.1 level in an individual two-tailed t-test

Table 3 presents the findings of our simultaneous quantile regressions for the 1st to 10th deciles (together with bootstrapped standard errors)[10]. Accordingly, for the 30th to 70th percentiles, feedback on electricity consumption is statistically significant and effects are highest in absolute terms and as a share of electricity consumption. For households below the 30th and above the 70th percentiles, however, feedback appears to have no effect on electricity consumption. While the point estimates differ across the 30th to the 70th percentile, from a statistical point the parameters cannot be distinguished (e.g. the confidence interval for *smart* for the 30 percentile ranges from - 39 kWh to - 260 kWh). In terms of sign and significance levels, the findings for the other parameter estimates in Table 3 in general are also quite similar to those in Table 2. Interestingly, income is only statistically significant for the lowest three deciles. 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.

10 We use observed consumption levels during the pilot phase to calculate the percentiles. Hence, consumption levels used are net of any feedback effects.

Table 3. Quantile regression results of electricity consumption equation

	q10		q20		q30		q40		q50		q60		q70		q80		q90	
Smart	-15.19		-24.97		-149.43	***	-174.27	**	-125.38	**	-107.37	*	-134.01	*	-69.73		-123.05	
	(72.89)		(54.44)		(56.28)		(68.98)		(62.29)		(59.22)		(71.07)		(75.09)		(176.33)	
Age5	125.93	*	32.24		79.59		138.36		181.72	**	121.11		158.90		246.69	*	209.17	
	(73.32)		(77.44)		(98.71)		(108.91)		(87.83)		(102.03)		(141.07)		(149.73)		(167.31)	
Age17	167.76	**	206.22	***	232.13	***	311.42	***	347.76	***	351.89	***	476.12	***	477.57	***	339.08	***
	(75.19)		(76.12)		(74.49)		(63.58)		(77.97)		(79.21)		(89.64)		(86.92)		(101.64)	
Age30	354.06	***	319.08	***	382.28	***	388.68	***	349.63	***	337.26	***	339.92	***	299.59	**	393.67	***
	(105.70)		(86.80)		(84.70)		(77.54)		(85.55)		(84.23)		(104.96)		(122.01)		(148.83)	
Age45	479.74	***	428.23	***	509.56	***	436.40	***	462.46	***	511.10	***	456.32	***	395.41	**	613.10	***
	(93.69)		(82.03)		(98.98)		(95.83)		(87.04)		(93.17)		(111.09)		(160.76)		(207.40)	
Age60	357.45	***	440.85	***	524.65	***	506.23	***	510.53	***	566.11	***	469.99	***	498.02	***	700.84	***
	(122.46)		(95.62)		(83.21)		(65.18)		(67.38)		(79.29)		(102.40)		(113.29)		(151.42)	
Age60plus	468.65	***	453.17	***	579.34	***	554.52	***	568.28	***	562.63	***	549.32	***	651.97	***	774.08	***
	(97.36)		(66.44)		(82.13)		(88.22)		(85.03)		(85.49)		(91.73)		(161.03)		(146.10)	
Floorsize	4.49	***	5.63	***	5.73	***	6.62	***	6.20	***	7.54	***	5.79	***	8.18	***	9.87	***
	(1.63)		(1.31)		(1.05)		(0.93)		(1.45)		(1.92)		(2.21)		(2.13)		(2.37)	
Income	165.87	**	155.33	***	91.82	*	73.89		57.86		31.51		70.09		84.43		-95.68	
	(65.42)		(50.58)		(47.23)		(59.26)		(65.80)		(77.26)		(87.28)		(110.70)		(151.19)	
Education	-74.36		-80.99		-109.21		-126.08		-144.43		-93.86		-122.06		-19.01		-89.05	
	(75.79)		(102.73)		(104.41)		(123.04)		(96.13)		(94.58)		(99.24)		(138.06)		(158.69)	
Fridge	222.01	*	282.08	***	289.33	**	298.75	**	374.55	***	330.23	***	421.94	***	431.09	***	595.12	***
	(134.78)		(100.66)		(117.07)		(131.13)		(134.23)		(126.21)		(130.08)		(142.89)		(163.50)	
Dryer	391.31	***	348.75	***	381.78	***	354.72	***	336.24	***	330.71	***	448.55	***	471.13	***	500.52	***
	(106.43)		(73.30)		(48.31)		(70.23)		(90.98)		(109.11)		(113.35)		(112.85)		(111.67)	
Freezer	77.79		181.79	***	213.13	***	195.80	**	183.97	**	209.20	**	232.40	**	205.33	**	204.89	
	(110.12)		(67.83)		(64.94)		(83.61)		(85.57)		(92.73)		(94.86)		(92.40)		(113.50)	
Dishwasher	154.31		47.81		82.56		107.17		102.99		102.84		43.78		0.48		-444.94	
	(99.97)		(83.69)		(81.40)		(91.38)		(110.47)		(129.37)		(181.99)		(165.13)		(359.31)	
Boiler	137.45	*	117.16	*	216.66	***	285.68	***	353.17	***	383.60	***	440.76	***	464.49	***	435.29	***
	(79.03)		(70.91)		(69.66)		(64.40)		(54.01)		(43.89)		(76.75)		(79.96)		(106.32)	
TV	82.21		99.12	*	146.37	***	133.33	**	201.09	***	206.94	***	216.19	***	201.05	***	151.28	
	(79.86)		(50.67)		(56.10)		(54.40)		(60.49)		(62.88)		(55.34)		(64.99)		(69.69)	
Computertime	43.10	***	32.32	***	34.39	***	49.55	***	54.67	***	40.74	***	39.38	***	44.17		75.90	**
	(10.34)		(8.38)		(9.45)		(16.12)		(10.56)		(12.04)		(14.96)		(29.71)		(31.31)	
Appliances	27.02		49.60	***	60.48	***	54.62	***	72.87	***	87.38	***	113.72	***	94.42	***	146.42	***
	(22.85)		(17.30)		(14.51)		(12.93)		(19.94)		(18.04)		(21.19)		(31.33)		(37.98)	
Constant	-630.05	***	-538.17	***	-492.08	***	-282.09		-306.78	*	-251.36		-136.91		46.88		555.15	
	(228.88)		(164.85)		(153.84)		(178.63)		(185.21)		(161.33)		(197.71)		(182.46)		(402.64)	
R^2 (pseudo)	0.2241		0.2563		0.2663		0.2718		0.2761		0.2814		0.2800		0.2820		0.2830	
Sample size	1070		1070		1070		1070		1070		1070		1070		1070		1070	
Smart in % of percentile consumption	-0.90%		-1.18%		-5.75%	***	-5.97%	**	-3.86%	**	-3.03%	*	-3.37%	*	-1.59%		-2.36%	

Note: *** indicates significance at the p=0.01 level, ** indicates significance at the p=0.05 level and * indicates significance at the p=0.1 level in an individual two-tailed t-test

4.2 Feedback types

To explore whether web-based feedback and written feedback are equally effective, we restrict our analysis to the 601 households in the pilot group. Of those 276 (i.e. 46%) chose to receive feedback via access to the internet portal. The two stage procedure described in Section 3 is employed to estimate equations (2) and (3). The number of *computers* serves as an instrument in the binary decision to chose web-based feedback rather than feedback by post[11]. Estimation results appear in Table A1 in the Appendix. The findings for the Probit selection equation are intuitive and suggest that households with members older than 45 or 60 years of age are less likely to chose the web-based feedback. On the other hand, higher household income, higher education, owning a TV, computer running time, and – notably – the number of computers (p=0.01) - increase the chances of a household choosing web-based rather than post feedback. The parameter estimates of the electricity consumption equation are quite similar to those presented in Table 2 and Table 3. The coefficient associated with web-based feedback is not statistically significant. However, we fail to reject the null hypothesis that ρ (or the Mill's ratio) is zero. It therefore seems plausible to consider feedback choice as random conditional on observed characteristics. As outlined in Section 3 we therefore estimate the consumption equation employing propensity scores as weights.

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11 Finding appropriate instruments is always challenging in these types of analyses. Intuitively though, *computers* seems plausible, i.e. households with (more) computers are more likely to select web-based feedback, ceteris paribus. To further corroborate our choice of instrument (i.e. our identification procedure), we also ran a regression including computers as an additional explanatory variable in the electricity consumption equation. The p-value associated with the parameter estimate of 0.343 supports our approach to include computers as an explanatory variable in the equation modeling feedback choice, but not in the electricity consumption equation.

Table 4. Propensity score weighted OLS results of electricity consumption equation

Web	-4,35	
	(132,31)	
Age5	282,68	**
	(139,31)	
Age17	354,20	**
	(161,48)	
Age30	576,63	***
	(140,43)	
Age45	710,08	***
	(169,99)	
Age60	631,64	***
	(128,30)	
Age60plus	690,46	***
	(115,98)	
Floorsize	3,43	*
	(1,89)	
Income	128,42	
	(94,79)	
Education	-213,43	
	(131,90)	
Fridge	460,66	**
	(190,88)	
Dryer	255,42	*
	(142,51)	
Freezer	196,52	
	(180,68)	
Dishwasher	405,52	*
	(220,12)	
Boiler	309,01	***
	(102,97)	
TV	230,66	**
	(90,20)	
Computertime	57,68	***
	(18,53)	
Appliances	16,09	
	(29,41)	
Constant	-481,46	
	(317,25)	
R^2 (adjusted)	0.4459	
Sample size	601	

Note: *** indicates significance at the p=0.01 level, ** indicates significance at the p=0.05 level and * indicates significance at the p=0.1 level in an individual two-tailed t-test

Table 4 displays the parameter estimates together with robust standard errors for the propensity score-weighted model. Most notably, the parameter estimate associated with the indicator variable for web-based feedback *web* is not statistically significant. Therefore, our findings do not provide support for the hypothesis that there are differences in the impact of feedback by type. Also note that the findings for the parameter estimates associated with the other control variables for the pilot group households in Table 4 are generally similar to those found for the full sample in Table 2 and Table 3.

4. CONCLUSIONS

In order to evaluate the effect of feedback information in a recent smart metering pilot study in the city of Linz in Austria, we econometrically estimated household electricity consumption. The results of our cross-section OLS analysis suggest that feedback information on electricity consumption leads to electricity savings of about 4.5 % for the average household in our sample. While the corresponding annual electricity cost savings of around 30 € are rather modest, our findings entail that more frequent metering (and billing) – the proposal by the EU commission for the new directive on energy efficiency requires monthly billing (EC 2011b) – effectively reduces electricity consumption.

The findings from our quantile regressions imply that in our sample, about half the households do not respond to feedback on 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[12]. Hence, our findings cast doubt on the effectiveness and efficiency of regulation rendering smart meters mandatory only for households with very high electricity consumption such as in the German Energy Law (EnWG 2011)[13]. In fact our findings suggest that smart metering is most effective for the 30th to 70th percentiles. 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.

12 In fact, the corellation between income and the income share of electricity consumption is negative (at $p<0.01$).

13 The suggested threshhold in EnWG 2011 of 6000 kWh per year corresponds to the 95 percentile in our sample.

While our estimated electricity savings (in percentage terms) are in the range of a recent study for Denmark (Gleerup et al. 2010)[14], they are at the lower end of those surveyed by Darby (2006) or Ehrhardt-Martinez et al. (2010). It should be noted, however, that our econometric analysis does not allow us to disentangle the effects of feedback about electricity consumption and from the effects of information about electricity-saving measures. In addition, when comparing results across studies, it should be kept in mind that feedback instruments differ significantly. According to Darby (2006), the more effective feedback programmes include direct feedback measures such as self-meter reading, direct displays (learning by looking or paying), interactive feedback (e.g. via PCs), ambient devices (e.g. an alarm or a flashing light if electricity consumption exceeds a certain limit), energy advice (via audits), or dynamic (time-of-use) pricing. Likewise, neither feedback type allowed for social comparisons of conservations efforts such as benchmarking of electricity use. Such norm-based feedback systems have proven effective, at least in the short run (Ayres et al. 2009). Nevertheless, our findings cast some doubt as to whether smart metering will contribute electricity savings of 10 % and more towards reaching medium- and long-term energy efficiency and climate policy targets, as expected, for example, by the European Commission (2011).

Further, we have no indication of whether the calculated savings made in response to feedback 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. On the one hand, feedback effects could be short-lived because household behaviour returns to long-term habits after a certain time. For example, van Dam et al. (2010) find that the initial savings of 7.8% in electricity consumption after 4 four months could not be sustained in the medium to long term. On the other hand, if information feedback results in a permanent change in habits, these effects could

14 While the control group in our study includes only households which were not exposed to any type of feedback, the control group in Gleerup et al. (2010) also includes households which had access to a web portal, which was the standard service in the area. Hence, the pilot (or treatment) group in Gleerup et al. (2010) consists of households receiving feedback by mail or short message service (sms). Unlike in our study though, the pilot group households in Gleerup et al. (2010) were not exposed to any additional brochures on how to save electricity, etc.

have a long-term impact on energy use.[15] Similarly. in the longer run, the effects of changed investment behaviour (e.g. purchasing more efficient appliances) in response to feedback information may materialize. 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 and Madlener 2008. Faruqui et al. 2010).

15 For residential water use, Ferraro et al. (2011) show that norm-based feedback exhibits persistent effects, but only if the feedback involves social comparisons.

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Table A 1. Results of two step treatment model

	Web access		Electricity consumption	
Age5	-0.03		252.82	**
	(0.13)		(113.70)	
Age17	-0.14		309.15	***
	(0.09)		(74.30)	
Age30	0.07		351.07	***
	(0.11)		(97.39)	
Age45	-0.16		500.09	***
	(0.13)		(102.75)	
Age60	-0.29	**	534.66	***
	(0.12)		(104.70)	
Age60plus	-0.40	***	649.44	***
	(0.12)		(123.15)	
Floorsize	0.00		5.50	***
	(0.00)		(1.10)	
Income	0.34	***	15.60	
	(0.09)		(102.96)	
Education	0.37	***	-311.38	**
	(0.12)		(132.71)	
Fridge	0.01		299.67	***
	(0.13)		(105.14)	
Dryer	0.07		363.18	***
	(0.12)		(100.06)	
Freezer	0.01		121.82	
	(0.11)		(88.49)	
Dishwasher	0.13		244.42	*
	(0.17)		(137.12)	
Boiler	-0.06		316.62	***
	(0.10)		(82.45)	
TV	0.12	*	91.82	
	(0.07)		(63.22)	
Computer	0.30	***		
	(0.08)			
Computertime	0.03	**	48.01	***
	(0.02)		(15.49)	
Appliances	0.04		30.77	
	(0.03)		(22.79)	
Web			833.89	
			(592.66)	
Constant	-1.55	***	-97.58	
	(0.26)		(215.06)	

	Web access	Electricity consumption
Rho	-0.448	
Lamda	-502.69	
	(360.68)	
Wald χ^2 (35)	467.68	***
Sample size	601	

Note: *** indicates significance at the p=0.01 level, ** indicates significance at the p=0.05 level and * indicates significance at the p=0.1 level in an individual two-tailed t-test