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WHICH SMART ELECTRICITY SERVICE CONTRACTS WILL CONSUMERS ACCEPT? THE DEMAND FOR COMPENSATION IN A PLATFORM MARKET

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Keywords Discrete Choice Experiment, smart energy, Willingness-to-Accept, platform markets

JEL Classification C18, C38, D12, L94, Q42, Q55

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Which Smart Electricity Services Contracts Will Consumers Accept?

The demand for compensation in a platform market

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Abstract

This paper considers the heterogeneity of household consumer preferences for electricity service contracts in a smart grid context. The analysis is based on original data from a discrete choice experiment on smart electricity service contracts that was designed and conducted in collaboration with Accent and 1,892 UK electricity consumers in 2015. The results suggest that while customers are willing to pay for technical support services, they are likely to demand significant compensation to share their usage and personally identifying data and to participate in automated demand response programs. Based on these findings potential platform pricing strategies that could incentivise consumers to participate in a smart electricity platform market are discussed. By combining appropriate participation payments with sharing of bill savings, service providers could attract the number of customers required to provide the optimal level of demand response. We also examine the significant heterogeneity among customers to suggest how, by targeting customers with specific characteristics, smart electricity service providers could significantly reduce their customer acquisition costs.

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Contribution

Existing literature consistently finds that the combination of economic incentives and enhanced information and communication technologies can foster electricity demand flexibility and hence the implementation of a 'smart' electricity grid. . While most studies analyse the impact of electricity demand management measures on consumption patterns, hardly any literature quantifies the value of services that emerge with the 'smart' technologies. The literature has not yet analysed which smart electricity services consumers would choose, if they were offered a menu of contracts bundling different service components together. This paper fills this gap. We address how household consumers value smart electricity services, which contract terms they would accept and what this implies for the optimal pricing strategies.

Introduction

In line with many other countries attempting to reduce carbon emissions and increase the use of renewable energy, the UK government is aiming to integrate larger quantities of intermittent wind and solar into the electricity grid. Such renewable energy resources result in variable electricity supply that must be matched with flexible demand. One way to achieve this is via demand response, i.e. via intentional modifications of electricity consumption patterns to alter the timing, level of instantaneous demand, or total electricity consumption (Albadi and El-Saadany, 2007).

Such demand response can be facilitated by the integration of the electricity grid with information and communication technology (ICT), as part of so-called 'smart grids'. The challenge is to improve monitoring and control of generation, storage, transmission, distribution and consumption of electricity such that both the renewables and the flexible demand can be matched in real time (Austin Energy, 2010). Residential households have particular potential for demand response, since the domestic sector makes up a significant share of total electricity consumption (around 30% across the year and up to 45% at peak times of the day in the UK). A ‘smart’ home incorporates a communication network that connects the key electrical appliances and allows them to be remotely controlled, monitored or accessed (DTI, 2003). Here, ‘smart’ refers to the connection and communication of different electrical devices in the home via the internet.

It is important to distinguish smart home devices from the smart energy services that emerge with them: smart home devices range from smart electricity meters and smart household appliances to integrated solar photovoltaic panels and electric vehicles that both smartly consume and deliver electricity. The combination of these devices, the data they provide and the control actions they enable facilitate a wide range of smart home services (GSMA, 2011). Electricity service providers can position themselves between suppliers and customers to bridge the gap between the smart technology and the required engagement of the consumer.

Recent regulation encourages consumer participation in electricity service contracts that incentivise consumers to partly give up control over their electricity devices to facilitate efficient grid management. However, there is no empirical evidence yet, which electricity services households would choose, if they were offered a menu of contracts bundling different service components such as remote and automated monitoring and control, data management, technical support and electricity bill savings. While some of these components might be valued by the consumer, others might be only acceptable if compensation is paid.

The level of utility obtained from the different service components is likely to be heterogeneous: while some consumers might value full automation and the ability to outsource control to an expert third party, others might only be willing to sign-up for a service contract against compensation for giving up part of their device ownership. A thorough analysis of such preference heterogeneity is crucial for the design of electricity service contracts and an understanding, estimation and prediction of the scope of feasible demand response. The main question in this paper therefore is: how do household consumers value smart electricity services, which contract terms would they accept and what does this imply for the optimal pricing strategies?

We estimate the demand for smart electricity services based on a stated choice experiment conducted with 1,892 electricity consumers in the UK in 2015. Our demand model takes different types of heterogeneity into account: a flexible mixed logit model in willingness-to-pay space is combined with posterior analysis to elicit consumer preferences and heterogeneity in valuations for smart electricity services. This allows us to directly estimate the consumers' valuation (WTP/WTA) of the distinct service components and to suggest possible pricing strategies that could incentivise contract adoption by the number of customers required to provide the optimal level of demand response. The findings could inform competition authorities, regulators and smart service providers and feed into future research in a smart grid context in which customer heterogeneity can be exploited for effective demand side management.

The paper is organised as follows. Section 2 provides background on smart homes and electricity services, the transition of the traditional electricity market to a platform market and on the relevant literature. Section 3 presents the econometric background and model. Section 4 describes the discrete choice experiment and the estimation strategy. Section 5 presents the data from the experiment and the background survey. The main results are discussed in section 6. Section 7 illustrates the practical implications of the results for electricity service contracts and pricing strategies. Section 8 discusses suggestions for further research and finally, section 9 concludes.

Smart Electricity Services and Platform Markets

In the traditional electricity market power flows from large generating stations via national/regional transmission networks on to local distribution networks that connect to final customers, while the network operators ensure the matching of demand and supply and the maintenance of power quality at all times. This involves, inter alia, ensuring that system frequency is maintained within narrow bounds, supply and demand are instantaneously in balance and that there is adequate reserve capacity on the system in the event of significant unforeseen changes in supply or demand, via the provision of so called ‘ancillary services’. Network operators can be seen as ‘intermediaries’ between producers and consumers. Traditionally, balancing is managed centrally, at the transmission level. There is no such market at the local distribution level. However, the electricity industry is structurally changing and two main features characterise this transformation: firstly, the rapid integration of intermittent, often highly distributed, renewable generation and, secondly, the introduction of ICT based products and services. These features will enable flexible demand response and change market definitions, producer-consumer relationships and create opportunities for innovation in new products, services and business models. In contrast to the traditional electricity system, balancing can take place on the local distribution level.

There are two main types of demand side management actions: firstly, load interruption for short periods with minimal impact on consumer comfort can provide frequency response energy services. This is usually considered for appliances that continuously use power (e.g. fridges and freezers). Secondly, demand shifting of appliances that operate in limited duration cycles can provide standing reserve and balancing energy services. This is usually considered for appliances that consume electricity during a fixed duration cycle (e.g. washing machines and tumble dryers).

Solutions to the load balancing problem include the introduction of dynamic (i.e. time varying) pricing or the taking of a degree of control over appliance use (according to pre-specified consumer preferences) to limit peak demand. Under these circumstances the residential customer can become a flexible resource for the electricity system: this possibility is at the heart of the transition to a platform market in residential electricity services.

Generally, a platform market is characterised by 1) the existence of one or more user groups linked by an intermediary, the platform provider, who coordinates their interactions and 2) the existence of network externalities, implying that the utility of users of a platform depends on the number of other users - either on the same side or the other side of the platform (Eisenmann and Alstyne, 2011). Weiller and Pollitt (2013) also consider ICT and the associated complementary innovation an essential component of platform markets: they create added-value that increases utility to all user groups.

The emerging electricity market can be considered as platform market. Residential consumers want electricity services supplied across the network; retailers (and their associated generation) want to sell electricity to consumers across the network (platform). These are the two sides of the market. Load balancing is required by the platform and the question is: which side of the market should pay for it? Match-making smart electricity service providers can position themselves as intermediaries between the retailers, who cannot predict their generation requirements, and consumers, who start to participate in demand management. Such platform service providers can offer balancing services by managing the electricity load of consumers and sell this service to the retailers (and associated generators), who are the main beneficiaries of the increased predictability of domestic load.

The value of such smart services to the whole market (system) depends on the number of consumers signing up for the services. The degree to which the retailers can effectively match supply and demand in such a world depends on the number and the degree of engagement of the residential consumers (i.e. on users on the other side of the platform). To make remote monitoring and control economic, a critical mass of consumers whose load can be managed is required. These are so-called cross-side externalities. Retailers have an interest in helping the platform attract sufficient consumers as are necessary to gain reliable aggregate control over their devices. There are also same-side externalities: smart electricity service providers are competing with each other to attract households.

Pricing in platform markets

Since there is a system-level benefit of the platform, platform pricing strategies are in fact a re-allocation mechanism of costs and value, without any change in total economic surplus. However, to align the provision of smart services with consumer preferences and generate sufficient volume and revenues to gain competitive advantages within the market, the pricing strategy of the service provider should be based on preference and willingness to pay analysis.

The new connectedness and differentiation of consumer preferences implies that the traditionally inelastic demand for electricity (services) becomes elastic as a function of quality (reliability, flexibility, security) and environmental benefits. This is a precondition for differentiated contracts, services and pricing. Weiller and Pollitt (2013) suggest that the entry of competing platform providers who offer new services such as renewable contracts or smart electricity services could bring along a transition from traditional transaction-based, marginal cost pricing of energy to two-part tariffs with a subscription fee and a transaction-based component.

A platform service provider can in principle price its service on both sides of the market. However, it is also possible to take over part or all of the costs of the platform for one side of the market in order to attract a sufficient number of users on the other side. We expect that this is likely.

The optimal pricing strategy to attract users on each side of the electricity service platform depends on the precise nature of the externalities. Whether customer compensation is efficient for example depends on the strength of the cross-side externalities (Weiller and Pollitt, 2013): if the network externalities are high enough, i.e. when the marginal cost of connecting an additional customer to the platform is lower than the marginal value of its connection for existing and prospective customers, the platform provider can apply negative prices to the consumers and still collect overall positive profits in equilibrium (Caillaud and Jullien, 2003; Economides and Katsamakas, 2006). Retailers (and their associated generation) are the main beneficiaries of the new balancing options, and they could bear the cost of compensation. As they benefit from cross-side network externalities in the sense that predictability and manageability improve with the number of customers participating, they could partly or fully pay for the platform service to attract the number of customers required to provide the optimal level of demand response.

Literature

One of the few studies investigating customer views on smart home appliances is reported in Paetz et al. (2012). They study consumer reactions to a fully furnished and equipped smart home based on four focus groups. The analysis looks at consumer perceptions of an energy management system which optimises electricity consumption based on different ICT solutions. They address variable tariffs, smart metering, smart appliances, and home automation. Consumers saw many advantages for themselves; especially the chance to save money. However, giving up high levels of flexibility and adapting everyday routines to fit in with electricity tariffs were regarded as difficult. Smart appliances that take over most of the work on the consumer side were therefore considered necessary. Duetschke and Paetz (2013) suggest that future design of energy (service) contracts needs to be transparent for customers and reflect their individual preferences as customer acceptance of the new technologies is essential for their effectiveness. They address consumer preferences for different types of dynamic pricing. They find that consumers are open to dynamic pricing, but prefer simple pricing programs. Their results indicate heterogeneity in customer preferences regarding dynamic prices and overall their results are in line with their 'high-comfort-low-price-presumption'. Silva et al. (2011) present a framework to assess the value of smart appliances to increase system flexibility and to provide new sources of ancillary services. They derive the value of smart appliances from the benefits of system efficiency, reduced operating costs and carbon dioxide emissions and take the potential reduction in comfort for the customer into account. While they recognise the importance of consumer acceptance, customer preferences for smart technologies are only touched upon briefly. The SMART A project focuses on the customers' willingness to adjust their behaviour and/or to adopt new smart appliances (Suschek-Berger, 2014). The results suggest a positive attitude towards smart appliances and a high level of acceptance. However, a willingness to pay or accept such new technologies and the related services has not been estimated so far.

Discrete Choice Experiment

The aim of this paper is to study how multiple consumer and product attributes jointly affect service contract choices and to estimate implicit prices not only for the bundled service, but also for its components that could be combined into a portfolio of contracts. Data from discrete choice experiments (DCE) can be exploited for demand estimation and analysis, identify consumer segments characterised by similar tastes and inform the design of products and services to match consumer preferences (Ackura and Weeks, 2014). The empirical analysis in this paper is based on original data from a stated choice experiment conducted with 1,892 respondents in the UK in 2015 to elicit customer valuations for smart electricity service attributes and contracts.

The demand for electricity services depends on the service fees, the service attributes and on socio-economic and demographic consumer characteristics. Since smart electricity service contracts are new to most customers, the number of attributes presented in the DCE is restricted to those likely to determine the substitution patterns between smart service contracts. Six attributes were chosen based on previous consumer research on smart homes and interviews conducted in the context of a pilot study. These were: (1) the monitoring of energy usage, (2) the control of electricity usage, (3) technical support with set-up and usage, (4) data privacy and security services as well as, (5) expected electricity savings, and (6) a fee for the service bundle.

We consider so-called 'shared savings contracts', in which the expected savings in the electricity bill are shared with the service company who enables these savings. This can be modeled by a monthly fee that is paid to the service provider in exchange for the service bundle that involves expected electricity savings (besides other services). The respondents were asked to choose between two electricity service contracts that differed in these six dimensions. Alternative 3 was a standard electricity contract without any smart services and at zero additional cost or saving. We set all attribute levels to the base level for this third alternative. Table 1 shows an example choice card presented to the respondents. The electricity service attributes and levels are summarised in Table **2** and explained in more detail below.

When making their choices, respondents were asked to assume that they were equipped with all necessary smart devices to facilitate the contract chosen at no additional cost, e.g. wireless internet connections, smart sensors or remote controls. A questionnaire accompanying the choice experiment included further questions on the customer such as socio-economic characteristics, demographics, technology savviness or previous experience.

Usage Monitoring

Understanding how much electricity is consumed and at what cost is the starting point for any electricity bill saving. Traditionally, households monitor their electricity usage and cost via their electricity bills or their prepayment meter. In-house monitors make it possible to track electricity usage in real time. More advanced features enable monitoring by device and alert messages at times of excessive or unusual usage (e.g. via the bill payer’s mobile phone or personal computer). Moreover, households can outsource the monitoring to an electricity service provider. The consumer might perceive the monitoring by a service company as valuable or intrusive, rendering the sign of the impact on the consumer utility ambiguous. The three types of usage monitoring included in the discrete choice experiment are: (1) via the monthly electricity bill or pre-payment meter, (2) real-time in-house monitoring by the household with alerts in case of unusual usage, and (3) remote monitoring by an electricity service provider who gives personalised feedback based on the monitored data and exploits the information for service design and load management.

Control of Electrical Devices

Smart ICT makes it possible to control electrical devices remotely or set them to work automatically based on pre-specified household preferences. On the one hand, consumers might value any electricity and carbon savings or increases in living comfort (e.g. from temperature related control of heating). On the other hand, the household might perceive remote control by a service company as intrusive and might want to be compensated for giving up part of their ownership rights associated with their devices. The sign of the impact of the remote control attribute levels on the consumer utility is thus ambiguous. In the discrete choice experiment three types of control were considered: (1) manual control by the household, (2) remote and automated control by the household and (3) remote and automated control by an electricity service provider.

Data Privacy and Security

The service attribute 'data privacy and security' refers to the manner in which electricity usage data and personal data are shared. Electricity companies have access to usage data and personal information. With smart metering technologies this data becomes increasingly granular and can provide insights into consumer behaviour and preferences. To enable advanced smart services and deliver the optimal electricity management and balancing services, the data may need to be shared with third parties in order to be fully exploited to help customers to tailor advertisements to specific customer segments and to help the balancing the electricity grid. Depending on whether the benefits of personalised services outweigh the costs of a loss in privacy for an individual consumer, the data sharing service can impact the utility positively or negatively. The three types of data sharing services considered are: (1) no sharing of data with any third party, (2) sharing of electricity usage data third parties engaged in research, marketing or advertising and (3) sharing of electricity usage data and personally identifying data (e.g. email addresses) with third parties engaged in research, marketing or advertising.

Technical Support

Smart homes are an opportunity to offer technical expert support services regarding the set-up and usage of smart devices. Those services can be included in the service contract and priced based on the type of support. Our hypothesis is that the respondents have a positive WTP for technical support. Three types of technical support services are considered in the discrete choice experiment: (1) basic support with set-up and usage of the devices for the initial 90 days of the service contract, (2) ongoing basic support with set-up and usage of the devices, and (3) ongoing technical premium support that includes set-up and usage of devices as well as customer specific, personalised support.

Expected Monthly Electricity Bill Savings

The service attribute 'expected monthly electricity bill savings' refers to the monthly electricity bill savings for the household. In the choice experiment the levels of expected savings are calculated as percentages of the household's current monthly electricity bill (0%, 5%, 10%, 15% and 20%). On the choice cards they were presented in monetary terms (£ per month). The coefficient of this attribute indicates the fees to expected savings ratio that consumers would accept. A positive WTP coefficient below 1 indicates that consumers are willing to pay for expected bill savings as long as the savings exceed the cost. A WTP above £ 1 per expected £ 1 saving could be an indication of consumers receiving utility from expected electricity savings that goes beyond the monetary savings. The coefficient can also be seen as a measure of risk aversion in the context of smart electricity services: a WTP below £ 1 per £ 1 expected savings is consistent with risk aversion of the respondent, a WTP equal to £ 1 is consistent with risk neutrality and a WTP above £ 1 per expected £ 1 saving could indicate risk affinity. Under the prior of risk averse respondents a positive WTP smaller than £ 1 is hence expected.

Monthly Fee

We include the two attributes 'expected electricity bill savings' and 'monthly fee' separately, because the expected savings involve uncertainty while the fee is paid with certainty. The willingness to trade-off certain payments against uncertain savings can shed light on consumers' risk preferences and on whether consumers' valuations go beyond the financial aspect of the savings. In the spirit of the shared savings contract the fee levels considered in the experiment are defined in percentages of the savings expected: 0%, 25%, 50%, 75%, 100% and 125% of the expected monthly electricity savings. However, in the experiment we present the absolute cost level in terms of £ per month. The actual levels are status quo specific and calculated based on the reported annual monthly electricity bill. In most cases the monthly fee is thus lower than the bill savings, but there are also contract options which involve a net financial cost for the customer.

Table 1 Choice Card Example

	Option 1	Option 2	Option 3 (standard)
Usage Monitoring	Real-time monitoring by electricity service provider who sends personalised feedback and advice	Real-time in-house monitor with alerts	Standard electricity bill
Control of Electrical Devices	Remote \ automated control by electricity service provider	Manual control by household	Manual control by household
Technical Support	On-going basic technical support	On-going premium support including personalised advice	On-going basic technical support
Data Privacy and Security	No data shared with third parties	Electricity usage and personally identifying data shared with third parties	No data shared with third parties
Expected Electricity Bill Savings (£)	7.5	2.5	0
Monthly fee (£)	3.4	1.2	0
Preferred option (tick)			

Table 2 Attributes and Levels

Attribute and Level Description	Variable Name

	Electricity Usage Monitoring	
Level 1 (base)	Electricity bill or prepayment meter	
Level 2	Real-time in-house monitor with alerts in case of unusual usage	monitor2
Level 3	Real-time monitoring & personalised advice by service provider	monitor3
	Control of Electrical Devices	
Level 1 (base)	Manual control by household	
Level 2	Remote \ automated control by household	control2
Level 3	Remote \ automated control by service provider	control3
	Technical Support	
Level 1 (base)	Initial 90 days basic technical support	
Level 2	On-going basic technical support	support2
Level 3	On-going premium support including personalised advice	support3
	Data Privacy & Security	
Level 1 (base)	No data shared with third parties	
Level 2	Only electricity usage data shared with third parties	privacy2
Level 3	Electricity usage \ personally identifying data shared with third parties	privacy3
	E(Electricity Bill Savings) (£ per month)	
5 levels	Calculated as 0%, 5%, 10%, 15%, 20% savings in status quo electricity bill	Esavings
	Monthly Service Fee (£ per month)	
5 levels	Calculated as 25%, 50%, 75%, 100%, 125% of electricity bill savings (based on status quo bill)	fee

Experimental Design

In our experiment[2] the attributes and levels selected for the study were combined into profiles and the profiles combined into sequences of choice situations according to a D-efficient experimental design. This design approach uses a search algorithm to find as statistically efficient a design as possible given prior values for the ultimate model to be estimated.

[2] Thanks to Paul Meltcalfe from PJM Economics, who designed the experiment and provided this summary of the experimental design.

A number of restrictions were placed on the design in order to prevent dominant and dominated alternatives within a choice situation, and to avoid combinations of attributes that were considered implausible. These included the following: more monitoring and control must lead to higher cost savings; remote and automated control required a smart monitor; and that better service should always imply a more expensive package. The design was segmented into 12 blocks, with 8 choices per block. The target measure of efficiency was the D-error, calibrated on the basis of an MNL model containing marginal utilities which were derived from analysis of the pilot data for the study. Sign-based priors only were used for the pilot study itself. A swapping algorithm (Huber and Zwerina, 1996) was implemented within the Ngene software package to obtain the experimental design that was ultimately adopted. In this design, levels were approximately, although not exactly, balanced across the design.

The final discrete choice experiment consisted of a panel of eight choices for each respondent. Each choice card consisted of two experimentally designed unlabeled alternatives and a base alternative that implied zero change in cost for the consumer.

Flexible Mixed Logit in WTP Space with Posterior Analysis

Our estimation approach is based on the assumption of heterogeneity in preferences and valuations for smart electricity services across customers. Since consumers might also differ in their randomness of choice, a model that can accommodate preference and so-called scale heterogeneity is employed. Scale heterogeneity might result from heterogeneous experience with smart technology, which might make less experienced consumers choose more randomly than consumers with experience or knowledge.

We specify the model in so-called WTP space. The distributional assumptions can then be imposed directly on the WTPs and their moments estimated directly from the data. Let the utility in WTP space be

$$U_{ijt} = (\sigma_i\alpha_i)[p_{jt} + (\boldsymbol{\omega}_i/\alpha_i)\mathbf{v}_{jt}] + \varepsilon_{ijt} \tag{1}$$

with $(\sigma_i\alpha_i) = \lambda_i$, $(\sigma_i\boldsymbol{\omega}_i) = \mathbf{c}_i$ and $(\boldsymbol{\omega}_i/\alpha_i) = \mathbf{w}_i$

where p_{jt} measures the price of contract alternative j and $\mathbf{v}_{jt}$ is a Kx1 vector of observable non-price attributes. α_i and $\boldsymbol{\omega}_i$ are individual specific vectors of attribute coefficients to estimate. σ_i can capture scale heterogeneity and (ν_{1it}, $\boldsymbol{\nu}_{2it}$) are random components that follow a multivariate distribution to be specified by the researcher and capture unobserved individual characteristics. In this WTP space specification the idiosyncratic error follows a standardised extreme value type I distribution ($Var(\varepsilon_{ijt})= \pi^2/6$), which allows estimation as a mixed logit (MXL) model.

The scale parameter σ_i does not directly impact the WTPs, but is picked up separately by λ_i , i.e. by the price coefficient in WTP space. λ_i incorporates any differences in scale across respondents (Train and Weeks, 2004). However, while the estimation in WTP space can yield unconfounded WTP estimates, the price coefficient, λ_i, remains confounded by scale. Any differences in model fit compared to models estimated on the same data in preference space are mainly a result of the distributional assumptions imposed on the parameters.

However, despite the lack of identification, we model the scale parameter explicitly and follow the model framework first proposed by Keane and Wasi (2013) and operationalised by Fiebig et al. (2013) and Hensher and Greene (2011): in the generalised multinomial logit (GMNL) the scale parameter is modeled as $\sigma_i = \exp(\boldsymbol{\sigma} + \tau\varepsilon_{0,i})$, where $\varepsilon_{0,i}$ follows a iid standard normal distribution such that the parameter σ_i is log-normally distributed. A parameter τ

significantly different from zero indicates significant heterogeneity in σ_i. This model is therefore a flexible mixed logit model in which the scale and preference coefficients are modelled separately, can be heterogeneous and follow the distributions described above. We therefore refer to the GMNL model as `heterogeneous scale mixed logit model`.

In addition, the heterogeneous scale mixed logit model in WTP space allows for the derivation of individual conditional distributions. Working with the conditional distributions allows us to infer the likely position of each sampled individual on the distribution of valuations exploiting the information on their choices made. Conditional distributions allow posterior analysis to be conducted (Hess and Rose, 2012). We perform classical rather than Bayesian simulation, but refer to `posterior analysis' in the sense that we explore the conditional estimates derived based on the individuals' choices. The individual-level conditional mean can be interpreted as the most likely value for a consumer i whose choices $\mathbf{y}_i$ were observed. The variance of the conditional means (the between variation) plus the variance around these means (the within variance) yields the total variance of valuations. If the between variance captures a sufficiently large share of the total variation, the individual conditional means and their variances have the potential to be useful in distinguishing customers (Train, 2003). While the estimation of the unconditional parameters can shed light on the average valuations of services in the population, the conditional estimates can provide more detailed insights on how electricity service contracts, service fees in particular, should be designed to incentivise the optimal number of customers to participate in the service contracts in order to maximise the surplus of the platform mediated two-sided electricity market.

Data and Empirical Results

The DCE was conducted with a representative sample of electricity customers in Great Britain. About 79 percent of the respondents were customers of one of the UK's big six electricity suppliers. The remaining 21 percent of respondents were customers of smaller companies. Many of these have potential to offer smart electricity services in the future. When asked for the preferred contractor for a smart electricity service, almost 50 percent of the respondents considered one of the big six energy suppliers. About 14 percent would opt for a contract with a specialist electricity management company.

Only about 10 percent of the respondents have bought or been given any smart devices in the last two years. The most common smart device among this group is an in-house monitor. Other smart devices mentioned are smart lighting, programmable thermostats, smart plugs and household appliances. The respondents without any smart appliances reported that they perceive the smart appliances as too expensive (28 percent), that they are not necessary (28 percent) and that they are difficult to understand (20 percent). Moreover, 17 percent of the respondents who did not have any smart appliances considered the impact on the electricity bill as too small, 14 percent did not know where to buy the appliances and 12 percent reported that they do not buy any smart appliances due to privacy concerns. When prompted more directly whether remote control was associated with any concerns, almost half of the sample indicated concerns regarding remote controlled appliances. Privacy concerns were regarded as the most common concern (21 percent). Other concerns included damage to the appliances, lack of flexibility in use and the accessibility of appliances when needed and the required behaviour change.

The survey also included a question on the respondents’ technology savviness, worded as ‘Which of the following best describes your typical reaction to new technologies?’. Four categories of technology savviness were considered (using a Likert Scale). Table **3** summarises the responses.

Table 3 Technology Eagerness

Technology Eagerness	Respondent Share
Always eager to try new ideas and products, regardless of what others say	13%
Keen to try out new products early on if some positive reviews heard	39%
Decision after most of friends and usually rely on the views of others	33%
Reluctant to adopt new technologies regardless of what others say	10%

Model Specification and WTP Space Results

For the service attributes each attribute level is indicated by dummy variables. Level 1 of each attribute serves as the base level and for the opt-out alternative all levels are set equal to this base level. The *fee* and *expected electricity bill savings* attributes are included as a continuous monetary variable. We include an alternative specific constant (ASC3) for the third alternative. A positive coefficient of this ASC indicates a preference to choose the standard contract, regardless of the levels of the service attributes. The equation for the expected utility in preference space is given as:

$$E(U_{jit})=\alpha_i fee_{jt}+\omega_{ASC3jit}+\omega_{1i}monitor2+\omega_{2i}monitor3_{ji}+\omega 3icontrol2_{jt}+\omega_{4i}control3_{jt}+\omega_{5ji}support2_{jt}$$

$$+\omega_{6i}support3_{jt}+\omega_{7i}privacy2_{jt}+\omega_{8i}privacy3_{jt}+\omega_{9i}Esavings_{jt}$$

Where fee_{jt} is the monthly service fee (£) and $monitor2_{jt}$, ..., $Esavings_{jt}$ are the variables capturing the attribute levels. As mentioned above, the cost and savings variable are included as levels in monetary terms based on the customers' status quo electricity bills. α_i, $\omega_{ASC3jit}$ and ω_{1i}, ..., ω_{9i}, are the attribute level coefficients.

For the reasons highlighted in section 3 we focus on the WTP space results. The conditional estimates can provide detailed insights on how targeted electricity service contracts, service fees in particular, might be designed to incentivise the optimal number of customers to participate in the service contracts in order to maximise the surplus of the platform mediated two-sided electricity market. Table 4 lists the summary statistics for the individual posterior mean valuations, derived from the heterogeneous scale mixed logit model in WTP space. The last three columns summarise the estimated unconditional parameters, from Table A1, as well as the ratio of the posterior between standard deviations to the total standard deviations.

Table 4 Summary Statistics Posterior Distributions

Service	posterior mean	between SD	min mean	max mean	prior mean	prior SD	ratio posterior/prior SD
monitor2	**0.14**	0.5	-2.71	2.73	0.13	1.036	48.40%
monitor3	**-0.55**	0.03	-0.73	-0.38	-0.55	0.079	44.45%
control2	**-0.04**	0.22	-1.36	1.16	-0.04	0.493	45.55%
control3	**-1.65**	0.64	-4.57	1.7	-1.64	1.262	51.02%
support2	**0.45**	0.14	-0.17	1.02	0.45	0.294	47.00%
support3	**0.48**	0.04	0.27	0.7	0.48	0.081	46.48%
privacy2	**-1.01**	0.65	-4.04	1.77	-1.00	1.295	50.22%
privacy3	**-3.17**	1.84	-10.81	5.64	-3.11	2.923	62.85%
E(Bill Savings) (£)	**0.33**	0.49	-1.4	2.18	0.34	0.674	72.72%

As theory suggests, the estimated posterior population mean valuations (column 1 in Table 4) lie very close to the estimated unconditional population means. The estimated posterior means (see monitor2) suggest that consumers have a positive, but not statistically significant WTP for smart monitoring via an in-house monitor that indicates consumption in real time and sends alerts in case of unusual usage. They do, however, want significant compensation for being monitored remotely by an electricity service provider. Their WTA is on average £

0.55 per month. The valuations for smart control are comparable: while the valuation of smart remote control by the household is insignificant, the average WTA smart remote and automated control by the service provider is about £ 1.65 per month (see control3). On the other hand consumers value technical support: they would pay about £ 0.45 per month for ongoing technical support (see support2) with set-up and usage of the devices and slightly more, £ 0.48 per month, if the service included personalised feedback (see support3). The valuations of usage and personally identifying data are also significant. To provide real-time usage data to third parties, customers would ask for a compensation of about £ 1 per month (see privacy2). In order to share personally identifying data in addition to this, the compensation would need to be three times as high: on average £ 3.17 per month. Per expected pound of bill saving, the customer would be willing to pay about £ 0.33, which supports the argument of risk averse consumers, who are only willing to pay for expected savings if the ratio of fee to expected savings is relatively low.

The between standard deviations (column 2 in Table 4) can shed light on the probability of sign reversal and more broadly on the likelihood with which an individual level conditional mean valuation falls into a specific value range. When based on the posterior means and between standard deviations, the probability of sign reversal is the probability that an individual's mean valuation has the opposite sign than the population mean. These posterior probabilities of sign reversal reveal that consumers are highly likely to demand compensation rather than to be willing to pay for smart service contract attributes such as remote monitoring or control. As an example, the posterior estimates indicate a probability of only four percent that a customer is on average willing to pay to share usage and personally identifying data. And the probability that a customer has a positive mean WTP for remote monitoring or control services is negligible. While a priori the parameter signs were ambiguous, we empirically find almost unambiguous parameter signs for all attributes.

For the expected savings attribute the probability of the mean valuation lying above or below 1 is likely to be of most interest. Table **5** lists the probabilities that the mean valuation for expected electricity bill savings lie in specific intervals, exploiting the normality assumption and the between standard deviations. With a probability of 75 percent the average individual valuation for electricity bill savings is positive, but the necessary fee to savings ratio varies widely. With a probability of about 39 percent the required fee to expected savings ratio is less than 0.5. The probability that consumers are willing to share more than 50 percent (but less than 100 percent) of the savings with the service provider is 28 percent.

Table 5 Posterior Probabilities of Valuations for Expected Bill Savings

Probabilities of intervals of fee to savings ratios	Probability (%)	Intuition
$Pr(\mu_i <0)$	25.03%	Pr(i likely not willing to pay)
$Pr(0< \mu_i <0.5)$	38.54%	Pr(i likely willing to pay less than half of savings)
$Pr(0.5< \mu_i <1)$	27.86%	Pr(i likely willing to pay more than half of savings)
$Pr(1< \mu_i)$	8.58%	Pr(i likely willing to pay more than expected savings)

The last column in Table 4 lists the ratios of the posterior between standard deviations to the total standard deviations. For the attributes remote control by the service provider, data privacy and electricity bill savings the variation of the posterior means makes up over 50 percent of the total variation in valuations. Almost 73 percent of the variation in WTPs for expected electricity bill savings for example is due to variation between (rather than within) individuals. Since the variation of the individual conditional means (i.e. the variation between individuals) captures a large share of the total estimated variation in that coefficient, they have potential to be useful in distinguishing customers (Train, 2003). This can be valuable for targeting contract designs on particular customers.

Implications for Electricity Service Contracts

Traditionally, settlement for domestic customers was performed using so-called load ‘profiling’ based on a small sample of the population and the rest of the population was assumed to have similar profiles (McKenna et al., 2012). Heterogeneity in customer profiles was mostly ignored at the retail level. The availability of smart meter data is expected to facilitate more customer specific load profiling. For electricity service providers the heterogeneity in valuations for different service attributes offers additional potential for consumer targeted contracting and pricing.

In our discrete choice experiment it is assumed that consumers are equipped at no additional cost with the devices needed to enable the smart services contract. Conditional on signing the contract the service provider charges a monthly fee that is paid by either side of the platform. This can be a fixed subscription fee, a transaction-based tariff, or a mixture of both. The challenge lies in the optimal design of the platform fee. Our results suggest that consumers are likely to ask for compensation to participate in smart electricity service contracts that involve remote and automated monitoring and control by the service provider. Following the more general results regarding pricing on platform markets of Caillaud and Jullien (2003) and Economides and Katsamakas (2006) we suggest that a mixture of fixed and transaction based payment to the consumers could incentivise them to sign up for the platform service contracts. The fixed payment could consist of a monthly compensation for remote monitoring and control by the service provider (e.g. the mean WTA). It could be supplemented with charges for technical support and/or compensations for data sharing.

Table 6 lists the average (fixed) compensation households would need to be paid per month when signing up for smart service contracts. These compensations are differentiated by service, but not by consumer type. They were calculated as the sum of the respective mean attribute valuations listed in Table 4. As an example, the mean compensation to be paid for a contract that combines remote monitoring and control by the service provider would need to be £ 2.19 (i.e. 1.64+0.55=2.19). The highest average compensation would need to be paid for customers who sign up for remote monitoring and control, do not want any technical support beyond the basic support, but are willing to share usage and personally identifying data against compensation (£ 5.36 per month). On average, the compensation required is lowest for consumers who sign up for the premium support but not for any data sharing (£ 1.71 per month). Data privacy services can be seen as a means to reducing the compensation required to acquire customers.

Table 6 Average Fixed Compensation for Different Service Bundles

Service Bundle	**Compensation (£ per month)**
Remote monitoring & control ONLY	-2.19
Remote monitoring & control PLUS	
+ usage data sharing	-3.20
+ usage and personally identifying data sharing	-5.36
+ ongoing support	-1.75
+ premium support	-1.71
+ ongoing support & usage data sharing	-2.76
+ ongoing support & usage and personal data sharing	-4.91

+ premium support & usage data sharing	-2.72
+ premium support & usage and personal data sharing	-4.88

Beyond the fixed part of the platform fee that consists of several components (e.g. remote monitoring and control, data and technology services), a transaction based fee could be paid for each £ 1 that the service provider expects to save in the electricity bill. The DCE yields the WTP for the expected bill savings per se, regardless of any other service contract attributes: consumers are willing to pay on average about 34 percent of the amount they expect to save in their bills.

Since we find significant heterogeneity in valuations for most of the service attributes, there is scope for differentiated contracts. The fixed part of the service fee could vary by the contract type (with or without technical support and/or data sharing policy chosen) and in certain dimensions by consumer type. In particular the significant heterogeneity in the WTP for data sharing and expected savings could justify customer differentiation. Moreover, depending on the bargaining power of the service provider, the heterogeneity in consumers' willingness to share savings could be exploited to increase the fixed compensation in exchange for a lower share of savings for those who are relatively risk averse, for example.

The conditional distributions can be exploited to identify and characterise customer types in the population. The individual conditional mean valuations can be grouped together into bigger customer clusters or considered on their own. And depending on the type of contract design of interest either the between variance, i.e. the variance of the individual-level posterior means, or the within variance, i.e. the variance of valuations around the subgroup mean or both might be relevant. We distinguish: 1) two types of posterior analysis that focuses on conditional mean valuations and their variation, i.e. the between variance, to inform the design of contract menus; and 2) posterior analysis of individual valuation profiles and the within variation to inform the design of customer specific contracts. Small niche service providers for example might want to attract customers whose preferences for electricity contracts are quite different from those of the other customer clusters. Under these circumstances, customer specific contract design might be viable and valuable.

Posterior Analysis of Conditional Mean Valuations for Contract Differentiation

We perform two types of posterior analysis of conditional mean valuations: first, we test for mean differences in individual level posterior valuations across different covariate categories. Second, we cluster the posterior valuations using a k-means algorithm and test mean differences in valuations and in respondent characteristics across the clusters.

First, when testing mean differences in valuations across different covariate categories, we find that high income respondents have significantly higher valuations for smart monitoring and smart energy savings than low and medium income respondents. The valuations for the other attributes do not differ across income categories. These findings are consistent with the estimates resulting from model specifications with the respective covariate-attribute interactions. In a simple MNL specification in preference space, for example, the coefficient of the fee-income interactions are significant and result in higher valuations for higher income consumer categories for some of the attributes.

Second, to illustrate how the posterior means can be used to identify and characterise customer segments in the population, we group the observations using k-means clustering on the nine posterior valuations for the service attributes into segments of respondents (following Train, 2003). Such clustering can shed light on the groups of customers that would accept contracts with similar characteristics. Respondents within one cluster hence are similar in multiple valuation dimensions.

Several different numbers of clusters k were tested. Starting from k=2 the number of clusters in the population was increased until significant mean differences in valuations were found that could be exploited for segment specific contract design and price discrimination. This was the case for k=4. We label these clusters: Unremarkable, Private data, Risk averse and Open Data. Across the four clusters significant mean differences in valuations for remote control by the service provider (*control3*), in the willingness to accept sharing of usage and personally identifying data (*privacy3*), and in the WTP for expected electricity bill savings (*Esavings*) are found. Table 7 summarises these mean valuations for each cluster.

Table 7 Mean Valuations by Cluster

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster name	Unremarkable	Private data	Risk averse	Open data
Share of observations	32%	15%	40%	14%
control3	-1.59	-1.62	-1.72	-1.58
privacy3	-2.29	-5.9	-3.93	-0.07
E(Bill Savings) (£)	0.35	0.44	0.24	0.41
average monthly bill (£)	57.45	61.19	54.58	56.20
age	4.87	4.85	4.95	4.74
female	54%	63%	57%	51%
SEG (DE)	24%	23%	26%	37%
occupants	2.21	2.19	2.07	2.35
PAG Tariff	17%	15%	14%	20%
technology type	2.49	2.55	2.72	2.33

concerns remote control	41%	53%	51%	39%
above avge choice confidence	50%	53%	52%	37%
above avge understanding of DCE	39%	38%	40%	31%
above avge perception of realism	67%	68%	59%	66%

In particular the mean compensation asked for sharing usage and personally identifying data varies remarkably from a low mean WTA of -£ 0.07 in cluster 4 to a mean valuation of -£ 5.90 in cluster 3. Service providers should thus ensure careful treatment of the consumers' data when targeting cluster 2, while they could exploit the potential to use consumer data for service improvements at relatively low cost based on cluster 4. The mean WTP for expected electricity bill savings varies from £ 0.25 per £ 1 expected savings per month in cluster 3 to £ 0.44 per £ 1 expected savings per month in cluster 2. However, in all clusters the desired shared savings contracts should at least offer expected bill savings that are more than twice the fee, i.e. in all clusters the mean fee to expected savings ratio is below 0.5.

Based on these findings cluster 2 can be considered as a cluster of respondents that particularly value their data privacy (hence named 'Private data' for the cluster). Cluster 3 is characterised by particularly risk averse respondents (hence named 'Risk averse') and cluster 4 does not call for compensation to share data (hence named 'Open data').

Table 7 also summarises respondent characteristics of the clusters. Tests of mean differences in these characteristics across the clusters indicate significant differences in the average age, the share of females, the share of deprived households and the number of occupants in the household, as well as in the share of households that is on a pay as you go tariff. Cluster 2 (private data) has a significantly higher share of females (63%) than the other clusters. Respondents in this cluster also report concerns regarding remote control, which is consistent with their valuations of data privacy. Cluster 3 (Risk averse) has a relatively high share of technology averse respondents, which is consistent with the fact that these respondents require relatively high expected savings for any given fee. This cluster also has on the oldest customer base. Cluster 4 (Open data) has a relatively low share of females (51 percent) and a high share of deprived respondents (37 percent). Related to this, a relatively big share of respondents is on pay as you go tariffs. Respondents in this cluster are less concerned about data privacy. Unsurprisingly, the share of people with concerns regarding remote control is relatively low in this cluster. Lastly, cluster 4 has a significantly lower share of respondents who indicate above average confidence and understanding of the choices.

To shed light on the acceptance rate of certain contract types, the distribution of the individual conditional estimates can be exploited. When calculating the probabilities of acceptance, the mean estimates attract around 50 percent of the consumers (since the valuations are normally distributed). More interesting are therefore the probabilities of acceptance of fees that lie on either side of the mean and the probabilities of acceptance when bundling multiple attributes together.

Table 8 summarises the subscription fees required to achieve acceptance rate of 1, 50, 75 and 99 percent in the population and in the four identified clusters. Negative subscription fees imply a demand for compensation by the consumers. They were calculated based on the conditional mean valuations within the population and within the four clusters.

Table 8 Acceptance Rates

Remote monitoring and control

	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4
		Unremarkable	Private data	Risk averse	Open data
1% acceptance	-0.5	-0.5	-0.04	-0.78	-0.08
50% acceptance	-2.23	-2.2	-2.22	-2.29	-2.18
75% acceptance	-2.55	-2.5	-2.61	-2.56	-2.6
99% acceptance	-3.83	-3.82	-3.87	-3.85	-3.72
Remote monitoring & control PLUS sharing of usage and personally identifying data					
acceptance rate	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4
		Unremarkable	Private data	Risk averse	Open data
1% acceptance	0.01	-2.41	-5.86	-4.6	2.04
50% acceptance	-5.52	-4.51	-7.86	-6.16	-2.46
75% acceptance	-6.62	-5	-8.65	-6.67	-3.06
99% acceptance	-9.82	-6.2	-11	-7.82	-4.51

Required pay in % of monthly bill					
	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Average monthly bill (£)	56.69	57.45	61.19	54.58	56.20
1% acceptance	0.88%	0.87%	0.07%	1.43%	0.14%
50% acceptance	3.93%	3.83%	3.63%	4.20%	3.88%
75% acceptance	4.50%	4.35%	4.27%	4.69%	4.63%
99% acceptance	6.76%	6.65%	6.32%	7.05%	6.62%

Required pay in % of monthly bill					
	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Average monthly bill (£)	56.69	57.45	61.19	54.58	56.20
1% acceptance	0.02%	4.20%	9.58%	8.43%	-3.63%
50% acceptance	9.74%	7.85%	12.85%	11.29%	4.38%
75% acceptance	11.68%	8.70%	14.14%	12.22%	5.44%
99% acceptance	17.32%	10.79%	17.98%	14.33%	8.02%

First, consider the basic platform service contract that just involves remote monitoring and control by a service provider (Table 8, top). About 45 percent of all customers would be willing to accept such a contract, if they receive the mean compensation of £ 2.20 per month. A compensation of £ 3.83 would achieve a 99 percent adoption rate. If the compensation was £ 2.55, 75 percent would accept remote monitoring and control by a service provider. The compensation required to achieve a certain acceptance rate of remote monitoring and control are comparable across the four clusters (recall that the most remarkable differences in valuations were discovered in the valuations for data privacy services). Depending on the required number of customers for optimal local grid balancing, service providers and suppliers could negotiate the compensation to be paid and the degree of customer differentiation.

The compensation required to attract consumers in cluster 2 (‘Private data’) is remarkably high, for example: for the acceptance of 99, 75 or 1 percent of the customers in cluster 2 £ 11, £ 8.65 or 5.86 need to be paid, respectively. These compensations are significantly higher than those required to attract similar percentages of consumers in cluster 4 (‘Open data’). To achieve an acceptance rate of 99 or 75 percent of the ‘open data’ cluster, only £ 4.50 or £ 3.05 need to be paid, respectively. More than 5 percent of the `Open data' customers are willing to pay for such a contract that combines remote monitoring and control with data sharing. From the service provider's point of view, hence this cluster could be targeted first.

Table 9 Acceptance Rates & Examples with Transaction Based Component

	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4
		Unremarkable	Private data	Risk averse	Open data
-£ 2.19 + £ 0.50 per exp. £ 1 saving	20%	21%	27%	13%	27%
-£ 2.19 + £ 0.33 per exp. £ 1 saving	24%	26%	33%	16%	34%
-£ 4 + £ 0.50 per exp. £ 1 saving	35%	36%	49%	26%	44%
-£ 4 + £ 0.33 per exp. £ 1 saving	46%	48%	60%	36%	59%

Now consider combinations of fixed and transaction based pricing components. Table 9 summarises the acceptance rate for example contracts that combine a fixed compensation payment with a transaction based component, namely a payment per £ 1 saved in the electricity bill. Again, the acceptance rates within the different clusters are also listed. As expected, the acceptance rate ceteris paribus decreases the lower the fixed subsidy and the higher the fee to expected savings ratio (i.e. the lower the share of the savings being granted to the customer is). Offering the average required compensation for remote monitoring and control, i.e. £ 2.19 and the average required fee to savings ratio of 0.33 would attract about 24 percent of all customers, for example. That is, 24 percent require a compensation below £ 2.19 *and* are willing to accept a fees to expected savings ratio above 0.33. A higher fixed monthly compensation can partly make up for higher fee to expected savings ratios, though: with a higher monthly compensation of £ 4, for example, and a fee to expected savings ratio of 0.33, around 46 percent of the customers would accept the contract. However, if the transaction based payment exceeds the amount of expected to be saved (i.e. the fee to expected savings ratio is larger than 1), only 9 percent of customers would accept (even if the compensation was much higher). Hence, even very high compensations do not incentivise consumers to participate, unless they receive a relatively high share of the expected bill savings. Table 9 also lists the acceptance rates for the different clusters. In all examples they are lowest for the risk averse cluster, indicating their relative reluctance to engage with smart electricity services.

Analysis of Individual Posterior Profiles for Contract Differentiation

The individual posterior mean valuations provide further insights into the peculiarities of individual preferences and can inform individual specific contract design. We present the mean valuations for an example respondent and discuss potential customer specific contract features that could incentivise this particular consumer to participate in the smart services market. Such contract design is most likely to occur for niche service providers who might want to attract customers whose preferences for electricity contracts are quite different from most others.

The respondent was identified based on his valuations for electricity services, which indicate his openness towards smart electricity services and his WTP for them. He is willing to spend £ 0.72 for being able to remotely monitor his usage, but prefers monitoring by himself over outsourcing the monitoring. He would also pay about £ 0.50 for technical support. Finally, his need for compensation to share his data seems relatively low and he is willing to pay £ 1.28 for each £ 1 saving in the electricity bill. This high WTP for savings in the electricity bill might be due to a perceived and valued environmental benefit on top of the monetary bill savings. The respondent's mean confidence regarding the choices made is fairly high and his understanding and his perceived realism of the tasks as measured on a four point Likert scale are also above average. His choice behaviour and valuations are consistent with his background characteristics and qualitative survey responses: the respondent considers himself as technology friendly and does not have any concerns regarding the remote control of his appliances. He is one of the few respondents who own a solar PV panel and smart appliances. His current electricity supplier is EDF Energy where he has signed up for an Economy 7 tariff, a time-varying tariff. His annual electricity bill lies with £ 750 (£ 62.50 per month) slightly above average. The respondent lives on his own in an urban area in England in a semi-detached house. Being between 64 and 75 years old he is retired and belongs to the rather socially deprived social class DE. His annual income lies between £ 15,000 and £ 52,000 per year. Overall, this respondent seems to be a technology savvy environmentally conscious consumer, who is already familiar with smart and energy efficient technologies. His survey responses and stated preferences indicate that he is a potential customer of smart electricity services.

Based on the estimated within variance, the likelihood that an individual′s valuation lies in a specific range can be calculated (e.g. a large within variation can imply a higher probability of sign reversal). The within variance can measure the precision with which the individual mean valuation is estimated and hence indicate the precision with which a contract is targeted at a specific customer i.

For each contract feature we can identify the probability of sign reversal for the customer. With a probability of at least 70 percent the presented consumer rejects a contract in which he is asked to pay for remote monitoring and control. However, based on his average valuations he could be offered a contract that combines a £ 1.05 compensation payment with a charge of

£ 0.50 for the premium support and a fee to savings ratio that is relatively high, namely 1.28. Such a customer hence needs relatively low compensation to participate in the smart service platform.

Limitations and Suggestions for Further Research

One limitation of this research is that it is based on hypothetical and hence stated choices of service contracts for which the market is still emerging. Some randomness of choice on the decision maker's side is therefore likely. In fact, we expect the randomness of choice to be heterogeneous across respondents: some consumers might have more experience with related ICT and thus likely to choose less randomly than others without this experience. To account for such heterogeneity in the randomness of choice, a heterogeneous scale parameter is included in the model. However, the scale parameter is not separately identified from the price parameter. If researchers are interested in the causes of scale heterogeneity, our model is not informative.

However, to address part of this issue, three types of questions, designed to shed light on the randomness of choice, were linked to the DCE: (1) after each of the eight choice tasks the respondents reported their level of choice confidence; and after the choice experiment the respondents reported (2) their understanding of the choice task and (3) their perceived realism. The responses were based on a five point Likert scale (e.g. 1 - very confident, 2- fairly confident, 3 - neither confident nor inconfident, 4 - fairly inconfident, 5 - very inconfident). According to the stated measures most respondents were fairly confident about their choices, understood the tasks well and perceived the experiment as realistic: the average confidence level across respondents was 1.93, the average understanding of the DCE as reported on the five point Likert scale was 1.8 and the average perceived realism was 2.3.

Based on these reported measures the heterogeneity of choice does not seem very pronounced.

However, the reported measures of confidence, understanding and perceived realism are likely to suffer from measurement error, which will bias the estimates. Hess (2013) argue that linking scale heterogeneity to measured characteristics is likely to give limited insights, while using respondent reported measures of the randomness of choice implies a risk of measurement error and endogeneity bias. Hess suggests a hybrid model in which survey engagement is treated as a latent variable to model the values of indicators of survey engagement in a measurement model component, as well as explaining scale heterogeneity within the choice model. This links part of the heterogeneity across respondents to differences in scale. Since our questions on choice confidence, understanding and perceived realism are comparable to those discussed by Hess (2013), researchers who aim to focus on a more detailed analysis of the randomness of choice could extend our research in this or similar directions. To accommodate heterogeneity in the randomness of choice, future work could also exploit our data to model the choices directly based on an assumption of stochastic preferences.

Another noteworthy limitation of this research regards so-called ‘packaging effects’. Such effects imply that, for the consumer, the sum of the attribute valuations is not equal to the value of the bundle of such attributes. If this is the case, adjustment factors should be derived and applied to the estimates to scale them appropriately.

Conclusion

The value of the domestic consumer as grid resource is at the heart of the transition to a platform market in residential electricity services. This paper illustrates how this value can be exploited via contract design that takes consumer heterogeneity flexibly into account. We analysed how consumers value smart electricity services and which electricity service contract terms they would accept. We start with the prior that most households want compensation to accept smart electricity services contracts that involve remote monitoring and control by an electricity service provider. The demand analysis is based on a stated choice experiment conducted with 1,892 electricity consumers in the UK in 2015, shedding light on the key attributes that drive demand for smart electricity services. The statistical modelling takes different types of heterogeneity into account: a flexible mixed logit model is combined with posterior analysis to elicit consumer preferences and heterogeneity in valuations for smart electricity services. We suggest possible pricing strategies that could incentivise contract adoption by the number of customers required to provide the optimal level of demand response.

We find significant heterogeneity in valuations for most of the considered contract attributes, suggesting that customer profiling based on posterior analysis could inform contract design. The results suggest that a mixture of fixed and transaction based payment to the consumers could promote the acceptance of smart electricity services contracts. A fixed monthly compensation for remote monitoring and control by the service provider could be supplemented by charges for technical support and data privacy services, depending on the consumer's preferences. The transaction based payment could be based on the expected electricity bill savings.

We find that consumers demand statistically significant compensation to accept remote monitoring and control by a service provider. And the most remarkable contract differentiation potential has been revealed to lie in the data services: the compensation needed to accept the sharing of usage and personal data is significant, but varies substantially across the identified customer clusters. The smart electricity platform service provider should hence consider carefully which customer segments to address regarding data sharing. By contrast, we find that consumers value technical support relatively homogeneously and would be willing to pay for it.

When considering the trade-off between fixed compensation payment and the fees to savings ratio, we find that even very high fixed monthly compensations do not incentivise consumers to participate, unless they receive a relatively high share of the expected bill savings. In practice, households that are willing to give up more control to service providers to shift, interrupt or reduce their energy consumption offer higher potential for volatility reduction and efficiency gains.

We also illustrate that while customer group profiles can inform the design of contract menus, individual profiles can inform customer specific contracts. Small niche service providers for example might want to attract customers whose preferences for electricity contracts are quite different from those of the other customer clusters. Under these circumstances, customer specific contract design might be viable and valuable.

Since the demand model does not separately identify the scale parameter, further research could exploit the survey responses on choice confidence, understanding and realism to explore the heterogeneity in the randomness of choice.

In combination with more information on local balancing cost and required customer acceptance rates, our results suggest efficient pricing strategies for platform service providers and suppliers that carefully take consumer preferences and engagement into account. Our paper only considers some of the aspects of smart electricity services. Other potential fields of application include microgeneration, on-site heat and power and electric vehicle technology. However, the findings of this paper could inform competition authorities, regulators and smart service providers and feed into future research in a smart grid context in which customer heterogeneity can be exploited for effective demand side management.

APPENDIX

Table A1 Heterogeneous Scale Mixed Logit Results

Heterogeneous Scale Mixed Logit Results (WTP Space)	
Mean	
ASC3	-2.400***
monitor2	0.133
monitor3	-0.548***
control2	-0.0376
control3	-1.643***
support2	0.446***
support3	0.483***
privacy2	-0.996***
privacy3	-3.110***
E(Bill Savings) (£)	0.338***
[Het] Const	-0.120 (0.0986)
T	1.016*** (0.0643)
SD	
ASC3	5.330***
monitor2	1.036***
monitor3	0.0787
control2	0.493**
control3	1.262***

support2	0.294
support3	0.0807
privacy2	1.295***
privacy3	2.923***
E(Bill Savings) (£)	0.674***
AIC	23591.4
BIC	23783.3

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