Better information on residential energy use may deter investment in efficiency: case study of a smart metering trial

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Abstract

Smart metering allows electricity utilities to provide consumers with better information on their energy usage and to apply time of use tariffs. These measures have been shown to reduce electricity consumption and induce time-shifting of demand. Less is known about how they affect residential energy efficiency investment behaviour. Using data from a randomised-controlled trial on a sample of over 2500 Irish consumers we show that exposure to time of use pricing and better information over a 12 month period can have the unintended effect of reducing investment in energy efficiency measures within the home.

Keywords Randomised-controlled trial; Smart-metering; Energy efficiency adoption;

JEL Classification O33; D12; Q40; Q55

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1 Introduction

Reducing energy consumption and increasing the adoption of energy saving measures and energy efficient appliances are seen as crucial elements in reducing energy demand. The EU Energy Efficiency Directive, EU (2012), aims to try and "*remove barriers and overcome market failures that impede efficiency in the supply and use of energy*". However users seems reluctant to engage fully with this process. This reluctance to adopt energy efficient appliances that offer them seemingly positive NPV is known as the "Energy Paradox" and has been widely studied[1]. Early work by Hausman (1979) indicates that consumers apply a 20 percent discount rate in the trade off between operating cost and initial purchase price when buying home air conditioning systems. Dubin and McFadden (1984) find similar discount rates are applied in space and water heating investments. Others would disagree about the magnitude of this; many authors, including Metcalf and Hassett (1999) and Allcott and Greenstone (2012) have raised the point that realised returns are generally less than engineering estimates would indicate[2]. Some would argue that the difference between this implicit discount rate and the interest rate offered by other investments could be seen as a market failure, Ruderman et al. (1987), while others argue that due to uncertainty over future energy prices and the irreversible nature of the investment, high discount rates might be appropriate and this would not constitute a market failure, Jaffe and Stavins (1994).

Jaffe and Stavins (1994) cite three potential sources of information market failure. 1) If improved information is a public good, the market might tend to provide less than the socially optimum level. 2) If information is conveyed by the adopter, and the adopter is not compensated by the market for the positive externality they create by adopting, this constitutes a market failure. 3) If whoever possesses the information doesn't benefit from the cost savings, i.e. if they are not the bill payer. They have no financial incentive to act on the information.

Insofar as this is an information problem, it may be possible to remedy by educating consumers. Allcott and Mullainathan (2010), cite the growing evidence of the effectiveness of behavioural interventions, rather than price-based approaches in changing consumer choices. Other work by Allcott and Greenstone (2012) argues that while lack of information may be a problem for some consumers, in order to account for consumer heterogeneity, it is crucial to design targeted policies. This point is also made by Golove and Eto (1996). Otherwise providing information may have some unintended consequences.

Recently in the UK, DEFRA commissioned a report called "Exploring Catalyst Behaviours", Brook-Lyndhurst (2011). The aim of this report was to review the literature on pro-environmental behaviour, to determine if policies aimed at encouraging certain types of pro-environmental behaviour "spill-over" into other domains[3].

This stream of research is informed by the environmental psychology literature and a number of studies have examined this. The idea that people strive to be consistent in their beliefs, attitudes and behaviours comes from a range of social-psychological theories rooted in Festinger (1962)'s theory of cognitive dissonance.

It is also possible that these spill-overs might be negative. For instance if individuals felt that they had already made a sacrifice, and have an "alibi", this might reduce their motivation to change their behaviour in other domains. Alternatively if faced with a number of options, individuals will take the one that is of least cost to them.

Thogersen and Olander (2003) conduct a three wave survey on a panel of Danish consumers. Questions were asked about their behaviours related to recycling, buying organic food, using sustainable transport and domestic energy conservation. The authors find some positive spill-over effects, but the magnitude is small. They also find evidence of some negative ones. They find that spill-over is higher amongst individuals who place a strong

[1] See Blumstein et al. (1980), Golove and Eto (1996) and Allcott and Greenstone (2012) for a review

[2] Primarily due to lab-based estimates of appliance performance not bearing out in reality. Also consumer heterogeneity and the typically slow diffusion rates of technically superior products must be considered.

[3] i.e. If one is encouraged to recycle, does this make them more likely to reduce electricity consumption?

value on environment-friendly behaviour.

Other work by Thogersen (2004) argues that if behaviours share the same motivational roots, we should expect them to be correlated. In a study on 309 consumers in a Danish shopping mall, the author find that correlations between various environmentally responsible behaviours do exist, but are small in magnitude. The issue of negative correlations is also raised. The results suggest that when people act inconsistently, it is because they dont find the contradictory behaviour to be morally important.

Whitmarsh and O'Neill (2010) investigate the existence of spill-over effects amongst UK consumers. They find environmental self-identity to be a strong predictor of environmentally friendly behaviour in a number of spheres; waste reduction, regular water and domestic energy conservation. They also conclude that spill-overs do exist but the underlying identity of consumers is more important and it is difficult to disentangle the two.

Many countries are implementing smart-metering programmes in order to provide consumers with better information in the hope that this will encourage a reduction in consumption, or a move of consumption from periods when increasing generation is expensive to periods when generating electricity is cheaper. A number of studies examine the effect of providing In-Home Displays (IHD) to consumers in order to encourage reduced consumption. Faruqui et al. (2010) provide a useful summary. Their review of a number of North American studies indicates that IHDs can induce consumers to reduce consumption by 7% on average[4]. Directly relevant to this research, the Commission for Energy Regulation (CER) in Ireland conducted a smart metering trial and found that customers reduced average overall usage by 2.5% and peak usage by 8%, CER (2011)[5].

Reduced consumption could be considered a short-term effect. Less is known about whether feedback can induce long-term behavioural change, by changing investment behaviour. This raises an interesting question: if consumers are motivated to reduce consumption, through an time of use pricing combined with more information in their bills or an in-home display, does this also encourage them to make capital investments in energy efficiency?

We exploit access to a unique dataset[6] in order to investigate this question. Our contribution is in showing that increased information can actually reduce investment, for a set of consumers who also reduced consumption of electricity. As far as we are aware, this has not been empirically demonstrated before. More generally we demonstrate how interventions to change certain behaviours in one domain can have unintended consequences in others. This is something that must be considered by policy makers when designing market interventions.

2 Data and Methods

2.1 Data

We use data from the CER Smart Metering Customer Behavioural Trial. This is a nationally representative sample of over 5,000 households in the Republic of Ireland, containing high frequency energy consumption data along with socioeconomic information on the participants. It took place over eighteen months; the benchmark period was from 1st July to 31st December 2009, and the test period was from 1st January to 31st December 2010 The survey was conducted on Electric Ireland customers who at that time represented 100 percent of Irish residential electricity demand. It was designed to quantify the effect better information and time of use pricing could have on overall electricity usage and on peak demand, not to examine investment behaviour. However we can exploit before and after survey questions related to a range of energy efficiency measures adopted within the home. Households self-selected into the trial and were randomly assigned to a control group or various

[4]Reduction was as high as 18% in some cases

[5]This was through the use of IHDs, other information stimuli and time of use tariffs

[6]CER Electricity Smart Metering Customer Behavioural Trial data.

treatment groups in order to estimate the effect of different stimuli on residential electricity demand. For further information on this study, please see CER (2011), Di Cosmo et al. (2014) and Carroll et al. (2013).

We start with $N = 3488$ households. We merge the pre-trial and post trial surveys and drop households who received a financial reward for achieving a reduction target. We also drop households who were on a "weekend" tariff as they did not receive a feedback stimulus. This leaves us with a sample of $N = 2456$ observations. This is divided into control and treatment groups as per table 2. Households received the following information stimuli and time of use tariffs:

1. Treatment 1: Bi-monthly electricity usage statement
2. Treatment 2: Monthly electricity usage statement
3. Treatment 3: Electronic in-house display and bi-monthly electricity usage statement[7]

Table 1: Time-of-Use Tariffs (/kWh) excluding VAT

	Night	Day	Peak
Tariff A	12	14	20
Tariff B	11	13.5	26
Tariff C	10	13	32
Tariff D	9	12.5	38

Table 2: Treatment Matrix

	Control	Treatment 1	Treatment 2	Treatment 3	Total
Control	693	0	0	0	693
Tariff A	0	199	219	208	626
Tariff B	0	82	89	67	238
Tariff C	0	226	220	205	651
Tariff D	0	81	89	78	248
Total	693	588	617	558	2,456

2.2 Methods

After the trial was conducted participants were asked whether they had adopted a range of energy efficiency measures over the previous 12 months. Details are below in table 3.

[7] This provides real-time consumption, cost and tariff information

Table 3: In-trial adoption of energy efficient measures

Energy saving measures installed	Number	Percent
Added double glazing to some or all of your windows	199	8%
Installed attic or wall insulation	676	28%
Replaced appliances with A rated ones	396	16%
Fitted a new lagging jacket on your hot water tank	326	13%
Fitted other energy saving devices	206	8%
Added solar panels	35	1%
Added draught-proofing to your doors or windows	241	10%
Replaced a central heating boiler with a more efficient one	164	7%
Added thermostatic controls to radiators	181	7%
None of these	1170	48%
Total	2,456	1

We are interested in the effect improved information had on in-trial adoption. The hypothesis we want to test is:

- H_0: The treatment had no effect on capital investment in energy saving measures
  vs
- H_A: The treatment had an effect on capital investment in energy saving measures

This is tested in a number of different ways. A simple t-test to check for equality of the mean number of in-trial adoptions was employed first. The hypothesis tested was $H_0 : \mu_c = \mu_t$ vs $H_A : \mu_c \neq \mu_t$. Where μ_c is the mean of the control group and μ_t is the mean of each of the different treatment groups.

Following this, a binary adopter variable was created (1 if they adopted any of the above measures, 0 otherwise). Using this as the dependent variable, a logit model was estimated to examine if treatment altered the probability of being an adopter. Formally, the hypothesis tested was H_0: $\beta_1 = 0$ vs H_A: $\beta_1 \neq 0$, where $Pr(Y = 1|x) = p(x)$ and $log\frac{p(x)}{1-p(x)} = \beta_0 + \beta_1 D_i \epsilon_i$.

Finally, a count variable was created to measures the number of adoptions each household made. This was used to examine if treatment changed the expected number of energy saving features adopted. As the data is over-dispersed, a Negative Binomial model was employed here rather than a Poisson model. The hypothesis tested was H_0: $\beta_1 = 0$ vs H_A: $\beta_1 \neq 0$, where $E[y_i|x_i, \epsilon_i] = exp(\beta_0 + \beta_1 D_i + \epsilon_i)$. D_i represents the different treatment groups in both of the above models. Further information on the dependent variables (y_i) used can be found in tables 11 and 12 in Annex B.

2.3 Randomisation

Of primary concern is the accuracy of the pre-trial randomisation. If systematic differences exist between control and treatment groups, this could lead to post trial outcomes that would not be due to the treatment. Of particular interest is the pre-trial stock of energy efficiency measures installed by households. From table 4 below we can see that this is very evenly distributed amongst control and treatment groups.

Table 4: Pre-trial adoption of energy efficient measures and electricity usage

Energy Efficiency Measure	Control	Treatment 1	Treatment 2	Treatment 3	Total
Proportion of energy saving lightbulbs (scale: 1-5)					
mean	2.86	2.85	2.90	2.83	2.86
sd	1.41	1.40	1.40	1.44	1.41
Proportion of double-glazed windows (scale: 1-5)					
mean	4.53	4.55	4.49	4.59	4.54
sd	1.18	1.14	1.24	1.12	1.17
Hot-water tank has a lagging jacket? ($1 = yes, 0 = no$)					
mean	0.83	0.82	0.85	0.84	0.84
sd	0.38	0.38	0.36	0.36	0.37
Attic insulation within the last 5 years? ($1 = yes, 0 = no$)					
mean	0.36	0.34	0.35	0.32	0.35
sd	0.48	0.47	0.48	0.47	0.48
Attic insulation over 5 years ago? ($1 = yes, 0 = no$)					
mean	0.54	0.56	0.55	0.57	0.55
sd	0.50	0.50	0.50	0.50	0.50
External wall insulation ($1 = yes, 0 = no$)					
mean	0.56	0.56	0.58	0.58	0.57
sd	0.50	0.50	0.49	0.49	0.50
Pre-trial electricity usage (kWh)					
mean	2048	2097	2091	2074	2077
sd	1019	993	1024	1006	1011

Tables 8, 9 and 10 in Annex A demonstrate how there are no systematic differences between control and treatment groups across a whole range of measures that include; socioeconomic factors, house variables, stock of household appliances and heating type. Di Cosmo et al. (2014) also found no individual or household characteristics to be a significant predictor of being in the control group. Another concern is that some element of the survey design influenced one group more than another. We have contacted the company that designed the experiment and have been assured that neither group received instructions as to energy efficient upgrades.

3 Results

This section presents the results of the tests for equality of means, a logit model examining if treatment altered the probability of adopting any measure, and a negative binomial model testing if treatment influenced the number energy saving measures installed in the home.

3.1 Equality of means

Examining the in-trial adoptions for control and treatment groups, it is immediately obvious from table 5 that the control group, on average, made more capital investments than any of the treatment groups in energy efficiency measures during the trial period.

Table 5: Summary statistics for in-trial adoption by group

	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
Control	693	1.128	0.052	1.373	[1.026 - 1.231]
Treatment 1	588	0.963	0.053	1.284	[0.859 - 1.067]
Treatment 2	617	0.896	0.048	1.196	[0.802 - 0.991]
Treatment 3	558	0.937	0.055	1.291	[0.830 - 1.045]

Further analysis on the difference between control and treatment group means, reported in table 6, allows us to reject the null hypothesis, that there is no difference between the mean of the control group and the mean of any treatment group[8]. Furthermore, we can conclude that the mean of the control group is greater than the mean of any treatment group[9]. Welch's t-test is used to allow for samples with unequal variance.

Table 6: Difference in mean in-trial adoption between control and treatment groups

Diff	Mean	Std. Err.	[95% Conf. Interval]	$H_A : diff \neq 0$	$H_A : diff > 0$
Control-Treatment1	0.166	0.074	[0.020 - 0.312]	0.026	0.013
Control-Treatment2	0.232	0.071	[0.093 - 0.371]	0.001	0.001
Control-Treatment3	0.191	0.076	[0.043 - 0.339]	0.012	0.006

3.2 Probability of adopting any energy saving measure

The results from the binary regression model further confirm the result that treatment had a negative effect on adoption. We report odds rations (OR). As can be seen from table 7 below, the treatment groups are less likely to adopt than the control group. Interpreting the odds ratios, we can conclude that the treatment group were 23%-28% less likely to adopt any energy saving measure over the 12 month trial period. Decomposing the dependent variable, we find the result is driven by the adoption of lagging jackets, attic insulation and double-glazing. No other variables are statistically significant.

3.3 Number of energy saving measures adopted

Treatment not only reduced the likelihood of adoption, but also reduced the number of energy saving investments that households made. The results of the negative binomial regression are also reported in table 7. Reporting the incident rate ratios (IRRs) it is found that being in the treatment group reduced the expected number of energy saving features adopted by 15%-21%.

[8]We reject H_0 at a 1% level of significance for treatment 2, and at a 5% level for treatments 1 and 3

[9]We reject H_0 at a 1% level of significance for treatments 2 and 3, and at a 5% level for treatment 1

Table 7: Regression results

	(1) Logit (OR)	(2) Negative Binomial (IRR)
Treatment 1	0.77**	0.85**
	(0.09)	(0.06)
Treatment 2	0.71***	0.79***
	(0.08)	(0.06)
Treatment 3	0.72***	0.83**
	(0.08)	(0.06)
Constant	1.37***	1.13**
	(0.11)	(0.05)
lnalpha		-0.34***
		(0.08)
Observations	2,456	2,456
ll	-1693	-3368
dfm	3	3
chi2	12.42	11.92
*** p<0.01	** p<0.05	* p<0.1

For robustness we also ran both of the above models including a range of household level control variables that may influence adoption. We do not report these results in the text as they do not significantly alter the magnitude or significance of our findings. We are happy to share these results with any interested reader. We tested for equality of coefficients in both of the above models and the treatment groups are not statistically different from each other.

4 Conclusion

We find that being supplied with better electricity usage information and time of use tariffs led to lower investment in energy efficiency measures. To our knowledge, this result has not been empirically demonstrated previously. It must be stressed that due to the short time-scale of this study, it was only possible to monitor behaviour over a 12 month period. Another interesting element to note is that while this was an electricity smart-metering trial, most of the capital investments related to heating, not electricity[10].

This raises an interesting question: Why were the treatment groups induced to reduce their investment behaviour? We are unable to answer this, given our data but a number of theories might explain this behaviour. One is that the prevailing wisdom amongst consumers is that one should invest in order to increase energy efficiency. However, once feedback quantifies the reduction in consumption that can be achieved through adaptation, this induces them to reduce their investment. Related to this is the idea of negative spill-overs. Perhaps reducing consumption gave people an alibi, they felt less inclined to invest as they had already made a sacrifice.

[10] Only 1 % of the sample have electric heating. See table 10 in Annex A

Reducing consumption is a lesser cost alternative to investing in energy efficiency measures. Further research could shed some light on this question. (question on influence of trial)

A concern is that there is some systematic difference between the control and treatment groups, due to the randomisation not having been conducted correctly. As outlined in section **??**, Annex A and as shown in Di Cosmo et al. (2014), we are confident that this is not the case. Alternatively, perhaps some aspect of the experimental design or survey questions influenced the behaviour of either control or treatment group with regard to investment in energy efficiency.

In terms of the policy relevance of this research, this result demonstrates the crucial need to design targeted policies when aiming to remove the market barriers to energy efficiency, as argued by Allcott and Greenstone (2012), amongst others. It also highlights the benefit of monitoring various other behaviours, beyond the specific target of the trial. Given the widespread implementation of smart-metering trials, we feel this opens a avenue for others to empirically test whether our results are reproduced in other countries and across different domains.

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5 Annexes

5.1 Annex A

Table 8: Pre-trial distribution of socioeconomic characteristics

Variable	control	treatment 1	treatment 2	treatment 3	total
Gender					
male	52%	47%	52%	51%	51%
female	48%	53%	48%	49%	49%
age					
18 – 25	0%	1%	0%	1%	0%
26 – 35	8%	10%	7%	9%	9%
36 – 45	18%	20%	20%	20%	19%
46 – 55	24%	24%	25%	24%	24%
56 – 65	21%	22%	24%	23%	22%
65+	28%	23%	22%	22%	24%
refused	1%	1%	1%	0%	1%
Employment Status					
employee	43%	49%	47%	47%	46%
self-employed (no employees)	4%	5%	5%	8%	5%
self-employed (with employees)	6%	7%	8%	5%	6%
unemployed (seeking work)	4%	3%	5%	4%	4%
unemployed (not seeking work)	3%	4%	4%	3%	4%
retired	38%	31%	30%	32%	33%
carer	2%	1%	1%	1%	1%
Social Class					
AB	12%	14%	16%	17%	15%
C1	25%	29%	27%	28%	27%
C2	18%	16%	15%	17%	16%
DE	42%	38%	38%	35%	39%
F	3%	2%	3%	2%	2%
refused	1%	1%	1%	1%	1%
Education					
no formal education	1%	1%	2%	1%	1%
primary	15%	10%	11%	11%	11%
secondary to junior cert	15%	19%	17%	16%	17%
secondary to leaving cert	30%	29%	28%	28%	29%
third level	34%	37%	37%	39%	36%
refused	5%	6%	5%	6%	5%

Table 10: Pre-trial distribution of appliance stock and heating type

Variable	Control	Treatment 1	Treatment 2	Treatment 3
Appliance				
washing machine	28%	24%	25%	23%
tumble drier	29%	23%	26%	22%
dishwasher	28%	24%	26%	22%
electric shower instant	28%	24%	26%	23%
electric shower pumped	27%	25%	25%	22%
electric cooker	29%	25%	24%	22%
stand alone freezer	27%	25%	25%	23%
water pump	28%	21%	28%	24%
immersion	28%	24%	25%	23%
solar panels to heat water	17%	26%	35%	22%
Heating Type				
electric	118%	89%	109%	80%
electric (plug-in)	213%	42%	119%	0%
gas	91%	103%	108%	99%
oil	97%	101%	100%	103%
solid fuel	113%	93%	91%	100%
renewable	63%	147%	117%	78%
other	89%	183%	75%	55%

Table 9: Pre-trial distribution of house characteristics

Variable	Control	Treatment 1	Treatment 2	Treatment 3	Total
House type					
apartment	2%	1%	1%	2%	2%
semi-detached house	30%	33%	29%	29%	30%
detached house	27%	26%	29%	27%	27%
terraced house	14%	15%	14%	14%	14%
bungalow	27%	24%	27%	27%	26%
refused	0%	1%	0%	0%	0%
Tenure type					
rent from a private landlord	2%	1%	1%	1%	1%
rent from a local authority	5%	4%	5%	4%	4%
own outright	58%	56%	56%	55%	56%
own with mortgage	35%	40%	38%	39%	38%
refused	0%	0%	0%	1%	0%
does house have a BER cert					
yes	1%	1%	1%	1%	1%
no	86%	88%	88%	87%	87%
don't know	13%	11%	11%	12%	12%
Number of people over 15					
1	4%	5%	5%	4%	4%
2	62%	58%	61%	61%	61%
3	20%	20%	17%	16%	18%
4	9%	12%	12%	12%	11%
5	3%	4%	3%	6%	4%
6	1%	1%	1%	0%	1%
7	0%	0%	0%	0%	0%
Number of people under 15					
0	77%	72%	72%	73%	74%
1	10%	11%	12%	13%	11%
2	8%	11%	9%	8%	9%
3	3%	4%	5%	4%	4%
4	2%	1%	1%	1%	1%
5	0%	0%	0%	0%	0%
6	0%	0%	0%	0%	0%
Number of bedrooms					
1	1%	0%	0%	1%	1%
2	11%	9%	6%	10%	9%
3	43%	46%	45%	40%	43%
4	35%	34%	35%	37%	35%
5	10%	11%	13%	12%	11%
6	0%	0%	0%	0%	0%
House age					
1900 – 1940	2%	2%	2%	1%	8%
1941 – 1960	3%	2%	3%	2%	10%
1961 – 1970	3%	3%	3%	2%	10%
1971 – 1980	6%	4%	5%	4%	18%
1981 – 1990	3%	3%	3%	3%	11%
1990 – 1997	2%	2%	2%	2%	8%
after 1997	6%	5%	5%	5%	21%

5.2 Annex B

Table 11: Count of in-trial adoptions. Dependent variable in negative binomial regression

count of adoptions	Freq.	Proportion
0	1,170	0.48
1	663	0.27
2	330	0.13
3	162	0.07
4	80	0.03
5	29	0.01
6	12	0.00
7	5	0.00
8	2	0.00
9	3	0.00
Total	2,456	1.00

Table 12: Dependent variable summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
depvar1	2456	0.52	0.50	0	1
depvar2	2456	0.99	1.29	0	9