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Why do preferences for electricity services differ? Domestic appliance curtailment contracts in Ireland

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ABSTRACT

Empirical evidence across several electricity markets reveals heterogeneous customer preferences for direct load control 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. The research finds that electricity customers' personal characteristics, including their environmental attitudes and behaviours, are associated with preferences for curtailment contract attributes though the scale of the relationship is more nuanced and muted than might have been anticipated. Age, family size, and environmental attitudes are the respondent characteristics with the strongest association with preferences, though the nature of the association varies substantially across attributes.

1. Introduction

The integration of renewable power generation technologies into power systems presents substantial challenges to network managers seeking to balance electricity supply and demand [1]. 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. As network operators strive to incorporate more power generation from renewable technologies onto the grid in an effort to reduce associated carbon emissions, the challenge of matching supply and demand 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 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 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 [2–4]. 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 [5]; about the longevity of price effects [4]; and also that the level of response is dependent on customer preferences [6]. 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. 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. For example, in Turkey smart scheduling of refrigerator cycles has the potential to shift 38% of fridge load out of the peak period [7], while shifting washing machine and dishwasher cycles can reduce peak loads related to these appliances by 13–24% in Latvia [8]. From a network operator perspective, demand response, of which DLC is one option, 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 [9,10]. But the implementation of such measures is dependent on customer acceptance, specifically with respect to ceding some control of their appliances to network operators.

In a US context Pipattanasomporn et al. [11] rank the demand response potential of large household appliances with clothes dryers having the greatest potential, followed by water heaters, air conditioners, dishwashers, clothes washers, refrigerators and finally electric

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ovens ranked as having no demand response potential. This appliance ranking is partially attributed to impact on customer convenience, as satisfactory customer experience is crucially important for successful role-out of DLC programmes. The operation of DLC load shifting is often imperceptible to electricity customers, especially when related to some heating and cooling appliances (e.g. freezers, refrigerators, space and water heating), though some concern has been expressed around loss of customer control [12,13]. However, DLC can also be applied to customer loads where the impact of curtailment is both easily observable by homeowners and potentially inconveniences their daily routines. For example, the curtailment of appliances such as ovens, dishwashers, washing machines and tumble dryers at times when homeowners wish to use these appliances directly disrupts their activities. Srivastava et al. [14] suggest that for programmes to be successful they should target small shifts in behaviour, avoiding the excess changes that might result in user inconvenience. It is because of this disruption that Pipattanasomporn et al. [11] conclude that ovens should not be curtailed.

To help electric utilities successfully implement DLC programmes, or demand side mechanisms in general, a better understanding of electricity consumers' preferences for electricity services is needed. For instance, 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 DLC mechanism, is important to effectively design a DLC programme. There is evidence that homeowner preferences for electricity services are not homogenous [15–17], which will also be reflected in preferences for DLC programmes. For each of the attributes of a DLC programme, some fraction of customers may be positively disposed towards the feature, whereas others may experience disutility. With strongly heterogeneous preferences, the design of a DLC mechanism with an associated one one-size-fits-all customer contract becomes challenging. While curtailment contracts are already a feature in some markets (e.g. related to air conditioning in the United States) they have not been extensively studied. The implementation of DLCs need to be cognisant of insights from both social psychology and behavioural economics in order to realise the potential benefits of such measures [18,19]. Customers have to be actively engaged if such initiatives are to be successful [20] and any remote load shifting regime that utilities seek to implement should be compatible with customers' lifestyles [21]. There is also the need to strike a balance between the simplicity of customer contracts and the ability for customers to tailor such contracts to their individual needs [22]. Australian research identifies customer trust in electric utilities as an important determinant in DLC uptake [23]. 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 [24]. A study in the United States also finds certain socio-demographic traits associated with DLC programme acceptance [25], 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. Swedish customers place substantial value on not being controlled and require much greater compensation to restrict appliance use relative to a domestic heating baseline [26]. 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 [27]. There are similar results from Finland too, with annual mean compensation of €199 required to accept electricity load curtailments during the evening peak period [28]. In Great Britain electricity customers also require statistically significant compensation to accept remote monitoring and load control by an external provider [29], though the magnitude of compensation is relatively low compared to the Finnish and Swedish studies. These studies [i.e. 26–29] reveal significant preference heterogeneity but say little on the sources of preference heterogeneity, though Richter and Pollitt [29] and Ruokamo et al. [28] attribute it to differences in income, age, education, technology savviness or socio-economic status. Based on the wider demand side management literature we know that affluence and social class are associated with public perception and acceptance of demand side management measures but a wide range of socio-demographic variables can impact positively or negatively on preferences including education level, family size, urban/rural location, as well as variables describing knowledge or concern for climate and environmental problems [5,14,30–33].

Understanding the drivers of preference heterogeneity and being able to systematically quantify which customer characteristics are either positively or negatively associated with DLC attributes is beneficial for the electricity market. For example, working families with young children may experience greater disutility associated with curtailment of laundry appliances compared to other electricity customers. Knowledge of this nature is beneficial for network operators in planning and forecasting demand, as well as for marketing DLC contracts to customers. Electricity contracts that include a DLC component are only beneficial to utilities and network operators if the contract is binding on customers (i.e. curtails use of a specific appliance that in absence of a DLC contract would be used). Information that helps identify where real potentially curtailable loads arise will help minimise dead-weight losses associated with DLC contracts. There is a growing literature examining customers preferences for electricity services, particularly surrounding dynamic pricing, with Dutta and Mitra [34] providing a literature review. Studies specifically examining customer preferences for DLC contracts have focused on issues such as customer privacy, and the control of electrical devices/heating (i.e. manual or automatic) [26,28,29]. The current research extends the examination of these issues providing greater insight on frequency of curtailment, advance notice and opportunities for curtailment opt-outs within contracts. But the focus of this research surrounds the drivers of preference heterogeneity associated with DLC electricity contracts, specifically what are the associated customer characteristics or other revealed origins of preferences. The current paper builds upon the standard random parameters logit methodology, similar to that undertaken in Broberg and Persson [26], Broberg et al. [27], Ruokamo et al. [28] and Richter and Pollitt [29], and uses estimates from the standard model to identify whether there are systematic or easily identifiable drivers, such as socio-demographic or behavioural variables, that have explanatory power related to preference heterogeneity for DLC contracts. A recent paper by Daniel [35] follows a similar approach.

The organisation of the paper is as follows. The next 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 in Ireland. Results are presented in Section 3, with policy implications discussed in Section 4 and conclusions in Section 5.

2. Methodology

The methods employed initially follows a common approach for examining heterogeneous preferences: survey data collection via discrete choice experiment (DCE) and using a random parameters logit model for data analysis. Several electricity curtailment contract studies follow this approach [i.e. 26–29]. The second stage, post model estimation, explores whether there are identifiable drivers of preference heterogeneity.

2.1. 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 real-life contract selection 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 allow researchers to determine the relative importance of contract attributes.

The analysis of customers' choice decisions is based on Lancaster's attribute theory [36], for which an individual's utility obtained by a certain good is the sum of the good's characteristics, and the Random Utility Model (RUM) [37]. With the RUM model a customer chooses from a number of 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). In particular, the random parameter logit (RPL) 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 RPL model the β coefficient is assumed to vary 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 [38,39]:

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

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

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

Eq. (4) is estimated using a simulated maximum likelihood estimator based on 1000 Halton draws, as the model cannot be evaluated analytically due to the integral operator [38,39]. The choice of the distributional form for θ is discretionary, though the most common alternative is to assume a normal distribution for non-monetary parameters and a fixed or log-normally distributed monetary coefficient. In this paper, we use normally-distributed non-monetary attributes and a fixed monetary attribute. The advantage of estimating a continuous probability distribution for the attributes is the possibility to retrieve individual-level parameters with the methodology proposed by Train [39]. When the RPL likelihood is simulated with R random draws, the expected value of a parameter $\hat{\beta}_n$ for an individual is computed using the RPL probabilities P_{njt} as follows:

$$\hat{\beta}_n = \frac{\sum_r P_{njt} \beta_r}{\sum_r P_{njt}} \tag{5}$$

for $r = 1, \ldots, R$. Together with individual parameters, the average Willingness to Accept (WTA) a curtailment contract attribute is shown for completeness. WTA is calculated as the negative of the quotient of the marginal utility of 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. The model is estimated in Stata™ using the mixlogit command [40] for main models and mixlbeta for Train's procedure to retrieve individual-level parameters.

2.2. Analysis of heterogeneity

Usually estimation of random parameters 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 subgroups within the population of electricity customers. First, those that have preferences for curtailment contracts, or aspects thereof, either positive or negative. Second, one or more groups of respondents that may have no preferences over curtailment contracts, as presented in the DCE survey, or have preferences that are substantially different for ideological or other reasons. A broad-based literature has developed around this issue in the environmental non-market valuation field, which ultimately concludes that what are often called protest responses should be modelled separately from respondents that positively engage with the hypothetical market in the DCE questionnaire [41–44]. 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. We are not assuming that non-engagement is necessarily a protest response, simply that respondents are not favourably disposed to any choices they faced (relative to the status quo) and consequently that their preferences for curtailment contracts are substantially different than other respondents. From a practical perspective, in the advent of a DLC programme being deployed in the market, engaged respondents are more likely to represent homeowners that would participate in such contracts and therefore a better understanding of the nature of their preferences is useful for the design of DLC contracts. A better understanding of the likelihood of non-engagement is also useful, potentially providing insight to electricity companies on customer cohorts that might participate in load shifting or curtailment initiatives.

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 engagement as a function of variables describing the socio-demographic and other characteristics of customers [43]. Statistically significant parameter estimates will indicate customer characteristics that are more closely associated with curtailment contract engagement.

The second strand focuses on customers that engaged with the curtailment contract DCE. To undertake this analysis the random parameters logit model (4) is estimated, conditional on engagement with the survey. Estimates of 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. β_n values are not known with certainty, they are the means of the underlying individual-specific distributions, and their inclusion as the dependent variable in a regression disregards this. Associated estimates of the standard errors are consistent though not necessarily efficient, so caution is required in interpreting the results [45]. Despite this limitation, this two-stage approach has been implemented widely to exploit the full distribution of respondents' marginal utility across the sample and gain insights on observable heterogeneity in preferences [39,46–51]. In several instances this approach reveals the impact of socio-demographic factors on preferences that are not evident in the primary preference model [48,49,51]. The common alternative to this two-stage approach is the inclusion of interaction effects in the choice model, which allows exploration of the sources of observed heterogeneity. However, in the current application exploring the effect of multiple determinants would entail estimation of a substantially higher number of parameters, which is not practically feasible.

The regression equations with β_n as dependent variable, 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 unknown driver of customer preferences. The seemingly unrelated regression (SUR) estimator [52], 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 estimator, rather than ordinary least squares (OLS), is that there can be an efficiency gain in simultaneous estimation by combining information on different equations. The SUR model is:

$$\beta_{ni} = z_i \gamma_i + \nu_i \quad i = 1 \ldots 6 \tag{6}$$

with M customer observations β_{ni} 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

$$\beta_n = z\gamma + \nu \tag{7}$$

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.[1]

2.3. Data

Data collection for the analysis was via online survey with a sample drawn from the panel book of a professional survey company. The sample was stratified by geographic location (NUTS III region), gender, age and employment status to match the 2016 Irish Census of Population returns for adults aged 18 and over. The survey was administered in the summer of 2018. Panel members were paid for their participation subject to completion of the survey, which is the standard operating model of the survey company for surveys based on its panel. As financial compensation is associated with survey completion there is an additional risk compared to conventional surveys that respondents will not provide earnest responses and rather focus on quickly completing the survey. To address this concern two screening questions were included in the questionnaire to ensure respondents were paying adequate attention to the survey questions. The survey company did not pay respondents that failed to correctly answer the screening questions. In total 1519 respondents completed the survey, of which 439 observations were excluded due to their failure to correctly answer the two screening questions.

The survey questionnaire comprised four sections, the first eliciting respondents' time-specific appliance use habits, the second contained the DCE component where respondents first viewed a 4-min animated video describing the hypothetical curtailment contracts. The third part involved a number 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. The length of time respondents spent completing the survey is also a reflection of the attention given to the questions and providing trustful answers. The minimum time necessary to read through the entire questionnaire, including viewing the explanatory video, for a respondent with high reading/literacy skills is 10–12 min. Respondents with a survey completion time less than 10 min, which totalled 229 people, were excluded from this analysis for the reason that insufficient attention was given to the task. Excessively long completion times are also problematic. The longest completion time exceeded 7 days, which suggests in that instance the survey was likely completed across multiple days. To competently complete the DCE component of the survey, recollection of the contextual explanations is necessary. Accordingly we excluded observations where completion time exceeded 60 min. The final sample comprises 812 respondents with an median survey completion time of 15 min and a mean of 17.3 min.

Descriptive statistics for the full sample, and engagement/ non-engagement sub-samples are reported in Table 1. The majority of the variables used in the modelling are self explanatory but a couple merit further discussion. The scale of environmental behaviours variable was constructed from a question that asked the respondent whether they agreed with five statements with the responses recorded using a 5-point Likert scale ranging from strongly agree (1) to strongly disagree (5).[2] The categorisation into 'low', 'medium', and 'high' groups was completed by summing assigned values and using two quantile cut points to create, as practically feasible, equal-sized groups. For the variable on the level of trust in electricity supplier, respondents were asked "on a scale between 0 (indicating no trust at all) and 10 (very high trust), how much do you trust your current supplier to respect the rules and regulations protecting consumers?" Respondents were asked to indicate which domestic appliances they possess in their homes from a pre-specified list (i.e. electric oven, dishwasher, etc.) and for each appliance they possess they were asked when it is mostly used, with four possible responses: morning, afternoon, evening, and night. This latter question was used to construct the final variable in Table 1. In the modelling analysis we use this variable rather than appliance ownership because use of an appliance rather than ownership is relevant for load shifting.

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. These attributes were identified in pre-survey focus groups as being the most important to customers. Respondents also had the possibility to choose the status quo alternative, which was defined as the contract as it is today with no discount. 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 the choice experiment. A Bayesian efficient experimental design, minimizing the Bayesian D-error, was used to generate 32 distinct choice scenarios [54–56]. Unlike orthogonal designs, so-called

[1] See Judge et al. [53, pg. 444] for more detailed exposition of the SUR model.

[2] The five statements are: (1) It is important to me that the products I use do not harm the environment; (2) I consider the potential environmental impact of my actions when making many of my decisions; (3) My purchase habits are affected by my concern for our environment; (4) I am concerned about wasting the resources of our planet; and (5) I would describe myself as environmentally responsible.

Table 1
Descriptive statistics: full, 'engaged', and 'not-engaged' samples.

	Full sample N = 812		'Not engaged' N = 111		'Engaged' N = 701	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Gender						
male	0.468	0.499	0.514	0.502	0.461	0.499
female	0.532	0.499	0.486	0.502	0.539	0.499
Age						
18–34	0.244	0.430	0.225	0.420	0.247	0.431
35–54	0.385	0.487	0.324	0.470	0.395	0.489
54+	0.371	0.483	0.450	0.500	0.358	0.480
Monthly after-tax income						
< €2000	0.265	0.441	0.279	0.451	0.262	0.440
€2000–€4000	0.484	0.500	0.477	0.502	0.485	0.500
> €4000	0.251	0.434	0.243	0.431	0.252	0.435
Education						
Up to secondary	0.259	0.438	0.297	0.459	0.253	0.435
Tertiary	0.364	0.481	0.351	0.480	0.366	0.482
Post-tertiary	0.377	0.485	0.351	0.480	0.381	0.486
Employment Status						
Other	0.438	0.496	0.568	0.498	0.418	0.494
Employed	0.562	0.496	0.432	0.498	0.582	0.494
Family size						
One	0.142	0.349	0.090	0.288	0.150	0.357
Two	0.383	0.486	0.387	0.489	0.382	0.486
Three	0.193	0.395	0.225	0.420	0.188	0.391
Four	0.169	0.375	0.144	0.353	0.173	0.378
Five+	0.113	0.317	0.153	0.362	0.107	0.309
Location						
rural	0.371	0.483	0.378	0.487	0.369	0.483
urban	0.629	0.483	0.622	0.487	0.631	0.483
Scale of environmental behaviours & attitudes						
High	0.382	0.486	0.396	0.491	0.379	0.486
Medium	0.362	0.481	0.360	0.482	0.362	0.481
Low	0.256	0.437	0.243	0.431	0.258	0.438
Level of trust in current electricity supplier (likert scale 0 = no trust to 10 = very high trust)						
Trust	7.02	2.215	7.364	2.286	6.965	2.201
Switched electricity supplier in past 3 years						
No	0.592	0.492	0.694	0.463	0.576	0.494
Yes	0.408	0.492	0.306	0.463	0.424	0.494
Payment type for electricity bill						
Cash/Card	0.191	0.393	0.243	0.431	0.183	0.387
Bank transfer	0.670	0.471	0.604	0.491	0.680	0.467
Prepay	0.086	0.281	0.117	0.323	0.081	0.274
Other	0.053	0.224	0.036	0.187	0.056	0.229
Proportion using specified appliances in evening period						
Oven	0.619	0.486	0.559	0.499	0.629	0.483
Washing machine	0.191	0.393	0.198	0.400	0.190	0.392
Dryer	0.164	0.370	0.144	0.353	0.167	0.373
Dishwasher	0.294	0.456	0.243	0.431	0.302	0.460

All variables, with exception of trust variable, are binary dummies.

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 h advance notice of a curtailment	Yes, No
Compensation	Contract compensation as a utility bill discount	€10, €20, €30 per bimonthly utility bill

efficient designs are able to produce more efficient data in the sense that more reliable parameter estimates can be achieved for a given sample size [57]. Priors used in the experimental design were estimated from the pilot study (n = 100). The full set of 32 choice cards were divided into 4 blocks of 8 cards, so that each respondent faced only 8 choice scenarios to avoid fatigue. Fig. 1 illustrates an example choice card.

The socio-economic variables selected as the independent variables, z, in Eq. (7) include the socio-economic characteristics of respondents, namely: gender, age, income, educational attainment, employment status, location, and family size. Additional variables in z comprise respondents' environmental behaviours and attitudes, a variable measuring trust 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.

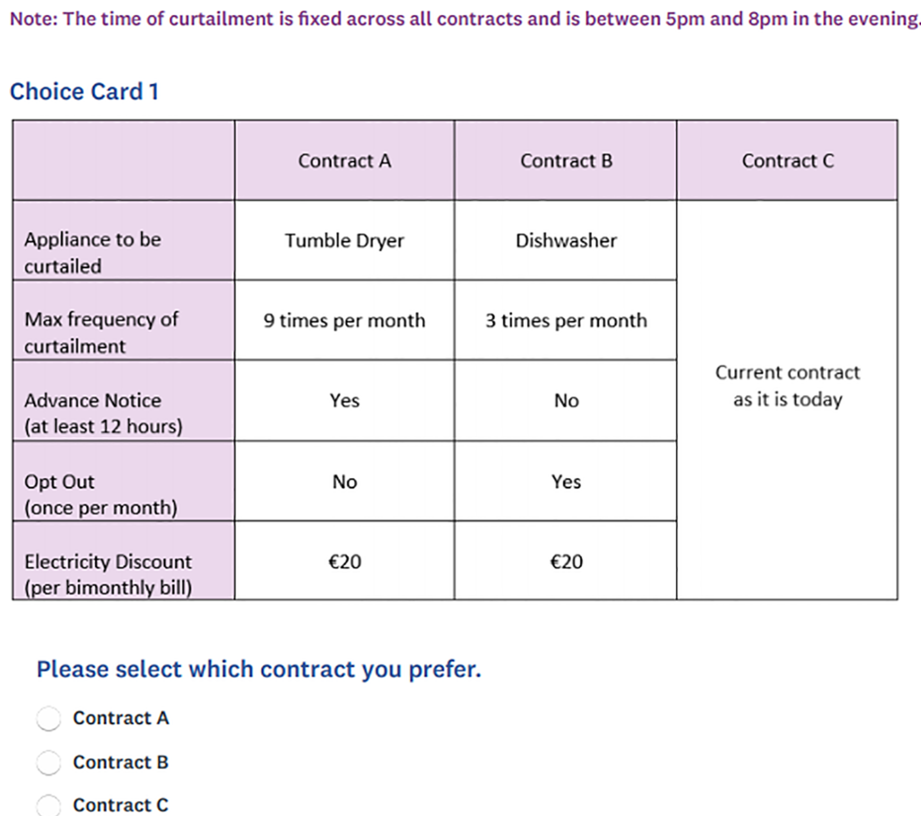
3. Results

The presentation of results is divided into two parts. First, results of the random parameters 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.

3.1. Random parameters logit modelling results

Results are presented in Table 3 both for the full sample of respondents, and for the sub-sample of 'engaged' respondents, i.e. respondents that selected a least one curtailment option in the DCE, as discussed in Section 2.2. 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. Our preferred model relates to the smaller sample of engaged respondents but we include estimates based on both samples, a comparison of which helps justify our choice of preferred model. The first point to note is that the exclusion of non-engaged respondents from the model estimation, who in every instance selected the status quo option, results in a substantial change in the coefficient estimates for the alternate specific constant (ASC), which relates to the status quo option. The mean for the ASC estimate changes sign between the two samples, from 0.149 to −0.440. The change to a negative sign indicates that, on average, the narrower sample see curtailment contracts as preferable to the existing standard residential contract. Using the coefficient of variation (CV), which is a standardized measure of dispersion, as an indicator of preference heterogeneity, a second notable difference between the two samples is evident.[3] The CV values for all attributes, with the exception of dishwasher, decline and in some instances quite substantially when moving from the larger to smaller sample. For example, in the case of clothes dryer curtailment contracts, the CV falls from 52.3 to 20.0. This indicates that when non-engaged respondents are excluded from model estimation, heterogeneity in preferences is drastically reduced. In the case of the ASC parameter, the CV value declines from 26.7 to 4.7. Our contention is that the non-

[3] CV is calculated as the absolute value of the ratio between the standard deviation and the mean of random parameters.



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

Fig. 1. Sample choice card.

engaged, who are a small share of respondents at 14% of the total sample (111/812), have a disproportionate effect in terms of heterogeneity of preferences, or that their preferences over curtailment contracts are substantially different from those of engaged respondents and should be considered separately. In the smaller sample where only engaged respondents are considered, CV values are almost all larger than 1, therefore, overdispersion or heterogeneity still matters and should be further explored.

Other coefficients maintain the same sign between samples and only their magnitude and significance level differ. The coefficients associated with oven and dishwasher curtailments have negative signs, which indicate that the utility is lower compared to washing machine

Table 3
Random parameters logit model estimates.

	Full Sample: N = 812				'Engaged' Sample: N = 701			
	Mean	Standard Deviation	Coefficient of variation	WTA	Mean	Standard Deviation	Coefficient of variation	WTA
Compensation	0.102***				0.099***			
	(0.005)				(0.004)			
Oven	−2.037***	2.263***	1.11	€19.95***	−1.935***	2.127***	1.10	€19.59***
	(0.146)	(0.167)		(1.48)	(0.137)	(0.153)		(1.38)
Dryer	0.037	1.935***	52.30	€−0.35	0.094	1.880***	20.00	€−0.95
	(0.103)	(0.143)		(1.01)	(0.102)	(0.130)		(1.03)
Dishwasher	−0.231**	1.348***	5.84	€2.26	−0.163*	1.338***	8.21	€1.65*
	(0.091)	(0.128)		(0.88)	(0.089)	(0.121)		(0.89)
Curtailment frequency	−0.106***	0.213***	2.01	€1.04***	−0.091***	0.183***	2.01	€0.92***
	(0.014)	(0.018)		(0.12)	(0.012)	(0.015)		(0.11)
Advance Notice	0.439***	0.727***	1.66	€−4.29***	0.429***	0.634***	1.48	€−4.34***
	(0.057)	(0.088)		(0.55)	(0.054)	(0.088)		(0.53)
Opt Out	0.252***	0.178	0.71	€−2.47***	0.242***	0.089	0.37	€−2.45***
	(0.048)	(0.207)		(0.48)	(0.047)	(0.185)		(0.47)
ASC	0.149	3.981***	26.72	€−1.45*	−0.440***	2.093***	4.76	€4.45***
	(0.204)	(0.212)		(1.98)	(0.151)	(0.141)		(1.59)
AIC		9877.963				9210.686		
BIC		9996.126				9326.645		
Observations		6496				5608		
Respondents		812				701		
AIC/N		1.52				1.42		
BIC/N		1.54				1.44		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

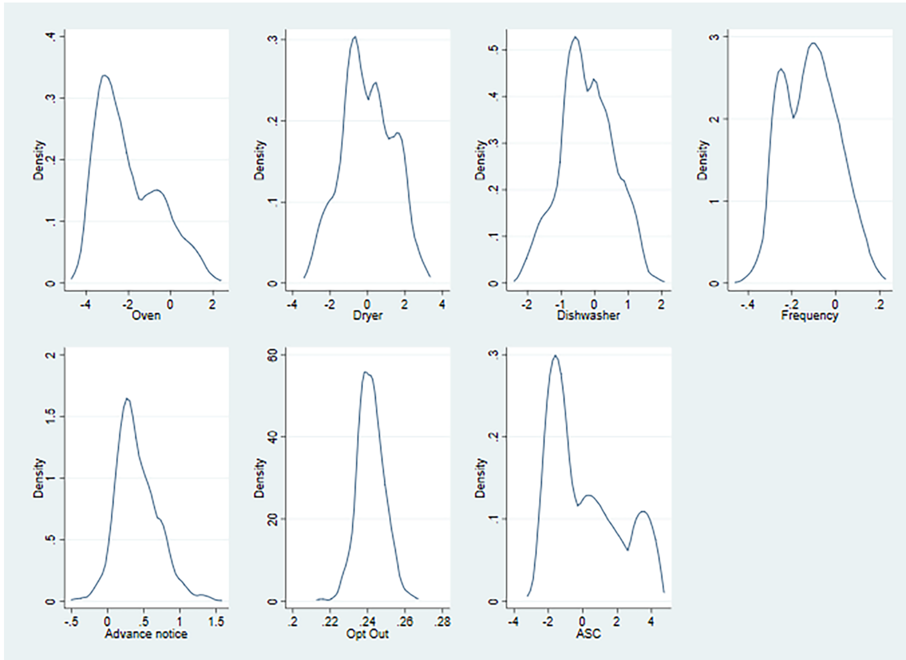


Fig. 2. Kernel densities of DCE individual-level attributes.

curtailments. The utility from the curtailment of dryers is higher compared to the utility from the curtailment of washing machines. The coefficient on the frequency of curtailment is negative, which indicates that utility decreases as the number of curtailments increase. Interestingly, the opt out coefficient is positive and significant, whereas the variance of the coefficient is not significant, which indicates lack of preference heterogeneity.

The distribution of individual level coefficients is illustrated in Fig. 2, which gives a visual representation of the dispersion of parameters due to heterogeneous preferences. All appliance attributes and curtailment frequency show a heterogeneous distribution. The variance for the opt out attribute was not significant and this is reflected in the distribution across the sample, which shows the density of parameters concentrated around the mean.

In addition to utility parameters, Table 3 provides the willingness-to-accept estimates generated from both the full sample and subsample random parameters 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 €2.50 for the ability to opt out of one curtailment event per month. While the differences are relatively small in magnitude in this instance (except for clothes dryer and dishwasher attributes, which are not significantly different than zero), when extrapolated to a DLC programme across possibly millions of households could result in substantial additional costs on a monthly basis.

More extensive analysis of these random parameters logit model estimates are available [58] but the primary focus of this paper is the heterogeneity of preferences, which is considered in the next section.

3.2. 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 21% of non-engaged respondents do not think that curtailment contracts are realistic, a further 31% did not like the options offered, while 40% do not want to limit appliance use. Just 5% had difficulty evaluating the options. This suggests that there is potentially 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. Other reasons for non-engagement could relate to the presence of a pre-pay electricity meter, which might not be compatible with a curtailment contract. However, 81% of respondents with pre-pay accounts engaged with the DCE questions. The logit model further explores whether there are systematic identifiable characteristics associated with the engagement/ non-engagement dichotomy with the estimates reported in Table 4. In general there are not many identifiable socio-demographic characteristics closely associated with whether households engage with curtailment contracts, which is reflected in the overall fit of the model. While the Count R^2 is nominally high at 0.86, McFadden's R^2 is relatively low at 0.05 and the likelihood ratio test for the fitted model, at $\chi^2_{24} = 34.76$, has a p-value of just 0.072. Nonetheless, we briefly describe the logit model's specific estimates next.

The logit model results are reported as odds ratios. A relatively small number of explanatory variables have statistical significance in explaining engagement among customers with curtailment contracts within the DCE. The likelihood of engagement among larger families is between one-third to one-half that of single person families. Across all the other socio-demographic variables, including variables describing customers' environmental behaviours and attitudes, none are statistically significant at the 5% level or higher. Overall, with the exception of family size, socio-demographic variables are not strongly associated with engagement/ non-engagement outcome for curtailment contracts. What these results show is that there is not strong evidence that we can easily categorise non-engaged respondents using the usual socio-demographic variables, which is an important result in itself, the policy implications of which are discussed later.

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

Table 4
Logit model results: engagement with curtailment contracts.

	Odds Ratio	Std. Error	p-value†
Gender – (male)			
Female	1.132	0.251	0.60
Age (18–34)			
35–54	1.01	0.297	0.97
54 +	0.671	0.218	0.13
Monthly after tax income (< €2000)			
€2000–€4000	1.044	0.283	0.88
> €4000	1.043	0.322	0.90
Education (up to secondary)			
Tertiary	1.001	0.272	1.00
Post-tertiary	0.954	0.27	0.87
Employment Status (other)			
Employed	1.653*	0.39	0.09
Household size (one person)			
Two	0.538**	0.21	0.03
Three	0.4***	0.169	0.00
Four	0.486**	0.224	0.02
Five +	0.295***	0.141	0.00
Location (rural)			
Urban	0.969	0.216	0.89
Scale of environmental behaviours & attitudes (high)			
Medium	0.998	0.251	0.99
Low	1.086	0.3	0.78
Level of trust in current electricity supplier			
Trust	0.928	0.047	0.12
Payment type for electricity bill (cash/card)			
Bank transfer	1.269	0.339	0.43
Prepay	0.83	0.326	0.60
Other	2.544	1.669	0.36
Switched electricity supplier in past 3 years (No)			
Yes	1.679*	0.4	0.09
Proportion using specified appliances in evening period			
Oven	1.225	0.27	0.40
Washing machine	1.377	0.348	0.28
Dryer	0.663*	0.194	0.08
Dishwasher	1.362	0.444	0.42
Constant	10.507	7.395	0.20

† p-value is from a z-test that the estimated odds ratio equals 1.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. McFadden's $R^2 = 0.054$; $\chi^2_{24} = 34.76$; Log-likelihood $= -302.79$.
Reference categories described in parentheses.

associated with each equation is between 0.02 and 0.08, so overall the models do not have much explanatory power. Using Chi-square tests, only in two 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. The R^2 statistics, while relatively low, contrast favourably to those from a broadly similar SUR model on Swedish DCE data for electricity curtailment contracts with maximum reported R^2 statistics of 0.03 [35].

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 have some explanatory power with respect to customers preferences for these attributes in curtailment contracts. At 1% significance, respondents aged 35 and older are more likely to accept more frequent curtailments compared to 18–34 year-olds. Only in the case of oven and clothes dryer curtailments is income significantly associated with differences in preferences across households. In the case of oven curtailments, relative to a washing machine reference category, respondents with a disposable monthly income in the medium or high income brackets are less likely to accept oven curtailment compared to the lower income class, but the coefficient of the medium income class is twice in absolute value compared to the high income class. With respect to dryer curtailments, the positive coefficients associated with income classes indicate that respondents on higher incomes are, on average, willing to accept contracts with dryer curtailments relative to both washing machine curtailments and lower income households.

Family size is the attribute most associated with differing preferences across respondents. The most clear-cut result is that families with more than one person have greater utility from the opt out attribute relative to single person families. In the case of curtailment frequency or advance notice there is practically no difference in preferences associated with family size. For the other contract attributes, when there is an effect of family size, this effect appears non-linear in the number of family members. Given that only some coefficients are significant, as well as the relative magnitude of the coefficients, it not clear overall if larger families value attributes more or less compared to smaller families.

Only in one of the six SUR equations are environmental attitudes associated with differing preferences for curtailment contracts, that related to curtailment frequency. The environmental attitudes reference category is the roughly one-third of respondents expressing the highest pro-environmental attitudes, as described earlier in Section 2. These respondents are associated with preferences for highest frequency of curtailments, with respondents scoring medium or low on the environmental attitudes questions associated with preferences for lower frequency of curtailments. This finding is as one would anticipate; more environmentally-conscious people are possibly more aware of energy and emissions benefits of peak load curtailments and therefore positively disposed to a higher frequency of curtailments. Across the other curtailment contract attributes, i.e. appliance type, opt-out, etc., differences in environmental attitudes are not associated with differing preferences across curtailment contract attributes. We noted earlier that customers who switched electricity supplier in the prior three years are more likely to engage with curtailment contracts but there is no evidence that such customers systematically have preferences for specific attributes of curtailment contracts. Neither is there any systematic association between electricity bill payment method or trust in electricity supplier and preferences for specific attributes.

The final explanatory variables in the SUR regression are dummy variables indicating whether respondents use the associated appliances during the evening peak load period. One would anticipate that respondents using these appliances in this curtailment period would be less in favour of curtailment contracts compared to respondents that do not use the appliances during this time. The estimates in Table 5 suggest that is the case for electric ovens but not for dishwashers (or clothes dryers at 10% significance level).

4. 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. 26–29], we find that there is strong preference heterogeneity with respect to electricity curtailment contracts. 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. We also find that electricity customers' personal characteristics, including their environmental attitudes and behaviours, are associated with preferences for curtailment contract attributes. Given the complexity and variability in people's lives this finding in not unanticipated but what is unexpected is that the scale of association is more muted than one might have anticipated. For instance, within the SUR regression there are just 16 parameter estimates that are statistically significant at the 5% level or better from a total of 123 parameters, excluding constant terms. This finding of muted association with socio-demographic variables is consistent with quite similar Swedish research [35], though the curtailment

Table 5
Seemingly unrelated regression model estimates: β_n regressed on socio-demographic variables.

	Electric Oven	Clothes Dryer	Dishwasher	Frequency	Advance Notice	Opt Out
Female	−0.032	−0.008	−0.107*	−0.014	−0.009	0.000
	(0.119)	(0.107)	(0.064)	(0.009)	(0.023)	(0.001)
Age (18–34)						
35–54	−0.140	0.175	0.011	0.055***	−0.030	0.001
	(0.151)	(0.136)	(0.081)	(0.011)	(0.029)	(0.001)
54+	0.068	−0.087	−0.171*	0.046***	−0.061*	0.001
	(0.172)	(0.155)	(0.093)	(0.013)	(0.034)	(0.001)
Monthly after tax income (< €2000)						
€2000–€4000	−0.456***	0.521***	0.124	0.010	−0.015	0.001
	(0.150)	(0.135)	(0.080)	(0.011)	(0.029)	(0.001)
> €4000	−0.286*	0.368**	0.106	−0.005	−0.024	0.000
	(0.170)	(0.152)	(0.091)	(0.013)	(0.033)	(0.001)
Education (up to secondary)						
Tertiary	0.004	−0.052	−0.031	0.014	0.020	−0.001
	(0.152)	(0.136)	(0.081)	(0.011)	(0.030)	(0.001)
Post-tertiary	0.189	−0.156	−0.085	−0.010	−0.002	−0.000
	(0.158)	(0.142)	(0.084)	(0.012)	(0.031)	(0.001)
Employment Status (other)						
Employed	0.133	−0.147	−0.052	−0.002	−0.014	0.000
	(0.130)	(0.117)	(0.070)	(0.010)	(0.025)	(0.001)
Family size (one person)						
Two	−0.402**	0.238	0.173*	−0.018	0.060*	0.002*
	(0.182)	(0.164)	(0.098)	(0.014)	(0.035)	(0.001)
Three	−0.124	0.228	0.277**	−0.006	0.052	0.002**
	(0.208)	(0.189)	(0.112)	(0.016)	(0.041)	(0.001)
Four	−0.247	0.482**	0.122	−0.009	0.065	0.002**
	(0.215)	(0.195)	(0.116)	(0.016)	(0.042)	(0.001)
Five+	−0.072	0.089	0.060	−0.019	0.073	0.002*
	(0.245)	(0.223)	(0.132)	(0.018)	(0.048)	(0.001)
Location (rural)						
Urban	−0.006	0.016	−0.065	−0.004	0.004	0.000
	(0.124)	(0.111)	(0.066)	(0.009)	(0.024)	(0.001)
Scale of environmental behaviours & attitudes (high)						
Medium	0.032	0.158	−0.021	−0.028***	0.006	−0.000
	(0.137)	(0.123)	(0.073)	(0.010)	(0.027)	(0.001)
Low	−0.055	−0.178	−0.001	−0.026**	−0.007	0.001
	(0.149)	(0.134)	(0.080)	(0.011)	(0.029)	(0.001)
Level of trust in current electricity supplier						
Trust	−0.044	−0.030	−0.009	0.001	0.007	−0.000
	(0.027)	(0.024)	(0.014)	(0.002)	(0.005)	(0.000)
Payment type for electricity bill (cash/card)						
Bank transfer	−0.294*	0.061	0.167**	0.001	−0.055*	0.000
	(0.158)	(0.142)	(0.085)	(0.012)	(0.031)	(0.001)
Prepay	0.084	−0.132	−0.095	0.003	−0.095**	−0.000
	(0.248)	(0.223)	(0.133)	(0.018)	(0.048)	(0.001)
Other	−0.433	0.035	0.010	0.015	−0.054	0.002*
	(0.283)	(0.254)	(0.151)	(0.021)	(0.055)	(0.001)
Switched electricity supplier in past 3 years (No)						
Yes	0.073	−0.050	−0.092	0.010	0.010	−0.001*
	(0.125)	(0.112)	(0.067)	(0.009)	(0.024)	(0.001)
Using the specified appliance in evening period						
Oven	−0.258**					
	(0.118)					
Dryer		0.250*				
		(0.138)				
Dishwasher			0.181***			
			(0.066)			
Constant	−0.846**	−0.205	−0.221	−0.105***	0.420***	0.240***
	(0.370)	(0.330)	(0.197)	(0.027)	(0.072)	(0.002)
R^2	0.057	0.058	0.056	0.078	0.023	0.031
χ^2_{21}	40.360	42.520	37.720	58.580	16.300	22.240
p-value	0.007	0.004	0.014	0.000	0.698	0.328

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

contract attributes differ from those examined in the present study. The analysis by Daniel [35] utilises data from Broberg and Persson [26], which had previously demonstrated strong preference heterogeneity with respect to curtailment contracts attributes. Though the scale of association between socio-demographic variables and preferences for curtailment contract attributes is less than one might have anticipated, the results do provide some insight on systematic drivers of preferences for electricity services.

From a representative sample of electricity consumers we find that approximately 7 in 8 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. Other research from Ireland finds that 75% of a lab experiment sample said they would be willing to have a smart meter installed in their home, after reading a letter about their benefits but most were reluctant to choose complex time-of-use tariffs [59]. For an electricity industry that may seek to deploy curtailment contracts to help reduce peak load, these findings are a promising indication of first engagement with the public but the research by Belton and Lunn [59] also suggests that substantial additional information will be necessary to convince consumers to commit to such contracts. Additionally, what these results show is that the dichotomy of engaged/non-engaged respondents is not simply associated with the usual socio-demographic variables, which means that electricity utilities may find it difficult to predict which customers are more likely to participate curtailment contracts.

From the random parameters logit estimates reported in Table 3 there are substantial differences in preferences for electric oven curtailments relative to other household appliances. Mean willingness to accept an oven curtailment is approximately €20 relative to a washing machine curtailment. WTA curtailments of other appliances are less than €2 relative to a washing machine. The kernel density estimates in Fig. 2 show the wide heterogeneity of preferences for curtailments in all three appliances relative to a washing machine. One might anticipate appliance users during the evening peak period are more likely to oppose curtailment contracts but the results show this is not necessarily the case. It is true in the case of ovens but not so for dishwashers (relative to washing machines). Similar to dishwashers, the coefficient on the clothes dryer variable is also positive but only significant at the 10% level. Why might ovens be different in this regard? Oven curtailments have the potential to substantially impact on a family's social activity (e.g. dinner), whereas curtailment of the other appliances merely delays the completion of household tasks or chores. Evening meal times are usually in the 6–7 pm period in Ireland, which is the centre of the evening peak electricity load. There are no strong cultural norms associated with the completion of dishwashing or laundry activities, nor do moderate delays in completing these tasks substantially impact family social activities. It is possibly for these reasons that there is a strong relative preference against oven contracts, and preferences in favour of curtailment contracts for other appliances even among respondents that regularly use these appliances during the curtailment period. This suggests that the financial discount is generally considered adequate compensation for the inconvenience associated with the curtailment. These findings are broadly consistent with results from Pipattanasomporn et al. [11], who rank the demand response potential of several large household appliances and also conclude that ovens should not be curtailed due to customer inconvenience.

The household characteristic most associated with differences in preferences for curtailment contracts across appliance types is family size. But the differences are nuanced rather than clear-cut. For several contract attributes, when there is an effect of family size, this effect appears non-linear in the number of family members but in general one cannot easily conclude whether larger families are more (or less) favourably disposed to curtailment contract attributes compared to smaller families. Where there is more clarity is with respect to the opt-out attribute, multi-person families value that attribute more compared to single person families. Overall, the implications for network managers wishing to offer curtailment contracts is that interest in curtailment contracts may differ depending on family size but further research is necessary to draw more definitive conclusions.

Preferences differ by respondent age, particularly with respect to curtailment frequency but are largely irrelevant across other contract attributes. The DCE choice scenarios considered up to 9 curtailment events per month, or roughly up to three times per week. Respondents were facing scenarios where curtailments had the potential to occur on a regular basis and with the exception of 18–34 year-olds this was not considered a particularly negative attribute of curtailment contracts. The other respondent characteristic associated with preferences on curtailment frequency relate to environmental attitudes and behaviours. Environmentally-conscious respondents are more positively disposed towards higher frequency curtailments than other respondents, which is consistent with research findings in other fora [60]. Overall, these results suggest that curtailment frequency is unlikely to discourage electricity customers from participating in curtailment contracts. These findings on the source of preference heterogeneity are consistent with research from Sweden and Finland, which also find that preference heterogeneity surrounding electricity curtailments during the evening peak period [26,35,28] and specifically in the case of Sweden that the heterogeneity is associated with socio-demographic variables (e.g. age, region) [35]. Advance notice, curtailment frequency nor opt-out attributes were specifically considered in these Swedish and Finish studies, as their primary focus is the timing of curtailments for electricity and heating services. In the Irish context there is clear evidence of preference heterogeneity with respect to the advance notice and curtailment frequency attributes, which suggests that these attributes should be considered in future research.

Similar to previous studies, we find that differences in income, age, and other socio-economic variables are associated with differences in preferences across curtailment contract attributes [29]. Previous research also suggests that customers place value on not ceding control to network operators [26,27,29]. Though there are substantial differences in the scale of preferences across countries, with Swedish customers expressing substantially higher values than those in the UK. The results for this Irish case study are closer to those by Richter and Pollitt [29] for the UK. From Table 3 we report that customers are willing to pay €2.45–4.34 for greater control over curtailment events (or reduce WTA) either in terms of having 12-h advance notice or a curtailment opt-out. However, there is no strong systematic difference in preferences for these types of contract attributes across respondent socio-demographic variables. The implication is that inclusion of contract features that enable customers to manage any disruption associated with curtailments, either by forward planning or the ability to skip a curtailment, appear to be prerequisites for the design of residential curtailment contracts irrespective of target socio-demographic cohort.

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 [e.g. [61,62]]. 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 benefits of such investments (e.g. lower energy demand or fuel costs) [e.g. [63,64]]. 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. For example, neither the parameter estimates associated with the electricity bill prepay variable, which is a proxy for income deprivation, nor low income suggest preferences over curtailment contracts systematically different than other socio-demographic cohorts. Unlike many government programmes encouraging transition to low-carbon alternatives (e.g. subsidies for electric vehicles, or home energy retrofit grants), curtailment contracts do not require co-financing and consequently may be more accessible.

5. Conclusions

Heterogeneity of customer preferences with respect to provision of electricity services, including curtailment contracts, has been established across several electricity markets [26,27,29,58] 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. The research finds that electricity customers' personal characteristics, including their environmental attitudes and behaviours, are associated with preferences for curtailment contract attributes, though the scale of the association is more nuanced and muted than might have been anticipated.

Across the curtailment contracts attributes, we find that contracts with respect to electric ovens are the least favoured among appliances, that a 12-h advance notice of curtailment is almost universally positively valued, while preferences over curtailment frequency is quite heterogeneous varying from negative to positive. Age, family size, and environmental attitudes are the respondent characteristics with the strongest association with preferences, though the nature of the connection varies substantially. For example, differences in either age or environmental attitudes are associated with preferences related to the frequency of curtailments and not with the other contract attributes considered. Also, family size is associated with preference heterogeneity across several of the curtailment contract attributes (e.g. appliance type, advance notice, opt-out), however, the association is quite nebulous. There is, for instance, no case where we can say that larger family sizes are unequivocally associated with positive/negative preferences for a particular contract attribute.

Another part of the story around preference heterogeneity concerning electricity curtailment contracts relates to the 'non-engaged', or the 1-in-8 respondents that exclusively selected the status quo electricity contract option in the DCE questions. This minority has a clear preference against curtailment contracts but we have little knowledge on what are the common characteristics of this group. The logit modelling analysis says that such respondents are more likely to be from smaller families but this is scant information to conclusively describe or understand why these respondents expressed preferences against curtailment contracts.

While several socio-economic variables associated with preference heterogeneity over electricity curtailment contracts are identified, it is not easy to provide a clear-cut, well-defined and distinct description of the relationship. The implication is that while electricity network operators and utility companies will understand the need to switch from a one-size-fits-all customer contract to a variety of contract types to accommodate preference heterogeneity, they will be unable to readily translate the research results into effectively designing or marketing tailored curtailment contracts for specific customer cohorts. Further research is necessary to understand the nature of preference heterogeneity but the focus should extend beyond the usual socio-demographic suspects (i.e. age, education, etc.) for answers. A possible future avenue to explore is the capture of information surrounding families' lifestyles, routines and work schedules, that may be more salient in the context of preferences for electricity services. For instance, the pace and nature of family life may have more relevance for when electricity powered services can and cannot be deferred within the evening peak load period compared to socio-demographic categories such as educational attainment, income or age. This avenue of research may also be more illustrative in understanding the dichotomy of respondents that either engaged with curtailment contracts within the context of the DCE survey or always selected the status quo alternative.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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