Which Smart Electricity Service Contracts Will Consumers Accept? The demand for compensation in a platform market

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Keywords smart energy services, preference heterogeneity, Discrete Choice Experiment, willingness-to-pay, platform markets
JEL Classification C18, C38, D12, L94, Q42, Q55

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Which smart electricity service contracts will consumers accept?

The demand for compensation in a platform market

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Abstract

This paper analyses the heterogeneity of household consumer preferences for electricity service contracts in a smart grid context. Platform pricing strategies that could incentivise consumers to participate in a two-sided electricity platform market are discussed. The research is based on original data from a discrete choice experiment on electricity service contracts that was conducted with 1,892 electricity consumers in Great Britain in 2015. We estimate a flexible mixed logit model in willingness to pay space and exploit the results in posterior analysis. The findings suggest that while consumers 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 involving remote monitoring and control of electricity usage. Cross-subsidisation of consumers combining appropriate participation payments with sharing of bill savings could incentivise the number of consumers required to provide the optimal level of demand response. We also examine the preference heterogeneity to suggest how, by targeting customers with specific characteristics, smart electricity service providers could significantly reduce their customer acquisition costs.

Keywords: smart energy services, preference heterogeneity, platform markets, consumer choice, posterior analysis, willingness-to-pay
JEL Codes: C1, D1, D4, M2, Q4

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1 Introduction

In line with many other countries attempting to reduce carbon emissions and increase the use of renewable energy, the UK government aims 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-side response (DSR), 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).[1]

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 supply and demand can be matched in real time (Austin Energy, 2010). Residential consumers have particular potential for demand response, since the domestic sector makes up a large share of total electricity consumption.[2] A 'smart' home incorporates a communication network that connects the key electrical appliances and allows them to be remotely controlled, monitored or accessed (Department for Trade and Industry, 2003). In this context, 'smart' refers to the connection and communication of different electrical devices in the home via the internet.

Smart home devices need to be distinguished from 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). 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. Electricity service providers can position themselves between suppliers and consumers to bridge the gap between the smart technology and the required engagement of the consumer. However, there is little empirical evidence yet, which electricity services consumers would choose, if they were offered a menu of contracts bundling a variety of 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

[1] There are two main types of demand-side management (DSM) actions: firstly, load interruption for short periods with minimal impact on consumer comfort. This can provide frequency response energy services and 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. This can provide standing reserve and balancing energy services and is usually considered for appliances that consume electricity during a fixed duration cycle (e.g. washing machines and tumble dryers).

[2] In the UK households consume around 30 per cent of the total electricity consumed across the year and up to 45 per cent at peak times of the day.

against some form of compensation.

Moreover, consumer valuations for the different service components are likely to be heterogeneous: while some consumers might value full automation and the ability to outsource control of household devices to an expert third party, others might not be willing to give up part of their device ownership or only against significant compensation. 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 under different pricing/compensation schemes. The main questions in this paper are therefore: how do household consumers value smart electricity services, which contract terms would different consumer segments 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 Great Britain in 2015. Our demand model takes different types of heterogeneity into account: a flexible mixed logit model in willingness-to-pay (WTP) space is combined with posterior analysis to elicit consumer preferences and heterogeneity in valuations for smart electricity services. This allows us to directly estimate not only the consumers' valuation of the bundled service, but also 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 energy 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 smart energy services and on the respective relevant literature. Section 3 presents the econometric model and estimation strategy. Section 4 presents the discrete choice experiment and experimental design. Section 5 presents the data and 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 limitations and suggestions for further research and, finally, section 9 concludes.

2 Smart Electricity Services & Platform Markets

2.1 The transition from traditional to smart grids

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. 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 rather than 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 into the grid and, secondly, the integration of ICT based products and services. These features enable increasingly flexible demand response, change market definitions and create opportunities for innovation in new products, services and business models. In contrast to the traditional electricity system, balancing services can be offered on the local distribution level.

Proposed solutions to the load balancing problem include the introduction of dynamic (i.e. time varying) pricing and the remote monitoring and control of consumer appliances (according to pre-specified consumer preferences) to limit peak demand. Such demand-side management (DSM) services imply that consumers have to give up part of their device ownership in exchange for more reliable electricity supply. The optimal choice of DSM measures depends on market conditions and the customer base. The potential of the residential consumer as a flexible grid resource is at the heart of the transition to a platform market in residential electricity services.

2.2 Pricing in electricity platform markets

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: firstly, matchmaking 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. There are hence two sides of the market. Retailers (and their associated generation) want to sell electricity to consumers across the network, while residential consumers want electricity services supplied across the network (platform). Platform service providers can act as intermediaries offering balancing services and the question is: which side of the market should pay for it?

Secondly, there are network externalities. The system-level value of smart energy services depends on the number of consumers signing up for them. The degree to which the retailers can effectively match supply and demand, and hence deliver increased reliability, depends on the number and the degree of engagement of the residential consumers (i.e. on users on the other side of the platform). These are so-called cross-side externalities.

Retailers have an interest in helping the platform provider 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.

The optimal pricing strategy to attract users on each side of the electricity service platform depends on the precise nature of the externalities. In principle a platform service provider can price its service on both sides of the market. 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. As an example, the platform providers could compensate consumers for their participation in the platform, manage their electricity load and sell this service to the retailers (and associated generators), who are likely to be the main beneficiaries of the increased predictability of domestic load. They benefit from cross-side network externalities in the sense that predictability and manageability improve with the number of customers participating. They could hence partly or fully pay for the platform service to attract the number of customers required to provide the optimal level of demand response.

Whether such de facto cross-subsidisation via customer compensation is efficient for example depends on the strength of the cross-side externalities (Weiller and Pollitt, 2013): if the network externalities are strong 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 platform participants, 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).

To align the provision of smart electricity 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. 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.

2.3 Literature

Existing literature consistently confirms that demand flexibility can be fostered effectively by a combination of economic incentives and enhanced ICT (DECC, 2013). While customers under traditional metering are likely to be unaware of their consumption and rates paid, they receive real time information on consumption and prices when equipped with smart meters and in-house displays. While many studies analyse the impact of smart technologies and other DSM measures on load profiles, hardly any literature quantifies how consumers value the services emerging with these measures and enabling flexible demand management by a service provider. Consumers who are willing to adopt the new technologies offer greater potential for flexible DSM than consumers who are not. It has not been analysed yet which smart home service contracts consumers would choose, if they were offered a menu of contracts bundling different services together to a smart service contract. This paper fills this gap. Rather than investigating the impact of smart technologies (such as remote monitoring and control) on electricity consumption, we investigate whether consumers would be willing to accept or pay for smart energy services that facilitate flexible demand management.

One of the few studies investigating customer views on the adoption of 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. Giving up high levels of flexibility and adapting everyday routines to fit in with electricity tariffs were regarded as difficult by consumers. 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. Their results indicate heterogeneity in customer preferences regarding dynamic prices and overall their results are in line with their high-comfort-low-price-presumption.

Kaufmann et al. (2013) investigate smart meter perceptions but emphasize several limitations of their study, offering the potential for further in depth analysis of customer preferences for smart homes and metering infrastructure. 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 or services are only touched upon briefly.

Parsons et al. (2014) are among the few who investigate and quantify consumers' WTP for smart energy devices. They focus on vehicle-to grid (V2G) electric vehicles and related contract terms. V2G electric vehicles can offer demand response services by returning power stored in their batteries back to the power grid at times when the grid needs reserve power and by charging when there is a power oversupply. The authors' main question is whether consumers embrace the idea of selling power to the power sector and, if so, at what price. They conduct a discrete choice experiment with 3,029 respondents to elicit valuations for V2G attributes such as the required plug-in time and the guaranteed minimum driving range. They do, however, not consider further services that could emerge with V2G-EVs or other smart home devices more generally. Based on a latent class random utility model they find that people place high value on flexibility in their driving lifestyle. The authors suggest two alternative strategies other than strict cash-back contracts to foster EV sales: firstly, power aggregators could operate on a pay-as-you-go basis without any contract requirements. Secondly, power aggregators could compensate consumers with up-front cash payments. Parsons et al. (2014) also refer to the possibility of a hybrid approach where some customers sign contracts and others use pay-as-you-go. We take these thoughts further, namely to energy services that emerge with the smart devices, such as remote control, technical advice and data protection services, and also consider hybrid contracting strategies.

3 Flexible Mixed Logit in WTP Space with Posterior Analysis

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 to different contract portfolios.

Our estimation approach is based on the assumption of heterogeneity in preferences and valuations for smart electricity services across consumers. 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.[3] Let the utility in WTP space be

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

where p_{jt} measures the price of contract alternative j and $\mathbf{v}_{jt}$ is a $(K \times 1)$ 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 $(\nu_{1it}, \boldsymbol{\nu}_{2it})$ 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 $Var(_{ijt}) = \frac{\pi^2}{6}$, which allows estimation as a mixed logit (MXL) model.

[3]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.

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.

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. (2010) and Hensher and Greene (2011): in the generalised multinomial logit (GMNL) the scale parameter is modelled as $\sigma_i = \exp(\bar{\sigma} + \tau\epsilon_{0,i})$ where $\epsilon_{0,i}$ follows an *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, 2010; Hess and Rose, 2012). We refer to 'posterior analysis' in the sense that we explore the conditional estimates derived based on the individuals' choices. The individual-level conditional mean, μ_i, can be interpreted as the most likely value for a consumer i whose choices y_i were observed. The variance of the conditional means across consumers (between variance) plus the variance around these means (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.

4 Discrete Choice Experiment (DCE)

The empirical analysis in this paper is based on original data from a stated choice experiment conducted with 1,892 respondents in Great Britain in 2015 to elicit customer valuations for smart electricity service attributes and 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 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 thus 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. The monthly fee is paid to the service provider in exchange for the service bundle that involves expected electricity savings (besides other services). The electricity service attributes and levels are summarised in table 1 and explained in more detail below.

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. 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. Table 2 shows an example choice card presented to the respondents.

4.1 Service attributes and levels

4.1.1 Electricity 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 payers 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) monitoring 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.

4.1.2 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 associated with the 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.

4.1.3 Data privacy & 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 sign of the impact of the data privacy and security attribute levels on the consumer utility is thus ambiguous. 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.

4.1.4 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.

4.1.5 Expected monthly electricity bill savings

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. 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 households current monthly electricity bill (0%, 5%, 10%, 15% and 20%). On the choice cards they were presented in monetary terms (£1 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. 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.

4.1.6 Monthly fee

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.

4.2 Experimental Design

In our experiment[4] 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

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

Table 1: Service Attributes and Levels

Electricity Usage Monitoring		**Variable**
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		**Variable**
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		**Variable**
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		**Variable**
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)		**Variable**
5 levels	0%, 5%, 10%, 15%, 20% savings in electricity bill (included as monetary savings based on status quo bill)	Esavings
Monthly Fee		**Variable**
5 levels	25%, 50%, 75%, 100%, 125% of electricity bill savings (included as actual cost levels, based on status quo bill)	fee

Table 2: Example Choice Card

What would you choose? (Please choose one of these options)			
	Option A	**Option B**	**None**
Usage Monitoring	Real-time monitoring by electricity service provider	Real-time in-house monitor with alerts	
Control of Devices	Remote & automated control by electricity service provider	Manual control by household	
Technical Support	On-going basic technical support	On-going premium support including personalised advice	
Data Privacy & Security	No data shared with third parties	Usage & personally identifying data shared with third parties	
Expected Electricity Bill Savings (£)	7.50	2.50	
Monthly fee (£)	3.40	1.20	
Preferred option (tick)			

statistically efficient a design as possible given prior values for the ultimate model to be estimated.

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.

5 Data

The discrete choice experiment was conducted with a representative sample of 1,892 customers in Great Britain. About 79 per cent of the respondents were customers of one of the big six electricity suppliers. The remaining 21 per cent 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 per cent of the respondents considered one of the big six energy suppliers. About 14 per cent would opt for a contract with a specialist electricity management company. Only about 10 per cent of the respondents had 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 per cent), that they are not necessary (28 per cent) and that they are difficult to understand (20 per cent). Moreover, 17 per cent of the respondents who did not have any smart appliances considered the impact on the electricity bill as too small, 14 per cent did not know where to buy the appliances and 12 per cent 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 per cent). Other concerns included damage to the appliances, lack of flexibility in use and the accessibility of appliances when needed and the required behaviour change. Further data was collected related to the energy and electricity consumption of the respondents.

6 Model Specification and WTP Space Results

In our empirical specification we use dummy variables to indicate the levels of the service attributes *monitoring*, *control*, *technology support* and *data privacy & security*. Level 1 of each attribute serves as the base level. 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.[5] The equation for the expected utility in preference space is given as:

$$\begin{aligned} E(U_{jit}) = \alpha_i \mathrm{fee}_{\mathrm{jt}} + \omega_{ASC3jit} + \omega_{1i}\mathrm{monitor2}_{\mathrm{jt}} + \omega_{2i}\mathrm{monitor3}_{\mathrm{jt}} + \\ \omega_{3i}\mathrm{control2}_{\mathrm{jt}} + \omega_{4i}\mathrm{control3}_{\mathrm{jt}} + \omega_{5i}\mathrm{support2}_{\mathrm{jt}} + \omega_{6i}\mathrm{support3}_{\mathrm{jt}} + \\ \omega_{7i}\mathrm{privacy2}_{\mathrm{jt}} + \omega_{8i}\mathrm{privacy3}_{\mathrm{jt}} + \omega_{9}\mathrm{Esavings}_{\mathrm{jt}}, \end{aligned} \tag{2}$$

[5] Given the zero cost change implied by the third alternative, one might expect some consumer inertia towards this alternative 3 simply because it did not imply any additional cost rather than due to a real preference for the standard electricity contract. From our analysis it is not possible to determine whether the choices of this alternative reflects a true preference for the standard contract or whether the alternative was chosen merely because it did not imply any additional costs for the respondent.

Table 3: Summary statistics individual posterior means (GMNL-II)

	Posterior (Conditional)				Priori (Unconditional)		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)%
Variable	$\hat{\mu}_{\mu_i}$	$\hat{\sigma}_{\mu_i}$	min $\hat{\mu_i}$	max $\hat{\mu_i}$	$\hat{\mu}_{prior}$	$\hat{\sigma}_{prior}$	$(\hat{\sigma}_{\mu_i}/\hat{\sigma}_{prior})$
monitor2	0.14	0.50	-2.71	2.73	0.13	1.036***	48.40%
monitor3	-0.55	0.03	-0.73	-0.38	-0.55***	0.0787	44.45%
control2	-0.04	0.22	-1.36	1.16	-0.04	0.493**	45.55%
control3	-1.65	0.64	-4.57	1.70	-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	0.70	0.48***	0.0807	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	-1.40	2.18	0.34***	0.674***	72.72%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

where fee_{jt} is the monthly service fee (£) and $\text{monitor2}_{\text{jt}}$, ..., $\text{Esavings}_{\text{jt}}$ are the variables capturing the attribute levels as described in table 1. As mentioned above, the cost and savings variables are included as actual cost and savings levels in monetary terms. α_i, $\omega_{ASC3jit}$ and ω_{1i}, ..., ω_{9i} are the attribute level coefficients to estimate.

While the estimation of the unconditional hyper-parameters can shed light on the average valuations of services in the population, conditional distributions allow to infer the likely position of each sampled individual on the distribution of sensitivities or valuations, exploiting the information on their choices made. The conditional distributions can be exploited to explore the heterogeneity in valuations. They can provide more detailed insights how electricity service contracts, service fees in particular, should be designed to incentivise the optimal number of customers to participate in the service contracts and maximise the surplus of the platform mediated two-sided electricity market.

Table 3 lists the summary statistics for the individual posterior mean valuations (A) and the posterior standard deviations (B), both derived from the heterogeneous scale mixed logit model in WTP space. Columns (C) and (D) summarise the corresponding individual posterior minimum and maximum mean evaluations. Columns (E) and (F) list the the estimated hyper-parameters, i.e. prior means and standard deviations ($\hat{\mu}_{prior}$ and $\hat{\sigma}_{prior}$). The full table of the unconditional estimates can be found in table J.1 in the Appendix. Column (G) lists the ratio of the posterior standard deviations to the total standard deviations ($\hat{\sigma}_{\mu_i}/\hat{\sigma}_{prior}$).[6]

The estimated unconditional means (column E) 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 (mon-

[6]As expected, the means of the individual posterior means (column A in table 3) are very close to the estimated population means (column E) and the between standard deviations ($\hat{\sigma}_{\mu_i}$) are smaller than the total standard deviations ($\hat{\sigma}_{prior}$), as the former abstract from the variation of valuations around the individual means.

itor2). They do, however, want significant compensation for being monitored remotely by an electricity service provider. Their WTA is on average £0.55 per month (monitor3). 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 £1.64 per month (control3). On the other hand consumers value technical support: they would pay about £0.45 per month for ongoing technical support (support2) with set-up and usage of the devices and £0.48 per month, if the service included personalised feedback (support3). The valuations of usage and personally identifying data are also significant. To accept the provision of real-time usage data to third parties, customers would ask for a compensation of about £1 per month (privacy2). 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. Finally, 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 significant unconditional standard deviations (column F in table 3), imply substantial variation of valuations across respondents. Such heterogeneity can be exploited for differentiated contracting.

When considering the posterior means and between standard deviations (column B in table 3), the so-called probability of sign reversal is the probability that an individuals mean valuation has the opposite sign than the population mean. Exploiting the normality assumption, 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 per cent 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.

Finally, column G in table 3 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 per cent of the total variation in mean valuations. Almost 73 per cent 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.

6.1 Investigating the sources of preference heterogeneity

The estimated model revealed significant heterogeneity in valuations. However, the random parameter models abstracts from the sources of heterogeneity, but capture it entirely in the random parameters in the model. To shed light on the drivers of the revealed heterogeneity, we also test models with interactions of attribute and respondent characteristics. A major challenge and drawback of such models is the difficulty to select the appropriate interactions and the increased complexity of the model as the number of included variables increases. However, simple MNL models with interaction terms of attribute and respondent characteristics can provide first insights into the drivers of heterogeneity.

We test various model specifications with interaction terms of attribute and respondent characteristics. Of particular interest are the interactions of the fee (i.e. price) variable with the income variable. These can reveal whether significant income effects are present. Table J.2 in the Appendix lists the results of the MNL model with the fee-income interactions, illustrating the heterogeneity in price sensitivities. Most remarkably, the fee-income interactions reveal significant but very small coefficients indicating that the price sensitivity of high income consumers (income higher than £52,000 per annum) is lower than for respondents with lower income. For the WTP this implies ceteris paribus larger WTP and lower WTA for these highest income consumers. Consumers with low and medium high income do not differ significantly in their price sensitivities.

We also test MNL models with interactions of the attribute variables with the following respondent specific characteristics: age, technology savviness and socio-economic group. This reveals that the fee sensitivity increases the less technology savvy and the older the respondent and the lower the socio-economic status.[7]

7 Implications for Electricity Service Contracts

Traditionally, settlement for domestic customers was performed using so-called electricity 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). The availability of smart meter data is expected to facilitate more customer specific load profiling and hence contract differentiation.

However, to optimally exploit the heterogeneous electricity load profiles for DSM, consumers have to be willing to accept new types of monitoring, control and pricing. Not only the heterogeneity in load profiles, but also the heterogeneity in the demand flexibility does hence become decisive for pricing strategies. Consumers who are not willing to adopt the new technologies offer less potential for DSM. For electricity service providers an understanding of the heterogeneity in valuations for different service attributes offers hence additional potential for consumer targeted contracting and pricing. The challenge

[7]The results are available upon request of the authors.

lies in the optimal design of the platform fee to facilitate optimal management of flexible demand.

Our results suggest that most 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 propose 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).[8] It could be supplemented with charges for technical support and/or compensations for data sharing.

Table 4 lists the average (fixed) compensation households would on average need to be paid per month for accepting the different smart service bundles. 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 3. 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 per month (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). The lowest average compensation is needed in case of contracts that involve premium support but no sharing of any data usage or personally identifying data (£1.71 per month). By keeping consumer data private and secure, the compensation required to acquire consumers can hence be reduced. Figure 1 illustrates the composition of the considered fixed compensating tariffs.

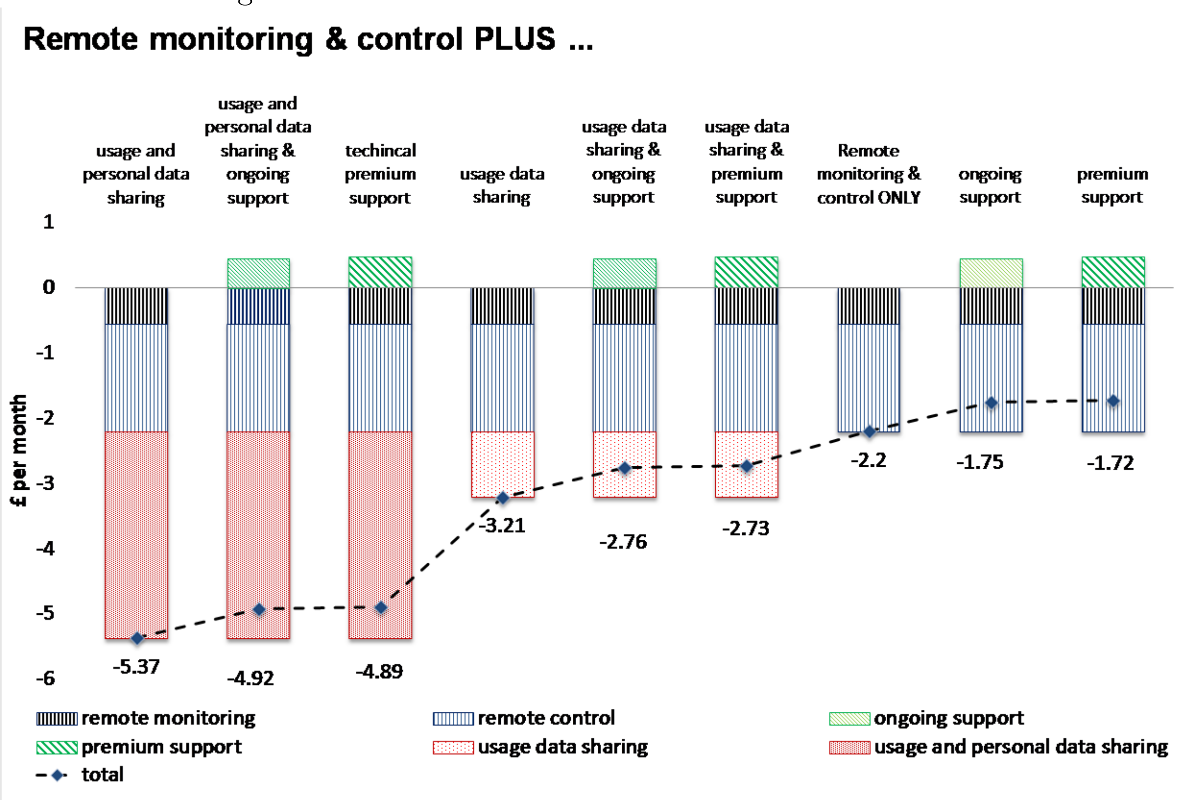
Beyond the fixed part of the platform fee that can consist of several service components, a transaction based fee could be paid for each £1 that the service provider expects to save in the monthly electricity bill. The DCE yields the WTP for the expected bill savings regardless of any other service contract attributes: consumers are willing to pay on average about 34 per cent of the amount they expect to save in their bills.

So far we considered the mean compensation required for acceptance of different service bundles combining remote monitoring and control with distinct other services. Given the significant heterogeneity in valuations for most service attributes, there is scope for further contract differentiation, namely based on consumer characteristics. This can be efficient since the electricity service market does not need full market penetration.[9] In fact, some consumers will be more valuable than others in terms of providing demand response. Given the costs of customer acquisition, the more valuable consumers should

[8]The compensation paid for remote monitoring and control and for data sharing could also be individual specific, since we find significant heterogeneity in valuations.

[9]The optimal level of platform adoption by consumers remains to be determined and is not in the scope of this paper.

Figure 1: Composition of fixed monthly tariffs for various service bundles combining remote monitoring & control with further services



The figure illustrates the contribution of different service components to compensation payments. Since consumer value echnical support services, they can decrease the cross-subsidies required for participation. Data-sharing on the other hand comes along with higher required mean compensation.

Table 4: Mean fixed tariffs for several service bundles combining remote monitoring & control with further services

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

Table 4 lists the average fixed compensation consumers would need to be paid per month when signing up for smart service contracts that bundle multiple service attributes together. The mean compensations were calculated as the sum of the respective mean attribute valuations. 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.

be targeted first. In practice, households that are willing to give up more control to the platform to shift, interrupt or reduce their energy consumption, offer higher potential for volatility reduction and efficiency gains. They should be compensated proportionally (Weiller and Pollitt, 2013). Moreover, the significant heterogeneity in WTP for data sharing and expected savings offer potential for consumer differentiation.

To inform the design of consumer targeted contract menus we perform posterior analysis and distinguish: 1) two types of posterior analysis that focus on the conditional mean valuations and their variation across customers (between variance) and 2) posterior analysis of individual specific valuation profiles and the variation around the individual mean (within variance). 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, individual consumer specific contract design might be viable and valuable.

7.1 Posterior analysis of conditional mean valuations

We perform two types of posterior analysis of conditional mean valuations: first, we test for mean differences in individual level posterior mean valuations across different covariate categories. Second, we cluster the posterior valuations using a k-means algorithm and test mean differences in individual mean valuations and in respondent characteristics across these 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 (see section 6.1).

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).[10] Such clustering can shed light on the groups of customers that would accept contracts with similar characteristics. Respondents within one cluster are hence similar in multiple valuation dimensions. Across the four clusters significant mean differences in valuations for remote control by the service provider (*control3*), in the WTP for sharing of usage and personally identifying data (*privacy3*), and in the WTP for expected electricity bill savings (*Esavings*) are found.

Table 5 summarises these mean valuations for each cluster.[11] 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 as high than 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. Cluster 3 is characterised by particularly risk averse respondents and Cluster 4 does not call for compensation to share data. We label the clusters based on the outcomes: Unremarkable (cluster 1), 'Private data' (cluster 2), 'Risk averse' (cluster 3) and 'Open Data' (cluster 4).

Table 5 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

[10]Several 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 $k = 4$.

[11]Age categories: 1 = 18 to 24, 2 = 25 to 34, 3 = 35 to 49, 4 = 50 to 64, 5 = 65 to 74.

Table 5: Valuations (£per month) and Background Characteristics by Customer Clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Observations	602	278	750	262
control3	-1.59	-1.62	-1.72	-1.58
privacy3	-2.29	-5.90	-3.93	-0.07
E(Bill Savings) (£)	0.35	0.44	0.24	0.41
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%
Cluster name	Unremarkable	Private data	Risk averse	Open data

go tariff: Cluster 2 (private data) has a significantly higher share of females (63%) than the other clusters. Respondents on 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 are on average more risk averse (they require relatively high expected savings for any given fee). The cluster of on average risk averse respondents (cluster 3) also has on the oldest customer base. Cluster 4 (open data) has a relatively low share of females (51 per cent) and a high share of deprived respondents (37 per cent). Related to this, a relatively big share of respondents is on PAG tariffs. Respondents in this cluster are less concerned about data privacy. That the share of people with concerns regarding remote control is relatively low in cluster 4 (the open data segment), is also intuitive. 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 for certain contract types, we exploit the distribution of the individual conditional estimates. Table 6 summarises the mean subscription fees required to achieve acceptance rate of 1, 50, 75 and 99 per cent in the population and in the four identified clusters.[12] 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.

Consider the basic platform service contract that just involves remote monitoring and control by a service provider (table 6, top). About 45 per cent of all customers would

[12]The optimal level of platform adoption by consumers remains to be determined and is not in the scope of this paper.

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 per cent adoption rate. The compensations required 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.

Considering a contract that involves remote monitoring and control plus usage and personally identifying data sharing illustrates how the cluster analysis can be exploited to shed light on potential customer targeted contracts (table 6, bottom). The service provider would need to offer a compensation of £9.82 to achieve acceptance of 99 per cent in the population. 75 per cent would accept, if they were offered a compensation of about £6.62. For this service contract bundle the required compensations to achieve a specific percentage of acceptance vary significantly across clusters.

The compensation required to attract consumers in cluster 2 (Private data) is remarkably high, for example: for the acceptance of 99, 75 or 1 per cent of the customers £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 per cent of the open data cluster, only £4.50 or £3.05 need to be paid, respectively. More than 5 per cent 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, this cluster could hence be targeted first.

Table 6: Fixed subscription fees (£) required to achieve acceptance rates of 1%, 50%, 75%, 99%

Remote monitoring & control

acceptance rate	All	Cluster 1 Customary	Cluster 2 Private data	Cluster 3 Risk averse	Cluster 4 Open data
1%	-0.50	-0.50	-0.04	-0.78	-0.08
50%	-2.23	-2.20	-2.22	-2.29	-2.18
75%	-2.55	-2.50	-2.61	-2.56	-2.60
99%	-3.83	-3.82	-3.87	-3.85	3.72

Remote monitoring & control PLUS sharing of usage & personally identifying data

acceptance rate	All	Cluster 1 Customary	Cluster 2 Private data	Cluster 3 Risk averse	Cluster 4 Open data
1%	0.01	-2.41	-5.86	-4.60	2.04
50%	-5.52	-4.51	-7.86	-6.16	-2.46
75%	-6.62	-5	-8.65	-6.67	-3.06
99%	-9.82	-6.20	-11	-7.82	-4.51

Now consider combinations of fixed and transaction based pricing components. Table 7 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. The acceptance rates within the different clusters are 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 per cent of all customers, for example. A higher fixed monthly compensation can partly make up for higher fee to expected savings ratios: with a higher monthly compensation of £4, for example, and a fee to expected savings ratio of 0.33, around 46 per cent of the customers would accept the contract.

Table 7: Acceptance Rates for Exemplary Contracts Combining Fixed Compensation & Transaction Based Component

	All	Cluster 1 Customary	Cluster 2 Private data	Cluster 3 Risk averse	Cluster 4 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%

Depending on the bargaining power of the service provider, the heterogeneity in consumers willingness to share savings could hence be exploited to increase the fixed compensation in exchange for a lower share of savings for those who are relatively risk averse, for example. 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 per cent of customers would accept (even if the compensation was much higher). Hence, even very high compensations do not incentivise consumers to participate, if they dont receive a relatively high share of the expected bill savings. In all examples acceptance rates are lowest for the risk averse cluster, indicating their relative reluctance to engage with smart electricity services.

7.2 Posterior analysis of individual specific valuation profiles

The individual level posterior mean valuations provide further insights into the peculiarities of individual preferences and can inform individual customer 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 platform market. Such specific 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 the services, which indicate his openness towards smart electricity services and his WTP for them. The respondent 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 and valuations indicate that he is a potential customer of smart electricity services.

Based on the estimated within variance, the likelihood that an individuals 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 per cent 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. These results are summarised in table J.3 in the Appendix.

8 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.

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 and Stathopoulos (2013) argues 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 and Stathopoulos (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.

9 Conclusion

The value of the domestic consumer as a 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 analyse how consumers value smart electricity services and which electricity service contract terms they would accept.

The demand analysis is based on a stated choice experiment conducted with 1,892 electricity consumers in Great Britain 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 in WTP space is combined with posterior analysis to elicit consumer preferences and heterogeneity in valuations for smart electricity services. 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 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 that consumers demand statistically significant compensation to accept remote monitoring and control by a service provider. 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 target regarding data sharing. By contrast, the results suggest that consumers value technical support relatively homogeneously and would be willing to pay for it.

The significant heterogeneity in valuations for most of the considered contract attributes suggests that customer profiling based on posterior analysis could inform contract design. A mixture of fixed and transaction based payment to the consumers could promote the acceptance of smart electricity services contracts. A possibly consumer segment specific 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.

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.

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.

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 can inform 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 micro-generation, 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.

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10 Appendix

Table J.1: WTP Space Results (£per month)

	GMNL-II
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)
τ	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

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table J.2: MNL with fee-income interactions

	MNL
Monthly Fee (£)	-0.199***
	(0.0167)
ASC3	-0.290***
	(0.0540)
monitor2	-0.0111
	(0.0431)
monitor3	-0.291***
	(0.0447)
control2	-0.00500
	(0.0360)
control3	-0.611***
	(0.0404)
support2	0.0433
	(0.0344)
support3	0.113***
	(0.0320)
privacy2	-0.233***
	(0.0331)
privacy3	-0.797***
	(0.0391)
E(Bill Savings) (£)	0.115***
	(0.00806)
feeXinc2 (£15k − £52k p.a.)	0.00761
	(0.0161)
feeXinc3 (> £52k p.a.)	0.0649**
	(0.0247)
feeXinc4 (refused to say)	-0.0435
	(0.0281)
N	45408

Cluster robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table lists the results from a MNL model with fee-income interactions. The coefficients of these interactions suggest a sensitivity to the fee that is lower for high income consumers. Reference group for income is the category with less than £15k p.a..

Table J.3: Individual Posterior Profile

Consumer	1	2
monitor2	0.72	
SD_i	0.88	
$P(\omega_{1i} < 0)$	7.19% 20.66%	
monitor3	-0.54	
SD_i	0.08	
$P(\omega_{2i} > 0)$	0%	
control2	-0.13	
SD_i	0.45	
$P(\omega_{3i} \lesseqgtr 0)$	38.63	
control3	-0.51	
SD_i	1.11	
$P(\omega_{4i} > 0)$	32.3%	
support2	0.49	
SD_i	0.31	
$P(\omega_{5i} < 0)$	5.7%	
support3	0.50	
SD_i	0.07	
$P(\omega_{6i} < 0)$	0%	
privacy2	-1.07	
SD_i	1.12	
$P(\omega_{7i} > 0)$	16.97%	
privacy3	-0.53	
SD_i	1.66	
$P(\omega_{8i} > 0)$	37.48%	
Expected savings (£)	1.28	
SD_i	0.29	
$P(\omega_{9i} < 0)$	0%	
country	England	
age	65-74	
occupation	retired	
SEG	DE	
electricity supplier	EDF Energy	
tariff	Economy 7	
annual bill	750	
monthly bill	62.5	
no solar	solar PV	
technology type	tech affine	
concerns remote control	no concers	
contractor	incumbent	
urban	urban	
home type	semi-detached	
occupants	1	
children	0	
income (annual)	15,601 to 52,000	
survey time (sec)	1041	
sp time (min)	6.15	
mean confidence	2	
above average confident	no	
above average understanding	yes	
above average realistic	yes	
gender	male	