Smart Meters: Do Prices Matter to Their Adoption and Do They Save Energy?

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Abstract

Understanding the underlying motivations of the energy efficiency gap is of societal importance. Partnering with British Gas (the U.K.'s largest utility) and utilizing their expansive smart meter roll out plan, we ran a large-scale natural field experiment with nearly 40,000 customers where we randomized different prices to adopt a smart meter with an in-home display. We find that prices positively impact the uptake of energy efficient products. Such small rewards (e.g. £5), lead to a treatment effects of about 30%. We used these price effects as an instrument to test the impact of smart meters on energy use. With over one million monthly energy use observations over a three-year period post adoption of the smart meters, we found that this technology led to no significant and meaningful change in energy use, for either electricity or gas.

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1. Introduction

The energy efficiency gap has become a very important societal problem. The gap suggests that people are not adopting enough energy-efficient products based on standard models of human behavior and investment. These models usually use engineering estimates to calculate the benefits of adopting energy-efficient technologies. There is now evidence that what engineers estimate in energy savings is very different from what the actual energy savings are (Fowlie et al., 2015; Burlig et al., 2017).

We take the example of the technology that has had the largest investment made by utilities to improve energy efficiency in the residential sector: *the smart meter*. Smart meters come in many different formats and have different levels of data collection, but the main functionality of a smart meter is that it allows the energy company to know how much energy is being used in the home and it tells the consumer how much energy they are using on a regular basis. The former can be good for the customer in terms of correct bills, but the latter is where many think the benefits come from. Smart meters have been heralded as the technology to help reduce the social energy-efficiency gap and reduce greenhouse gas emissions (Carroll et al., 2014; Clastres, 2011; Hargreaves et al., 2013). Billions of dollars have been spent all around the Western world to arm consumers with the latest smart meter in the hope of reducing energy use.

In economic theory, it is ambiguous how smart meters change the consumption of households. On the one hand, it might increase consumption since the household might not know whether they are consuming too little energy in the moment or that the cost is lower than expected so that they use more. On the other hand, it might decrease consumption since the household might not know whether they are consuming too much energy in the moment or that the cost is higher than expected so that they use less. In our natural field experiment, we do not shed light on the mechanisms, but we shed light on the reason to adopt the smart meter and the impact that the smart meter actually has on energy consumption. This is the existing gap in the literature.

For the first objective, there is a lack of evidence of how sensitive consumers are to different prices of energy efficient products (Gerarden et al., 2017). There has been increasing work in this area of technology adoption with information and other types of nudges (Allcott and Sweeney, 2014; Allcott and Taubinsky, 2015; Houde, 2014; Palmer et al. 2013; Sanstad et al., 2006). We are the first to randomly assign different prices for adopting the energy-efficient product across consumers who are eligible for the energy-efficient product in a natural field experimental setting. The change in prices for adopting the smart meter comes through changing the equipment purchase cost of the technology.

This allows us to understand how price responsive customers are without any selection into the experiment. Whilst there have been important studies with selection into the experiment shedding light on the reasons for technology adoption and their effects on consumption (see Allcott and Taubinsky, 2015; Jessoe and Rapson, 2014), the external validity of such framed field experiments is questionable (Al-Ubaydli et al., 2017). Also, some research on the take-up and effectiveness of smart meters has the problem of simultaneous changes in energy pricing and payment plans (Gans et al., 2013).

Due to the fact that we have different prices for adopting the technology, and that if customers are responsive to the different prices, then we have a good encouragement design that allows us to estimate the treatment effect of the smart meters as if it were random. We will uncover the local average treatment effect (LATE) of those who were encouraged to adopt the smart meter versus the total group who were not encouraged.

Our natural field experiment is with the largest energy supplier in the U.K. As a result, these smart meters are the most common in the U.K. and are the default for many other energy suppliers around Europe and North America. We found three important results. First, we found that offering a small monetary reward to adopt the smart meter lead to a significant and meaningful increase in the amount of people who adopted a smart meter. Second, we found that the size of the reward was not a big predictor of adoption. Going from £5 to £10 had no impact on the adoption rates. Third, using our encouragement design and up to three years of ex post consumption data, we find that the smart meters do not significantly or meaningfully impact on monthly energy use – both electricity and gas.

The implications of our research are the following. Firstly, prices of the energy efficient technologies matter and do impact on adoption rates. Secondly, whilst smart meters might provide many benefits to the utility, such as to better manage energy demand and equate it with supply, the benefits to the consumer in terms of a change in energy use is uncertain. From our design, we do not find any systematic impacts on energy use for three years after the smart meter has been adopted.

2. Experimental Design

We used a representative sample of British Gas customers who had not adopted smart meters in 2013 and ran two waves of the field experiment. For wave 1, we sent a cold letter asking them to adopt a smart meter. The smart meter includes an in-home display (worth £100), a meter frequently measuring their energy use, and more updated and accurate bills. We randomized the customers into three different groups.

British Gas identified 26,025 customers who might be able to adopt a smart meter with British Gas in March 2013. We used this sample for our experiment and then randomized the customers into three groups:

1. Control (no incentive)
2. £5 equivalent incentive for adopting the smart meter
3. £10 equivalent incentive for adopting the smart meter

The letters were sent out in standard mail in April 2013. To adopt the meter, the household customer has to call British Gas to arrange an appointment to have the smart meter installed in their home/apartment. The customer has to be home when the engineer arrives and for the whole duration of the installation of the smart meter (between 60 and

90 minutes). For those in the £5 and £10 groups, they only were accredited with the reward if the installation was successful.

We identified all of their background customer information, and blocked the randomization on age, gender, customer value, and previous consumption. Table 1 shows that the groups are similar in the customer background characteristics in age and gender. Everyone in our sample receives and pays their bill every quarter.

We ran a second wave of the experiment two months after the first wave. We identified a different set of customers who have not had a smart meter but who were eligible. We identified 13,108 British Gas customers who did not adopt a smart meter with British Gas. We used this sample for our second wave of the experiment and then randomized the customers into three groups:

1. Control (no incentive)
2. £1000 equivalent prize draw incentive for adopting the smart meter
3. £10 incentive for adopting the smart meter.

The second wave also used Nectar points to accredit the monetary values. In the analysis of how the incentives impact on smart meter adoption, we will analyze the two waves separately. We will them join them together to estimate the impact that smart meters have on energy consumption.

3. Results

3.1 Understanding the impact of prices on smart meter adoption

Result 1: *People are responsive to receiving a reward for adoption.*

Table 2 shows the marginal causal effects of the smart meters of the two incentive groups in comparison to the control group. Column (1) provides the effects of the two prices, £5 and £10, on booking an appointment. We found that 18.07% of the control group made an appointment. The £5 group significantly increased take-up by 6.1% ($p < 0.01$) – with a total appointment rate of 24.17%. The £10 group also significantly increased take-up by 6.1% ($p < 0.01$) – with a total appointment rate of 24.17%.

Column (2) examines the effects on actual adoption – i.e., installation. We find that 14.14% of the control group adopted the smart meter. The £5 group significantly increased adoption by 4.2% ($p < 0.01$) – with a total take-up rate of 18.44%. The £10 group also significantly increased adoption by 4.5% ($p < 0.01$) – with a total appointment rate of 18.64%.

Column (3) examines the fall off of customers from booking an appointment and adopting the smart meter – column (1) minus column (2). It is clear that the two incentive groups did not significantly increase the likelihood of making an appointment but then not adopting the smart meter.

Table 3 below shows the marginal causal effects of the smart meters of the two incentive groups in comparison to the control group. Column (1) provides the effects of the two prices, £1000 equivalent prize draw incentive and the £10 gift card, on booking an appointment. We found that 16.00% of the control group made an appointment. The £1000 prize draw group increased appointments by 1.2% but not significantly so. The £10 group significantly increased appointment rates by 3.2% ($p < 0.01$) – with a total appointment rate of 19.2%.

Column (2) examines the effects on actual installation. We find that 10.9% of the control group adopted the smart meter. The £1000 prize draw group significantly increased adoption by 1.6% ($p < 0.01$) – with a total take-up rate of 11.69%. The £10 group significantly increased adoption by 2.6% ($p < 0.01$) – with a total appointment rate of 12.69%.

Column (3) examines the fall off of customers from booking an appointment and adopting the smart meter. The prize draw incentive group did significantly increase the likelihood of making an appointment but then not adopting the smart meter – by 4.5% more dropped customers from a baseline of 21.71% of the control sample. The reasons for this could be numerous, such as less likely being home on the agreed appointment date and time.

Result 2: *£5 pricing incentive has the same effect as £10.*

We have some information on the segments of the customer base in experiment 1. For instance, we analyzed their Experian segmentation codes as well as the level of engagement with the points based loyalty scheme. In Table 4, we find that the incentives have no differing impacts across the Experian segments. Young and old segments behave very similarly with respect to incentives.

In Table 5, we find that the incentives have an impact on the adoption of the smart meters depending on utilization of the Nectar card (where the money will be accredited). In this case, 0 means low utilization while 11 means very frequent utilization of the loyalty scheme. Unknown means that they probably have never used it or fully registered the loyalty scheme. We find that all of the effects come from customers who have little experience with the loyalty scheme in the past. These customers therefore might not necessarily know the true value of the points offered and as a result are more motivated to take up the smart meters.

3.2 Understanding the impact of smart meter adoption on energy use

We will proceed to the two-stage least squares regression based of the first stage. Our instrument in the first-stage is strong – randomly offering price incentives encourages smart meter adoption. We will use this random encouragement as an instrument to understand the impact that smart meters have on energy use.

The underlying assumptions for our estimation strategy using the LATE are that: (a) the change in participation in smart meters (SMART) (from no participation (0) to participation (1)) is induced by the randomized price encouragement and not by any other variables; and (b) that this change is orthogonal to any factors that impact on energy use (E). In our experiment, the encouragement T_i is randomly assigned, so that E_{SMARTi}, $SMART_i(T_i) \perp Ti$. This means that the encouragement is assigned independent of possible outcomes of the individual household.

As a result, the estimated LATE in our example is simply:

$$LATE = [E_{Ti=1} - E_{Ti=0}] / [SMART_1 - SMART_0],$$

which is the difference in average energy consumption of those who received an encouragement price versus those who did not, divided by those who adopted the smart meter versus those who did not. While our experiment satisfies the condition that the encouragement is randomly assigned to households, our LATE estimator embeds the monotonicity/uniformity assumption. This assumption states that if control group household (no encouragement) adopted a smart meter when not encouraged, the household will participate when encouraged. We do not observe the latter, and so our LATE estimator is the ATE of a subpopulation whose choice is impacted by the random variation in the pricing encouragement. It is impossible to know the counterfactual of those who are likely to gain with a smart meter and therefore the types of households that adopt a smart meter through the encouragement (Heckman and Vytlacil, 2005).

Our specification is the intention-to-treat (ITT) analysis. We use an OLS regression to understand the marginal impact of being in the treatment group on energy consumption following the delivery of the encouragement pricing to each individual household *i*. We estimate an OLS equation designed to control for the effects of observable factors that affect energy consumption trajectories for households that adopt a smart meter (irrespective of treatment group):

$$E_{imt} = ß(T)_{imt} + \partial E^{b}_{im} + p_m + g_i + e_{imt}$$

where E_{imt} measures energy consumption of household *i* in month *m* and year *t*. The T indicator variable switches from zero to one in the month after a household receives the pricing encouragement. We include month-by-year controls for baseline usage, denoted ∂E^{b}_{im}, where E^{b}_{im} is household i's average energy usage in the same calendar month during the baseline period. This accounts for permanent differences in a household's energy consumption across months. We include month-by-year fixed effects, p_m, to control for the average effects of time-varying factors (e.g., winter temperature) that generates variation in average consumption across all households, and wave fixed effects, g_i. In this regression, standard errors are clustered over time at the level of randomization.

Our LATE specification is estimated using a two stage least squares (2SLS), where being in a treatment group will be the instrument used in the second stage to analyze the impact that being on CARE has on gas consumption. The parameter of interest is ß, which measures the mean difference in energy consumption between being in the smart meter adopted group versus the non-adopted group, after adjustment for the fixed effects. In this instrumental variables (IV) framework, ß is identified using the exogenous variation in adopting a smart meter that is generated via the random assignment of the pricing encouragement; this is the estimation of the LATE.

We always provide the intent-to-treat (ITT) and local average treatment effect (LATE) for each specification. For the LATE, we instrument for actual installation with random assignment to the pricing incentives. The parameters of interest are "Post-Letter · Encouragement" and "Post Install". For our data, we analyzed consumption data starting January 2012 up until March 2016. The letters were sent in April of 2013, so we have around 16 months of pre-smart meter data and then around two to three years of post-smart meter adoption data.

We have many different data specifications and we will report each one for transparency. Everything is reported for each fuel type (electricity and gas) for the full sample with the two phases (waves 1 and 2) joined together and not separated out in terms of impacts on energy use. We have six main specifications, that all trim the data slightly differently:[1]

1. Household (HH) FEs and month-of-sample (HHMos) and exclude outliers (top and bottom 1%)
2. Same as (1) but use HH and month-of-sample-by-location (14 geographic regions in the UK) FEs
3. Same as (1) but also exclude observations based on consumption being over 2SDs of the average
4. Same as (2) but exclude outliers (top and bottom 1%)
5. Same as (4) but use HH and month-of-sample-by-location FEs
6. Same as (4) but also exclude observations based on consumption being over 2SDs of the average

We will use these eight specifications to look at the ITT and LATE for electricity and gas separately.

Result 3: *Smart meters have no meaningful impact on electricity and gas demand.*

Table 6 presents the ITT estimates for electricity for the whole-time period where the control mean electricity use is 296kWh per month. The 'post-letter' variable is capturing the difference in electricity consumption for the entire sample once the letters have been sent out to before the letters were sent out. It is clear that electricity demand significantly reduced since April-May 2013 until the end of the period in 2015. We find that electricity demand reduced by about -1.38 to -3.18 kWh per month. This is

[1] For comparison:

- Electricity mean (SD) excluding p1/p99 overall: 295.9146 (169.0462)
- Electricity mean (SD) excluding p5/p95 overall: 283.9303 (127.8998)
- Gas mean (SD) excluding p1/p99 overall: 1207.051 (1031.296)
- Gas mean (SD) excluding p5/p95 overall: 1125.382 (824.2485)

equivalent to around a 0.5% to 1.1% reduction in monthly electricity use – both significant at the five per cent level. The 'post-letter . encouragement' variable is the change in consumption in the treatment groups using price to encourage the adoption of the smart meter – this is the ITT. It is clear that in all six specifications, the ITT coefficient is very small. It varies between -0.04 to -0.15 kWh per month and is not significant at the five per cent level.

Table 7 presents the LATE for electricity, based off the ITT results. The variable of interest here is 'Post Install' – that is the LATE we are interested in. The estimates range from -4.13kWh to -1.29kWh per months across the specifications, but none of them are significant at any conventional levels. The standard errors range between 16.6 and 24.0. These point estimates are equivalent to a reduction in energy use by around 1.4% to 0.4%. It is clear that none of these estimates are any close to being meaningful from a statistical or economic pint of view.

The evidence above suggests that smart meters do not impact on electricity use. We next turn to whether there are strong impacts on gas use per month. Table 8 below presents the ITT estimates for gas. From our specifications, we find that gas demand largely decreased after April and May of 2013. The estimates range between -10.60 ($p<0.01$) and 0.83 ($p>0.1$) kWh per month. The -10.6 kWh value is still economically small, since it equates to only a 0.88% reduction. The ITT coefficient also varies between being positive and negative, with no clear pattern or real economic significance with the different specifications. Table 9 below presents the LATE for gas use based off the ITT. As before, the variable of interest here is Post Install. It is clear that five out of the six LATE coefficients are positive. This is showing that smart meters do not decrease the gas use of those who adopt a smart meter. The point estimates actually suggest the opposite result.

4. Conclusion

Many energy-efficient technologies have been heralded as a way to reduce energy use in the economy and curtail residential energy use. While the benefits to energy companies from smart meters might be clear, it is less clear how they benefit the consumer. We find that the smart meters have no significant impact on energy use, both electricity and gas. However, households in our sample are responsive to being offered a reward to adopt such a technology, and our paper provides evidence that it is impossible to stimulate adoption through traditional routes of pricing.

Our example is in the case where prices were not changing at the same time as the smart meters were adopted. We wanted a clean laboratory to identify simply only the impact of smart meters with a clear counterfactual. This isolation however could be one of the reasons why our results complement the existing literature, such as Jessoe and Rapson (2014). It seems like information and prices might be complementary in the energy domain, and that both information/technology and incentives have to be changing at the same time in order for the information and incentives to be fully salient and to be internalized by consumers.

Given the vast amount of money being invested into smart meters and smart grids, we hope that the results in our paper will allow policymakers to be more cautious about the benefits of smart grids and meters to the residential and commercial sectors. We believe that governments and energy organizations should be testing the impact that smart meters and technologies have on energy use before they are rolled out to the public.

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Tables

Table 1: Summary statistics of households

Group	N	Age	Male
Control	8,668	57.6yrs	49.3%
£5	8,677	57.5yrs	49.3%
£10	8,680	57.7yrs	49.3%

Table 2: Impact of the prices from the first experiment on adoption

	(1) Appointment booked	(2) Installation	(3) Who doesn't follow through with Installation
£5	0.061***	0.043***	0.019
	(0.007)	(0.006)	(0.014)
£10	0.061***	0.045***	0.008
	(0.007)	(0.006)	(0.014)
N	26,025	26,025	5,708
Psuedo R2	0.0042	0.0032	0.0003
Baseline	18.07%	14.14%	21.71%

Notes: Marginal coefficients presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Impact of the prices from the second experiment on adoption

	(1) Appointment booked	(2) Installation	(3) Who doesn't follow through with Installation
Lottery	0.012	0.016**	-0.045*
	(0.008)	(0.007)	(0.024)
£10	0.032***	0.026***	-0.028
	(0.008)	(0.007)	(0.024)
N	13,108	13,108	2,287
Psuedo R2	0.0013	0.0015	0.0011
Baseline	16.00%	10.09%	21.71%

Notes: Marginal coefficients presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Impact of incentive across different segments

	(1) Young couple HH	(2) Family HH	(3) Empty nest HH	(3) Retired, Vulnerable HH
£5	0.050**	0.062***	0.067***	0.061***
	(0.017)	(0.013)	(0.020)	(0.010)
£10	0.053***	0.053***	0.087***	0.059***
	(0.017)	(0.012)	(0.020)	(0.010)
N	3,252	6,082	3,335	13,292

Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Impact of incentives on adoption across Nectar scheme utilization

	(1) 0 to 1	(2) 2 to 3	(2) 4 to 6	(2) 7 to 10	(2) 11 plus	(2) Unknown
£5	-0.005	0.006	-0.009	-0.007	0.003	0.091***
	(0.006)	(0.008)	(0.005)	(0.003)	(0.004)	(0.011)
£10	-0.004	0.006	-0.009	-0.004	0.002	0.0884***
	(0.006)	(0.008)	(0.005)	(0.003)	(0.004)	(0.011)
N	1,456	1,620	2,288	3,457	5,355	11,845

Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: The ITT for Monthly Electricity Consumption

	(1) Electricity use	(2) Electricity use	(3) Electricity use	(4) Electricity use	(5) Electricity use	(6) Electricity use
Post-letter	-3.184***	-2.808***	-1.487*	-2.249***	-1.905***	-1.376**
	(0.854)	(0.862)	(0.792)	(0.675)	(0.682)	(0.647)
Post-letter x	-0.141	-0.150	-0.048	-0.094	-0.112	-0.077
Encouragement	(0.872)	(0.871)	(0.804)	(0.681)	(0.681)	(0.643)
N	1,209,835	1,209,835	1,169,296	1,169,296	1,116,224	1,090,094
R2	0.794	0.794	0.840	0.807	0.807	0.841

Notes:_Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regression (1): Household (HH) FEs and month-of-sample (HHMos) and exclude outliers (top and bottom 1%). Regression (2): Like (1) but use HH and month-of-sample-by-location (14 geographic regions in the UK) Fes. Regression (3): Like (1) but also exclude observations based on consumption being over 2SDs of the average. Regression (4): Like (2) but exclude outliers (top and bottom 1%). Regression (5): Like (4) but use HH and month-of-sample-by-location Fes. Regression (6): Like (4) but also exclude observations based on consumption being over 2SDs of the average.

Table 7: The LATE for Monthly Electricity Consumption

	(1) Electricity use	(2) Electricity use	(3) Electricity use	(4) Electricity use	(5) Electricity use	(6) Electricity use
Post-Install	-3.841	-4.125	-1.294	-2.441	-2.934	-1.997
	(23.664)	(24.020)	(21.527)	(17.680)	(17.880)	(16.577)
Post-letter	-3.291***	-2.908***	-1.518***	-2.311***	-1.969***	-1.423***
	(0.620)	(0.627)	(0.579)	(0.497)	(0.510)	(0.485)
N	1,209,835	1,209,835	1,169,296	1,169,296	1,116,224	1,090,094
R2	0.794	0.794	0.840	0.807	0.807	0.841

Notes:_Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regression (1): Household (HH) FEs and month-of-sample (HHMos) and exclude outliers (top and bottom 1%). Regression (2): Like (1) but use HH and month-of-sample-by-location (14 geographic regions in the UK) Fes. Regression (3): Like (1) but also exclude observations based on consumption being over 2SDs of the average. Regression (4): Like (2) but exclude outliers (top and bottom 1%). Regression (5): Like (4) but use HH and month-of-sample-by-location Fes. Regression (6): Like (4) but also exclude observations based on consumption being over 2SDs of the average.

Table 8: The ITT for Monthly Gas Consumption

	(1) Gas Use	(2) Gas use	(3) Gas use	(4) Gas use	(5) Gas use	(6) Gas use
Post-letter	-5.152	-0.832	-7.682*	-9.848***	-2.970	-10.600***
	(4.479)	(4.538)	(4.239)	(3.425)	(3.456)	(3.368)
Post-letter x	0.066	-0.154	1.757	2.552	2.286	3.034
Encouragement	(4.080)	(4.067)	(3.773)	(3.054)	(0.681)	(2.923)
N	1,216,499	1,216,499	1,197,655	1,120,877	1,120,877	1,106,129
R2	0.777	0.780	0.781	0.794	0.797	0.796

Notes:_Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regression (1): Household (HH) FEs and month-of-sample (HHMos) and exclude outliers (top and bottom 1%). Regression (2): Like (1) but use HH and month-of-sample-by-location (14 geographic regions in the UK) Fes. Regression (3): Like (1) but also exclude observations based on consumption being over 2SDs of the average. Regression (4): Like (2) but exclude outliers (top and bottom 1%). Regression (5): Like (4) but use HH and month-of-sample-by-location Fes. Regression (6): Like (4) but also exclude observations based on consumption being over 2SDs of the average.

Table 9: The LATE for Monthly Gas Consumption

	(1) Gas Use	(2) Gas use	(3) Gas use	(4) Gas use	(5) Gas use	(6) Gas use
Post-Install	1.727	-4.090	45.737	68.085	61.777	80.538
	(106.840)	(107.741)	(98.179)	(81.873)	(82.687)	(78.261)
Post-letter	-5.100	-0.723	-6.297*	-7.846***	-1.355	-8.198***
	(3.632)	(3.682)	(3.483)	(2.774)	(2.798)	(2.770)
N	1,216,499	1,216,499	1,197,655	1,120,877	1,120,877	1,106,129
R2	0.777	0.780	0.781	0.794	0.797	0.796

Notes:_Notes: Marginal effects presented. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regression (1): Household (HH) FEs and month-of-sample (HHMos) and exclude outliers (top and bottom 1%). Regression (2): Like (1) but use HH and month-of-sample-by-location (14 geographic regions in the UK) Fes. Regression (3): Like (1) but also exclude observations based on consumption being over 2SDs of the average. Regression (4): Like (2) but exclude outliers (top and bottom 1%). Regression (5): Like (4) but use HH and month-of-sample-by-location Fes. Regression (6): Like (4) but also exclude observations based on consumption being over 2SDs of the average.

Appendix

Control letter

British Gas
Looking after your world

Contact us now
0800 975 5555*
Mon - Fri 8am - 8pm,
Sat 8.30am - 5pm

Account Number:
##########

Date: **23rd April 2013**

Cut down on energy waste by upgrading to smart meters and be one of the first customers to see your home in a new light

Dear Xx Xxxxxxxx,

Your gas and electricity meters are due for replacement so as a valued British Gas customer, we'd like to offer you a **free upgrade** to smart meters. These innovative new meters put you in control of your energy usage, help you cut down on energy waste and become more efficient so that you can reduce your energy bills. What's more, they make meter readings and estimated bills a thing of the past with accurate automatic readings.

Understand how you're using energy and manage it better
Along with your smart meter you'll get a handy smart energy monitor, which will help you:

- **See in pounds and pence how much energy you're using**, as you use it
- Make choices and changes to cut energy waste and **save money on bills**

Get smarter about energy today – call 0800 975 5555* to book your appointment
When we get your call we'll organise a visit – at a time to suit you. We'll also tell you more about smart meter technology and answer any questions you may have.

To find out more, visit britishgas.co.uk/smartmeters
Online you'll see what happens when you have a smart meter installed and the benefits they bring. You'll find answers to most of your questions. And you'll also find our Smart Meter Customer Charter which explains your choices and our commitment to you.

Call us today to make an appointment and begin your journey to seeing your home in a whole new light, where you can control how you cut down your energy waste and start saving too.

Yours sincerely,

Signature

Director, Smart Customer Service

£5 letter

British Gas
Looking after your world

Contact us now
0800 197 8043*
Mon - Fri 8am - 8pm,
Sat 8.30am - 5pm

Account Number:
###########

Date: **23rd April 2013**

Upgrade to smart meters and collect 1,000 Nectar points

Dear Xx Xxxxxx,

Your gas and electricity meters are due for replacement so as a valued British Gas customer, we'd like to offer you a **free upgrade** to smart meters. These innovative new meters put you in control of your energy usage, help you cut down on energy waste and become more efficient so that you can reduce your energy bills. What's more, they make meter readings and estimated bills a thing of the past with accurate automatic readings. Be one of the first customers to see your home in a new light.

Call us before 5th May to collect 1,000 Nectar points

Once you've made an appointment and we've installed your smart meter, we'll give you 1,000 Nectar points. All you need to do is make sure you're home at the date and time agreed.

Understand how you're using energy and manage it better

Along with your smart meters you'll get a handy smart energy monitor, which will help you:

- **See in pounds and pence how much energy you're using**, as you use it
- Make choices and changes to cut energy waste and **save money on bills**

Get smarter about energy today – call 0800 197 8043* to book your appointment

When we get your call we'll organise a visit – at a time to suit you. We'll also tell you more about smart meter technology and answer any questions you may have.

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Call us today to make an appointment and begin your journey to seeing your home in a whole new light, where you can control how you cut down your energy waste and start saving too.

Yours sincerely,

Signature

Director, Smart Customer Service

£10 letter

British Gas
Looking after your world

Contact us now
0800 197 8043*
Mon - Fri 8am - 8pm,
Sat 8.30am - 5pm

Account Number:
###########

Date: **23rd April 2013**

Upgrade to smart meters and collect 2,000 Nectar points

Dear Xx Xxxxxx,

Your gas and electricity meters are due for replacement so as a valued British Gas customer, we'd like to offer you a **free upgrade** to smart meters. These innovative new meters put you in control of your energy usage, help you cut down on energy waste and become more efficient so that you can reduce your energy bills. What's more, they make meter readings and estimated bills a thing of the past with accurate automatic readings. Be one of the first customers to see your home in a new light.

Call us before 5th May to collect 2,000 Nectar points

Once you've made an appointment and we've installed your smart meter, we'll give you 2,000 Nectar points. All you need to do is make sure you're home at the date and time agreed.

Understand how you're using energy and manage it better

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To find out more, visit britishgas.co.uk/smartmeters

Online you'll see what happens when you have a smart meter installed and the benefits they bring. You'll find answers to most of your questions. And you'll also find our Smart Meter Customer Charter which explains your choices and our commitment to you.

Call us today to make an appointment and begin your journey to seeing your home in a whole new light, where you can control how you cut down your energy waste and start saving too.

Yours sincerely,

Signature

Director, Smart Customer Service

£1000 lottery letter

Contact us now
0800 197 8043*
Mon - Fri 8am - 8pm,
Sat 8.30am - 5pm

Account Number:
8500444444444

Mrs Sample
Address1
Address2
Town & Postcode

Date: 8 June 2013

Upgrade to smart meter for your chance to win 1,000,000 Nectar points

Dear Mrs Sample,

Your gas and electricity meters are due for replacement so as a valued British Gas customer, we'd like to offer you a **free upgrade** to smart meters. These innovative new smart meters put you in control of your energy usage, help you cut down on energy waste and become more efficient so that you can reduce your energy bills. What's more, they make meter readings and estimated bills a thing of the past with accurate automatic readings. Be one of the first customers to see your home in a new light.

Call us now for your chance to win 1,000,000 Nectar points

To ensure you get the most out of this opportunity:

- We have automatically entered you into our prize draw to win 1,000,000 Nectar points
- All you need to do is ring us on the number below to book an appointment and then make sure you're at home when our enginner comes to carry out your free upgrade so that you **don't miss out** on this opportunity.

Get smarter about energy today – call 0800 197 8043* to book your appointment

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- Make choices and changes to cut energy waste and **save money on bills**

To find out more, visit britishgas.co.uk/smartmeters

And you'll also find our Smart Meter Customer Charter which explains your choices and our commitment to you.

Call us today to make an appointment and begin your journey to seeing your home in a whole new light, where you can control how you cut down your energy waste and start saving too.

Yours sincerely,

Name Surname
Director, Smart Customer Service