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

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

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## 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 some international trials. This paper attempts to uncover the underlying drivers of such information-led reductions by exploring two research questions. First, does feedback improve a household's knowledge of energy reducing behaviors? And second, do knowledge improvements explain demand reductions? Data is from a randomized controlled smart metering trial (Ireland) which also collected extensive information on household attitudes towards and knowledge of electricity use. Results show that feedback significantly increases a household's knowledge but 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. Given this result, it is possible that feedback acts mainly as a reminder and motivator, rather than an educational tool.

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# 1 Introduction

Smart metering facilitates real-time communication between the customer and the utility company and enhances the potential for detailed historical and comparative 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. Such information can help households to understand what activities consume the most, and then to amend their consumption patterns, behaviours and appliance composition to reduce their electricity bill and carbon footprint. In addition, smart meters facilitate the use of time-of-use tariffs which can help reduce peak demand and smooth daily consumption (termed *demand response* programs in the literature).[2] Additional demand response can be facilitated by coupling the 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*).

Smart metering also provides benefits to other stakeholders of the electricity system. Electricity suppliers 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 $CO_2$ emissions by between 5 and 16%.

Quantifying 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 electronic in-house display (IHD), reduces demand by between 3 and 13% (average 7%). The importance of usability and clarity in such electronic feedback systems has been highlighted in Stevenson and Rijal (2010). Fischer (2008) summarizes the results of twenty-two 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 the studies in her review show reductions, the typical savings are in the region of 5 to 12%. Abrahamse et al. (2005) also emphasizes the importance of feedback frequency, but also finds that households responded well to reduction incentives in the form of financial rewards. However, Darby (2010), in another extensive review of feedback mechanisms, finds that enhanced billing (more frequent and more accurate consumption information) is not always associated with lower demand, and that written, generalized (non-specific) information appears to have no significant effect. Similar findings are reported by Ofgem (2011), where the combination of generalized information and historic feedback is found to be ineffective. Ofgem, however, do generally find that an IHD has a significant reducing effect (around 3%).

For time of use pricing, trials have shown large and significant peak reductions. Faruqui and Sergici (2011) find that peak-time rebates reduce peak demand by between 18% and 21%,

[2] Newsham and Bowker (2010) discuss the main pricing alternatives 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).

and that adding an ‘Energy Orb’, which reminds households of peak periods (changes color depending on the tariff rate applied), 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) also find similar 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, 2011b). The trial simultaneously applied various levels of feedback (more accurate and detailed billing and/or an IHD and generalized information/advice on how to reduce) and time-of-use tariffs to a large and representative sample of Irish households. Overall, treated households reduced their total demand by 2.5% and their peak demand by 8.8%. One interesting finding was that household reductions in peak and overall demand were not significantly different across tariff treatments – households seemed to respond to the presence of a peak/off-peak price differential, but not its magnitude. In contrast, differences were observed in the effects of varying levels of feedback, with households receiving an IHD showing the largest reductions of 3.2% and 11.3% respectively (across all tariff rates).

To date, international trials investigating the effects of smart metering, demand response and enhanced feedback have tended to find that these sorts of measures can reduce residential energy demand, shift use away from peak times and give rise to a range of accompanying benefits for households, utility companies and the environment. However, the mechanisms behind residential demand response behaviour are still not fully understood. In particular, the importance of gaining a deeper understanding of the inherent *value* that consumers place on feedback has been recently highlighted in the literature. Faruqui et al. (2010) question whether consumers actually use and benefit from this quantitative and qualitative information and incorporate it into their consumption decisions, or if increased feedback simply acts as ‘reminders to conserve’. This question is highly relevant for quantifying the effects of feedback in the long term – if it is the latter which is driving reductions, the effect of these reminders may diminish over longer durations and demand reductions could be short-lived.

Underlying this concept of a value-led demand reduction is the idea that increased feedback may be correcting a market failure brought about by imperfect information. Prior to smart metering, households were consuming in what was unquestionably an informational void, with little understanding of what appliances and behaviours consume the most, and when. The only feedback available was through the utility bill, which aggregated consumption over lengthy periods, disconnected instantaneous usage and behaviours from cost and often provided inaccurate consumption information due to estimation (bills based on previous readings). Smart metering has the potential to reduce this market failure by taking the imperfectly informed consumer closer to a state of *complete* consumption information (in the case of real-time electronic feedback). As highlighted by Gram-Hanssen (2010), such improvements in knowledge are a key component of bringing about a behavioural change.[3]

[3] The author used *Practice Theory* to explore how households reduce their standby consumption. The theory shows how technological configurations, routines, knowledge and engagement interact to bring about changes in household behaviour.

Whether or not households actually 'learn' something new is the motivation of our first research question – *does the increased consumption feedback provided through smart meters lead to improvements in a household's knowledge of how to reduce their electricity consumption*? Our second research question then seeks to quantify the effects of such, if present – *do improvements in knowledge lead to decreases in electricity demand*? These hypotheses are summarized in Figure 1.1. A direct causal link between stage 1 and 3 is established in the literature, both in Ireland and internationally (for the most part). Significant links between stages 1, 2 and 3 would suggest that imperfect information prior to smart metering was causing overconsumption and that this market failure has been addressed by increased consumption feedback. If a link is observed between stage 1 and 2 but not between 2 and 3, knowledge improvements are not actually an important driver of demand reductions and feedback has reduced demand through some other mechanism. If this is the case, imperfect information, despite being present, was not causing overconsumption and, in short, there was no market failure to correct.

Of course, in practice we cannot directly observe the level of knowledge held by a household pertaining to energy demand and efficiency. Instead, we use self-reported knowledge about a number of related domains as an indicator of actual knowledge. We also focus on *changes* in knowledge rather than the *level* of knowledge, since such indicators may be more robust to individual differences in reporting behaviour. The paper proceeds as follows: Section 2 outlines the data employed for this analysis and describes how 'knowledge' change is measured in the surveys. The econometric methods are described in Sections 3. Section 4 presents the results and Section 5 concludes the analysis.

**Figure 1.1 here**

## 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, 2011b).[4] The overall objective of the trial was to test the impact and viability of smart metering technology in Ireland, and to explore the demand reducing effects of various feedback mechanisms and time-of-use tariffs. Recruitment of the nationally representative stratified random sample involved a number of phased postal invitations (five), with each round adding new participants with the goal of increasing the representativeness of the sample (according to location and electricity use).

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.[5] During the test period (January to December 2010), treated households received one of three levels of feedback and were assigned to one of five tariff rates. The control group, which also had smart meters installed, did not receive any new information and also had no changes to their usual billing process. In addition to demand data, 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.

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[4] 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*.

[5] Using available usage data and pre-trial survey responses, an allocation algorithm ensured that each cell (feedback and tariff combination) was approximately the same across a number of behavioural, demographic and attitudinal perspectives. See CER (2011a) for further details.

Feedback stimuli were applied to households in three treatment groups. All treated 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, plus more generalized information detailing average appliance consumption levels and tips to lower costs, particularly during peak times.[6] One group (*BI-MST* henceforth) received just the energy statement on a bi-monthly (every two months) basis, while a second group (MST) was billed on a more frequent monthly basis. The third group (*IHD*) received an electronic in-house display (IHD) in combination with the bi-monthly usage statement.[7] This unit provided real-time consumption, cost and tariff information.

Four time-of-use tariff types were developed (Table 2.1). 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 day-time hours and reductions for night-time hours to reflect the underlying wholesale cost of electricity at these times (all prices exclude value added tax). The time-of-use price increases/decreases were designed to keep the average household's electricity cost unchanged (peak cost increases to balance with savings off-peak).[8] The samples receiving each treatment combination are displayed in Table 2.2.

**Table 2.1 here**

**Table 2.2 here**

The pre and post-trial surveys explore each household's attitude towards and knowledge of how to reduce their electricity usage. The knowledge statements – to which there are five response options from strongly agree ('1') to strongly disagree ('5') – are summarized in Table 2.3 and 2.4. '*K1*' explores knowledge of electricity reducing actions (termed 'general knowledge' henceforth) and asks respondents if '*I know what I need to do in order to reduce electricity usage'*. This first statement is unquestionably broad, and the types of knowledge contained within could range from operational (knowing how to adjust appliance controls to save electricity) to behavioural (remembering to switch off appliances when leaving the room) to technical (understanding the energy efficiency technologies available). '*K2*' explores knowledge of appliance consumption (termed 'appliance knowledge' henceforth) and households were asked to agree/disagree with the statement – *'I do not know enough about how much electricity different appliances use in order to reduce my usage'.* These data are used to create two response change categorical variables with three outcomes (bottom of tables): 'moved to disagree', 'no change' and 'moved to agree'. Knowledge deteriorations could be the result of confusion or perhaps information overload for some of the trial households. Furthermore, given that knowledge is self-reported, misreporting or statistical 'noise' is expected to be relatively high, and this will tend to increase the variance of these response change variables.

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[6] We acknowledge that such generalized information is not 'feedback'. This information, however, is auxiliary to consumption feedback, in that it aids households to act upon their specific feedback. However, both 'feedback' and 'generalized information' would both improve what we define as 'knowledge' below.
[7] A third stimulus – an *Overall Load Reduction* (OLR) – financially rewarded households for meeting a reduction target. This stimulus is excluded from our analysis as the data was unavailable.
[8] A fifth 'weekend' tariff also involved large increases at peak times, but only on weekdays. This treatment was not combined with a feedback stimulus and is therefore not considered.

For *K1* (Table 2.3), the majority (59% for total sample) states a good understanding of electricity reducing methods (responded with either a '1' or '2'). However, 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.[9]

**Table 2.3 here**

For *K2* (Table 2.4), 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 average across all 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. Section 4.1 formalizes these preliminary investigations.

**Table 2.4 here**

To investigate if knowledge changes differed by household type/demographic, data from the pre-trial survey is employed. Six categorical variables, including tenure, building type, age, education, gender and children, are created and Table A.1 (Appendix A) presents their descriptive statistics. 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).[10]

# 3 Methods

A multinomial logit (MNL) model is used to explore if treatment increased knowledge (research question one). As the model is standard its description is left to Appendix B.[11] The MNL model is employed when there is no obvious order in the dependent variable. In this application, the knowledge change variable takes on 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 (all feedback stimuli combined) and then upon the individual feedback stimuli simultaneously (control group the excluded reference category). The second set of models (Section 4.2) then re-estimate the models of Section 4.1 but interact a number of socio-demographic variables with the treatment dummies. MNL models are estimated for each of the six demographic variables separately and results are summarized as marginal effects in

[9] 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.

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

[11] The model is estimated using STATA version 11.2.

Tables 4.5 and 4.6 for each knowledge change variable respectively.[12] 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 for a one unit change (zero to one) in the categorical demographic variable being analyzed (further details/examples 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 can be employed to explore the 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 Ordinary Least Squares and is described by (see Wooldridge (2010), for example):

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

where $y_{it}$ is electricity demand for household $i$ in period $t$, $Y2$ is the period two dummy and $T$ is the treatment dummy ($u_{it}$ the usual noise term). The coefficient $\beta_1$ describes the temporal change in demand for the control group and $\beta_2$ describes the difference in demand between control and treatment groups in period one. The main coefficient of interest is the interaction term $\beta_3$, which describes how the demand of the treatment group changed in period two (compared to the control group), or more formally:

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

where subscript $C$ represents the control group. The model can also be estimated in a panel data setting by adding a fixed effect ($e_i$) to the error term and using a Within Regression Estimator. However, all time-invariant terms, such as $T_i$, are swept away by this time-invariant unobserved heterogeneity term and the model then reduces to:

$$y_{it} = \beta_0 + \beta_1 Y2_{it} + \beta_3 Y2_{it} T_i + e_i + u_{it} \quad (3)$$

In Section 4.3, this model is employed to explore the effects of treatment on electricity demand (for comparison against the original CER reports). Section 4.4 then explores if knowledge improvements explain these reductions by adding further interactions (the knowledge change variables) with each treatment group.

# 4 Results

## 4.1 The Effects of Feedback on Household Knowledge

The MNL results and marginal effects of feedback on *K1* change (general knowledge) are displayed by overall treatment (‘TREAT’ – all feedback stimuli combined) and by individual feedback in Tables 4.1 and 4.2 respectively. Section 2 showed that, 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). Results show that trial participation has increased this knowledge further with improvements significantly larger in the treatment

[12] Estimating these interactions simultaneously is not possible due to the size of the dataset. 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 by stimulus for both knowledge statements). Interested readers can, however, contact the corresponding author for the raw results.

groups. Overall (Table 4.1), the marginal effects demonstrate that treatment significantly increases the probability of improving knowledge ('moved to agree') by 8.9 percentage points and reduces the probability of lowering knowledge (move to disagree) by 7.3 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 11.5 percentage points more likely than the control group to show improvements.

**Table 4.1 here**

**Table 4.2 here**

A household's appliance knowledge is explored in *K2*. Overall (Table 4.3), trial participants are significantly more likely to show an improvement (move to disagree for *K2*) than the control group. Specifically, the marginal effects demonstrate that trial involvement increases the probability of an improvement by 7.5 percentage points and lowers the probability of a deterioration by 3.9 percentage points. Table 4.4 again shows the IHD to be most important stimulus 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.

**Table 4.3 here**

**Table 4.4 here**

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, followed by the MST and BI-MST respectively (the latter not significant for *K2*). This is consistent with the amount of 'feedback' that each stimulus contains.

### 4.2 Socio-Demographic Interactions

Table 4.5 and 4.6 present the marginal effects of feedback for a number of socio-demographic indicators.[13] The last column of these tables describes the overall treatment effect for each demographic, while columns one through three show the effect by feedback stimulus. Each marginal effect gives the percentage point change in probability for a zero-one change in the categorical demographic relative to the reference group (the excluded category within the demographic variable being explored). To illustrate, in Table 4.5, the marginal effect of TENURE1 at BI-MST on 'moved to disagree' is -0.13 which implies that renters who received this stimulus are less likely to show a deterioration (decreases the probability by 13 percentage points) than non-renters (households who own outright or have a mortgage). This is, however, the only significant effect for tenure and, in general, renters did not respond any different to treatment. The house-type interactions show similar results with apartment dwellers responding no differently to overall treatment or to each individual stimulus (than non-apartment dwellers). The age categories are significant at BI-MST (also overall for the oldest age category) where the results demonstrate that younger households (18-35 years; the base category) are 17 percentage points more likely than AGE2 (36-55 years) and 12

[13] Tables 4.5 and 4.6 display the marginal effect and the statistical significance indicator only. These tables summarize the results from twelve separate regressions and it is therefore not possible to display the full results.

percentage points more likely than AGE3 (55+ years) to improve their general knowledge.[14] The presence of children is significant (overall) – households without children are 5.3 percentage points more likely to show a deterioration. Finally, 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 significantly more likely to show an improvement (4.4 percentage point increase, overall).

**Table 4.5 here**

The interacted marginal effects for *K2* (appliance knowledge) are displayed in Table 4.6 and show a small number of significant effects. Renting households display a negative treatment effect at 'moved to disagree' (overall). This therefore implies that non-renters are more likely to show an improvement in appliance knowledge than renters (probability of a move to disagree 9.3 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. While age and the presence of children show no significant effects, households headed by females are more likely (4.2 percentage points) to show an improvement, overall. For education, it is possible that third-level households benefited from the IHD, but only in that they are significantly less likely to show a deterioration (reduces the probability of a deterioration by 6 percentage points).

**Table 4.6 here**

### 4.3 The Effects of Treatment on Demand

Table 4.7 displays the effect of each stimulus on total, peak and off-peak demand using the DID model. Table 4.8 summarizes these effects as percentage changes. 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 main variables of interest are the interaction terms which describe the difference in 2010 demand for each feedback stimuli (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 60.33 kWh or by 2.9% (versus control group levels in the treatment year). This is followed by the IHD and BI-MST (the latter not significant), which show reductions of 43.03 kWh (2.1%) and 7.13 kWh (0.4%) respectively. Overall (all feedback groups combined), treatment has significantly lowered total demand by 36.95 kWh (1.8%).[15] Subsequent auxiliary regressions (not displayed) also show that these feedback-led reductions differ by a household's appliance composition (interacting feedback stimuli with appliance dummies). For example, households with high-consuming devices, such as electric immersion heaters (77% of the sample) and storage heaters (4%), show larger reductions than households without.[16] However, this is perhaps expected as households without such items have significantly lower electricity demand and thus less capacity to reduce.

[14] The effects of the two age categories are estimated simultaneously. The reference group is therefore AGE1 (young households).
[15] Model results for the overall effect are not shown, but are estimated using the same methodology but replacing the individual feedback dummy variables with the single overall treatment dummy (TREAT).
[16] These secondary results, while certainly of a general interest, extend beyond our core research questions. To maintain clarity, therefore, we have not included these extra tables of results. Interested readers can, however, contact the corresponding author for details.

Peak reductions are relatively higher, and treatment is significant both overall and by feedback type. The average peak reduction is 7.8%, and this is strongest for the IHD (9.4%), followed by the MST (8.7%) and the BI-MST (5.4%). Furthermore, the majority of the total demand reductions occurred during peak times – overall, 59% of total reductions occurring during this two hour period. This dominant peak effect is also supported by the lack of significance at off-peak times, both overall and by stimulus, in all but the MST.

**Table 4.7 here**

**Table 4.8 here**

### 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 DID methodology, this section explores if this decrease can be explained by an improvement in a household's knowledge (Research Question Two). The results in Table 4.9 show the effects of a change in *K1* (general knowledge) on total, peak and off-peak demand. 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.[17]

The 2010 dummy, in this setting, describes the change in demand for control households that showed no improvement or deterioration in their general knowledge (the excluded reference group for the knowledge change dummy variables). These households increased their total demand by 49.47 kWh (compared to 2009). The stimuli interactions show how this differed for treated households (again, for those who kept their response unchanged).[18] The three-way interactions then show if treated households with knowledge improvements/deteriorations reduced significantly more/less. In this regard, there are few significant effects, and where significant, the coefficients are not of the expected sign. For example, for the MST and IHD, households with large improvements ('large move to agree') have significantly higher total demand in 2010 than households who kept their response unchanged (higher even than households who showed a deterioration). Furthermore, for peak and off-peak, improvements, large or small, do not accompany significantly larger reductions and, again, in most cases, the signs even suggest the opposite. Table 4.10 shows the effect of appliance knowledge change (*K2*) on demand. As with *K1*, there are few significant three-way interaction effects and the direction of the relationship is inconsistent with expectations. In only a number of cases – for example, households with the MST and small improvements ('small move to disagree') – is the sign of the coefficient as expected (but, again, is not significant).

These results appear to be robust to a household's appliance composition (not shown). For example, interacting the knowledge variables with appliance dummies (estimated separately

[17] 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'.

[18] Although these appear considerably larger than Section 4.3, the net effect [Y2 + (Y2 * TREATMENT)] is closer to Table 4.8.

for immersion and storage heaters) does not change this general result.[19] Furthermore, if we exclude households who started with a high initial knowledge from the analysis (households that could not improve) our conclusions, in general, do not change.[20]

**Table 4.9 here**

**Table 4.10 here**

# 5 Conclusion

Smart metering trials in Ireland and internationally have identified significant societal benefits. International findings, while varying in magnitude, generally show that a combination of demand response and increased customer feedback can yield reductions in 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, 2011a) 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 statistically significant and economically 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 behavioural 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 1.8% 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 (2.1%) and the bi-monthly user statement (0.3% – not significant). These reductions, while generally 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 11.5 and 13.9 percentage points (general and appliance respectively) relative to the control group.

Our last set of models show no relationship between self-reported 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 self-assessed understanding of how to reduce electricity consumption. Overall, 48% of treated households

[19] We test this as households without these high-consumption items may 'feel' their knowledge has increased but, without these items, may have no capacity to make sizable reductions. Given the small sample size, we avoided a fourth interaction and tested this hypothesis on treated households only (exclude the control group). These tests are not shown but are available on request from the corresponding author.

[20] With one exception for appliance knowledge (out of twelve knowledge-feedback interactions) – households with the MST who made a 'small move to disagree' (a small improvement) had significantly lower off-peak demand in the reduced sample. This is, however, clearly an isolated result among many tests.

[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.

showed improved levels of general knowledge (35% small improvement and 11% large improvement) and 51% showed improved appliance knowledge (32% small and 18% large). However, our results imply that these improvements had no significant association with 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.

Policymakers need be aware of the mechanisms by which feedback and information reduce energy demand. The obvious role of feedback is to make energy use more visible and to improve a household's knowledge of how to reduce consumption by better understanding what appliances and behaviours consume the most, and when. Or – more formally – it may serve to remove a market failure brought about by imperfect information. However, our results suggest that reductions in demand following introduction of smart metering and time of use tariffs were not brought about by an improvement in knowledge, or at least the component of knowledge correlated with the self-reported proxies available to us. In summary, we found no evidence that knowledge improvements *per se* were necessary or sufficient for reducing electricity demand, and it therefore seems unlikely that imperfect information pre-trial was leading to higher electricity demand.

However, and crucial for policy formulation, is that these results do not indicate that feedback is irrelevant, but only that feedback reduces short-run demand through some other mechanism. Some alternative explanations have been proposed in the literature. Allcott (2011), for example, suggests that many energy reducing actions, such as turning off lights, adjusting thermostats and closing blinds, are likely to be behaviours that most households are aware of already, and that feedback/information drives reductions by drawing attention to or increasing the 'moral cost' of energy use (pg. 1088).[22] It is also possible that increased feedback simply increases the frequency of reminders, which then increases a household's motivation to reach its conservation targets (see MIT (2011) pg. 162 and Faruqui et al. (2010) pg. 1607). This motivational component of behavioural change has also been discussed by Gram-Hanssen (2010). The insignificant demand-reducing effects of the bi-monthly user statement versus the significant effects of the monthly (same information but more frequent) supports this possibility. Furthermore, in the demand response literature, Faruqui and Sergici (2011) show how a pure reminder (*The Energy Orb*) facilitates significantly larger peak reductions.

It is important to highlight that our results only hold in the short-run – during our twelve months of data, the technologies and efficiency levels within the majority of household are fixed, particularly so for very high consumption items such as cookers, immersions and heating systems which get replaced over much longer timeframes. Over such durations, increased awareness of appliance consumption would likely motivate more efficient appliance purchases and renovation decisions, and the effects of such may outweigh any of the short-run motivation-led reductions (assuming this is the driver in the short-run). If this is the case, the appropriate policy is then to provide frequent reminders to increase a household's motivation in the short-run, but to maintain an educational component to facilitate knowledge-led reductions in the long-run. The likelihood of the latter, however, remains the work of future research using data from longer panels.

[22] Behavioural changes observed following the comparative feedback and generalized information provided though OPOWERS's *Home Energy Reports* in the US

There are, however, a number of limitations to our data. As the trial simultaneously applied time-of-use tariffs and various levels of feedback in combination, it is not possible to wholly isolate the presence of a pure feedback-led 'conservation' effect. Although relative peak reductions are higher and suggest that the tariffs are the main behavioural driver, peak to off-peak load-shifting would have lowered a 'pure' conservation effect during off-peak times. A further limitation of the data is the reliability of our 'knowledge' data, which is self-reported and therefore subject to reporting error. The possibility of this bias could be removed if future trials included tests of the actual knowledge of their participants. Furthermore, the size of our dataset limits deeper levels of knowledge interactions which could provide further insight. For example, although large knowledge improvements are not significant, it would be interesting to explore if households with low initial knowledge stocks and subsequent large improvements also showed no reduction in demand.

Finally, the extensive research of Ofgem (2011) also highlights a potential issue in smart metering trials which may bias the true effects of feedback. 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 here**

**Table A.2 here**

## 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):

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

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

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

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 ( $\beta$ ) maximizes the log-likelihood function:

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

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

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

and

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

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).

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**Figure 1.1: Research Questions**

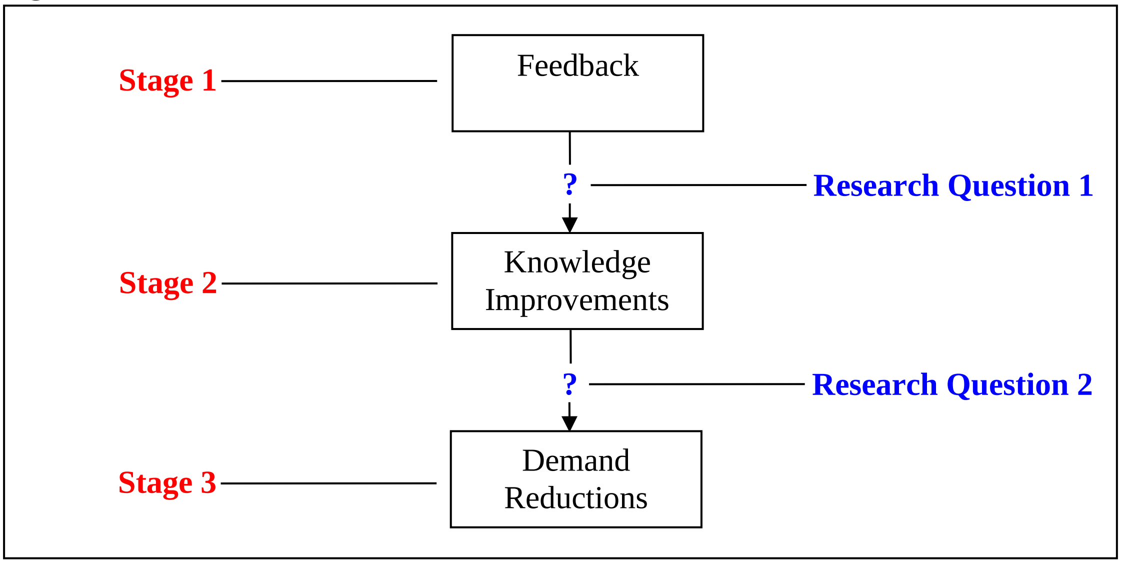

**Table 2.1: Time-of-Use Tariffs (€/kWh) excluding VAT**

| | 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 |

**Table 2.2: Treatment Matrix**

| | | Feedback Stimulus | | | | |
|---|---|---|---|---|---|---|
| | | **CONTROL** | **BI-MST** | **MST** | **IHD** | **TOTAL** |
| **Tariff** | **CONTROL** | 758 | 0 | 0 | 0 | **758** |
| | **A** | 0 | 225 | 237 | 232 | **694** |
| | **B** | 0 | 90 | 96 | 82 | **268** |
| | **C** | 0 | 249 | 244 | 232 | **725** |
| | **D** | 0 | 92 | 95 | 90 | **277** |
| | **TOTAL** | **758** | **656** | **672** | **636** | **2,722** |

**Table 2.3: K1 Descriptive Statistics**

K1: "I know what I need to do in order to reduce electricity usage"

*PRE-TRIAL RESPONSE*

| | TOTAL | CONTROL | BI-MST | MST | IHD |
|---|---|---|---|---|---|
| **1 - 'Strongly Agree' (%)** | 26.82% | 26.78% | 29.57% | 25.89% | 25.00% |
| **2** | 31.93% | 32.59% | 30.18% | 32.44% | 32.39% |
| **3** | 18.74% | 17.68% | 20.43% | 16.96% | 20.13% |
| **4** | 15.03% | 15.30% | 14.33% | 14.73% | 15.72% |
| **5 - "Strongly Disagree' (%)** | 7.49% | 7.65% | 5.49% | 9.97% | 6.76% |
| **Mean Response** | 2.44 | 2.44 | 2.36 | 2.50 | 2.47 |

*POST-TRIAL RESPONSE*

| | TOTAL | CONTROL | BI-MST | MST | IHD |
|---|---|---|---|---|---|
| **1 - 'Strongly Agree' (%)** | 45.79% | 37.63% | 50.77% | 46.47% | 49.82% |
| **2** | 28.11% | 27.96% | 26.15% | 29.06% | 29.32% |
| **3** | 14.47% | 17.57% | 13.33% | 14.12% | 12.23% |
| **4** | 7.23% | 10.69% | 4.96% | 6.24% | 6.47% |
| **5 - "Strongly Disagree' (%)** | 4.40% | 6.15% | 4.79% | 4.11% | 2.16% |
| **Mean Response** | 1.96 | 2.20 | 1.87 | 1.92 | 1.82 |

*RESPONSE CHANGE*

| | TOTAL | CONTROL | BI-MST | MST | IHD |
|---|---|---|---|---|---|
| **Moved to Disagree (%)** | 21.62% | 27.23% | 20.34% | 20.36% | 17.45% |
| **No Move (%)** | 32.35% | 33.24% | 34.19% | 30.38% | 31.47% |
| **Moved to Agree (%)** | 46.03% | 39.53% | 45.47% | 49.26% | 51.08% |
| **Mean Change (Pre minus Post Response)** | 0.48 | 0.26 | 0.49 | 0.53 | 0.67 |

## Table 2.4: K2 Descriptive Statistics

K2: "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' (%)** | 32.32% | 32.79% | 30.87% | 32.67% | 32.85% |
| **2** | 25.11% | 25.91% | 26.93% | 23.51% | 23.99% |
| **3** | 13.80% | 14.98% | 12.28% | 14.35% | 13.37% |
| **4** | 14.82% | 12.15% | 14.33% | 16.18% | 17.07% |
| **5 - "Strongly Disagree' (%)** | 13.95% | 14.17% | 15.59% | 13.28% | 12.72% |
| **Mean Response** | 2.53 | 2.49 | 2.57 | 2.54 | 2.53 |

| | *POST-TRIAL RESPONSE* | | | | |
|---|---|---|---|---|---|
| | **TOTAL** | **CONTROL** | **BI-MST** | **MST** | **IHD** |
| **1 - 'Strongly Agree' (%)** | 20.19% | 24.55% | 20.11% | 20.00% | 15.10% |
| **2** | 17.87% | 20.36% | 17.11% | 18.99% | 14.36% |
| **3** | 15.04% | 16.47% | 15.52% | 15.46% | 12.34% |
| **4** | 20.73% | 17.96% | 20.46% | 20.50% | 24.68% |
| **5 - "Strongly Disagree' (%)** | 26.17% | 20.66% | 26.81% | 25.04% | 33.52% |
| **Mean Response** | 3.15 | 2.90 | 3.17 | 3.12 | 3.47 |

| | *RESPONSE CHANGE* | | | | |
|---|---|---|---|---|---|
| | **TOTAL** | **CONTROL** | **BI-MST** | **MST** | **IHD** |
| **Moved to Disagree (%)** | 49.68% | 44.31% | 47.80% | 49.75% | 58.20% |
| **No Move (%)** | 25.33% | 27.84% | 27.16% | 24.54% | 21.18% |
| **Moved to Agree (%)** | 24.99% | 27.84% | 25.04% | 25.71% | 20.63% |
| **Mean Change (Pre minus Post Response)** | -0.60 | -0.39 | -0.57 | -0.58 | -0.92 |

## Table 4.1: Mlogit Results – Effect of Treatment (overall) on K1[23]

K1 "I know what I need to do in order to reduce electricity usage"

| | Coef. | Std. Err. | DY/DX | Std. Err. |
|---|---|---|---|---|
| ***Outcome 1 – Moved to Disagree:*** | | | | |
| TREAT (D) | -0.291** | 0.120 | -0.073*** | -0.017 |
| Constant | -0.207** | 0.098 | - | - |
| ***Outcome 2 – No Change (base):*** | | | | |
| TREAT (D) | - | - | -0.016 | -0.021 |
| Constant | - | - | - | - |
| ***Outcome 3 – Moved to Agree:*** | | | | |
| TREAT (D) | 0.245** | 0.105 | 0.089*** | -0.022 |
| Constant | 0.167** | 0.090 | - | - |
| ***Model Stats:*** | | | | |
| N | 2445 | LR chi test stat. | 22.07 | |
| Log-Likelihood | -2565.403 | P > chi | 0.000 | |
| Pseudo R-Squared | 0.0043 | | | |

[23] Where 'K1' is the general knowledge change categorical variable 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 Results – Effect of Feedback Stimuli on K1[24]

K1 "I know what I need to do in order to reduce electricity usage"

| | Coef. | Std. Err. | DY/DX | Std. Err. |
|---|---|---|---|---|
| ***Outcome 1 – Moved to Disagree:*** | | | | |
| BI-MST (D) | -0.309* | 0.024 | -0.070*** | 0.024 |
| MST (D) | -0.19 | 0.023 | -0.067*** | 0.024 |
| IHD (D) | -0.389** | 0.000 | -0.097*** | 0.023 |
| Constant | -0.207** | 0.000 | - | - |
| ***Outcome 2 – No Change (base):*** | | | | |
| BI-MST (D) | - | - | 0.009 | 0.027 |
| MST (D) | - | - | -0.03 | 0.026 |
| IHD (D) | - | - | -0.018 | 0.027 |
| Constant | - | - | - | - |
| ***Outcome 3 – Moved to Agree:*** | | | | |
| BI-MST (D) | 0.112 | 0.000 | 0.058** | 0.028 |
| MST (D) | 0.314** | 0.028 | 0.097*** | 0.027 |
| IHD (D) | 0.311** | 0.027 | 0.115*** | 0.028 |
| Constant | 0.168* | 0.000 | - | - |

***Model Stats:***

| | | | |
|---|---|---|---|
| N | 2445 | LR chi test stat. | 27.330 |
| Log-Likelihood | -2562.77 | P > chi | 0.000 |
| Pseudo R-Squared | 0.0053 | | |

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

## Table 4.3: Mlogit Results – Effect of Treatment (overall) on K2[25]

K2 "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) | 0.293*** | 0.110 | 0.075*** | 0.023 |
| Constant | 0.461*** | 0.093 | - | - |
| ***Outcome 2 – No Change (base):*** | | | | |
| TREAT (D) | - | - | -0.036* | 0.019 |
| Constant | - | - | - | - |
| ***Outcome 3 – Moved to Agree:*** | | | | |
| TREAT (D) | -0.014 | 0.124 | -0.039** | 0.019 |
| Constant | -0.011 | 0.103 | - | - |
| ***Model Stats:*** | | | | |
| N | 2382 | LR chi test stat. | | 10.79 |
| Log-Likelihood | -2475.96 | P > chi | | 0.0045 |
| Pseudo R-Squared | 0.002 | | | |

[25] Where 'K2' is the appliance knowledge change categorical variable.

## Table 4.4: Mlogit Results – Effect of Feedback Stimuli on K2

K2 "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) | 0.108 | 0.028 | 0.035 | 0.028 |
| MST (D) | 0.236* | 0.028 | 0.053* | 0.028 |
| IHD (D) | 0.553*** | 0.028 | 0.139*** | 0.028 |
| Constant | 0.461*** | 0 | - | - |
| ***Outcome 2 – No Change (base):*** | | | | |
| BI-MST (D) | - | - | -0.009 | 0.025 |
| MST (D) | - | - | -0.032 | 0.025 |
| IHD (D) | - | - | -0.068*** | 0.025 |
| Constant | - | - | - | - |
| ***Outcome 3 – Moved to Agree:*** | | | | |
| BI-MST (D) | 0.000 | 0.000 | -0.027 | 0.025 |
| MST (D) | -0.027 | 0.025 | -0.021 | 0.025 |
| IHD (D) | -0.021 | 0.025 | -0.071*** | 0.024 |
| Constant | -0.071 | 0.024 | - | - |

| ***Model Stats:*** | | | |
|---|---|---|---|
| N | 2382 | LR chi test stat. | 25.03 |
| Log-Likelihood | -2468.85 | P > chi | 0.000 |
| Pseudo R-Squared | 0.005 | | |

## Table 4.5: Summary of Socio-Demographic Marginal Effects for K1

K1 "I know what I need to do in order to reduce electricity usage"

| | BI-MST | MST | IHD | TREAT |
|---|---|---|---|---|
| **TENURE1 (households that rent)** | | | | |
| Moved to Agree | 0.028 | 0.009 | -0.136 | -0.034 |
| Moved to Disagree | -0.130** | -0.010 | 0.002 | -0.039 |
| No Change | 0.102 | 0.002 | 0.133 | 0.073 |
| **HOUSE1 (apartments)** | | | | |
| Moved to Agree | 0.120 | 0.081 | 0.036 | 0.076 |
| Moved to Disagree | -0.062 | -0.062 | -0.085 | -0.076 |
| No Change | -0.057 | -0.018 | 0.049 | -0.001 |
| **AGE2 (36-55 years)** | | | | |
| Moved to Agree | -0.170*** | 0.011 | -0.056 | -0.076 |
| Moved to Disagree | -0.020 | -0.042 | -0.038 | -0.029 |
| No Change | 0.190*** | 0.031 | 0.093 | 0.105 |
| **AGE3 (55+ years)** | | | | |
| Moved to Agree | -0.120* | -0.035 | -0.092 | -0.087** |
| Moved to Disagree | -0.034 | -0.033 | 0.038 | -0.007 |
| No Change | 0.154** | 0.068 | 0.054 | 0.094** |
| **CHILD (presence of children under 15 years)** | | | | |
| Moved to Agree | 0.073 | 0.036 | 0.014 | 0.041 |
| Moved to Disagree | -0.077** | -0.014 | -0.074** | -0.053*** |
| No Change | 0.005 | -0.022 | 0.060 | 0.013 |
| **FEMALE (female respondent)** | | | | |
| Moved to Agree | -0.065 | -0.069* | 0.009 | -0.044* |
| Moved to Disagree | 0.038 | 0.000 | -0.051 | -0.003 |
| No Change | 0.026 | 0.069* | 0.042 | 0.047** |
| **EDU3 (third level education)** | | | | |
| Moved to Agree | 0.066 | -0.005 | 0.071 | 0.044* |
| Moved to Disagree | -0.020 | -0.003 | -0.036 | -0.020 |
| No Change | -0.046 | 0.007 | -0.034 | -0.024 |

## Table 4.6: Summary of Socio-Demographic Marginal Effects for K2

K2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

| | BI-MST | MST | IHD | TREAT |
|---|---|---|---|---|
| **TENURE1 (households that rent)** | | | | |
| Moved to Agree | 0.073 | 0.072 | -0.031 | 0.033 |
| Moved to Disagree | -0.124 | -0.152* | -0.025 | -0.093* |
| No Change | 0.051 | 0.081 | 0.057 | 0.061 |
| **HOUSE1 (apartments)** | | | | |
| Moved to Agree | -0.253*** | 0.078 | -0.025 | -0.079 |
| Moved to Disagree | 0.021 | 0.172 | 0.055 | 0.083 |
| No Change | 0.232 | -0.249*** | -0.030 | -0.004 |
| **AGE2 (36-55 years)** | | | | |
| Moved to Agree | 0.039 | -0.055 | -0.060 | -0.023 |
| Moved to Disagree | -0.032 | 0.027 | 0.041 | 0.007 |
| No Change | -0.006 | 0.029 | 0.020 | 0.017 |
| **AGE3 (55+ years)** | | | | |
| Moved to Agree | 0.089 | -0.047 | -0.008 | 0.013 |
| Moved to Disagree | -0.074 | 0.076 | -0.031 | -0.012 |
| No Change | -0.015 | -0.029 | 0.039 | -0.001 |
| **CHILD (presence of children under 15 years)** | | | | |
| Moved to Agree | -0.046 | -0.053 | -0.006 | -0.035 |
| Moved to Disagree | 0.068 | -0.012 | 0.020 | 0.024 |
| No Change | -0.023 | 0.065 | -0.014 | 0.011 |
| **FEMALE (female respondent)** | | | | |
| Moved to Agree | -0.012 | 0.037 | 0.012 | 0.013 |
| Moved to Disagree | 0.062 | 0.016 | 0.053 | 0.042* |
| No Change | -0.049 | -0.054 | -0.065* | -0.055*** |
| **EDU3 (third level education)** | | | | |
| Moved to Agree | 0.006 | 0.033 | -0.060* | -0.007 |
| Moved to Disagree | 0.030 | -0.045 | 0.015 | 0.001 |
| No Change | -0.035 | 0.011 | 0.046 | 0.006 |

**Table 4.7: DID FE Model Results - Effect of Feedback Stimuli on Demand**[26]

| | TOTAL | | PEAK | | OFF-PAEK | |
|---|---|---|---|---|---|---|
| | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** |
| **Y2 (D)** | 6.168 | 14.622 | -1.957 | 2.360 | 8.125 | 12.998 |
| **Y2 * BI-MST** | -7.127 | 21.467 | -15.099*** | 3.465 | 7.972 | 19.083 |
| **Y2 * MST** | -60.333*** | 21.330 | -24.585*** | 3.443 | -35.748* | 18.961 |
| **Y2 * IHD** | -43.033** | 21.648 | -26.583*** | 3.494 | -16.450 | 19.244 |
| **Constant** | 2091.660 | 5.456 | 290.235 | 0.881 | 1801.425 | 4.850 |
| ***Model Stats:*** | | | | | | |
| Observations | 5444 | | 5444 | | 5444 | |
| Groups | 2722 | | 2722 | | 2722 | |
| F stat. | 4.42 | | 70.18 | | 1.52 | |
| Prob. > F | 0.000 | | 0.000 | | 0.195 | |

**Table 4.8: Percentage Reductions in Treatment Groups**[27]

| | **TOTAL** | **PEAK** | **OFF-PEAK** |
|---|---|---|---|
| **BI-MST** | -0.348 | -5.371*** | 0.452 |
| **MST** | -2.949*** | -8.746*** | -2.025* |
| **IHD** | -2.103** | -9.456*** | -0.932 |
| **TREAT** | -1.806** | -7.849*** | -0.844 |

[26] Where 'DID' indicates difference-in-difference model and 'FE' indicates fixed effects. 'Y10' is the treatment period dummy.
[27] Reductions are relative to the control group demand levels in the treatment year

## Table 4.9: DID FE model results – Effect of K1 Change on Total Demand

K1 "I we know what I we need to do in order to reduce electricity usage"

| | TOTAL | | PEAK | | OFF-PAEK | |
|---|---|---|---|---|---|---|
| | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** |
| **Y2** | 49.473* | 26.566 | 2.811 | 4.320 | 46.662** | 23.616 |
| | | | | | | |
| **Y2 * BI-MST** | -74.976* | 38.817 | -20.174*** | 6.312 | -54.802 | 34.507 |
| **Y2 * MST** | -125.273*** | 39.645 | -30.076*** | 6.446 | -95.197*** | 35.243 |
| **Y2 * IHD** | -105.564*** | 40.264 | -34.774*** | 6.547 | -70.789** | 35.794 |
| | | | | | | |
| **Y2 * Large move to disagree** | -21.214 | 81.482 | -0.663 | 13.249 | -20.551 | 72.435 |
| **Y2 * Small move to disagree** | -62.794 | 41.393 | -10.393 | 6.731 | -52.401 | 36.797 |
| **Y2 * Small move to agree** | -32.140 | 38.183 | -1.369 | 6.209 | -30.771 | 33.943 |
| **Y2 * Large move to agree** | -179.421*** | 59.299 | -19.203** | 9.642 | -160.218*** | 52.715 |
| | | | | | | |
| **Y2 * BI-MST * Large move to disagree** | 130.917 | 122.757 | 12.873 | 19.961 | 118.044 | 109.127 |
| **Y2 * BI-MST * Small move to disagree** | 170.999*** | 64.414 | 21.474** | 10.474 | 149.525*** | 57.262 |
| **Y2 * BI-MST * Small move to agree** | 74.151 | 55.072 | 3.162 | 8.955 | 70.990 | 48.957 |
| **Y2 * BI-MST * Large move to agree** | 62.818 | 83.862 | -1.484 | 13.636 | 64.302 | 74.550 |
| | | | | | | |
| **Y2 * MST* Large move to disagree** | 91.664 | 132.357 | 20.420 | 21.521 | 71.244 | 117.660 |
| **Y2 * MST* Small move to disagree** | 72.227 | 63.740 | 4.066 | 10.364 | 68.161 | 56.662 |
| **Y2 * MST* Small move to agree** | 65.320 | 54.850 | -0.187 | 8.919 | 65.508 | 48.760 |
| **Y2 * MST* Large move to agree** | 280.115*** | 82.521 | 33.446** | 13.418 | 246.668*** | 73.359 |
| | | | | | | |
| **Y2 * IHD* Large move to disagree** | 20.699 | 126.439 | 0.155 | 20.559 | 20.545 | 112.400 |
| **Y2 * IHD * Small move to disagree** | 23.244 | 68.431 | 3.209 | 11.127 | 20.035 | 60.832 |
| **Y2 * IHD* Small move to agree** | 69.784 | 56.168 | 8.835 | 9.133 | 60.950 | 49.932 |
| **Y2 * IHD* Large move to agree** | 213.775*** | 80.373 | 18.809 | 13.069 | 194.966*** | 71.449 |
| | | | | | | |
| **Constant** | 2100.260*** | 5.738 | 292.418*** | 0.933 | 1807.841*** | 5.101 |
| ***Model Stats:*** | | | | | | |
| Observations | 4866 | | 4866 | | 4866 | |
| Groups | 2433 | | 2433 | | 2433 | |
| | | | | | | |
| F stat. | 2.27 | | 12.37 | | 1.65 | |
| Prob. > F | 0.0011 | | 0 | | 0.0341 | |

**Table 4.10: DID FE model results – Effect of K2 Change on Total Demand**

K2: "I do not know enough about how much electricity different appliances use in order to reduce my usage"

| | TOTAL | | PEAK | | OFF-PEAK | |
|---|---|---|---|---|---|---|
| | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** | **Coef.** | **Std. Err.** |
| **Y2** | 19.271 | 29.377 | 0.593 | 4.779 | 18.678 | 26.123 |
| | | | | | | |
| **Y2 * BI-MST** | -31.263 | 43.650 | -15.675** | 7.101 | -15.588 | 38.815 |
| **Y2 * MST** | -68.975 | 44.300 | -29.203*** | 7.206 | -39.771 | 39.393 |
| **Y2 * IHD** | -100.047** | 47.527 | -40.724*** | 7.731 | -59.323 | 42.263 |
| | | | | | | |
| **Y2 * Large move to disagree** | -86.973* | 50.524 | -14.443* | 8.219 | -72.530 | 44.928 |
| **Y2 * Small move to disagree** | 2.319 | 40.763 | -2.110 | 6.631 | 4.428 | 36.248 |
| **Y2 * Small move to agree** | 3.927 | 45.013 | 2.161 | 7.322 | 1.766 | 40.027 |
| **Y2 * Large move to agree** | 24.666 | 64.863 | 2.772 | 10.551 | 21.894 | 57.678 |
| | | | | | | |
| **Y2 * BI-MST * Large move to disagree** | 69.678 | 72.339 | 8.313 | 11.768 | 61.365 | 64.327 |
| **Y2 * BI-MST * Small move to disagree** | 52.344 | 60.264 | 6.453 | 9.803 | 45.891 | 53.589 |
| **Y2 * BI-MST * Small move to agree** | -2.157 | 66.907 | -8.645 | 10.884 | 6.487 | 59.496 |
| **Y2 * BI-MST * Large move to agree** | -2.603 | 104.797 | -0.070 | 17.048 | -2.533 | 93.189 |
| | | | | | | |
| **Y2 * MST* Large move to disagree** | 122.205* | 71.588 | 14.371 | 11.645 | 107.834* | 63.658 |
| **Y2 * MST* Small move to disagree** | -78.708 | 60.162 | -9.325 | 9.787 | -69.383 | 53.498 |
| **Y2 * MST* Small move to agree** | 38.044 | 67.333 | 11.908 | 10.953 | 26.136 | 59.875 |
| **Y2 * MST* Large move to agree** | 92.427 | 97.070 | 26.504* | 15.791 | 65.922 | 86.317 |
| | | | | | | |
| **Y2 * IHD* Large move to disagree** | 130.808* | 72.129 | 26.891** | 11.733 | 103.917 | 64.139 |
| **Y2 * IHD * Small move to disagree** | 47.196 | 62.540 | 12.426 | 10.174 | 34.770 | 55.613 |
| **Y2 * IHD* Small move to agree** | 31.512 | 73.510 | 8.634 | 11.958 | 22.878 | 65.368 |
| **Y2 * IHD* Large move to agree** | 26.775 | 103.832 | 21.512 | 16.891 | 5.263 | 92.331 |
| | | | | | | |
| **Constant** | 2103.512*** | 5.816 | 293.051*** | 0.946 | 1810.460*** | 5.171 |
| | | | | | | |
| ***Model Stats:*** | | | | | | |
| Observations | 4746 | | 4746 | | 4746 | |
| Groups | 2373 | | 2373 | | 2373 | |
| | | | | | | |
| F stat. | 1.88 | | 14.57 | | 1.18 | |
| Prob. > F | 0.0102 | | 0 | | 0.2626 | |

**Table A.1: Descriptive Statistics of Interaction Variables[28]**

| 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 |

**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** | 2039.52 | 1010.73 | 283.06 | 153.49 | 1756.46 | 873.41 |
| **BI-MST** | 2102.88 | 1013.19 | 292.62 | 150.53 | 1810.26 | 879.16 |
| **MST** | 2132.71 | 1068.41 | 295.43 | 157.27 | 1837.28 | 927.02 |
| **IHD** | 2098.85 | 1014.72 | 290.84 | 154.63 | 1808.02 | 877.57 |
| 2010 | | | | | | |
| **Control** | 2045.69 | 1029.12 | 281.10 | 152.55 | 1764.59 | 893.99 |
| **BI-MST** | 2101.92 | 1000.31 | 275.57 | 143.30 | 1826.36 | 872.59 |
| **MST** | 2078.55 | 1033.94 | 268.89 | 148.40 | 1809.66 | 901.87 |
| **IHD** | 2061.99 | 1011.11 | 262.30 | 140.92 | 1799.69 | 886.31 |

[28] Where 'D' indicates dummy variable