Reducing Electricity Demand through Smart Metering: The Role of Improved Household Knowledge

James Carroll [a b] *
Seán Lyons [c b]
Eleanor Denny [a b]

Abstract

The international rollout of residential smart meters has increased considerably in recent years. The improved consumption feedback provided, and in particular, the installation of in-house displays, has been shown to significantly reduce residential electricity demand in the majority of international trials. This paper attempts to uncover the underlying household motivations of such information-led reductions by exploring the effect of feedback on the level of electricity reducing knowledge and the role of knowledge improvements in demand reductions. Data is from a randomized controlled smart metering trial (Ireland) which also collected extensive information on household attitudes towards and knowledge of (stated) electricity use. Results show that feedback significantly improves a household's knowledge but such improvements are not correlated with observed demand reductions. Increasing the level of knowledge *ceteris paribus* is therefore unlikely to bring short-run demand reductions in residential electricity markets. The true underlying demand-reducing motivations in smart metering trials are hypothesized.

[a] Department of Economics, Trinity College Dublin
[b] Electricity Research Centre, University College Dublin, Ireland
[c] Economic and Social Research Institute, Dublin, Ireland
[*] Corresponding Author. Email: jacarrol@tcd.ie. Address: Department of Economics, Arts Building, Trinity College Dublin, College Green, Dublin 2, Ireland. Ph: +353 1 896 13

1 Introduction

Smart metering facilitates real-time communication between the customer and the utility company, and considerably enhances the potential for detailed consumption feedback for electricity customers. Coupled with an in-house display, households can view their electricity usage in real-time and track their energy and cost movements with each and every turn of the switch. Smart meters also facilitate enhanced historical and comparative feedback, either through the utility bill or through an internet connected device. Equally important for lowering demand, smart-metering allows for time-of-use tariffs which can reduce peak demand and therefore smooth daily consumption (termed *demand response* programs in the literature). [1] Additional demand response can be achieved by coupling the smart meter with a number of household appliances (thermostats and air-conditioning units, for example) which respond to peak signals from the meter and/or to direct signals from the utility company (known as *enabling technologies*).

The demand reducing effects of various levels of feedback has been the focus of a large number of studies. Faruqui et al. (2010) review the results of 12 separate trials from the USA, Canada, Australia and Japan. They find that direct feedback, in the form of an in-house display (IHD), reduces demand by between 3 and 13% (average 7%). Fischer (2008) summarizes the results from 22 studies between 1987 and 2006. She concludes that the most effective forms of feedback are provided frequently over a long period of time, give appliance-specific breakdowns of consumption and involve electronic interaction with the households – although not all studies show a reduction in household electricity costs, the typical savings are in the region of 5 to 12%. Abrahamse et al. (2005) also emphasizes the importance of feedback frequency and, furthermore, finds that households responded well to reduction incentives in the form of financial rewards. However, Darby (2010), in yet another extensive review of feedback mechanisms, finds that enhanced billing – more frequent and more accurate consumption information – has reduced demand in only a number of studies, and that written, generalized information appears to have no significant effect. Similar findings are observed by (Ofgem, 2011), where only one (of four) of their surveyed trials finds the combination of advice and historic feedback to be effective (they do, however, generally find a significant IHD effect of around 3%).

Demand response programs generally show large peak reductions. Faruqui and Sergici (2011) find that peak-time rebates reduce peak demand by between 18% and 21%, and that adding an ‘Energy Orb’ (changes color depending on the tariff) increased this reduction to between 23% to 27%. Ofgem (2011) also find significant time-of-use pricing effects, but are smaller in magnitude and up to 10%. Two trials summarized by Faruqui et al. (2010) find that time-of-use and critical-peak pricing (in combination with direct feedback (IHD)) reduce peak and critical demand by 5% and 30% respectively (Newsham and Bowker (2010) find similar

[1] Newsham and Bowker (2010) discuss the main pricing alternative within demand response trials. These are *time-of-use* (different tariffs for different times of the day), *critical peak* (higher prices applied only on pre-advertised ‘event days’), *real time* (tying customer prices to wholesale electricity prices) and *peak time rebates* (refunds for reaching targets during peak/critical times).

reductions). Finally, Faruqui and George (2005) find that time-of-use rates with a peak to off-peak ratio of two to one produce peak reductions in the region of 5%.

In Ireland, the first major smart meter trial was undertaken between 2009 and 2010 by the Commission for Energy Regulation (CER). The trial applied various combinations of time-of-use tariffs and levels of feedback (usage statements and an IHD) to a large and representative sample of Irish households (extensive details below). On average, the trial lead to a significant 8.8% reduction in peak demand and a 2.5% reduction in overall demand. The IHD in combination with a bi-monthly (every two months) usage statement was found to show the largest reductions across all tariff types (CER, 2011c). Furthermore, while four alternative time-of-use tariffs were applied, they all showed similar reductions, despite significantly different peak rates.

Smart-metering clearly has the potential to provide real benefits to all stakeholders. Households benefit from their monetary savings and through their reduced carbon footprint. Utility companies and generators benefit from increased grid information and smoother load profiles, both of which improve the operational efficiency and stability of the system (Faruqui et al., 2010). The potential to reduce the number and duration of blackouts (through immediate outage detection) is also highlighted by Krishnamurti et al. (2012). Nationally, potential reductions in total and peak demand and decreased variability will aid in reducing greenhouse gas emissions and, depending on the regulatory framework, the level of carbon tax. For example, Hledik (2009) suggests that the roll-out of a smart grid in the U.S. (which has smart metering and time-of-use tariffs at its core) would reduce CO2 emissions by between 5 and 16%.

To date, the many international trials investigating the effects of smart metering, demand response and enhanced feedback, with some exceptions, are broadly in agreement, and the energy reducing effect and accompanying benefits to households, nations and the environment are convincing. However, the importance of gaining a deeper understanding of demand reductions and the inherent value of feedback to customers has been recently highlighted in the literature. For example, Faruqui et al. (2010) suggests that if feedback serves mainly as a short-term reminder of over-consumption, the long-term effects could be diminished.[2] If, however, feedback is truly valued and incorporated into consumption decisions, behavioral changes may then be expected to persist.

Using the CER trial data in combination with pre/post-trial household surveys, this paper aims to investigate the value of feedback by exploring if participating household's show significant improvements in their understanding of energy reducing methods, and subsequently, if such improvements play any role in explaining demand reductions. These steps in the behavioral chain are summarized by two research questions in Figure 1.1. A direct link between stage 1 and 3 is clearly established, both in Ireland and internationally. Significant links between stages 1, 2 and 3 would suggest that feedback has filled an

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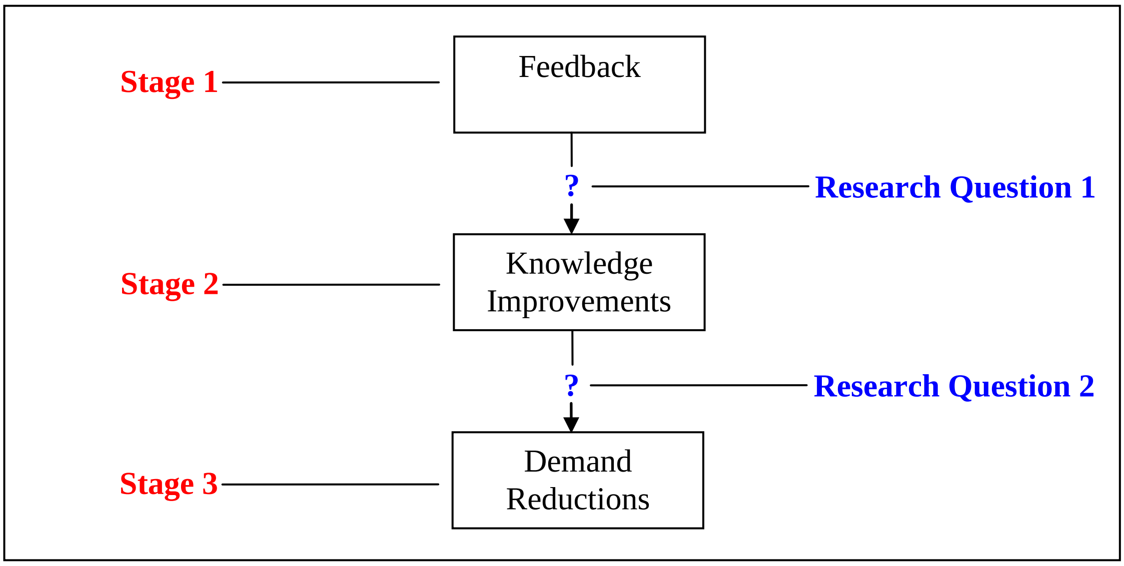
informational gap, and that households then used this improvement in knowledge to lower their consumption. If a link is observed between stage 1 and 2 but not between 2 and 3, it would suggest that knowledge improvements are not actually an important driver of overall demand reductions. In this instance, it is possible that feedback reduced demand through some other mechanism. Both of these questions are clearly relevant for the content of future information-led campaigns to reduce demand. This paper proceeds as follows: Section 2 outlines the data employed for this analysis and Sections 3 and 4 presents the econometric methods and results. Section 5 concludes the analysis.

Figure 1.1: Research Questions



2 Data – The Residential Smart Meter Trial

The Irish residential smart meter trial was carried out between 2009 and 2010 and involved the installation of over 5000 smart meters into residential households (CER, 2011c, CER, 2011a).[3] A benchmark analysis was conducted (July to December 2009) where pre-trial demand data (half-hourly readings) was collected and control/treatment groups were established. During the test period (January to December 2010), varying time-of-use tariff types and demand side management stimuli were deployed in the treatment group while the control group received no changes to their usual billing process. Furthermore, pre and post-trial surveys were carried out (late 2009 and early 2011 respectively) in which a large amount of household information was collected, including characteristics of the dwelling (including building type and size, appliances use and heating/water systems), demographics and attitudes towards energy use.

Five time-of-use tariff types were developed. While the control group were charged their usual 14.1 cent per kilowatt hour (c/kWh), the treatment tariffs (A through D) generally involved large price increases during peak times and reductions for night to reflect the underlying wholesale cost of electricity at these times (all prices exclude VAT). The time-of-use price increases/decreases were designed to keep the average household's electricity

[3] The overall project commenced in 2007 and was overseen by the Commission for Energy Regulation (CER) with trials carried out by *ESB Networks* and *Electric Ireland*.

cost unchanged (peak cost increases to balance with savings off-peak). A weekend tariff (E) also involved large increases at peak times, but only on weekdays (10 c/kWh tariff for all times on the weekend).

Table 2.1: Time-of-Use Tariffs (€/kWh) excluding VAT

	Night	Day	Peak
Tariff A	12.00	14.00	20.00
Tariff B	11.00	13.50	26.00
Tariff C	10.00	13.00	32.00
Tariff D	9.00	12.50	38.00
Tariff E (Mon – Fri)	10.00	14.00	38.00
Tariff E (Sat – Sun)	10.00	10.00	10.00

Two demand side management (DSM) stimuli were applied to the treatment group. All households received a new 'Energy Usage Statement' which contained detailed information on the household's electricity use by day of the week, time-of-use and relative to previous bills and other customers, and also specific energy reducing advice which detailing average appliance consumption levels and tips to lower costs, particularly during peak times. The second DSM was an in-house display (IHD). This unit provided real-time consumption, cost and tariff information, and also allowed the household to input a daily budget target. The two DSM were applied to three separate treatment groups. The first ('BI-MST' henceforth) received just the energy statement on a bi-monthly (every two months) basis while the second ('MST') on a more frequent monthly basis. The third ('IHD') received the display in combination with the bi-monthly usage statement.

The pre and post-trial surveys explore a household's attitude towards and knowledge of electricity usage. The knowledge statements – to which there five response options from strongly agree ('1') to strongly disagree ('5') – are summarized in Table 2.2 and 2.3. These data are used to create two response change categorical variables with three outcomes (bottom of tables): 'moved towards disagree', 'no change' and 'moved towards agree'. Knowledge deteriorations could be the result of confusion or perhaps information overload for some of trial households. Furthermore, given that knowledge is self-reported, misreporting and/or bias are expected to widen the variance of the response change variables.

ATD1 (Table 2.2) explores a household's knowledge of electricity reducing actions (termed 'general knowledge' henceforth). While the majority (59% for total sample) state a good understanding of electricity reducing methods (responded with either a '1' or '2'), there remains a large proportion of the sample who lie somewhere between 'strongly disagree' and 'neutral'. The positive mean response change of 0.48 implies that households, on average, moved almost half a unit of response in the direction of 'strongly agrees'. Furthermore, there are a large proportion of households stating an improvement (46% compared to 22% deterioration). While this is observed in both the control and treatment groups, the increase is significantly larger in the latter (comparing differences in mean change), particularly so for the IHD category, where the percentage of 'strongly agree' responses almost doubled.[4]

Table 2.2: ATD1 Descriptive Statistics

ATD1: "I/we know what I/we need to do in order to reduce electricity usage"

	PRE-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	27.06%	27.21%	29.66%	25.88%	25.15%
2	31.61%	32.42%	29.39%	32.21%	32.56%
3	18.79%	17.45%	20.95%	16.91%	19.91%
4	15.05%	15.10%	14.56%	14.85%	15.74%
5 - "Strongly Disagree' (%)	7.49%	7.81%	5.44%	10.15%	6.64%
Mean Response	2.44	2.44	2.37	2.51	2.46
	POST-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	45.69%	37.59%	49.85%	46.24%	50.18%
2	28.34%	28.16%	27.30%	29.25%	28.80%
3	14.45%	17.56%	13.50%	14.22%	12.01%
4	7.15%	10.60%	4.75%	6.21%	6.71%
5 - "Strongly Disagree' (%)	4.37%	6.10%	4.60%	4.08%	2.30%
Mean Response	1.96	2.19	1.87	1.93	1.82
	RESPONSE CHANGE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
Moved towards 'strongly disagree' (%)	21.75%	27.14%	20.86%	20.42%	17.67%
No Move (%)	32.20%	33.38%	33.28%	30.39%	31.45%
Moved towards 'strongly agree' (%)	46.05%	39.48%	45.86%	49.18%	50.88%
Mean Change (Pre minus Post Response)	0.48	0.26	0.50	0.53	0.66

Statement ATD10 explores awareness of appliance consumption (termed 'appliance knowledge' henceforth). The pre-trial mean response of 2.5 (total sample) indicates that households, in general, consider their lack of appliance knowledge to be an impediment to their demand reductions (57% agree, 29% disagree and 14% neutral). There is, however, a large improvement (shift towards 'strongly disagree') post-trial, particularly so for the treatment group (mean change in response is -0.39 units for the control group and -0.68 across treatment groups). Both are significantly different to zero and the treatment mean is significantly larger than the control. The move towards disagree is particularly large for the IHD group who, on average, show an almost full unit shift in that direction. In general, therefore, the change in both statements suggests that the trial has improved both general and appliance knowledge. Section 4.1 formalizes these preliminary investigations.

[4] Significance here refers to a two-sample mean-comparison t-tests (at a 95% confidence level) comparing the mean change of control and treatment group.

Table 2.3: ATD2 Descriptive Statistics

ATD2: "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	PRE-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	32.29%	33.29%	30.10%	33.13%	32.70%
2	25.07%	25.7%	26.72%	23.30%	24.33%
3	14.01%	14.91%	13.36%	14.22%	13.43%
4	14.70%	11.98%	14.21%	16.19%	16.90%
5 - "Strongly Disagree' (%)	13.93%	14.11%	15.61%	13.16%	12.64%
Mean Response	2.53	2.48	2.59	2.53	2.52
	POST-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	20.02%	24.55%	19.21%	20.23%	15.19%
2	18.26%	20.68%	18.10%	19.06%	14.65%
3	14.96%	16.37%	15.24%	15.38%	12.48%
4	20.59%	17.86%	20.32%	20.40%	24.41%
5 - "Strongly Disagree' (%)	26.17%	20.54%	27.14%	24.92%	33.27%
Mean Response	3.15	2.89	3.18	3.11	3.46
	RESPONSE CHANGE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
Moved towards 'strongly disagree' (%)	49.61%	44.35%	47.94%	49.67%	57.87%
No Move (%)	25.44%	27.98%	26.98%	24.75%	21.34%
Moved towards 'strongly agree' (%)	24.95%	27.68%	25.08%	25.59%	20.80%
Mean Change (Pre minus Post Response)	-0.60	-0.39	-0.57	-0.58	-0.91

To investigate if knowledge changes differed by household type/demographic, data from the pre-trial survey is again utilized. A number of categorical variables are created and Table A.1 (Appendix A) presents descriptive statistics. Descriptive statistics are also presented for a number of variables used in the demand models, including number of occupants, bedrooms (proxy for overall house size) and appliances. Finally, the electricity demand data is collected at half-hourly intervals. This is aggregated for peak, off-peak and total consumption by household and by year (benchmark and trial) and descriptives are presented in Table A.2 (Appendix A).[5]

3 Methods

A multinomial logit (MNL) model is used to explore research question one (has treatment lead to improvements in knowledge). The techniques applied are standard to all modern econometric packages and their description is therefore left to Appendix B.[6] The MNL model is employed when there is no obvious order in the dependent variable. In this application, the

[5] While trial data spans all of 2010, pre-trial (benchmark) data is only available from July 14th, 2009. To avoid seasonal variations in consumption, only data from this date is used for 2010.

[6] The model is estimated using STATA version 11.2 Our STATA do-file is downloadable at http://www.eleanordenny.org/index_files/Page533.htm

knowledge change variable takes three values – improvements, no change or deteriorations. Two sets of MNL models are estimated in Section 4 below. In the first set (Section 4.1), each knowledge change variable is regressed upon an overall treatment dummy and then upon the three individual DSM categories simultaneously (control group excluded). The second set of models (Section 4.2) then re-estimate these models but interacts a number of socio-demographic variables (tenure, house-type, age, education, tenure and children). MNL models are estimated for the six demographic variables separately (by overall treatment and by DSM) and results are summarized as marginal effects in Tables 4.5 and 4.6 for each knowledge change variable respectively.[7] The estimation of marginal effects for interaction variables is less straightforward in non-linear models. The approach taken follows the applied methodology presented in Karaca-Mandic et al. (2012) and we compare the change in the predicted probability of each outcome for a one unit change in the demographic variable (further details provided below in Section 4.2).

A difference-in-difference (DID) approach is employed to investigate the effects of knowledge improvements/deteriorations on electricity demand (research question two). The DID model is employed for uncovering the true effects of a policy change when data from two periods (pre and post-policy) and two groups (treated and untreated) are available. The DID model is generally estimated by pooled OLS, but can also be estimated in a random effects (RE) panel data setting by adding a time-invariant unobserved heterogeneity term (c_i) to the error term: [8]

$$y_{it} = \beta_0 + \beta_1 Y2_{it} + \beta_2 T_i + \beta_3 Y2_{it} T_i + c_i + u_{it} \qquad (1)$$

where y_{it} is electricity demand for household i in period t, $Y2$ is the period two dummy, T is the treatment dummy and c are assumed to be random draws from the population. Fixed effects is not possible in this setting as the independent variables are not time-varying. In practice, however, running the regression with fixed effects (and without the time-varying inputs) produces identical results. The coefficient β_1 describes the temporal change in demand for the control group and β_2 describes the difference in demand for the control and treatment groups in period one. The main coefficient of interest is the interaction term β_3, which gives the difference in the temporal change in demand for the treatment group (compared to the control group), or more formally:

$$\beta_3 = \left(\bar{y}_{T,Y2} - \bar{y}_{T,Y1}\right) - \left(\bar{y}_{C,Y2} - \bar{y}_{C,Y1}\right) \qquad (2)$$

where subscript C represents the control group. Generalized Least Squares (GLS) is used instead of OLS as the latter does not produce efficient results due to autocorrelation in the heterogeneity term. In Section 4.3, this model is employed to explore the effects of treatment

[7] The results are summarized as it would not be possible to present full results from the 24 models (six separate demographic interactions by overall treatment and DSM for both knowledge statements).

[8] As usual, the RE model requires strict exogeneity of the independent variables conditional on c_i ($\mathrm{E}[u_{it} \mid \mathbf{x}_i, c_i] = 0$) and zero correlation between c_i and the explanatory variables [$\mathrm{E}[c_i \mid \mathbf{x}_i] = 0$].

on electricity demand (for comparison against the original CER reports). A number of demand determinants are also incorporated, including number of occupants, bedrooms and appliances. Section 4.4 then investigates if there is any correlation between knowledge change and demand change.

4 Results

4.1 The Effects of Feedback on Household Knowledge

The MNL results and marginal effects of feedback on ATD1 change (general knowledge) are displayed by overall treatment and by feedback type in Tables 4.1 and 4.2 respectively (Research Question One). Prior to the trial, almost 60% of the sample felt they had a sufficient understanding of electricity reducing actions (either agreed or strongly agreed with the statement). Trial participation has increased this knowledge further, and the results demonstrate that the improvement is significantly larger for the treatment groups. Overall (Table 4.1), the marginal effects demonstrate that treatment significantly increases the probability of improving knowledge (‘moved to agree’) by 9 percentage points and reduces the probability of lowering knowledge (move to disagree) by almost 7.1 percentage points compared to the control group. This effect is highest for the MST and the IHD (Table 4.2), where households are 9.7 and 11.4 percentage points more likely than the control group to show improvements.

Table 4.1: Mlogit model – effect of overall treatment on ATD1[9]

ATD1 "I/we know what I/we need to do in order to reduce electricity usage"

	Coef.	**Std. Err.**	**DY/DX**	**Std. Err.**
Outcome 1 – Moved to Disagree:				
TREAT (D)	-0.269**	(0.119)	-0.071***	(0.017)
Constant	-0.207**	(0.098)	-	-
Outcome 2 – No Change (base):				
TREAT (D)	-	-	-0.019	(0.021)
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
TREAT (D)	0.256**	(0.104)	0.090***	(0.022)
Constant	0.168**	(0.089)	-	-
Model Stats:				
N	2519	LR chi test stat.		21.68
Log-Likelihood	-2643.71	P > chi		0.000
Pseudo R-Squared	0.0041			

[9] Where ‘ATD1’ is the general knowledge change categorical variable described in Section X.X and ‘TREAT’ is a dummy variable capturing overall treatment. ‘DY/DX’ indicates marginal effect and significance levels are highlighted by ‘***’ (1%), ‘**’ (5%) and ‘*’ (10%).

Table 4.2: Mlogit model – effect of feedback type on ATD1[10]

ATD1 "I/we know what I/we need to do in order to reduce electricity usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
BI-MST (D)	-0.260*	0.147	-0.063***	0.023
MST (D)	-0.190	0.152	-0.067***	0.024
IHD (D)	-0.370**	0.159	-0.095***	0.023
Constant	-0.207**	0.098	-	-
Outcome 2 – No Change (base):				
BI-MST (D)	-	-	-0.001	0.026
MST (D)	-	-	-0.030	0.026
IHD (D)	-	-	-0.019	0.027
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
BI-MST (D)	0.153	0.126	0.064**	0.027
MST (D)	0.314**	0.129	0.097***	0.027
IHD (D)	0.313**	0.131	0.114***	0.028
Constant	0.168*	0.090	-	-

Model Stats:

N	2519	LR chi test stat.	26.02
Log-Likelihood	-2641.53	P > chi	0.000
Pseudo R-Squared	0.0049		

A household's appliance knowledge is explored in ATD2. Overall (Table 4.3), trial participants are significantly more likely to show an improvement (move to disagree) than the control group. Specifically, the marginal effects demonstrate that trial involvement increases the probability of an improvement by 7 percentage points and lowers the probability of a deterioration by 4 percentage points. Table 4.4 again shows the IHD to be most important DSM for improving knowledge (BI-MST not significant here) and households who received this type of feedback are 13.5 percentage points more likely to show an improvement than the control group.

[10] BI-MST refers to the bi-monthly statement, MS to monthly statement and IHD to the in-house display.

Table 4.3: Mlogit model – effect of overall treatment on ATD2[11]

ATD2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
TREAT (D)	0.285***	0.110	0.072***	0.022
Constant	0.461***	0.093	-	-
Outcome 2 – No Change (base):				
TREAT (D)	-	-	-0.035*	0.019
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
TREAT (D)	-0.013	0.124	-0.037**	0.019
Constant	-0.011	0.103	-	-
Model Stats:				
N	2453	LR chi test stat.		10.3
Log-Likelihood	-2551.73	P > chi		0.006
Pseudo R-Squared	0.002			

Table 4.4: Mlogit model – effect of feedback type on ATD2

ATD2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
BI-MST (D)	0.114	0.134	0.036	0.028
MST (D)	0.236*	0.137	0.053*	0.028
IHD (D)	0.537***	0.142	0.135***	0.028
Constant	0.461***	0.093	-	-
Outcome 2 – No Change (base):				
BI-MST (D)	-	-	-0.010	0.025
MST (D)	-	-	-0.032	0.025
IHD (D)	-	-	-0.066***	0.025
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
BI-MST (D)	-0.063	0.151	-0.026	0.024
MST (D)	0.044	0.155	-0.021	0.025
IHD (D)	-0.015	0.167	-0.069***	0.024
Constant	-0.011	0.103	-	-
Model Stats:				
N	2453	LR chi test stat.		23.77
Log-Likelihood	-2545	P > chi		0.001
Pseudo R-Squared	0.0046			

[11] Where 'ATD2' is the appliance knowledge change categorical variable.

In summary, there is strong evidence that trial participation and increased levels of feedback increase a household's general and appliance knowledge. In both cases, receiving the IHD has the strongest effect and increases the probability of improving a household's general and appliance knowledge by 11.4 and 13.5 percentage points respectively. This is followed by the MST and BI-MST respectively (the latter not significant for ATD2). Overall (all DSM combined), the effects are highly significant and treatment increases the probability of improving general and appliance knowledge by 9 and 7.2 percentage points respectively.

4.2 Socio-Demographic Interactions

Table 4.5 and 4.6 present the marginal effects of feedback for a number of socio-demographic indicators.[12] The first column of these tables ('TREAT') describes the overall treatment effect (all DSMs combined using an overall treatment dummy) for each demographic, while the remaining columns show the effect by DSM. Each marginal effect describes the change in outcome probability for the demographic in question relative to the reference group (the excluded category within the variable). To illustrate, in Table 4.5 the marginal effect of TENURE1 at BI-MST on 'moved to agree' is 0.025, and suggests that, at this DSM, people renting their property are 2.5 percentage points more likely to improve their general knowledge than non-renters (own property outright or have a mortgage). However, this effect is not significant.

This is also the case for the remaining tenure and house-type interactions – renters and apartment dwellers did not respond differently to overall treatment or each DSM (than non-renter and non-apartment dwellers). The age categories are significant overall (significance driven by the effects at BI-MST), and the results demonstrate that younger households (18-35 years; the base category) are 7.6 percentage points more likely than AGE2 (36-55 years) and 9.6 percentage points more likely than AGE3 (55+ years) to improve their general knowledge.[13] The presence of children (overall) leads to an increase in knowledge – having children increases the probability of an improvement (moving to agree) by 4.6 percentage points, while not having children increases the probability of a deterioration (move to disagree) by 5.5 percentage points. The interaction of gender and education demonstrates that being female increases the probability of a 'no change' while households with a third level education are more likely to show an improvement (overall).

[12] Tables 4.X and 4.X display the value of the marginal effect and the statistical significance indicator only. The full results used to create these tables are available from the corresponding author.
[13] The effects of the two age categories are estimated simultaneously. The reference group is therefore AGE1 (young households).

Table 4.5: Summary of Socio-Demographic Marginal Effects for ATD1

ATD1 "I/we know what I/we need to do in order to reduce electricity usage"

	TREAT	BI-MST	MST	IHD
TENURE1 (households that rent)				
Moved to Agree	-0.032	0.025	0.009	-0.135
Moved to Disagree	-0.027	-0.074	-0.010	0.000
No Change	0.059	0.049	0.002	0.135
HOUSE1 (apartments)				
Moved to Agree	0.076	0.114	0.081	0.037
Moved to Disagree	-0.078	-0.066	-0.062	-0.087
No Change	0.003	-0.048	-0.018	0.050
AGE2 (36-55 years)				
Moved to Agree	-0.076*	-0.159***	0.011	-0.058
Moved to Disagree	-0.027	-0.021	-0.042	-0.030
No Change	0.103**	0.180***	0.031	0.088
AGE3 (55+ years)				
Moved to Agree	-0.096**	-0.142**	-0.035	-0.092
Moved to Disagree	-0.007	-0.031	-0.033	0.038
No Change	0.102**	0.172***	0.068	0.054
CHILD (presence of children under 15 years)				
Moved to Agree	0.046*	0.080*	0.036	0.019
Moved to Disagree	-0.055***	-0.071**	-0.014	-0.081**
No Change	0.008	-0.010	-0.022	0.062
FEMALE (female respondent)				
Moved to Agree	-0.037	-0.045	-0.069*	0.011
Moved to Disagree	-0.009	0.021	0.000	-0.053*
No Change	0.046**	0.024	0.070*	0.042
EDU3 (third level education)				
Moved to Agree	0.045*	0.069*	-0.005	0.067
Moved to Disagree	-0.017	-0.012	-0.003	-0.036
No Change	-0.028	-0.056	0.007	-0.031

The interacted marginal effects for ATD2 (appliance knowledge) are displayed in Table 4.6. Renting households display a negative overall treatment effect at ‘moved to disagree’. This therefore implies that non-renters are more likely to show an improvement in appliance knowledge than renters (probability of a move to disagree 9.9 percentage points higher). In this regard, the MST appears to be particularly valuable to non-renters, who are over 15.2 percentage point more likely to show an improvement. Overall, age does not influence appliance knowledge. However, at the DSM level, AGE3 is significant at BI-MST, where it is evident that older households are more likely to show a deterioration (‘moved to agree’). The presence of children and gender both show some significant overall treatment effects – households without children are more likely (3.7 percentage points) to show a deterioration in appliance knowledge (than households with) while households headed by females are more likely (4.1 percentage points) to show a improvement. Further child-related effects are present for the BI-MST, where there is a significant difference between households with and without children – the former more likely to show an improvement. For education, it is apparent that third-level households benefited more from the IHD and are significantly less likely to show a deterioration (reduces the probability of a deterioration by 6 percentage points).

Table 4.6: Summary of Socio-Demographic Marginal Effects for ATD2

ATD2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	TREAT	BI-MST	MST	IHD
TENURE1 (households that rent)				
Moved to Agree	0.041	0.099	0.072	-0.034
Moved to Disagree	-0.099**	-0.141	-0.152*	-0.021
No Change	0.057	0.042	0.081	0.055
HOUSE1 (apartments)				
Moved to Agree	-0.080	-0.254***	0.078	-0.027
Moved to Disagree	0.085	0.021	0.172	0.059
No Change	-0.005	0.233	-0.250***	-0.032
AGE2 (36-55 years)				
Moved to Agree	-0.019	0.046	-0.055	-0.055
Moved to Disagree	0.000	-0.041	0.027	0.030
No Change	0.018	-0.005	0.029	0.025
AGE3 (55+ years)				
Moved to Agree	0.020	0.108*	-0.047	-0.009
Moved to Disagree	-0.016	-0.081	0.076	-0.031
No Change	-0.004	-0.027	-0.029	0.039
CHILD (presence of children under 15 years)				
Moved to Agree	-0.037*	-0.042	-0.053	-0.015
Moved to Disagree	0.032	0.080*	-0.012	0.028
No Change	0.005	-0.037	0.065	-0.013
FEMALE (female respondent)				
Moved to Agree	0.005	-0.029	0.037	0.009
Moved to Disagree	0.041*	0.052	0.016	0.058
No Change	-0.046**	-0.023	-0.054	-0.067**
EDU3 (third level education)				
Moved to Agree	-0.005	0.011	0.033	-0.060*

Moved to Disagree	-0.005	0.009	-0.045	0.015
No Change	0.010	-0.019	0.011	0.045

4.3 The Effects of Treatment on Demand

Table 4.7 displays the effect of each DSM on total, peak and off-peak demand using the DID RE model described in Section 3 and Table 4.8 summarizes these treatment effects. A number of control variables are included in the analysis and are predominantly significant and of the expected signs – household demand (total, peak and off-peak) increases with the number of occupants, house size (bedrooms used as proxy) and the number of appliances.[14] For example, each additional child increases total demand (aggregate July through December) by 304.78 kWh (marginal effect calculated at sample means) and this can be disaggregated into peak (43.90 kWh) and off-peak (260.88 kWh) effects. The coefficient for Y2 (2010 dummy variable) describes the change in demand for the control group between the benchmark period (2009) and the treatment period (2010) and is not significant, as expected. The treatment dummy variables (BI-MST, MST and IHD) compare the benchmark period demand of the DSMs to the control group. Again, as expected for a random sample, the 2009 demand of treatment and control groups is not significantly different.

The main variables of interest are the interaction terms which describe the difference in 2010 demand for each DSM (compared to the control group), and it is evident that treatment has significantly reduced total demand in 2010. For example, the MST has the largest effect and has lowered total demand by 59.91 kWh or by 2.9% (verses control group levels in the treatment year). This is followed by the IHD and BI-MST (*not significant*) which show reductions of 38.84 kWh (1.9%) and 19.03 kWh (0.9%) respectively. Overall (all DSM groups combined), treatment has significantly lowered total demand by 38.73 kWh (1.9%).[15]

Peak reductions are relatively higher, and treatment is significant both overall and by DSM. The average peak reduction is 8.2%, and this is strongest for the IHD (9.6%), followed by the MST (8.7%) and the BI-MST (6.3%). Furthermore, in most cases total demand reductions are strongly driven by peak – overall, 59% of total reductions occurring during this two hour period. At the DSM level, the peak share of total reductions is as high as 92% for the BI-MST and 69% for the IHD (40% for the MST). This dominant peak effect is also supported by the lack of significance at off-peak times, overall and by DSM, in all but the MST.

[14] Although the coefficient for the number of bedrooms is negative, the squared term is positive and large. The overall marginal effect for bedrooms (calculated at sample means) is therefore positive: 174.90 kWh.
[15] Overall effects are estimated using the same methodology but replacing the DSM dummy variables with the single overall treatment dummy.

Table 4.7: DID RE model results - The Effect of Treatment on Demand[16]

	TOTAL		*PEAK*		*OFF-PEAK*	
	Coef.	**Sd. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
ADULTS	486.431***	54.357	82.580***	8.383	403.851***	47.203
ADULTS squared	-28.266***	10.031	-5.667***	1.536	-22.598***	8.715
CHILDREN	329.306***	53.025	47.169***	8.234	282.136***	45.757
CHILDREN squared	-24.432	18.563	-3.256	2.965	-21.176	15.890
BEDROOMS	-224.169**	109.199	-18.152	15.592	-206.015**	95.702
BEDROOMS squared	57.397***	16.043	5.275**	2.291	52.121***	14.053
WASHING	19.855	136.400	-6.209	22.503	26.064	115.919
DRYER	237.833***	31.268	32.248***	4.621	205.585***	27.423
DISHWASHER	260.957***	31.246	39.347***	4.589	221.609***	27.470
INSTANT SHOWER	-10.698	33.771	2.165	4.818	-12.864	29.727
PUMPED SHOWER	25.463	34.105	2.244	4.860	23.219	30.072
ELECTRIC COOKER	158.451***	33.721	43.704***	4.757	114.746***	29.615
ELECTRIC HEATER	104.543***	31.845	6.633	4.609	97.910***	28.055
FREEZER	150.572***	29.888	15.815***	4.364	134.757***	26.235
WATER PUMP	93.748**	41.062	7.725	5.980	86.024**	36.143
IMMERSION	98.688***	34.574	17.883***	5.055	80.805***	30.277
STORAGE HEAT	99.304	100.897	5.878	13.560	93.426	89.056
Y2 (D)	5.495	14.264	-1.877	2.104	7.371	12.711
BI-MST (D)	14.464	39.687	1.885	5.992	12.578	34.791
MST (D)	21.552	42.035	3.632	6.208	17.920	36.894
IHD (D)	24.223	40.786	4.356	6.268	19.867	35.688
Y2 * BI-MST	-19.027	20.227	-17.595***	3.282	-1.432	17.971
Y2 * MST	-59.909***	22.661	-24.244***	3.452	-35.665*	20.159
Y2 * IHD	-38.843*	20.271	-26.881***	3.339	-11.962	18.025
CONSTANT	400.898*	207.692	12.4589*	31.195	388.439**	180.714
Model Stats:						
Observations	5654		5654		5654	
Groups	2827		2827		2827	
R-Squared	0.409		0.409		0.396	
Wald (chi squared) stat.	1986		2309		1863	
Prob. > chi	0.000		0.000		0.000	

Table 4.8: Percentage Reductions in Treatment Groups[17]

	TREAT	**BI-MST**	**MST**	**IHD**
TOTAL	1.899**	0.933	2.937***	1.904*
PEAK	8.119***	6.292***	8.669***	9.612***
OFF-PEAK	0.910	0.081	2.026*	0.680

[16] Where 'DID' indicates difference-in-difference model and 'RE' indicates random effects. 'Y10' is the treatment period dummy.
[17] Reductions are relative to the control group demand levels in the treatment year

4.4 The Effects of Knowledge Change on Demand

The previous section has shown a significant reduction in total and peak demand as a direct result of treatment. Using the same difference-in-difference (RE) methodology, this section explores if this decrease can be part-explained by an improvement in a household's knowledge for the treatment sample (Research Question Two). The results in Table 4.9 show the effects of a change in ATD1 (general knowledge) on total, peak and off-peak demand for the treatment sample. Between pre and post-surveys, 48% of households (treated) showed an improvement in their general knowledge, 20% showed a deterioration and 32% did not change their response. This knowledge-change categorical variable has been disaggregated into five groups to investigate the consistency of the correlations – a large improvement, for example, should, if relevant, lead to a larger decrease in demand than a small improvement.[18]

A number of controls are again included to account for household heterogeneity and their effects are similar to the previous section. The 2010 dummy, in this setting however, describes the change in demand of households who kept their response unchanged between surveys (the 'reference group' for this section). These households reduced their total demand by 50.83 kWh or 2.4% (compared to 2009), which is complementary to the results of Section 4.3 above. The coefficients on the knowledge change variables (non-interacted), while insignificant, are negative for both improvements and deteriorations, which suggests that these households had lower electricity demand (total) than the reference group in the benchmark year.[19] The interaction terms compare the change in demand of households that either improved or disimproved their general knowledge to that of the reference group. Although the sign for knowledge deteriorations (move to disagree) is as expected – smaller demand reductions compared to the reference group – the effects are not significant. Furthermore (and again insignificant), the sign for knowledge improvements is contrary to expectations and implies, for example, that the 11% of households who showed large improvements (large move to agree) reduced their demand *less* than the reference group.

Table 4.10 shows the effect of appliance knowledge change (ATD2) on demand. Again, the non-interacted knowledge-change coefficients are insignificant. As with ATD1, there are few significant interaction effects and the direction of the relationships is inconsistent with expectations – the signs suggest that households with improved *and* deteriorated appliance both have lower total demand reductions than the reference group. The signs of the peak effects are as expected, with lower reductions for deteriorations (moved to agree) and larger reductions for improvements. This is, however, significant for large deteriorations ('large move to agree') only.[20]

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[18] For the knowledge change variables a 'large move' indicates a 3 or 4 unit shift in response and a 'small move' indicates a 1 or 2 unit shift. For example, if a household responded with a 1 in the pre-trial survey and a 4 in the post-trial survey, their change of -3 would be represented as a 'large move to disagree'.

[19] An alternative interpretation here is that households with lower consumption are more likely to change their response.

[20] Given the number of hypothesis tests applied, this isolated result could be due to chance rather than representing a robust association in the data.

Table 4.9: Effect of ATD1 Change on Total Demand – DID RE model results

ATD1 "I we know what I we need to do in order to reduce electricity usage"

	TOTAL		*PEAK*		*OFF-PEAK*	
	Coef.	**Sd. Err.**	**Coef.**	**Sd. Err.**	**Coef.**	**Sd. Err.**
ADULTS	518.164***	67.639	86.439***	10.737	431.725***	58.468
ADULTS squared	-32.501***	12.246	-6.156***	1.938	-26.345**	10.588
CHILDREN	385.956***	63.849	53.026***	10.235	332.930***	54.751
CHILDREN squared	-46.605**	22.143	-5.438	3.746	-41.167**	18.716
BEDROOMS	-304.197**	143.706	-34.790*	20.934	-269.407**	125.206
BEDROOMS squared	67.048***	20.941	7.445**	3.044	59.602***	18.246
WASHING	107.382	181.472	21.624	27.027	85.758	156.602
DRYER	200.882***	39.970	23.208***	5.938	177.673***	35.030
DISHWASHER	278.926***	38.336	38.992***	5.669	239.934***	33.717
INSTANT SHOWER	-27.169	41.609	3.406	5.915	-30.575	36.599
PUMPED SHOWER	36.491	41.129	2.302	5.854	34.189	36.311
ELECTRIC COOKER	171.800***	41.191	46.559***	5.822	125.241***	36.114
ELECTRIC HEATER	140.456***	39.935	12.984**	5.798	127.471***	35.139
FREEZER	104.647***	36.691	8.468	5.356	96.178***	32.210
WATER PUMP	133.802***	50.224	15.964**	7.455	117.837***	44.095
IMMERSION	111.789***	42.046	16.520***	6.374	95.268***	36.648
STORAGE HEAT	6.522	119.945	-7.944	17.743	14.466	104.271
Y2 (D)	-50.830***	19.001	-26.429***	2.988	-24.401	16.861
ATD1 Change:						
Large move to disagree	-86.075	119.021	-16.597	17.697	-69.477	103.711
Small move to disagree	-84.180	57.133	-10.908	8.813	-73.272	49.707
No change	*Reference Group*		*Reference Group*		*Reference Group*	
Small move to agree	-30.242	43.195	-5.024	6.502	-25.218	38.028
Large move to agree	-11.917	64.209	0.703	9.459	-12.620	56.428
Y2*Large move to disagree	58.801	42.497	11.145	8.129	47.657	37.303
Y2* Small move to disagree	20.183	31.809	-0.147	5.255	20.330	28.024
Y2*No change	*Reference Group*		*Reference Group*		*Reference Group*	
Y2*Small move to agree	32.244	23.850	2.936	3.965	29.308	21.217
Y2*Large move to agree	11.340	28.863	-0.704	5.075	12.044	25.635
CONSTANT	487.880*	284.023	23.249	41.161	464.632*	247.518
Model Stats:						
Observations	3656		3656		3656	
Groups	1828		1828		1828	
R-Squared	0.418		0.411		0.406	
Wald (chi squared) stat.	1405		1606		1325	
Prob. > chi	0.000		0.000		0.000	

Table 4.10: Effect of ATD2 Change on Total Demand – DID RE model result

ATD2: "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	TOTAL		*PEAK*		*OFF-PEAK*	
	Coef.	**Sd. Err.**	**Coef.**	**Sd. Err.**	**Coef.**	**Sd. Err.**
ADULTS	531.901***	68.197	86.283***	10.997	445.6172***	58.823
ADULTS squared	-34.327***	12.332	-6.024***	1.986	-28.302***	10.633
CHILDREN	384.451***	63.635	53.629***	10.264	330.822***	54.539
CHILDREN squared	-45.680**	22.033	-5.548	3.756	-40.131**	18.613
BEDROOMS	-295.280**	148.086	-31.946	21.438	-263.334**	129.145
BEDROOMS squared	64.832***	21.566	6.913**	3.113	57.919***	18.808
WASHING	90.918	189.698	21.013	28.214	69.906	163.660
DRYER	192.435***	40.420	23.272***	5.977	169.163***	35.451
DISHWASHER	278.002***	38.815	37.761***	5.731	240.241***	34.154
INSTANT SHOWER	-6.304	41.870	6.077	5.931	-12.381	36.855
PUMPED SHOWER	46.872	41.838	3.572	5.964	43.300	36.930
ELECTRIC COOKER	174.384***	41.566	47.668***	5.834	126.716***	36.472
ELECTRIC HEATER	147.777***	40.573	13.181**	5.907	134.596***	35.711
FREEZER	93.109***	37.112	7.317	5.409	85.792***	32.597
WATER PUMP	138.031***	50.548	17.498**	7.562	120.533***	44.329
IMMERSION	103.822***	42.797	15.805**	6.468	88.017**	37.314
STORAGE HEAT	19.112	120.794	-5.795	17.926	24.908	104.944
Y2 (D)	-40.590*	21.032	-26.515***	3.564	-14.076	18.549
ATD2 Change:						
Large move to disagree	51.637	56.250	12.841	8.773	38.796	49.108
Small move to disagree	55.391	51.220	3.618	7.863	51.773	44.757
No change	*Reference Group*		*Reference Group*		*Reference Group*	
Small move to agree	-42.475	57.584	-8.508	8.863	-33.967	50.285
Large move to agree	-70.591	78.449	-15.040	12.906	-55.551	67.813
Y2*Large move to disagree	3.954	28.480	-2.836	5.231	6.790	25.169
Y2* Small move to disagree	1.470	28.178	-0.620	4.615	2.090	25.028
Y2*No change	*Reference Group*		*Reference Group*		*Reference Group*	
Y2*Small move to agree	17.739	29.348	5.465	4.930	12.274	25.905
Y2*Large move to agree	43.980	38.386	14.617**	7.118	29.363	33.115
CONSTANT	423.618	295.498	12.162	42.745	411.456	257.571
Model Stats:						
Observations	3558		3558		3558	
Groups	1779		1779		1779	
R-Squared	0.418		0.413		0.406	
Wald (chi squared) stat.	1359		1572		1276	
Prob. > chi	0.000		0.000		0.000	

5 Conclusion

Smart metering trials in Ireland and internationally have identified significant benefits for all stakeholders of the electricity system. International findings, while varying in magnitude, generally show that a combination of demand response and increased customer feedback leads to reductions in overall demand, particularly at peak times, and a large-scale roll-out of smart meters would lead to lower and smoother load profiles and significant reductions in CO_2. For Ireland, (CER, 2011b) explores the costs and benefits (for networks, suppliers, generators and end-users) of alternative smart metering technologies and levels of feedback, and conclude that the national rollout of smart meters would bring significant and substantial net benefits.[21]

This paper attempts to gain a deeper understanding of demand reductions by exploring the role of increased household knowledge through improved feedback. Understanding the mechanisms of behavioral change is important for formulating policy, in particular policy that has an informational component. Three main findings are apparent. First, consistent with the original CER (2011a) findings, treatment has lowered demand, and in 2010, total demand is 1.9% lower than the control group. Regarding the effects of different types of feedback, households who received the monthly user statement made the largest reductions (2.9%) followed by the in-house display (1.9%) and the bi-monthly user statement (0.9% – not significant). These reductions, while significant, are certainly at the lower end of trial findings internationally (particularly studies that combine time-of-use and feedback), where total demand reductions are estimated to range anywhere between zero and 14%. Secondly, treatment has led to significant improvements in both general and appliance knowledge – while the control group also showed improvements, the gains for the treatment sample (overall) are significantly higher, particularly for households receiving the in-house display, which increased the probability of knowledge improvements by 11.4 and 13.5 percentage points (general and appliance respectively) relative to the control group. Finally, our last set of models show no relationship between knowledge change and demand change – in general, the results were neither significant nor consistent with expectations.

During the trial a large proportion of the sample increased their understanding of how to reduce electricity consumption. Overall, 48% of treated households showed improved levels of general knowledge (37% small improvement and 11% large improvement) and 51% showed improved appliance knowledge (32% small and 19% large). However, our results imply that these improvements played no significant role in the observed demand reductions and imply, for example, that the 19% of households who showed a large improvement in their appliance knowledge did not reduce their electricity consumption more than households who kept their response unchanged (25% of the sample). In most cases, the signs even suggest the opposite.

[21] The authors calculate the net present value of a roll-out, and state that their estimates are likely to be conservative and be at the lower end of expected benefits. They find that bi-monthly billing without the IHD generally provides the highest net present value (but including the IHD only reduces the NPV marginally in most cases). Results are, however, quite sensitive to the tariff rates chosen.

Our findings should be considered when formulating future information-led policy campaigns to reduce energy demand. The obvious role of feedback is to inform, to fill an informational gap and to improve the overall conservation knowledge and capacity to reduce of customers. However, our results suggest that knowledge improvements are unlikely to lead to *short-run* demand reductions, *ceteris paribus*, and as such, may not be an appropriate independent policy goal. These results do not highlight the irrelevance of feedback, but only that feedback reduces demand through some other less-obvious mechanism. Uncovering the true underlying behavioral driver(s) of feedback remains the work of future research. Some explanations (untested) have been proposed in the literature. Allcott (2011), for example, highlights that much of the energy reducing behaviors observed, such as turning off lights, adjusting thermostats and closing blinds, are likely to be behaviors that most households were aware of already, and that information/feedback drives reductions by drawing attention to or increasing the 'moral cost' of energy use (pg. 1088). It is also possible that increased feedback simply increases the frequency of reminders and then a household's effort to reach its conservation targets (see MIT (2011) pg. 162 and Faruqui et al. (2010) pg. 1607). The insignificant demand reducing effects of the bi-monthly user statement verses the significant effects of the monthly (same information but more frequent) supports this possibility. Furthermore, the insignificant effect of household knowledge may be a short-run issue – increased awareness of conservation methods and appliance consumption levels may motivate more efficient appliance purchases and renovation decisions. Such investment decisions are highly likely to be important knowledge-led drivers of demand reductions over longer timeframes.

Finally, the trial simultaneously applied time-of-use tariffs and various levels of feedback in combination, and it is therefore not possible to accurately isolate the presence of an information-led conservation effect. Although the relative peak/off-peak demand reductions (8.2/0.9%, the latter insignificant), suggest the tariffs are the dominant driver of behavioral change (with feedback acting mainly as an auxiliary informational support), it is also probable that the tariffs lead to peak load-shifting which would have lowered information-led reductions at off-peak times. Furthermore, the extensive trials of Ofgem (2011) also highlight a potential issue in smart metering trials which may bias the true effects of information. Their findings suggest that the physical presence of the meter is important and that feedback – including an in-house display, energy efficiency advice, historic feedback and financial incentives – in the absence of a smart meter has no effect. Of particular interest, is that when the meter is installed as a 'routine replacement' and its presence not communicated effectively to the household (in trials testing in-house displays) there is also no significant effect. It is possible that in the contemporary world of desirable 'smart' consumer products, the actual labeling of the meter may have increased a household's engagement, motivation and subsequent utilization of informational aids.

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Appendix A

Table A.1: Descriptive Statistics of Independent Variables[22]

Label		Description	Mean	Std. Dev.
TENURE1	D	rents	0.063	0.242
TENURE2	D	owns outright	0.555	0.497
TENURE3	D	owns mortgage	0.383	0.486
HOUSE1	D	apartment	0.016	0.126
HOUSE2	D	attached	0.441	0.497
HOUSE3	D	detached	0.543	0.498
AGE1	D	18-35 years	0.094	0.292
AGE2	D	36-55 years	0.442	0.497
AGE3	D	55+ years	0.457	0.498
AGER	D	refused to respond to age	0.007	0.082
CHILD	D	presence of young children	0.269	0.443
FEMALE	D	respondent female	0.497	0.500
EDU1	D	primary	0.128	0.334
EDU2	D	secondary	0.455	0.498
EDU3	D	third-level	0.364	0.481
EDUR	D	refused to respond to education	0.053	0.224
ADULTS	C	number of adults	2.209	1.059
CHILDREN	C	number of children	0.501	0.962
BEDROOMS	C	number of bedrooms	3.474	0.849
WASHING	D	washing machine	0.984	0.124
DRYER	D	tumble dryer	0.679	0.467
DISHWASHER	D	dishwasher	0.659	0.474
INSTANT SHOWER	D	instant electric shower	0.694	0.461
PUMPED SHOWER	D	pumped electric shower	0.293	0.455
ELECTRIC COOKER	D	electric cooker	0.757	0.429
ELECTRIC HEATER	D	electric heater	0.312	0.464
FREEZER	D	freezer	0.504	0.500
WATER PUMP	D	water pump	0.191	0.393
IMMERSION	D	immersion	0.769	0.422
STORAGE HEAT	D	storage heater	0.041	0.199

Table A.2: Descriptive Statistics for Aggregate Electricity Demand (kWh) 2009/2010

	Total		**Peak**		**Off-Peak**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
2009:						
Control	2034.055	1007.275	281.560	153.240	1752.495	870.338
BI-MST	2107.114	1031.748	292.622	151.445	1814.492	897.214
MST	2126.887	1068.194	294.542	156.942	1832.346	927.123
IHD	2098.601	1023.197	291.174	157.754	1807.427	883.126
2010:						
Control	2039.827	1025.756	279.674	152.298	1760.153	890.895

[22] Where 'D' indicates dummy variable and 'C' continuous

BI-MST	2093.529	1019.928	273.165	143.446	1820.365	892.002
MST	2072.597	1036.339	268.443	148.666	1804.154	903.945
IHD	2065.253	1020.501	262.416	142.605	1802.837	894.2892

Appendix B

The starting point of the multinomial logit model (MNL) is the standard logit which estimates the response probability of a binary outcome *y* (Wooldridge, 2010):

$$P(y=1|\mathbf{x})=G(\mathbf{x}\beta) \quad (3)$$

where, **x** is a one-by-K vector of explanatory variables (first element unity) and β is a K-by-1 vector of coefficients. The cumulative distribution function, *G*, is derived from an underlying latent variable model:

$$y^{*}=\mathbf{x}\beta+e, \quad \text{where } y = 1 \text{ if } y^{*}>0 \quad (4)$$

where *y** is the latent variable assumed to represent the level of utility attached to the binary outcome and *e* is the logistically distributed error term. The maximum likelihood estimator ($\hat{\beta}$) maximizes the log-likelihood function:

$$L(\beta)=\sum_{i=1}^{N}\{y_i \log[G(\mathbf{x}_i\beta)]+(1-y_i)\log[1-G(x_i\beta)]\} \quad (5)$$

In the model, *y* takes on *J* values and **x** affects the response probabilities of each outcome $P(y=j|\mathbf{x}),\ j=0,1,2,...,J$ (summing to one). The MNL model then has the following response probabilities:

$$P(y=j|\mathbf{x})=\exp(\mathbf{x}\beta_j)/\left[1+\sum_{h=1}^{J}\exp(\mathbf{x}\beta_h)\right], \qquad j = 1,..., J \quad (6)$$

and

$$P(y=0|\mathbf{x})=1/\left[1+\sum_{h=1}^{J}\exp(\mathbf{x}\beta_h)\right], \qquad j = 1 \quad (7)$$

The estimated coefficients from the MNL model are not easily interpretable, and describe the change in the log of the ratio of predicted probabilities for outcome *J* relative to the base category (known as the log-odds ratio). To estimate the marginal effects of a categorical independent variable on the probability of outcome *j*, the predicted probabilities are calculated for the variable at zero and at one (holding all other independent at their means). The marginal effect is then the difference between the two.

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