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Consumer Engagement in Energy Markets: The Role of Information and Knowledge

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JEL Classification C25, D21, Q49, R29

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1. Introduction

Consumer engagement in markets for services such as retail banking, insurance (home, car, life, travel, etc.) and household energy (electricity and gas) offers the potential for significant savings from active participation (Keaveney 1995). Nevertheless, actual switching rates are low, which reflects transactions costs (real and perceived) might be high.

In the 1990s, Great Britain became the first country to allow retail competition in the residential electricity and gas sectors. Consumer switching behavior is a key factor in understanding retail energy markets, as it may reveal the state of the competition in the market and the nature of consumer engagement on homogeneous goods (Defeuilley 2009) since there is no difference between a particular electron or molecule of natural gas. Despite the potential for financial gains by changing their energy supplier and/or renegotiating the contract with their existing supplier, the average residential consumer is not active enough in searching out alternative tariffs or providers to get a better deal (Giulietti et al. 2010; ECME Consortium 2010). In recent years, the annual switching rates have remained below pre-2008 levels, leading to a loss of significant potential savings for British households. Even if a consumer does not switch suppliers however, there are other means of engaging in the retail market while remaining with the same supplier including changing tariffs or changing payment method, for example, by moving to direct debit.

The British energy regulator, Ofgem (Office for Gas and Electricity Markets), has sought to encourage households to be more active in the market (Ofgem 2011) and this attention has been amplified by political concern over energy prices (He & Reiner, 2017) and more active engagement of consumer groups. As the issue of energy prices became more politically salient in the UK and prices rose over the 2007-10 period, Ofgem launched an ‘energy supply probe’ in 2008 followed by a Retail Market Review (RMR) launched in 2010. As a result, a number of additional information-related measures were introduced over the subsequent years aimed at helping consumers to understand available tariffs and navigate the market. For instance, in 2014 Ofgem introduced an array of comparison tools or mechanisms including Cheapest Tariff Messaging (CTM), Tariff Comparison Rates (TCR) and Personal Projections (PPs) (Ofgem 2014), in addition to the 'Be An Energy Shopper' campaign and began imposing Standards of Conduct license conditions (from 2013, amended in 2017) (Ofgem 2017).

Apart from regulatory efforts, there are numerous independent price comparison websites (PCWs) in the UK that have operated for many years. Of the ten largest, 70% of supplier switches were made using three sites: uSwitch (established in 2000), MoneySuperMarket (1999) and Cheap Energy Club (affiliated with moneysavingexpert.com that launched the Club in 2013) (CMA 2017, p149). In spite of the diversity of options and the relative ease of switching, 56% of domestic customers in the UK energy market claimed to never have switched supplier, 34% of respondents have never considered switching supplier, according to the Competition and Markets Authority (CMA) survey report (2016). TNS (2016) also noted that a significant (but declining) share of consumers remain on the 'standard variable tariff' (SVT), which is the 'default' tariff and is generally the most expensive over time. TNS (2016) claimed that price and the desire to achieve savings were the strongest drivers for switching and comparison activity in the energy market, while acknowledging that price does not seem to be a strong motivator for some consumers, particularly less engaged consumers.

Still not satisfied with the state of retail markets, the CMA was asked to conduct an investigation into competition in UK energy markets (CMA 2016). The CMA identified 'weak customer engagement' as the most significant concern and found that Ofgem's reforms after 2011 actually weakened competition in the sector.

The actions by Ofgem, on the one hand, have generally not satisfied consumer groups and politicians eager to see more active intervention, and on the other, have been found to be problematic by many economists reviewing the evidence. Littlechild (2016) argues that from

2008, "The competitive market glass had gone from half-full to half-empty". The empirical basis of Ofgem polices, its non-discrimination clauses, and attention given to reducing the number of tariffs rather than tariff innovations have been questioned (Waddams Price & Zhu 2016; Pollitt & Haney 2014). Although the regulator Ofgem is nominally independent of government, it was buffeted between its mandates to defend consumers and political pressures. Even in the UK which has taken the lead in opening its energy markets, and where consumers have the longest experience with competition and have switched more than virtually anywhere else, the notion of energy being a different sort of consumer good remains (FDS 2008).

We use Ofgem's own detailed market research to investigate the motives and obstacles associated with household behavior in energy markets, with a focus on the role of information, given all the attention the subject has received. The rest of the analysis proceeds as follows: Section 2 reviews the relevant literature; Section 3 presents the methodological framework, while Section 4 outlines the main features of the survey investigation, variable definitions and the statistics. Section 5 presents the results of the econometric analysis, and finally, Section 6 concludes.

2. Literature

Switching barriers, which act to prevent consumers from switching or increase the difficulty of switching, have been associated with direct switching costs, consumer preferences, emotional and cognitive ability, interpersonal relationships, as well as financial, social, and psychological risks (Mattila 2001; Burnham et al. 2003; Ek & Söderholm 2008; Wolter et al. 2017; Hortaçsu et al. 2017).

Burnham et al. (2003) define switching costs as "the onetime costs that customers associate with the process of switching from one provider to another, as opposed to the ongoing costs associated with using a product or provider once a repeat-purchase relationship is established." In particular, we emphasize here the "onetime" nature of switching costs (Porter

1980; Burnham et al. 2003). In this context, the concept of switching cost, in a broad sense, involves search, learning, and transactions costs, as well as customer habits, cognitive effort, and a wide range of risks (Fornell 1992).

Some studies seek to distinguish the subtle differences between switching costs and search costs. For instance, Honka (2014) defines search costs as the cost to the consumer of conducting one search, and switching costs as the cost a consumer incurs upon switching providers after the search has been completed. Similarly, Wilson (2012) defines search costs as “the costs incurred by a consumer in identifying a firm's product and price, regardless of whether the consumer then buys the product from the searched firm or not”, and switching costs as “the costs incurred by a consumer in changing suppliers that do not act to improve the consumer's pre-purchase information”, and shows that gathering and processing necessary information about alternative suppliers produces the key difference between the two costs.

As switching costs in the broad sense need not be incurred immediately upon switching (Burnham et al. 2003), and search (or switching) costs need not be limited to financial costs, it is sometimes difficult to distinguish between the two costs in practice. Whether price or non-price factors are used to explain barriers to switching has largely been a function of the discipline conducting the study. Economists tend to approach switching behavior from an absolute or net gains or loss perspective and primarily emphasize price whereas psychologists tend to focus on non-price considerations and decision-making shortcuts and heuristics. Obviously, this is primarily a question of emphasis in both instrument design and in presenting results, rather than a deliberate exclusion of alternative explanations and both literatures try to grapple with questions of search costs in their own ways.

Burnham et al. (2003) identify three types of switching costs: (a) financial costs; (b) procedural costs (time, effort, and uncertainty in identifying and adopting a new provider); and (c) relational costs (e.g., personal relationship with supplier). When a consumer faces switching costs, the rational consumer will not switch to the supplier offering the lowest price if the costs outweigh the price differential between the suppliers.

Inertia is a powerful force in the market (Daglish 2016). Studies taking more of a psychological perspective pay greater attention to non-price sources of inertia. For example, Shah et al (2016) find that those paying with more 'painful' payment forms (such as cash or check) increase their emotional attachment to the existing product and reduce their commitment to alternatives. Moreover, inattention to the task of choosing a better tariff is likely to be a substantial problem in energy markets. Hortaçsu et al. (2017) explore two sources of inertia in electricity markets – (i) households do not frequently consider offerings of alternative retailers and (ii) they attach a significant brand advantage to the incumbent – and conclude that non-price sources of inertia are likely to be the primary barrier, which may be reduced by low-cost information intervention.

Studies bring to light the importance of knowledge and information. Ratchford (2001) points out lifestyle differences are simply due to differences in knowledge or expertise at engaging in different activities. Six et al. (2017) find that better–informed customers have a significantly higher switching probability, using availability of an online price comparison tool as the indicator for access to information. The difference between initial information setup costs and ongoing information usage costs over time and consumers' time preferences explains consumers' reluctance to search extensively for better alternatives and ultimately switch (Zauberman 2003).

Willingness to switch would decrease if consumers perceive an increase in the costs of information search (Urbany 1986). Search costs can be divided into internal and external costs (Smith et al. 1999). Internal costs include the mental effort given over to undertaking the search, sorting through the information, and integrating it with what the consumer already knows. Internal costs depend on a consumer's ability to undertake the search, and that ability is associated with levels of knowledge, education, etc. External costs include the monetary costs of acquiring the information, and the opportunity cost of the time put into searching out this external information. There may also be interactions, for example, Giulietti et al (2014) argue that even as search costs fell over time, the proliferation of ever more complicated tariffs discouraged switching.

Our interest here is in exploring the importance of information in different contexts and their potential impacts on different forms of household participation in energy markets. Our analysis is based on three surveys commissioned by the British regulator Ofgem and carried out by the market research firm TNS BMRB in 2014, 2015 and 2016 (TNS 2016). The questionnaires collected information about behavior in gas and electricity markets, views and attitudes towards the market, as well as socio-economic characteristics. Although not completely identical, both the order and the vast majority of questions were kept consistent over the course of the three years. Based on a multiple binary-choice framework, we analyze three different forms of participation of households in the energy market over the year prior to the survey.

3. Methodology

Previous studies modeling switching behaviors in retail markets generally focus on change between retailers, and most use single equation logistic or probit regressions as the preferred estimation method (Ek & Söderholm 2008; Xiao et al. 2014; Six et al. 2017). In line with Littlechild (2000), the success of retail competition should not be judged solely by the share of customers who have switched supplier, rather we suppose changing energy suppliers (ESs), energy tariffs (ETs) and energy bill payment methods (PMs) are all related elements of market participation. We estimate the determinants of these three behaviors together using a multivariate probit model, in which the equations for each outcome are estimated simultaneously under the assumption that the error terms follow a joint normal distribution

(Greene 2008). If these behaviors are correlated, then joint estimation would produce more precise standard errors. Furthermore, it allows us to test for the existence of unobserved factors influencing all outcomes, through the statistical significance of such correlations.

Our analysis employs an analytical framework which embraces both economic and psychological motives behind consumer behavior. Our study differs from others insofar as it investigates various types of consumer switching behavior simultaneously, within a single econometric framework. Moreover, the multi-year dataset allows us to explore the dynamics of household behavior in the market and explore whether and/or the extent to which different factors which influence the likelihood that households participate in the market also changed.

3.1. Hypotheses

Consumer decision making on switching typically involves several stages. The first step is to recognize the problem, i.e. to identify a motivation to switch followed by searching out information on the options available. The next step involves comparing and evaluating alternatives and then the switching stage itself.

Many economic studies of consumer choice have used a random utility model framework, assuming rational behavior, i.e., that individuals maximize subjective expected utility with perfect information. By contrast, bounded rationality assumes that individuals' decisions are "determined not only by some consistent overall goal and the properties of the external world, but also by the knowledge that decision makers do and don't have of the world" (Simon 2000). Information is essential for consumers making decisions in the energy market – access to information and the ability to process will impact switching behaviors. We introduce different forms of information to capture any effects of bounded rationality on household decisions.

Consumers seeking information must navigate both an internal context and an external context (within which the information seeker operates) (Foster 2004). Internal search typically incurs little cost of time or money while external search often involves significant expenditures in terms of money and time and may involve uncertainty. Internal search involves identifying the alternatives from one's own memory and will be unique to each information seeker. "Internal" information is particularly important for experiential products where consumers are more likely to rely on internal search for qualitative/experience type attributes (Moore & Lehman 1980; Grant et al. 2007). The internal context is primarily the level of experience and prior knowledge held by the information seeker (Foster 2004).

When better alternatives are absent in the market, consumers will not switch. Similarly, if customers have not recognized that there are better options available in the market, the customer will not switch, even if she or he is not satisfied with their current supplier (Ping 1993). Consumers choosing not to switch may result from a belief that there is no difference between suppliers rather than loyalty to the current supplier. Daglish (2016) suggests many customers may be unaware of the possibility of switching or may have only partial information regarding the potential benefits. There may even be a concern that switching will not lead to savings but would turn out to be costlier and there is some evidence that a fraction of switchers actually wind up on a worse tariff (Wilson & Waddams, 2010). Therefore, we assume that if consumers have a better sense of their energy expenditures and of energy tariffs, they can more accurately evaluate the gains by switching. Accordingly, we propose the following hypotheses:

H1: Belief that there are no tariff differences between suppliers decreases engagement in energy markets.

H2: Knowledge of one's own energy expenditure is related to greater engagement in energy markets.

H3: Greater familiarity with energy tariffs leads to greater engagement in energy markets.

The types of information which underpin engagement with the market are all based on an individual's estimations and professed knowledge (of their energy bill) and judgments (of the availability of alternatives), but no assessment is made as to the accuracy of those perceptions. We use binary variables to measure these perceptions.

External information search involves asking friends or neighbors' opinions, referring to websites, user manuals, advertisements or media coverage, making inquiries with brokers or directly with firms, etc. As information search has migrated to the Internet, switching behaviors might be expected to follow. Flores and Waddams Price (2018) suggest internet-based remedies are particularly effective amongst those who are already active, rather than stimulating activity among the less engaged. The Internet can eliminate or at least greatly reduce search costs and improve the efficiency of information dissemination (Klein 1998; Pereira 2005; Khatwani & Das 2015). However, collecting more information from one information source does not necessarily reduce the efforts put into other sources (Bei et al. 2004). We propose the following hypotheses as possible mechanisms for consumer engagement with external information:

H4: Internet access promotes consumer engagement in energy markets.

H5: Messages from energy suppliers promotes greater consumer engagement in energy markets.

H6: There may be an interaction between the two types of external information.

Internet access and messages from suppliers have very different implications for information exchange. Ease of access to Internet services and trust in online information could affect the frequency of online information search, the diversity of online information obtained, and the preference for using the Internet in any initial search (Xiao et al. 2014). The frequency of online activity is, perhaps unsurprisingly, largely explained by ease-of-use and the perceived usefulness of information obtained from the Internet (Bei et al. 2004). We derive our variable for Internet-derived information based on how often consumers get online. Obviously, the level of engagement not only reflects the channel by which consumers seek information, but also captures how much effort they will need to put into browsing and screening the information online, assuming that those generally more familiar with the Internet will find it easier to collect the requisite information at lower cost. In comparison to the other main form of external information, seeking information via the Internet is more complicated because it may include interactions between internet users, between consumers and suppliers and with different third-party sources such as PCWs. We expect that the effect of Internet use on household engagement will be positive.

Households may receive messages from suppliers with "passive attention"[1] People spend substantially more time receiving information passively than actively (Robinson 2010). When a consumer receives a message from a supplier, the message will not be very helpful in making decisions if the consumer does not understand it or does not process it. If the consumer was able to put more effort into processing it, the message could play a more useful role. Thus, the message and Internet variables should enhance each other in encouraging participation, in other words, the coefficient of the cross-term is expected to be positive (Hypothesis H6).

Moreover, the information patterns measured by the supplier's message can be partially reflected in the Internet information. For instance, the message can be provided both by email and the supplier's website. Therefore, these two types of external information are homogenous to a certain degree, in terms of content and source. When such information is separated into two variables and their cross term is included in the regressions, the relationship should be complementary (i.e., the coefficient of the cross-term should be positive).

On the other hand, the interactive effect between the message and the Internet information might be negative. When a vast amount of information is available, information overload may result (Lee & Lee, 2004). Simon (1957) noted information consumes attention, which is a

[1] Wilson (1997) suggests that information-seeking behavior consists of active search, passive search, passive attention, and on-going search, where "passive attention" is defined as "information acquisition may take place without intentional seeking".

scarce resource. Our ability to deploy the knowledge that is relevant to their decision-making is severely limited (Simon 2000) as is our capacity for processing information (Miller 1956). The amount of information scales faster than the attention of human decision makers who have to make decisions about which information has priority, and what will be shunted away (Van Knippenberg et al. 2015). Hence, consumers may have to choose between various information sources. Therefore, it is also possible that some external information channels may act as substitutes for others or as a proxy for the full set of information available.

Previous studies (Economides et al. 2008; Miravete 2003) suggest that relatively few demographic variables are useful predictors of the ability of consumers to make accurate decisions. However, the amount of effort a consumer puts into information search and processing, and preferences for different information sources depend on a number of factors, including consumer characteristics (level of education, level of knowledge, etc.), and the market (e.g., how many suppliers there are, and how great the differences between suppliers or tariffs are expected to be). As a result, household characteristics can directly or indirectly affect consumers' decision making, and their effects should be controlled to avoid biases in estimation. We also consider regional characteristics and time effects.

Specifically, the demographics that are controlled for include social grade, gender, working status, primary language, family size, economic situation (including income and perceived financial pressure), age, and educational attainment. In addition, we assume that consumers who are active in retail markets more generally have some common characteristics. A variable indicating those who have ever participated in other markets is used to control for the common personality type. Market engagement might embody a group effect, which is largely realized at a regional level and therefore affected by regional feature, so we also control regional effects. When a household moves to a new residence, they are very likely to change suppliers or tariffs. The surveys do not allow us to distinguish between those who actively switched and those who switched because they moved home, so an indicator for moving to a new house is introduced to control for the effect of moving on levels of engagement. When regressing with pooled data, year dummies for 2014 and 2016 are included to control for time-varying effects.

3.2. Multivariate probit regressions

We examine three binary decisions on switching: (a) if households have switched their energy supplier (ES); (b) if have changed their energy tariffs (ET); and (c) if they have changed their payment method (PM) and are respectively labeled y_{ES}, y_{ET}, and y_{PM}.

These three dichotomous decisions on market participation are not considered to be mutually exclusive since they may be influenced by the same unobserved factors. In other words, we assume the unobserved factors influencing the three decisions may be correlated, and potential correlation can be positive or negative. If the assumption holds, then modelling these decisions separately as a single choice can lead to less-efficient estimates.

We use a multivariate probit regression (MPR) approach to simultaneously evaluate the factors influencing the three decisions (Greene 2008). MPR analysis is characterized by the relaxing of the restrictive assumption of mutually exclusive alternatives, which is especially suitable for modeling discrete choice situations where individuals are exercising multiple choices as opposed to a single discrete choice. The first study introducing a multivariate probit model was Ashford and Sowden (1970). Recent examples include Baltas (2004) on the selection of multiple brands, and Becker et al. (2017) analyzing car-sharing membership.

In a MPR, Probabilities of consumer participation in the energy market can be expressed as follows,

$$
\begin{cases}
P(y_{ES} = 1|X) = G_1(\beta_1 X_1 + \varepsilon_1), \;\; y_{Es} = 1 \;\; if \;\; {U_s}^* > 0 \\
P(y_{ET} = 1|X) = G_2(\beta_2 X_2 + \varepsilon_2), \; y_{ET} = 1 \;\; if \;\; {U_c}^* > 0 \\
P(y_{PM} = 1|X) = G_3(\beta_3 X_3 + \varepsilon_3), \; y_{PM} = 1 \;\; if \;\; {U_c}^* > 0
\end{cases}
\tag{1}
$$

$$
E(\varepsilon_i) = 0, \; Var(\varepsilon_i) = 1, \;\; cov(\varepsilon_i, \varepsilon_j) = \rho_{ij}
$$

where G(βX) represents the cumulative distribution function that maps βX into the response probability. It can be a probit model, by assuming a joint normal distribution of the error terms ε_i (Wooldridge 2002). X_1, X_2 and X_3 are the set of explanatory variables in the respective regression. Let the correlation coefficients between the error terms be ρ_{ij}. The null hypothesis is $\rho = 0$, implying the three types of switching behaviors are independent of one another. If the null hypothesis is accepted, the probit regressions in a MPR can be estimated separately, otherwise, the MPR model is appropriate.

3.3. Model

The specific MPRs for estimation can be rewritten as follows,

$$
\begin{cases}
y_{ES}{=}c_{es} + \alpha_{es} Inf + \theta_{es} Exf + \gamma_{es} Exf_1 Exf_2 + \delta_{es} Control + \varepsilon_1 \\
y_{ET}{=}c_{et} + \alpha_{et} Inf + \theta_{et} Exf + \gamma_{et} Exf_1 Exf_2 + \delta_{et} Control + \varepsilon_2 \\
y_{PM}{=}c_{pm} + \alpha_{pm} Inf + \theta_{pm} Exf + \gamma_{pm} Exf_1 Exf_2 + \delta_{pm} Control + \varepsilon_3
\end{cases}
\tag{2}
$$

Inf is a vector of variables describing the internal information and Exf is a vector of the two external information variables. The parameters α measure the effects of consumer beliefs, knowledge and awareness of the energy market, corresponding to hypotheses H1, H2, and H3 respectively. θ describes the effects of external information on consumer behavior, in line with hypotheses H4, H5, and H6, and $Exf_1 Exf_2$ is the two-way interaction term between the two sources of external information. The variable γ captures the effect of the interaction, which is negative for a substitutive relation, and positive for a complementary relationship. The main parameters of interest are $\alpha,\ \theta,$ and γ. $Control$ is a vector of control variables.

4. Data and variables

As part of the monitoring and evaluation framework introduced as part of its Retail Market Review (RMR) reforms, in spring 2014, Ofgem commissioned TNS BMRB to conduct a nationally representative face-to-face survey of over 6,000 energy consumers in Great Britain. The aim was to contribute towards the establishment of a baseline of consumer attitudes and behavior in the early stages of the RMR interventions (TNS 2016). Thereafter, the survey was repeated two additional times in 2015 and 2016 to examine changes in these attitudes and behaviors. As such, it is one of the very few multi-year nationally representative, publicly available surveys of consumers in a major retail market (Burroughs & Rindfleisch, 2002).

Our analysis is based on the three surveys that were independently conducted from 2014 to 2016. In other words, the data is not based on a longitudinal survey so the sample composition changed for each of the three surveys. Moreover, there were marked changes in the prices in the energy market in the UK in the run up to each of the three surveys (which were conducted in the spring of each year). Average energy prices increased rapidly from late 2011 through late 2013 (far outstripping other consumer prices), were stable for most of 2014, before falling dramatically in 2015. The issue of energy prices became highly salient in British politics with the leader of the main opposition party calling for a freeze on energy prices as one of his top priorities (Waddams Price & Zhu 2016; He & Reiner 2017). The changes in the sample composition and the market might result in biases when regressing by pooling data. We will address this problem in our discussion of the empirical analysis.

4.1. Outcome variables

The survey asked households about their past decisions to change gas and electricity suppliers. We derive binary outcome variables based on the following three questions.

> Y_{ES}*: In last 12 months, have you switched gas/electricity supplier?*
>
> Y_{ET}*: In last 12 months, did you change tariff you were on with your existing gas/electricity supplier (without switching supplier)?*
>
> Y_{PM}*: In the last 12 months, have you changed the payment method with your gas / electricity supplier (without switching supplier)?*

If the respondent gave a positive response to the question, the corresponding binary outcome variable, *Y*, is assigned a value of 1, 0 otherwise. Additionally, to provide a more holistic picture of household engagement, we create a comprehensive indicator, designated as 'active', by integrating the responses to the three questions above. If a respondent gave a positive response to any of them, the binary outcome variable is assigned a value of 1, 0 otherwise. Given the question framing, it should be noted these three behaviors cannot happen at the same time, but they can happen over the same observed period.

The left-hand panel of Table 1 describes the changes in consumer behavior in British energy markets over the three years of the survey. Overall, the annual rate of switching suppliers in the UK energy market has fluctuated in a fairly narrow band between 12% and 15%. The rates of switching tariffs, roughly 14% to 16%, are slightly higher than switching suppliers, while the rates of changing payment methods are below 5%. The disparity is unsurprising, since whereas there are many suppliers and several tariffs for any given supplier at a point in time, changing payment methods is generally a once-and-for-all decision, so that a shift to direct debit is likely to be maintained in future switches of tariff or supplier. If we turn to the comprehensive indicator of switching behavior, "*active*", the overall rates are over a quarter (26%) in all three years. This also indicates that relatively few will have undertaken switching across multiple dimensions in a single year.

The right half panel of the table presents household participation rates, grouped by payment method and fuel type. Compared to other households, those paying by direct debit are more active in the market overall and in particular show clearly higher participation rates in switching ESs and changing ETs.

Table 1 Market participation rates in the last 12 months

	All	Year			Direct debit		Dual-fuel [a]	
		2014	2015	2016	Y	N	Y	N
Active	0.2674	0.2634	0.2619	0.2770	0.3150	0.1698	0.2684	0.2959
	(0.443)	(0.441)	(0.440)	(0.448)	(0.465)	(0.376)	(0.443)	(0.457)
Switch ESs	0.1338	0.1335	0.1235	0.1444	0.1489	0.1036	0.1352	0.1320
	(0.341)	(0.340)	(0.329)	(0.352)	(0.356)	(0.305)	(0.342)	(0.339)
Change ETs	0.1525	0.1405	0.1587	0.1588	0.1966	0.0607	0.1582	0.1804
	(0.360)	(0.348)	(0.366)	(0.366)	(0.397)	(0.239)	(0.365)	(0.385)
Change PMs [b]	0.0431	0.0494	0.0410	0.0386	0.0422	0.0450	0.0385	0.0553
	(0.203)	(0.217)	(0.198)	(0.193)	(0.201)	(0.207)	(0.192)	(0.229)
Obs.	18041	6151	5934	5956	12192	5272	9456	909

Notes: The standard deviations are reported in parentheses.

(*a*) Data for dual fuel users are not available for 2014. This type of behavior refers to comparisons of energy tariffs in general; therefore, it includes any comparison of tariffs with their current supplier or other suppliers.

(*b*) When customers compare tariffs of different suppliers, they are actually comparing the suppliers.

The surveys did not ask explicitly whether respondents switched to have their gas and electricity provided by the same supplier in a given year, so being on a dual-fuel contract might be a result of prior engagement in previous years. Depending on payment method, such arrangements can offer savings of 8% - 23% (CMA 2016). If households are classified by their switching patterns, dual-fuel households are slightly more active in changing supplier, but less active in changing tariff than others. By inquiring as to the last time respondents switched supplier/tariff and the factors that mattered most in making such a switch, a dual-fuel contract can be treated more like a motivation for switching rather than as an outcome.

We might expect that household switching behavior may be positively correlated with payment method and/or patterns of fuel use, and the correlation might differ depending on the type of participation.

4.2. Information variables

Across the three surveys, a large minority (37.6%) of respondents found it difficult to compare different tariffs for electricity or gas, and a similar percentage (38.2%) felt they were not familiar with the range of tariffs available. These numbers imply that limited knowledge of various options and consumer uncertainty are likely to be barriers to participating in the market. Thus, improving communications in this area may help raise household switching rates.

An indicator for cognition of energy tariff differences, labeled "*n_belief*", is created based on the question on whether respondents agree with the statement there are no real differences between suppliers in the prices they charge.

An indicator of energy expenditure knowledge, labeled "*knowspd*", is created based on the question "how much do you spend on your home energy?" The variable is assigned 1 for respondents that provided their consumption or energy expenditure data, zero otherwise. Proceeding in this way, we can measure the impact of respondents not knowing their expenditures compared to those who do know (or at least claim to know) their expenditure levels.

The indicator for energy tariff knowledge, labeled "*familiar*", is based on the question on whether consumers are familiar with tariffs available from energy suppliers in general. If the respondent gave a positive answer the variable equals 1, 0 otherwise.

For Hypothesis 4, we explore the impact of supplier messages. The questionnaire asks respondents if they recalled having received any of the following messages from their suppliers over the past 12 months: (a) an annual summary or review; (b) at least one bill or direct debit / prepayment statement; (c) a price increase notification letter; or (d) a letter informing them that their fixed term tariff is coming to an end. We created a variable for message by integrating the responses to the four statements above. If the response to any of the statements is positive, the variable equals 1, 0 otherwise.

To test the impact of the Internet information, we construct an indicator, labeled "*reg_int*", to identify regular internet users, where 'regular' refers to daily usage.

4.3. Variable definitions

Table 2 presents the variable definitions. First, we list the dependent variables, reflecting past consumer activities in the energy market. Next are the five explanatory variables of interest. We then present the control variables to address demographics: age, education, income and region are all categorical variables, and the intervals for each of them cannot be considered equally spaced. Specifically, age is treated as a three-category variable in ascending order, indicating younger (under 35), middle aged (35 to 64) and older respondents (65 and over).

The income variable, labeled "*income_n*", has 11 categories. As is typical in most public surveys (Riphahn & Serfling, 2005), when asked about income, the respondents that refused or otherwise declined accounted for as much as 30% of the sample. Simply excluding these observations from the sample may significantly reduce the precision of analysis. We put these observations into one category and take it as the reference category for income.[1]

Table 2 Variable definitions

[1] Choice of the reference category of income does not generate any changes in estimates of other variables, except the income categories remaining in the regression. To illustrate this, in Table A-2 of the Appendix we report the results of the baseline model, where the 10th income level is taken as the reference category.

Variable	Coding	Definition
switch ES	1 Yes; 0 No	Switched energy suppliers in last 12 months
change ET	1 Yes; 0 No	Changed energy tariffs in last 12 months
change PM	1 Yes; 0 No	Changed payment method in last 12 months
n_belief	1 Agree; 0 Don't agree;	Agree with statement there are no real differences between suppliers in the prices they charge
knowspd	1 provide an answer; 0 missing value | refused | don't know	Can specify their approximate expenditure on home energy (or consumption).
familiar	1 Yes; 0 No	Whether familiar with tariffs available from energy suppliers in general
reg_int	1 frequent user; 0 others	Whether customers use Internet roughly every day
message	1 Yes; 0 No	Whether customers recall receiving any supplier communication (annual summary, bill, PIN, EOFTN) [a]
lenspd	Annual levels	Logarithm of annual energy expenditure, continuous
spd_n	0, don't know; 1~5, quintiles (where 1 is bottom 20%, 5 is top 20%)	Categories of energy expenditure
switchother	1 Yes; 0 No	Any switching in other markets in the last 12 months
socgrade	1 AB | C1; 0 C2 | DE	Social class
male	1 Male; 0 Female	Gender
work	1 Full/Part time; 0 others	Working status
language	1 Yes; 0 No	English as the first or main language
movehouse	1 Yes; 0 No	Whether customers moved house in the last 12 months
numbhh	Exact number	Number of household members
finstr	1 Agree; 0 Don't agree;	Whether customers agree that financially things are a bit of a struggle.
income_n	1. Under £5000; 2. £5000-£9999; 3. £10000-£14999; 4. £15000-£19999; 5. £20000-£24999; 6. £25000-£39999; 7. £35000-£49999; 8. £45000-£59999; 9. £60000-£79999; 10. £80000+; 11. Refused | don't know| no work	Category of household annual income (£)
age	1. <35; 2. 35-64; 3. 65+	Age of respondent
edu	1 No formal education; 2 GCSE, GNVQ, ONC; 3 A levels, HND/HNC; 4 Professional qualification | undergrad degree | post grad	Education level
region	1 England; 2 Wales; 3 Scotland	Region
TCR [b]	1 Yes; 0 No	Energy suppliers are now required to provide a Tariff Comparison Rate (TCR) for each tariff they offer. Do customers recall seeing a message like this?
dual fuel [b]	1 Yes; 0 No	Same energy supplier for both gas and electricity?
direct debit	1 Yes; 0 No	Are gas and electricity paid by direct debit?
everswitch	1 Yes; 0 No	Has the household ever switched gas or electricity supplier (without moving), prior to last 12 months?

Notes: (*a*) PIN is a price increase notification letter; and EOFTN (end of fixed term notice) is a letter to inform customers that their fixed term tariff is coming to an end. (*b*) Not available for 2014.

In addition to the income variable, we introduce another variable to control for the effect of household finances, labeled "*finstr*". The variable was created based on the responses to the question on whether consumers agree "financially things are a bit of a struggle for me" and therefore reflects households' perception of financial hardship whether or not that is reflected in more 'objective' income data. The two variables are correlated with a coefficient of -0.236. We include both variables in the regressions for two reasons: first, income may affect other independent variables, such as education and social grade, so it can be regarded as a confounding variable and its effect should be controlled for, regardless of whether it results in a collinearity problem or not. Second, the '*finstr*' variable has the advantage in that it captures how households perceive a relative change in energy expenditure (and/or commodity prices) with respect to their income.

Finally, the bottom panel displays the variables that will be used to investigate robustness. TCR is used as an alternative to the '*message*' variable and '*everswitch*' to indicate whether the household had ever switched supplier prior to the last 12 months.

4.4. Descriptive statistics

Table 3 presents the statistical descriptions for the variables included in the analysis. Most households (84%) claim they know how much they spend on energy, but only 38% knew about energy tariffs, and 43% did not think there are any differences between the energy prices available in retail markets although 80% had received messages from their own suppliers. Clearly, a relatively small fraction can be considered as knowledgeable or aware of energy markets. In the three years of the survey, only 63-68% of respondents were daily Internet users, which is smaller than ONS (2017b) estimates of 78% for 2015, although this figure is for daily or near daily Internet use.

Obviously, Internet access and supplier messages are the main ways households can acquire external information. By contrast, only about 20% of households had some knowledge of TCRs.

Table 3 Descriptive Statistics by participant type

	All respondents				Active group		Non-active group	
	Obs.	Mean (SD)	min	max	Obs.	Mean (SD)	Obs.	Mean (SD)
n_belief	17034	0.432 (0.495)	0	1	4697	0.340 (0.474)	12337	0.466 (0.499)
knowspd	18041	0.841 (0.365)	0	1	4824	0.900 (0.300)	13217	0.820 (0.384)
Spd_n	18041	2.475 (1.685)	0	5	4824	2.678 (1.590)	13217	2.401 (1.412)
enspd	15182	1234 (817)	1	28800	4344	1247 (816)	10,838	1229 (817)
familiar	18041	0.382 (0.486)	0	1	4824	0.535 (0.499)	13217	0.327 (0.469)
reg_int	18035	0.652 (0.476)	0	1	4822	0.655 (0.475)	13213	0.651 (0.477)
message	17268	0.815 (0.388)	0	1	4680	0.860 (0.347)	12588	0.799 (0.401)
switchother	18041	0.278 (0.448)	0	1	4824	0.377 (0.485)	13217	0.242 (0.428)
socgrade	18041	0.441 (0.496)	0	1	4824	0.543 (0.498)	13217	0.403 (0.491)
male	18041	0.480 (0.500)	0	1	4824	0.474 (0.499)	13217	0.482 (0.500)
work	18041	0.431 (0.495)	0	1	4824	0.479 (0.500)	13217	0.414 (0.493)
language	18041	0.904 (0.295)	0	1	4824	0.929 (0.257)	13217	0.895 (0.306)
movehouse	17967	0.110 (0.313)	0	1	4807	0.160 (0.367)	13160	0.092 (0.290)
numbhh	18041	2.362 (1.516)	1	64	4824	2.513 (1.327)	13217	2.306 (1.575)
finstr	17797	0.359 (0.480)	0	1	4777	0.324 (0.468)	13020	0.372 (0.483)
income_n	18041	6.648 (3.607)	1	11	4824	6.744 (3.333)	13217	6.613 (3.702)
age	18041	2.144 (0.724)	1	3	4824	2.076 (0.705)	13217	2.168 (0.729)
edu	17778	2.545 (1.136)	1	4	4787	2.801 (1.091)	12991	2.450 (1.138)
region	18041	1.239 (0.604)	1	3	4824	1.218 (0.581)	13217	1.246 (0.612)
TCR [a]	10911	0.198 (0.398)	0	1	2993	0.316 (0.465)	7918	0.153 (0.360)
Dual fuel [a]	10366	0.912 (0.283)	0	1	2807	0.904 (0.294)	7558	0.915 (0.278)
Direct debit	17464	0.698 (0.459)	0	1	4735	0.811 (0.392)	12729	0.656 (0.475)
everswitch	16362	0.461 (0.498)	0	1	3255	0.513 (0.500)	13107	0.448 (0.497)

Notes: Standard deviations are reported in parentheses. (a) Data are not available for 2014.

(*a*) The value of variable EnSpd is obtained based on two question, the first was "Approximately how much do you spend on home energy?", which was followed by another question indicating the expenditure duration (weekly, fortnightly, every four weeks, a calendar month, quarterly, twice yearly, and annual). Some of observations show a very high level of annual energy expenditure. For instance, 14 observations of the sample show a level of annual expenditure over 10,000 pounds. We noticed that most of these abnormal observations have a claimed duration of a month, and therefore the possibility of reporting errors exist (e.g., the respondent reported a correct figure of annual expenditure and wrong code of duration. However, this would not change the conclusions of this study, since the proportion of such seemly abnormal observations is very low; moreover, the variable *EnSpd* is only used once in the robustness test (see table A-4 of the appendix).

(*b*) There are four observations with a claimed family size of over 20 household members, which seems unusual. However, this problem can hardly cause an estimation bias because these observations accounted for a very low proportion in the sample and therefore their effect can be ignored.

On the right-hand side of the table, the observations are split into two groups – active consumers and non-active consumers – according to whether households had changed supplier, tariff or payment method. Active participants are more likely to believe that there are differences in the prices that suppliers charge, and more likely to claim to know more about their energy expenditure. Over half of participants (53.5%) express familiarity with energy tariffs available in the market, compared to one-third (32.7%) of non-participants. Almost half (46.6 %) of non-participants do not believe there is a difference in the tariffs available compared to only one third (34%) of active participants. With respect to supplier messages, slightly more market participants (86.0%) recall receiving such messages compared to those not actively engaged (79.9%). Further, almost one third (31.6%) of active participants were aware of the TCR price comparison tool, which is double the rate of non-participants (15.3%). These comparisons suggest that participants are far better informed about the energy market than non-participants.

Overall, about 70% of the households pay energy bills by direct debit, although the popularity of direct debit differs between groups by as much as 15.5 percent. Demographically, active consumers in the energy market are more likely to be those who are also active in other product markets, with a higher social grade (AB and C1), female, younger, have a job, a larger family, higher educational attainment, face less financial pressure, use English as their main language, and have moved home.

A large majority of the respondents describe English as their first language (90.4%) and live in England (85%). This corresponds well to the most recent data from the UK Office of National Statistics (ONS 2017a), which found English was the main language of 92.3% of the population in England and Wales and the population of England was 84.1% of the UK population.

There might be concern over possible multicollinearity problems, since there are many explanatory variables, particularly the demographic controls. Our correlation tests find that the absolute values of the correlations between independent variables are all less than 0.7, the threshold value that indicates a serious co-linearity that could interfere with regression results (Lind et al. 2002). Moreover, most coefficients have an absolute value below 0.1, suggesting weak correlations. Based on these results, we can conclude that multicollinearity problems that can interfere with the estimation are not serious.

Moreover, the correlation coefficients between the variables, "*n_belief*", "*knowspd*" and *"familiar*", are all below 0.1, indicating the internal information that they capture have little homogeneity, which means they measure different aspect of respondent's cognition of the market. The variable "*message*" shows a positive correlation with the variable "TCR", with a correlation coefficient of 0.166. This implies that while they are distinguishable from one another, there is a certain degree of overlap in the information they convey.

5. Results

Since the data was generated from three independent surveys rather than a longitudinal survey, we first discuss the results from pooled estimation and use heteroscedasticity-robust standard errors to deal with possible heteroscedasticity problems. To investigate if the regression model is heterogeneous with time, we also report the results from cross-section estimation.

5.1. Results from the baseline model

Table 4 displays the results from the MPRs with pooled data, which is based on seemingly-unrelated regressions (SUR) because our multiple DVs for ES, ET and PM, are not independent of one another (an approach similar to that adopted in Valsesia et al. (2016)). Hereafter, we take the model in the left-hand panel as the baseline model. Specification 1 on the right-hand side is a small modification of the baseline model. The difference between the two specifications is the message variable. The baseline model uses the variable "*message*" to represent the information offered by the consumer's current supplier. The other one uses TCR to measure the information provided by one's own supplier or other energy suppliers.

We first discuss the results from the baseline model. A lack of belief in tariff difference reduces the probability of changing ES and ET, but does not affect the probability of changing

PM. In the equations on switching ES and changing ETs, the parameters of the belief variable are similar in size and consistent in sign. For the other two internal information variables, '*knowspd*' and '*familiar*', the effects are all positive, and this is consistent across different switching behaviors.

Table 4 Estimation results with pooled MPRs

	Baseline [a]			Spec.1 [b]		
	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}
n_belief	-0.3594***	-0.1315***	-0.0220	-0.4095***	-0.1332***	-0.0681
	(0.027)	(0.026)	(0.037)	(0.035)	(0.033)	(0.049)
knowSpd	0.1362***	0.2584***	0.1480**	0.1662***	0.3040***	0.0639
	(0.041)	(0.042)	(0.058)	(0.052)	(0.053)	(0.072)
familiar	0.2998***	0.4530***	0.1104***	0.2601***	0.4270***	0.0548
	(0.026)	(0.025)	(0.036)	(0.034)	(0.033)	(0.048)
reg_int	0.1842**	0.1668*	0.2407**	0.3693***	0.3396***	0.1659**
	(0.072)	(0.091)	(0.110)	(0.056)	(0.055)	(0.073)
message	-0.2643***	0.1969**	0.1025			
	(0.069)	(0.084)	(0.107)			
reg_int×messg	0.1135	0.2429**	-0.0085			
	(0.078)	(0.095)	(0.119)			
TCR				0.0100	0.4079***	0.0194
				(0.099)	(0.086)	(0.141)
reg_int×TCR				0.102	0.146	0.1291
				(0.107)	(0.094)	(0.152)
rho	rho_{12}: 0.211***; rho_{13}: 0.334*** ; rho_{23}: 0.320***			rho_{12}: 0.199***; rho_{13}: 0.333***; rho_{23}: 0.327***		
Wald chi2	973			660		
Controls & year dummy	Y			Y		
Obs.	16128			9859		

Notes: The MPRs were estimated using the Maximum Likelihood method with seemingly unrelated regressions (ML-based SUR). The numbers in brackets are robust standard errors, adjusted for heteroscedasticity. *, **, and *** represents significance of 0.05, 0.01, and 0.001 levels, respectively. All equations include a constant term, and same demographic controls such as *switchother, socgrade, male, work, language, movehouse, numbhh, finstr, income_n, age, edu* and *region*.

(*a*) Table A-1 in the appendix provides the full results for the baseline model.

(*b*) Spec.1 is based on pooled data for 2015-16 since data for TCR was not available for 2014 (TCRs only became available in 2014).

As shown by the results in the following sections, when additional variables are included in regressions, or the regressions are implemented with cross-section data, the results regarding changing PM show poor robustness. This is hardly surprising since households that reported changing PMs comprise less than 5% of the sample. The number of respondents who switched

PM is so small (240~304 in each year) that it is hard to generate efficient estimates. Our discussions thereafter focus on switching ESs and ETs.

The findings presented above provide support for hypotheses H1, H2 and H3 on beliefs, knowledge and awareness of the energy market respectively. A lack of belief in tariff differences, which means expecting no gains from participating in the energy market, would have a negative influence on switching behaviors. Both professed knowledge of energy expenditure and familiarity with energy tariffs play a positive role.

To test our statement on expenditure, we regressed four variants of the baseline model by including variables to capture the level of claimed expenditure as detailed in the Appendix A.1. Overall, knowledge of expenditure is better predictor for switching decisions, compared to expenditure levels; indeed, there is no clear relationship between expenditure level and switching (Table A-4). Thus, unlike Six et al. (2017), we find the level of expenditure on electricity has no influence on switching decision nor intention, rather, our analysis emphasizes what matters is claimed knowledge of expenditure, not the expenditure level itself.

Consistent with our expectations, the Internet variable exhibits a positive relationship for all three types of switching behaviors, regardless of the model specification. This provides strong support for hypothesis H4 that Internet-based information can promote consumer engagement in the energy market.

As for the Message variable, its impact varies with the form of participation. There is a negative association with ES switching; that is, a supplier message can increase consumer loyalty to their current supplier. In fact, as seen in other specifications presented in the following subsections, the negative effect of this Message variable on ES switching is strongly robust, regardless of model specification. Though somewhat unexpected, it can be interpreted by the message source and the difference in uncertainties between switching ETs and ESs. When a consumer receives communication from their supplier, he or she may perceive the supplier as being more solicitous and engaged, further deepening the consumer 'relationship' with their supplier and leading to the perception that their supplier is more trustworthy, which would discourage switching to other suppliers. For convenience, we call this "incumbent bias".

Moreover, consumers are generally more familiar with their own supplier than with other suppliers and find it easier to compare between offers from the same supplier versus offers from different suppliers. As a result, changing suppliers may be perceived as riskier than changing tariffs, because the former is seen as involving greater uncertainties. Thus, messages from a single source do not provide a basis for comparison between suppliers and cannot reduce uncertainty so the '*message*' would have a negative relationship with supplier switching.

By contrast, if the above logic holds, then the *'message'* variable should have a positive effect on changing tariffs, because the information contained in the message from the current supplier can help the consumer differentiate between a supplier's different tariffs. The estimate of the effect that the message variable has on changing tariffs (ET) confirms our reasoning, with a significantly positive coefficient.

Since an "incumbent bias" is produced when receiving supplier messages from a single source, it could be corrected by diversifying information sources. The interaction of Internet information with message should therefore be positive. We find the interactive effect between Internet information and the message on changing tariffs is positive and significant, which confirms Hypothesis H6 that the message, combined with efforts to process information promotes engagement. In contrast to the cross term in the ET equation, the parameter of the cross term in the ES equation is not significant, and smaller in magnitude. Again, we attribute this to the greater uncertainty and complexity of switching suppliers. As shown in the following subsections, this argument is supported by results from other specifications – the cross term between the Internet and the message variables exhibits a consistently stronger effect for changing tariffs than changing suppliers.

As suggested above, supplier messages can have a negative effect on switching ESs because the information it measures is from single source – their current supplier. A natural question to ask is whether the effect on switching ESs is positive if the messages are from various suppliers rather than a single supplier. We introduce the variable "TCR", to represent Tariff Comparison Rates, reflecting the effects of information from suppliers in general.

TCRs, as a comparison tool, facilitate greater consumer scrutiny of their energy consumption and spending, and comparison between suppliers and tariffs. The 2015 and 2016 questionnaires asked respondents if they had seen any TCRs. Since TCRs have been mainly provided by price comparison websites (PCWs), their effectiveness might be associated with effort put into online information searching. Thus, we use the interaction of TCR with the Internet variable to identify such engagement.

We turn now to the right-hand panel of Table 4, where the results of the MPR from including TCR and using 2015-16 pooled data, are displayed. For the first four variables, we see the coefficients resemble the ones in the reference model, both in terms of the direction of the relationship and significance level. In spite of the changes in magnitude of the parameters, our conclusions about hypotheses H1, H2, H3 and H4 still hold.

Consider the coefficient of TCR. As expected, its effect is positive for all three choices, but only significant for changing tariffs. Parameters of the cross-term between TCR with Internet use are positive, but not significant in all equations.[1] The coefficient of TCR is positive because the "incumbent bias" resulting from a single message source disappears. The cross-term coefficients are not significant, which suggests that online information does not strengthen the effectiveness of the variable 'TCR'. We reason that since TCRs are provided online, measuring access to TCRs has covered the efforts involved in online information searching for the TCRs.

[1] The conclusions on TCR based on pooled estimation are consistent with that from cross-section estimation (see Table A-3).

An important assumption embodied in the baseline model is that the variances in the error terms are the same for all observations. The implication is that households are identical in seeking, understanding and processing information in retail markets, conditional on individual socio-demographic characteristics. According to the statistical analysis presented in Section 4, household participation rates in energy markets vary by fuel type and payment method. This is particularly visible between households paying by direct debit and others. Accordingly, we included additional variables to control for the effects of payment method and fuel type to investigate whether ignoring them could result in clear changes in other variables. The results (Table A-5) confirm that the previous findings about the effects of information on switching tariffs and suppliers are robust (see Appendix A.2 for detailed discussion).

5.2. Cross-sectional estimations

Using cross-sectional data and dropping the year dummies, we re-estimated the MPRs with the baseline model. The results are reported in the left-hand panel of Table 5. Our discussions focus on switching behavior for both suppliers and tariffs.

By comparing the cross section results, not only the magnitudes but also even the signs of some parameters change. For instance, in the ES equations, the variable "*knowspd*" is not significant in 2014 in both ES and ET equations. Only in the cross-sectional estimation of 2015, does internet use reveal a significantly positive effect on both switching supplier and tariff (for 2014). This might be associated with the information shock of introducing mandatory comparison tools in April 2014 (just after the 2014 survey was completed), when most of these tools became accessible online.

In the ES and ET equations, the signs of the variables are all in agreement across the cross-sections and consistent with the pooled estimations found using the baseline model. The changes in cross-section estimates suggest the association between information search and participating in energy markets can be influenced by changes in the external environment.

Estimation with pooling data mixes the dynamics in the market, to a certain extent, by averaging effects over the observed period. In spite of that, the main conclusions emerging from the pooled baseline model still hold for switching suppliers and tariffs, given the cofounding influence of other variables being controlled.

Table 5 Results from cross-section estimation

		MPR			Approximately linear regression		
		2014	2015	2016	2014	2015	2016
$\mathbf{Y_{ES}}$	*n_belief*	-0.2771***	-0.4283***	-0.4038***	-0.0544***	-0.0793***	-0.0828***
		(0.043)	(0.049)	(0.050)	(0.008)	(0.009)	(0.010)
	knowspd	0.0967	0.1257 *	0.2033***	0.0140	0.0227*	0.0371***
		(0.064)	(0.074)	(0.076)	(0.011)	(0.012)	(0.014)
	familiar	0.3189***	0.2674***	0.3122***	0.0687***	0.0547***	0.0706***
		(0.043)	(0.047)	(0.047)	(0.009)	(0.010)	(0.011)
	reg_int	0.0472	0.4905***	0.0201	0.0084	0.0975***	0.0007
		(0.116)	(0.139)	(0.127)	(0.022)	(0.024)	(0.028)
	message	-0.1331	-0.3833***	-0.3421***	-0.0180	-0.0414**	-0.0626***
		(0.109)	(0.141)	(0.118)	(0.018)	(0.018)	(0.023)
	reg_int×message	0.0369	0.1070	0.2897**	0.0018	-0.0244	0.0535*
		(0.125)	(0.154)	(0.138)	(0.023)	(0.024)	(0.029)
$\mathbf{Y_{ET}}$	*n_belief*	-0.1191***	-0.1249***	-0.1334***	-0.0278***	-0.0306***	-0.0313***
		(0.043)	(0.045)	(0.048)	(0.009)	(0.010)	(0.011)
	knowspd	0.2076***	0.2450***	0.3502***	0.0351***	0.0490***	0.0639***
		(0.068)	(0.071)	(0.079)	(0.011)	(0.013)	(0.013)
	familiar	0.4049***	0.4789***	0.4942***	0.0900***	0.1185***	0.1191***
		(0.043)	(0.044)	(0.047)	(0.010)	(0.011)	(0.011)
	reg_int	0.1351	0.3408**	0.0405	0.0113	0.0300 *	0.0030
		(0.147)	(0.171)	(0.160)	(0.016)	(0.017)	(0.022)
	message	0.1936	0.2652 *	0.1394	0.0130	0.0135*	0.0059
		(0.137)	(0.160)	(0.142)	(0.013)	(0.009)	(0.019)
	reg_int×message	0.2242 *	0.1351	0.3746**	0.0563***	0.0696***	0.0951***
		(0.115)	(0.178)	(0.168)	(0.017)	(0.020)	(0.023)
$\mathbf{Y_{PM}}$	*n_belief*	0.0229	-0.0651	-0.0678	0.0015	-0.0052	-0.0041
		(0.057)	(0.065)	(0.071)	(0.006)	(0.006)	(0.006)
	knowspd	0.2499**	0.0369	0.1342	0.0150**	0.0007	0.0051
		(0.099)	(0.094)	(0.110)	(0.006)	(0.008)	(0.008)
	familiar	0.1470**	0.0967	0.0831	0.0156***	0.0088	0.0064
		(0.057)	(0.065)	(0.069)	(0.006)	(0.006)	(0.006)
	reg_int	0.2969	0.2891	0.1299	0.0112	0.0125	0.0057
		(0.189)	(0.192)	(0.191)	(0.011)	(0.014)	(0.015)
	message	0.2110	0.1536	-0.0969	0.0084	0.0054	-0.0069
		(0.188)	(0.189)	(0.178)	(0.008)	(0.011)	(0.012)
	reg_int×message	-0.0580	-0.1301	0.1632	0.0078	-0.0021	0.0134
		(0.205)	(0.209)	(0.207)	(0.012)	(0.014)	(0.016)

rho	rho_{12}: 0.209***;	rho_{13}: 0.344***;	rho_{23}:0.305***	rho_{12}: 0.090***;	rho_{12}: 0.132***;	rho_{23}: 0.108***
Wald chi2	346	381	316	334	446	337
controls	Y	Y	Y	Y	Y	Y
Obs.	6142	5290	4696	6142	5290	4696

Notes: This table reports the estimation results for the baseline model, using cross-sectional data and dropping the year dummies; the remaining control variables are the same as in Table 4.

Our findings provide evidence to support hypotheses H1, H2 and H3. The conclusions on the internal information regarding switching ESs and ETs are consistent across different specifications, no matter using pooled data or cross-section data. For specific types of switching behavior, effect size of the same variable of internal information does not distinguish much between specifications. The only exception is that the effect of energy expenditure knowledge on switching suppliers is not significant in 2015.

With regards to external information, hypotheses H4, H5 and H6 hold, conditional on specific types of participation and changes in the market. The empirical association between the message and ES switching behavior seem to provide evidence contrary to the initial hypothesis H5. We have provided evidence (and an argument) that the effects of the current supplier's message differ from messages offered by other suppliers. Hypothesis H5 thus might better be divided into two: 5a - *Messages from existing energy suppliers encourage consumers to switch tariffs but discourages them from switching suppliers*. Supplier message and Internet information are complementary, conditionally. The complementarity depends on information source, participation type and the market. For single-source supplier messages, which can offer only limited information and which will be perceived as biased, greater online search efforts can increase the positive effect of the message on household participation in energy market. Based on the findings described above, we conclude that external information is the primary source of evidence leading to changes in household decision-making over time.

5.3. Further discussion

Just as in a general probit model, the relationship between the probability and the predictors is non-linear, so the magnitude of the parameters from the probit model is not equal to the marginal effect of variable on the probability (Greene 2008). In order to quantitatively interpret the results of the MPR model, we make use of the estimation results from linear simultaneous regressions to derive an approximation of the marginal effects. Of course, several problems arise from this approximation. The commonly recognized drawback is that the estimated probabilities with linear regressions can never have the typically S-shaped distribution function in a probit model, therefore, the fitted probabilities can go below zero or above one (Lewbel et al. 2012). However, even accepting the weaknesses, the linear approximation model often seems to provide good estimates of the partial effects on the response probabilities near the center of the distribution of X (Wooldridge 2002).

The right-hand panel of Table 5 displays the results the above described linear approximation of the switching model, based on cross-section data. The coefficients reflect the partial effect on the probability to have switched due to a one unit change or due to the change from zero to one in the independent variables. Comparing the linear model with the cross-section model, we find they result in almost the same significance levels, and fully consistent parameter signs.

What do these results suggest about our hypotheses? As an illustration, consider the results regarding switching ESs, for the cross-sectional data from 2016. A lack of belief in differences in energy tariffs leads to a decrease of 8.28% in the probability of switching. A household's knowledge of its energy expenditure yields a higher probability of switching suppliers by 3.71%, while familiarity with energy tariffs increases the probability of switching by 7.06%.

For 2016, the Internet variable is not significant, but can affect switching behavior via its interaction with Message. For consumers who do not regularly search for information online, receiving messages from the current supplier reduces their probability of switching to other suppliers by over 6%. By contrast, for users who often get online, receiving supplier messages reduces the possibility of switching by less than 1%.

Finally, although appraising the information variables may be imperfect, measurement problems do not weaken the reliability of the main results. If anything, the impact of Message and its interactive influence with Internet information may be understated. There are two reasons for the possible underestimation. First, the Internet has become the main channel of information communication. Part of the supplier messages conveyed by the Internet has been included in the variable for Internet information. Second, the Message variable was based on household awareness of supplier message rather than understanding and processing. The impact of any information received, without processing could be greatly discounted. Although the measurement problem may lead to a bias in the estimation results, it does not change our basic conclusions regarding external information sources.

So far, our discussions have focused on the role of information on switching behavior. But the estimation results of alternative models show that some of the socioeconomic covariates proposed in our analysis present significant influences on household participation in energy market. For the sake of simplicity, we present the complete results of the socioeconomic covariates of the baseline model, in Table A-1 of the Appendix. Here we only discuss the main findings.

In most of our alternative models, social grade, income, financial pressure, age, education and region have significant influence on switching behaviors, but the estimated parameters are not robust, as the signs and significance levels change with model specification and type of participation.

With regard to changing ESs and ETs, the variables related to language, gender, work, and family size are robust in the different models. Consumers with English as their main language and who have a larger family are more likely to be active in the market, other things being equal. Males or those not in employment, are less likely to be active in the market, all else being equal.

Respondents who have switched in other product markets are more likely to be active in the energy markets, compared with the non-switchers. This conclusion holds for all three types of switching behavior and is robust in different models. The finding about switchers of other products highlights the potential importance of switching experience in other circumstances, which is consistent with the conclusion of other studies (He & Reiner 2017; Six et al. 2017). Activities in other retail markets provide consumers the opportunity to learn how to process information, compare offers and choose the best supplier; these advantages may lead to increased capability of switching. This finding also highlights that inactive consumers are not only losing out in energy markets but in a host of other markets such as insurance, personal banking, broadband and mobile phones where the gains from switching may be even larger and that the nature of these consumers may be difficult to alter. Moreover, switching rates in energy markets is higher than other competitive markets such as mobile, broadband or retail banking although lower than car insurance (Ofcom 2016).

6. Conclusions

Household participation in energy markets is a complex social issue affected by multiple factors including cognitive, environmental and psychological constraints. Our analysis focuses on the impacts of information and knowledge on three decisions regarding market participation: (a) switching to an alternative electricity and/or gas supplier; (b) switching to an alternative electricity and/or gas tariff; and (c) changing payment methods for household energy bills.

Our study contributes to a growing evidence base on the factors influencing household participation in energy markets and more widely on questions of customer stickiness and brand loyalty (such as Ping 1993, Mattila 2001, and Wolter et al. 2017). 'External' information and 'internal' knowledge produce different effects on participation of households in energy market, and different “external” information are complementary in promoting participation. The conclusions are robust with regard to decisions over switching suppliers and tariffs. Difficulty in reaching conclusions on payment method is unsurprising, because of the small numbers switching payment method over the three years of the survey – most consumers on direct debit will have made a once-and-for-all switch long before 2014.

Belief in energy tariff differences reflects consumer understanding of market competition, particularly expectation of the gains from participating in markets. Our results confirm the initial hypothesis that a lack of belief in differences across energy tariffs reduces the probability of participation. These findings suggest that improving consumer understanding of the range of available tariffs would be helpful in promoting greater engagement.

If consumers are unclear about their own energy spending, they will be uncertain about how much savings they can obtain from switching to a new supplier. We find that knowing one’s own household energy expenditure, and familiarity with general energy tariffs are both related to a greater probability of participation. In that sense, targeted information campaigns may be effective. Households that have learned about their energy spending still may not know how to go about comparing and switching, which might prevent them from taking further actions such as changing tariffs or suppliers. Various forms of social interaction can raise knowledge of how to switch, and therefore motivate engagement in the market.

Our study provides evidence that receiving messages from their existing energy provider may discourage households from switching suppliers. Meanwhile, the positive effect of Internet information reveals the importance of information and knowledge, since Internet access provides consumers with an important channel for obtaining information related both to their energy spending and to comparing deals.

Due to the differences in reliability between various sources of information, the imbalanced effects of information have implications for household participation in the market.

For example, messages offered by a single source and other offline information (for instance, opinions from friends and colleagues) may be incomplete, leading to a bias in household decision making. Internet-based information (price comparison websites for example) can deliver relatively accurate and comprehensive information, which in turn helps prospective switchers to make the right choices and thereby promotes market competition.

We find external information clearly has different impacts on different forms of participation. In particular, the interaction between Internet information and supplier messages produces a stronger effect on changing tariffs than changing suppliers. We conclude that the uncertainty and complexity in changing suppliers is larger than in changing tariffs. This finding highlights the potential importance of targeted information with regards to specific forms of engagement.

Our results also provide evidence that different forms of participation are significantly related to each other. Overall, the level of activity in changing tariffs is higher than that of changing suppliers and payment method, although the level of specific forms of participation varies by group. For example, all else being equal, households that pay their energy bills by direct debit, are less likely to switch suppliers and more likely to change tariffs, compared to other households dual-fuel users are more likely to switch suppliers and payment methods.

We find the strength of information effect varies by year, which may reflect shifts in the wider social and political climate, given the fact that the effect is particularly strong in 2015 when energy markets were particularly newsworthy. We reason this variation might be due to changes in policy and the rapid shift in energy prices and the ensuing public attention, although the timing and the impact of different variables such as actual price changes versus media and political scrutiny needs to be accurately identified by further research. In spite of that, our conclusions on the role internal information plays with regard to switching suppliers and tariffs is in good agreement across various specifications. External information appears to be the primary reason for household decision-making changes. Our finding opens up the potential for exploring other influences on household activity such as promotion of price comparison websites, media discourse and public debate, which raise consumer attention to their activities in the market.

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Appendix

Table A-1 Complete results from baseline multivariate probit regression (MPR)

	Switch ES		Change ET		Change PM	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
n_belief	-0.3594***	(0.027)	-0.1315***	(0.026)	-0.0220	(0.037)
knowSpd	0.1362***	(0.041)	0.2584***	(0.042)	0.1480**	(0.058)
familiar	0.2998***	(0.026)	0.4530***	(0.025)	0.1104***	(0.036)
reg_int	0.1842**	(0.072)	0.1668*	(0.091)	0.2407**	(0.110
message	-0.2643***	(0.069)	0.1969**	(0.084)	0.1025	(0.107)
reg_int×message	0.1135	(0.078)	0.2429**	(0.095)	-0.0085	(0.119)
d2014	-0.0523*	(0.032)	-0.1557***	(0.031)	0.0234	(0.043)
d2016	0.0836***	(0.032	-0.0178	(0.031)	-0.0243	(0.046)
switchother	0.2457***	(0.029)	0.2010***	(0.028)	0.1563***	(0.039)
socgrade	0.0513*	(0.030)	0.1304***	(0.030)	-0.0944**	(0.044
male	-0.0612**	(0.026)	-0.0578**	(0.026)	-0.0462	(0.036)
work	-0.0576**	(0.032)	-0.0875***	(0.033)	-0.0838*	(0.044)
language	0.2739***	(0.050)	0.2736***	(0.051)	-0.1728***	(0.058)
movehouse	0.5284***	(0.038)	0.0834**	(0.042)	0.4863***	(0.048)
numbhh	0.0371***	(0.009)	0.0101	(0.010)	-0.0060	(0.014)
finstr	0.0325	(0.029)	-0.0117	(0.029)	0.0749**	(0.038)
income（cat.11 as the ref.)						
1	-0.0038	(0.071)	-0.2015**	(0.079)	0.1175	(0.088)
2	0.0486	(0.049)	-0.1591***	(0.051)	0.0973	(0.065)
3	0.0553	(0.045)	0.0192	(0.044)	-0.0173	(0.065)
4	0.0779	(0.054)	0.1454***	(0.050)	0.2149***	(0.068)
5	0.0638	(0.053)	0.1877***	(0.050)	0.0472	(0.074)
6	0.0841*	(0.049)	0.2068***	(0.046)	0.1621**	(0.065)
7	0.1373**	(0.057)	0.1469***	(0.055)	-0.0789	(0.086)
8	0.1475**	(0.059)	0.1611***	(0.057)	0.0115	(0.087)
9	0.2164***	(0.068)	0.1416**	(0.068)	0.1475	(0.098)
10	0.2480***	(0.072	0.3411***	(0.070)	0.0870	(0.109)
age_2	0.0081	(0.035)	0.2859***	(0.036)	-0.0696	(0.046)
age_3	0.0227	(0.048)	0.4089***	(0.048)	-0.1722***	(0.065)
edu_2	0.0103	(0.041)	0.0523	(0.042)	0.0056	(0.058)
edu_3	-0.0139	(0.049)	0.1311***	(0.048)	0.0264	(0.066)
edu_4	0.0419	(0.046)	0.1737***	(0.045)	0.0652	(0.064)
region_2	-0.0375	(0.059)	0.0357	(0.057)	0.0531	(0.078)
region_3	-0.0355	(0.046)	0.0311	(0.044)	0.0996*	(0.059)

Notes: This table reports the complete results from the baseline MPR model (left-hand of Table 4) with pooled data.

*, **, and *** represent significance of 0.05, 0.01, and 0.001 levels, respectively. The figures in brackets are robust standard errors. For income, the 11th category is the reference group; for education, age and region, the first category is the reference group in each case.

Table A-2 Results from pooled MPR (using 10th income level as reference category)

	Switch ES		Change ET		Change PM	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
n_belief	-0.359***	(0.027)	-0.131***	(0.026)	-0.022	(0.037)
knowSpd	0.136***	(0.041)	0.258***	(0.042)	0.148**	(0.058)
familiar	0.300***	(0.026)	0.453***	(0.025)	0.110***	(0.036)
reg_int	0.184**	(0.072)	0.167*	(0.091)	0.241**	(0.110)
message	-0.264***	(0.069)	0.197**	(0.084)	0.103	(0.107)
reg_int×message	0.113	(0.078)	0.243**	(0.095)	-0.008	(0.119)
d2014	-0.052*	(0.032)	-0.156***	(0.031)	0.023	(0.043)
d2016	0.084***	(0.032)	-0.018	(0.031)	-0.024	(0.046)
switchother	0.246***	(0.029)	0.201***	(0.028)	0.156***	(0.039)
socgrade	0.051*	(0.030)	0.130***	(0.030)	-0.094**	(0.044)
male	-0.061**	(0.026)	-0.058**	(0.026)	-0.046	(0.036)
work	-0.058*	(0.032)	-0.087***	(0.033)	-0.084*	(0.044)
language	0.274***	(0.050)	0.274***	(0.051)	-0.173***	(0.058)
movehouse	0.528***	(0.038)	0.083**	(0.042)	0.486***	(0.048)
numbhh	0.037***	(0.009)	0.010	(0.010)	-0.006	(0.014)
finstr	0.033	(0.029)	-0.012	(0.029)	0.075**	(0.038)
income（cat.10 as the ref.)						
1	-0.252***	(0.097)	-0.543***	(0.102)	0.030	(0.134)
2	-0.199**	(0.083)	-0.500***	(0.083)	0.010	(0.122)
3	-0.193**	(0.079)	-0.322***	(0.077)	-0.104	(0.119)
4	-0.170**	(0.082)	-0.196**	(0.079)	0.128	(0.119)
5	-0.184**	(0.081)	-0.153**	(0.078)	-0.040	(0.121)
6	-0.164**	(0.077)	-0.134*	(0.075)	0.075	(0.114)
7	-0.111	(0.082)	-0.194**	(0.080)	-0.166	(0.126)
8	-0.100	(0.082)	-0.180**	(0.080)	-0.075	(0.125)
9	-0.032	(0.088)	-0.200**	(0.087)	0.060	(0.132)
11	-0.248***	(0.072)	-0.341***	(0.070)	-0.087	(0.109)
age_2	0.008	(0.035)	0.286***	(0.036)	-0.070	(0.046)
age_3	0.023	(0.048)	0.409***	(0.048)	-0.172***	(0.065)
edu_2	0.010	(0.041)	0.052	(0.042)	0.006	(0.058)
edu_3	-0.014	(0.049)	0.131***	(0.048)	0.026	(0.066)
edu_4	0.042	(0.046)	0.174***	(0.045)	0.065	(0.064)
region_2	-0.037	(0.059)	0.036	(0.057)	0.053	(0.078)
region_3	-0.035	(0.046)	0.031	(0.044)	0.100	(0.059)
rho	rho12: 0.211*** ;	rho13: 0.334*** ;	rho23: 0.320***			
Wald chi2	973					
Controls & year dummy	Y					
Obs.	16128					

Notes: This table reports results of the baseline MPR with pooled data, using 10th income decile as the reference category.

*, **, and *** represent significance of 0.05, 0.01, and 0.001 levels, respectively. The figures in brackets are robust standard errors. For income, the 10th category is the reference; for education, age and region, the first category is the reference group in each case.

Table A-3 Cross-section estimation results from MPR including TCR

	2015			2016		
	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}
n_belief	-0.4391***	-0.1215***	-0.0721	-0.3877***	-0.1332***	-0.0645
	(0.050)	(0.047)	(0.068)	(0.049)	(0.048)	(0.070)
knowSpd	0.0996	0.2416***	0.0083	0.2191***	0.3687***	0.1318
	(0.076)	(0.074)	(0.097)	(0.073)	(0.077)	(0.105)
familiar	0.2449***	0.4450***	0.0994	0.2795***	0.4216***	0.0188
	(0.048)	(0.047)	(0.068)	(0.047)	(0.047)	(0.069)
reg_int	0.5394***	0.3523***	0.1444	0.2468***	0.3367***	0.1961**
	(0.086)	(0.079)	(0.104)	(0.075)	(0.078)	(0.102)
TCR	-0.0808	0.2783**	0.0986	0.0197	0.4834***	-0.0493
	(0.189)	(0.136)	(0.198)	(0.120)	(0.110)	(0.203)
reg_int×TCR	0.1974	0.2313	0.0336	0.0957	0.1104	0.1976
	(0.198)	(0.147)	(0.215)	(0.133)	(0.123)	(0.218)
rho	rho_{12}: 0.233***; rho_{13}: 0.273***; rho_{23}: 0.298***			rho_{12}: 0.166***; rho_{13}: 0.398***; rho_{23}: 0.359***		
Controls	Y			Y		
Wald chi2	359			330		
Obs.	4951			4908		

Note: This table reports the results of the MPR where the variable "*message*" is replaced by TCR, using cross-sectional data and dropping the year dummies. All equations include a constant term and same demographic controls as in Table 4. Because TCR data is not available for 2014, here only the results for 2015 and 2016 are reported.

*, **, and *** represents significance of 0.05, 0.01, and 0.001 levels, respectively.

A.1. The role of actual energy expenditures

Rather than only examining the binary variable of whether respondents claim to know their expenditure, we tried to explore whether the actual expenditure (or at least claims of the actual levels) were related to switching behavior. We created a variable '*spd_n*' categorizing energy expenditure into six categories, thereby replacing the binary variable '*enspd*' by the new variable in regressions. The first category of '*spd_n*', i.e. spd_0, indicates the respondents who did not know their expenditure. For the respondents who reported their expenditure, we calculated their annual expenditure levels,[1] and categorized these annual values into quintiles.

[1] The questionnaire offered the respondents the possibility to choose between seven categories for report their expenditure: weekly, fortnightly, every four weeks, calendar month, quarterly, twice yearly, and annual, which we then aggregated as appropriate to obtain annual expenditures.

Thus, we obtain the other five categories (from *spd_1* to *spd_5*), where *spd_1* refers to the bottom 20% in terms of expenditure and *spd_5* refers to the top 20% (Table 2).

For the model variant Specification A1, we take *spd_0* as the reference category. This allows us to compare every category of those who know their expenditure with those who did not know. The results are presented in the first set of columns of Table A-4 (Spec.A1). Since the estimation results for other variables do not differ significantly from the baseline model, our analysis focuses on variable '*spd_n'*. Almost all categories of respondents who knew their expenditure are more likely to switch ETs and ESs, compared to those who did not know their expenditure. This finding confirms our earlier conclusion that knowing one's energy expenditure does matter for switching. However, there is no evidence the effect becomes any weaker or stronger with greater expenditure.

Next, we use '*spd_1'* as the reference category to enable a comparison with those on the lowest expenditure level. The results are presented in the columns labeled Spec.A2. Compared to the lowest expenditure category, while the respondents who did not know their expenditure are more likely to change ETs, a few categories are more likely to switch ESs or ETs. Still here is no evidence for an increasing/decreasing effect of the expenditure.

One might be concerned that the non-significance of the expenditure level is caused by a correlation between the income and expenditure variables since they are both included in the model, so we excluded the income variable and obtain Specification A3. The regression results presented in the third set of columns (Spec.A3) show there is no significant difference between the results of Spec.A2 and Spec.A3.

Finally, we directly used a continuous variable '*lenspd*', measured by logarithms of the expenditure values, to further test if the expenditure itself influences switching decisions. The results displayed in the rightmost set of columns (Spec.A4) show that the expenditure has influence on neither switching ESs nor ETs.

Table A-4 Estimation results with pooled MPRs, including level of energy expenditure [a]

	Spec.A1[a]			Spec.A2[b]			Spec.A3[c]			Spec.A4[d]		
	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}
n_belief	-0.3600***	-0.1305***	-0.0231	-0.3600***	-0.1305***	-0.0231	-0.3611***	-0.1321***	-0.0237	-0.3753***	-0.1379***	-0.0347
	(0.027)	(0.026)	(0.037)	(0.027)	(0.026)	(0.037)	(0.027)	(0.026)	(0.026)	(0.029)	(0.027)	(0.039)
spd_0				-0.0794	-0.2097***	-0.0618	-0.0881*	-0.2117***	-0.0794			
				(0.049)	(0.050)	(0.070)	(0.049)	(0.050)	(0.050)			
spd_1	0.0794	0.2097***	0.0618									
	(0.049)	(0.050)	(0.070)									
spd_2	0.1959***	0.3414***	0.1527**	0.1166***	0.1317***	0.0909	0.1192***	0.1418***	0.0884			
	(0.048)	(0.049)	(0.070)	(0.043)	(0.042)	(0.061)	(0.043)	(0.041)	(0.041)			
spd_3	0.1673***	0.2418***	0.1008	0.0879**	0.0321	0.0389	0.0922**	0.0476	0.0345			
	(0.048)	(0.049)	(0.069)	(0.043)	(0.042)	(0.061)	(0.043)	(0.042)	(0.042)			
spd_4	0.1320***	0.2921***	0.2057***	0.0526	0.0824*	0.1438**	0.0585	0.1027**	0.1385**			
	(0.050)	(0.050)	(0.070)	(0.045)	(0.044)	(0.063)	(0.045)	(0.044)	(0.044)			
spd_5	0.1149**	0.2003***	0.2255***	0.0355	-0.0094	0.1637***	0.0452	0.0141	0.1600**			
	(0.050)	(0.051)	(0.069)	(0.045)	(0.045)	(0.063)	(0.045)	(0.044)	(0.044)			
lenspd										0.0214	0.0237	0.0819**
										(0.027)	(0.026)	(0.042)
familiar	0.2979***	0.4513***	0.1143***	0.2979***	0.4513***	0.1143***	0.2943***	0.4438***	0.1094***	0.3074***	0.4394***	0.0946**
	(0.026)	(0.025)	(0.036)	(0.026)	(0.025)	(0.036)	(0.026)	(0.025)	(0.025)	(0.028)	(0.027)	(0.038)
reg_int	0.1813**	0.1652*	0.2416**	0.1813**	0.1652*	0.2416**	0.1794**	0.1816**	0.2476**	0.1748**	0.2324**	0.2377*
	(0.072)	(0.091)	(0.110)	(0.072)	(0.091)	(0.110)	(0.072)	(0.091)	(0.091)	(0.081)	(0.103)	(0.122)
message	-0.2667***	0.1909**	0.1105	-0.2667***	0.1909**	0.1105	-0.2638***	0.2001**	0.116	-0.3094***	0.2606***	0.1121
	(0.069)	(0.084)	(0.107)	(0.069)	(0.084)	(0.107)	(0.069)	(0.084)	(0.084)	(0.079)	(0.097)	(0.120)
reg_int×messg	0.115	0.2450**	-0.0106	0.115	0.2450**	-0.0106	0.123	0.2533***	-0.0163	0.1471*	0.1985*	0.0024
	(0.079)	(0.095)	(0.119)	(0.079)	(0.095)	(0.119)	(0.079)	(0.095)	(0.095)	(0.088)	(0.108)	(0.133)
rho_{12}; rho_{13}; rho_{23}	0.210***; 0.335***; 0.320***			0.210***; 0.335***; 0.320***			0.212***; 0.333***; 0.319***			0.192***; 0.322***; 0.304***		
Wald chi2	978			978			953			817		
Controls & year dummy	Y			Y			No control for income			No control for income		
Obs.	16128			16128			16128			13816		

(*a*) Spec.A1 is different from the baseline specification by dropping variable '*KnowSpd*' and including a categorical variable '*spd_n'* , where category '*spd_0'*, indicating "do not know energy expenditure" is taken as the reference category. (*b*) Spec.A2 is different from Spec.A1 by using the category *spd_1*, the lowest level of energy expenditure, as the reference. (*c*) Spec.A3 is different from Spec.A2 by dropping the categorical variable for *income*. (*d*) Spec.A4 is different from Spec.A3 by replacing categorical variable '*spd_n'* with a continuous variable measuring the values of energy expenditure, labeled '*lenspd*''.

A.2. Including fuel type and payment method

We consider whether ignoring payment method and fuel type could result in clear changes in estimates of other variables (Table A-5).

To investigate the effect of payment method, we introduce the variable '*direct debit*', into the regressions, but the possible reverse causality between this variable and the engagement behaviors could lead to an endogeneity problem. We cannot exclude the possibility that households have chosen to pay by direct debit as a consequence of previous switching decisions.

We use an additional regression to address the endogeneity problem. In the additional regression, a new variable, '*everswitch*', is used as the instrumental variable for '*direct debit*'. As described in Table 2, '*everswitch*' indicates whether the households had ever switched suppliers prior to last year. [1] Since it is a predetermined variable, it can be regarded as exogenous and taken as the instrument for endogenous explanatory variables. Accordingly, the regression model (2) is amended as follows:

$$\begin{cases} y_{ES} = c_{es} + \alpha_{es} Inf + \theta_{es} Exf + \gamma_{es} Exf_1 Exf_2 + \delta_{es} Control + \vartheta_{es} add + \varepsilon_1 \\ y_{ET} = c_{et} + \alpha_{et} Inf + \theta_{et} Exf + \gamma_{et} Exf_1 Exf_2 + \delta_{et} Control + \vartheta_{et} add + \varepsilon_2 \\ y_{PM} = c_{pm} + \alpha_{pm} Inf + \theta_{pm} Exf + \gamma_{pm} Exf_1 Exf_2 + \delta_{pm} Control + \vartheta_{pm} add + \varepsilon_3 \\ add = I(\varphi_0 + \varphi_1 everswitch + \varphi_2 Control + \varepsilon_4) \end{cases} \quad \text{(A-1)}$$

In Model (A-1), ε_i still follow a joint normal distribution, and $cov(\varepsilon_i, \varepsilon_j) = \rho_{ij}$. add denotes an endogenous dummy variable. $I(\cdot)$ is an indicator function. It equals one if the

[1] '*Everswitch*' was created by integrating two questions. Respondents were asked "have you ever switched your gas or electricity supplier?" By combining the responses with the responses to the ES question (i.e., whether households had switched energy supplier in the last year), we identified the households that switched suppliers prior to last year. Recoding this way, we excluded the possibility of reverse causation between this variable and others.

latent variable (·) is positive, and 0 otherwise. φ_1 measures the effects of consumers' past switching behaviors on their choice of payment method. Thus, we obtain a simultaneous-equation structural model with one instrumented regression for the endogenous variable. The test for endogeneity of a variable can be performed after fitting an endogenous model, with the help of ρ_{ij}. If ρ_{ij}=0 for i =4 and j =1, 2, 3 cannot be rejected, the endogeneity problem does exist; otherwise, model (7) is appropriate. Similarly, ignoring the endogeneity of the variable '$dual\_fuel$' can lead to a bias of estimation.

In the first set of columns of Table A-5, we present the results of the MPRs for Specification B1 (Spec.B1), by adding one additional variable, $'direct\_debit'$ to the baseline model. In the second set of columns Spec.B2, we include one additional regression to Spec.B1, where the endogenous variable where the endogenous variable tariff calculator was instrumented by mobile tariff information was instrumented by past switching behavior ('*everswitch*'). Similarly, columns Spec.B3 and Spec.B4 respectively display the results of the MPRs with one additional variable '$dual\_fuel$', and the MPRs including the instrumented regression for the variable.

By comparing Spec.B1 and Spec.B2, we find that whether or not the endogeneity problem is considered directly influences the conclusion on payment method, particularly with regards to switching ESs. The estimate of the additional variable, $'direct\_debit'$, based on Spec.B1, suggests the households paying energy bills by direct debit are more likely to switch ESs than the others (with a parameter of 0.1818); while the estimate based on Spec.B2 reveals an opposite conclusion (with a parameter of -1.4385). In Spec.B2, the correlations between the instrumented regression and other equations show the endogeneity assumption on $direct\_debit$ cannot be rejected; therefore, Spec.B2 is reliable.

All else being equal, the households that pay energy bills by direct debit, are less likely to switch ESs; however, it does not follow those direct debit customers should be considered inactive. The parameter estimated from the additional regression confirms our expectation that consumers now paying by direct debit are more likely to have switched at some point in the past. A negative association between direct debit and propensity to switch supplier may simply reflect a lack of motivation to change ES because of a belief that the best possible provider was already identified via the prior switch. That households paying by direct debit are more likely to change ETs reflects the more intense competition in the direct debit segments than in other payment-method segments, since, as reported by CMA (2016), the number of tariffs on offer in the direct debit segments is more than in other tariff segments while the direct debit tariffs are cheaper than other payment-method tariffs.

In comparing Spec.B3 with Spec.B4, we see that ignoring the endogeneity of $dual\_fuel$ would lead to different conclusions on this variable. Since an assumption of endogeneity for $dual\_fuel$ cannot be rejected, Spec.B4 will be the more reliable variant of the model. Accordingly, we can conclude that households whose gas and electricity are supplied by the same supplier are more likely to switch ESs and PMs than others, but there is little evidence of an impact on changing ETs.

As for other explanatory variables, comparing the estimation results between Spec.B2, Spec.B4 and the baseline model, it is immediately striking that there is a high degree of similarity between the estimated coefficients of the different models. The significance levels resemble each other; the same explanatory variables are significant in three models. These findings confirm the effects of information on switching tariffs and suppliers are robust.

Table A-5 Including fuel type or payment method

	Spec.B1 *add*: direct debit			Spec.B2 [a] Spec.B1 + instrumented reg.			Spec.B3 [#] *add*: dual fuel			Spec.B4 [# a] Spec.B3 + instrumented reg.		
	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}	Y_{ES}	Y_{ET}	Y_{PM}
n_belief	-0.4125***	-0.1209***	-0.0733	-0.3024***	-0.1215***	-0.0682	-0.4468***	-0.1363***	-0.0582	-0.3114***	-0.1308***	-0.0457
	(0.036)	(0.034)	(0.050)	(0.029)	(0.033)	(0.049)	(0.037)	(0.035)	(0.051)	(0.030)	(0.035)	(0.051)
knowSpd	0.1870***	0.3102***	0.0994	0.1194**	0.3093***	0.0967	0.1568***	0.2946***	0.0696	0.1116***	0.2918***	0.0610
	(0.054)	(0.054)	(0.075)	(0.046)	(0.053)	(0.074)	(0.056)	(0.056)	(0.076)	(0.040)	(0.056)	(0.075)
Familiar	0.2823***	0.4788***	0.0847*	0.2223***	0.4741***	0.0830*	0.2954***	0.4844***	0.0626	0.2097***	0.4835***	0.0484
	(0.034)	(0.033)	(0.048)	(0.027)	(0.032)	(0.048)	(0.035)	(0.034)	(0.051)	(0.027)	(0.034)	(0.050)
reg_int	0.2443**	0.1999	0.2003	0.1887**	0.1844	0.1943	0.2364**	0.2039	0.2610**	0.1936***	0.2034	0.2474*
	(0.096)	(0.122)	(0.141)	(0.074)	(0.121)	(0.140)	(0.099)	(0.125)	(0.148)	(0.071)	(0.124)	(0.146)
Message	-0.3866***	0.1657	0.0068	-0.2157***	0.1414	0.0155	-0.4265***	0.1995**	0.0900	-0.2664***	0.2006*	0.1017
	(0.094)	(0.112)	(0.135)	(0.076)	(0.111)	(0.133)	(0.097)	(0.114)	(0.143)	(0.070)	(0.114)	(0.140)
reg_int×message	0.1702	0.2050	0.0201	0.1097	0.2203*	0.0208	0.2211**	0.2419**	-0.0741	0.1265	0.2422*	-0.0776
	(0.105)	(0.127)	(0.153)	(0.082)	(0.126)	(0.152)	(0.109)	(0.130)	(0.160)	(0.078)	(0.130)	(0.158)
add	0.1818***	0.5005***	0.0754	-1.4385***	0.7833***	-0.1650	0.0325	-0.0937*	-0.1418*	1.3380***	-0.0370	0.3196***
	(0.042)	(0.046)	(0.060)	(0.052)	(0.111)	(0.112)	(0.062)	(0.053)	(0.079)	(0.047)	(0.085)	(0.108)
Instrumented regression [a]												
Everswitch				0.4866***						-0.3295***		
				(0.026)						(0.028)		
rho	rho$_{12}$: 0.199***			rho$_{12}$: 0.104***	rho$_{14}$: 0.924***		rho$_{12}$: 0.220***			rho$_{12}$: 0.186***	rho$_{14}$: -0.907***	
	rho$_{13}$: 0.321***			rho$_{13}$: 0.321***	rho$_{24}$: -0.191***		rho$_{13}$: 0.361***			rho$_{13}$: 0.374***	rho$_{24}$: -0.060*	
	rho$_{23}$: 0.338***			rho$_{23}$: 0.322***	rho$_{34}$: 0.148**		rho$_{23}$: 0.313***			rho$_{23}$: 0.294***	rho$_{34}$: -0.308***	
Wald chi2	666			1957			610			1494		
Controls & year dummy	Y			Y			Y			Y		
Obs.	9547			10792			8716			9855		

Notes: This table reports the results of the MPRs from including an additional regression on fuel type or payment method, using pooled data.

(*a*) Correlation tests between the equation residual errors support the endogeneity of the additional variable, direct debit, and dual fuel, respectively in Spec B2 and Spec B4.

(#) This estimation uses 2015-16 pooled data, as the data for dual fuel users are not available for 2014.