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Understanding preference heterogeneity in electricity services: the case of domestic appliance curtailment contracts

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Abstract: Various demand side mechanisms are advocated to reduce peak electricity loads, including direct load control, which comprises remotely shifting load to peak periods. Empirical evidence across several electricity markets reveals heterogeneous customer preferences for these and other electricity service offerings but relatively little is understood concerning the drivers of this preference heterogeneity. Using a discrete choice experiment examining the potential role of domestic appliance curtailment contracts as a means of shifting load, this paper investigates potential drivers of preference heterogeneity with respect to electricity services. Among the research findings are that almost 4-in-5 customers engage with the proposition of appliance curtailment contracts within the context of the survey environment. Customers that previously switched electricity supplier are among those more likely to consider curtailment contracts. From a policy perspective the results highlight the potential of appliance curtailment contracts as a tool to manage peak loads, as well as, the nature of preferences with respect to curtailment contract attributes. The research also finds that there is no substantial association between either the usual socio-demographic characteristics (e.g., education, etc.) or attitudes to environmental sustainability and preferences for various attributes of appliance curtailment contracts (e.g. appliance type, frequency of curtailment, opt outs, etc.). The absence of such a relationship makes it more difficult to forecast demand, to plan for infrastructure, and to design and market appliance curtailment contracts to customers.

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Keywords: demand side management, direct load control, load shifting, preferences, behaviour, attitudes

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Abstract

Various demand side mechanisms are advocated to reduce peak electricity loads, including direct load control, which comprises remotely shifting load to off-peak periods. Empirical evidence across several electricity markets reveals heterogeneous customer preferences for these and other electricity service offerings but relatively little is understood concerning the drivers of this preference heterogeneity. Using a discrete choice experiment examining the potential role of domestic appliance curtailment contracts as a means of shifting load, this paper investigates potential drivers of preference heterogeneity with respect to electricity services. Among the research findings are that almost 4-in-5 customers engage with the proposition of appliance curtailment contracts within the context of the survey environment. Customers that previously switched electricity supplier are among those more likely to consider curtailment contracts. From a policy perspective the results highlight the potential of appliance curtailment contracts as a tool to manage peak loads, as well as, the nature of preferences with respect to curtailment contract attributes. The research also finds that there is no substantial association between either the usual socio-demographic characteristics (e.g. age, education, etc.) or attitudes to environmental sustainability and preferences for various attributes of appliance curtailment contracts (e.g. appliance type, frequency of curtailment, opt outs, etc.). The absence of such a relationship makes it more difficult to forecast demand, to plan for infrastructure, and to design and market appliance curtailment contracts to customers.

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1. Introduction

Supplying peak period electricity loads represents a considerable challenge for electricity network managers, and is one that is likely to become more acute with the increased integration of renewable energy sources, such as solar and wind power onto the grid. Demand for electricity is concentrated during certain periods of the day, specifically in the evening between 5pm and 8pm. This poses challenges to network operators who must provide additional capacity to the grid in order to meet this demand, as supply and demand for electricity must be matched to ensure voltage stability. As network operators strive to incorporate more power generation from renewable technologies onto the grid in an effort to reduce associated carbon emissions, this problem becomes exacerbated due to the non-dispatchable feature of many renewable energy sources. Whereas supply side solutions traditionally involve methods such as the provision of

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additional power, facilitated by bringing more generators online or utilising technologies such as pumped storage, increasing levels of attention are now being placed upon demand side solutions, that is, reducing the need for increased supply in the peak period.

Several demand side management (DSM) mechanisms have been proposed to reduce peak loads. Dynamic, time-of-use or critical-peak pricing, facilitated by smart meters, are broadly one approach. Real-life trials indicate that such pricing mechanisms can be effective in reducing peak period demand [12, 13, 34]. However, a number of concerns regarding implementation of such pricing mechanisms have been raised, including consumers' apprehensions about how such measures work in everyday life [10]; about the longevity of price effects [34]; and also that the level of response is dependent on customer preferences [33]. Another approach is direct load control (DLC), which shifts load to periods of lesser demand. DLC typically involves a remotely operated switch cycling off specific loads (e.g. freezers, air conditioners, water heating) for short periods of time. The operation of DLC load shifting is often imperceptible to electricity customers, though concern has been expressed around loss of customer control [38, 44]. Evidence from Great Britain suggests that electricity tariffs permitting DLC are preferable to time-of-use tariffs, within specific parameters [14]. DLC can also be applied to customer loads where the impact of curtailment is easily observable by homeowners, for example, where the curtailed appliances may include ovens, dishwashers, washing machines and tumble dryers. During such curtailment events homeowners are directly inconvenienced and homeowners' willingness to participate in DLC may differ depending on the nature of the appliances under control. Irrespective of whether the policy mechanism to curtail peak loads is a price signal encouraging active decisions by consumers (e.g. time-of-use pricing), or a passive decisions (e.g. participation in DLC) similar challenges are facing electricity utilities. To successfully implement such policies requires a strong understanding of customer preferences, a topic where there is a considerable gap in knowledge.

Historically, electricity utilities were not particularly interested in understanding the detailed nature of customer demand. A main concern of electricity utilities was that they had sufficient infrastructure to supply loads at any particular time. They used standard customer-supply contracts and usually had no information on individual customer's load profiles through time, rather they were concerned with cumulative loads at electricity nodes. From an electrical engineering perspective residential customers were treated as homogenous for the purpose of designing distribution networks. Utilities' understanding of customers was confined to monthly or bi-monthly electric meter readings with no information on the purpose of the load nor about their customers (e.g. socio-demographic information). But there is considerable evidence that homeowner preferences for electricity service are not homogenous [e.g. 46, 45, 25].

To help electric utilities successfully implement demand side mechanisms a better understanding of electricity consumers' preferences for attributes of electricity services would be useful. First, an understanding of preferences for electricity services is beneficial. In the context of DSM mechanisms this includes knowledge of preferences for various attributes of the service, including frequency of curtailments, or opt out mechanisms, as well as a measure of the price elasticity towards the DSM mechanism. As noted, heterogeneity in preferences with respect to DSM mechanisms should be anticipated. For each of the attributes of the DSM mechanism some fraction of customers may be positively disposed towards the feature, whereas others may experience disutility from the attribute. With strongly heterogeneous preferences, the design of a DSM mechanism and the associated customer contracts becomes challenging. In addition to an understanding of the preference heterogeneity with respect to electricity services, the second piece of beneficial intelligence is being able to systematically quantify which customer characteristics are either positively or negatively associated with DSM attributes. For example, working families with young children may experience greater disutility associated with curtailment of laundry appliances compared to other electricity customers. Intelligence of this nature is beneficial for network operators in planning and forecasting demand, and for marketing DSM contracts to customers. DSM contracts that incorporate, for example, a DLC component that potentially curtails a specific appliance are only beneficial to utilities and network operators if the contract is binding on customers. If a designated appliance is rarely used during the curtailment period, e.g. the evening peak, there is no network benefit from its curtailment. Information that helps identify where real potentially curtailable loads arise will help minimise dead-weight losses associated with DSM contracts. Across these three areas there is already a growing literature. For example, Dutta and Mitra [11] provide a review of literature focused on the dynamic pricing of electricity, whereas several studies examine customer preferences for various DLC contracts including revealing the nature of preference heterogeneity [e.g. 4, 43]. There is less research on the drivers of preference heterogeneity associated with DSM electricity contracts, specifically what are the associated customer characteristics or other revealed origins of preferences. This paper contributes to that literature, exploring systematic or easily identifiable drivers of customer preferences for residential DLC curtailment contracts. We find that neither electricity customers' personal characteristics nor their environmental behaviours are associated with their preferences for electricity supply contracts. While there is strong preference heterogeneity for electricity supply service, as experienced in other empirical studies, there is relatively little insight into the drivers of preferences across customers.

The concept DLC curtailment contracts, as presented in this paper, represents a technologically feasible means of implementing demand side management to reduce load during the evening peak by utilising smart appliances and smart grid technology. Through such contracts customers cede the ability to curtail the use of their appliance(s) to their electricity provider or network operator, usually in exchange for monetary compensation. Consequently electricity providers can shift load to periods when demand is lower, hence reducing the need to increase generation activities, while customers receive financial compensation. Curtailment contracts are not technically difficult to implement but there is a need to investigate issues surrounding customer acceptance and associated behaviours [49], as these may represent barriers to successful implementation. If curtailment contracts are to become commonplace, a better understanding of the critical design features of the contracts will be required, including the needs of different customer types.

The organisation of the paper is as follows. The next section provides further background on the policy context for domestic curtailment contracts and reviews prior literature in the area. The methodology section outlines both the standard approach used to model customer preferences and then outlines the methods applied to investigate the underlying drivers of preference heterogeneity. The empirical application is based on a discrete choice survey dataset examining preferences towards DCL curtailment contracts for specific domestic appliances. Results are presented in section 4, with policy implications discussed in section 5 and conclusions in section 6 .

2. Background and Literature Review

With the overwhelming majority of the scientific community in agreement that the emission of greenhouse gases from human activities is having a destabilising effect on the global climate [6], it is becoming increasing apparent that there is a need to decouple electricity production from carbon intensive fossil fuels, and to transition towards greener renewable generation technologies, such as wind and solar. Within the

European Union there are collective and Member State targets for renewable energy generation [54]. One means available to meet these targets is the implementation of peak load demand management tools. The principal motivation for the implementation of such measures is the increased variability in generation associated with renewable power sources in comparison to traditional fossil fuel generation technologies. The integration of renewable power generation technologies into power systems presents substantial challenges to network managers seeking to balance electricity supply and demand [24]. The problem of matching supply and demand becomes especially critical during peak evening periods, where demand for power increases significantly, as individuals return home from work and education. One method of alleviating this pressure upon the network is to increase demand side flexibility, specifically as facilitated by smart devices with the ability to delay or curtail appliance use until a period when network load is lower. While such an approach presents a number of technical challenges from an engineering perspective, there are also likely to be a number of societal challenges if customers' use of appliances is to be (voluntarily) restricted and thereby requiring behavioural change.

Several studies have established that DLC related to domestic appliances, such as refrigerators and dishwashers, can be successful in the sense that customers defer sufficient load to provide network benefits. In Turkey smart scheduling of refrigerator cycles has the potential to shift 38% of fridge load out of the peak period [57], while shifting washing machine and dishwasher cycles can reduce peak loads related to these applicants by 13–24% in Latvia [30]. In a study from the United States the demand response potential among six household appliances ranked clothes dryers as having the greatest demand response potential, followed by water heaters, air conditioners, dishwashers, clothes washers and refrigerators [40]. Electric ovens were ranked as having no demand response potential, as curtailment of oven loads would significantly impact customer convenience. From a network operator perspective, demand response is seen as a means of better integrating renewables, lowering operational costs, providing higher levels of reliability, lowering emissions and providing reserve services to the network [9, 39]. From a network management perspective such an approach has clear benefits, but the implementation of such measures is dependent on customer acceptance, specifically with respect to loss of control of their appliances.

While curtailment contracts are a feature in some markets (e.g. related to air conditioning in the United States) they have not been extensively studied. The implementation of demand management measures via DLCs need to be cognisant of insights from both social psychology and behavioural economics in order to realise the potential benefits of such measures [17]. Customers have to be actively engaged in demand response activities if such initiatives are to be successful [16] and any remote load shifting regime that utilities seek to implement should be compatible with customers' lifestyles [27]. There is also the need to strike a balance between the simplicity of the customer contracts and the ability for customers to tailor such contracts to their individual needs [21]. Australian research identifies customer trust in electric utilities as an important determinant in DLC uptake [51]. A meta-analysis of domestic electricity demand response programmes finds that programme success is also associated with certain socio-spatial characteristics, including the level of urbanisation, economic growth, and in areas with renewable energy policy supports [50]. A study in the United States also finds certain socio-demographic traits associated with DLC programme acceptance [56], however, the socio-demographic traits are very broadly defined (e.g. ethnicity of while/non-white; political affiliation of republican/democrat/independent) which limits the practical usefulness of the results either for load forecasting or curtailment programme marketing purposes. A few studies have examined preferences for specific attributes of DLC contracts via discrete choice experiments. A Swedish study finds that customers place substantial value on not being controlled and require much greater compensation to restrict appliance use compared to domestic heating, though they are more accommodating in extreme situations [4]. A subsequent Swedish study confirms that high levels of compensation (i.e. higher than the marginal cost of electricity supply) are required to offset higher levels and durations of DLC curtailments [3]. In Great Britain electricity customers also require statistically significant compensation to accept remote monitoring and load control by an external provider [43], though the magnitude of compensation is relatively low compared to the Swedish studies. These studies [i.e. 4, 3, 43] reveal significant preference heterogeneity but the estimated models do not reveal the sources of heterogeneity, though in one instance via a multinomial logit model (MNL) attribute heterogeneity to differences in income, age, technology savviness and socio-economic status [43]. The current paper builds upon the standard mixed logit analysis, similar to that undertaken in [4, 3] and [43], and uses estimates from the standard model to identify whether respondent characteristics, such as socio-demographic or behavioural variables, have any explanatory power related to preference heterogeneity.

3. Methodology

The methodological approach initially follows a common approach to examining heterogeneous preferences: survey data collection via discrete choice experiment (DCE) and using a mixed logit model for data analysis. Several electricity curtailment contract studies follow this approach [e.g. 4, 3, 43]. The second stage, post model estimation, explores whether there are identifiable drivers of preference heterogeneity.

3.1. Discrete Choice Experiment

Electricity customer decisions on each attribute of curtailment contracts are not made in isolation. Customers are usually presented with a number of contract options, similar to the experience today when customers switch electricity suppliers, from which they make a choice. A DCE mimics the real-life contract selection decision and customers' decisions reflect their underlying preferences for electricity services. A DCE survey elicits preference data based on a realistic hypothetical electricity 'market'. Within the survey customers are asked to state their choice over different hypothetical alternatives, one of which is always the customer's existing, or status quo, electricity contract that has no appliance curtailment features. The survey responses allows researchers to determine the relative importance of contract attributes.

The analysis of customers' choice decisions is based on the Random Utility Model (RUM) [35]. With the RUM model a customer chooses from a number contract options comprising various contract attributes (e.g. curtailment frequency, opt outs, compensation) and selects the contract that yields the highest expected utility level. The utility that customer n derives from contract alternative j is

$$U_{nj} = \beta' X_{nj} + \epsilon_{nj} \tag{1}$$

where X_{nj} is a vector of contract attributes, β a vector of unobserved coefficients, and ϵ_{nj} is an unobserved error term. A number of approaches are commonly used to quantitatively model choice decisions and estimate the parameters of the utility function (1). The mixed logit model[1] approach allows for preference heterogeneity plus it explicitly models the panel nature of the data where within DCE surveys respondents are presented with several choice decisions. In the mixed logit model the β coefficient is assumed to vary

[1]Also referred to as random parameter logit (RPL), mixed multinomial logit (MMNL), kernel logit and hybrid logit

across customers in the population with density $f(\beta_n|\theta)$, where θ represents the true parameter of preferences. Under that assumption the utility that customer n derives from contract alternative j is

$$U_{njt} = \beta_n' X_{njt} + \epsilon_{njt} \tag{2}$$

with β_n a vector of unobserved random coefficients and t is the index for the DCE choice decision. Assuming the error term is identically and independently distributed (iid) extreme value, the conditional choice probability of contract i for customer n on choice occasion t is [22, 52]:

$$P_{njt}|\beta_n = \frac{exp(\beta_n' X_{njt})}{\sum_{j=1}^{J} exp(\beta' X_{njt})} \tag{3}$$

With β_n unobserved, the unconditional probability is the integral of $P_{njt}|\beta_n$ over all values of β_n

$$P_{njt} = \int \left(\frac{exp(\beta_n' X_{njt})}{\sum_{j=1}^{J} exp(\beta' X_{njt})}\right) f(\beta_n|\theta) d\beta_n \tag{4}$$

Equation (4) is estimated using a simulated maximum likelihood estimator based on 1,000 Halton draws, as the model cannot be evaluated analytically due to the integral operator [22, 52]. Although this paper is concerned with drivers of preference heterogeneity rather preferences estimates reported in willingness to pay/willingness to accept space, willingness to accept (WTA) estimates are reported for completeness. WTA is calculated as the negative of the quotient of the marginal utility the non-monetary contract attributes within the β_n vector and the marginal utility of money, which is the element of the β_n vector associated with the compensation attribute in the curtailment contract.

3.2. Analysis of Heterogeneity

Having estimated the mixed logit model the next stage is to examine whether there are identifiable drivers of preference heterogeneity. One approach to examine drivers of heterogeneity is the use of latent class models where the observed distribution of customer preferences is a mixture of the preferences of a finite number of groups with the drivers of heterogeneity investigated through the explanatory variables for group membership [36]. While the latent class model has parallels with the mixed logit model above, it is a separately estimated model. The approach followed here persists with the mixed logit model estimates and undertakes post-estimation analysis.

Usually estimation of mixed logit models is based on all completed DCE survey responses, allowing for any necessary data cleaning. If the survey sample is representative of the population of interest, i.e. all electricity customers, the model results can be easily extrapolated for policy purposes. However, there may be distinct sub-groups within the population of electricity customers. Those that have preferences for curtailment contracts, or aspects thereof, either positive or negative, and those that have no preferences over curtailment contracts, as presented in the DCE survey, for ideological or other reasons. A broad-based literature has developed around this issue in the environmental non-market valuation literature, which ultimately concludes that protest responses should be modelled separately from respondents that positively engage with the hypothetical market in the DCE questionnaire [28, 29, 18, 2]. Taking that approach our analysis follows two strands; respondents in the DCE that engage with curtailment contracts and respondents that do not. For our purposes we define non-engagement with curtailment contracts as customers that always select the status-quo option in the DCE survey.

The first consideration of the drivers of preference heterogeneity is modelling engagement/ non-engagement. A standard logit model is proposed to estimate the probability of non-engagement as a function of variables describing the socio-demographic and other characteristics of customers [18]. Statistically significant parameter estimates will indicate customer characteristics that are more closely associated with curtail contract engagement.

The second strand focuses on customers that engaged with the curtailment contract DCE. To undertake this analysis the mixed logit model (4) is estimated, conditional on engagement with the survey . Estimates of β_n are usually reported as both the mean and standard deviation of β_n and from which customer specific coefficient estimates of β_n for each attribute in the DCE curtailment contract are recovered. These β_n values are customer specific estimates of the marginal utility associated with each curtailment contract attribute. To help understand the potential drivers of these preference values, the β_n are regressed on customers' socio-demographic characteristics. These regression equations, of which there are six in the empirical application, could be estimated separately but the error terms across equations are likely to be correlated due to some driver of customer preferences unknown to the researcher but which has an effect on utility from all contract attributes. The seemingly unrelated regression (SUR) estimator [58], which assumes a joint distribution for the error terms from the individual equations, is used to estimate the equations. The motivation for using the SUR rather than an ordinary least squares (OLS) estimator is that there can be an efficiency gain in simultaneous estimation by combining information on different equations. The SUR model is:

$$\beta_{n_i} = z_i \gamma_i + \nu_i \qquad i = 1 \ldots 6 \tag{5}$$

with M customer observations β_{n_i} is a $M \times 1$ vector, z_i is a $M \times k_i$ matrix of explanatory variables, γ_i is a $k_i \times 1$ vector, and ν_i is a $M \times 1$ vector of errors. The dimension of k_i may vary between equations (i.e. the number of explanatory variables may differ across equations). Stacking the equations the system can be expressed as

$$\beta_n = z\gamma + \nu \tag{6}$$

The assumptions on the error term are that $\mathbf{E}[\nu_i] = 0$ and $\mathbf{E}[\nu_i \nu_j'] = \sigma_{ij} I$. The latter assumption allows errors in different equations corresponding to the same respondent electricity customer to be correlated and it is this assumption that makes the SUR estimator more efficient than OLS estimates equation by equation.[2]

3.3. Data

The dataset was collected as part of an online survey undertaken in the summer of 2018. The sample recruited for the survey was designed to be statistically representative of the Irish population in terms of age, gender, region, and employment status, as recorded by the 2016 census of population. The survey comprised four distinct sections, the first eliciting respondents' time-specific appliance use habits, the second contained the DCE component where respondents first watched an animated video describing the hypothetical curtailment contracts and afterwards faced eight separate choice tasks. The third part involved a number

[2]See [26] for more detailed exposition of the SUR model (p. 444).

of post DCE debriefing questions, and the last part collected information on respondents' background and attitudes. Two pilot studies were undertaken to establish the suitability of DCE attributes and levels, and test the other questions, tutorial video and the overall layout of the survey.

In total 1,519 respondents completed the survey, though 539 observations were dropped due to their failure to correctly answer two screening questions in the survey instrument. The screening questions were included to ensure data quality by determining whether respondents were paying adequate attention rather than arbitrarily selecting responses. Observations within the 5% fastest and and slowest survey completion times were also excluded reducing the sample by a further 108 observations. The final sample comprises 972 respondents with an average survey completion time of 15 minutes. Descriptive statistics for the full sample, and engagement/ non-engagement sub-samples are reported in Table 1

For the purposes of this study curtailment contracts are defined by a number of attributes outlined in Table 2, including four named domestic appliances to be curtailed, the maximum number of curtailments per household per month, whether there is a twelve hour advanced notice of a curtailment, and whether a household is permitted to opt out of one curtailment event per month, and finally the compensation associated with each contract in the form of a utility bill discount (UBD). These attributes were identified in pre-survey focus groups as being the most important to customers. As appliance curtailment contracts were not in operation within the Irish domestic electricity market at the time of the study, and due to the relative complexity of the experiment, an explanatory animated video was used to explain the concept of curtailment contracts, the constituent parts of the contract, and how to participate in a choice experiment. A Bayesian efficient experimental design, minimizing the Bayesian D-error, was used to generate 32 distinct choice scenarios [1, 15, 47]. Priors used in the experimental design were estimated from the pilot study (n=100). Respondents were randomly assigned one of four blocks of eight choice scenarios to avoid fatigue. Figure 1 illustrates an example choice card.

The socio-economic variables selected as the independent variables, z, in equation (3.2) include the socio-economic characteristics of respondents, namely: gender, age, income, educational attainment, employment status, location, and household size. Additional variables included in z include respondents' environmental behaviours and attitudes, as well information related to their interactions with electricity suppliers, namely, their in electricity suppliers, electricity bill payment methods, as well as, whether they switched electricity supplier in the previous three years. In the modelling analysis we examine whether any of these variables are associated with, or can be considered drivers of, customers' preferences for curtailment contract attributes. Further information on these variables is included in Table 1

4. Results

The presentation of results is divided into two parts. First, results of the mixed logit model estimates are presented, which is the standard approach to modelling preference heterogeneity in DCE surveys. The second set of results focuses on the exploration of the drivers of preference heterogeneity.

4.1. Mixed Logit Modelling Results

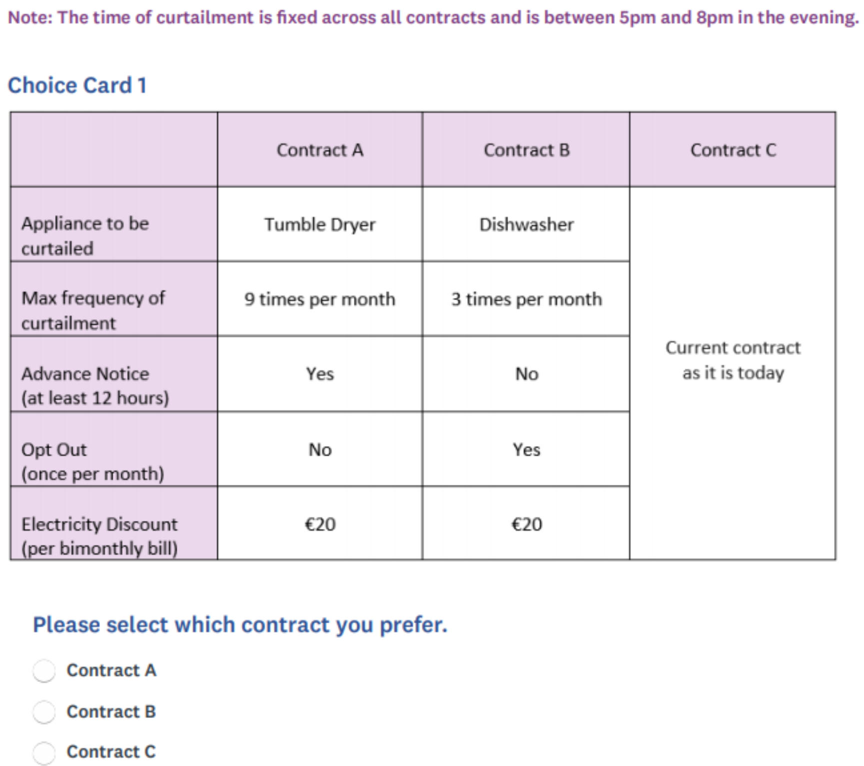
The model was estimated in Stata$^{\text{TM}}$ using the `mixlogit` command [23]. Results are presented in Table 3 both for the full sample of respondents, and for the sub-sample of 'engaged' respondents, i.e. respondents

Table 1: Descriptive statistics: full, ‘engaged’, and ‘not-engaged’ samples

		Full sample N=972		‘Engaged’ N=810		‘Not engaged’ N=162	
Variable	Min, Max	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Gender							
male	0, 1	0.459	0.499	0.506	0.502	0.449	0.498
female	0, 1	0.541	0.499	0.494	0.502	0.551	0.498
Age							
18-34	0, 1	0.265	0.442	0.241	0.429	0.27	0.444
35-54	0, 1	0.391	0.488	0.352	0.479	0.399	0.490
54+	0, 1	0.344	0.475	0.407	0.493	0.331	0.471
Monthly after-tax income							
<€2000	0, 1	0.256	0.437	0.278	0.449	0.252	0.434
€2000–€4000	0, 1	0.488	0.500	0.457	0.500	0.494	0.500
>€2000	0, 1	0.256	0.437	0.265	0.443	0.254	0.436
Education							
Up to secondary	0, 1	0.262	0.440	0.278	0.449	0.258	0.438
Tertiary	0, 1	0.354	0.479	0.364	0.483	0.352	0.478
Post-tertiary	0, 1	0.384	0.487	0.358	0.481	0.389	0.488
Employment Status							
Other	0, 1	0.419	0.494	0.519	0.501	0.399	0.490
Employed	0, 1	0.581	0.494	0.481	0.501	0.601	0.490
Household size							
One	0, 1	0.144	0.351	0.123	0.33	0.148	0.355
Two	0, 1	0.366	0.482	0.364	0.483	0.367	0.482
Three	0, 1	0.193	0.395	0.216	0.413	0.189	0.392
Four	0, 1	0.18	0.384	0.136	0.344	0.189	0.392
Five+	0, 1	0.116	0.321	0.16	0.368	0.107	0.310
Location							
rural	0, 1	0.362	0.481	0.352	0.479	0.364	0.482
urban	0, 1	0.638	0.481	0.648	0.479	0.636	0.482
Scale of environmental behaviours & attitudes							
Low	0, 1	0.373	0.484	0.346	0.477	0.379	0.485
Medium	0, 1	0.351	0.477	0.346	0.477	0.352	0.478
High	0, 1	0.276	0.447	0.309	0.463	0.269	0.444
Level of trust in current electricity supplier (likert scale 0=no trust to 10=very high trust)							
Trust	0, 10	6.949	2.232	7.15	2.395	6.908	2.198
Switched electricity supplier in past 3 years							
No	0, 1	0.588	0.492	0.679	0.468	0.570	0.495
Yes	0, 1	0.412	0.492	0.321	0.468	0.430	0.495
Payment type for electricity bill							
Cash/Card	0, 1	0.195	0.397	0.235	0.425	0.188	0.391
Bank transfer	0, 1	0.659	0.474	0.611	0.489	0.669	0.471
Prepay	0, 1	0.091	0.287	0.123	0.33	0.084	0.277
Other	0, 1	0.055	0.227	0.031	0.173	0.059	0.236
Proportion using specified appliances in evening period (5–8pm)							
Oven	0, 1	0.629	0.483	0.574	0.496	0.640	0.48
Washing machine	0, 1	0.213	0.410	0.198	0.399	0.216	0.412
Dryer	0, 1	0.177	0.382	0.148	0.356	0.183	0.387
Dishwasher	0, 1	0.303	0.460	0.241	0.429	0.316	0.465

Table 2: Discrete Choice Experiment: Curtailment Contract Attributes and levels

Attribute	Explanation	Attribute levels
Appliance	The appliance type to be curtailed during peak period	Electric oven, Tumble dryer, Washing machine, Dishwasher
Frequency	The maximum number of curtailment events per month	3, 6, 9
Opt Out	Whether the customer can opt out one curtailment event per month	Yes, No
Advance Notice	Whether the customer receives 12 hour advance notice of a curtailment	Yes, No
Compensation	Contract compensation as a utility bill discount	€10, €20, €30 per bimonthly utility bill



Note: The time of curtailment is fixed across all contracts and is between 5pm and 8pm in the evening.

Choice Card 1

	Contract A	Contract B	Contract C
Appliance to be curtailed	Tumble Dryer	Dishwasher	Current contract as it is today
Max frequency of curtailment	9 times per month	3 times per month	
Advance Notice (at least 12 hours)	Yes	No	
Opt Out (once per month)	No	Yes	
Electricity Discount (per bimonthly bill)	€20	€20	

Please select which contract you prefer.

Contract A

Contract B

Contract C

Figure 1: Sample Choice Card

that selected a least one curtailment option in the DCE, as discussed in section 3.2. The difference between the two samples is that the smaller 'engaged' sample excludes respondents that expressed no preference in favour of curtailment contracts, potentially for ideological or other reasons. The exclusion of respondents is reflected in the coefficient estimate for the alternate specific constant (ASC), which relates to the status quo option. While the estimates of the mean for the ASC are broadly similar between the two samples, the estimate of the standard deviation is less than half in the 'engaged' sample. The second notable difference between the two samples is that there are more statistically significant coefficient estimates for the 'engaged' model compared to the full sample. For example, in the case of the clothes dryer the estimate of the mean is statistically significant for the 'engaged' sample but not for the full sample. For the 'engaged' sample the estimates suggest that preferences for the Opt Out attribute are random across respondents, whereas that is not the case for the full sample. In both samples the mean coefficient for the dishwasher is not statistically different than the washing machine reference category.

In addition to utility parameters, Table 3 provides the willingness-to-accept estimates generated from both the full sample and sub sample mixed logit models. Values remain relatively consistent between the two models across most attributes. For example, customers require approximately €20 additional compensation to contract for an oven curtailment relative to a washing machine. For each unit increase in the maximum number of curtailment events per month, mean compensation sought by customers is €1 but they are willing to forgo almost €4 compensation for advance notice of curtailments and €3 for the ability to opt out of one curtailment event per month.

More extensive analysis of these mixed logit model estimates are available [20] but the primary focus of this paper is the heterogeneity of preferences, which is considered in the next section.

4.2. Analysis of Heterogeneity

The first results are a logit model of engagement/ non-engagement with curtailment contracts, which are reported in Table 4. Before discussing the model estimates it is worthwhile exploring the reasons for non-engagement. After completing the DCE questions respondents were asked about the reasons for their responses. Some 19% of non-engaged respondents do not think that curtailment contracts are realistic, a further 35% did not like the options offered, while 37% do not want to limit appliance use. Just 4% had difficulty evaluating the options. Consequently there is good reason to believe preferences for curtailment contracts as considered in the DCE among the non-engaged cohort are substantially different from engaged respondents' preferences. The logit model explores whether there are systematic identifiable characteristics associated with the engagement/ non-engagement dichotomy.

The logit model results are reported as odds ratios. A relatively minor number of explanatory variables have statistical significance in explaining engagement among customers with curtailment contracts within the DCE. Customers are 1.6 times more likely to engage with curtailment contracts if they had previously switched electricity supplier. This potentially indicates a price or cost conscious customer. Customers in gainful employment are 1.5 times more likely to engage with a curtailment contract that those not in gainful employment, while likelihood of engagement among larger sized households is lower. The highest likelihood of engagement occurs among customers who's payment method for their electricity bill is classified as 'other'. While further details on the exact circumstances of this category are not available, it comprises a relatively small proportion of customers, at 5% of the sample. Across all the other socio-demographic

Table 3: Mixed logit model estimates

	Full sample N=972		'Engaged' N=810	
	Coefficient	Std. Error.	Coefficient	Std. Error.
Compensation (UBD)	0.092***	0.005	0.09***	0.005
Random Parameters - mean				
Appliances - reference category washing machine				
Oven	-1.857***	0.142	-1.773***	0.136
Dryer	0.144	0.096	0.221**	0.094
Dishwasher	-0.065	0.087	-0.044	0.085
Curtailment frequency	-0.099***	0.013	-0.085***	0.012
Advance Notice	0.359***	0.049	0.355***	0.049
Opt Out	0.271***	0.043	0.264***	0.042
Alternative Specific Constant (ASC)	0.357*	0.193	-0.378***	0.136
Random Parameters - standard deviations				
Appliances - reference category washing machine				
Oven	2.150***	0.141	2.118***	0.148
Dryer	1.806***	0.141	1.783***	0.130
Dishwasher	1.311***	0.131	1.299***	0.119
Curtailment frequency	0.179***	0.018	0.161***	0.014
Advance Notice	0.664***	0.088	0.581***	0.089
Opt Out	0.141	0.112	0.172*	0.100
Alternative Specific Constant (ASC)	4.302***	0.244	2.086***	0.114
Willingness to Accept				
Oven	€20.11***	1.445	€19.78***	1.445
Dryer	€-1.55	1.058	€-2.46**	1.071
Dishwasher	€0.70	0.934	€0.50	0.949
Curtailment frequency	€1.07***	0.123	€0.95***	0.118
Advance Notice	€-3.88***	0.533	€-3.96***	0.548
Opt Out	€-2.93***	0.480	€-2.94***	0.479
Alternative Specific Constant (ASC)	€-3.87*	2.056	€4.22***	1.589

*** p<0.01, ** p<0.05, * p<0.1

variables, including variables describing customers' environmental behaviours and attitudes, none are statistically significant. Overall, with the exception of a few variables, socio-demographic variables are not strongly associated with engagement/ non-engagement outcome for curtailment contracts

The second set of results are from the SUR model, which was estimated using the `sureg` command within Stata™. The dependent variables in the model are the β_n coefficients associated with each of the six attributes in the DCE curtailment survey calculated for each survey respondent. The estimates are reported in Table 5. The R^2 statistic associated with each equation is between 0.02 and 0.07, so overall the models do not have much explanatory power. Using Chi-square tests, only in three of the six equations can we reject at the 5% level, a null hypothesis that the fit of an intercept-only model and the models estimated are equal. The inclusion of socio-demographic and behavioural/attitudes information as explanatory variables has not improved the fit of the model in these instances. This applies to the Opt Out and Advance Notice regressions and marginally so in the case of the Dishwasher regression.

In the case of the appliance regressions, i.e. Electric Oven, Clothes Dryer, as well as the Frequency regression, socio-demographic and behavioural/attitudes information has some explanatory power with respect to customers preferences for these attributes in curtailment contracts. Household size is the attribute most associated with customers' expressed preferences. In the case of electric oven curtailments, larger sized households experience disutility relative to single occupancy households. However, contrary to what one might expect the level of effect declines with household size with the estimated coefficients increasing in magnitude from -0.618 in case of two person household to -0.363 for four person household and a statistically insignificant coefficient even at 10% level for larger households. In the case of the other two appliances (i.e. clothes dryer and dishwasher) relative to the washing machine, estimated coefficients are positive in sign, whereas the coefficient magnitudes are broadly similar across household size relative to a single occupancy household. Relative to the washing machine, customers with larger families are more positively disposed to curtailment contracts with respect to their dishwasher or clothes dryer.

Across gender, age, income and education there is no obvious driver or association between these customer characteristics and preferences for curtailment contract attributes. In most instances the coefficient estimates for these socio-demographic variables are statistically insignificant. Where they are statistically significant it is difficult to deduce an obvious trend across curtailment attributes. There are similar results in the case of the variable capturing customers' scale of environmental behaviours. This variable represents a customer's score on how concerned they are for environmental sustainability, including in the actions they take (e.g. purchasing decisions). Our expectation was that customers with a greater concern for environmental sustainability may be more disposed to undertaking actions that increase the integration of renewable generation on the electricity network and reduce peak loads supplied by fossil fuel generation, as experienced in other fora [55]. The estimates show no support for such a hypothesis. In fact, the only coefficient estimates that are statistically significant are counter to that hypothesis, indicating that those with higher concern for environmental sustainability experience disutility from higher levels of curtailment events.

We noted earlier that customers who switched electricity supplier in the prior three years are more likely to engage with curtailment contracts. There is no evidence that such customers systematically have preferences for specific attributes of engagement contracts. Neither is there any systematic association between electricity bill payment method or trust in electricity supplier and preferences for specific attributes.

Table 4: Logit Model Results: Engagement with curtailment contracts

	Odds Ratio	Std. Error
Gender - (male)		
Female	1.124	0.208
Age (18-34)		
35-54	0.907	0.218
54+	0.660	0.176
Monthly after tax income (<€2000)		
€2000–€4000	1.109	0.255
>€2000	0.901	0.231
Education (up to secondary)		
Tertiary	0.826	0.192
Post-tertiary	0.853	0.207
Employment Status (other)		
Employed	1.491**	0.297
Household size (one person)		
Two	0.733	0.220
Three	0.562*	0.187
Four	0.780	0.285
Five+	0.398**	0.148
Location (rural)		
Urban	0.899	0.170
Scale of environmental behaviours & attitudes (low)		
Medium	0.876	0.190
High	0.740	0.166
Level of trust in current electricity supplier		
Trust	0.959	0.039
Payment type for electricity bill (cash/card)		
Bank transfer	1.179	0.267
Prepay	0.729	0.241
Other	2.976*	1.688
Switched electricity supplier in past 3 years (No)		
Yes	1.599**	0.314
Used specified appliance in evening peak period		
Oven	1.252	0.232
Washing machine	1.349	0.291
Dryer	0.823	0.201
Dishwasher	1.369	0.371
Constant	7.247***	4.131

Reference categories described in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Seemingly Unrelated Regression Model Estimates: β_n regressed on socio-demographic variables

	Electric Oven	Clothes Dryer	Dishwasher	Frequency	Advance Notice	Opt Out
Gender - (male)						
Female	-0.001	-0.086	-0.086	-0.013*	-0.027	0.003
	(0.110)	(0.094)	(0.059)	(0.007)	(0.019)	(0.003)
Age (18-34)						
35-54	-0.141	0.233**	0.046	0.038***	-0.042*	0.003
	(0.138)	(0.117)	(0.074)	(0.009)	(0.024)	(0.003)
54+	0.075	-0.017	-0.093	0.036***	-0.065**	0.001
	(0.156)	(0.133)	(0.084)	(0.010)	(0.027)	(0.004)
Monthly after tax income (<€2000)						
€2000–€4000	-0.301**	0.369***	0.048	0.008	-0.024	0.001
	(0.140)	(0.119)	(0.075)	(0.009)	(0.024)	(0.003)
>€2000	-0.167	0.317**	0.110	-0.007	-0.014	-0.002
	(0.159)	(0.134)	(0.085)	(0.010)	(0.028)	(0.004)
Education (up to secondary)						
Tertiary	-0.015	0.009	0.001	0.017*	0.023	-0.001
	(0.141)	(0.119)	(0.075)	(0.009)	(0.025)	(0.003)
Post-tertiary	0.102	-0.047	-0.006	-0.005	0.006	0.003
	(0.146)	(0.123)	(0.078)	(0.009)	(0.025)	(0.003)
Employment Status (other)						
Employed	0.105	-0.074	-0.030	0.005	-0.009	-0.004
	(0.122)	(0.103)	(0.065)	(0.008)	(0.021)	(0.003)
Household size (one person)						
Two	-0.618***	0.293**	0.234***	-0.018*	0.050*	0.002
	(0.169)	(0.144)	(0.091)	(0.011)	(0.030)	(0.004)
Three	-0.429**	0.291*	0.276***	-0.010	0.030	0.006
	(0.193)	(0.165)	(0.103)	(0.012)	(0.034)	(0.004)
Four	-0.363*	0.387**	0.223**	-0.011	0.055	0.008*
	(0.196)	(0.168)	(0.105)	(0.012)	(0.034)	(0.004)
Five+	-0.152	0.188	0.157	-0.020	0.065	0.008
	(0.227)	(0.194)	(0.122)	(0.014)	(0.040)	(0.005)
Location (rural)						
Urban	0.050	0.054	-0.086	-0.002	0.017	-0.002
	(0.115)	(0.098)	(0.061)	(0.007)	(0.020)	(0.003)
Scale of environmental behaviours & attitudes (low)						
Medium	-0.065	0.120	-0.020	-0.022***	-0.016	-0.002
	(0.127)	(0.108)	(0.068)	(0.008)	(0.022)	(0.003)
High	-0.136	-0.155	0.032	-0.025***	-0.010	0.002
	(0.137)	(0.116)	(0.073)	(0.009)	(0.024)	(0.003)
Level of trust in current electricity supplier						
Trust	-0.046*	-0.018	-0.013	0.001	0.007	-0.000
	(0.025)	(0.021)	(0.013)	(0.002)	(0.004)	(0.001)
Payment type for electricity bill (cash/card)						
Bank transfer	-0.336**	0.112	0.161**	0.004	-0.056**	0.002
	(0.145)	(0.123)	(0.077)	(0.009)	(0.025)	(0.003)
Prepay	0.031	-0.016	-0.056	0.005	-0.053	0.001
	(0.227)	(0.193)	(0.121)	(0.014)	(0.040)	(0.005)
Other	-0.437*	0.105	0.044	0.007	-0.055	0.004
	(0.260)	(0.220)	(0.139)	(0.017)	(0.045)	(0.006)
Switched electricity supplier in past 3 years (No)						
Yes	0.126	0.018	-0.087	0.007	0.016	-0.005*
	(0.115)	(0.098)	(0.062)	(0.007)	(0.020)	(0.003)
Using the specified appliance in evening period						
Oven	-0.206*					
	(0.109)					
Dryer		0.300***				
		(0.116)				
Dishwasher			0.087			
			(0.061)			
Constant	-0.599*	-0.327	-0.167	-0.098***	0.368***	0.264***
	(0.338)	(0.283)	(0.178)	(0.021)	(0.058)	(0.008)
R^2	0.059	0.050	0.041	0.071	0.028	0.025
χ^2	47.310	42.730	32.360	60.500	23.080	20.210
p-value	0.001	0.003	0.054	0.000	0.285	0.445

Standard errors in parentheses. Reference categories also described in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Discussion

The objective of the paper is to explore whether there are systematic or easily identifiable drivers of customer preferences for residential DLC curtailment contracts. Similar to prior research [i.e. 4, 3, 43], we find that there is strong preference heterogeneity with respect to electricity curtailment contracts. However, we find that neither electricity customers' personal characteristics nor their environmental behaviours are strongly associated with their preferences for attributes of such contracts. Although this might be considered a non-finding it does have implications for the electricity sector.

Electricity curtailment contracts obviously require customer consent. In some cases curtailment of residential electricity loads will have no impact on customers. For example, where loads for refrigeration (incl. freezers) and possibly battery charging are curtailed for relatively short periods of time, customers may not even be aware of the curtailment. Without being inconvenienced it is likely that gaining customer consent in these instances will be relatively easy. Where customers are inconvenienced by appliance curtailments and have to adjust their daily activities eliciting consent may be more difficult. Both this and prior research suggests that there there is appetite for appliance curtailment contracts, almost 4 in 5 customers surveyed contemplated such contracts in this study, though preferences across contract attributes is quite heterogeneous. Understanding the drivers of preference heterogeneity should help electricity suppliers to better design and market such contracts. For instance, the analysis here suggests that curtailment contracts for electric ovens would be very unpopular and would require high levels of compensation to encourage participation. What we know is that a single, or even a few, standard curtailment contracts are unlikely to be favoured by a majority of customers due to strong preference heterogeneity. What this paper additionally finds is that there are no obvious contract types in terms of attribute features that electricity suppliers can design that are likely to be more strongly favoured by particular customer cohorts. For example, a contract targetting customers in employment and with large families who might favour contracts with greater opt out flexibility for curtailment events; or a contract for customers more sensitive to higher frequency of curtailment events. In essence, from a curtailment contract marketing perspective electricity suppliers will not know in advance which customers are likely to prefer the different types of contracts it develops. Instead, customers will self-select to the contracts that best fits their preferences and lifestyle.

That there is considerable preference heterogeneity for electricity services is not surprising given the change in lifestyles, job types, and pace of living over recent decades. In hindsight, given the complexity and variability in people's lives it should not be surprising also that no obvious systematic drivers of preference heterogeneity have been isolated. Attitudes or behaviour with respect to environmental sustainability have recently been advocated as possible drivers underpinning customer choices with respect to energy, specifically space heating and energy efficiency decisions, but there has been little supporting empirical evidence including from the analysis undertaken here [31, 42, 7].

Appliance curtailment contracts may be subject to adverse selection. In the absence of fully transparent smart metering data, including appliance loads, electricity suppliers have limited information to execute contracts that will deliver system wide benefits associated with reducing peak loads. At present electricity suppliers generally know aggregate customer loads across billing periods but usually have no detailed information at finer time resolution or what appliance or other activity is associated with the load served. With that level of information asymmetry, contracts may be executed that are not constraining on customers based on their normal daily activities. Such contracts provide no benefit to the electricity supplier nor the wider electricity system. This research, which fails to isolate drivers of preference heterogeneity with respect to usual socio-demographic variables, means that at present electricity suppliers will be unable to reduce the level of information asymmetry. With the financial risk of such contracts, electricity suppliers are unlikely to offer appliance based curtailment contracts without detailed customer information on time-of-use loads. The role-out of smart metering will facilitate the introduction of curtailment contracts, though individual appliance curtailments will also necessitate suitably enabled appliances.

The transition to a low carbon future envisages households contemplating many behaviour changing decisions. For example, switching to electric vehicles or investing in energy efficiency home retrofits. Empirical studies find that such investments are more highly concentrated within certain socio-demographic profiles, especially related to income, education, and among families that own their homes [48, 32, 53, 19]. Lack of access to domestic finance, and the split incentive between tenants and landlords, among other barriers, preclude a substantial share of families from recovering the associated benefits (e.g. lower energy demand or fuel costs) of such investments [41, 8, 5, 37]. The analysis here suggests that curtailment contracts may be accessible to a broader spectrum of customers. We find little convincing evidence that any cohort of customers are likely to feel precluded from participation in curtailment contracts when they are offered by electricity suppliers. Unlike many government programmes encouraging transition to low-carbon alternatives (e.g. subsidies for electric vehicles, or home energy retrofit grants), curtailment contracts may be more equitable in their appeal.

6. Conclusions

Heterogeneity of customer preferences with respect to provision of electricity services, including curtailment contracts, has been established across several electricity markets [4, 3, 43, 20] but investigation of the drivers of preference heterogeneity has been largely absent. The current paper builds upon a DCE study of customer preferences for appliance curtailment contracts to explore whether there are systematic, identifiable drivers of customer preferences for various attributes of residential curtailment contracts. Subject to some exceptions, the broad-brush conclusions of the research are that we are unable to find association between either the usual socio-demographic characteristics (e.g. age, gender, education, income, etc.) or attitudes to environmental sustainability and preferences for various attributes of appliance curtailment contracts (e.g. appliance type, frequency, opt outs, etc.). The dearth of empirical studies exploring such preference heterogeneity in the published literature may reflect this ambiguous message on the drivers of preference heterogeneity.

There are several notable research findings nonetheless. From a representative sample of electricity consumers we find that approximately 4 in 5 people are willing to contemplate appliance curtailment contracts. It would be naive to assume that sign-up for such contracts in reality would be so high, however, a substantial majority of customers are willing to evaluate the option. That is a promising proposition for an electricity industry that may seek to deploy curtailment contracts as a policy to help reduce peak load. Of the few indicators statistically associated with engagement with curtailment contracts is whether the respondent had previously switched electricity provider. One might assert that switchers are price conscious and market savvy customers, which ultimately may be the type of customer for which a curtailment contract may be suitable. While switching practice is associated with curtailment contract engagement, there is no evidence that it is a driver of, or associated with, any of the contract attributes considered. Electricity supply switchers are not uniform with respect to preferences for contract attributes.

With asymmetric information with respect to appliance use patterns favouring the customer rather than the electricity supplier, and without a strong understanding of the nature of preference heterogeneity, it is unlikely that appliance curtailment contracts will be widely deployed in the Irish market in the immediate future. The role out of smart meters and other associated technology to enable contract enforcement plus improving information asymmetry will eventually facilitate appliance curtailment contracts. In the meantime moral hazard and adverse selection may pose too high a financial risk on electricity suppliers. In locations where appliance contracts are currently available (e.g. United States) contracts focus on air conditioning where there is a high level of ownership and usage patterns align with peak load periods. In Ireland ownership rates for dishwashers and clothes dryers are substantially lower at approximately 65% and 55% of households and little information is available on whether the loads associated with these appliances aligns with system peak loads. Hence the financial risk to electricity suppliers associated with appliance curtailment contracts in Ireland is likely to be high compared to contracts related to air conditioner use in the United States.

The lack of identifiable socio-demographic drivers associated with appliance curtailment contracts may suggest there are less participation barriers associated with appliance curtailment contracts than other policy instruments that have been used to encourage more sustainable energy use. Beyond the role out of some enabling technology, including smart meters, no substantial out-of-pocket investment is required by customers to participate in such schemes. The households that are excluded from other schemes, due to lack of access to finance for example, may be the price conscious customers that will ultimately participate in curtailment contracts.

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