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Smart metering in Germany and Austria – results of providing feedback information in a field trial

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Abstract

In this paper, we present the results from a field study on smart metering in Germany and Austria, focusing on the effects of providing feedback information on average electricity consumption. Econometric analyses are applied using a cross section of observations for more than 2000 households served by nine utilities. More than half of these households received feedback on their electricity consumption together with information about electricity saving measures (pilot group). The remaining households served as a control group. To evaluate the impact of feedback information, we econometrically estimated household electricity consumption. Explanatory variables include a wide range of socio-economic factors (income, education, age, household size, age composition, etc.) as well as the household appliance stock (large appliances, boiler, computers, TV, etc. ...). The results suggest that the feedback provided under the smart metering programme results in electricity savings of around 3.7%.

Keywords

Smart metering, feedback, household electricity consumption

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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. Among other things, 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 2010, 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 Germany, various smart metering concepts are now being tested in several pilot projects. Focussing on setting minimum standards, smart metering regulation in Germany relies on market forces to develop suitable meter systems, associated products and services. In particular, regulations in Germany allow power users to choose their preferred Metering Point Operator (MPO) or Measuring Service Provider (MSP), respectively. While current metering and billing practices mean that power users receive only limited information about their energy consumption - typically once a year - more frequent and timely feedback and the search for the most appropriate MPO are expected to raise awareness and improve information about energy use patterns and energy costs. This kind of feedback is expected to help overcome information-related barriers and lead to lower energy use. The regulations further require electricity providers to implement optional tariff structures which can be varied either by time or by load for their customers until the end of 2010. 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.

Recent reviews of (the few) studies evaluating the effects of feedback information on electricity consumption report savings in the ranges of 5-15% (Darby 2006, Ehrhardt et al. 2010) and 5-12% (Fischer 2008). 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) 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). In her review of the literature, Fischer (2008) concludes that successful feedback schemes allow the user to choose from several options, involve interactive elements, provide feedback over a long time at frequent intervals (more often than monthly) and at an appliance-specific level and provide comparative information on past electricity consumption (benchmarking). Abrahamse et al. (2005) point out that feedback is more effective when combined with other strategies, such as providing information on energy-efficient measures. Hence, while regulation on smart metering may create markets and marketing opportunities for MPOs and utilities and lead to a range of new products and services, profitable products and services may have to be tailored to the specific needs of clustered target groups and account for social and socio-economic circumstances.

The German research project Intelliekon (Sustainable energy consumption in households through intelligent metering, communication and tariff systems) was launched in 2008 with the objective of offering insights into potential target groups, their needs and preferences concerning energy consumption information and their energy behaviour while using feedback information based on smart metering. Participating households were split in two groups - households in the pilot group received information on the energy consumed and energy saving measures, while households in the control group did not receive such information. In this paper, we present the first results from this study on feedback-related electricity savings. To assess the impact of feedback information, household electricity consumption was estimated econometrically, controlling for a wide range of socio-economic factors as well as household appliance stock. We also tested whether differences in household characteristics between the pilot group and the control group resulted in biased parameter estimates (sample selection bias).

The remainder of this paper is organised as follows. Section 2 describes the field trial in detail and the types of feedback provided. Data, econometric analyses and results are given in Section 3. The concluding section summarizes and discusses the main findings and also indicates further research.

2 Design of the field trial

The field experiment in the Intelliekon project was conducted in eight German municipalities located in five federal German states: Celle, Hassfurt, Kaiserslautern, Krefeld, Münster, Oelde, Schwerte and Ulm. Besides the eight German utilities, a utility from Austria (Linz) also participated in Intelliekon. Recruiting the participating households took place in three steps. In a first step, an initial pool of potential participants was identified by the respective utilities 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 in November 2008. 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 the privacy agreement. Hence, participation may not be completely random. Households in the pilot group also chose their preferred feedback mode, i.e. access to a web portal or written feedback by mail (i.e. by post).

The field work started between May and July of 2009 in every municipality but Münster. Technical reasons delayed the start in Münster until November 2009. Since the field phase ended in November 2010 for all municipalities, every household participated for at least 12 months. The pilot households could access a web portal or receive written feedback. The electricity consumption of households in both the pilot group and the control group was recorded. During the field experiment, the households of the pilot group were interviewed three times: at the beginning, in the middle and at end of the field phase. The households of the control group were interviewed at the beginning and at the end. These interviews were computer-assisted telephone interviews, relying on standardized questionnaires about household appliance stock, attitudes and socio-demographic characteristics.

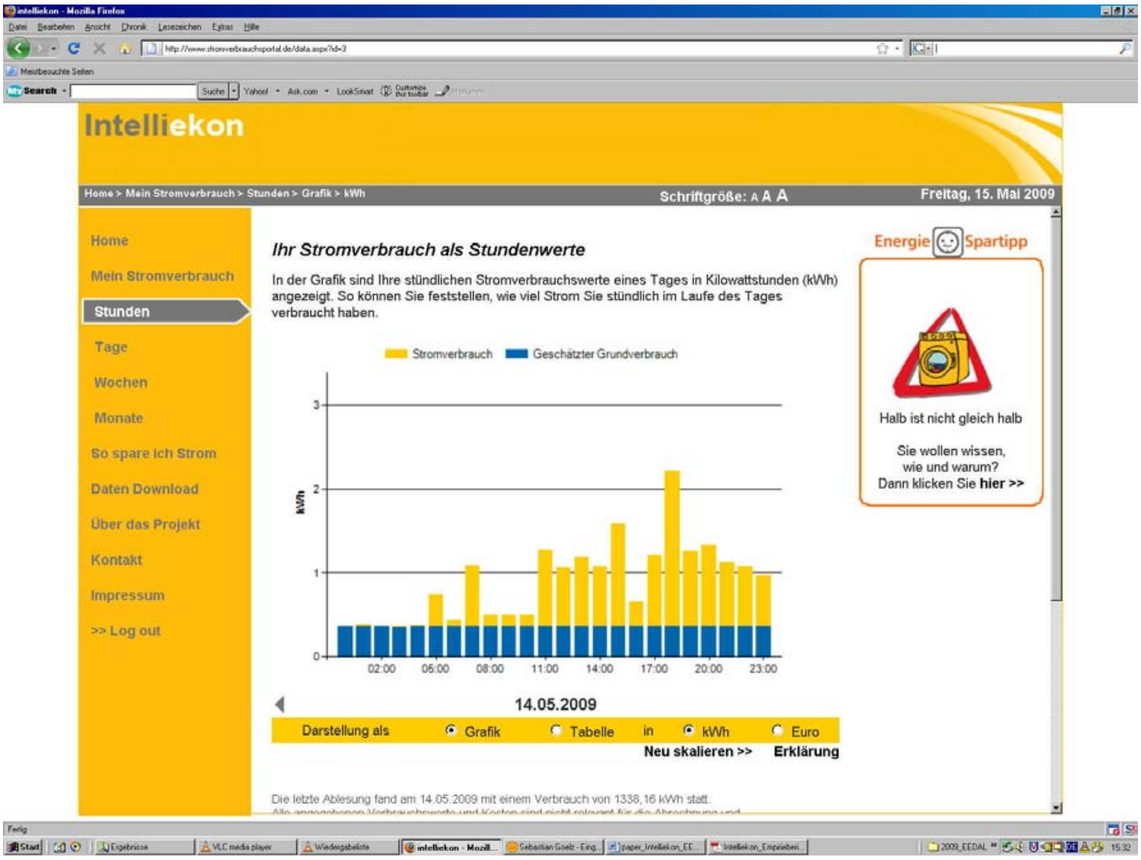
2.1 Feedback

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. The development of the feedback instruments in the project followed the paradigm of Kempton and Layne (1994), who postulate that both consumers and institutions (utilities, research institutes) have specific strengths in their ability to analyse energy consumption. Kempton and Layne (1994) put the diagnosis and decisions about actions in the hands of the households, since households can be assumed to best know their options to act. These actions should, in turn, be based on information (e.g. energy use) provided by the institutions. This paradigm was extended within the project under the hypothesis that consumers can only exploit their advantage from diagnosing energy use and deciding on energy saving measures if the feedback information is tailored appropriately to their abilities and needs, framed by their social, socio-economic and cognitive setting. Thus, one task of the project was to develop suitable feedback instruments. To better integrate the perspectives of the consumers and the objectives of the utilities, 76 qualitative interviews were conducted with household members in three of the municipalities. These interviews allowed initial evidence to be gathered on various feedback options in different social groups and the needs of the users to be explored regarding the feedback instruments and feedback visualisation (Birzle-Harder et al. 2008). It became clear that it is not really useful to provide information about real-time electricity consumption because individuals may be unable to adequately process and interpret the data (Gölz and Götz 2009). Instead, electricity consumption information should be based on manageable time intervals and allow for benchmarking. 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 for the pilot group: access to a web-portal and written feedback information via mail. Systems providing instantaneous feedback on power consumption like energy clocks or mobile phone applications were not available.

2.1.1 Web portal

The web portal is 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 can 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 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 3).

Figure 1: Screenshot of the web portal feedback instrument



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. In addition, users were able to participate in a game and eventually become “energy saving king/queen”. The game was supposed to increase motivation for energy saving. Hints on how to save energy were presented by room type (kitchen, living room, ...) and according to the typical appliances of German households. 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 data download function and contact information for further inquiries.

Written feedback

The written feedback option consisted of two pages including colour-printed information on 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 for energy experts to offer advice to help consumers understand the information on energy use and energy saving measures for individual households.

2.2 Technical implementation

The technical metering systems were selected by the participating utilities and differed slightly across municipalities. All the systems fulfilled the project requirement of being able to provide hourly consumption data, which could be read at the end of each day by remote systems. Typically, the system included a smart meter which could also feature as an energy gateway and collect data from digital gas or water meters (multi utility communication). 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 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 respective utility. To allow the same feedback system in all the municipalities, the technical partner, EVB Energy Solutions, set up a server platform which hosted the web portal and generated the monthly printed feedback information as PDF-documents from the portal. Utilities then sent these documents to those pilot households in their municipality which had requested this option. The consumption data were transported via automated data export from the server of the utilities to the project server platform. Initially, the field trial was scheduled to start in April 2009 and several municipalities had the systems installed in time. In a test phase, however, it became clear that the automated data export was not reliable and data for feedback were not available from the web portal as intended. Also, not all the utilities had all the meters installed in time. Finally, for several households, meter management, data reading and data communication were not completely reliable by April 2009. As a consequence, the start of the field trial differed across municipalities. 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.

3 Data availability and econometric estimations

The availability of data on socio-economic variables and details of the household appliance stock render the collected data unique in assessing the effectiveness of feedback systems. 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. During the field trial, 38 households moved and were removed from the subsequent analyses. Data on the household cumulative electricity consumption since the start of the trial were stored in a second database. For example, the energy consumed in any given day can be calculated by simply subtracting the cumulative consumption of one day from the previous day. Since, for any given point in time, the data transmitted by the meter correctly represent the accumulated amount of energy consumed until then, missing data due to temporary system failures could be easily reconstructed by interpolation. Eventually data was available for 977 control group households and 1114 pilot group households, of which 533 pilot group households received feedback via web portal and 581 households received written feedback.

While the smart metering feedback started at different points in time, all pilot households received feedback for more than one year. Since data on electricity consumption is not sufficiently available, a difference-in-difference approach to assessing the effects of feedback on electricity consumption is not feasible as applied in Gleerup et al. (2010). Instead, our analysis is based on cross-sectional data.

3.1 Dependent variable

The dependent variable used in the econometric analysis is annual household electricity consumption.

3.2 Explanatory variables

To estimate the electricity consumption equation, we regress the dependent variable *electricity* on a set of explanatory variables characterizing the household, the appliance stock and the residence. Variables reflecting household characteristics include income[1], education level[2], number of persons in the household for the following six age groups: 0-5, 6-17, 18-30, 31-45, 46-60, > 60; floor size is included in levels and squared terms to allow for linear and non linear impacts of the size of the residence on electricity consumption; count variables indicate the number of the following electrical appliances in the household: refrigerator, dryer, freezer, dishwasher, boiler, computer, and TVs. In addition, we included a variable which sums up the number of other appliances in the household such as microwaves, play stations, or espresso machines. Dummy variables were included for the municipalities to capture municipality-specific effects on household electricity consumption. To prevent singularity of the regressor matrix, no dummy was included for Celle. Since electricity prices are the same for all the households in a municipality, prices were not included in the regression analyses. Last, but not least, a dummy titled "*smart*" is supposed to capture the effect of feedback from the smart metering programme. *Smart* takes on the value of 1 if the household receives feedback via web access or post. Hence, *smart* does not differ by type of information. All variables enter the regression equation in levels.[3] Data on all the explanatory variables were available for 1379 households.[4]

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1 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 (incl. transfer payments) is below 1500 €, between 1500 € and 2500 € and above 2500 €, respectively.

2 Represented by a dummy variable which takes on the value of 1 if the survey respondent is assigned to a medium or high level of education and zero otherwise. High education refers to A-levels or above (incl. university degrees); medium level refers to secondary school (10 years of education).

3 Additional analyses (not shown to save space) do not support the hypothesis that there are differences in the impact of feedback by type.

4 For example, more than 150 households failed to report information on income. To abstract from "unreasonable" consumption levels, annual electricity consumption was restricted to the range of 700 to 8000 kWh. As a result, 2 observations were excluded.

Table 1 provides descriptive statistics of the variables used in our econometric analyses. For example, the mean of 0.55 for the variable *smart* reflects that 55% of the households in our sample received feedback about electricity consumption. Similarly, a mean of 0.17 for *age0-5* means that on average there were 0.17 children aged 5 or younger in a sample household. Also note that almost 80% of the sample households are from Linz.

Table 1: Descriptive statistics of the variables used

Variable	Unit	Total Obs.	Total Mean	Total Std. Dev.	Total Min.	Total Max.	Pilot mean	Control mean
electricity	kWh/year		3.289	1.498	703	7.965	3.284	3.295
Smart	0/1 dummy		0.55	0.50	0.00	1.00	1.00	0.00
age0-5	number		0.17	0.46	0.00	3.00	0.14	0.20
age6-17	number		0.42	0.76	0.00	4.00	0.40	0.44
age18-30	number		0.37	0.64	0.00	4.00	0.35	0.40
age31-45	number		0.63	0.79	0.00	3.00	0.64	0.62
age46-60	number		0.55	0.76	0.00	3.00	0.53	0.57
age60plus	number		0.37	0.70	0.00	3.00	0.41	0.32
floorsize	m^2		106	46.5	25	538	109	102
income	1/2/3 dummy		2.16	0.79	1.00	3.00	2.16	2.15
education	0/1 dummy		0.58	0.49	0.00	1.00	0.55	0.61
fridge	number		1.24	0.48	0.00	4.00	1.26	1.21
dryer	number		0.43	0.49	0.00	1.00	0.44	0.42
freezer	number		0.73	0.57	0.00	3.00	0.76	0.70
dishwash	number		0.85	0.39	0.00	2.00	0.88	0.82
boiler	number		0.36	0.57	0.00	4.00	0.35	0.37
Tv	number		0.88	0.80	0.00	5.00	0.90	0.85
computer	number		1.26	0.93	0.00	5.00	1.29	1.23
appliances	number		7.65	2.94	2.00	29.00	7.77	7.50
Hassfurt	0/1 dummy		0.06	0.23	0.00	1.00	0.05	0.06
Schwerte	0/1 dummy		0.02	0.14	0.00	1.00	0.02	0.02
Oelde	0/1 dummy		0.01	0.07	0.00	1.00	0.01	0.00
Ulm	0/1 dummy		0.01	0.12	0.00	1.00	0.00	0.03
Kaiserslautern	0/1 dummy		0.03	0.17	0.00	1.00	0.01	0.05
Muenster	0/1 dummy		0.04	0.19	0.00	1.00	0.03	0.04
Krefeld	0/1 dummy		0.04	0.19	0.00	1.00	0.03	0.04
Celle	0/1 dummy		0.03	0.16	0.00	1.00	0.05	0.00
Linz	0/1 dummy		0.78	0.42	0.00	1.00	0.80	0.75

The figures in Table 1 generally indicate that households in the control group and in the pilot group are quite similar, but small differences exist, e.g. for age composition. In general, observed and unobserved household heterogeneity between pilot and control group may result in biased parameter estimates. In our econometric analyses we control for these possible participation-based sample selection biases.

3.3 Results

STATA 11 is used to perform the econometric analyses. To test for unobserved heterogeneity we first estimate the joint distribution of a Probit model capturing selection in the pilot group and the electricity consumption equation via maximum likelihood methods (e.g. Mills and Schleich, 2009)[5]. Results, however, do not imply a selection bias from unobserved heterogeneity.[6] Therefore, estimating the electricity consumption equation individually via OLS is appropriate (e.g. Imbens 2004). Table 2 presents the parameter estimates from OLS regressions together with heteroskedasticity-robust standard errors.[7]

5 Explanatory variables for estimating the Probit equation are given in Table 1.

6 Based on a Wald test we fail to reject the hypothesis of independence of the selection and the consumption equations ($\chi^2(1)=$ 0.76, Prob. > χ^2 = 0.3823).

7 To account for observed heterogeneity, we also estimated the electricity consumption equation using observation weights. Specifically, the propensity scores from the Probit model for participation in the pilot group are used to generate individual observation weights (e.g. Price 2005, Mills and Schleich 2009). Results, however, were almost identical to the findings presented in Table 2. Hence, the variables included in estimating the electricity consumption appear to adequately account for observed heterogeneity in household participation in the feedback program. All findings not shown are available from the authors upon request.

Table 2: Results from OLS regressions in kWh/year

	Parameter estimates (robust standard errors)	
smart	-125.40	**
	(62.65)	
age0-5	165.68	**
	(70.67)	
age6-17	301.69	***
	(53.09)	
age18-30	315.57	***
	(63.17)	
age31-45	447.22	***
	(72.24)	
age46-60	474.56	***
	(67.95)	
age60plus	520.60	***
	(66.57)	
floorsize	6.07	***
	(0.93)	
income	73.03	
	(46.34)	
education	-115.12	*
	(64.65)	
fridge	252.32	***
	(89.85)	
dryer	478.67	***
	(66.91)	
freezer	225.49	***
	(60.09)	
dishwasher	129.39	
	(90.41)	
boiler	281.53	***
	(56.58)	
tv	101.71	**
	(42.33)	
computer	147.05	***
	(43.19)	
appliances	68.32	***
	(17.63)	

	Parameter estimates (robust standard errors)	
Hassfurt	39.13	
	(249.50)	
Schwerte	354.54	
	(299.95)	
Oelde	253.89	
	(400.295)	
Ulm	-140.03	
	(292.63)	
Kaiserslautern	259.76	
	(272.43)	
Münster	-70.47	
	(256.09)	
Krefeld	525.06	*
	(280.91)	
Linz	139.97	
	(217.07)	
constant	-213.74	***
	(251.34)	
R^2	0.4666	
Sample size	1379	

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 a two-tailed t-test

The (corrected) R^2 of 46.66% suggest that the model explains a fairly large share of the variation in household electricity consumption.

The parameter estimates associated with *smart* is significant at p=0.05. The point estimate suggest that the feedback provided under the smart metering programme results in electricity savings of around 125 kWh, which translates into average percentage savings of about 3.7% total average electricity consumption of pilot group household. Electricity consumption positively depends on the number of household members in each *age* group and tends to increase with age. Larger residences are associated with higher electricity consumption of around 6 kWh per year and additional m^2. Higher *education* is associated with lower electricity consumption (p=0.1). In comparison, *income* would be statistically significant at p=0.12. Arguably, the effects of income on electricity consumption are, to a large extent, reflected in the size of the residence and the appliance stock. Parameter estimates of appliances exhibit the expected positive sign, are statistically significant at least at p=0.1 (*dishwasher* at p= 0.15) and take on reasonable values. Only the municipality dummy for Krefeld is statistically significant (p=0.1).

4 Conclusions

To evaluate the effect of feedback information in a recent smart metering pilot study in eight German municipalities we econometrically estimated household electricity consumption. The results of our cross section analysis suggests that feedback information on electricity consumption, leads to average electricity savings of about 3.7%. These electricity savings translate into annual energy cost savings of around €30 for the average household. Our estimated energy savings are at the lower end of those typically found in the literature (e.g. Darby 2006 or Ehrhardt-Martinez 2010), but are in the range of a recent study for Denmark (Gleerup et al. 2010)[8]. It should be noted, however, that our econometric analysis does not allow us to disentangle the effects of feedback about

8 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. Hence, the pilot (or treatment) group in Gleerup et al. (2010) only consists of households receiving feedback by mail. The fact that households may be expected to adjust electricity consumption also in response to feedback information from a web portal, is likely to partially explain the relatively low estimate for the effects of feedback in by Gleerup et al. (2010).

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 time-of-use pricing.

Results further suggest that out estimates do not suffer from biases resulting from unobserved or observed household heterogeneity in receiving feedback on electricity consumption. Nevertheless, applying a difference-in-difference estimator based on panel data may lead to different findings, since panel econometrics allows the elimination of also unobserved effects which are fixed over time (e.g. Gleerup et al. 2010). In a cross section analysis, these effects may influence parameter estimates, including those capturing feedback effects.

In our model specification, which includes apartment size and a wealth of information on household appliance stock as explanatory variables, income was not found to affect electricity consumption. Hence, households' failure to report income data might not result in biased parameter estimates if income was omitted as an explanatory variable.

In our regression models, average effects were calculated across all households. Future research could explore whether the response to feedback differs by household type. That is, households may be more or less receptive to information on energy use and energy saving measures (van Dam et al. 2010), or the potentials to reduce energy use may differ across households. In particular, our analysis did not directly allow for differences in motives and attitudes towards the environment, energy use, or energy conservation. Further, we have no indication of whether the calculated savings made in response to feedback will be sustained over time. 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 have a long-term impact on energy use (Darby 2006). Similarly, in the longer run, the effects of changed investment behaviour (e.g. purchasing more efficient appliances) in response to feedback information may materialize. Again, these effects can interact with socio-economic variables. For example, high income households have been found to prefer changes in investment behaviour rather than changes in everyday behaviour (Poortinga et al. 2003). Another issue meriting future research is the use of feedback and information processing by households. Analyses could relate the frequency of feedback information or logging into a web portal to changes in behaviour. Similarly, it could be explored how feedback impacts on routines of gathering and processing information. 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.

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