Smart Meter Devices and The Effect of Feedback on Residential Electricity Consumption: Evidence from a Natural Experiment in Northern Ireland

by

Will Gans,[a] Anna Alberini[a] and Alberto Longo[b]

[a] AREC, University of Maryland, College Park
[b] Gibson Institute for Land Food and Environment, UKCRC Centre of Excellence for Public Health (NI), School of Biological Sciences, Queen's University, Belfast

June 2011

Abstract:
Using a unique set of data and exploiting a large-scale natural experiment, we estimate the effect of real-time usage information on residential electricity consumption in Northern Ireland. Starting in April 2002, the utility replaced prepayment meters with "smart" meters that allow the consumer to track usage in real-time. We rely on this event, account for the endogeneity of price and payment plan with consumption through a plan selection correction term, and find that the provision of information is associated with a decline in electricity consumption of up to 20%. We find that the reduction is robust to different specifications, selection-bias correction methods and subsamples of the original data. At £17-20 per metric ton of CO_2e (2009£) (based on our preferred estimate of the effect of smart meter), the smart meter program delivers cost-effective reductions in carbon dioxide emissions.

JEL Classification: Q40, Q41, D8

Keywords: Residential Energy, Electricity Demand, Feedback, Smart Meter, Information

We wish to thank Iain Bryson of the Northern Ireland Statistics and Research Agency, Gerry Forde and Maureen Delaney of Northern Ireland Energy, Joy McFarland of Phoenix Gas, George Hutchinson of Queen's University, Belfast, Severin Borenstein, and participants of Queen's University Energy Economics Workshop, held in Belfast in January 2011 for their help with this project.

Smart Meter Devices and The Effect of Feedback on Residential Electricity Consumption: Evidence from a Natural Experiment in Northern Ireland

by

Will Gans, Anna Alberini and Alberto Longo

1. Introduction and Motivation

Residential buildings account for a large share of the world's energy consumption, and offer a natural target for policies that seek to reduce CO_2 emissions from (fossil-fuel) power generation, dependence on imported fuels, and vulnerability to supply shocks. For these reasons, there is tremendous policy interest in programs to reduce energy consumption and increase energy efficiency.

It is difficult for consumers to keep track of current electricity usage and/or predict future electricity demand.[1] Many observers argue that providing better information and feedback on consumption helps improve the energy efficiency of the residential sector—by themselves or when combined with other traditional policy tools such as economic incentives, pricing and regulation. Earlier evaluations of information-based approaches, however, relied upon short-lived pilot projects or small sets of data (Ehrhardt-Martinez et al., 2010), and have been complicated by self-selection issues due to the voluntary nature of certain initiatives, such as utility-provided audits (Hartman, 1988; Waldman and Ozog, 1996).

Advanced metering infrastructure (AMI, or "smart" meters) can give consumers feedback on consumption by combining frequent automated usage readings with accessible displays. AMI has received much recent attention and, at least in the US, generous federal funding and

[1] Other goods that share these features include, for example, cell phone minutes and internet access time (Grubb, 2009). Della Vigna and Malmendier (2006) and Lambrecht and Skiera (2006) study preferences for three-part tariffs and flat rate even when the consumer would save money by choosing alternate pricing schemes, which they attribute to underestimating the variance of future demand, risk and loss aversion, and disutility associated with the price per se.

incentives for deployment.[2] Despite the scale of support from the government and the utility industry, there has been little evaluation of these programs.

In this paper, we use an AMI implementation in Northern Ireland to provide the first large-scale evidence of the effect of usage feedback on residential consumption. Specifically, we estimate household response to the provision of immediate feedback about electricity consumption.

Northern Ireland is a unique setting for studying residential energy consumption for three reasons. First, the retail residential rates are among the highest in the United Kingdom and Europe, but, until recently, consumers lacked an alternative provider for electricity. This suggests that they may be willing of making behavioral changes to save on their energy bills when given an opportunity to do so.[3]

Second, there are a host of payment plan options for electricity in the Northern Ireland market. These include credit accounts, direct debit accounts, and prepayment accounts. The variation in attributes across plans allows us to identify the effect of price and changes in other important plan features.

Third, one of these plans (prepayment) recently experienced an exogenous change in technology (the keypad) which provides immediate feedback about usage. Moreover, because this plan requires prepayment, it suggests that households on it *will* be monitoring their usage. The switch between the previous meter that served prepayment customers, which did not have these capabilities, occurred in April 2002. We interpret this as the treatment in a natural experiment and use it to identify how electricity consumption was affected among the

[2] See, for example, http://www.smartgrid.gov/ to get an idea for recent projects funded by the U.S. federal government.

[3] These incentives should be particularly strong for so-called "fuel poor" households. Government estimates suggest that about one-third of the households in Northern Ireland are "fuel poor," with fuel poverty being defined when 10% or more of the household income is spent on all household fuel use (DSDNI, 2006).

"treatment" customers. Our "controls" are customers in other plans (which do not use AMI meters and do not provide real-time information about usage to the consumer). This is a large scale natural experiment, since 14% (over 75,000) of the NIE customer base was on a prepayment plan at the time of the switch to the keypad metering technology.

We develop a simple theoretical model where unwanted energy waste is controlled with monitoring and information. This framework does not provide unambiguous predictions about the effect of information on energy consumption, due to countervailing incentives to substitute electricity savings for savings on monitoring. Whether or not feedback (i.e., the keypad) about usage enables consumers to reduce their electricity demand (through conservation or energy-efficiency investments) is, therefore, an empirical issue.

We examine this matter using data from 18 waves of Northern Ireland's Continuous Household Survey (from 1990 to 2009), which we merge with price and plan information from the electricity utility, and weather data. Our dataset is a multi-year cross-section and is comprised of over 45,000 usable observations. Despite the single-provider electricity market, prices varied over time and across payment plans during our study period. Since electricity price depends on the plan, but plan choice may depend on unobserved household characteristics that influence both consumption and plan selection, we implement the Dubin-McFadden (1984) correction in our demand equations. We also account for unobserved heterogeneity using geographic fixed effects. We find that controlling for housing type, heating, household characteristics and selection into the plan, the keypad results in 15-20% less electricity use.

The keypad may provide a cost-effective alternative to large scale rebate or efficiency incentive programs in meeting emission reduction and demand response goals. In terms of CO_2 emissions reduction, we find that the cost-effectiveness of implementing a keypad program—

£17-£20 per metric ton of CO_2e assuming a 17% reduction in usage—is comparable to the current cost of abatement of carbon dioxide (buying Certified Emissions Reductions [CERs] on the European exchange). CERs cost around £11 per tonne CO_2e, but the UK government uses a policy target price of £25 per tonne CO_2e. In addition to cost-effective emissions reductions, there may be other benefits associated with implementing a program of this type, such as reduced utility service costs.

The remainder of the paper is organized as follows. Section 2 reviews the previous literature. Section 3 describes the utilities of Northern Ireland, prices and plans for the residential sector. Section 4 presents a theoretical motivation. Section 5 describes the data. Section 6 lays out the econometric models and estimation techniques. Section 7 presents the results. Section 8 concludes.

2. Previous Literature

Imperfect information and uncertainty about the *price* of electricity have received much attention in the energy economics literature. Shin (1985) discusses consumers' use of the average price of electricity (as opposed to the marginal price) when it is difficult to track due to seasonal price changes, block tariffs, and fuel surcharges. Hassett and Metcalf (1993) and Metcalf and Rosenthal (1995) study the effects of uncertainty about future energy prices on the pattern of energy efficiency investments. Ito (2010) summarizes alternative models of consumer behavior in the presence of block pricing, showing that people will invest effort in finding out the price of energy only to the point in which the gains from re-optimizing consumption decisions exceed the cost of the effort spent monitoring and investigating prices.

In contrast, the literature on consumer response to information about energy *usage* (as opposed to price) is relatively scant. Traditionally, utilities have provided information to a customer about his or her energy consumption level (and on how to reduce it) by offering free or low-cost audits.[4] Individualized audits, however, are typically utilized by only a small fraction of the customer base. Because they are voluntary, it is likely that people who reduce energy use after an audit would have done so anyway. Hartman (1988) finds that audits do decrease energy usage, but that failure to account for self-selection grossly overstates the impact of the audit program. To illustrate, during 1977-1981 (his study period) the average conservation truly attributable to the program is 951 kWh/yr—only 39% of the savings calculated based on a naïve comparison between participants and non-participants.

Waldman and Ozog (1996) use a sample of participants and non-participants in a choice-based sampling framework, and assume that, absent any type of incentive, there is a "natural" level of conservation, which they identify using the consumers who are not aware of the existence of utility incentives (and consequently have zero incentive). They estimate that the program truly accounts for only 71% of the total conservation, the remaining 29% being "natural" conservation (i.e. that would have happened regardless).

Dulleck and Kaufmann (2004) use monthly time series data for household electricity usage in Ireland from 1976 to 1993 and relate them to Demand Side Management policies that provided information and offered minor incentives to customers. Their analysis is constrained by the fact that they observe only aggregate data, so they estimate a seasonally-adjusted time-series model of energy usage. They find that the introduction of information programs reduces long-term electricity usage by 7%.

[4] These are often included in the utilities' Demand Side Management (DSM) programs, along with other initiatives for encouraging conservation and peak load management. See Loughran and Kulick (2004) and Auffhammer et al. (2008) who compute the cost per kWh saved by DSM programs in the US in the 1990s.

While audits are typically one-off events, recently attention has been focused on ways to provide continuous, or at least frequent, feedback to consumers about their energy usage. Darby (2006) surveys earlier studies involving the provision of information, both direct ("immediate, from the meter or an associated display monitor"), and indirect ("feedback that has been processed in some way before reaching the energy user, normally via billing"). Reductions in consumption are in the 5-15% and 0-10% range, respectively. These are in line with the estimates documented in the review by Ehrhardt-Martinez et. al (2010).

One way to enhance or manipulate the feedback provided by regular utility bills is to augment it with "social norms" contents. In a randomized field experiment involving 80,000 households in Minnesota, information about the energy usage of neighbors and visual cues about doing "better" or "worse" in electricity usage relative to similar neighboring homes has been found to reduce energy consumption by 1.9% relative to the baseline (Allcott, 2008). The effect decayed over time, perhaps because of the diminishing scope for learning from a neighbor's bill over time.

Effects of similar magnitude (2% and 1.2%, respectively) were observed in similar large-scale randomized trial experiments in Sacramento, California, and Portland, Oregon (Ayres et al., 2009). These declines in usage were sustained over time, and were generally proportionally larger among households with large pre-treatment consumption. In one of the two study locales (Sacramento) electricity consumption actually increased among households with low pre-treatment usage.

Gleerup et al. (2010) study SMS cell phone and e-mail messaging to alert consumers when usage levels are exceptionally high, and find that these approaches reduced consumption by about 3%. In this paper, however, we are concerned with the feedback about electricity usage

provided by devices placed in the consumer's home. Matsukawa (2005) estimates the effect of feedback information on residential energy usage in Japan. He finds that those residential customers who were given access to an informational display explaining how to use appliances more efficiently reduced energy usage by 1%, even though the display was not connected with any one appliance and no monetary incentives were offered to encourage conservation.

Recent advanced metering technology—the so-called "smart meters"—can be set up to allow electricity customers to view how much power is used at any given time. Presumably, this usage information assists consumers in adjusting consumption through conservation or by investing in energy-efficiency equipment. Advanced metering is an important component of the so-called "smart grid" and in 2009 the US federal government awarded over $4 billion to projects aimed at modernizing the grid under the "Stimulus Act."[5]

To our knowledge, however, only few projects funded by the federal government or the utilities have allowed consumers to access information about usage in real time. The majority of these projects have been small in scope and duration, or have omitted important variables, thwarting efforts to evaluate the impacts of information on electricity consumption.[6] Ideally, one would like to observe a relatively large group where the information feedback is varied across individuals, and compare results with those from a group with no information treatment.

What we describe in this paper is one such natural experiment. We take advantage of the introduction of an advanced metering device to a group of utility customers in Northern Ireland in 2002. This device replaced a preexisting meter that did not display information. The meters

[5]Advanced or "smart" meters allow utilities to communicate wirelessly and in near real-time with customers. This allows the utilities to monitor usage remotely, without having to physically read the meter, and it allows customers to receive instantaneous updates on their consumption, for example by using an in-home display. As part of the American Recovery and Reinvestment Act, $ 11 billion was allocated to improve the nation's electrical grid; the Office of Electricity and Energy Reliability received $4.5billion to invest in the smart grid. See http://www.smartgrid.gov/ for recent projects funded by the government.

[6] ACEEE (2010), for example, classifies a study as a "large" study when there are as few as 100 subjects.

and meter replacement affected only customers on a prepayment plan; those on other plans were not affected, suggesting that the latter serve as a "control group."[7] We have a large sample with tens of thousands of households, a wealth of dwelling and household characteristics, and we take advantage of the variety of utility plans available in Northern Ireland to shed new light on this important question.

3. Background on Utilities and Pricing Schemes in Northern Ireland

As we explain in detail below, we use data from a large multi-year cross-section survey of households in Northern Ireland. Our study period is 1990-2009, and during this time Northern Ireland Electricity (NIE) was the electric monopoly for the residential sector in all of Northern Ireland. As of September 2010, NIE had approximately 750,000 residential customers with an average annual consumption of 4100 kWh.[8, 9] We use their historical tariff information, from 1990 to present, to construct our electricity price data and convert bills to kWh used.

NIE has offered a variety of pricing and payment schemes throughout our study period (see tables 1 and 2).[10] The default payment frequency is quarterly, but there are discounts available for customers who choose to pay by direct deposit, or who choose a pay-as-you go (prepayment) plan. As shown in table 1, from 1990 until 1997 NIE charged its customers a fixed fee and a constant tariff per kWh. Starting in April 1997, a two-part tariff was instituted, with a fixed fee and decreasing block pricing. The prices were 9.16 pence per kWh in the first block (up

[7] In a paper examining payment behavior of prepayment customers, Brutscher (2011) uses a propensity score matching technique to estimate a consumption reduction for NIE keypad customers. However, his approach is limited by (i) the omission of price from his demand equation, and (ii) the short time period and small sample from which he draws his data.
[8] Communication by Gerry Forde of NIE, 7 December 2010.
[9] The Northern Ireland residential market was opened to competition in June 2010, and NIE estimates that it loses about 3000 customers a month because of this. Competition existed before 2010 in the commercial and industrial markets.
[10] Detail on NI Electric's latest prices are available at http://www.nieenergy.co.uk/latestprices.php.

to 250 kWh per quarter) and 8.16 pence per kWh thereafter. In April 1999, NIE eliminated both the block tariff and the fixed fee, and introduced a constant rate per kWh.

Nominal prices per kWh increased regularly over our study period, and a steep hike occurred in July 2008, when the rate per kWh increased by almost one-third. Prices subsequently went down somewhat, but never return to the pre-July 2008 levels. In addition to this variation in the structure of electricity pricing and in the rate per kWh over time, discounts were and are given to customers on various plans, as summarized in table 2. For example, starting in April 1997, EasySaver and Budget customers received a 1.5% discount, not to exceed £10 per year.[11] Since April 2002, those customers on NIE's direct debit monthly and direct debit quarterly plans ("managed" plans with even monthly or quarterly payments) have received a 4% and 2.5% discount, respectively, up to a specified maximum annual discount (which was initially £5 and is now £40 for the monthly and £25 for the quarterly schemes, respectively).

Throughout our study period, NIE offered a prepayment program to customers. Originally, a coin-operated device was used that had to be "charged" with coin deposits in order to dispense electricity. In 1993, NIE replaced coin-operated devices for new customers with electronic systems, introducing the powercard, which used a plastic debit-type card. In 2002, all prepayment customers were switched to a new program called Home Energy Direct (commonly dubbed "keypad"). The keypad system eliminated the equipment charge for prepayment, and the entire stock of older prepayment devices was replaced with the new technology. Concurrent to

[11] An EasySaver card is a scheme that allows customers to flexibly pay their bill in installments. If, at the time of issuing a new bill, there is less than 10% balance on their card (or less than £10), they receive a discount. Under a budget account, the customer gets a discount by agreeing to make fixed regular payments. If they miss payments, they lose the discount. While the discounts are identical for these plans, the budget is a "managed" plan with regular and fixed payment amounts, whereas an EasySaver plan allows payment amounts and frequencies to vary.

the switch to the keypad, customers on this plan started receiving a 2.5% discount (with no maximum limit) and the fixed fee was eliminated.[12]

The keypad meters combine a rechargeable card control with an interactive display that allows consumers to easily monitor their electric usage and cost.[13] The keypad meters can be considered sophisticated versions of the "smart meters" propagating in the U.S. today: both types of devices automatically monitor electricity usage at very frequent intervals, often many times per hour. Keypads offer the additional functionality of a pay portal and a usage display.

The keypad customer adds money to the keypad card (at a store kiosk or online, for example), then inserts the plastic card into the meter and enters his or her customer code to activate it. Using the keypad display, customers can check at any time how much credit they still have on the card, and a small credit (£1) is automatically granted when the credit on the card runs out.

As of November 2010, households on the keypad accounted for 34% of the NIE residential customer base, direct debit monthly plans for 26%, direct debit quarterly for 4.7%, budget accounts for 0.2% and EasySavers for 6.3%. Customers on no particular plan (e.g., such as those who receive quarterly bills and pay them in cash or by check) accounted for 27.7% of the NIE residential customer base.[14]

---

[12] Variation in prices was introduced for customers on other plans at the same time.

[13] According to the NIE website (last accessed 2 January 2011), a pushbutton menu allows customers to (1) see the number of days of credit left, based upon the previous week's usage; (2) see how much electricity was used during the previous day, week, or month; (3) see the current electricity consumption, and thereby deduce the load of certain appliances.

[14] Personal communication from Gerry Forde, NIE, 15 December 2010.

4. Theoretical Motivation

We are interested in modeling the response to information that a typical prepayment customer will experience after the introduction of the keypad device. A customer with perfect information would always know their electricity consumption and the associated bill, based on the usage patterns of household members, the load of each electrical device and the weather realization at every point in time, combined with retail price. A consumer with perfect information and on a prepayment plan would likewise know the remaining balance on their prepayment card. Displaying usage information would therefore have no effect on such a consumer.

What fully informed and rational consumers would do is one thing; what happens to real-life consumers is another. We argue that inattention is unavoidable: For many consumers, the gains from monitoring usage are insufficient to justify much monitoring effort (Ito, 2010). Interpreting the feedback provided by the bill is complicated by the delay between consumption and billing, variability in weather, and other exogenous and non-recurrent events (blackouts, breakdown in equipment, visitors, absences from home, etc.). As a result, little monitoring of usage occurs, and consumers imperfectly observe their electricity usage. We attribute any "surprise" in the amount of usage to inattention on the part of the consumer. Observed changes in consumption after an informational device is provided suggest that the device did provide "surprise" to inattentive consumers.

Easier-to-read, real-time information about usage may increase the productivity of monitoring, or may serve as a substitute for it. As we show below, economic theory does not provide unambiguous predictions as to whether information increases or decreases monitoring and electricity consumption.

Consider a consumer whose utility depends on electricity *E* (which is used for lighting, cooking, heating the home, etc.) and consumption of a composite commodity *X*, subject to a budget constraint. Also assume without any loss of generality that some electricity is wasted (perhaps because the consumer fails to unplug appliances when not in use, or uses them improperly, etc.) and let $H(m,I) > 0$ be the portion of total electricity wasted by the household, which is a function of the amount of monitoring, *m*, and the amount of information that the consumer receives about his usage, *I*. This means that while the consumer derives utility from *E*, he is billed for $E + E \cdot H(m,I))$.

Function *H*( ) is decreasing in monitoring and information. We assume decreasing marginal utility from electricity. We also assume that the marginal returns to monitoring and information, are decreasing (i.e., the second derivatives of *H*( ) with respect to *m* and *I*, respectively, are negative), but make no assumptions on the cross-partial derivative of H with respect to monitoring and information. It is possible to envision situations where $\partial^2 H / \partial m \partial I$ is negative, implying that *m* and *I* are complements, as well as cases where $\partial^2 H / \partial m \partial I$ is positive, i.e., *m* and *I* are substitutes.

The consumer chooses *E*, *X*, and *m* to maximize utility subject to his budget constraint:

(1) $$y = X + p_E \cdot E \cdot (1 + H(m,I)) + p_m \cdot m,$$

where y is income, p_E is the price per kWh, and p_m is the price per unit of monitoring. The first-order conditions with respect to *m* and *I* are

(2) $$U_E - \lambda p_E \left(1 + H\left(m^*, I\right)\right) = 0 \quad \text{and}$$

(3) $$p_E \cdot E^* \cdot \partial H / \partial m + p_m = 0$$

Their interpretation is straightforward: People use electricity to the point E^* where their marginal willingness to pay for the services of electricity is equal to the price at which they are

billed $(p_E + p_E \cdot H)$, and engage in monitoring m^* until the marginal saving in the utility bill is equal to the price per unit of monitoring.[15] The demand for electricity and monitoring will depend on the prices of electricity and monitoring, income, and the shape of function H.

Suppose there was an exogenous increase in *I*. What is the effect on the optimal monitoring and electricity consumption? Gans et al. (2011) show that optimal m^* may be raised or reduced, depending on the tradeoff between monitoring and information $H(m,I)$, among other things. Even if the net effect is to reduce wastage *H*, electricity demand may increase or decrease. The competing effects of productivity gains in monitoring from information and an income effect that enables more consumption or monitoring make the direction of the effect indeterminate.[16]

Since economic theory does not offer unambiguous predictions as to the effect of a change in *I* on m^* and E^*, the effect of enhanced information on electricity use is an empirical question. As mentioned, we use data from Northern Ireland households before and after an exogenous change in feedback, supplemented with a group of customers who were presumably unaffected by this feedback, to assess this effect. In our empirical work, we focus on the effects on electricity use, since we do not observe monitoring.

[15] Monitoring can be "purchased" at the price of the individual's time, or at the rate of an external consultant or purchase of a technological aid. We model it as a divisible market good.

[16] The comparative statics are complicated by the presence of a non-linear budget constraint (monitoring, which can be purchased directly, provides utility indirectly through its effect on energy savings implicit consumption). Following the approach developed in Edlefson (1981), we developed a simplified expression for the comparative statics of interest, but they could not be definitively signed.

5. Empirical Approach

A. The Experiment and the Treatment

Suppose individuals in a population were assigned at random to a treatment and control group for the purpose of determining the effect of the treatment on an outcome variable. Also assume that observations were taken on the outcome variable for both control and treated subjects over multiple time periods, and that some of these periods were prior to the application of the treatment. Under these assumptions, the observed difference in mean outcome is a consistent estimate of the average treatment effect on the treated:

(4) $$E(y_i \mid c_i = 1) - E(y_i \mid c_i = 0) = E(y_{1i} - y_{0i} \mid c_i = 1),$$

where *c* is a dummy that takes on a value of one when the treatment is in place, and zero otherwise, y_i is individual i's observed outcome, and y_1 and y_0 are the potential outcomes with and without the treatment (see Angrist and Pischke, 2009).

Suppose now that the assignment to the treatment and control groups is not random. Then the right-hand side of (4) contains an additional term, namely the selection bias, which is equal to $E(y_{0i} \mid c_i = 1) - E(y_{0i} \mid c_i = 0)$. Conventional approaches, such as the difference-in-difference estimator or OLS regressions, fail to control for selection bias, but it is possible to get around this problem by using propensity score matching, Heckman two-step methods, or other procedures to construct a term that soaks up the selection bias (Vella, 1998).

As mentioned, in this paper, we exploit the fact that in April 2002, NIE introduced a new metering device—the keypad—that allows customers to track consumption in real time, and a new pricing structure for its prepayment plan. New prepayment customers were placed directly on the keypad plan, and preexisting customers were moved en masse to the keypad, thus

replacing the existing meters with the more advanced ones and applying the new pricing structure. At the same time, the pricing of other plans was changed.

We interpret the introduction of the new metering device as the treatment of interest, customers on prepayment as the treatment group, and electricity consumption as the outcome of interest. Our control group is comprised of customers on all other plans. Since the price depends on the plan, customers select into their plan, and plan choice may be correlated with energy use patterns, there is potential for selection bias. We control for selection bias by using the Dubin-McFadden selection correction approach, which is well suited to the situation in which people select into one of a finite number of possible states.

B. Electricity Demand

We begin with estimating the regression equation:

(5) $$\ln E_{ijt} = \beta_{0j} + \beta_1 \ln p_{it} + \beta_2 \ln INC_{ijt} + \mathbf{x}_{ijt}\gamma + \eta_{ijt},$$

where E is electricity usage (in kWh), p is the price per kWh, INC is household income, and **x** is a vector of variables thought to influence electricity consumption (weather, characteristics of the home and of the household, type of heating and appliances used, dummies for the month or year when the household was interviewed). Subscripts i, j and t denote the household, area where the household resides, and wave of the CHS surveys, respectively. Clearly, equation (5) is an electricity demand function, and β_1 and β_2 are the price and income elasticities, respectively, of electricity demand.

As previously explained, the price of electricity varies across plans, and households select their electricity plans. Unobservable household characteristics may influence both a household's choice of plan, and hence the price per kWh it faces, as well as this household's electricity

consumption. This makes price and consumption endogenous. To remedy this problem, we implement a two-step estimation methodology based on Dubin and McFadden (1984).

Specifically, we assume that households choose a plan to maximize utility. We posit that a household's indirect utility is a function of characteristics of the households and the home:

(6) $$V_{ik} = \mathbf{Z_i}\alpha_{\mathbf{k}} + \varepsilon_{ik},$$

where i denotes the household, k denotes the plan, **Z** is a vector of characteristics of the household and/or the home, and ε is an i.i.d. extreme value error term with scale 1. The household chooses the alternative with the greatest utility, and so the probability of choosing plan k is:

(7) $$\Pr(k) = \exp(\mathbf{Z}_i \boldsymbol{\alpha}_k) \Big/ \left[\sum_{j=1}^{J} \exp(\mathbf{Z}_i \boldsymbol{\alpha}_j) \right]$$

with $\boldsymbol{\alpha}_1$ normalized to zero for identification.

We allow for possible correlation between η and ε, which makes electricity usage and the choice of plan endogenous. To obtain consistent estimates of the coefficients in equation (5), we must condition on the choice of plan. Dubin and McFadden assume that

(8) $$E(\varepsilon \mid \eta) = \frac{\sigma\sqrt{6}}{\pi} \sum_{m \neq k}^{K} r_m (\varepsilon_m - E(\varepsilon_m))$$

where r_m is the correlation coefficient between η and ε_m. Dubin and McFadden show that the coefficients in equation (5) can be estimated consistently by running OLS on

(9) $$\ln E_{ijt} = \beta_{0j} + \beta_1 \ln p_{it} + \beta_2 \ln INC_{it} + \mathbf{x}_{it}\boldsymbol{\gamma} + \sum_{m \neq k} \alpha_m \left(\frac{\hat{P}_{imt} \cdot \ln \hat{P}_{imt}}{1 - \hat{P}_{imt}} \right) + \alpha_k \cdot \ln \hat{P}_{ik} + e_{ijt}$$

where k is the plan selected by household i, m denotes a plan, the $\hat{P}$s denote the predicted probabilities of selecting the various plans from the first-step multinomial logit of the observed

plan choices, and the αs are the correlation coefficients from (8) rescaled by the standard deviation.

Bourguignon et al. (2007) compare the performance of the Dubin-McFadden correction term in (9) with a simplified version that imposes the constraint that the α coefficients sum to zero, and with the selection correction procedures developed by Lee (1983) and Dahl (2002). They conclude that (9) is the most robust. We report regression results based on (9), but for good measure repeat the same regressions with alternate selection correction procedures.

Since our sample is comprised of multi-year cross-sections drawn from the population of Northern Ireland, it is impossible to include household-specific effects, and we lack information to develop pseudo-panels based on detailed geography and housing type information (Deaton, 1985).[17] We control for unobserved heterogeneity by including ward-specific intercepts (the β_{0j} in equation (5)), under the assumption that the households and/or the dwellings in a ward are similar.[18]

C. The Effect of Usage Information on Usage

The question at the heart of this paper is whether providing feedback about consumption of electricity makes consumers change their usage levels. As we explained in section 3, in April 2002 NIE replaced the powercard plan with the keypad plan, which offered discounted prices,

[17] Other research (e.g., Bernard et al., 2010) has exploited multi-year cross-sections to construct pseudo panels based on the type of dwelling and geographical area where the household resides (which can be linked with a utility's service territory). Bernard *et al.* (2010) have multi-year cross-section data about electricity and gas consumption and prices in Quebec from 1989-2002, and their analysis is based on constructing pseudo-panels, i.e., relatively similar groups defined by area and house-size categories for which the relevant variables are the group averages.

[18] Northern Ireland is divided into twenty-six local governmental units called districts. Each district is a collection of wards. In Belfast County borough district, for example, there are 52 wards. There are currently 599 wards in Northern Ireland. Government officials are elected to represent several wards, and Census statistics are compiled at the ward level. For example, the 2001 Census outputs use the 582 electoral wards in existence at Census Day. All of these 582 wards had more than 100 residents/40 households.

dropped the annual meter charge, and substituted the old meter with a more advanced device that displayed real-time information. What is the (average) effect of such a change?

To answer this question, we amend equation (5) to include dummies for the type of plan the household is on. Formally,

$$\ln E_{ijt} = \beta_{0j} + \beta_1 \ln p_{it} + \beta_2 \ln INC_{ijt} + \mathbf{x}_{ijt}\boldsymbol{\gamma} + \mathbf{D}_{ijt}\boldsymbol{\delta} + \eta_{ijt}, \tag{10}$$

where **D** is a vector of dummies for the electricity scheme the household is on, and vector $\boldsymbol{\delta}$ captures the effect that the type of plan has on electricity, above and beyond that of the price associated with that plan. We estimate equation (10) in two steps, using the selection correction approaches described in section 5.B, since the choice of plan is likely influenced by unobserved characteristics of the home or the household that also influence usage of electricity.

The effect of feedback on log consumption, at least for those households that are on prepayment plans, is thus $\delta_{KEYPAD} - \delta_{POWERCARI}$. This is equivalent to a prepayment dummy × post 2002 dummy interaction term. For the "perfectly informed consumer" of section 4, the effect would be zero. An effect different from zero suggests less-than-perfect information (inattention), which the meter helps correct. Since we do not know whether the customer actually checks the meter, this is an "intention to treat" effect (see Angrist and Pischke, 2009, p. 163).

D. The Sample

We pooled the data from 18 consecutive waves of the Continuous Household Survey of Northern Ireland, starting with the 1990-91 wave and ending with the 2008-09 wave. The Continuous Household Survey (CHS) is an annual survey conducted by the Northern Ireland Research and Statistics Agency (NISRA). It is representative of the (civilian) population of Northern Ireland. The CHS elicits information about the dwelling (including type and size of the

home, tenure, heating, and various living expenses, such as energy), health, education, employment and welfare payments.

The surveys are conducted year-round, with approximately 300 households surveyed in each month, and cover different housing types, income levels, and geographic regions. Different households are interviewed in each wave of the survey, and so by pooling several waves we obtain a multi-year cross-section dataset, rather than a panel. A breakdown of the data by year is presented in table 3.

Characteristics of the dwelling (including the type of structure, size and age, and ownership) come from the "Tenure" section of the questionnaire, whereas information about heating and energy use comes from the "Heating" module of the questionnaire. The respondent is asked whether the home has central heating, and what fuels are used for heating the home, distinguishing for summer and winter heating. He is also asked if each of these fuels is used for heating water and for cooking. The questionnaire also elicits the expenses associated with each of the fuels. Next, the interviewer is instructed to ask the respondent to produce the most recent electricity bill, and to record the amount billed for the last quarter. Further questions inquire about how the respondent's household pays for electricity (plan and mode of payment), how much he paid most recently, and what period that payment covered.

E. The Choice of Independent Variables

Vector **x** in equations (5) and (10) is comprised of variables that we expect to influence to the demand of electricity directly (e.g., house size, etc.) or via the cost of monitoring. It thus includes the home type (e.g., single-family, semi-detached, etc.), size (measured as the number of rooms) and the age of the home. It also includes the number of years the household has been

living in this home, which we regard as a proxy for the household's familiarity with the energy efficiency of this dwelling and the vintage of heating and electrical equipment.

Dummies for the type of heating system and characteristics of the household (its size, number of children, number of elderly persons, number of workers, education, and whether the household is comprised of unrelated adults) are also included. We note here that education and other household characteristics may also serve as proxies for the cost of monitoring electricity usage. Finally, an important component of **x** is the weather. We include heating degree days and cooling degree days over the three months prior to the date when the household was interviewed.

Vector **Z** (equation 6) includes some of the same variables, plus—for identification purposes—others that might influence the choice of plan but should have no direct influence on electricity consumption. This set of "excluded variables" is comprised of whether the household owns a car, lives in the metro Belfast area, has income in the bottom 25% of the sample distribution, has one or more members with a disability that causes serious mobility impairment, since lack of transportation may make plans that require physically going out to pay bills less attractive. It is also likely that individuals may choose a plan over another based on word of mouth or this plan's popularity with neighbors and friends. For this reason, we include in **Z** (but not in **x**) the percentage of the *other* residents of the same ward in the CHS that use: (i) a prepayment plan or (ii) a direct debit plan.

6. The Data

Attention is restricted to those households that presumably have a reasonable degree of control over the use of energy at their premises. For this reason, we excluded from the initial sample (N=55,065) i) squatters and households who live at a given location rent-free, ii)

households for whom the dwelling serves as a business premise, and iii) observations where the respondent refused to provide information about tenure. We also excluded iv) persons or households that rent a single-room within a house or apartment, as that is likely to capture lodgers and other types of temporary housing arrangements where the respondent has little control over fuel use and bills. Items (i)-(iv) together account for around 1% of the original sample.

Finally, we excluded observations where the most recent electricity bill is missing, those with missing information about the selected plan, as well as those for households with an electric storage heater, since these households would typically adopt the Economy7 tariff schedule, which makes it impossible for us to calculate the kWh used based on the CHS data.[19] For good measure, we further trim the bottom and top 1% of the distribution of electricity kWh in the sample. This left us with N=45,149 usable observations for our regressions. In subsequent regressions, we further exclude households that rented their dwelling from the Housing Executive (i.e., public or assisted housing, which account for 21.77% of the original sample) or from a housing association (a private charity that provides low-cost housing: 2.40% of the original sample), which results in a sample of 34,779 observations.

Table 3, panels (B) and (C), shows the breakdown of the final two samples (with and without public housing) by year. Table 4 displays descriptive statistics about the housing units in our samples, which are comprised primarily of single-family homes (38% and 44%), followed by semi-detached and terraced homes (21 and 33%, respectively).

In the sample that includes those that live in public housing, approximately 32% of the households own the home outright, 38% are paying a mortgage, and the remaining 30% rent

[19] NIE however reports that only about 7% of the households subscribe to this tariff plan, which is effectively a time-of-use plan with nighttime prices much lower than daytime prices.

their homes. The majority of those who rent their homes rent them from the Housing Executive (about 22%) or from a housing association (2.39%). Only 6.43% of the sample rent their homes from private landlords. When households who rent from the Housing Executive or a housing association are excluded from the usable sample, renters account for 6.89% of the sample and all of them rent from private landlords.

Information about heating is reported in table 5. Northern Ireland has a mild climate, with the temperature rarely higher than 75º Fahrenheit (24º Celsius), and thus little demand for air conditioning. As a consequence, much of the energy usage in the residential sector in Northern Ireland is for heating. Homes are heated with coal, fuel oil, natural gas, electricity, wood or peat, as well as other non-traditional fuels. In fact, a majority of homes in our sample use more than one fuel in their home. Tables 6 and 7 present statistics on household characteristics and income, respectively.

Weather data are taken from several monitors in Northern Ireland available from the T3 Global Surface Summary of the Day from NOAA. Because the survey asks respondents about past energy consumption (typically quarterly), we use a three-month moving average of the heating degree days (HDD) and cooling degree days (CDD) relative to 65º F (18 ºC), as is standard practice with the US Department of Energy. The mean three-month average for HDD is 490.65.

Energy demand should, of course, be influenced by the presence of energy efficiency investments and appliances in the home. Unfortunately, the CHS does not routinely inquire about energy-efficiency investments. The only exception is the 2008-09 CHS (the last wave of surveys we use in this paper). Based on specific questions on energy efficiency, we know that by 2008-09 about 83% of the homes covered by the CHS had attic insulation, 59% had cavity wall

insulation, 76% had insulated the hot water tank, 56% had insulated the hot water pipes, 83% had double-paned windows, 36% had been weather-proofed, 58% had installed low-energy lightbulbs, and 15% had a programmable thermostat.[20]

In the same wave of the CHS, the questionnaire also elicited information as to whether the respondent had availed himself of incentives and subsidies for energy efficiency investments. Only about 3% had received incentives from the Warm Homes program, and a similar share had received other incentives for attic, wall and boiler insulation.[21]

All homes in the CHS are served by electricity. We identify tariff plan exactly in the CHS data and assign marginal electricity price based on the historical tariff data provided by NIE. Prices are all deflated to 2009 constant British Pounds using the Real Price Index.[22] We use the price information to calculate the kWh used in the last quarter by each household.[23] Descriptive statistics for electricity consumption and prices are displayed in table 8. The average household

[20] See Clinch and Healy (2000) for a discussion of energy efficiency investments in homes in Ireland and policies that potentially encourage them. O'Doherty et al. (2008) examine the relationship between "potential energy use," income, and home type and size in Ireland.

[21] The Warm Homes scheme was launched in 2001 by the Department of Social Development to address fuel poverty in Northern Ireland. The scheme provides insulation measures, heating measures and energy efficient lightbulbs to people on low incomes, targeting 8,250 households every year. Heatsmart is another program, started in April 1999 and managed by the Northern Ireland Energy Agency, which provides free and independent heating and energy saving advice to tenants across Northern Ireland. Winter fuel payments were introduced in 1997 to help low-income seniors with the costs of keeping warm during the winter (People aged between 60 and 79 years receive £250 per household, and those over age 80 receive £400). A separate cold winter payment of £25 each week, between November 1st and March 31st, is available when the temperature is freezing or below for any period of seven consecutive days. This extra payment is available to those low-income households receiving Pension Credit, Income Support, Income-based Jobseeker's Allowance or Income-related Employment and Support Allowance (ESA). It has been in existence since 1991.

[22] The real price index (RPI) is compiled by the UK government: http://www.statistics.gov.uk/STATBASE/Source.asp?vlnk=1442.

[23] We use the posted price per kWh. For most of the study period, this is the same as the marginal price per kWh. Explicit block pricing was applied for electricity only for a short period in the late 1990s, and was later replaced by a tariff schedule with a constant rate per kWh and no fixed fee, where marginal and average price are the same. Discounts were given to customers on different plans. The fact that such discounts in some cases were not to exceed a specified maximum effectively re-creates a form of (increasing) block pricing, but these apply only at extremely high levels of demand (around the 98th percentile of the distribution of usage in our sample), and so we ignore this effect.

uses about 4200 kWh per year, a figure that is similar to the estimates provided by NIE (and much lower than consumption in the US).

Information about the choice of payment plans for electricity is displayed in table 9. Combined with tables 1-2, this allows us to construct a complete picture of prices, plan features and percentage of the sample that selects each plan.

7. Results

A. Electricity Demand

Figure 1 displays average log electricity consumption over time separately for prepayment and all other households, based on the sample that includes public housing and for the years 1996-2009 (the Peace Process was put in place in Northern Ireland in 1997, and this is the beginning of a much more economically and socially stable period for this region). The graph suggests that prepayment and all other customers were quite similar until CHS survey year 2003, which corresponds to the period when the keypad was introduced, and that (log) usage dropped for the prepayment group after survey year 2003. The other customers likewise reduced consumption (perhaps because of rising electricity prices or energy efficiency campaigns), but not quite so fast nor to the extent of the prepayment households.

As explained in Section 5, we estimate the demand for electricity in two steps. The first step is a multinomial logit model, where the probability of choosing one of the seven possible payment plans listed in table 9 depends on household and dwelling characteristics. In the second step we estimate the demand for electricity (equation (5)) using the correction terms from the first-step MNL estimation.

The results for several specifications of equation (5) are displayed in tables 10 and 11. All of them include geographic fixed effects, but omit the interview month and year dummies, which we found to be too strongly correlated with weather and prices. Regressions are reported for the full study period, as well as for 1997 and later, and 1999-2006 in an effort to narrow the window around the introduction of the keypad meter. All t statistics are based on standard errors clustered at the ward level.

We first estimate equations where consumption depends on price, weather, income, dwelling and household characteristics (standard explanatory variables in a model of energy demand). The results of these regressions for the broader sample are reported in table 10, columns (A)-(C), and suggest that our data are plausible and consistent with a well-behaved electricity demand function. Starting with run (A), the price elasticity is -0.94 and the income elasticity is 0.17. We emphasize that this should be interpreted as the income elasticity conditional on knowing the income of the household.[24]

Both elasticities get smaller as we add explanatory variables: In specification (C), for example, the price elasticity is -0.74 and the income elasticity is 0.04.[25] We attribute this result to the presence of regressors that are correlated with income, such as the type of home and the education and ages of the household members (see Alberini et al., 2010).

Turning to the other regressors, the weather does influence electricity usage: The three-month moving average of HDD is positively and significantly associated with electricity usage in

[24] In the CHS, household income is top-coded, and so we include a dummy that keeps track of this. We also control for missing income in the model. The coefficients on the missing income and top-coded dummies are positive and significant, suggesting that households that do not report their income might be wealthy or otherwise have significantly larger electricity consumption than those that do. Top earners consume 14% more than is explained by their imputed income alone.

[25] Our estimates of the income elasticity are consistent with Meier and Rehdanz (2010) for heating expenditure in the rest of the UK.

all specifications.[26] Housing characteristics are likewise associated with energy consumption, as expected. Consumption of electricity is positively and significantly associated with the number of rooms in the home (with each additional room increasing electricity usage by 4.7-7.9%). Semi-detached and terraced homes, which share one or more walls with a neighbor (and are therefore more insulated from cold weather), tend to use, all else the same, 9 to 17% less than single-family homes, depending on the specification.

We control for the vintage of the home with period dummies. All else the same, older homes (built before 1945) and homes built between 1945 and 1965 use roughly the same amount of electricity as homes built after 1985 (which is our omitted category). Homes built between 1965 and 1985 use between 2.6% and 3.9% more. These results are intuitive: Newer homes are expected to be more energy efficient; older homes may have been retrofitted or perhaps contain fewer appliances. We also note that during the 1965-85 period there was a small construction boom in Northern Ireland, with homes being built quickly and inexpensively.[27] Finally, consumption depends in a quadratic fashion on the time the occupants have lived in their home.

In specification (B), we add variables that describe the type of heating in the home. Gas, electricity, oil, wood and coal (the heating fuel dummies entered in the model) are used by 98% of our sample. Many homes in Northern Ireland use more than one fuel type for heating (e.g., central oil heating with supplemental electric heating). Despite limitations in the data,[28] the coefficients on heat type are highly significant and intuitively appealing: Homes with electric

[26]Because of the cool weather, Cooling-Degree Days (CDD) are effectively almost always zero for Northern Ireland, so they are excluded from our regressions.
[27] George Hutchinson, personal communication, 14 December, 2010.
[28] The CHS questionnaire elicits information about up to 10 different types of fuel for heating purposes, but does not allow us to recognize which is the primary type of fuel. For this reason, our heating variables are not mutually exclusive: They merely denote the presence or absence of a certain heating type in the home.

heating use more electricity (about 14-17% more), all else the same, and homes heated with gas, oil, wood or coal about 7-9% less than the baseline category (all other fuel types).

Specification (C) adds household variables to the model: the number of household members in (broad) age groups, the education level, the number of workers, and whether the home is rented. Most of these variables are significant. The number of children and adults is positively correlated with energy usage, but the coefficient on the number of elderly persons is negative. In other words, adding an adult increases usage, but at a lower rate if this adult is an elderly person. We suspect that the elderly might engage in more energy conservation and use fewer appliances than younger individuals.

Households with greater education levels and more employed persons are associated with less electricity usage. The presence of a college-educated adult implies 4.3% less usage. An additional worker implies a 2% drop in electricity consumption. We interpret these results to represent the likelihood of households to take steps to improve energy efficiency, and also to proxy the amount of time spent in the home. Renters use less electricity than owners, most likely because they have smaller homes and fewer electricity-using devices.

B. What is the Effect of the Feedback?

Since the keypad device is provided only to pre-payment customers starting in April 2002, any change in electricity usage attributable to this device should be observed only on pre-payment customers, while all others should be unaffected. Focusing on a relatively small window around the adoption of the keypad (1999-2006) to avoid capturing long-term trends, log usage for pre-payment customers indeed declined from 6.87 in 1999-2002 to 6.73 in 2003-2006 (t statistic 4.86), while that of “account” customers (the most popular plan) remained virtually

unchanged (6.82 and 6.81, respectively, for a t statistic of 1.06). In what follows, we check whether these trends remain in place after we control for household and dwelling characteristics and can be attributed to the keypad device.

In specification (D) in table 10, we include dummy variables for the different electricity plans to see if they have an effect on consumption that goes beyond the price per kWh that they carry. The omitted plan is the traditional "account" plan, the standard offer service for NIE, whereby customers are billed quarterly and pay by cash, check or through their EasySaver. We hypothesize that the keypad system better enables individuals to monitor their usage, which may encourage conservation steps and energy efficiency, and hence lowers usage. Our theoretical model does not provide unambiguous predictions about the effect of a monitoring facilitation device like the keypad, but conventional wisdom in policy circles indicates that this type of device should have some role in reducing consumption.

Who are our keypad customers? In our sample, keypad customers have homes with fewer rooms and are more likely to be in a terraced home than a detached home. They also have slightly lower household income and are more likely to be renters than those in other plans. Keypad homes are also slightly less likely to use electric heat. Our regressions, however, already control for these characteristics, as well as selection into the plan.

As shown in (D) in table 10, households on the keypad *do* use 11% less electricity than the baseline group, even accounting for house type and size, heating type, income and household characteristics. The net effect of the keypad treatment, above and beyond the price discount it offers, is computed as the coefficient on keypad minus the coefficient on the powercard dummy. Based on (D), this effect is thus a reduction by almost 17.5%.

In column (E), the sample is restricted to 1997 and later, since 1997 is the first year when variation was introduced in the price of electricity.[29] There is virtually no difference between usage levels between powercard users and standard "account" holders, once we control for price, income and dwelling and household characteristics. Moreover, the coefficient on the keypad dummy is -0.13 and is virtually the same as its counterpart in col. (D), resulting in a net average reduction by 15.3% in electricity usage among prepayment households. For good measure, in this specification we have added an interaction term between being a control household and the post-2002 dummy, and the coefficient on this term is very small and statistically insignificant.

Further restricting the sample to 1999-2006 (panel (F)) gives very similar results: The coefficient on the keypad is -0.13, the powercard per se has no effect beyond that of price, income, house and household characteristics, and the net effect of keypad is a 14% reduction in electricity usage.

For good measure, we also re-run models (D)-(F) with the Lee and Dahl selection correction terms instead of the unrestricted Dubin-McFadden approach. The Lee approach results in negative and significant estimates (keypad -0.066, powercard 0.10, difference -0.166), whereas the Dahl approach produces slightly more modest effects (-0.14 keypad, powercard 0.036, difference -0.104) of the impact of the introduction of the keypad.

D. Other Robustness Checks

The sample used for the regressions of table 10 includes households who live in publicly-assisted housing. Since these households tend to be poorer, we wondered whether they had a different price and income elasticity, and a different response to the change in the meter and

[29]Although assessed with a fixed charge for their meter, prepayment customers received the same price as standard offer service customers until 2002.

price schedule associated with the introduction of the keypad. In table 11 we report the same regressions as in table 10, but based on a sample that omits public/assisted housing. The coefficients are similar to their counterparts in table 10, and the "average treatment effect" of the introduction of the keypad ranges from a 13% reduction in electricity usage (specification (F)) to a 19% reduction (specification (D)).

We remind the reader that in our regression the price of electricity is the marginal price per kWh. This is certainly appropriate after 1999, when NIE dropped the standing charge (fixed monthly fee) and adopted a constant price per kWh.[30] Even after 2002, prices may vary across plans, but the price per kWh is constant, regardless of quantity, for any given plan. All results are virtually unchanged when the analysis is restricted to 1997 and later years. Omitting the geographic fixed effects results in a change of the key coefficients, namely the price and income elasticity, by at most 5%.

To make sure that we do not incorrectly attribute to the keypad a general decrease in electricity consumption in Northern Ireland over time, we conducted a "falsification test" on the customers not on the keypad. Specifically, we ran the regression of equation (10) on non-keypad, non-prepay customers (i.e., our control group), with a post-2002 dummy. If the introduction of the keypad had no effect other than on keypad customers, the coefficient on this dummy should be insignificant. We find that this coefficient is positive, small (the difference in consumption is less than 1%), and statistically insignificant at the conventional levels (t stat 1.53). This reinforces our result that the reduction in usage given house size, income, etc. after the

[30] To handle the period in which NIE applied block pricing, we did attempt to instrument for the marginal price using the same approach Nieswiadomy and Molina (1989), but the results were unstable and disappointing. This is because i) block pricing applies for a short period of time in the middle of our study period, ii) is subsequently replaced by constant price per kWh and no fixed charge, which makes marginal and average price the same for a substantial portion of our study period, and iii) even when the discount caps apply, which in theory creates increasing block pricing, they become binding as levels of consumption so high that hardly anyone is bound by them.

introduction of the keypad is specific to a group—the prepayment group—and does not extend to the rest of the customer base. For comparison, if the same regression is run using a sample that is comprised only of prepayment customers, the coefficient on the post 2002 dummy is a strongly significant -0.175.

8. Discussion and Conclusion

We have identified the effect of real-time feedback on electricity consumption from a smart-meter device using a policy change that we interpret as a large-scale natural experiment in Northern Ireland. We have used unique data on residential electricity consumption over 18 years in a setting with extensive payment plan variation and an exogenous treatment (the introduction of the keypad device in 2002) on a well-defined group (all prepayment customers). We have focused exclusively on customers who pay their own bills, corrected for selection into the plan, and accounted for unobserved heterogeneity using geographic fixed effects.

Our investigation suggests that households do respond to the provision of information by using less electricity, even accounting for type of home, heat, household characteristics and possible selection of households into pre-payment plans. This effect is quite pronounced (15-17%), providing support for earlier claims in the literature for smart metering and feedback displays (e.g. Darby 2006), which were however based on small and short-lived pilot programs. To our knowledge, this is the first attempt to estimate the effect of information using both a large-scale experiment and a large sample.

Our data do not document how households managed to reduce usage—whether they engaged in more careful conservation behavior, unplugged appliances, cut down on usage of energy-intensive appliances or undertook energy-efficiency investments (or all of the above). We

hope that in the future household-level data will be collected to answer specifically this question. We also hope that in future rounds of surveys consumers on the keypad will be specifically asked whether they do check their usage using this device, as this information is not currently gathered in the CHS. For this reason, our results should be interpreted as intention-to-treat effects.

In sum, our results suggest that displaying real-time information to consumers might help reduce electricity usage, and hence the conventional pollutants and carbon emissions. Are the reductions in carbon emissions attained at low cost?

The cost of a keypad meter is comprised of the purchase and installation costs, plus the cost of operation. Owen and Ward (2007) estimate these costs to be an £37-43 (purchase and installation) and £25-30 (present value of the operating costs) per meter, respectively.[31] Assuming no changes in the operating costs in the future, total per-unit costs for the life of keypad devices (assumed to be 10 years) are £62-73. Each kWh of grid electricity in the UK is estimated to generate 0.544 kgCO_2e (DEFRA, 2009).

We consider usage reductions ranging between two extremes—10% and 17% (table 10, model (D)). A 17% reduction in average prepayment usage (4016 kWh per year), over a span of 10 years, equates to 3714 kg CO_2e (371.4 per year) for the mean keypad consumer. This implies a carbon reduction cost of £16.69 – 19.66 per metric ton CO_2e. The cost per metric ton CO_2e is £28.73 – 33.41 for 10% reductions in electricity usage. At this time, credits for Certified Emissions Reductions (CERs) can be bought and sold on the European exchange at about £11 per tonne CO_2e,[32] but the UK government relies on a policy price of carbon of £25 per tonne

[31] Owen and Ward (2007) base their estimates on 300,000 installed units, which is slightly more than the 250,000 installed units in NIE, but indicate that unit costs have been falling over time. On balance we find their estimates reasonable.

[32] Based on June 2011 market price for CO2e CER contract (€12.86, which is equal to £11.29 at prevailing exchange rates), accessed April 1, 2011. CER contract prices in 2010 fluctuated between €12 and €14, [REF]

CO_2e in 2009 (DECC, 2009).[33] The cost-effectiveness of the keypad is thus comparable to that of other, more traditional abatement measures.

These calculations are performed from the point of view of the regulator, and ignore any gains and losses for the utility. The utility loses revenue when electricity sales are reduced, but also saves on operating costs by using smart meters, suggesting little or no loss of profit.[34] There may be a number of social benefits from a keypad-type program, which we do not attempt to quantify in this paper. For example, it may help meet politically important fuel poverty policy goals by providing discounted electricity to a historically low-income prepayment customer class (Livingstone, 2011). Other social benefits include reductions of other air pollutant byproducts of power generation (which may be experienced at other locations in the UK), benefits from foregone imports of fossil fuel, and the security and macroeconomic cost savings that these imply. Private benefits include energy savings to consumers (a 17% reduction is equivalent to an annual savings of £89.98 in the electricity bill of the average prepayment customer).

[33] The "traded" price of carbon is used for appraising policies that affect emissions in sectors covered by the EU ETS (i.e. the power sector). It is based upon estimates of future EUA and global carbon market prices.

[34] At least in the US, utilities seeking to install smart meters estimate the reductions in costs due to the smart meters to be large. See, for example, http://tinyurl.com/SMECOAMI. NIE initially planned to install 75,000 keypad meters, but now has over 250,000, evidence of some derived benefit to the utility. Utility representatives cite lower service costs for customers (no billing or collection costs, lower customer support costs) as benefits of the keypad program (Livingstone, 2011).

References

Alberini, Anna and Massimo Filippini (2010), "Response of Residential Electricity Demand to Price: The Effect of Measurement Error," CEPE Working Paper 75, Centre for Energy Policy and Economics, ETH Zurich, July (available at http://www.cepe.ethz.ch/publications/workingPapers/CEPE_WP75.pdf)

Alberini, Anna, Will Gans, and Daniel Velez (2010), "Residential Consumption of Gas and Electricity in the U.S.: The Role of Prices and Income," forthcoming, *Energy Economics*

Allcott, Hunt (2010) "Social Norms and Energy Conservation" *Unpublished Working Paper* http://web.mit.edu/allcott/www/Allcott%202010%20-%20Social%20Norms%20and%20Energy%20Conservation.pdf

Angrist, Joshua D. and Jorn-Steffen Pischke, (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton University Press.

Ayres, Ian, Sophie Raseman and Alice Shih (2009), "Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage," NBER Working paper 15836, Cambridge, MA: September.

Auffhammer, Maximillian, Carl Blumstein, and Meredith Fowlie, (2008), "Demand-Side Management and Energy Efficiency Revisited", *The Energy Joumat.* Vol. 29, No. 3.

Bernard, Jean-Thomas *et al.* (2010), "A Pseudo-Panel Data Model of Household Electricity Demand," *Resource and Energy Economics* 32, (4),

Bourguignon, Francois, Martin Fournier and Marc Gurgand (2007), "Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons," *Journal of Economic Surveys* 21(1), 174-205

Brutscher, Phillip-Bastian (2011), "Payment Matters: An Exploratory Study into Pre-Payment Electricity Metering," *Cambridge EPRG Working Paper* EPRG1108

Chiang, Alpha C. (1984), *Fundamentals of Mathematical Economics*, McGraw-Hill, New York

Clinch, Peter, and John Healy (200), "Domestic Energy Efficiency in Ireland: Correcting Market Failure," *Energy Policy*, 28(1), 1-8.

Dahl, G. B. (2002), "Mobility and the Returns to Education: Testing a Roy Model with Multiple markets," *Econometrica*, 70, 2367–2420.

Darby, Sarah (2006), "The Effectiveness of Feedback on Energy Consumption: A Review for DEFRA of the Literature on Metering, Billing and Direct Displays," Environmental Change Institute, University of Oxford.

Deaton, Angus (1985) "Panel Data from Time Series of Cross Sections". *Journal of Econometrics*, 30, 109-26.

DECC, (2009), "Carbon Valuation in UK Policy Appraisal: A Revised Approach Climate Change Economics," *UK Department of Energy and Climate Change*, July 2009

DEFRA (2009), "Guidelines to Defra/DECC's greenhouse Gas conversion factors for company reporting," *Department for Environment Food and Rural Affairs (DEFRA)*, http://www.defra.gov.uk/environment/business/reporting/pdf/20090928-guidelines-ghg-conversion-factors.pd

Della Vigna, Stefano and Ulrike Malmendier (2006), "Paying Not to Go to the Gym," *The American Economic Review*, 96(3), 694-719.

Department For Social Development Northern Ireland (2006), *Ending Fuel Poverty. A Strategy for Northern Ireland*, available at http://www.dsdni.gov.uk/ending_fuel_poverty_-_a_strategy_for_ni.pdf

Dubin, Jeffrey A. and Daniel McFadden (1984), "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption," *Econometrica*, 52(2), 345-362.

Dulleck, Uwe, and Sylvia Kaufmann (2004), "Do Customer Information Programs Reduce Household Electricity Demand?--the Irish Program," *Energy Policy*, 32(8), 1025-1032.

Edlefsen Lee E. (1981),"The comparative statics of hedonic price functions and other non-linear constraints," *Econometrica*, 49(6)

Ehrhardt-Martinez, Karen, et al., (2010) "Advanced Metering Initiatives and Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities," American Council for an Energy-Efficient Economy, Report No. E105

Finkelstein A (2009). EZ-Tax: Tax Salience and Tax Rates, *Quarterly Journal of Economics*, 124(3): 969-1010

Gans, Will, Anna Alberini, and Alberto Longo, (2011) "Smart Meter Devices and The Effect of Feedback on Residential Electricity Consumption: Evidence from a Natural Experiment in Northern Ireland", *FEEM working paper 2011.036*, http://www.feem.it/userfiles/attach/2011519940254NDL2011-036.pdf

Gleerup, Maria, Anders Larsen, Soren Leth-Peterson and Mikael Togeby (2010), "The Effect of Feedback by Text Message (SMS) and Email on Household Electricity Consumption: Experimental Evidence," *The Energy Journal*, 31(3), 113-132.

Grubb, Michael D. (2009), "Selling to Overconfident Consumers," *American Economic Review*, 99(5), 1770-1807.

Hartman, Raymond S., (1988), "Self-Selection Bias in the Evaluation of Voluntary Energy Conservation Programs," *The Review of Economics and Statistics*, 70(3)

Hassett, Kevin and Gilbert Metcalf (1993), "Energy Conservation Investment: Do Consumer Discount the Future Correctly?" *Energy Policy*, 12(6), 710-716.

Ito, Koichiro (2010), "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing," draft paper, University of California, Berkeley, November.

Lambrecht, Anja and Bernd Skiera (2006), "Paying too Much and Being Happy About It: Existence, Causes, and Consequences of Tariff-Choice Biases," Journal of Marketing Research, XLIII, 212-223.

Lee, L. F. (1983), "Generalized Econometric Models with Selectivity," *Econometrica*, 51, 507–512.

Livingstone, Jenny, (2011) "Fuel Poverty Interventions, A Utility Perspective" Presentation given at the International Energy Agency (IEA) Fuel Poverty Workshop, Dublin, Ireland January 28-29: www.iea.org/work/2011/poverty/pres8_LIVINGSTONE.pdf Accessed *on April 5, 2011*.

Loughran, David S and Jonathan Kulick, (2004), "Demand-Side Management and Energy Efficiency in the United States," *The Energy Journal*, 25 (1)

Matsukawa, Isamu, (2005), "The Benefits of Information on the Efficient Usage of Consumer Durables: Experimental Evidence Concerning Residential Energy Conservation," *Musashi University Discussion Paper No. 38*

Meier, Helena and Katrin Rehdanz (2010), "Determinants of Residential Space Heating Expenditures in Great Britain," *Energy Economics*, 32, 949-959.

Metcalf, Gilbert and Donald Rosenthal (1995), "The 'New' View of Investment Decisions and Public Policy Analysis: An Application to Green Lights and Cold Refrigerators", *Journal of Policy Analysis and Management*. 14(4) 517-531.

Nieswiadomy, Michael L. and David J. Molina (1989), "Comparing Residential Water Demand Estimates under Decreasing and Increasing Block Rates using Household Data," *Land Economics*, 65(3), 280-289.

O'Doherty, Joe, Sean Lyons, and Richard S.J. Tol (2008), "Energy-Using Appliances and Energy-saving Features: Determinants of Ownership in Ireland," *Applied Energy*, 85(7), 650-662.

Owen, Gill and Judith Ward (2007), "Smart Meters in Great Britain: the next steps?" *Report published by Sustainability First*, July, http://www.sustainabilityfirst.org.uk

Shin Jeong-Shik (1985), "Perception of Price When Price Information Is Costly: Evidence from Residential Electricity. Demand," *Review of Economics and Statistics*, 67(4), 591-598.

Vella, Francis (1998), "Estimating Models with Sample Selection Bias: A Survey," *The Journal of Human Resources*, 33(1), 127-169

Waldman, Donald M., and Michael T. Ozog, (1996), "Natural and Incentive-Induced Conservation in Voluntary Energy Management Programs," *Southern Economic Journal*, 62(4)

Wei, Max, Shana Patadia and Daniel M. Kamman, (2010)."Putting Renewables and Energy Efficiency to Work: How many jobs can the clean energy industry generate in the US?" *Energy Policy*, 38(2)

Figure 1. Log electricity consumption: Average for prepayment (treatment) and control households (not adjusted for household characteristics) by year (1996-2009).

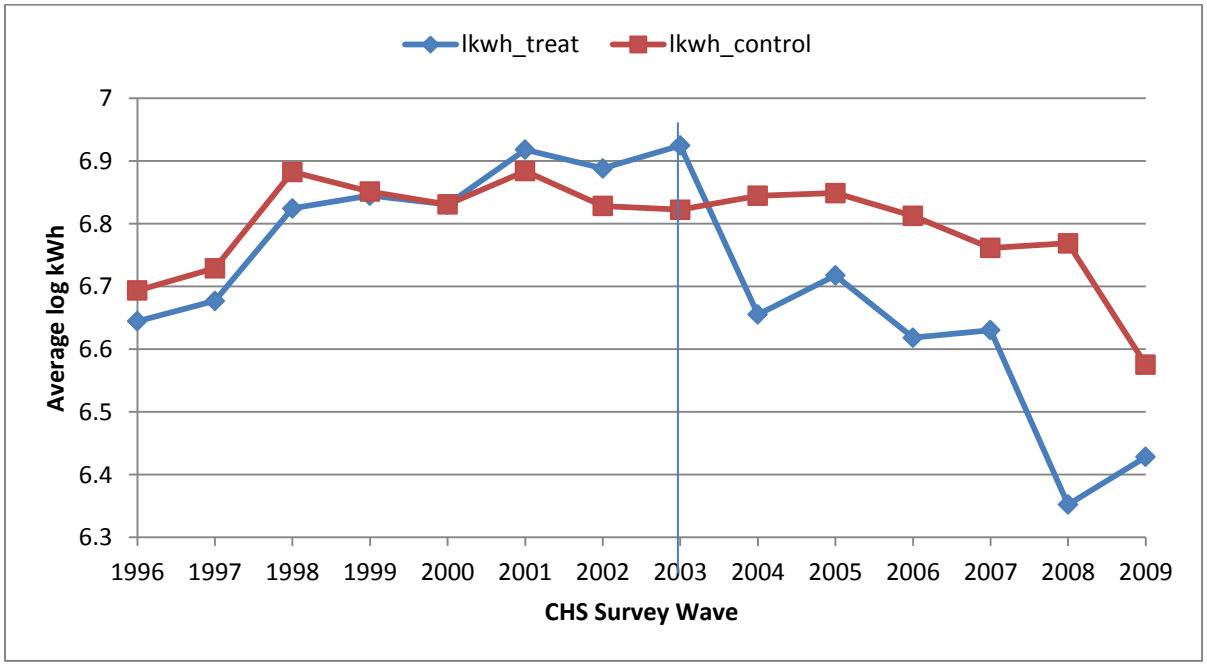

Table 1. Northern Ireland Electricity Tariffs.

	Standing charge per quarter	Unrestricted price (pence per kWh)	Max. discount per year for Quarterly Direct Debit Plan	Max. discount per year for Monthly Direct Debit Plan
Apr-90	£11.80	6.84		
Apr-91	£13.09	7.41		
Apr-92	£13.61	7.71		
Apr-93	£14.15	7.87		
Apr-94	£13.95	7.75		
Apr-95	£14.84	8.25		
Apr-96	£15.20	8.45		
Apr-97	£7.94	9.16 first 250 kWh/8.16 thereafter		
Apr-98	£7.94	9.16 first 250 kWh/8.16 thereafter		
Apr-99		9.00		
Apr-00		8.60		
Apr-01		9.38		
Apr-02		9.38	£5.0	£10.0
Apr-03		9.38	£14.0	£28.0
Apr-04		9.64	£14.0	£28.0
Apr-05		9.95	£14.0	£28.0
Apr-06		11.02	£14.0	£28.0
Apr-07		10.69	£14.0	£28.0
Nov-07		11.11	£22.0	£34.0
Jul-08		12.66	£22.0	£34.0
Oct-08		16.88	£26.0	£40.0
Jan-09		15.06	£26.0	£40.0
Oct-09		14.31	£26.0	£40.0
Oct-10		14.31	£26.0	£40.0

Notes:

Prices exclude VAT. Domestic VAT of 8% was introduced in 1994 and was changed to 5% in 1997 where it has remained until now.

Discounts are 4% for monthly direct debit, and 2.5% for quarterly direct debit, up to the maximum total shown in the table.

Keypad metering was introduced in April 2002 with a discount (uncapped) of 2.5% to the standard domestic tariffs.

Table 2. Discounts offered to specific electricity plans in Northern Ireland.

Acronym used in this paper	name	since	discount	max discount per year (£)	frequency of payment	conditions for extending the discount
	Easy Saver	April 1997	1.50%	10	unspecified	if balance in the account is no more than £10 or 10% of the total bill
BUDGE	Budget	1970s, discounts since 1997	1.50%	10	regular, even payments, usually weekly-monthly	if balance in the account is no more than £10 or 10% of the total bill
DDM	Direct Debit Monthly	April 2002	4%	40 at present. Has changed over the years--see table 1.	even monthly payments	
DDQ	Direct Debit Quarterly	April 2002	2.50%	26 at present. Has changed over the years--see table 1	even quarterly payments	
Keypad	Keypad	April 2002	2.50%	uncapped	prepay	

Table 3. Composition of the sample by year.

	(A) Full CHS, all years		**(B) Sample used in this paper (electricity regressions)**		**(C) Excluding Housing Executive**	
year	N	percent	N	Percent	N	Percent
1991	3,166	5.75	2,862	6.34	1,976	5.68
1992	3,107	5.64	2,799	6.2	1,885	5.42
1993	3,097	5.62	2,557	5.66	1,755	5.05
1994	3,182	5.78	2,760	6.11	1,927	5.54
1995	3,220	5.85	2,823	6.25	1,990	5.72
1996	3,221	5.85	2,752	6.09	2,023	5.82
1997	2,892	5.25	2,467	5.46	1,808	5.2
1998	3,024	5.49	2,554	5.66	1,944	5.59
1999	2,809	5.1	2,364	5.24	1,790	5.15
2000	3,039	5.52	2,579	5.71	1,972	5.67
2001	2,800	5.08	2,350	5.2	1,821	5.24
2002	2,806	5.1	2,342	5.19	1,901	5.47
2003	2,787	5.06	2,242	4.97	1,836	5.28
2004	2,769	5.03	2,091	4.63	1,798	5.17
2005	2,773	5.04	2,059	4.56	1,769	5.09
2006	2,603	4.73	1,967	4.36	1,713	4.93
2007	2,726	4.95	1,904	4.22	1,652	4.75
2008	2,567	4.66	1,914	4.24	1,699	4.89
2009	2,476	4.5	1,766	3.91	1,520	4.37
Total	55,064	100	45,152	100	34,779	100

Table 4. Characteristics of the Home: Descriptive Statistics

		(A) Full Sample			(B) Excluding Housing Executive		
Variable	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
SFhome	Single-family (detached) home dummy	45152	0.387	0.487	34779	0.491	0.500
SDhome	Semi-detached home dummy	45152	0.215	0.411	34779	0.243	0.429
terracehome	terraced home dummy	45152	0.330	0.470	34779	0.234	0.424
totroom	total number of rooms	45151	6.793	1.865	34778	7.154	1.900
h_1945	built before 1945 dummy	45152	0.139	0.346	34779	0.167	0.373
h_1945_65	built 1945-65 dummy	45152	0.156	0.363	34779	0.153	0.360
h_1965_85	built 1965-85 dummy	45152	0.315	0.465	34779	0.279	0.449

Table 5. Heating: Descriptive Statistics

		(A) Full Sample			(B) Excluding Housing Executive		
Variable	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
gasheat	gas heat dummy	45152	0.096	0.295	34779	0.104	0.306
oilheat	heating oil heat dummy	45152	0.504	0.500	34779	0.618	0.486
woodheat	wood heat dummy	45152	0.198	0.398	34779	0.188	0.391
coalheat	coal heat dummy	45152	0.440	0.496	34779	0.390	0.488
electheat	electric heat dummy	45152	0.270	0.444	34779	0.254	0.436

Table 6. Household Characteristics: Descriptive Statistics

		(A) Full Sample			(B) Excluding Housing Executive		
Variable	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
numadult	Number of adults in household	45152	2.022	0.959	34779	2.130	0.956
ndepkids	number of children 18 or younger …	45143	0.770	1.187	34772	0.773	1.169
renter	household rents the home (dummy)……..	45152	0.053	0.224	34779	0.069	0.253
nelderly	number of household members 65 and older….	45151	0.350	0.622	34778	0.337	0.627
nworkers	number of household members who work……	44956	0.193	0.600	34610	0.216	0.636
college	household member has attended college (dummy)…	45152	0.110	0.314	34779	0.136	0.343
students	unrelated adults, probably students…	45152	0.047	0.213	34779	0.059	0.235

Table 7. Household Income: Descriptive Statistics

		(A) Full Sample			(B) Excluding Housing Executive		
Variable	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
inc_r	annual household income (2009 £)	39061	20448	13482.2	29665	23663.10	13555.63
recodedlinc_r	recoded ln inc_r	45152	8.375	3.378	34779	8.420	3.553
incomemissing	missing dummy	45152	0.135	0.342	34779	0.147	0.354
topcoded	topcoded dummy	45152	0.108	0.310	34779	0.139	0.346

Table 8. Electricity Demand and Price

		(A) Full Sample			(B) Excluding Housing Executive		
Variable	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
kwh	electricity usage (kwh per quarter)	45152	996.45	544.61	34779	1045.59	549.12
electprice_r	marginal price (£ per kWh, 2009 £)	45152	0.115	0.01	34779	0.115	0.008
lkwh	ln kWh	45152	6.754	0.57	34779	6.814	0.547
lmargprice_r	ln electprice	45152	-2.166	0.06	34779	-2.166	0.067

Table 9. Choice of Electricity Plan: Frequencies.

			(A) Full Sample		(B) Excluding Housing Executive	
decision	Acronym and Description	Tariff	Freq.	Percent	Freq.	Percent
1	Account (incl. EasySaver & Cash)	Mostly unrestricted tariff	33,518	74.23	26,645	76.61
2	DDM	See tables 1 and 2	4,012	8.89	3,803	10.93
3	DDQ	See tables 1 and 2	304	0.67	269	0.77
4	Budget Account	See tables 1 and 2	1,986	4.4	1,567	4.51
5	DHSS	Unrestricted tariff	492	1.09	195	0.56
6	Powercard	Unrestricted tariff	3,158	6.99	1,229	3.53
7	Keypad	See tables 1 and 2	1,682	3.73	1,071	3.08
Total			45,152	100	34,779	100

Table 10. Electricity Demand: Effect of Price, Income, House and Household Characteristics. Dep. Var.: ln kWh per quarter.

Model	(A)	(B)	(C)	(D) Plan Dummies	(E) Post 1997	(F) 1999 - 2006
Constant	1.90***	1.95***	2.85***	2.86***	3.66***	4.60***
	(0.20)	(0.20)	(0.18)	(0.18)	(0.19)	(0.30)
ln price (2009 GBP)	-0.94***	-0.69***	-0.74***	-0.72***	-0.66***	-0.56***
	(0.051)	(0.053)	(0.050)	(0.052)	(0.057)	(0.086)
recodedlinc_r	0.17***	0.14***	0.038***	0.041***	0.031***	0.018*
	(0.0068)	(0.0054)	(0.0049)	(0.0050)	(0.0074)	(0.0085)
lHDD	0.020***	0.037***	0.029***	0.030***	0.056***	0.047***
	(0.0048)	(0.0050)	(0.0049)	(0.0048)	(0.0059)	(0.0072)
Electricheat		0.13***	0.16***	0.16***	0.13***	0.11***
		(0.0045)	(0.0047)	(0.0048)	(0.0053)	(0.0060)
DDM				-0.049***	-0.068***	-0.056***
				(0.013)	(0.015)	(0.015)
DDQ				-0.048	-0.047	-0.11
				(0.042)	(0.062)	(0.081)
Budge				0.055*	0.033	0.0098
				(0.023)	(0.028)	(0.026)
Powercard				0.072***	0.036	0.027
				(0.020)	(0.021)	(0.018)
Keypad				-0.12***	-0.13***	-0.13***
				(0.021)	(0.022)	(0.024)
DHSS				0.067	-0.061	-0.14*
				(0.041)	(0.045)	(0.055)
Control*Post					0.0041	-0.016
					(0.0083)	(0.0084)
Ward effects	Yes	Yes	Yes	Yes	Yes	Yes
Heating Type	No	Yes	Yes	Yes	Yes	Yes
Dwelling chars.	No	Yes	Yes	Yes	Yes	Yes
Household Chars.	No	No	Yes	Yes	Yes	Yes
R-squared	0.14	0.21	0.30	0.30	0.29	0.30
N.of cases	45149	45121	44917	44917	28444	17918

Dwelling characteristics omitted from the table include home type, house age, number of rooms. Household characteristics omitted from the table include number of adults, dependent children, elderly, and workers in the household, how long the household has lived in this home (duration), duration squared, a college education dummy, renter dummies, and a student house dummy. Full regression results are available upon request from the authors.

Table 11. Electricity Demand excluding Housing Executive renters
Dep. Var.: ln kWh per quarter

Model	(A)	(B)	(C)	(D) Plan Dummies	(E) Post 1997	(F) 1999 - 2006
Constant	2.08***	2.32***	2.85***	2.83***	3.71***	4.13***
	(0.29)	(0.27)	(0.26)	(0.27)	(0.24)	(0.42)
ln price (2009 GBP)	-0.90***	-0.66***	-0.70***	-0.67***	-0.63***	-0.53***
	(0.070)	(0.064)	(0.059)	(0.059)	(0.063)	(0.12)
recodedlinc_r	0.17***	0.13***	0.030***	0.033***	0.025**	0.014
	(0.0076)	(0.0071)	(0.0073)	(0.0075)	(0.0082)	(0.0099)
lHDD	0.029***	0.041***	0.036***	0.037***	0.054***	0.044***
	(0.0054)	(0.0054)	(0.0049)	(0.0047)	(0.0056)	(0.0071)
Electricheat		0.092***	0.12***	0.12***	0.093***	0.080***
		(0.0057)	(0.0057)	(0.0057)	(0.0064)	(0.0070)
DDM				-0.11***	-0.11***	-0.064**
				(0.016)	(0.017)	(0.021)
DDQ				-0.17**	-0.13	-0.062
				(0.050)	(0.068)	(0.088)
Budge				-0.049	-0.047	-0.011
				(0.028)	(0.031)	(0.034)
Powercard				-0.035	-0.037	0.011
				(0.030)	(0.032)	(0.031)
Keypad				-0.24***	-0.23***	-0.12**
				(0.030)	(0.029)	(0.039)
DHSS				-0.30***	-0.29***	-0.26**
				(0.045)	(0.050)	(0.076)
Control*Post					-0.0067	-0.017
					(0.0094)	(0.0095)
Ward effects	Yes	Yes	Yes	Yes	Yes	Yes
Heating Type	No	Yes	Yes	Yes	Yes	Yes
Dwelling chars.	No	Yes	Yes	Yes	Yes	Yes
Household Chars.	No	No	Yes	Yes	Yes	Yes
R-squared	0.13	0.19	0.29	0.30	0.30	0.31
N.of cases	34777	34759	34584	34584	23082	14531

Dwelling characteristics omitted from the table include home type, house age, number of rooms. Household characteristics omitted from the table include number of adults, dependent children, elderly, and workers in the household, how long the household has lived in this home (duration), duration squared, a college education dummy, renter dummies, and a student house dummy. Full regression results are available upon request from the authors.