STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's Thesis in economics
Academic year 2018–2019

Assessing the Benefits from Electricity Real-Time Pricing for Heterogeneous Consumer Demand Groups

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Abstract

Real-time pricing (RTP) of electricity avoids the market inefficiencies caused by flat-rate pricing and can help to integrate a greater share of renewable energies. However, RTP for household consumers has met fierce opposition, often on the grounds that it will have adverse redistributional effects. Modelling the British electricity market under RTP while accounting for the merit-order effect of renewable energies, we use hourly data on the electricity consumption by households from 17 different socio-economic groups to estimate the short-run impact of a mandatory switch to RTP on the welfare of these groups. For households from all groups we find only negligible changes in welfare. Moreover, we find little differences in the welfare impact of RTP across socio-economic groups, contrasting with the commonly expressed worry that RTP will negatively affect already disadvantaged consumers, thereby exacerbating energy poverty.

Keywords: Real-Time Pricing, Electricity Sector, Energy Pricing, Energy Policy

JEL: L94 Q41 Q48

Supervisor: Chloé Le Coq
Date submitted: May 13, 2019
Date examined: May 29, 2019
Discussant: Roshni Nandwani
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Table of Contents

Abbreviations & Notation

Abbreviations

CCGT	Closed Cycle Gas Turbine
CHP	Combined Heat and Power Generation
CPP	Critical Peak Pricing
CPR	Critical Peak Rebate
DSR	Demand Side Response
DUKES	Digest of UK Energy Statistics
ENTSO-E	European Network of Transmission System Operators for Electricity
FRP	Flat-Rate Pricing
GB BZN	Great Britain Bidding Zone
GBP	British Pounds (£)
kWh	Kilowatt Hour
LCOE	Levelized Costs of Electricity
OCGT	Open Cycle Gas Turbine
OPSD	Open Power System Data
O&M	Operations and Management Cost
MSE	Mean Squared Error
MWh	Megawatt Hour
RTP	Real-Time Pricing/ Real-Time Price
TOU	Time-of-Use Pricing
UK	United Kingdom

Notation

A_h	Anchor of aggregate demand at hour h
Q_h	Traded volume of electricity at hour h h
p_h	Electricity price at hour h
$D_h(p_h)$	Aggregate electricity demand at price p_h
ε	Absolute price elasticity of demand
$MC(Q_h)$	Marginal cost of generating quantity Q_h
$\bar{p}$	Flat rate price of electricity
$\overline{w}$	Weighted average marginal cost of electricity
$\bar{r}$	Constant surcharge $\bar{r}$ covering fixed costs and transmission charges
$weeklypattern_g(t)$	Mapping function for weekly pattern of group g at hour t of the week
a_{gtw}	Standardized anchor for a representative household in group g for hour t in week number w
$\bar{a}_{gw}$	Weekly arithmetic mean of anchor series for a representative household in group g
$\bar{a}_{dw}$	Weekly arithmetic mean of anchor series for the average domestic household
σ_{gw}	Weekly standard deviation from the mean of anchor series for a representative household in group g
σ_{dw}	Weekly standard deviation from the mean of anchor series for the average domestic household
α_{gw}	Parameter for week number w capturing the ratio of the group-wise weekly arithmetic mean of the anchor series for a representative household in group g with respect to weekly arithmetic mean of the anchor series for the domestic average
β_{gw}	Parameter for week number w capturing the ratio of the group-wise weekly standard deviation of the anchor series for a representative household in group g with respect to weekly standard deviation of the anchor series for the domestic average

1 Motivation

1.1 The Case for Real Time Pricing

The value of electricity varies throughout the day because large-scale power storage remains technologically unfeasible. Whereas prices for end consumers are generally time-invariant, marginal costs faced by the generators vary every instant, as supply is adjusted to meet demand. Since marginal benefit and marginal cost align only by chance, the market suffers from chronic over- and under-consumption compared to the social optimum (Jessoe & Rapson, 2015). This market inefficiency results in substantial deadweight loss, estimated at 5-10% of the Californian wholesale electricity market during the early 2000s (Borenstein, 2005). In the short run, electricity retailers thus subsidize the high marginal costs of peak-time generation via higher overall flat-rate prices. In the long run, avoiding blackouts during peak hours requires excess investment in generation and transmission capacity.[1]

Load volatility may increase further in the coming years, thus exacerbating the market inefficiency problem. On the demand side, the spread of electric cars and individual heat pumps could increase household electricity use. If this electricity is drawn during the peak consumption times hours due to missing price signals, demand volatility will be exacerbated (Møller Andersen, Baldini, Hansen, & Jensen, 2017). Moreover, the growing share of non-dispatchable renewables in the form of solar and wind energy introduces increasing supply-side volatility, which translates into more volatile residual demand for dispatchable generation (Ambrosius, Grimm, Sölch, & Zöttl, 2018).

In recent years, many economists have called for the introduction of electricity real-time pricing (RTP), whereby retail prices vary hourly to accurately reflect scarcity, as the clear “first best policy” (Borenstein, 2005; Jessoe & Rapson, 2015; Joskow & Wolfram, 2012). In some jurisdictions, notably Spain and Illinois, retail companies have started offering RTP to domestic customers on a voluntary basis (Fernández, Payán, Santos, & García, 2017; The Citizens' Utility Board & The Environmental Defense Fund, 2017).

Assuming non-zero price elasticity on the part of end consumers, RTP should reduce demand volatility, lowering both short-term costs (by shifting the electricity mix towards lower-marginal-cost baseload generation) and long-run costs (by reducing the generation and transmission capacity needed to meet peak demand) (Ambrosius, Grimm, Sölch, & Zöttl, 2018; Borenstein & Holland, 2005).

1.2 Potential Issues with RTP

At the same time, regulators and the wider population have expressed reservations about RTP, centered around two main concerns.

The first concern relates to the potential for price shocks, namely that customers may receive a much larger bill than they budgeted for after consuming large amounts of electricity during a time when prices skyrocket (Borenstein, 2007). However, the fact that customers budget for electricity on a bi-

[1] *Of course, rather than making costly investments in mostly idle backup capacity, countries could choose instead to tolerate some number of blackouts. However, most developed countries have a strong aversion even to rare electricity blackouts, due to their immense economic cost (Jessoe & Rapson, 2015).*

weekly or monthly basis insulates them somewhat from volatility in hourly prices. Borenstein (2007) also shows that simple hedging products can eliminate 80% of volatility of the seasonally-adjusted monthly bill. Finally, electricity consumers can avoid such extreme periods with relative ease if generation companies provide them with prior warnings, since such periods tend to be of short duration, and because they are based on day-ahead prices which are known by the afternoon of the previous day.[2]

The second concern is that RTP may have unfair redistributive effects (Borenstein, 2007; Dutta & Mitra, 2017). Such concerns are growing increasingly pertinent amid rising policy awareness of the adverse consequences of energy poverty on households' health and wellbeing (EU Energy Poverty Observatory, 2019). In 2016, the UK government considered 11.1% of English household to be living in energy poverty (Department for Business, Energy, and Industrial Strategy, 2018a). At the same time, most residential electricity consumption goes towards basic needs: 57% of electricity consumed by an average German three-person household goes towards refrigeration, washing/drying, cooking, light, and dishwashing (Nier, 2019). Since electricity is a necessity, its share in household expenditures is much higher for lower income groups; changes in electricity prices therefore have a larger impact on the poor (Centre for Competition Policy, 2018). The widespread adoption of RTP would inevitably produce winners and losers, as it would remove the cross-subsidies currently received by those who consume disproportionately large quantities during periods when wholesale prices are high (Borenstein & Holland, 2005). Removing this subsidy may be socially unjust if already disadvantaged consumers are particularly hard-hit. This may be the case if disadvantaged customers have a less elastic demand, or if they tend to disproportionately consume during peak hours (Dutta & Mitra, 2017). The purpose of this paper will be to address the latter concern.

1.3 Research Question and Outline

Understanding who stands to benefit or lose from mandatory RTP should allow policy-makers to avoid unintended policy consequences and introduce accompanying measures when needed, for instance in the form of targeted lump-sum aid to the losing groups. It should also prove helpful in building a coalition to support more widespread adoption of RTP, which governments have been loath to embrace due to the perceived political risks (Wolak, 2011).

Against this backdrop, we extend the existing literature on the welfare effects of RTP by estimating the magnitude and direction of the consumer surplus change resulting from a switch from flat-rate pricing to RTP for consumer groups with dissimilar demand patterns, and comparing the differences in this welfare effect across groups in the short-run.

We begin our discussion by outlining the existing literature on the topic in section 2, followed by a detailed description of the data we use in section 3. Since mandatory RTP has never been implemented for domestic electricity consumers, a simulation of equilibrium under RTP must precede the analysis of heterogeneity in consumption patterns. We do this by using a model of electricity generation based on demand and generation cost data from Great Britain, outlined in section 4. Having constructed

[2] *For instance, ComEd, the electric utility monopolist in Northern Illinois, offers warnings via text message, e-mail, or automated phone call as part of its RTP tariff (ComEd, 2019). Such an arrangement involves low costs, while benefitting both generation companies (by allowing them to maintain less back-up capacity to meet peak demand) and households (by helping them to avoid high-cost periods).*

simulated RTP prices, we turn to calculating demand patterns for different consumer groups in section 5. Combining our model of the British electricity market with the demand curves for various consumer groups, obtained in section 4 and 5 respectively, we calculate the impact of RTP on the consumer surplus of these distinct groups. A discussion and interpretation of the results is provided in section 6. Finally, section 7 discusses the limitations of our analysis, while section 8 contains concluding remarks.

2 Literature

Although there is a growing literature on dynamic pricing in general and RTP in particular, surprisingly little attention has been paid to how heterogenous demand patterns across different subpopulations may affect the assessed benefits from RTP. Many papers do acknowledge that load patterns might systematically vary with socio-economic group – implying that the costs and benefits of RTP would be concentrated in certain sections of society (Borenstein, 2005; Joskow & Wolfram, 2012). Without accompanying compensating measures, introducing RTP could thus lead to unintended redistributions. However, this interaction of demand heterogeneity and RTP is often only considered briefly, on the basis of intuitions. In part, this is explained by the lack of hourly data on household electricity consumption until the recent proliferation of cheap smart metering technology (The Citizens' Utility Board & The Environmental Defense Fund, 2017). Another likely factor is the persistence of flat-rate retail pricing and resulting scarcity of RTP field studies.

This paper contributes to the literature by allowing for heterogeneity in demand patterns and estimating the impact of RTP on different subsections of society. Importantly, demand patterns are extracted from real-world household consumption data that includes socio-economic characteristics of the households in question. We believe that this approach allows for a more nuanced view on the benefits from RTP. Moreover, understanding how RTP impacts different segments of society will provide a basis for policy measures to accompany the introduction of RTP.

Finally, despite the fact that intermittent renewables have a growing impact on wholesale costs, and although several authors have noted that RTP can help integrate a much larger share of intermittent renewables, only a handful of papers explicitly account for renewables when modelling dynamic pricing (Dütschke & Paetz, 2013; Joskow & Wolfram, 2012). By accounting for intermittent renewable generation, our model better reflects the realities of the contemporary hourly wholesale prices which provides the basis for real-time.

2.1 Literature Review

As far as we are aware, the only paper that focuses on heterogeneous consumer benefits from RTP is a 2017 empirical study simulating how 344,717 flat-rate customers of northern Illinois' electricity generation and retail monopolist would have fared if they had chosen the companies' RTP tariff instead (The Citizens' Utility Board & The Environmental Defense Fund, 2017). The study exposes significant heterogeneity in households' load patterns. Assuming consumption remains the same, fully 95% of households would have saved money under the RTP tariff, with the top 5% saving an average 31% on their bill, and only the bottom 3% losing money. However, this remarkable result can be explained by the fact that the flat-rate offered was much higher than the weighted average real-time price, thereby forcing consumers to pay a large premium for the security of their flat-rate tariff.

Several authors have simulated or measured the impact of residential RTP on *average* consumer surplus; all find a positive effect amounting to a few percentage points of consumer surplus. Borenstein (2005) simulates the long-run impact of RTP on consumer surplus, using Californian consumption data between 1999 and 2003. He concludes that switching 99.9% of consumers to RTP increases total annual consumer surplus by several hundred million dollars, equivalent to several percentage points of the total bill (the exact increase in consumer surplus depends on the assumed demand elasticities).

Evaluating the first program to offer residential RTP in the US, Alcott (2011) finds that, in the short-run, participating households enjoy a small increase in consumer surplus, amounting to 1-2% of yearly electricity costs on average. Interestingly, although households reduce consumption during expensive peak hours, they do not significantly increase consumption during off-peak hours. Adapting the model that also provided the basis for Borenstein's 2005 paper, Holland and Mansur (2006) simulate RTP for the PJM electricity market that covers parts of Pennsylvania, Delaware, New Jersey, and Maryland between 1998 and 2000. They find a modest increase in consumer surplus of 2.5% in the short-run. Simulating the impact of universal RTP adoption for a single year, the New York Systems Operator found market-based customer cost savings in the range of 2–5% (Faruqi, 2010). Wolak (2011) compares consumer responses to RTP, critical peak pricing and peak rebate pricing during a pilot project in Washington DC, confirming that households do respond to RTP and suggesting that households that heat with electricity are more responsive.

Although we are not aware of any paper that investigates the interaction of RTP and heterogenous load patterns, there are some papers that consider heterogenous load patterns in related contexts. A 2010 whitepaper sponsored by the Edison Foundation's Institute for Electric Efficiency, a charitable organization primarily backed by investor-owned utilities, found that low-income consumers benefit from dynamic pricing, based on four pilot studies of various simpler dynamic pricing schemes in the US, including critical peak pricing (CPP), critical peak rebates (CPR) and time-of-use pricing (TOU) (Faruqui, Sergici, & Palmer, 2010).

Crucially, the authors' bill impact simulation implies that 65-79% of low-income customers would benefit from CPP or CPR even without changing their consumption. This is because low income customers tend to have flatter-than average load curves (implying that, under flat-rate pricing, low income customers in fact subsidize others with 'peakier' load patterns). Assuming all consumers have the same demand elasticity, low-income consumers should therefore benefit from RTP.

McLoughlin, Duffy, and Conlon (2015) employ unsupervised clustering algorithms to group Irish electricity consumers into ten common types according to their load shapes. They then link each type to a wide range of household characteristics using multinomial logistic regression. However, the links between household characteristics and consumption type often are not statistically significant. Nonetheless, the authors find peakier-than-average demand to be associated with a greater number of bedrooms, more electricity-intensive household appliances like dishwashers and tumble dryers, and middle-aged or old people. These findings suggest that flat-rate pricing may in fact subsidize mostly better-off households.

To summarize then, the literature on the consumer welfare effects of RTP generally finds a modest but positive impact, both in the short-run and in the long-run. Moreover, some papers considering the relationship between income and demand patterns suggest that peakier-than-average demand patterns may be associated with better-off households.

3 Data

The critical inputs for our electricity market model are demand elasticity and hourly load profile, as well as costs and capacities of the various generation technologies. In order to model load pattern heterogeneity, we also rely on household level data on load and socioeconomic background.

3.1 Electricity Market Data

We focus on the electricity bidding zone of Great Britain (“GB BZN”), comprising England, Wales, and Scotland. As an island, Britain has relatively few interconnectors for exports or imports. Domestically produced power therefore covers almost all of Britain’s electricity loads, allowing us to abstract from exports and imports.[3] Furthermore, Britain’s electricity mix includes significant quantities of all major generation technologies (nuclear, coal, gas, solar, and wind) with the exception of reservoir hydropower, which is extremely difficult to model correctly (Staffel & Green, 2015b).[4] This provides a varied composition of the supply-side. Finally, we have access to power consumption patterns from a sample of households that are categorized into one of 17 socio-economic groups of the UK, which becomes the basis for introducing heterogeneity, thereby making it possible to generalize their demand patterns across the UK. We consider the timeframe spanning from the 1st of January 2013 to the 31st of December 2017.

The electricity supply stack is defined by the capacity and marginal cost of different generation technologies. We take installed capacities from chapter 5.7 of the Digest of UK Energy Statistics (DUKES 5.7) and group them into 11 distinct generation types, based on underlying fuel sources and technologies. We update generation capacity on a yearly basis to account for the substantial changes in the capacity mix that took place during our period of interest, primarily to replace coal with wind and CCGT generation. Due to scheduled and unscheduled outages, installed generation capacity is significantly greater than the available capacity at any point in time. We de-rate installed capacity accordingly, based on assumed breakdown rates from Parsons Brinckerhoff (2013), except pumped-storage generation, for which we draw data from the National Grid ESO (2017). A detailed description of the methodology on construction of generation types can be found in Appendix A.

To obtain marginal costs associated with our eleven generation types, we use yearly average fuel and emissions permit prices to update estimations of marginal costs in 2010 from Staffel and Green (2015a). A more detailed explanation is provided in Appendix B.

The non-dispatchable capacity between 2015 and 2017 is given by the actual generation from wind and solar generation at any given hour, as sourced from the Open Power System Data (OPSD, 2018) based on data from the European Network of Transmission System Operators for Electricity (ENTSO-E, 2019). Actual generation data for intermittent renewables is not available for previous years. For 2013, we therefore simulate hourly generation from non-dispatchable sources by combining data on installed renewable capacities from chapter 5.7 of the Digest of UK Energy Statistics (DUKES 5.7), as

[3] Net imports accounted for 4.2% of electricity supplied in 2017 (Department for Business, Energy, and Industrial Strategy, 2018b).

[4] Peak-shaving models of reservoir hydro-power deployment, whereby reservoir hydro plants are assumed to have a reservation price above which they enter the generation market, have proven rather inaccurate (Staffel & Green, 2015b).

well as capacity factors estimated based on historical weather patterns from OPSD (Pfenninger & Staffell, 2017). For further explanations see Appendix C.

To estimate the aggregate hourly demand curve, we require prices and associated aggregate demand in the baseline flat-rate scenario, as well as an estimate of demand elasticity. Aggregate demand under flat-rate pricing is given by the actual hourly load in the British day-ahead market, sourced from the OPSD and based on data from ENTSO-E.

Average flat-rate prices for domestic consumers are taken from the Department for Business, Energy, and Industrial Policy (2018e).

3.1.1 Price Elasticity of Demand

As already mentioned, the two main factors determining how RTP affects individual households are the price elasticity of demand and the load pattern throughout the day. More price-elastic households are better able to take advantage of RTP.[5]

In experimental studies of critical peak pricing (CPP) and time-of-use pricing (TOU), some authors find low-income customers to be more responsive (Faruqui & Palmer, 2012; Wolak, 2011). Others, however, suggest the opposite (Wang, Biviji, & Wang, 2011). Evaluating four pilot studies on various CPP, CPR, and TOU programs, a whitepaper by the industry-funded Edison Foundation's found that low-income customers' degree of price-responsiveness relative to the average varies across the programs reviewed, with lower income customers are either equally or less-responsive.

Since there is no clear consensus on the price elasticity of low-income consumers relative to the price elasticity of the average consumer, and a significant share of papers find that the price elasticity of low-income consumers is not statistically significantly different from the average, we choose to assume that households are homogenous with regards to their price elasticity. However, we conduct our analysis using a range of different elasticities. Hence, we also obtain estimates of consumer surplus changes for low-income consumers under lower price elasticities.

The level of the short-run price elasticity of electricity is likewise much debated in the literature, however, few estimates of the very-short-run price elasticity exist that are relevant for RTP. Estimates of the price elasticity of electricity are further complicated by the fact that it varies with the use of electric cooling or heating, as well as enabling technologies such as in-home displays of energy prices and smart appliances (Gottwalt, 2011; Lijesen, 2007; Faruqui, Sergici, & Akaba, 2014). Summarizing the literature on elasticity in Time-of-Use (TOU) electricity prices, Lijsen (2007) finds estimates ranging between 0.013 and 0.158. Given the technologies for demand response available at the time, Borenstein (2005) considers various short-run price elasticities ranging in a similar range; in his central scenario price elasticity is 0.1. Simulating the short-run welfare impact of RTP, Holland and Mansur (2006) likewise assume a constant price elasticity of demand of 0.1. For our model, we also assume a central scenario with a constant price elasticity of $\varepsilon = 0.1$ across all consumer types. However, we also

[5] *Note however that consumer surplus does not increase linearly in elasticity: Borenstein (2005) suggests that consumers experience diminished returns from increased elasticity*.

conduct our analysis on elasticities ranging from 0.025 to 0.150 in order to cover the full range of common elasticity estimates.

3.2 Household Data

The data we rely on to model heterogeneity is taken from the London Data Store (2014) and covers a representative sample of 4,372 households throughout the year 2013. It includes half-hourly consumption for each household, as well as their Acorn group. Acorn is a segmentation tool that divides the UK households into five broad categories, subdivided into 17 socio-economic groups (CACI, 2013). Each group is assigned a letter, listed along with the relevant group's share of UK households in the year 2013 and the broader category it belongs to in Table 1.

Table 1: Acorn groups and their share of the UK population

			Share
AFFLUENT ACHIEVERS – very wealthy, large dwellings			
A	Lavish Lifestyles	*middle-aged/older entrepreneurs/ professionals*	1.31%
B	Executive Wealth	*middle-aged, combining job and family*	12.48%
C	Mature Money	*old and usually retired*	8.92%
RISING PROSPERITY – prosperous, smaller dwellings			
D	City Sophisticates	*young singles/ couples, childless*	3.26%
E	Career Climbers	*young singles/ couples/ families*	6.10%
COMFORTABLE COMMUNITIES – average income			
F	Countryside Communities	*older, working in skilled trades/ agriculture*	6.38%
G	Successful Suburbs	*families, average-sized dwellings*	6.12%
H	Steady Neighborhoods	*middle-aged, both families and empty nesters*	8.32%
I	Comfortable Seniors	*older, usually retired empty nesters*	2.54%
J	Starting Out	*younger couples starting a family or career*	4.05%
FINANCIALLY STRETCHED – low income & smaller houses			
K	Student Life	*Students/ recent graduates living in halls/ flats*	2.53%
L	Modest Means	*singles/ families/ single parents in small housing, above-average unemployment*	7.53%
M	Striving Families	*Families with often high number of kids, above-average unemployment*	8.11%
N	Poorer Pensioners	*Retired and living in social housing*	4.46%
URBAN ADVERSITY – *the most deprived areas in UK*			
O	Young Hardship	*younger, singles/ couples with/without children,*	5.25%
P	Struggling Estates	*Many children, and single parents, above-average unemployment*	7.89%
Q	Difficult Circumstances	*Many single parents, above-average unemployment, many with health issues*	4.76%

Since the period of interest only spans five years, and because we find no reason to assume a substantial change in the composition of British society throughout this time, we assume that the above-listed shares remain constant from 2013 to 2018.

For calculating the number of households in each Acorn group, we refer to annual data on the number of households living in Britain by the Office of National Statistics (2018). In order to avoids large jumps in the assumed number of households from one year to the next, we linearly interpolate the number of households, assuming a constant change throughout each year. To find the number of British households per group, we take the product of Acorn group shares with the total number of households interpolated for any given hour.

3.3 Selection of Years for Research

Our data set on hourly household consumption by Acorn groups covers the year 2013. We therefore begin by estimating the impact of RTP on different household types during that year.

However, the share of non-dispatchable renewables grew significantly in the following years, increasing from 8.16% in 2013 to 17.41% in 2017.[6] Since intermittent renewable generation increases the volatility of residual demand and hence marginal costs, and because its ability to dampen such volatility is one of the major arguments advanced in favor of RTP, we are also interested in modelling the effect of RTP on different household types when the share of intermittent generation is higher. In a second step, we therefore extrapolate from consumption patterns observed in 2013 to obtain hypothetical demand patterns for each Acorn group for the years 2015 to 2017. We skip the year 2014 due to a change in the way load data was recorded, and because data on actual hourly generation from renewables is only available from 2015 onwards. We do not consider the years after 2017 because some of the data mentioned above is not available due to publication lags.

Hence, we obtain two sets of estimates of the impact of RTP on household welfare: estimates for 2013 using actual household load data, and estimates for 2015 – 2017, using projected household load.

[6] *Own calculations based on data from the Department for Business, Energy, and Industrial Strategy (2018c; 2019c).*

4 Simulating Real-Time Prices

Our modelling proceeds in two steps. First, we construct aggregate demand and supply curves in order to retrospectively simulate hypothetical real-time prices in the British retail market for the years 2013 and 2015 – 2017. This step is necessary because observed loads during our period of interest were obtained under flat-rate pricing. In the second step, outlined in section 5, we introduce heterogeneity with regards to consumers' demand profiles, followed by a calculation of different consumer groups' consumer surplus under RTP in section 6.

Our paper builds on previous work by Borenstein (2005) in two respects. First of all, we adopt the same constant elasticity of demand curve. Secondly, we follow Borenstein in assuming that the flat-rate tariff faced by consumers in the base-line scenario can be decomposed into the weighted average marginal cost of generation per hour and a constant surcharge per hour.

We apply our model to the electricity market in the British bidding zone (GB BZN) for the years 2013 and 2015 through 2017, with the aim of calculating consumer surpluses under RTP for distinct customer groups. Buyers and sellers in the spot market for electricity submit their bids 24 hours ahead of delivery, with prices set at an hourly basis. After the market closes at 15:30, prices and trade volumes for the next day are known (Epex Spot, 2019).

The British spot market for electricity is peculiar insofar it uses half-hourly rather than hourly pricing; as a consequence, original trading volumes are published in kWh per half hour. However, we use data from OSDP, which lists trading volumes on an hourly basis for the sake of comparability with other countries. We therefore model the British spot market assuming that in the retail market, prices are set on an hourly basis.

4.1 Modelling Supply

We approximate the electricity supply stack using a supply curve that increases in steps according to the marginal generation cost, MC, of electricity. Our supply curve can be decomposed into time-invariant and time-varying components, reflecting the difference between dispatchable and non-dispatchable sources of generation.

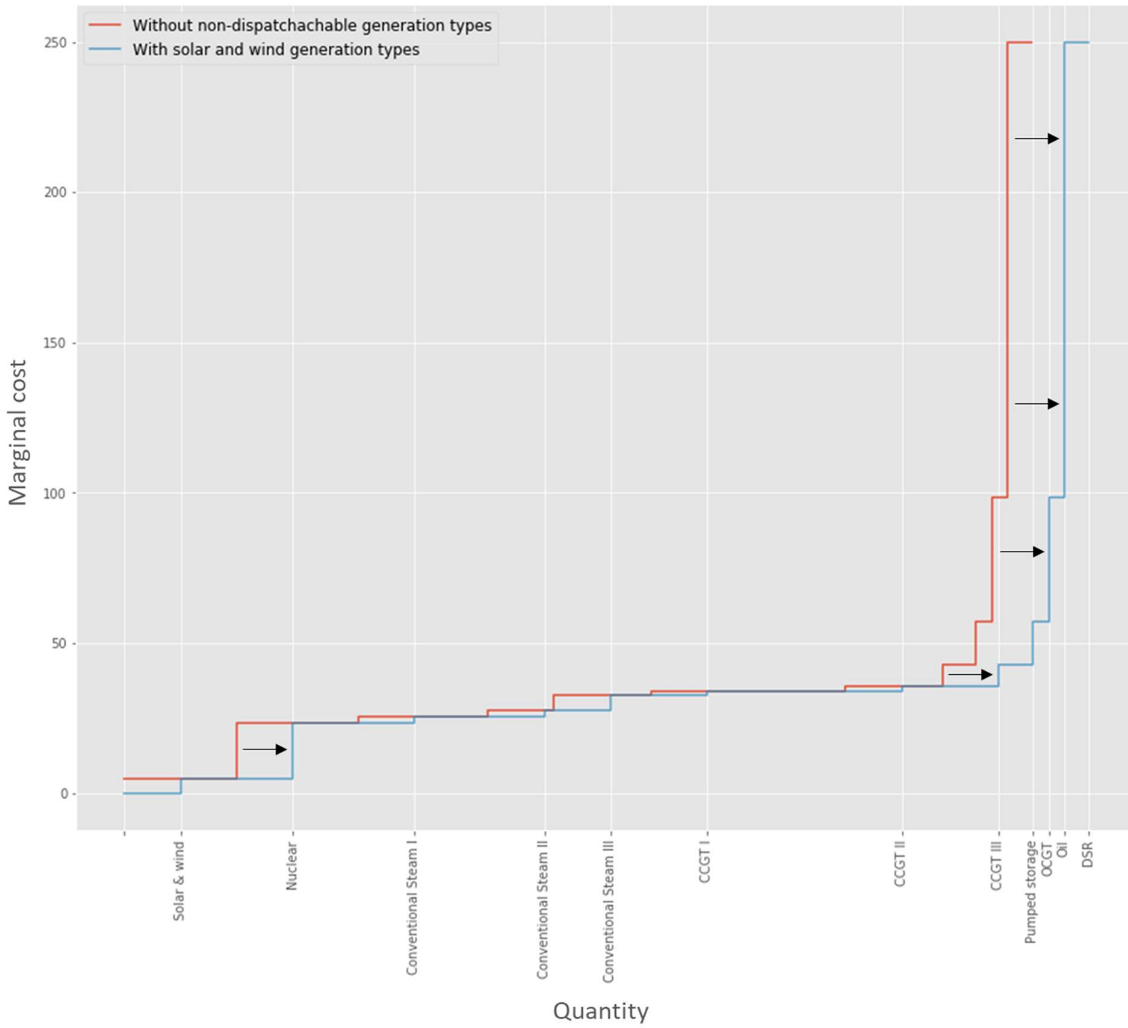
4.1.1 Dispatchable Supply

The time-invariant component of the supply curve comprises all dispatchable generation technologies. Combining data on the marginal cost and installed capacity of these different technologies, we can construct the marginal cost curve for dispatchable generation. We group individual technologies into eleven generation types on the basis of similar marginal costs. In order of ascending marginal cost, these are: nuclear, biomass, conventional steam generation I, conventional steam generation II, conventional steam generation III, combined-cycle gas turbine (CCGT) I, CCGT II, CCGT III, pumped storage, Open Cycle Gas Turbine (OCGT), and oil generation. As already noted in section 3.1, we therefore abstract from reservoir hydropower generation and imports. Conventional steam and CCGT generation are divided into three tranches of increasing efficiency, to reflect the resulting differences in marginal cost. (For a more detailed explanation, see Appendix A.) We abstract from further heterogeneity within generation types, as well as technological start-up and ramping restrictions. Hence, throughout each year, the marginal cost of production is constant for any given generation type. Moreover, in assuming generation is dispatched in order of marginal cost, we assume that generation companies do not intentionally withhold lower-marginal cost generation from the market in order to deploy a price-setting generation unit with a higher marginal cost.

The time-invariant component of the supply curve therefore takes on its characteristic stepped appearance, where each step corresponds to a distinct generation type such that its function value reflects marginal cost and its length reflects installed capacity (Figure 1). Following the UK Competition and Markets Authority (2016a), we also add 1,000MW of demand side response (DSR) at the end of the stack. The conventional component of our electricity supply curve therefore has eleven steps, compared to three steps for the supply curve set out by Borenstein (2005).

Note that the resulting marginal cost curve gives rise to discontinuities whenever a perceptible price increase is necessary for the next-least-expensive generation unit to enter the market, i.e. whenever the next-least-expensive unit is of a different generation type. However, these discontinuities pose no problems for finding the intersection of supply and demand: the supply curve simply becomes vertical as generating companies raise prices to ensure supply equals demand (Szekeres, 2008).

Figure 1: Electricity supply curve with and without non-dispatchable generation



We model aggregate supply as the sum of dispatchable generation (which is constant throughout all hours of the year) and non-dispatchable generation (which varies by hour). Hence, the aggregate supply curve at hour h (blue) is simply equal to the supply curve for non-dispatchable generation (red), shifted outwards by the amount of non-dispatchable energy generated during that hour.

4.1.2 Non-Dispatchable Supply

The time-varying component of our supply curve accounts for non-dispatchable generation, namely solar and wind power. These differ from dispatchable generation sources, not only due to their intermittency, but also due to their negligible marginal costs. The addition of renewable generation capacities over the last two decades has caused a merit-order effect, whereby conventional generations is displaced by renewable generation with lower marginal costs. Holding demand constant, a new unit of cheap generation entering the market may cause the most expensive unit currently dispatched to leave the market. Consequently, price may fall. From 2010 to 2018, the share of solar and wind in the UK's electricity mix rose from 2.7% to 21% (Department for Business, Energy, and Industrial Strategy, 2019c). In contrast to many older papers, this merit-order effect from renewable generation has become too large to ignore.

In the case of additional dispatchable generation like biomass, we can simply model the merit-order effect of renewables by inserting the newly installed capacity at the appropriate place in the merit order stack. This approach does not work for intermittent renewables, since only a small, constantly fluctuating fraction of installed capacity can actually generate electricity at any point in time.

The most common approach to model the impact of intermittent renewables on electricity prices is to work with residual load instead. Under this modelling approach, demand is first stilled by zero-marginal cost renewables. Conventional generators are assumed to face only the remaining residual demand, which can then be modelled in the usual way (Sensfuß, Ragwitz, & Genoese, 2018; Wagner, 2014).

However, since we are interested in consumer surplus, we chose to preserve the original total demand curve, and directly account for the merit order effect on the supply stack. We do this by inserting hourly generation from wind and solar before baseload capacity for every hour in our dataset. As a result, our supply curve shifts inwards or outwards hourly, according to the current generation from solar and wind (see Figure 1). For the years 2015–2017, we simply use actually observed wind and solar infeed; for the year 2013, we simulate wind and solar generation, since data on actual generation is unavailable (for further details on simulating solar and wind generation see Appendix C).

4.2 Modelling Demand

We adopt the demand curve for our base simulation from Borenstein (2005). For any given hour h, aggregate electricity demand $D_h(p_h)$ is given by a constant elasticity of demand function:

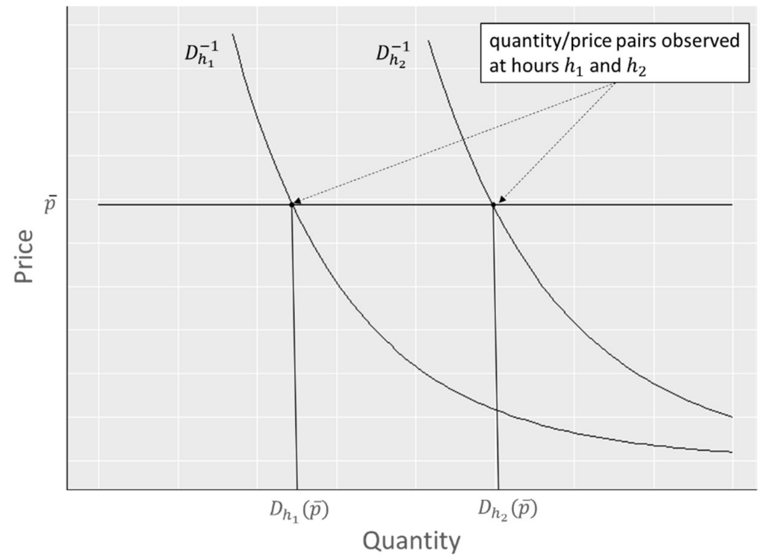
$$D_h(p_h) = A_h p_h^{-\varepsilon}$$

Given the level of price elasticity $\varepsilon = 0.1$ and the constant-price elasticity functional form, demand is thus fully specified by the hourly scale parameter A_h. Following Borenstein's parlance, we refer to it as 'anchor'. Note that the price elasticity of demand ε remains constant both along the hourly demand curve and across hours (as reflected by the fact that ε does not have an h subscript).

By adjusting A_h, we can ensure that the demand curve goes through a given price/quantity pair. In our data set, A_h is therefore defined by the actually observed consumption at hour h and the average flat-rate $\overline{p_h}$ for domestic consumers in Britain during the relevant year (see Figure 2).[7] These defining price-load data points for each hour are referred to as anchor points. In contrast to Borenstein, we forego modelling long-run dynamics by endogenizing firms' capacity choices. Instead, we simply set the flat-rate price $\bar{p}$ equal to the observed average electricity flat-rate for British consumers in a given year.

[7] *Although $\bar{p}_h$ does not change hourly, we include a time subscript to reflect the fact that it changes yearly.*

Figure 2: Illustration of inverse hourly demand curves at two different times



Demand $D_h(p_h) = A_h p_h^{-\varepsilon}$ varies hourly according to the hourly scale parameter A_h. Given the constant price elasticity of demand functional form and assumed elasticity ε, we can construct A_h, and therefore D_h, using a single observation on price and the associated quantity demanded at that hour. The price-quantity pairs we rely on consist of the observed flat-rate price $\bar{p}$ and the observed demand, given $\bar{p}$, during the hour of interest.

Of course, the flat-rate for all customers in the market is not actually equal to the average flat-rate faced by domestic consumers. Domestic consumption accounts for only a third of electricity consumption in Britain and commercial, state, and industrial users often pay significantly lower prices (Department for Business, Energy, and Industrial Strategy, 2018b).[8] Ceteris paribus, assuming a higher flat-rate price $\bar{p}$ implies a higher anchor A_h. Since we are ultimately interested in calculating consumer surplus for domestic households, we choose to calculate the anchors for aggregate consumption based on the flat-rate faced by household consumers. However, as Borenstein argues, the main contribution of his demand model lies in accurately modelling the *shape* of the demand distribution over time; assumptions on the level of the retail flat-rate are therefore of secondary importance (Borenstein, 2005).

Having chosen $\bar{p}$ and $\varepsilon = 0.1$, we calculate the time-series of anchors $\{A_h\}$ to obtain aggregate demand functions for every hour. Note that by assuming hourly demand functions are additively separable over time, we implicitly assume that cross-price elasticities are zero.

[8] *For instance, real electricity prices per MWh for the industrial sector are around £30 lower than the prices faced by domestic throughout our period of interest (Department for Business, Energy, and Industrial Strategy, 2018e; 2019a).*

4.3 Simulating Prices and Load under RTP

In order to calculate RTPs, we first need to identify the difference between wholesale marginal costs of electricity generation and RTP as charged towards end-consumers. Based on observed consumption and yearly average retail flat-rates for domestic consumers, we can calculate the surcharge imposed under flat-rate pricing to cover transmission charges, reimburse fixed costs, etc. We begin by following Borenstein (2005) in assuming that the retail flat-rate can be decomposed into a the sum of the weighted average marginal cost of electricity, $\overline{w}$, and a constant surcharge, $\bar{r}$, covering fixed costs and transmission charges. The flat-rate $\bar{p}$ for any given year is therefore

$$\bar{p} = \overline{w} + \bar{r} \qquad \text{where} \quad \overline{w} = \frac{\sum_h Q_h MC(Q_h)}{\sum_h MC(Q_h)}$$

Since we only model the short-run welfare effects of RTP, we simply set the flat-rate $\bar{p}$ paid by consumers equal to the yearly average flat-rate actually observed during our period of interest. The surcharge $\bar{r}$ in our model therefore also accounts for taxes and any potential profits. The surcharge calculated from subtracting weighted average wholesale costs from observed retail flat-rates are listed in Table 2 below.

Table 2: Actual flat-rate, weighted average marginal cost, and surcharge during the years of interest

Year	$\bar{p}$ in £/MWh[9]	$\overline{w}$ in £/MWh	$\bar{r}$ in £/MWh
2013	147.2	32.11	115.09
~~*2014*~~	-	-	-
2015	150.5	30.14	120.36
2016	150.5	27.41	123.09
2017	151.0	32.64	118.36

Following Borenstein (2005), we assume that the retail surcharge $\bar{r}$ remains the same under the RTP regime. The real-time price for end consumers at any given hour is therefore simply the sum of marginal generation costs and the surcharge.

Combining our demand and supply function, and accounting for the retail surcharge, we therefore obtain hourly consumption and consumer prices under RTP.

4.4 Discussion of Simulated RTP

The minimum price in 2013 was £139.79/MWh, and the maximum price was £158.61/MWh, representing only moderate deviations from the 2013 flat-rate price of £147.2/MWh. Between 2015 – 2017, prices ranged from £113.86/MWh to £154.5/MWh, compared to yearly flat-rates of around £150.50/MWh. The household-demand weighted average RTP was £146.94/MWh for 2013 and

[9] *Source: Department for Business, Energy, and Industrial Strategy (2018e)*

£150.60/MWh for the years 2015 – 2017. Hence, demand-weighted average real-time prices deviated only negligibly from the flat-rate prices for those years.

This very modest range of RTP results from the fact that Britain did not suffer from pronounced capacity shortages during the periods of interest, combined with the British electricity supply curve's relative flatness around mid-merit generation types. These results contrast with results obtained by Borenstein (2005) in modelling the California electricity market, as he finds that the highest demand hour would account for fully 4.2% of the annual electricity bill (also assuming a price elasticity of demand of 0.1).

Table 3: Overview of RTP prices (values in £ per MWh)

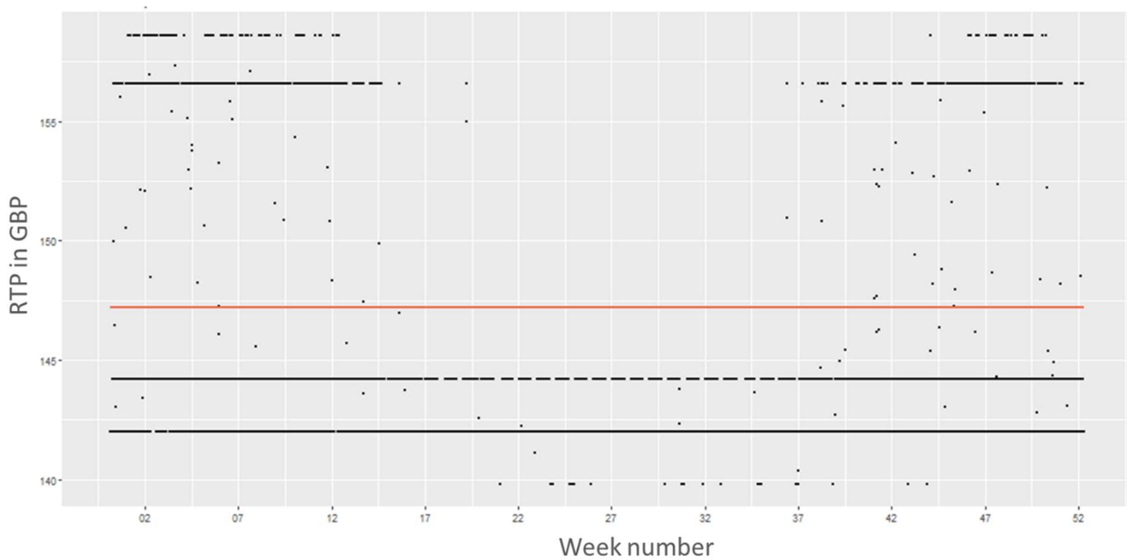
	2013	**2015 – 2017**
Household-demand weighted average	146.93	150.60
First quartile	142.00	148.53
Third quartile	144.21	150.93
Minimum	139.79	118.36
Maximum	158.61	154.50
Standard deviation	5.61	2.18

Figures 2 and 3 display the scatter plots of hourly RTP in 2013 and 2015 – 2017, respectively, with yearly average flat-rate prices indicated in orange. The price levels at which observations are clustered correspond to the marginal costs of the price-setting generation technologies (mainly conventional steam II-III and CCGT I-II). The observations scattered in between correspond to the vertical sections of the supply curve. Higher RTPs occur mostly during winter months; the volatility in RTP is also greater during these months. These observations can be explained by the greater overall level and variability of demand during winter months, respectively. Moreover, the range of RTP falls significantly in 2016 and 2017, as increases in the marginal cost of coal generation and favorable gas prices reduce the price differences between the various types of conventional steam and gas generation. By contrast, RTP in 2013 and 2015 are more volatile around the flat-rate price. Hence, demand pattern heterogeneity may beget bigger winners and losers compared to the flat-rate base scenario in 2013 and 2015.

The resulting cumulative distribution functions of RTP for 2013 and 2015 – 2017, respectively, are displayed in Figures 4 and 5. Note that the cumulative distribution function for 2015 – 2017 has a greater number of steps due to the fact that marginal costs are assumed to vary by year in order to account for changes in fuel and emissions prices.

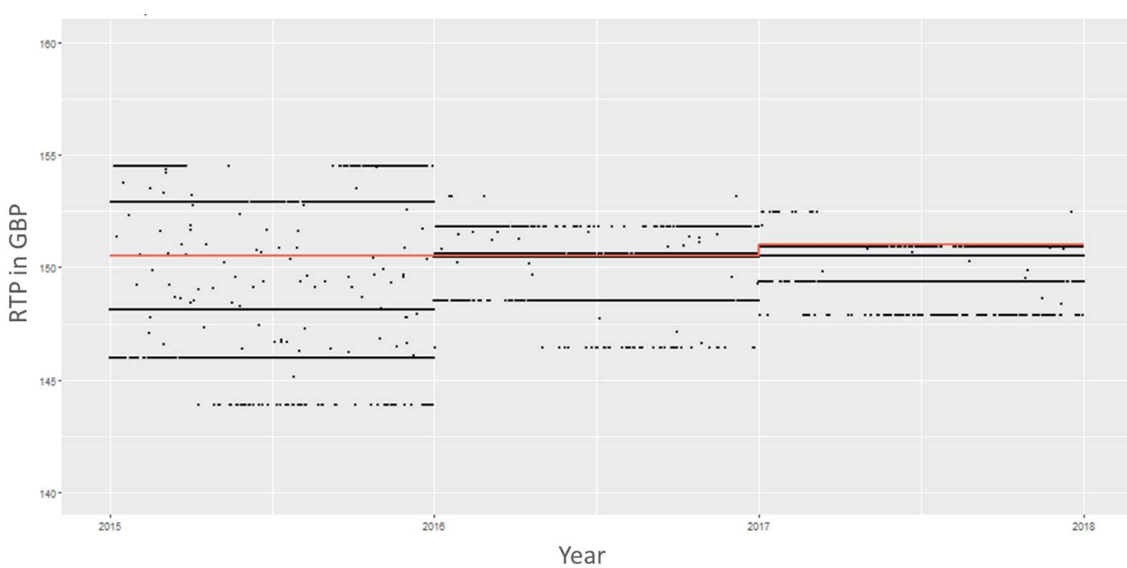
In summary then, our simulation does not buttress widespread fears of extreme price spikes during peak-demand hours under RTP-schemes. The exception are a few negative outliers with unusually low prices due to very high levels of zero-marginal-cost solar and wind generation. The lower range of RTP implies a smaller price signal price signal from RTP, but it also significantly limits the potential increase of customer bills from unfavorable demand patterns.

Figure 3: Simulated equilibrium RTP (black) & actual household flat-rate (red) (2013)



Simulated equilibrium RTP in 2013 cluster at certain price levels, corresponding to the horizontal sections of the electricity supply curve. RTP peak during winter weeks at the beginning and the end of the year; conversely, the lowest RTP are observed during summer weeks.

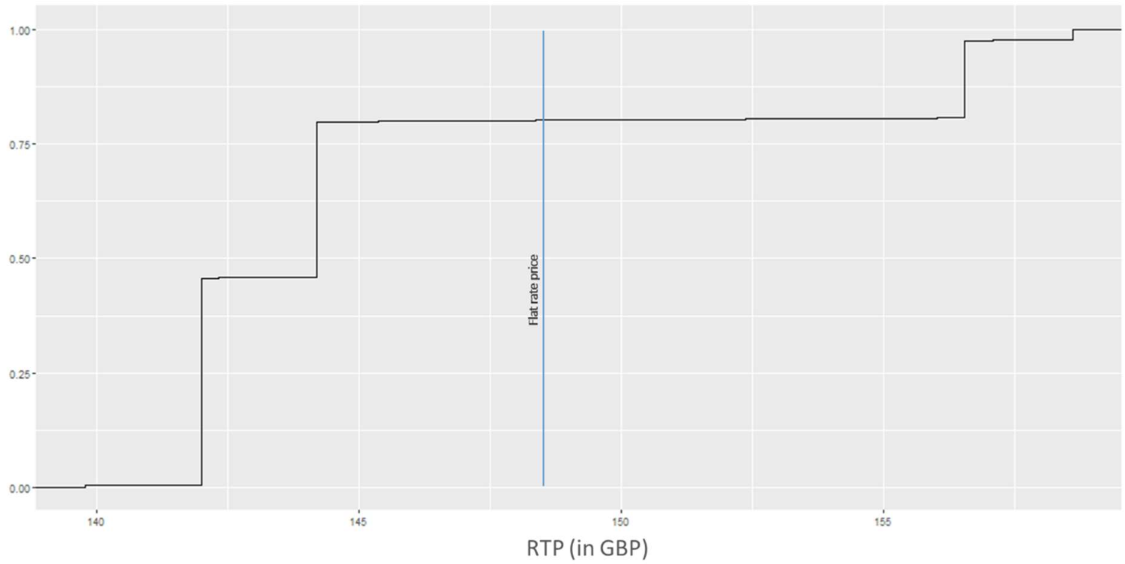
Figure 4: Simulated equilibrium RTP (black) & actual household flat-rate (red) (2015 – 2017)



Note: For better visibility, this plot is curtailed at £140/MWh, omitting six instances where RTP was below this price.

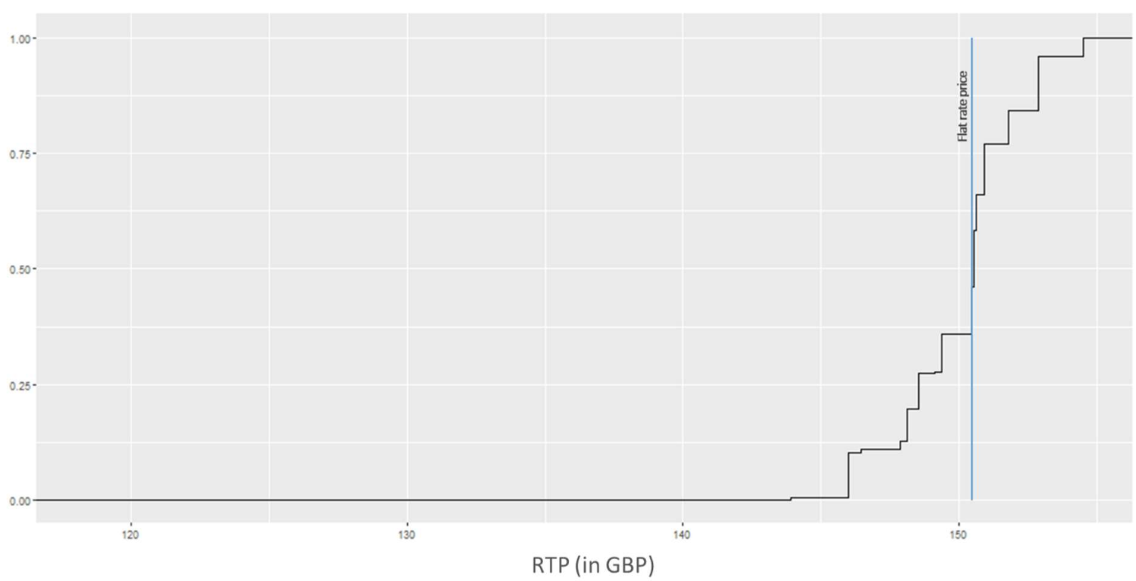
Again, for 2015 – 2017, RTP peak during winter weeks at the beginning and the end of the year; conversely, the lowest RTP are observed during summer weeks during the middle of the year. Equilibrium RTP are noticeably more volatile during 2015.

Figure 5: Cumulative distribution function for RTP (2013)



In 2013, simulated RTP were lower than or equal to the observed flat-rate prices during ca. 80% of all hours. Simulated RTP displays relatively low variance throughout the year (see Table 3 for exact figures).

Figure 6: Cumulative distribution function for RTP (2015 – 2017)



Throughout 2015 – 2017, simulated RTP were lower than or equal to the observed flat-rate prices during ca. 45% of all hours. Simulated RTP does not displays frequent and large price spikes, the maximum simulated RTP is only £154.50/MWh, compared to flat-rates of around £150.50/MWh (see Table 3 for exact figures).

5 Modelling Household Groups

In this section, we develop our unique specification that outlines the modelling of heterogeneous household groups. Differences in the hourly demand functions across groups are entirely due to differences in these groups' anchor series (since we assume that groups are homogenous with respect to their price elasticity, as discussed in section 3.1.1). To capture demand heterogeneity for different socio-economic groups, we therefore construct of these separate anchor series for all time-periods of our analysis.

For every time-period, we are interested in anchor series at two levels of granularity. At the group-wise level, for each of the seventeen groups, the "representative household" anchor series simply reflects the average demand per household within that group. The "aggregate household" series is extracted from the representative household series and scaled up by the number of households in a group, as calculated using the methodology described in section 3.2.

Finally, we also consider the UK domestic sector as a whole, irrespective of socio-economic groups. By summing up the 17 group-wise anchors across for each hour, we obtain the "aggregate domestic demand" anchor series. Dividing by the total number of households yields the "average domestic demand" anchor series.

5.1 Forming the 2013 Group-Wise Anchor Series

From the London Data Store 2013 data on 4,372 households, we calculate the anchor series for each group, averaged by the number of households in that group. Hence we obtain seventeen group-wise representative household series for the year 2013. Taking the product of these series with the number of households in the respective group yields the aggregate group-wise anchor series. Summing the aggregate household series across groups leads us to the series of aggregate domestic anchors. Dividing this series by the total number of households generates the average domestic anchor series (i.e. the series of anchors for an average household in the domestic sector).

5.2 Extrapolation of the 2015 – 2017 Group-Wise Anchor Series

The construction of the 2015 – 2017 group-wise anchor series is less straightforward than that of the 2013 series due to the unavailability of microdata. We extrapolate the 2015 – 2017 group-wise anchor series from the 2013 series using an adaptive mapping approach, described in the following sub-section.

The 2013 representative household anchor series for all groups are modelled as following a normal distribution. They are decomposed to obtain a base pattern captured by the standardized anchor series. These standardized anchor series are eventually reassembled through the reverse of standardization process using correctly estimated contemporary means and standard deviations, which represent level and scale effects respectively.

This sub-section first explores the key features of the 2013 group-wise anchor series that help design the mapping approach, then describes the model used in the adaptive mapping into second time-period, and finally presents justifying comments, robustness checks and a discussion on the household anchor patterns.

It suffices to extrapolate only the representative household series from 2013 to 2015 – 2017, since other three kinds of series can be derived from this. Hence, the entire extrapolation process addresses the representative household series.

5.2.1 Base (or Weekly) Patterns

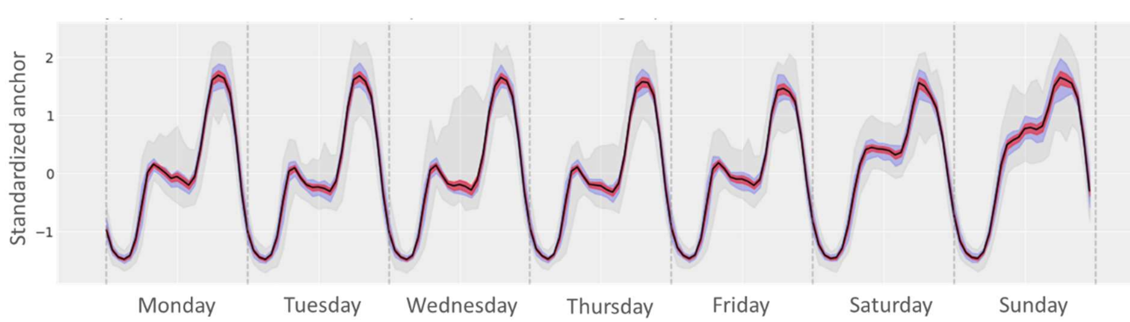
Each of the groups' representative household anchors are standardized by subtracting the mean of anchors within that week and then dividing the result by the standard deviation of anchors in that week. It is observed for all groups that the standardized anchor series throughout the year approximately follows the same weekly patterns, with little deviations. The *weeklypattern* is a mapping function, which records, for all 168 (=24×7) hours of the week, the averages of all 53 weeks of the year. For each of the 168 hours, indexed by t, the weekly pattern is defined as:

$$weeklypattern_g(t) = \frac{\sum_{w=1}^{53} a_{gtw}}{53}$$

Where g is the subscript for group and w is the subscript for week number. a_{gtw} is the standardized anchor for a representative household in group g for hour t in week number w.

Our procedure is illustrated using the example of Acorn Group H – Steady Neighborhoods, which is one of the largest household groups and displays fairly typical demand pattern. The shape of the demand pattern is remarkably similar across Acorn groups; however, the extent to which this pattern is pronounced varies.

Figure 7: Weekly pattern of standardized anchor for representative household in group H



The figure above displays the standardized anchor series for group H along with deviations represented using the 95% confidence intervals (red area), interquartile ranges (blue area) and full ranges (grey area). The areas are very tightly wrapped around the weekly pattern, indicating that there is little deviation from the weekly pattern across weeks. As expected, the consumption for representative household in group H peaks in the early evening, reaches its lowest level in the early morning, and is higher during the usual working hours on weekends. Similar trend is noticeable for all groups. For some groups like J – "Starting Out" and P – "Struggling Estates", the peak is observed later in the evenings.

The weekly patterns of standardized anchors from 2013 are stored to be later reconstructed using the features of 2015 – 2017 overall anchor series. We believe that these base patterns are fairly resistant to changes over short periods of time, unless there are structural changes in the demography or domestic power usage.

5.2.2 Weekly Downsampling for Mean and Standard Deviation Extraction

In order to reconstruct the group-wise anchor curves in 2015 – 2017, we require the weekly means and standard deviations of standardized anchors that we would expect to observe in 2015 – 2017. Although these may be correlated with the group-wise weekly means and standard deviations from 2013, using the latter to model the former would be a naïve approach and would capture all of the noise from 2013. Instead, we relate the group-wise mean and standard deviation series with the contemporary average domestic means and standard deviations. It must be noted that the average domestic anchor series for both time periods of observation represent the group composition as observed in all of UK data using Acorn shares reported in Table 1 rather than those observed in sample data from London Data Store. Thus, we maintain comparability between the time-periods of 2013 and 2015 – 2017.

Since we are interested in means and standard deviations for each week, we start by weekly downsampling the original (not standardized) 2013 anchor series for each group, that is, recording one mean and one standard deviation for each of the 53 weeks, which are the within-week averages. We compare these with average domestic weekly-downsampled means and standard deviations respectively. We indeed find a high degree of correlation for both statistics, as recorded in Table 4.

Table 4: Correlation coefficients for the representative household and average domestic statistics for 2013

Group	Correlation between weekly means of average groups with domestic average	Correlation between weekly standard deviations of average groups with domestic average
A	0.99	0.99
B	0.88	0.94
C	0.99	0.99
D	0.99	0.98
E	0.99	0.98
F	1.00	0.98
G	0.99	0.99
H	0.99	0.99
I	0.98	0.98
J	0.98	0.96
K	0.99	0.97
L	0.99	0.99
M	0.99	0.98
N	0.99	0.98
O	0.96	0.93
P	0.96	0.84
Q	1.00	0.99

The high coefficients of correlation can also be intuitively expected because representative households behave similar to the overall average domestic. All events that result in a certain shift of demand curve for average domestic must also be impacting individual households for all groups to a substantial extent in the same direction.

5.2.3 Extrapolation Methods

Our intention is to link group-wise representative household weekly means and standard deviations with the domestic average means and standard deviations respectively. One approach is to record the ratio of representative household statistic to average domestic statistic from 2013 and replicate the series of those ratios in 2015 – 2017. However, such translation risks passing on the noise from 2013 as well.

5.2.3.1 Denoising

In order to leave behind the noise transferred from 2013, we use a simplified process to smoothen the weekly mean and standard deviation series for the average domestic and all seventeen representative households. The denoising process uses a rolling window of five weeks, meaning that each observation is replaced with the moving average of the two previous, two following and the observation itself. Figures 7 and 8 illustrate the denoised weekly mean and standard deviation series for all groups, while highlighting the average domestic and representative household from our example group H.

Figure 8: Denoised weekly means of group-wise anchors

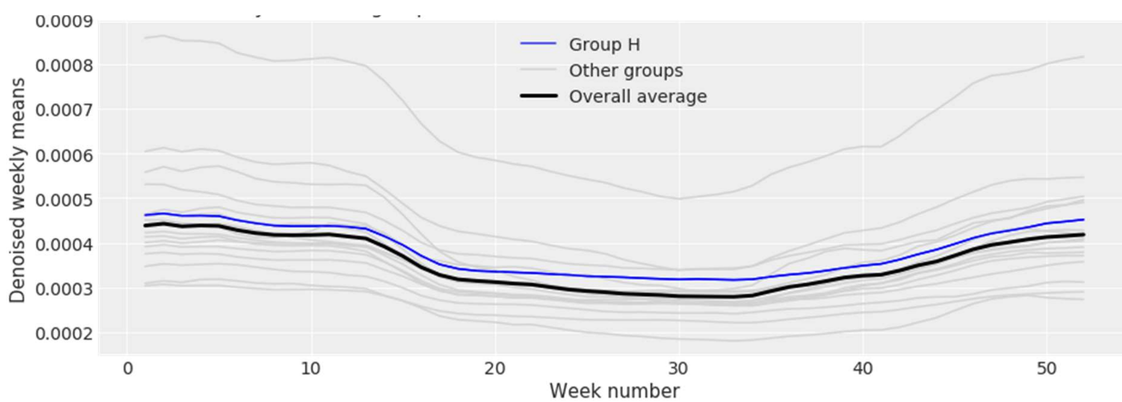
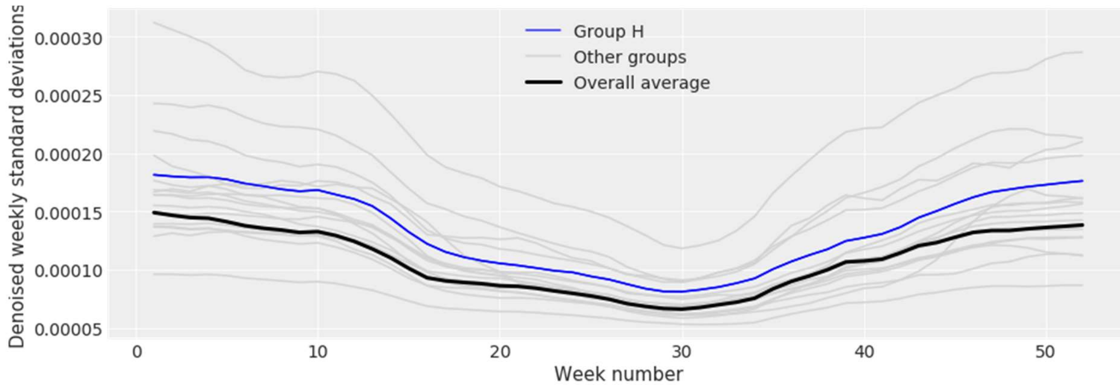


Figure 9: Denoised weekly standard deviations of group-wise anchors



The following ratios are defined using observed values from 2013:

$$\alpha_{gw} = \frac{\bar{a}_{gw}^{denoised}}{\bar{a}_{dw}^{denoised}}$$

$$\beta_{gw} = \frac{\sigma_{gw}^{denoised}}{\sigma_{dw}^{denoised}}$$

Where $\bar{a}_{gw}$ is the weekly arithmetic mean of anchor series for a representative household in group g, $\bar{a}_{dw}$ is the weekly arithmetic mean of anchor series for average domestic household, σ_{gw} is the weekly standard deviation from the mean of anchor series for a representative household in group g and σ_{dw} is the weekly standard deviation from the mean of anchor series for average domestic household. As before, the average domestic household is composed of all of UK's Acorn group proportions. The superscript $denoised$ refers to series that have been smoothened using a moving average of five observations.

These ratios represent the level and scale effect parameters respectively, and their weekly values are assumed to remain the same over years. Thus, each weekly parameter is replicated for each group for both moments.

5.2.3.2 Reconstructing the Group-Wise Anchor Series

The α_{gw} and β_{gw} observed in 2013 are extracted to calculate the representative household weekly means and standard deviations for 2015 – 2017. We assume that the ratio between representative household moments and average domestic moments remains the same for same week numbers across the years. While we used denoised statistics in 2013 to calculate the ratios, in 2015 – 2017 we use the original weekly downsampled series. We use the following to calculate weekly statistics for representative households:

$$\bar{a}_{gw}^{predicted} = \alpha_{gw} * \bar{a}_{dw}$$

$$\bar{\sigma}_{gw}^{predicted} = \beta_{gw} * \sigma_{dw}$$

The superscript $predicted$ refers to estimated variables.

As already mentioned, α_{gw} and β_{gw} take on the same values as observed in the denoised 2013 series. Before the extrapolation of the 2015 – 2017 representative household series is completed, we do not have the 2015 – 2017 values for $\bar{a}_{dw}$ and σ_{dw}. Instead of actual extrapolated values, we use a "placeholder" anchor series of the average domestic for 2015 – 2017. A detailed description and derivation of the placeholder series is discussed in the following sub-section.

Finally, we finish the mapping process by estimating the hourly anchor series for each group's representative household using:

$$a_{gh}^{predicted} = weeklypattern_g(h \bmod 168) * \sigma_{gw}^{predicted} + \bar{a}_{gw}^{predicted}$$

Where h is one of the 8,760 hours of the year.

5.2.4 Constructing the Placeholder Average Domestic Anchor Series for 2015 – 2017

As previously discussed, in the calculation of α and β group-wise weekly parameters of 2013, the weekly statistics series for the average domestic represent all of UK's Acorn domestic consumer segment, excluding other consumer segments like industry, services and transportation. A comparable base, which excludes other consumer segments, is required for calculation of representative household weekly statistics series. Hence, we derived the average domestic series for 2015 – 2017 using a similar process.

We used the calculated aggregated domestic anchor series from 2013 as previously mentioned and recorded the ratio of domestic anchor to overall (all consumer segments) anchor for every hour. We transferred this domestic ratio series to 2015 – 2017 by weekly downsampling and translating the weekly statistics series using the exact same methodology as we adopted while extrapolating representative household anchor series. From the transferred domestic ratios in 2015 – 2017, we recovered the total domestic anchor series using the observed overall anchor series of 2015 – 2017. This domestic anchor series was then divided by the total number of households in each hour to obtain average domestic anchor series for 2015 – 2017.

5.2.5 Model Justification

There are some conspicuous reasons why we adopt the model specification explained above.

The observation that households follow the same weekly patterns over the weeks with very little deviations makes it tempting to exploit the similarity. Although there are also strong inter-group similarities (as noted in section 5.2.2), we choose not to use that as the basis for our modelling. Doing so would be contradicting with our intention to analyze heterogeneity across groups.

Moreover, when extrapolating from 2013 to 2015 – 2017, there is a large risk of transferring the noise from 2013. A naïve approach would have been to draw out the ratio for each hour, and replicate that ratio to the following years for each of the 8,760 hours of those years. Another approach would be to estimate a single ratio of representative household series to average domestic series for the entire year, which would miserably fail to account for the fact that demand patterns of consumers develop differently over the year.

However, our current model is robust to such risk using double layer. First layer is using weekly patterns, such that within-week noise is controlled. Second layer is the denoising of weekly downsampled statistics series, such that noise across weeks is diminished.

A comment is in order regarding the selection of weekly granularity for downsampling. In the alternate scenario, if downsampling was monthly, we would overcontrol for the noise and fail to observe the weekly seasonal patterns of the series. On the other hand, any downsampling of higher than weekly granularity, but less than daily granularity, would fail to capture variation over the week, for example, that households have slightly different consumption patterns between weekdays and weekends. Finally, daily downsampling will allow too much noise to be transferred – what if the second Saturday of January 2013 hosted a large convention for students, and none of the students were home to consume electricity? We refuse to assume that the convention will occur exactly on second Saturdays of January for all of the following years!

5.2.6 Robustness Checks

First, we investigate robustness of using weekly pattern of standardized anchors as the base series. Table 5 below records the group-wise cross-validated Mean Squared Errors ("MSE") of weekly pattern series. For the MSE calculations, we use training periods of eleven months and test periods of one month. The calculations are iterated over each hold-out month and each of the 12-fold MSEs are averaged to calculate the final cross-validated MSE score of weekly patterns.

Table 5: 12-fold cross-validated MSEs of weekly patterns

Group	Cross-validated MSE score	Group	Cross-validated MSE score
A	0.1028	J	0.2872
B	0.2190	K	0.0910
C	0.0903	L	0.0664
D	0.0807	M	0.1043
E	0.0942	N	0.0904
F	0.0594	O	0.1296
G	0.0951	P	0.1667
H	0.0589	Q	0.0607
I	0.1824		

Compared with the range of standardized anchor weekly pattern series, the MSE scores for all groups are very small, although there is some inter-group variation. For example, for group H, they range from -1.45 to 1.70. The MSE score of 0.0589 is rather small compared with this range. An extreme example is group J where the MSE score is 0.2872 and the range is similar to that of group H. However, the MSE score is still contained within substantially small bounds.

The low MSE scores imply that weekly pattern retention form 2013 standardized anchor series is highly generalizable to unseen months.

Next, we comment on the goodness of fit for the entire model specification. Table 6 below records the coefficient of determination ("R^2") on the training set of hourly anchor series from 2013.

Table 6: R^2 of reconstructed anchor series on training data

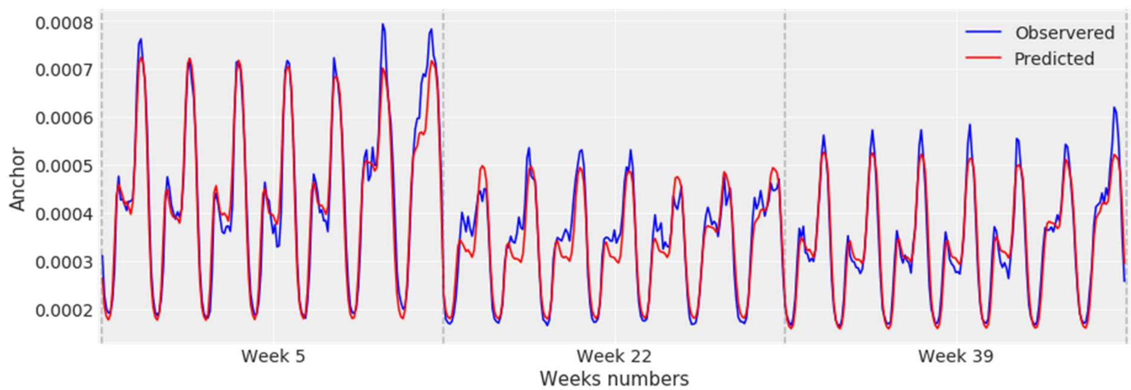
Group	R^2
A	0.9246
B	0.8174
C	0.9241
D	0.9385
E	0.9357
F	0.9477
G	0.9277
H	0.9466
I	0.8620

Group	R^2
J	0.8470
K	0.9223
L	0.9385
M	0.9198
N	0.9216
O	0.8820
P	0.8725
Q	0.9424

It is worth noting that these R^2s are based on the observed weekly mean and standard deviation series of 2013, resulting in optimistically high R^2s. When the model is transferred to 2015 – 2017 time-period, the representative household anchor series will be estimated based on weekly patterns together with the representative household weekly statistics series of 2015 – 2017. Since the latter are themselves predicted using parameters estimated in 2013 and the modelled weekly statistics of average domestic, the R^2s are expected to be slightly lower in 2015 – 2017. This is motivated by the fact that, as evaluated above, the weekly patterns seem to generalize well to new unseen data. The remaining controllable parts of our model are the weekly means and standard deviations. Since these signals are denoised, we are focusing on capturing and only transferring the high-level patterns of these, not short-lived variation. Therefore, by assuming that the pattern of weekly statistics of the group-wise representative household series is roughly aligned with that of the average domestic, we believe that the model in entirety will generalize well to unseen year 2015 – 2017.

Figure 9 below illustrates the observed and predicted representative household anchor series for group H for three evenly selected weeks from 2013.

Figure 10: Comparison between observed and predicted values for group H



5.2.7 Discussion of Household Anchor Patterns

As expected, the standard deviation of anchors around the weekly mean increases in the mean, both across groups and across time. As a consequence, demand variability is greater during winter months and for households with higher demand, particularly households from Acorn groups A to D. Households from higher socio-economic classes, who tend to consume more, also tend to have demand that varies more throughout the year and week, with particularly pronounced peak consumption. This suggests that household belonging to higher socio-economic classes will likely be harder-hit by RTP (as their peak-time consumption is currently subsidized by households with less pronounced peak consumption).

6 Results

To identify the welfare effects experienced by different household groups after moving from flat-rate pricing to RTP, we calculate the implied changes in consumer surplus.

We use a constant-elasticity demand function, for which consumer surplus is undefined. However, changes in consumer surplus can be calculated between two finite prices. For every hour h, the change in consumer surplus is thus given by

$$\Delta CS_h = \frac{anchor_h}{1-\varepsilon}\left[\bar{p}_h^{1-\varepsilon} - p_h^{1-\varepsilon}\right]$$

where $anchor_h$ is a placeholder for the relevant anchor. (Apart from changes in the relevant anchor, the functional form of the demand function remains the same; hence we can use the same formula to calculate consumer surplus changes for both the average household and aggregate consumer surplus for each group, as well as the consumer surplus for all domestic consumers.)

Note that the size of a representative household varies across groups. For example, Group K – "Student Life" comprises mostly single households, whereas Group M – "Striving Families" might contain three to five family members. Since we have no data on average household sizes for different Acorn groups, we cannot compare consumer surplus changes per individual. Hence the magnitude of consumer surplus changes is not comparable across groups. Likewise, the magnitudes of aggregate consumer surplus change cannot be compared across groups because different groups contain different numbers of households.

We find that the overall consumer surplus changes resulting from a change to RTP are of negligible magnitude (cf. section 6.1) and that the impact of RTP on consumer surplus does not vary significantly across socio-economic groups (cf. section 6.2). That is, we find no evidence for consumer welfare gains from RTP, nor do we find significant redistributive effects.

6.1 Overall Welfare Effects of RTP

Summed over all hours, the aggregate household consumer surplus changes going from flat-rate prices to RTP add up to negative £9.6 million in 2013 and an average of £3.8 million per year for 2015 – 2017. This corresponds to only 0.13% and 0.05% of the average yearly bill under flat-rate pricing, respectively, implying that either positive consumer surplus changes for some groups are cancelled out by negative consumer surplus changes for other groups, or that consumer surplus changes are very low for all groups.

Figures 10 and 11 below record the hourly changes in aggregate household consumer surplus for the years 2013 and 2015 – 2017. Although monthly or quarterly consumer surplus is what ultimately matters to consumers, considering hourly changes in consumer surplus illustrates the way in which RTP impacts consumer surplus across time. This in turn should allow policy-makers to better identify measures improving consumer surplus under RTP.

For both time-periods, except for the year 2017, large negative spikes in aggregate consumer surplus tend to be more common and of even greater magnitude than large upward spikes, especially during the winter months. This can be explained by the greater overall and peak-time demand during winter months. Reducing peak-time consumption during winter months, e.g. by reducing reliance on electric space heaters for additional heating, should help to reduce demand volatility and therefore peak-time RTP, which in turn should increase consumer surplus during winter. The fact that the aggregate change in consumer surplus for 2013 is slightly negative can be explained in this context: significant decreases in consumer surplus during the peak hours in winter are not fully compensated for by the more modest increases throughout the year.

The variance of consumer surplus is much higher in 2013 and 2015. This is because deviations of RTP – and hence consumer surplus – from the flat-rate depend largely on difference in marginal costs for different generation technologies. Large differences in marginal costs of least expensive production technologies, coupled with unusually low demand anchors results in huge positive consumer surplus changes in some hours.

Figure 11: Hourly changes in aggregate household consumer surplus (2013)

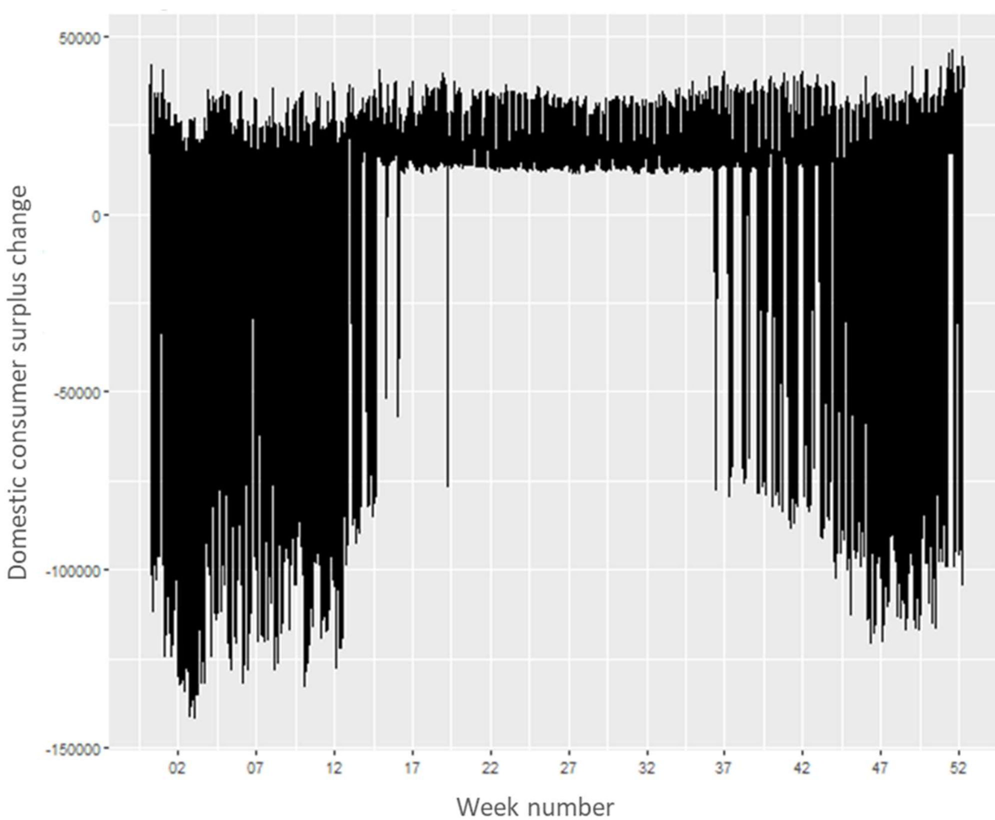
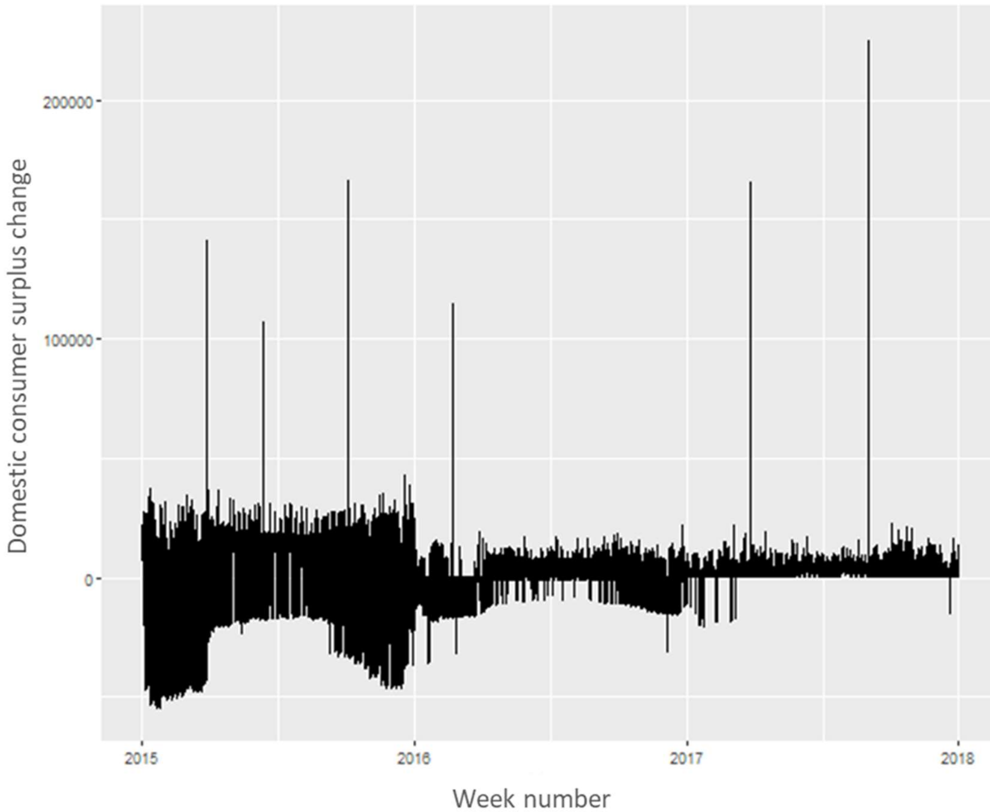


Figure 12: Hourly changes in aggregate household consumer surplus (2015 – 2017)



6.2 Welfare Effects of RTP on Different Socio-Economic Groups

Table 7 presents the group-wise simulated yearly consumer surplus changes going from flat rate price to RTP if $\varepsilon = 0.1$, both for the average household in each group and for the total number of households in each group (note that the number and size of households differ across groups).

Table 7: Yearly consumer surplus changes by Acorn group for $\boldsymbol{\varepsilon = 0.1}$ (in £)

	Group name	Representative household		Aggregate of households	
		2013	**2015/16/17**	**2013**	**2015/16/17**
A	Lavish Lifestyles	-1.19	0.17	-401,755.47	61,392.79
B	Executive Wealth	-0.51	0.07	-1,656,596.46	225,770.71
C	Mature Money	-0.91	-0.02	-2,101,699.67	-24,767.81
D	City Sophisticates	-1.30	-0.06	-1,099,947.29	-43,011.37
E	Career Climbers	-0.47	0.19	-735,902.13	313,795.79
F	Countryside Communities	-0.35	0.11	-579,347.10	194,513.22
G	Successful Suburbs	-0.83	0.05	-1,308,808.04	77,782.88
H	Steady Neighborhoods	-0.56	0.06	-1,204,839.94	129,742.02
I	Comfortable Seniors	-0.92	-0.05	-602,117.64	-32,863.45
J	Starting Out	-0.04	0.43	-35,767.97	453,312.93
K	Student Life	-0.33	0.11	-216,977.90	75,789.55
L	Modest Means	-0.40	0.07	-778,149.15	153,483.69
M	Striving Families	-0.66	0.07	-1,380,500.37	150,853.30
N	Poorer Pensioners	-0.39	0.07	-452,298.74	79,789.04
O	Young Hardship	-0.11	0.13	-146,772.81	178,414.61
P	Struggling Estates	1.47	0.77	3,005,966.89	1,573,141.72
Q	Difficult Circumstances	0.08	0.18	100,163.44	231,901.87
	Weighted[1] average	**-0.37**	**0.14**	**-**	**-**
	Sum	-	-	-9,595,350.37	3,799,041

[1]*Weighted by the proportion of households in the overall household sector.*

Across all Acorn groups, the short-run change in consumer surplus that would result from a switch to RTP is very low, of the order of less than £1.50 per year. The differences in demand patterns across Acorn groups do no translate into significant redistributions of consumer surplus. The fact that none of the 17 Acorn groups experiences any significant losses of consumer surplus should alleviate fears that introducing RTP might significantly harm certain consumer groups.

At the same time, we do not find significant welfare gains from a switch to RTP for any socio-economic group. Concentrating on the short-run impact of RTP thus fails to make a case for RTP from the consumer perspective, especially considering the costs of smart meters[10] and the widespread psychological aversion to RTP.

[10] *The cost to electricity companies of installing a smart-meter in a UK household is estimated to be around £100 (UK Power, 2018). Since smart-meters have been shown to aid consumers in identifying wasteful consumption patterns, the benefits of smart-meters go beyond enabling RTP, i.e. investments in smart-meters do not solely*

The magnitude of the consumer surplus changes resulting from a switch to RTP remains negligible when we consider elasticities that differ from our central scenario of $\varepsilon = 0.1$. In line with the range of estimates that can be found in the literature, we also estimate consumer surplus changes per representative households for elasticities ranging from 0.025 to 0.15. Results for the year 2013 can be found at the end of this section in Table 8.

The observation that both the magnitude of consumer surplus changes for different groups, as well as the difference in consumer surplus changes across these group is very small can be explained by the shape of the British electricity supply curve over our periods of interest. The latter features relatively low marginal cost differentials and large capacities of mid-merit (i.e. conventional steam and gas) generation. Variations in load and residual load brought about by variations in household demand and non-dispatchable energy generation, respectively, therefore cause only limited variations in marginal cost.

It should be noted that consumer surplus from switching to RTP are likely to be significantly higher in the long run, since generation companies should pass on the savings from capacity reduction to consumers in the form of lower surcharges. However, note that by reducing demand volatility, RTP discourages investments in peak-time generation with high marginal and low fixed costs to the benefit of renewable, baseload, and mid-merit generation with lower marginal and higher fixed costs. Holding demand patterns constant, significant heterogeneity in the welfare changes implied by a switch to RTP should therefore only arise if there is a greater range in the marginal costs of the final generation technologies dispatched to meet demand. This could happen, for instance, if the share of generation technologies with very low marginal costs (i.e. wind, solar, and nuclear energy) becomes great enough that conventional steam and gas generation is not dispatched for a large number of hours.

depend on RTP for profitability. The UK government has set a goal of installing a smart meter in every home by 2020; one quarter of British households already have a smart-meter (UK Power, 2018).

Table 8: Sensitivity Analysis for Different Demand Elasticities ε

Group name		Consumer surplus change by Acorn group for different ε (in £, over the year 2013)					
		ε =0.025	ε =0.050	ε =0.075	ε =0.100	ε =0.125	ε =0.150
A	Lavish Lifestyles	-1.32	-1.27	-1.23	-1.19	-1.14	-1.10
B	Executive Wealth	-0.59	-0.56	-0.54	-0.51	-0.49	-0.46
C	Mature Money	-1.00	-0.97	-0.94	-0.91	-0.88	-0.86
D	City Sophisticates	-1.40	-1.37	-1.33	-1.30	-1.27	-1.24
E	Career Climbers	-0.54	-0.51	-0.49	-0.47	-0.45	-0.42
F	Countryside Communities	-0.41	-0.39	-0.37	-0.35	-0.33	-0.31
G	Successful Suburbs	-0.90	-0.87	-0.85	-0.83	-0.81	-0.78
H	Steady Neighborhoods	-0.64	-0.61	-0.58	-0.56	-0.54	-0.51
I	Comfortable Seniors	-0.98	-0.96	-0.94	-0.92	-0.89	-0.87
J	Starting Out	-0.11	-0.08	-0.06	-0.04	-0.01	0.01
K	Student Life	-0.40	-0.38	-0.35	-0.33	-0.31	-0.29
L	Modest Means	-0.47	-0.44	-0.42	-0.40	-0.38	-0.36
M	Striving Families	-0.73	-0.70	-0.68	-0.66	-0.64	-0.61
N	Poorer Pensioners	-0.45	-0.43	-0.41	-0.39	-0.37	-0.35
O	Young Hardship	-0.16	-0.14	-0.13	-0.11	-0.09	-0.07
P	Struggling Estates	1.44	1.45	1.46	1.47	1.48	1.49
Q	Difficult Circumstances	0.03	0.05	0.07	0.08	0.09	0.11
Weighted* average		**-0.44**	**-0.42**	**-0.39**	**-0.37**	**-0.35**	**-0.33**

**Weighted by the proportion of households in the overall household sector.*

7 Limitations

For ease of modelling and reasons of data availability, the above analysis abstracts from several important features of the electricity market. Below, we will list some of the limitations of our analysis as well as the mechanisms we abstract from, and discuss their impact on our analysis.

One limitation of our analysis arises from seeming inaccuracies of our supply stack model. Compared to actual data on electricity production by generation type from ENTSO-E, our model implies much less frequent deployment of pumped storage generation under flat-rate prices. Whereas ENTSO-E records suggests that (albeit small) capacities of pumped storage generation are deployed for a few hours almost every day, our model suggests that under flat-rate pricing, pumped-storage is only deployed sporadically.

There are several possible explanations for this shortcoming. Since the British electricity zone does not allow locational pricing, our model requires that all cheaper units of electricity are already deployed before pumped storage generation is dispatched. In reality, pumped storage generation in location A may be deployed even though generation capacity with lower marginal costs is available at a faraway location B even without explicit locational pricing, e.g. due to transmission line congestion. Alternatively, such a phenomenon could arise because firms exert market power by purposefully refusing to dispatch a cheaper unit of generation in order to increase the wholesale price (which is set by the generation unit with the highest marginal cost). By contrast, since we abstract from such behavior in the wholesale market, we assume that all available generation is dispatched in order of marginal cost.

Since there is a noticeable jump in marginal cost from conventional steam/ gas generation to peak (i.e. pumped-storage, OCGT, and oil) generation, our model supply curve is likely less steep than the real supply curve. As a consequence, our model may somewhat understate the bill differences across different consumer groups under RTP. Under the real, steeper supply curve, consumer groups with peakier-than-average demand pay for much pricier pumped storage; by contrast, consumers with flatter-than-average demand patterns can realize greater savings compared to the flat-rate, since they are no longer forced to subsidize much more expensive peak generation. Given that lower-income customers in our sample tended to have flatter-than-average demand, however, we do not believe this limitation will substantially alter our conclusions.

On the demand side, we make the simplifying assumption that elasticities are the same for all hours. However, although studies of price elasticity under time-of-use pricing schemes vary with respect to their estimated elasticities, they almost unanimously suggest that elasticity is greater in peak hours and lower during off-peak hours (Lijesen, 2007). Since the savings from RTP compared to flat-rate pricing come primarily from reduced peak-time demand, our analysis therefore likely understates the benefits from RTP (Borenstein, 2005).

Moreover, as explained in detail in section 3.1.1, we assume that the price elasticity of demand is the same for all household groups, since a substantial portion of the literature suggests that price elasticity of demand does not vary with income, while a significant minority of papers imply that low income customers are either less or more price elastic than the average consumers. If already disadvantaged socio-economic groups have lower than average demand elasticity, their welfare gains from RTP will be lower. Partly to address this issue, we have calculated the group-wise welfare impact of RTP for different elasticities ranging from 0.025 to 0.15. We found that even at lower elasticities, consumer surplus changes for low-income groups remain negligible. Nonetheless, further research into the relationship between socio-economic group and RTP is necessary to gain an understanding of the relationship between household income and price-elasticity, and thus a more holistic picture of its impact on various social groups.

We also make the simplifying assumption that demand is additively separable across hours, implying that cross-price elasticities are zero. This assumption significantly reduces the computational complexity of our model by abstracting from intertemporal substitution of consumption. However, the literature suggests that cross-price elasticities for electricity are dwarfed by own-price elasticities (Alcott, 2011; Holland & Mansur, 2006). Moreover, holding own-price elasticity constant, allowing positive cross-price elasticity will further decrease peak-time consumption when peak-time prices rise (Borenstein, 2005). Conversely, it will increase off-peak consumption. Positive cross-price elasticity should therefore increase the benefits from RTP.

In extrapolating household demand patterns (as defined by the relevant series of anchors), we assume that no structural changes in demand patterns or the relative size of groups have occurred throughout our period of study. Since our household consumption data was compiled for a balanced sample of the London population, it has limited generalizability to drawing conclusions on the impact of RTP on different segments of the British population in general. Members of a given Acorn group living in London are likely to differ from members of the same Acorn group in e.g. a small town. Our calculations of the consumer surplus changes for the UK domestic sector as a whole were only intended to deliver rough estimates. To gain a nuanced view of the impact of RTP on different socio-economic groups, further research incorporating potential variation of demand patterns across geographical areas is thus necessary

Finally, the extrapolation methodology for the weekly pattern series from 2013 to 2015 – 2017 assumes that standardized anchors follow a normal distribution. However, some of the representative household series are very slightly positively skewed. This could have been controlled for by introducing other factors that can explain some of the remaining signal.

8 Conclusion & Outlook

Economic theory suggests that RTP is the most efficient way to price electricity and that it can contribute to a reduction in emissions by enabling a greater share of intermittent renewable generation. Nonetheless, real-time electricity pricing has been met with strong opposition from policy-makers, on the grounds that it may have adverse redistributional effects, reducing the welfare of already disadvantaged consumers. So far, such theoretical concerns have not been put to test empirically. Combining simulations of the British electricity market under RTP with actual and simulated electricity demand for households from various socio-economic groups, we have estimated the short-run welfare effects of RTP on these different groups. We emphasize upon two important findings, namely that RTP in general only has a negligible effect on consumer welfare and that the welfare changes resulting from a switch to RTP do not vary to any meaningful extent across socio-economic groups. Our results therefore do not provide a strong case for RTP in Britain in the short run, however, nor does it confirm the widespread concerns over unfair distributional effects of RTP.

This paper provides only first investigations into potential differences in the welfare impact of RTP across different socio-economic groups. Further research should account for the long-run welfare effects of RTP by endogenizing generation firms' capacity decisions. By focusing on the short-run effects of RTP, we assume that the merit order stack remains unchanged after switching from flat-rate pricing to RTP and ignore the changes in the capacity mix that would likely result from mandatory RTP in the long run. Reduced volatility of residual demand for dispatchable generation should lead generation companies to disinvest peaker capacity, characterized by high marginal and low fixed costs. In the long run, RTP should therefore remove idle peak capacity. Competitive pressures should translate the resulting fall in fixed costs into lower surcharges $\bar{r}$.

Our paper also abstracts from several other factors with the potential to cause different welfare impacts across groups. In particular, future research should incorporate potential heterogeneity in the price elasticity across hours and consumer groups.

Finally, it should be noted that the differences in welfare changes (or lack thereof) across groups largely results from the flatness of the British supply curve during our period of interest. Considerations of the redistributional effects of RTP in other parts of the world must therefore take into account differences in the relevant capacity mix.

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Appendix A – Constructing Conventional Generation Types

Data on installed generation capacities in Great Britain for the years 2013-2018 is taken from chapter 5.7 of the Digest of UK Energy Statistics (DUKES 5.7) (Department for Business, Energy, and Industrial Strategy, 2018f).

DUKES 5.7 lists capacities installed at the end of December of each year; for data availability reasons, we use them for modelling the *following* calendar year. For instance, we assume that generation capacities throughout the year 2013 are equal to the capacities recorded by DUKES 5.7 at the end of December of 2012.

The DUKES 5.7 distinguishes between six types of dispatchable generation, namely nuclear, conventional steam (primarily coal), CCGT, 'other renewables' (mainly biomass), pumped storage, and OCGT/oil. To better reflect heterogeneity in production technologies, we further split these categories according to different marginal costs. We abstract from hydro natural flow generation, as well as imports and exports. Moreover, we de-rate capacities to account for planned and unplanned outages (cf. section A1.7). The construction of our model's generation capacities and the underlying DUKES 5.7 categories summarized in Table 9 with more detailed explanations given below.

Table 9: DUKES generation types & corresponding types in our model

DUKES 5.7 Generation Type	**Capacity category in our model**
Nuclear	Nuclear
Other renewables*	Biomass
Conventional Steam Stations**	Conventional Steam I Conventional Steam II Conventional Steam III
CCGT	CCGT I CCGT II CCGT III
Pumped Storage	Pumped storage
OCGT and oil generation	OCGT Oil
-	Demand side response (DSR)

**primarily biomass*

***mainly coal, also includes CHP electric generation capacity*

A.1 Nuclear Generation

In the case of nuclear power generation, we simply preserve the original category from DUKES 5.7

A.2 Biomass Generation

Marginal cost of biomass generation varies substantially by generation plant and type of input used (E4Tech, 2010). Unfortunately, we do not have access to more detailed data in the installed capacities and marginal costs of different types of biomass generation. However, biomass generation directly precedes coal in the merit order stack (Competition and Markets Authority, 2016b). We therefore make the simplifying assumption that biomass has the same marginal cost as the most efficient tranche of conventional steam generation.

This assumption should not much impact market prices in our model. Over our period of interest, biomass capacity represents at most one half of the conventional generation tranche I capacity. Thus, the cheapest units of biomass are so low on the merit order stack that only rarely they will be the final unit dispatched. Consequently, biomass generation will rarely set the market price in our model.

A.3 Conventional Steam & CCGT Generation

Following Staffel & Green (2015b), we split both conventional steam generation and CCGT generation into three efficiency tranches. Efficiencies of the different tranches are taken from the same source, and reflect the mean $\pm$ one standard deviation, respectively. The tranches are assumed to stand in a fixed 25:50:25 ratio to one another, with the following associated efficiencies.

Table 10: Assumed relative efficiencies of different tranches of conventional steam and CCGT generation

DUKES 5.7 Generation Type	Tranche	Efficiency (LHV)*	Efficiency relative to average efficiency
Conventional Steam	Conventional Steam I	0.3350	0.9178
	Conventional Steam II	0.3650	1.0000
	Conventional Steam III	0.3950	1.0822
CCGT	CCGT I	0.5050	0.9528
	CCGT II	0.5300	1.0000
	CCGT III	0.5550	1.0472

**LHV (Lower heating value) efficiency is the standard measure of electrical generation efficiency in Europe, in contrast to HHV (higher heating value) efficiency commonly used in the US.*

The marginal cost of tranche II is just the average marginal cost of the relevant generation type. The marginal cost of tranches I and III are assumed to be equal to the marginal costs of tranche II, multiplied by the corresponding relative efficiency. By increasing marginal cost – as opposed to fuel costs only – according to decreases in efficiency, we assume that variable O&M costs are proportional to efficiency. We choose to make this assumption because less efficient plants tend to be older, increasing costs for supervision and management.

A.4 Pumped-storage generation

Pumped storage generation represents a distinct category in our merit order stack, since its marginal costs are significantly higher than those of upper-mid-range generation, and significantly lower than those of fossil oil. We hence retain the separate category for pumped storage from DUKES 5.7.

A.5 Demand-side response (DSR)

The UK's demand-side response scheme compensates mainly large industrial users for reducing their electricity consumption in order to balance the grid during times of extremely high load. Again following the UK Competition and Markets Authority, we add 1000MW of demand side response at the end of the merit order stack (2016a).

A.6 OCGT & Oil Generation

Since OCGT and oil generation have vastly different marginal costs, we also split the "OCGT and oil category" found in DUKES 5.7 into two separate categories. To do so, we rely on data from the ENTSO-E Transparency Platform (2019), which lists installed generation capacity by fuel type. We subtract installed capacity of oil generation as listed int ENTSO-E from DUKES 5.7 category "OCGT & oil generation", in order to obtain separate categories for OCGT and oil generation, respectively.[11] Note that, according to ENTSO-E, no oil generators were in service from 2018 onwards.

A.7 De-rating Capacities

To account for the effect of planned and unplanned plant outages on available capacity, we de-rate installed capacity. That is, we multiply installed capacity for a given generation type by that type's average availability throughout the year, in order to obtain available capacities. Estimates of availability vary somewhat across the literature. This is because availability is influenced by weather, plant type and age, etc. We draw availability estimates mainly from Parsons Brinckerhoff estimations for the UK's Department of Energy and Climate Change (Parsons Brinckerhoff, 2013). Assumptions on availability are summarized in Table 10.

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[11] *For the year 2018, we can compare the OCGT capacity suggested by our own approach with that recorded in a list including all British OCGT plants from DUKES 5.11 (Department for Business, Energy, and Industrial Strategy, 2018d). Our own approach suggests an installed OCGT capacity of 1590 MW at the beginning of 2018, compared to 1489 MW in May of 2018, according to DUKES 5.11.*

Table 11: Plant availability by generation type

Generation technology	Availability	Source
Nuclear	91.0 %	Parsons Brinckerhoff, 2013, p. 44
Biomass	90.0 %	Parsons Brinckerhoff, 2013, p. 47
Conventional Steam	90.0 %	Parsons Brinckerhoff, 2013, p. 36
CCGT	92.8 %	Parsons Brinckerhoff, 2013, p. 31
Pumped Storage*	98.0 %	National Grid, 2017, p. 30
OCGT	94.7 %	Parsons Brinckerhoff, 2013, p. 46
Oil	94.7 %	National Grid, 2017, p. 30

**Availability estimates for pumped storage are based on summer 2016 only. Firms often schedule maintenance for summer when demand in the UK is lower; hence the cited figure may somewhat understate actual average availability throughout the year.*

Appendix B – Estimating Marginal Generation Costs

Whereas the literature abounds with papers estimating the levelized costs of electricity (LCOE) for various generation types, estimates of the marginal costs, which are necessary to estimate the supply curve, are much harder to come by. To our best knowledge, relevant marginal cost estimates for our period of interest are not available. We therefore calculate marginal costs by updating the marginal costs for 2010 as calculated in Staffel & Green (2015a) with current fuel and carbon prices. For coal and gas generation, we use their estimates for large plants, since during our period of interest the capacities of small plants amount to only a negligible share of total generation within their respective type (Department for Business, Energy, and Industrial Strategy, 2018d).

For coal-based, gas, and oil generation, we use yearly average prices of fuels purchased by major UK power producers as published in QEP 3.2.1 (Department for Business, Energy, and Industrial Strategy, 2019a). For carbon prices we calculate yearly averages based on price data from Sandbag.org.uk (2019). The prices underlying our marginal cost calculations are listed below in Table 12 (rounded to two decimal points for ease of presentation).

Table 12: Average cost of electricity generation fuels and CO_2, by year

Fuel (in £/MWh)	2013	2014	2015	2016	2017	2018
Coal	8.42	7.79	6.69	7.47	10.16	10.56
Natural Gas	44.89	40.53	27.03	23.93	30.83	38.56
Oil	22.99	18.90	15.86	12.76	15.24	19.25
CO_2	4.46	6.00	7.69	5.35	5.84	16.03

Taking into account the different efficiencies associated with different tranches of conventional steam and gas generation, the above fuel and emission certificate prices allow us to estimate he marginal cost of conventional steam, CCGT, oil, and biomass generation.

We assume that the marginal cost of nuclear energy remains constant at Staffel & Green's (2015a) estimation of £5/MWh.

In estimating the marginal cost of pumped storage, we rely on the UK Competition and Markets Authority's (2016a) assumption that the marginal cost of pumped storage is equal to the marginal cost of the least efficient CCGT plant, plus 5%. We therefore set the marginal cost of pumped storage equal to the marginal cost of CCGT tranche III generation, plus four times the standard deviation, increased by 5%. Finally, we also follow the Competition and Markets Authority (2016a) in assuming the cost of DSR is £250/MWh.

We obtain the following marginal costs (rounded to two decimal points in the table below for ease of presentation).

Table 13: Marginal cost of generation, by generation type and year

MC in £/MWh	2013	2014	2015	2016	2017	2018
Nuclear	5.00	5.00	5.00	5.00	5.00	5.00
Biomass	24.70	24.56	23.53	23.35	29.53	38.45
Conventional Steam I	24.70	24.56	23.53	23.35	29.53	38.45
Conventional Steam II	26.91	26.76	25.64	25.44	32.17	41.90
Conventional Steam III	29.12	28.96	27.75	27.53	34.82	45.34
CCGT I	41.47	36.23	32.53	27.37	31.03	40.16
CCGT II	43.52	38.03	34.14	28.73	32.57	42.15
CCGT III	45.57	39.82	35.75	30.08	34.10	44.14
Pumped storage	50.87	47.46	42.61	35.85	40.65	52.60
OCGT	76.03	65.07	57.27	46.76	54.31	72.44
Oil	149.92	138.03	98.37	86.81	108.29	*141.11*[*]
DSR	250	250	250	250	250	250

[*]*Marginal costs for oil generation would have jumped to £141.11*/MWh *in 2018, however, no oil generation capacity was operational that year*

Note that in 2017 and 2018, the merit order changes, and some tranches of coal generation become more expensive than gas generation.

B.1 Discussion of Own Marginal Cost Estimates Compared to the Literature

The Energy Market Investigation Final Report from the UK CMA (2016b) censors marginal cost data to protect competition in the market; however, it provides a graph of the British merit order stack in the winter of 2013. Marginal costs are broadly in line with our own estimates for 2013, although generally somewhat higher for conventional steam and coal generation. Finally, Charles River Associates (2016) suggests marginal costs for CCGT vary between £42.3/MWh for newer types and £46.3/MWh for older types, and £64.7/MWh for OCGT.

Appendix C – Simulating Non-Dispatachable Generation for 2013

Data on actual generation from solar and wind sources is only available from 2015 onwards. In order to create a supply curve for the year 2013 that accounts for the merit order effect of intermittent renewables, we rely on simulated hourly wind and photovoltaics capacity factors from OPSD (Pfenninger & Staffell, 2017). These hourly capacity factors were calculated based on historical weather and satellite data. They describe what fraction of installed capacity was available for electricity generation at any point in time. Since we assume that wind and solar generation have the lowest marginal cost, and because available renewable generation is dwarfed by load in all hours of 2013, we assume that all available generation capacity was used at any hour. We can therefore simulate wind and photovoltaics generation for every hour by multiplying hourly capacity factors from OPSD with installed capacities as listed in DUKES 5.7. Note that, since listed generation capacities of small solar and wind power generators were de-rated according to assumed average availability throughout the year, we first have to undo this de-rating in order to obtain actual installed capacities.