Wholesale cost reflectivity of GB and European electricity prices

A project commissioned by Ofgem

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Preface

The Office of Gas and Electricity Markets (Ofgem) commissioned University College London (UCL) in February 2018 to conduct a study of the cost reflectivity of Great British (GB) and European electricity wholesale prices, as part of the project 'Assessment of wholesale Cost pass-through and reflectivity in GB and major European electricity markets' (ACE). This project report derives from a collaboration led by UCL involving Imperial College London and was designed to inform Ofgem's flagship report 'State of the Energy Market'.

Wholesale expenses are the largest component of electricity costs to GB consumers, consisting of nearly 40% of electricity bills. The largest five generators represent a combined share of nearly 60%. The presence of market power (or the lack of competition) would likely lead to higher electricity wholesale prices, hence more expensive electricity bills to consumers. It is therefore crucial to monitor the wholesale electricity market and ensure its competitiveness. One way is to inspect whether the electricity prices it yields are 'cost-reflective'. This means investigating how proportionately the costs borne by generators are internalised into prices. If it costs less for generators to produce electricity, then customers should pay proportionately less for that electricity.

This report aims to understand the principal determinants of electricity wholesale prices in GB and a sample of major European markets; and to investigate the competitiveness of these markets by studying how the major fuel costs borne by generators are reflected into electricity prices.

The electricity markets considered are: GB, Germany, France, Italy, Spain, Netherlands, and Norway, during the period 2012–2017. The primary determinants of day-ahead electricity wholesale prices are inspected by quantifying the shares at the margin of the major fuel-intensive technologies in each market. An econometric analysis is used to estimate the pass-through rate of fuel prices into the electricity wholesale price in each market.

Our work also considers the influence of the largest five generators in GB on electricity prices, based on their internalisation of imbalance costs during the period 2014–2017. Imbalances are typically unforeseen, so they cannot be factored into electricity prices in advance. We therefore consider whether previously incurred imbalance costs appear to be factored in. The impact of the studied input costs on the volatility of GB and European electricity prices is also examined. Finally, the presence of causality and asymmetric[1] pass-through of fuel prices and both national and firm-level imbalance costs into electricity prices is considered. An additional analysis examines these questions on an annual basis.

[1] An 'asymmetric' response occurs when electricity prices rise more strongly, or quickly, following an increase in an input's cost, than they fall following a corresponding reduction in the input cost.

Executive Summary

Fuel cost reflectivity of GB and European electricity prices

1. In 2017, the **GB** electricity price was close to a threshold **consistent with very strong cost reflectivity**, with a substantial increase compared to 2016.

> *Based on movements in the cost of gas, the GB electricity wholesale market is more cost-reflective than a sample of five major European wholesale markets.*

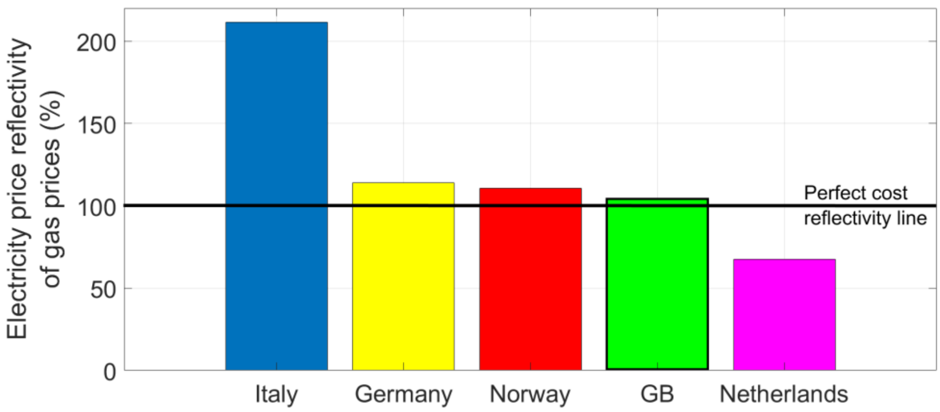
2. Based on movements in the cost of gas, **the GB electricity wholesale market is more cost-reflective than a sample of five major European markets**.

3. The extent to which electricity prices are cost-reflective of gas is not constant. Instead, it fits a *cyclical pattern* during the period 2012–2017, fluctuating by 23% per year around a mean of 104%.

4. The >100% mean rate estimated for GB is consistent with **some degree of market power by GB gas generators** during 2012–2017. There is evidence of **temporary periods of market power** throughout this timeframe.

5. During 2012–2017, Italian electricity prices increased much more than justified by the positive changes in gas prices, whereas Dutch electricity prices experienced the lowest proportionate rise of European markets.

6. The GB electricity price responded symmetrically to changes in the gas price, meaning prices rose and fell equally with gas price increments and



reductions. However, we found *asymmetric*[2] *responses to changes in the coal price*, which coincided with a period of mostly falling coal prices. This means that coal generators increased electricity prices in response to increases in the coal price more strongly than they decreased the electricity price when the coal price fell.

7. Coal prices did not have a statistically significant impact on mean GB electricity prices during 2012–2017. Instead, they largely contributed to the volatility of GB electricity prices. This may be due to GB no longer having abundant coal capacity or annual output. The inflexibility of coal could also have had a role in determining these results. Yet we find that coal's influence on the price increased substantially, *relative to its overall role in power generation (which declined far more)*.

8. Italy is the only electricity market which displayed asymmetric responses of the electricity price to changes in the gas price. In other words, electricity prices increased more in response to changes in gas prices than they decreased.

Internalisation of imbalance costs by GB generators

9. Generators in GB are likely to have somewhat **internalised previously incurred imbalance costs** into electricity prices between 2012 and 2017.

10. Imbalance prices have *caused* changes in GB electricity prices in 2016 and 2017. Yet there is no evidence of causality running from imbalance prices to electricity prices over longer periods of time (2012–2017).

11. **Imbalance costs do not have a substantial impact on the GB electricity price.**

12. The pass-through rate of imbalance prices into the electricity wholesale price increased considerably in 2016. This could be due to the change in the imbalance price formula[3] occurred in 2015 or, more likely, due to the presence of spiky imbalance prices.

13. There appears to be a significant relationship between EDF's imbalance costs and the electricity price relative to other firms, although EDF displayed relatively small negative imbalance positions. While this could be explained by EDF being the largest generation company, the impact was very small in an absolute sense.

[2] An 'asymmetric' response occurs when electricity prices rise more strongly, or quickly, following an increase in an input's cost, than they fall following a corresponding reduction in the input cost.

[3] The new pricing formula was designed to improve cost reflectivity by sharpening the imbalance price at times of system stress.

14. Both **national imbalance costs and prices** were associated with **asymmetric responses in the GB electricity price** during the period 2014-17.

15. The largest firms are generally the creditors of the imbalance market whereas the smallest ones are debtors.

Determinants of wholesale electricity prices

16. **Gas, coal and oil are currently responsible for setting the electricity price 77% of the time.** The remainder is almost entirely covered by imports (mostly from France and the Netherlands) and hydro (both run of river and pumped storage).

17. In 2017, gas-fired power plants set the wholesale price of Britain's electricity more than any other technology. They were at the margin 65% of the time, an 8% increase compared to 2016.

18. Coal plants set the GB electricity price in 2017 only 11% of the time, a 6% reduction relative to 2016. Oil-fired plants set the price <0.5% of the time.

19. **Gas-fired plants have never been so influential in setting the GB electricity price as in 2017.**

20. From setting the price just under half the time in 2012, relative trends suggest that gas has directly substituted for coal to become by far the dominant price-setter. The shares of coal and gas in setting prices were roughly stable over 2013-16. Overall, **gas use increased, displacing coal, but it was used more at baseload.**

21. **In 2017, gas was more influential in setting the price in GB than in other major European electricity markets** (Germany, Italy, Spain, Netherlands and Norway). The gas marginal share in GB was 1.5 times greater than in the Netherlands, 2–2.5 times greater than Spain and Italy, and nearly 5 times greater than Germany.

22. Although the **GB coal marginal share** has decreased substantially it was still **second highest of the major European markets** in 2017, after Germany (24%), which has an especially coal-intensive electricity sector.

23. **GB wholesale electricity prices increased 18% in the year after the 2016 EU referendum.** The dominant factor was input costs rising due to the exchange rate impact: Sterling depreciated by 15% against the US dollar and the Euro. The impact of the referendum on exchange rates thereby appears to correspond almost exactly to the increase of 5.7% in retail electricity prices from 2016 to 2017.

24. There were no other statistically significant impacts on average electricity prices during the year after the **referendum**, except for an **increase in electricity price volatility by 50%**.

This report was requested by the Office of Gas and Electricity Markets (Ofgem). It is a collaboration led by UCL involving Imperial College London and was designed to inform Ofgem's State of the Energy Market report.

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ABOUT UCL

University College London (UCL) is a public research university in London, England, and a constituent college of the federal University of London. The UCL Institute for Sustainable Resources and the UCL Energy Institute deliver world-leading learning, research and policy support on the challenges of climate change, energy security, and energy affordability. We are part of the Bartlett: UCL's global faculty of the built environment. Our institutes bring together different perspectives, understandings and procedures in energy research, transcending the boundaries between academic disciplines. They coordinate multidisciplinary teams from across the University, providing critical mass and capacity for ambitious projects.

ABOUT OFGEM

The Office of Gas and Electricity Markets (Ofgem) is the independent energy regulator for Great Britain. It is a non-ministerial government department and an independent National Regulatory Authority, recognised by EU Directives. Ofgem's principal objective when carrying out its functions is to protect the interests of existing and future electricity and gas consumers. Ofgem's governing body is the Gas and Electricity Markets Authority (GEMA).

We are happy to hear from you. The main contacts for this work are Giorgio Castagneto Gissey (UCL) and Wei Xiao (Ofgem), who may be reached via email respectively at: g.castagneto-gissey@ucl.ac.uk and wei.xiao@ofgem.gov.uk.

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DISCLAIMER

Contents

Wholesale cost reflectivity of GB and European electricity prices

1 Competition in GB and European electricity markets

MOST European electricity markets have a small number of firms producing large shares of total electricity generated (European Commission, 2015; Aurora, 2018). The six largest generators account for over 60% of national electricity generation in Great Britain (GB), and over 75% in Germany (BNetzA, 2016; Ofgem, 2017). This naturally leads to concerns relating to the potential exercise of market power which could substantially reduce the affordability of electricity to consumers.

The Gas and Electricity Markets Authority (GEMA) referred the GB electricity markets for an investigation by the Competition and Markets Authority (CMA). In contrast to the CMA's findings relating to the retail market, conclusions highlighted that competition in the GB wholesale market appears to be working reasonably well (CMA, 2016).

Yet in recent years, wholesale electricity prices rose in GB to become amongst the highest in Europe during 2014-16 and remain well above the EU average (Grubb and Drummond, 2018).[4] As well as reflecting relative coal and gas prices, Ofgem (2017) attributes this to policy factors such as higher carbon taxes and the allocation of network charges, rather than weak competition. They found market concentration in GB to be low relative to EU electricity markets when looking at ownership of both overall and flexible capacity. As with 2014 and 2015, they find the absolute level of hours of market power ('pivotality') to be very low. However, they suggest that it is possible for there to be greater scope for market power at a sub-national level due to transmission constraints, a conclusion similarly reached by the CMA

[4] Comparison is complicated by exchange rate effects, which for comparison to continental countries contributed to increase and subsequent decrease after the EU referendum; different industrial bands; and the fact that in the UK more environmental costs are added into the electricity price for which energy intensive users in the UK then receive direct compensation (which is not available to other industries), whereas continental systems tend to use more direct exemption and less compensation.

(2016). Recent analyses based on historic calculations of electricity wholesale price mark-ups over marginal costs for GB and Germany implied that competition in Britain is at least as effective as in Germany in driving system costs down to the cost components (Aurora, 2018).

The second liberalisation directives of the European Union (EU), adopted in 2003, have been transposed into national law by Member States by 2004, with some provisions entering into force only in 2007. Consequently, more Member States are taking measures to secure electricity supply, such as implementing capacity markets, which may impact competition in the internal electricity market. The Commission has launched a Sector Inquiry, as well as established a Working Group with Member States and started individual assessments of Member States' capacity aid schemes (EU Commission, 2018).

An earlier Sector Inquiry – published in 2007 – showed that concentration in wholesale electricity markets was high in certain areas, especially in national markets (EU Commission, 2007). The Inquiry found that only 8 out of 25 Member States had moderately concentrated national markets, 5 had highly- and 12 very highly-concentrated markets (Altmann *et al.*, 2010). Generally, market concentration in national electricity markets remains substantial in GB as in many other European markets (Ofgem, 2017).

Competition in wholesale markets varies over time (Ofgem, 2017) and must be periodically monitored to ensure the protection of consumer's interests. Wholesale costs are the largest component of electricity costs to GB consumers, consisting of nearly 40% of a typical GB electricity bill (Ofgem, 2018), with similarly large shares also reported for other EU Member States (EU Commission, 2014a). The effectiveness of wholesale market competition can therefore greatly affect consumer bills in GB and other EU countries.

Market concentration and other measures such as market shares, or pivotality analysis, may be useful indicators of market power in electricity markets, but they do not specifically consider how specific wholesale costs incurred by generators are passed through to consumers. They cannot therefore be used to assess the extent by which components of the electricity value chain are competitively internalised by generators. Cost reflective internalisation of input costs is critical to the economical and sustainable delivery of electricity to customers and represents the main topic of this study. **This report studies whether key wholesale costs are internalised cost-reflectively into electricity prices and investigates the presence of market power in GB and other major European electricity markets.**

"A pass-through rate above 100%, under wide assumptions, is inconsistent with perfect competition, and so is strong evidence for some degree of market power"

– Ritz (2015)

For these purposes, deriving the 'pass-through' rates of generation costs into electricity prices is an important addition to the evidence base surrounding the competitiveness of generators in an electricity market. Pass-through rate analysis can be used to infer how competitively markets tend to internalise specific generation costs, such as the cost of fuels, into electricity wholesale prices.

A pass-through rate above 100% is, under wide assumptions, inconsistent with the notion of perfect competition, and so is *strong evidence for some degree of market power*. On the other hand, a 100% pass-through is consistent with perfect competition – but it is also consistent with a monopoly or oligopoly, and so cannot constitute "proof" of any particular mode of competition (Ritz, 2015).[5]

By evaluating the pass-through rates of various fuel costs incurred for electricity generation, Castagneto Gissey (2014) determined that GB was among the most cost-reflective in a sample of European electricity wholesale markets during the period 2008–2012. These results are consistent with inference made by Ofgem (2015), which reported that the GB electricity market appeared reasonably competitive and compared well with other European markets.

Fuel costs account for most of electricity wholesale costs and over a third of final electricity prices (Ofgem, 2017). Natural gas generation is the leading form of flexibility in the GB wholesale electricity market. Wholesale electricity is widely traded in the day-ahead market and gas takes the role of price-setter many of the times it is called upon, as based on 'merit', which is determined by the marginal cost of generation.

Another component of wholesale electricity costs relates to energy imbalances. Elexon is the regulator of the energy imbalance market. It is responsible for comparing how much electricity generators and suppliers said they would produce or consume with actual volumes, and transfers funds accordingly after gate closure of the wholesale market. The imbalance market is responsible for electricity settlements equivalent to £1.5bn of electricity customers' funds per year (Elexon, 2017). These costs are borne by generators and their alteration could potentially affect electricity prices.

The internalisation of fuel and imbalance costs into electricity prices can be quantified and described by computing the associated pass-through rates using time series econometric analysis, as these are the main generation wholesale costs which vary over time.

1.1 Wider literature on competition and pass-through

Competition in electricity markets has been assessed in several ways. Traditional measures include market shares and market concentration.

Market shares show how large a company is in relation to the rest of the market, while market concentration indicates the extent to which a market is dominated by one or more firms. Pivotality analysis is also widely used (Ofgem, 2017) and helps to assess how relevant each

[5] Saying more about the precise degree of competition would require more detailed structural industrial-economics modelling of the underlying demand and supply market conditions.

firm is in meeting electricity demand. Clearly, models falling in this category account for the impact of individual firms.

Most work considering pass-through rates are based on reduced-form economic models that do not make wide theoretical assumptions about the underlying information set and relationships between variables. They derive an industry-wide measure of pass-through in an analogous way to the present study. These studies have so far focussed on the cost pass-through of carbon emission allowances into electricity prices in the context of the European Union Emission System (EU ETS). These studies include Jouvet and Solier (2013); Mirza and Bergland (2012) and Zachmann and Von Hirschhausen (2008) and extend the work of Sijm *et al.* (2006), who use Sijm *et al.* (2006) equilibrium prices and fuel cost data for the German electricity market finding pass-through rates between 60% and 117%.

Jouvet & Soulier and Mirza & Bergland use a cost-price approach, while Mandal et al. use a Philips curve approach to explain pass-through into wages. Zachmann and Hirschhausen (2008) consider whether the pass-through rate responds asymmetrically to positive and negative shocks in costs. Bushnell *et al.* (2013) study a structural break occurred in April 2006 in EU ETS carbon prices to derive the pass-through rate. More recently, Castagneto Gissey (2014) used one year ahead data for four European countries during 2008–2012, showing that pass-through rates ranged between 88% and 137%. Nazifi (2016) considered the Australian National Electricity Market and used a statistical analysis to provide evidence that the 2012 Carbon Pricing Mechanism in Australia significantly affected electricity prices in New South Wales and Victoria and that carbon costs are fully passed through to wholesale prices.

Other studies reported a structural analysis of market conditions. Fabra and Reguant (2014) use micro data to directly assess the response to carbon prices by firms, finding rates of 44% to 117% for the Spanish electricity market, depending on market conditions. This study is closely related to Reguant and Ellerman (2008), which also examines how firms internalized the costs of carbon emissions in Spain. McGuinness and Ellerman (2008) find that UK electric utilities altered their operations based on the EU ETS carbon price, although they do not directly assess if such responses are consistent with full cost internalisation.

Using structural modelling, Besanko *et al.* (2001) and Fabinger and Weyl (2012) find that the estimation of pass-through rates can be greatly affected by functional form assumptions of demand. The study of strategic behaviour in electricity markets is discussed in Green and Newbery (1992) and von der Fehr and Harbord (1993). Ellerman *et al.* (2010) provides a review of these studies.

There are several similar studies reported in the literature which consider the markets for other pollutants. For example, Kolstad and Wolak (2003) consider how firms used NOx prices to exercise market power in the electricity market of California. Here they test for cost internalization by using structural equations from the multi-unit auction literature, in a way similar to Fabra and Reguant (2013). This paper finds evidence that firms respond differently to environmental cost shocks relative to shocks in other marginal costs. Fowlie (2010) studied firms' responses in the NOx Budget Program, whereby they exploit the differences in allocation regimes finding that firms internalized the costs of emissions and particularly that the degree of internalization was a function of the subsidization rate.

Our work studies the issue of cost pass-through from an industry-wide perspective and considers how groups of generators, particularly gas and coal, tend to internalise wholesale costs into electricity prices. As opposed to other reduced-form modelling studies it accounts for generation shares at the margin and thermal efficiencies, thereby producing inference that is ad-hoc to the type of generation technology under consideration.

Inferring the pass-through rate of input costs is useful because it can indicate the presence of a degree of market power if these exceed 100%. Determining the cost reflectivity of electricity prices to certain input costs is crucial to better understand how electricity prices are formed, to monitor the presence of market power, and to design improved electricity markets that truly minimise costs to electricity consumers.

1.2 Aims of this study

This study seeks to understand how generators internalised major wholesale costs into electricity prices during recent years. It derives the degree of reflectivity of GB and European electricity prices to these costs and informs about the presence of market power in GB and a sample of major European electricity markets. Our research programme has four main objectives, namely to:

(1) quantify the degree to which GB and European generators internalise fuel prices into electricity wholesale prices. We clarify how cost reflective GB electricity prices are in absolute terms, and in relation to other markets, and whether GB seems to have maintained its competitive position. We also consider whether, and quantify how, imbalance prices and national energy imbalance costs are internalised in GB electricity wholesale prices;

(2) measure whether and to what extent the largest five GB generators and distribution-connected generators internalised the cost of energy imbalances into GB electricity wholesale electricity prices. This informs our understanding of the influence of the largest generators in the country on electricity prices by means of their energy imbalance costs;

(3) quantify the shares at the margin of fuel-intensive power plants in GB and European electricity wholesale markets. This analysis feeds into our calculation of fuel price pass-through rates and indicates the main determinants of wholesale electricity prices in GB and major European electricity markets; and to

(4) reveal whether fuel prices and imbalance costs are passed through asymmetrically to electricity prices. We define an *asymmetric response of electricity prices* to a given input cost changes as positive cost increases having a larger influence on electricity prices relative to negative cost changes of the same absolute magnitude. Note the latter does not indicate the competitiveness of generators (Ritz, 2015) and, as such, is provided for purely informative purposes.

An electricity price responds asymmetrically to the change in a given input cost when a positive cost increase has a larger influence on the electricity price relative to a corresponding negative cost change

Our analysis considers the GB electricity wholesale market and a sample of European markets, including Germany (EEX), France (Powernext), Italy (GME), the Netherlands (EPEX), and Norway (NordPool), during the period 2012–2017.

Due to our coverage of the determinants of wholesale prices up to 2017, our study examines additional research questions that have general relevance to the electricity industry: (a) it examines how the behaviour of GB electricity prices changed after the 2016 EU referendum, which was associated with a sharp fall in the exchange rate, and (b) generates insights in relation to the transmission of volatility from input prices and costs toward electricity prices.

The remainder of this work is structured as follows. Section 2 explores our main results, which are discussed in Section 3. Concluding remarks are provided in Section 4. The methodologies and data used in this study are reported in Section 5.

2 Results

This section reports our main findings and is organised as follows.

Section 2.1 reports the pass-through rates of wholesale costs into GB and European electricity prices, which indicate the degree of cost reflectivity of electricity prices and are used to generate insights about market power in electricity markets. This section also identifies the presence of asymmetric responses of electricity prices to input costs in GB and European markets (Section 2.1.4) and provides evidence in relation to the determinants of electricity price volatility.

Section 2.2 shows how often fuel-intensive power generators have set the price during recent years (Section 2.2.1). Finally, we cover how the June 2016 exchange rate depreciation affected the wholesale price of electricity in GB (Section 2.2.2).

2.1 Pass-through rates

The gas price pass-through rates are reported in Section 2.1.1, while findings relating to other fuel prices are discussed in Section 2.1.2. Our work also sheds light on the internalisation of imbalance costs in GB, with Section 2.1.2 providing evidence based on both national and firm-level imbalance costs.[6]

2.1.1 Gas prices

2.1.1.1 Great Britain

Figure 1 shows the gas price pass-through rate up to 2017, when it was nearly 10% below its mean for the full period under study.

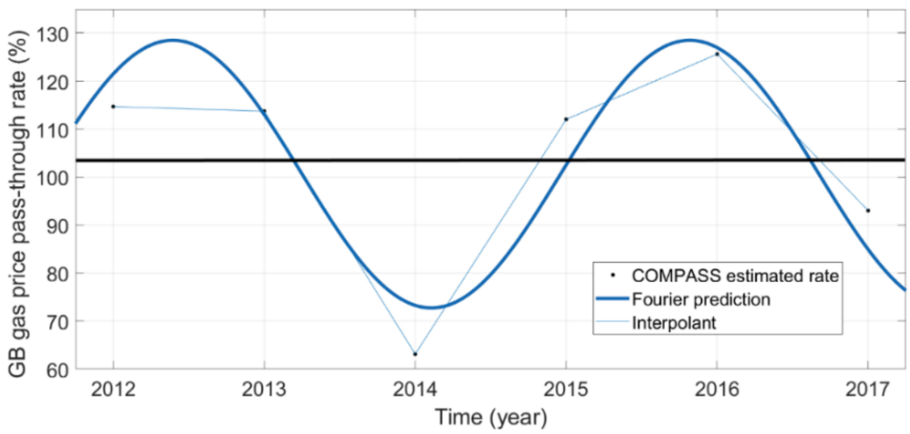

Figure 1. Mean annual gas price pass-through rate during 2012–2017. The mean rate for the whole period is indicated by the black horizontal line. The GARCH(1,1) model was selected in this specific model. Appendix Table A12 reports the relative conditional mean values.

[6] Appendix Tables A7 to A11 show our results for the conditional mean and variance of electricity prices. These are based on the different estimation specifications described in the Methods section (Section 5).

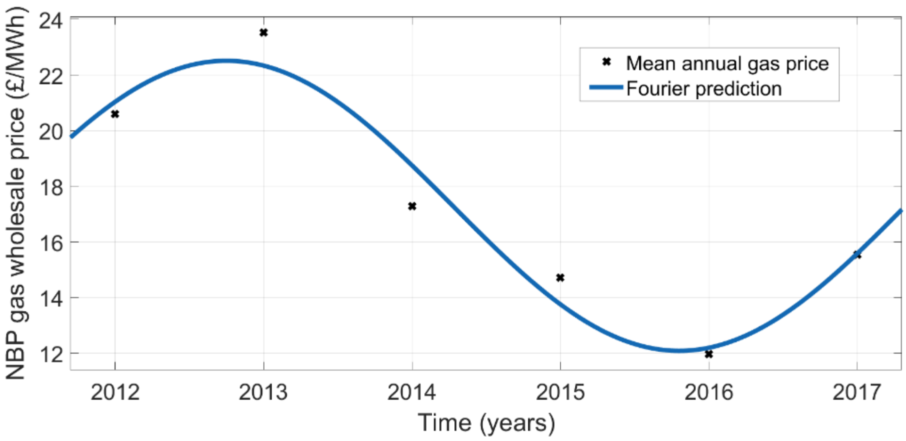

Figure 2. Annual NBP natural gas wholesale price during 2012–2017, fitted with a Fourier (R^2 of 0.95).

Pass-through rates vary widely over the studied period, from a minimum of 63% to a maximum of 126%. This is consistent with the arguments by Ofgem (2017) that competition in the GB electricity market is not static. The gas price pass-through rate was greater than 100% in two thirds of the years between 2012 and 2017. During these years, it was on average 17% larger relative to the threshold of 100%, which represents perfect cost reflectivity. The lowest pass-through rate was recorded as only 63%, for 2014.

The inter-annual standard deviation was 23%, indicating that cost reflectivity tends to deviate annually from the mean by a meaningful amount. The gas price pass-through rate deviation for GB was intermediate relative to other countries, which displayed annual variations of comparable magnitude. Italy had the lowest standard deviation of 16% (with pass-through rates ranging between ~172–244%), followed by Germany with 25% (~78–142%), the Netherlands with 34% (~40–88%), and Norway with 35% (~67–147%).

Yet while the year-on-year variation is substantial, Figure 1 suggests that the competitiveness of GB generators is reasonably stable around the mean pass-through rate of 104%. The notion of cyclicality is more formally confirmed by fitting the estimated annual rates using a cyclical Fourier function, which is also illustrated in the same figure.[7]

Our hypothesis is that gas generators might increase the rate at which they internalise the cost of gas into electricity prices as gas prices fall. We therefore tested for the potential *exercise* of market power by comparing the evolution of the pass-through rate to that of the input price. Figure 18 shows that the mean annual gas price fell over the period 2013–16, with rises in 2012 and 2017. By comparing Figure 1 and Figure 2 we can see little relationship between the two curves. We find the annualised correlation between the annual NBP gas prices and GB gas price pass-through rates to be negative but small (-4.4%). This is not a strong correlation, so we conclude that the behaviour of gas generators' pass-through rates does not provide convincing evidence to support this hypothesis. In comparison, the same correlation for the Netherlands was -12.4%. It is possible to argue that these correlations are small and therefore show no unambiguous evidence of any exercise of market power.

[7] The Fourier is a function of one sine and one cosine and exhibits an adjusted R^2 of 0.70.

2.1.1.2 GB vs European markets

Figure 3 shows the gas price pass-through rates for GB and other five European markets.[8] It can be easily appreciated that GB is the closest to the black horizontal line, which indicates perfect cost-reflectivity on average during the full period.

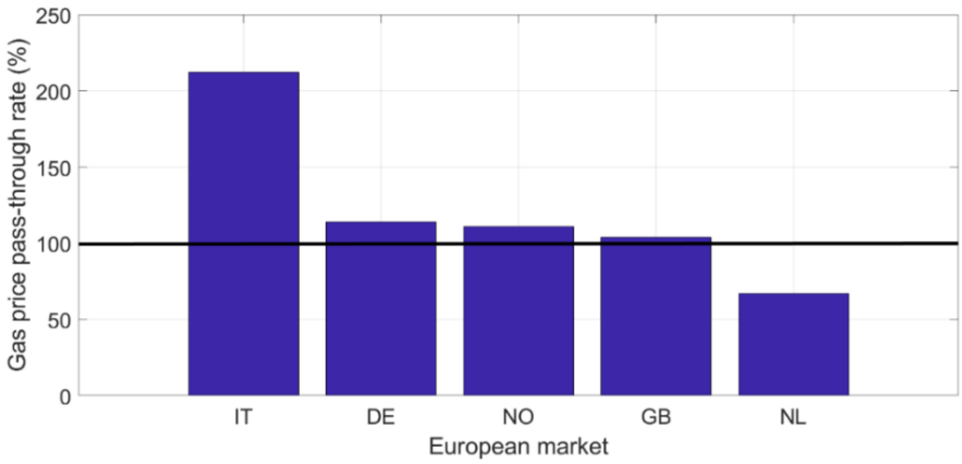

Figure 3. Mean annual gas price pass-through rate during 2012–2017. The perfect cost reflectivity threshold of 100% is shown as a black horizontal line.

We found a very high pass through rate of 212% for Italy, indicating a degree of market power and a substantial response of electricity prices to changes in the price of gas. Germany displayed a rate of 114%, followed by Norway with 111%. The Netherlands showed a rate of 67%, which indicates poor cost reflectivity of electricity prices to gas price changes compared to most other markets. The <100% rate also suggests losses by Dutch gas generators. The latter is consistent with the fact that gas prices decreased in the Netherlands for most of the period under study.

The GB rate is typically closer to 100%, so GB electricity prices are more reflective of the gas price compared to the examined European markets. If we omit the high values for Italy and the Netherlands, which can be viewed as outliers, the European average rate would be 112%, which would still support this conclusion.

Furthermore, GB electricity prices became more reflective of the price of gas in 2017 relative to 2012–2017, and particularly so relative to 2016.

2.1.2 Other fuel prices

We were unable to identify robust pass-through rates for coal, oil or carbon prices, in GB and most of the studied markets during the period 2012–2017, with the important exception of an average pass-through rate of coal prices at 84% for Germany. Aspects of this apparently surprising result are discussed in the next section. We also found sporadic evidence of statistically significant responses of the electricity price to changes in the coal price in Spain,

[8] We were unable to define a statistically valid rate for France. This is likely due to the little use of gas for electricity generation in France. The same occurred for Spain, but most likely due to excessively noisy data.

Italy, France and Norway in some years, although these were very low (0.18 to 0.59). France displayed a strong negative correlation with coal prices in 2014.

These results are not surprising since Germany is very coal intensive, while Spain, Italy, France and Norway use little if any coal for electricity generation. Yet it is surprising that the impact of coal prices did not reach statistical significance over the full period in the Netherlands. Appendix Table A7(a) reports the regression coefficient for each of the markets.

2.1.3 National and firm-level imbalance costs

This section presents the results from our estimation of the pass-through rate of imbalance costs into the GB electricity price. Results are reported relative to the internalisation of the imbalance price (£/MWh) and the imbalance cost (£), both at a national level and at the firm-level. The latter explicitly considers the impact on GB electricity prices of past imbalance costs borne by the largest five GB generators and distribution-connected firms.

Neither the imbalance price nor cost were statistically significant predictors of the GB electricity price in 2017. Where reaching statistical significance, the impacts of these variables on the electricity price were not substantial.[9]

No evidence exists in the literature in relation to the pass-through of imbalance costs into electricity wholesale prices. Since the imbalance market opens after gate closure of the wholesale market, it may be that imbalance costs are mostly unforeseen so are not internalised into wholesale prices. We therefore opted to investigate the impact of imbalance costs and prices from previous days into the GB day-ahead electricity price, using up to three days' lagged imbalance costs and prices.

2.1.3.1 Imbalance price

We found that, on average over the period 2012-17, a marginal increase in the imbalance *price* of £1/MWh was associated with a minor marginal increase in the GB electricity price of £0.05/MWh. This is a causal effect, as shown using VAR-X and Granger causality analysis in Section 2.1.3.4.

We find there has been a considerable increase in the pass-through rate of the imbalance price between 2013 and 2016, which appeared after accounting for the new imbalance price formula. The latter was implemented in 2015 and replaced the dual imbalance price. The estimated imbalance price pass-through rates are shown in Figure 4 where recorded as statistically significant.

[9] Appendix Table A13 reports the imbalance cost coefficients.

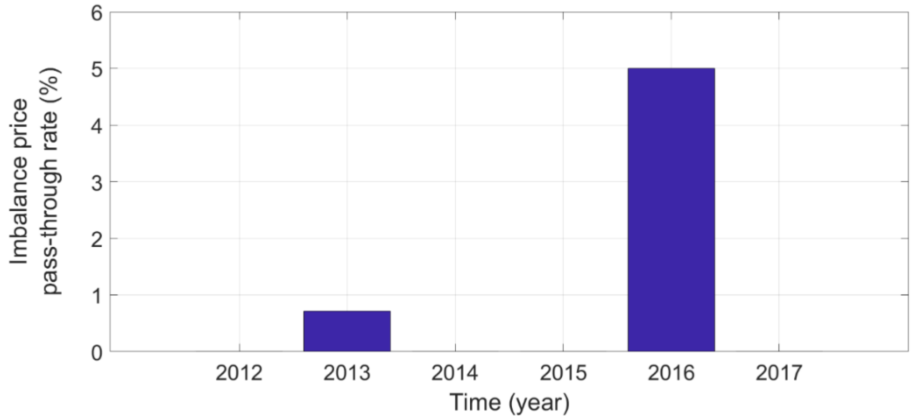

Figure 4. Imbalance price pass-through rate in GB electricity prices during 2012–2017. Values appearing as zero mean that the coefficient on the imbalance price was not statistically significant at the 5% significance level.

2.1.3.2 National imbalance cost

We also considered the impact of national imbalance *costs* on the GB electricity price. On average over the period 2014-17, a national imbalance cost increase by £1,000 was associated with a very small increase in the GB electricity price of £p0.0067/MWh. The overall imbalance charge and the national imbalance cost are therefore not meaningful drivers of the GB electricity price, as expected.

2.1.3.3 Firm-level imbalance costs

Our work also covered the impact of firm-level imbalance costs on GB electricity prices. We investigated how the imbalance costs of the largest five GB generators and distribution-connected firms affected the wholesale electricity price between 2014 and 2017. The imbalance cost pass-through coefficient for each of the largest five GB electricity generators and distribution-connected firms (DX) is shown in Figure 5. This coefficient is interpreted as the change in the GB electricity price (£p/MWh) per £1m increase in the imbalance cost.

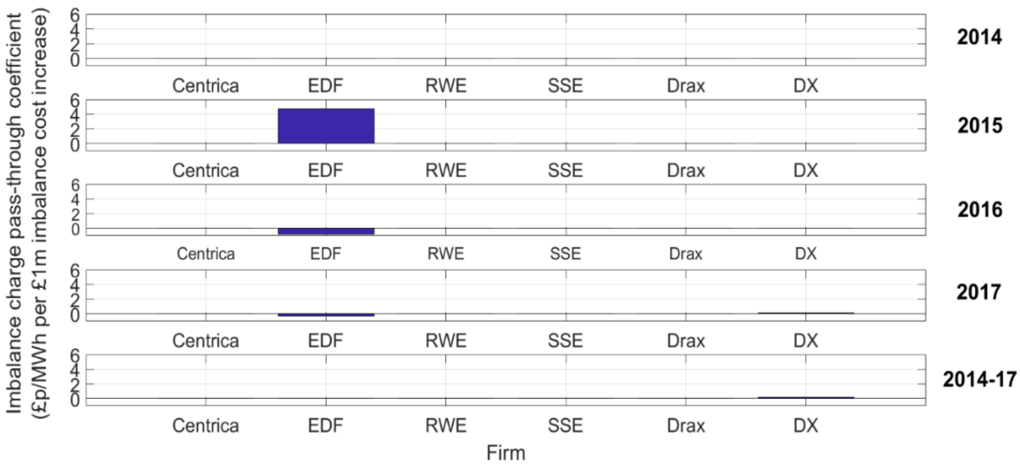

Figure 5. Imbalance cost pass-through rate between 2012 and 2017, including at firm level. Values appearing as zero mean the imbalance cost coefficient was not statistically significant at the 5% level. DX means distribution-connected firms. Appendix Table A14 reports the estimated imbalance cost model coefficients.

Only for EDF, which has much more generation than retail relative to other firms, and is the largest generation company, does there appear to be a statistically significant relationship between imbalance costs and the electricity price. For other firms, there does not appear to be a statistically significant relationship, except for distribution-connected firms, where there is a relationship only in 2017. Between 2015 and 2017, a £1m increase in the EDF imbalance charge was associated with a marginal change in the GB electricity price of +£4.70/MWh in 2015, -£0.78/MWh in 2016 and -£0.30/MWh in 2017.

During the longer period 2014–2017, distribution-connected firms which, combined, made up a share of total wholesale electricity generation exceeding 20%, had the largest effect on the GB electricity price. This suggests that, collectively, smaller firms tended to be more influential in affecting the electricity price through imbalance costs over longer periods of time relative to larger firms. Our analysis shows that a £1m increase in the distribution-connected firms' imbalance charge was associated with a marginal change in the GB electricity price of less than £0.20/MWh, which demonstrates the absence of an important impact of imbalance costs on electricity prices, even when considering the imbalance costs borne by a large group of firms.

2.1.3.4 Causality from imbalance prices

Following a VAR-X analysis, we additionally investigated whether there was evidence of causality running from the imbalance price toward the GB electricity price. We used up to three lags of the imbalance price, although only the previous day's lag generally resulted as statistically significant. The results are reported in Table 1.

	2012–2017	**2016**	**2017**
Chi2	22.14	2.47	0.09
Degrees of freedom	2.00	2.00	2.00
p-value	<0.0001	0.29	0.96

Table 1. VAR-X-based Granger-causality test assessing causality running from the imbalance price to the GB electricity price. This is an inverse significance test, so a value of p>0.05 implies causality.

Table 1 shows there is causality running from the imbalance price to the GB electricity price in 2016 and 2017. It indicates that generators are likely to internalise the cost of imbalances into the electricity price. Yet our analysis over the full period 2012–2017 indicates a lack of causality over longer periods of time.

2.1.4 Asymmetric cost internalisation effects

To complete our analysis, we provide supporting evidence aiming to shed light on cost internalisation from a different angle. We consider whether these costs are associated with an asymmetric response of electricity price volatility.[10]

We found no evidence of asymmetric effects in GB electricity prices associated with the gas price. Interestingly, we found that the coal price is associated with an asymmetric response in the volatility of GB electricity prices of 34% over the full period (2012–2017). This means that

[10] Appendix Table A13 reports the imbalance cost coefficients.

increases in the price of coal were on average related to 34% larger increases in the electricity price than the negative changes in the electricity price recorded in response to decreases in the coal price of the same magnitude. More coverage of the determinants of GB electricity price volatility, including the coal price, is reported in Section 2.1.5, below. These results reinforce our inference that coal had more of an impact on the volatility rather than the mean level of GB electricity prices.

In relation to other European electricity markets, we found asymmetric effects of the gas price only for Italy (46%) but could not find evidence of such effects for any other country or in relation to the prices of other fuels. This confirms and reflects our prior evidence regarding evidence of market power by gas generators in Italy.[11]

The same examination applied to the costs of imbalances uncovered an asymmetric pass-through effect (40%) of the imbalance price in GB over the full period under analysis, 2014-2017. We additionally found evidence of an asymmetric pass-through of the imbalance cost associated with the largest five generators as a whole (48%) over the full period, 2014-17. We also recorded a moderate imbalance cost asymmetric pass-through effect (4%) in 2017 only for Centrica. We did not find any evidence of an asymmetric pass-through effect for Centrica, nor for any other firm, in 2016.

2.1.5 Volatility of electricity prices

Table 2 reports the conditional variance model results for GB and European electricity prices in relation to the period 2012–2017.[12] It shows that GB electricity wholesale price volatility was particularly driven by coal prices over the examined period, which exerted a greater influence as compared to gas prices. This is an interesting finding since gas plants tended to be at the margin substantially more often than coal plants during this period.

[11] Appendix Tables A15 and A16 provide the asymmetry coefficients for gas and coal prices, respectively.
[12] A more detailed table with technical parameters can be found in Appendix Table A7(b).

Variable	GB	DE	FR	IT	ES	NL	NO
Load	0.0002 (0.0001)	0.00002 (0.00006)	0.0002*** (0.00006)	0.00006 (0.00004)	0.0002*** (0.00009)	0.00009 (0.0001)	0.001*** (0.0001)
Gas price	0.238 (0.391)	0.175** (0.068)	0.272*** (0.099)	0.262** (0.116)	0.194 (0.125)	0.376*** (0.064)	0.317*** (0.083)
Coal price	0.307*** (0.101)	0.252 (0.323)	-0.068 (0.299)	-0.131 (0.169)	-0.342** (0.168)	-0.092 (0.069)	-0.212 (0.190)
Oil price	-0.179 (0.172)	-0.405 (0.539)	-0.065 (0.160)		0.071 (0.254)	0.037 (0.079)	-0.046 (0.136)
Carbon price	-0.480 (0.457)	-0.102 (0.636)	-0.129 (0.398)		0.578 (0.932)	0.216 (0.249)	-0.238 (0.286)
Imbalance price	0.023*** (0.006)						
Variable renewable generation	-0.0003*** (0.0001)	0.0001*** (0.00004)	0.00003 (0.00027)	0.0002 (0.0002)	0.00009 (0.00008)	-0.0003 (0.0003)	-0.002 (0.003)
Interconnection index						-0.600*** (0.054)	
Winter	0.019 (0.177)	0.029 (1.153)	0.157 (0.284)		1.281*** (0.381)	0.434*** (0.144)	0.653** (0.327)
Fall	0.156 (0.174)	1.008*** (0.384)	-0.0323 (0.212)		0.605 (0.330)	0.167 (0.130)	0.162 (0.219)
Spring	-0.011 (0.163)	0.109 (0.363)	0.039 (0.216)		0.798** (0.331)	0.179 (0.132)	0.642*** (0.198)
Constant	-0.013 (1.319)	-0.666 (0.564)	0.903*** (0.424)	1.098*** (0.250)	-1.318 (0.559)	0.254 (0.156)	-1.383*** (0.296)

Table 2. Conditional variance model of GB and European electricity prices showing the determinants of electricity wholesale price volatility during 2012–2017. One, two and three asterisks indicate statistical significance at the 10%, 5% and 1% significance levels.

In an analogous way to GB, Spanish electricity price volatility was mostly affected by coal prices, whereas volatility transmission toward electricity prices mostly occurred via gas prices in Germany, France, Italy, the Netherlands and Norway. On average during 2012–2017, an increase in the coal price by £1/t was associated with an increase in the standard deviation of the GB electricity price of £0.6/MWh deviations from its mean.

2.2 Determinants of electricity prices

2.2.1 Fuel shares at the margin

We calculate the annual mean shares at the margin of gas-, coal- and oil-fired power plants. These indicate the average share out of the total number of hours during a given year that these plants are at the top of the supply curve (lowest in the merit order), so are the most expensive based on marginal costs and the last to be dispatched. In other words, they tell us the fraction of times in a year in which each of these plants sets the electricity wholesale price. Figure 6 illustrates these shares for GB.[13]

[13] The average shares at the margin of coal and gas for the different European markets are reported in Table A6 of the Appendix. Oil is excluded as *all* countries have marginal shares of oil-fired generation of less than 1%.

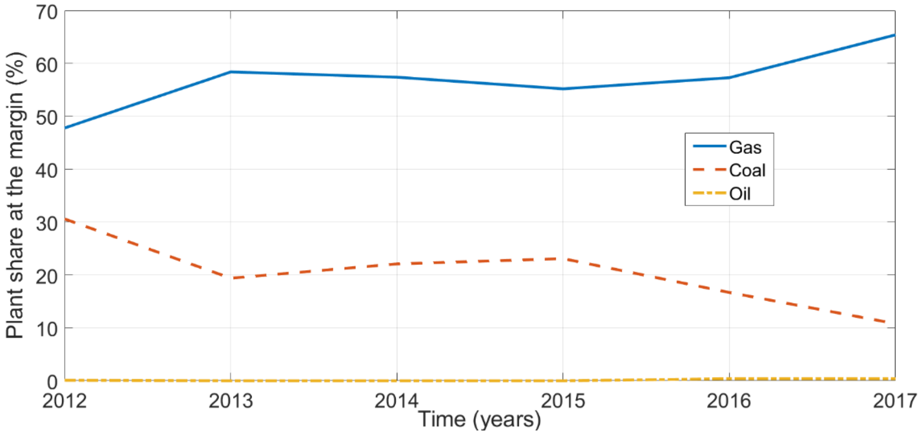

Figure 6. **Shares at the margin for gas- (CCGT), coal- and oil-fired generation in GB. We focussed on fuels, and intentionally neglected other technologies at the margin in this graph. The remainder of the total fuel marginal share in GB is typically made up by hydro and imports.**

In 2017, gas plants set the price 65.4% of the time, coal plants 10.8% of the time, and oil plants only 0.4% of the time. From 2016 to 2017, the shares at margin increased by 8.1% for gas, decreased by 5.9% for coal, and remained constant for oil. The total share at the margin from these fuels is therefore 76.6%, with the remaining 23.4% due to other technologies such as imports and hydropower.

In addition, we find that gas plants have never since 2012, and in history, been so influential in the determination of electricity prices as in 2017. In terms of longer-term trends, gas took over from coal in 2011 when both set the price 40% of the time and, back in 2009, gas was the price-setter 25% of the time versus 51% for coal.

Between 2016 and 2017, there has been the steepest increase in the annual marginal share of gas plants (+8.1%) since between 2012 and 2013 (+10.6%). In other words, electricity price-setting by gas plants has never increased so much since 2012. As shown in Figure 6, between 2016 and 2017, the rise in the gas marginal share is associated with a more than proportionate fall in the coal marginal share.

We compare the shares at the margin of the three major carbon intensive units (gas, coal and oil) for GB and other six major European electricity markets. Figure 7 shows these shares for GB, Germany, France, Italy, Spain, the Netherlands, and Norway, in 2017.

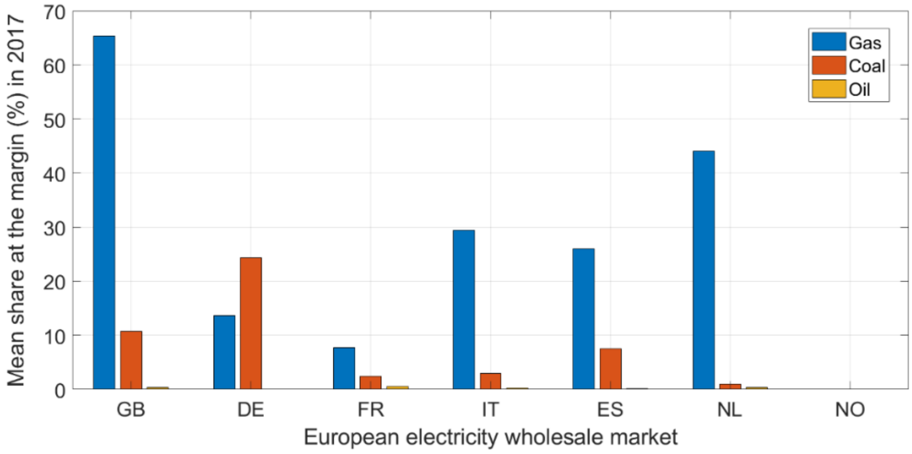

Figure 7. **Marginal shares of gas-, coal- and oil-fired plants in GB ad other six European countries in 2017.**

In 2017, gas plants in GB have evidently set the electricity price substantially more compared to the other European electricity markets examined. The gas marginal share was 21% greater than the Netherlands and 36% greater than Italy. In relative terms, the GB gas share is 1.5 times greater than the Netherlands, 2–2.5 times greater than Spain and Italy, and nearly 5 times greater than DE. More generally, gas plants in GB generally have set the electricity price much more relative to other major markets in Europe over the period 2012–2017.

The GB coal marginal share decreased 20% from 2012 to 2017. Yet, although the GB coal share at the margin is substantially decreasing over time, it was 11% in 2017 and was therefore only second-placed after Germany (24%), whose electricity sector is known to be very much coal intensive.

Oil now sets the price only 0.4% of the times in GB, with this share having remained the same in 2017 as it was in 2016. This is a result of the very high price of oil relative to that of other fuels, and the low capacity of oil-fired plants in GB.

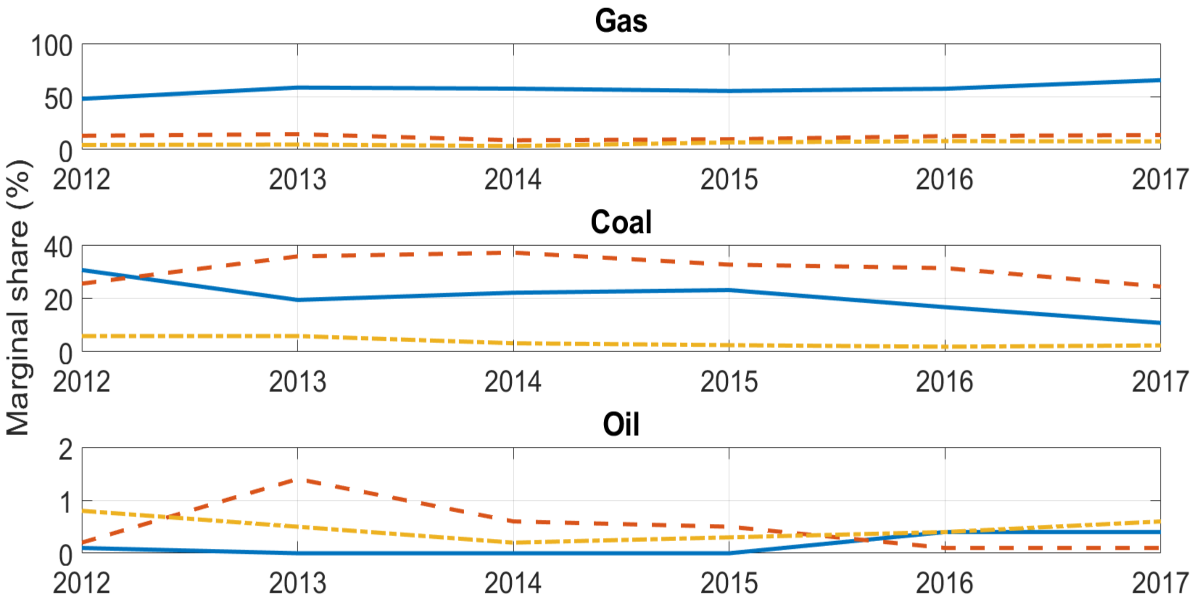

Figure 8. Fuel marginal shares for GB, DE and FR. Key: GB DE FR .

Figure 8 depicts the fuel marginal shares for GB, Germany and France. In 2017, the German coal marginal share was 10 times as large as France, and more than double that for GB. In the same year, the GB oil share at the margin was at a similar level to those calculated for other six major European electricity markets.

2.2.2 GB events – June 2016

The left panel of Figure 9 shows the behaviour of the GB electricity wholesale price, whilst the right panel shows the GBP to Euro exchange rate. Both are shown between 2012 and 2017, with the black line indicating the 2016 EU referendum date.

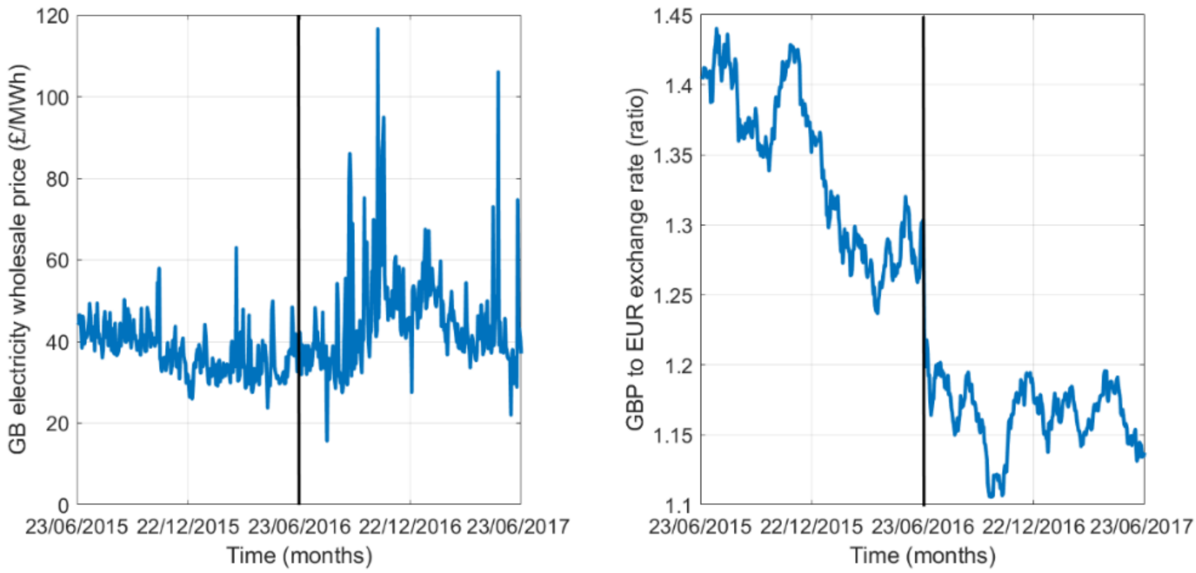

Figure 9. Electricity wholesale price (left panel) and the GBP to EUR exchange rate (right) before and after the referendum. The exchange rate against the USD experienced an identical (ca. 15%) fall to the GBP to EUR rate.

Table 3 shows the electricity price mean and standard deviation during the period 2012–2017, as well as one year before and after the vote.

GB electricity price mean (£/MWh)	GB electricity price st. dev. (£/MWh)	Time period
38.63	5.91	1 year before EU referendum (2015-16)
45.49	12.74	1 year after EU referendum (2016-17)

Table 3. Daily electricity wholesale price mean and standard deviation before and after the 2016 vote.

Mean day-ahead prices were higher by nearly 18% in the year after the EU referendum date (23 June 2016) compared to one year before. The dominant influence was through the exchange rate impact on the cost of inputs to generation linked to the drop in the GBP to EUR and GBP to USD exchange rates, which fell by 15% in the year after the vote. When this is accounted for in our model, there was no other statistically significant impact on average electricity prices.

Variable	Coefficient	z	LCI	UCI
Load	0.00003 (0.00005)	0.55	0.00	0.00
Gas price	0.58 (0.67)	0.87	-0.72	1.88
Coal price	-0.13 (0.30)	-0.44	-0.71	0.45
Oil price	-0.24 (0.17)	-1.44	-0.57	0.09
Carbon price	-30.98 (25.53)	-1.21	-81.03	19.06
Variable renewable generation	-0.00002 (0.00)	-0.15	0.00	0.00027
EU referendum (Boolean indicator)	0.51*** (0.16)	3.15	0.19	0.84
Interconnection flows index	0.03*** (0.00482)	6.55	0.02	0.04
GBP/EUR	-16.41 (29.45)	-0.56	-74.13	41.32
GBP/USD	-8.94 (23.08)	-0.39	-54.18	36.31
Winter	0.50 (0.27)	1.86	-0.03	1.02
Spring	0.33 (0.21)	1.57	-0.08	0.73
Fall	0.62** (0.25)	2.51	0.14	1.11
Constant	0.47 (0.40)	1.18	-0.31	1.24
ARCH L1	0.08 (0.09)	0.85	-0.10	0.25
GARCH L1	0.52*** (0.19)	2.72	0.15	0.89
df	6.63 (1.58)		4.37	11.05

Table 4. Conditional variance model of GB electricity prices between 2014 and 2017. LCI = Lower Confidence Interval; UCI = Upper Confidence Interval. LL -2018.60; df 31.00; Wald χ2(13) 1431.71; Prob>χ2 (model) P<0.0001; AIC 4099.20; BIC 4243.91; Q(l) 8.3099; p 0.14. One, two and three asterisks indicate statistical significance at the 10%, 5% and 1% significance levels.

As shown in Table 4 – which reports the 2014–2017 GB electricity price conditional variance model results – the impact of the Boolean indicator accounting for the period following the referendum date implies substantially higher electricity price volatility following the vote. The volatility of electricity wholesale prices was subject to a statistically significant increase of 51% in the year after the referendum compared to the year before, and this was most likely associated with the difference between the volumes of Sterling to US dollars traded in the two periods. This impact on volatility may more easily be appreciated by inspecting the first differences of the electricity price after June 2016, as shown in Figure 10.

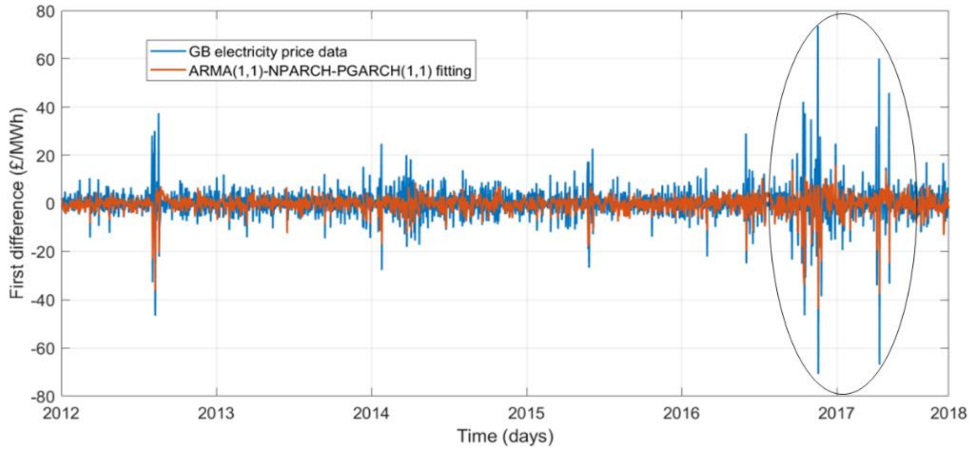

Figure 10. Electricity price first difference since 2012 and during the 23 June 2016 EU referendum (circled).

Furthermore, we found a stabilising effect of gas price volatility transmission toward GB electricity price volatility in 2017. An increase in the volatility of gas prices was associated with a 61% drop in GB electricity price volatility during that year, whilst there was no statistically significant impact in 2016.

3 Discussion

We quantified the cost-reflectivity of European electricity prices relative to gas and other fuel prices and considered how closely GB electricity prices reflect the price of energy imbalances and both national and firm-level energy imbalance costs. Our analysis also investigated the issue of causality running from the imbalance price to the GB electricity price and the presence of asymmetric effects in the internalisation of costs in GB and European electricity prices. The determinants of price volatility in the examined electricity markets was also explored.

The report also studied the shares at margin of fuel-intensive generators with the aim to measure the importance of gas, coal, and oil generation in setting the electricity price for GB and six major European markets. Finally, we considered how the events occurred in GB during June 2016 affected the price of GB electricity.

3.1 Cost pass-through and reflectivity

3.1.1 Gas prices

Our analysis aimed to quantify the pass-through rates of gas prices into electricity wholesale prices, for GB and six other major European electricity markets. The employed modelling framework was not intended to derive the intensity of competition but rather to quantify the degree of cost reflectivity of electricity prices. A major aim of this work was thereby to uncover evidence of market power, which is visible with rates greater than 100%.

The average pass-through rate of 104% recorded over the period 2012 to 2017 suggests that GB is the most cost-reflective among major European electricity markets by way of gas cost internalisation. While GB electricity price are highly cost-reflective, this degree of pass-through is *inconsistent* with strong competition (for which pass-through cannot be greater than 100%) and so is clear evidence of some non-zero degree of market power.

On the other hand, Italy showed the lowest degree of gas cost reflectivity with a very high rate that exceeded 200% and displayed the highest deviation from the perfect cost reflectivity threshold. The rates for Germany and Norway were estimated as 114% and 111%, whereas the Netherlands was the only country with a pass-through rate lower than 100%. These results are similar to those reported in Castagneto Gissey (2014) and are broadly in agreement with Ofgem (2017), which suggests that competition in GB compares well with other European markets.

The long-term pass-through rate estimated for GB is very close to the threshold consistent with strong competition so is broadly in alignment with the conclusions of the CMA (2016), which found competition in GB to be working reasonably well. Recent analyses based on historical wholesale price mark-ups suggested that competition in GB is at least as effective as in Germany in driving system costs down to the actual cost components (Aurora, 2018). Our work shows GB to be even more cost-reflective than Germany as judged by inspection of the mean gas cost reflectivity of electricity prices during the period 2012–2017.

The GB electricity market was highly reflective of gas prices in 2017, displaying a pass-through rate of 93%. This was a substantial improvement over 2016, when a rate of 126% was recorded. This represented the largest rate estimated over 2012–2017 and demonstrates a period of evident market power. While 2016 coincided with a steep fall in the exchange rate, this event was controlled for, and in any case would not have justified a greater pass-through rate.

GB pass-through rates were above the 100% perfect cost reflectivity threshold in four of the six years between 2012 and 2017. During these four years, they surpassed this threshold by about 20%. This disagrees with the notion of perfect competition and suggests the presence of temporary periods of market power, a result also shared with the CMA (2016).

We further considered whether the estimated pass-through rates demonstrated a relationship with gas prices over time and so whether there is evidence of exploiting a position of market power. Here, our conjecture was that gas generators might increase the rate at which they internalise the cost of gas into electricity prices as the price of gas – hence, all else equal, their profit – falls. While we did find a negative correlation to signify this, it was very small, so we conclude there is insufficient evidence to indicate the *exercise* of market power by GB gas generators. [14]

More generally, the cost reflectivity of gas prices was shown to vary widely year-on-year. This is consistent with prior inference discussed by Ofgem (2017) which concluded that competition in the GB electricity market varies over time. When assessed through the internalisation of gas costs, our work shows that pass-through rates vary by more than 20% from year to year.

Our study found that the gas price reflectivity of electricity prices assumes a pattern of cyclicality in the short-term but displays a stable mean over longer periods of time. This behaviour is most likely associated with generators trading in the forward markets to hedge their current contracts to deliver electricity. Since the privatisation of the 1990s, GB generators have covered most of their long-term sales in the bilateral contract market (Green, 1999). Further work could therefore feature forward contracting and the related feature of vertical integration into the retail market more prominently in the econometric analysis, and in so doing would provide a valuable continuation of this study.

3.1.2 Other fuel prices

We showed that coal prices were a major determinant of the *volatility* of GB electricity prices, but they did not exert a meaningful pressure on the *average* price of electricity. The extensive closure of coal plants and the steeply falling coal share at the margin could be the reason for the lack of a statistically significant relationship between coal and GB electricity mean prices and hence of a robust coal price pass-through rate for GB. An additional reason for this might be related to the use of daily data, which potentially masked the intensity by which coal prices were associated to the electricity price which was instead visible when assessing marginal

[14] Many generators in GB are also suppliers (House of Commons, 2016), which raises transparency issues as generators and suppliers trade with each other since they are often arms of the same organisation.

shares, as these were computed based on hourly *generation* data. Coal is traded in Europe on a daily basis, so an hourly analysis would not have been possible. Globally, our results suggest that we no longer have sufficient coal capacity or annual output for coal prices to have a significant effect on electricity prices.

Carbon prices strongly increased between 2012 and 2016, substantially reducing coal use and carbon emissions. Because the fuel mix and marginal fuel switched towards gas, that could have offset the effects of the carbon price on individual plant operating costs. If, for example, the carbon price had risen in Poland (where there is only coal generation) it would have been passed through 1:1 into the electricity price. Because we have other generation options here, the effect was dampened to the point of the coal price becoming statistically insignificant.

A similar reasoning might also help explain the lack of a statistically meaningful association between carbon and GB electricity prices. The average gas price in Western Europe during 2012–2017 was £17/MWh, whereas the coal price was nearly half, or £10/MWh. Only two to three years after the introduction of the carbon price support was the carbon price sufficient to make coal more expensive than gas, which occurred toward the end of the examined period. The little interconnection capacity present in GB and the largely rising share of variable renewables suggests that any increase in the carbon price was not enough to lead to a substantial reduction in the use of gas, which is our most flexible asset for electricity generation.

The lack of a statistically significant impact of carbon prices on GB electricity prices in this analysis is nevertheless surprising. Sijm et al. (2006), Fabra and Reguant (2013), and Castagneto Gissey (2014) all found carbon cost pass-through rates that are on average close to 100%, so these findings contradict prior literature.

Our null result was likely due to several reasons, including short term issues (coal plants being inflexible relative to gas), longer-term issues (lags in terms of timescales of gas contracts for power plants), and hedging contracts perhaps associated with fuel contracts, in contrast to 1-2 years ahead for carbon emission allowances. Moreover, whilst the differential between gas and coal prices was too large for earlier carbon prices to flip the merit order, with falling gas prices and the UK price floor, it had done so in the most recent years and that is what has really been driving coal out of the system (Grubb and Newbery, 2018). By reducing the carbon intensity of generation at the margin, in aggregate this would tend to offset the impact on individual plant costs. It is very difficult to pick up all such effects in econometric analysis, but these possibilities can help to explain the apparent lack of pass-through from carbon prices, in addition to the low role of coal prices.

The only robust coal price pass-through rate we uncovered was that of Germany, for which we estimated a mean pass-through rate of nearly 85%. This is not surprising since Germany is by far the most coal-intensive generation market but demonstrates that German electricity prices did not fully reflect the price of coal. A likely explanation for this may be related to the downward pressure due to adding zero-marginal cost renewables into the German power system.

Finally, our analyses did not identify valid pass-through rates for GB relative to oil prices. The <0.5% share at the margin we estimated for oil is a probable reason for the lacking power of oil prices in explaining the domestic electricity price.

3.1.3 National and firm-level imbalance costs

We tested whether up to three days' lags of the imbalance costs could partly explain the behaviour of the electricity price. Generally, we find some impact of imbalance costs, both at the national and firm levels, but, where these were present, they were found to be very small. This is not surprising since imbalance costs are very small compared to other generation costs. Yet our results suggest that the cost of energy imbalances could be passed through to the GB electricity price. Nevertheless, the imbalance price and national imbalance cost were not found to be statistically significant predictors of the GB electricity price in 2017.

3.1.3.1 Imbalance prices and costs

Our study indicates that the imbalance *price* could feed into the electricity price. An increase in the energy imbalance price by £1/MWh was associated with a minor change in the GB electricity price of £0.05/MWh. The pass-through rate of imbalance prices was positive in 2013 and 2016. While these impacts were small in magnitude, we found the first evidence that the imbalance price Granger-caused the GB electricity price. This shows that the imbalance price does play a role in affecting the electricity price, albeit a small one.

The increase in the imbalance price pass-through rate between 2013 and 2016 appeared after accounting for the new single imbalance price formula, which was fully operative starting from 2015. This new formula replaced the former dual imbalance price and was designed to sharpen the imbalance price at times of system stress.[15] It could therefore be possible for the higher pass-through rate found in 2016 to be linked to the imbalance price reform, which was specifically intended to improve the cost reflectivity of imbalance prices. Yet these effects were transitory and not sustained in time.

System conditions, particularly in 2016, could be important drivers of this result. This was a relatively extreme year, with particularly peaky imbalance prices. Due to the nature of the imbalance price reform, it is worth also noting that imbalance prices would have been peaky even without the 2015 imbalance calculation reform. This suggests that it was the extreme nature of the system and corresponding prices that drove this result.

Our work also found that national imbalance *costs* are associated with very small changes in the GB electricity price. The overall imbalance charge therefore is likely not a meaningful driver of the electricity price, confirming our expectations.

3.1.3.2 Firm-level imbalance costs

We investigated how the imbalance costs of the largest GB generators affected the electricity price between 2014 and 2017. Figure 11 shows the market shares of GB electricity generation

[15] https://www.elexon.co.uk/wp-content/uploads/2014/12/234_09_P316_Assessment_Report_v1.0.pdf

in 2017. Since electricity and imbalance prices are driven by common factors, and that the imbalance market is essentially an extension of the wholesale market, we would expect the wholesale market shares to determine the magnitudes of coefficients.

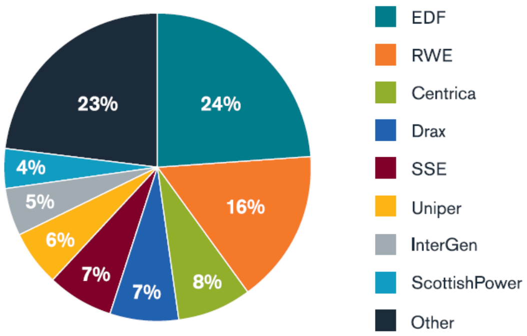

Figure 11. Market shares of wholesale electricity supply (2016). Source: Ofgem (2017).

EDF is by far the largest generator in GB, producing nearly one quarter of total generation in the country. We found that, through its imbalance costs, EDF was the only major firm to be regularly associated with changes in the electricity price. Notably, the firm did not display among the largest energy imbalance volumes. Its impact on electricity prices was very small and the magnitude of the imbalance charges incurred suggest that EDF did not have an extensive position in the imbalance market.

On the other hand, distribution-connected firms had the largest influence on the GB electricity price when assessed over the full period 2014–2017. Yet the associated change in the electricity price was very small, confirming prior evidence that imbalance costs are unlikely a substantial driver of the GB electricity price.

3.1.4 Asymmetric cost internalisation effects

To shed light on the potential *exercise* of market power, our work further investigated the possibility of cost internalisation asymmetry. We thereby considered whether increases in costs had larger effects on the electricity price than did cost decreases of the same absolute magnitude. No evidence of asymmetric effects in GB were found in association with gas prices. We found asymmetric effects associated with the gas price only for Italy.

Coal prices exhibited asymmetric effects on the electricity price in GB but not in any other European market, including Germany. While most of the changes in the coal price between 2012 and 2016 were negative, it seems that GB coal generators tended to internalise positive cost changes substantially more when compared to negative cost changes. While this effect may also be seen in a competitive market (Ritz, 2015), coal price rises may coincide with coal plant retirements, which pushes up prices, so it may be possible that the declining coal generation capacity may have had a role in determining this result. Yet this is perhaps not a major concern due to the declining share of coal in the GB electricity system. In addition, we found evidence of some imbalance cost asymmetry in GB electricity prices. This supports our prior evidence and supports the conjecture that previously incurred imbalance costs might effectively be internalised into electricity prices.

3.2 Fuel shares at the margin

3.2.1 Great Britain

We quantified the annual mean shares at the margin of fuel-intensive plants during the period 2012–2017 for GB, Germany, France, Italy, Spain, the Netherlands, and Norway. These indicate the fraction of times during a given year in which these types of power plants set the electricity price.

Our results show that the GB electricity wholesale price level is most strongly influenced by the wholesale gas price. In 2017, gas plants have never been so influential in determining electricity prices and have set the price mean more than 65% of the time. This share appears to be increasing over time. The high gas marginal share is consistent with the current fuel mix, where gas is also the major source.

In contrast, coal has set the price less than 11% of the times in 2017. The UK carbon price floor, in addition to the Large Combustion Plant Directive[16] (LCPD), has led to a decreasing profitability and use of coal for electricity generation (Ofgem, 2018), which in turn determined extensive closures of coal plants in GB. In turn, coal prices largely decreased between 2012 and 2016 from £110/t to slightly over £40/t. The very low marginal share of coal reflects its reduced and falling role in the fuel mix. The inflexibility of coal operation could also be the reason why gas continues to be the major price-setter.

The UK's carbon price support came into effect from April 2013 at £4.94/t and then increased to £9.55/t in 2014. When it increased to £18/t the following year, the coal share of generation began falling rapidly, and the marginal contribution to price fell in 2017.

Other technologies also tend to set the electricity price when used at the margin. In 2017, imports (particularly from France and the Netherlands) were marginal for 13% of the time, and hydro (both run of river and pumped storage) were marginal for 11% of the time.

Our analysis also found that gas took over from coal in 2011 when both coal and gas set the price 40% of the time. In contrast, back in 2009, gas was the price-setter only 25% of the time versus 51% for coal. Furthermore, we showed that the influence of gas plants on the electricity price has never increased so much year-on-year since 2012. The increasing marginal share of gas-fired generation in GB between 2016 and 2017 was responsible for all of the reduction in coal as well as a portion of imports from Netherlands and France as marginal technologies.

GB is clearly reliant on gas for electricity generation, and this reliance is expected to increase over the next years. Much of our gas supplies are produced domestically, with 43% coming from the North Sea and the East Irish Sea. However, GB also imports its largest share (44%) via pipelines from Europe and Norway[17], which is typically purchased in foreign currency. The extensive influence of gas generators on the electricity price therefore makes consumers

[16] The EU's Large Combustion Plant Directive (LCPD) requires all coal- and oil-fired plants that are reluctant to fitting sulphur-scrubbing equipment to close by end 2015.
[17] British Gas (2018).

heavily exposed to the exchange rate. Similarly, coal and imports which make up a combined marginal share of nearly 24% are also bought in foreign currency, and so are many of the other input components in the fuel mix, which makes the issue even more far-reaching.

On the assumption that price setting must overall be dominated by thermal plant, we took the quarterly statistics[18] to look at the overall percentage of generation of different fuels relative to total thermal generation, as shown in Figure 12.

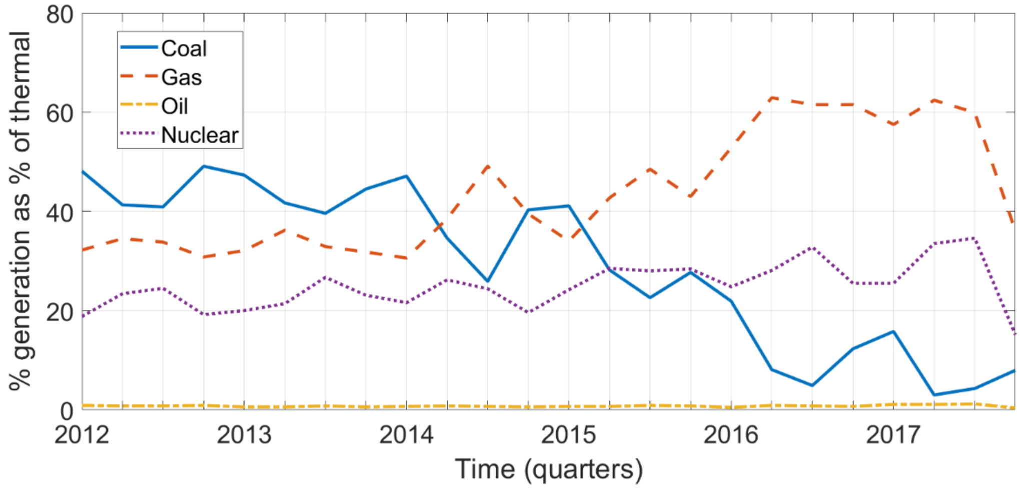

Figure 12. Percentage of generation as percentage of total thermal generation, by fuel and nuclear.

Taking the annual average shares at the margin we had previously calculated and dividing by the above values, we conclude that we have moved from a situation in 2012-14 where gas was price-setting around 1.5 times as much as its share of thermal generation would suggest, to a situation in which it was price-setting roughly in proportion to its share of thermal generation. Coal moved from being clearly inframarginal 2012-14[19], to where by 2016 it was setting the price 2–3 times as much as its share of overall generation. Our interpretation is then that indeed coal was pushed to the margin (in terms of merit order), and its influence on the price increased substantially *relative to its overall role in power generation* but decreased in absolute terms. It may also be that for some of the time, coal is operating in a mid-merit position, preceded and largely displaced by modern efficient CCGTs, but with older and less efficient gas plants still operating at the price-setting margin.

3.2.2 Great Britain vs European markets

As we compare these shares at the margin with the other European markets, GB's reliance on gas becomes even more evident. Gas is found to have the largest influence on electricity prices relative to all six major European electricity markets. The gas marginal share was 1.5 times greater in GB compared to the Netherlands, 2–2.5 times greater than Spain and Italy, and nearly 5 times greater than Germany.

[18] https://www.gov.uk/government/statistics/electricity-section-5-energy-trends

[19] i.e., the impact on the electricity price being substantially less than its share of generation.

The combined marginal shares of coal, oil and gas in the other examined markets is lower than 100%. In an analogous way to GB, the remainder marginal share not made up from these fuels is typically composed by hydro and imports.

Electricity price setting by coal-fired generators has never been so low since the liberalisation of the GB electricity market in 1990. While the coal marginal share has substantially decreased since 2012, by 20%, it is still second-placed in Europe after Germany, where coal is not only the largest price-setter, but also the source of nearly half of its total generation. While the higher UK carbon price was shown to be responsible for an enormous three-quarters of the decline in coal generation, some argue that an even higher carbon price is required to completely phase out UK coal generation in the next seven years (Aurora, 2018).

Oil has been a price-setter less than 0.5% of the time. This represents a considerable increase relative to the 0.1% share in 2012 which most likely occurred due to the huge (50%) drop in oil prices occurred between 2014 and 2016. Nevertheless, the oil marginal share remains low due to the level of oil prices, which is still very high relative to other fuels. The fact that the carbon intensity of oil is meaningfully lower compared to that of coal suggests that the carbon price was not a strong driver of the reduction in oil use compared to coal. Our work also found that oil has set the electricity price in GB a similar share of times compared to most of the other major European electricity markets considered in this study.

3.3 Increased GB electricity price volatility in 2016

We also considered how the events that characterised the UK economy in 2016 affected the GB electricity wholesale price. The EU referendum held on 23 June started the UK's process of withdrawing from the European Union. Heightened expectations for the potential of capital outflows contributed to Sterling's depreciation of 15% against the Euro and the US dollar. Since much of gas, coal and oil supplies are traded in these foreign currencies, this exchange rate effect drove up the cost of fuels used in GB electricity generation, contributing to an increase in the GB mean day-ahead electricity price by almost 18%.

The effect of the referendum in driving the observed price increase disappeared when we directly accounted for the exchange rate, leaving no other statistically significant impact on average prices. This suggests the exchange rate is the sole mechanism through which the effect is manifested. With wholesale costs accounting for over a third of the final price, the impact of the referendum on exchange rates therefore appears to correspond almost exactly to the 2016/2017 increase of 5.7% in retail electricity prices[20]. Hence, the exchange rate impact on wholesale costs accounted for nearly all of the observed increase in domestic retail prices.

The volatility of electricity wholesale prices increased by about 50% during the year following the referendum compared to the year before. This is most likely due to the volume of Sterling to US dollars and Euros and might also have potentially been a result of the perceived risks and uncertainties prevailing across the UK energy sector, and other sectors of the economy.

[20] Domestic retail electricity price data was retrieved from BEIS (2018).

4 Conclusions

The main aim of this work was to investigate the degree by which GB and other major European electricity wholesale markets internalised into electricity prices the marginal cost of fuels between 2012 and 2017. We completed our analysis by quantifying how often fuel-fired generators set the electricity price during this period. Our study also considered several other issues related to the topics of cost reflectivity and competition in electricity markets.

4.1 GB is among the most cost-reflective of European electricity markets based on movements in the price of gas

Generally, the mean rate at which gas-fired generators in GB internalised the gas price suggests some degree of market power by GB gas generators on average during 2012–2017, in addition to temporary periods of market power in recent years. The pass-through rate estimated for GB in 2017 was consistent with strong cost reflectivity. There was substantial improvement compared to 2016, when the price of gas was internalised into electricity prices substantially more than proportionately.

The GB electricity wholesale market was shown to be more cost-reflective than other major European wholesale electricity markets, including Germany, Italy, Spain, Netherlands and Norway. These results are in accordance with Aurora (2018), which implied that competition in GB is at least as effective as in Germany in driving system costs down to actual cost components. We conclude that GB is strongly cost-reflective of the marginal gas cost as observed based on movements in the price of gas over 2012–2017. In contrast, Italy showed very high cost reflectivity with pass-through rates substantially higher compared to many other European markets, indicating the presence of market power in the Italian electricity market.

GB's average pass-through rate of gas prices was found to be only 4% above the perfect cost reflectivity threshold of 100%. Our core results are also in good accordance with recent findings by the CMA (2016), which found that competition in the wholesale market is working reasonably well. While this shows a degree of market power, it is worth noting that some degree of market power is likely necessary for generators to maintain a sensible level of incentives to innovate and to maximise the quality of the electricity and services they provide.

On the other hand, using market power to exploit a dominant position is really what could be detrimental to electricity markets. We used a novel test to determine the potential for *exercise* of market power by considering whether pass-through rates tended to increase as the relevant input price – in this case, the price of gas – fell. We hypothesised that gas generators might increase the rate at which they internalised the cost of gas into electricity prices as the price of gas – hence, all else equal, their profits – decreased. While we did find a negative correlation to indicate this, this was very small, so we concluded there was insufficient evidence to indicate the exercise of market power by GB gas generators.

4.2 Gas has never been so influential in setting the GB electricity price

Our analysis found that, over 2012-17, the wholesale market appears on average to have been operating competitively on average as reflected in price pass-through rates close to 100%, albeit with significant annual variations. Yet, as the proportion of gas generation has risen, gas generation has consequently never been so influential in setting the electricity price in GB as it currently does. In 2017, gas set the price 65% of the hours, representing an 8% increase compared to 2016. Gas-fired plants set the price much more in GB compared to other major European electricity markets. The GB gas marginal share is 1.5 times greater than the Netherlands, 2–2.5 times greater than Spain and Italy and nearly 5 times greater than Germany.

About half of GB gas is imported. Coal and electricity imports, which make up a combined marginal share of nearly 24% are also bought in foreign currency, which makes the marginal price of GB electricity heavily reliant on the exchange rates against the NOK, Euro and more indirectly the US dollar.

In contrast, coal plants have never been so uninfluential in setting the electricity price. The GB coal share in marginal price-setting decreased 20% between 2012 and 2017. The extent to which coal-fired power plants may determine the electricity price is now down to less than 11%, a 6% reduction compared to 2016. Even at this level, GB was second only to Germany (24%) among the major European power markets, an electricity system well-known to be highly coal-intensive. The rise in the use of gas at the margin between 2016 and 2017 has entirely displaced coal in addition to a share of imports from France and the Netherlands. Yet the influence of coal on the electricity price increased substantially *relative* to its overall role in power generation. Oil-fired plants have set the price <0.5% of the time.

4.3 Coal not a key driver of average electricity prices in GB, but largely influences electricity price volatility

We showed that coal prices were not a key determinant of the mean GB electricity price during the period between 2012 and 2017. Yet we showed that they had a major impact on GB electricity price volatility. This is consistent with and reflects the marginal share of coal which continues to fall over time. We discussed that this may be a result of GB no longer having sufficient coal capacity or annual output to have a strong-enough influence on average electricity prices. Furthermore, it is also possible that the inflexibility of coal could also have had a role in determining these results. Nevertheless, we found that the influence of coal on the electricity wholesale price has increased substantially, but rather than in an absolute sense, it increased relative to its falling overall role in power generation.

Furthermore, our work uncovered the presence of asymmetric responses of GB electricity prices to changes in the coal price. Interestingly, this coincided with a period of mostly falling coal prices. In other words, coal generators were associated with positive changes in the electricity price that were substantially larger (in absolute magnitude) following increases in the coal price compared to falls in the electricity price occurred after falls in the coal price.

4.4 Imbalance costs may be somewhat internalised into electricity prices

We tested whether previously-incurred imbalance costs might explain part of the behaviour of electricity prices in GB. In general, imbalance costs do not have a substantial impact on electricity wholesale prices, but our results suggest that generators may have partly internalised the price of energy imbalances into electricity wholesale prices. While the effect of imbalance prices on electricity prices is small, we found that imbalance prices Granger-caused the GB electricity price in 2016 and 2017. While already minor, this association disappears when examined over longer periods of time. We conclude that imbalance prices are sometimes internalised by generators when they are foreseen, but their impact on electricity prices is very small.

We found that the pass-through rate of the imbalance price increased by a considerable amount in 2016 compared to 2013. This coincided with a reform of the imbalance price formula in late 2015, which implemented the single imbalance price that replaced the former dual price and was specifically designed to improve the cost reflectivity of imbalance prices by sharpening the imbalance price at times of system stress. While this result could suggest that the change in the imbalance price formula was likely effective in improving cost reflectivity, it is notable that the effect was not sustained, so this limits the extent to which we attribute this result to the reform. More likely, the fact that the improved reflectivity of electricity prices to changes in the imbalance price occurred in 2016 was a result of the particularly peaky imbalance prices recorded during that year.

We additionally examined whether firm-level imbalance costs have tended to affect the electricity price between 2014 and 2017. We found that, although EDF was not among the most active in the imbalance market, its imbalance costs may have had an effect on the electricity price, although this impact was not consistent from year to year. While this could derive from EDF being the largest generator on the market, its impact was not important. Distribution-connected firms also had a relatively measurable impact on prices over the full period, 2014–2017. The associated changes in the electricity price from changes in these costs were however very small, confirming our expectations and prior evidence.

4.5 GB electricity price volatility largely increased after June 2016

Electricity wholesale prices increased 18% in the year following the EU referendum date relative to the year before because of the increased expectations for capital outflows from the UK. Our work showed that the dominant factor was the rise in input costs resulting from the fall in exchange rates, as Sterling depreciated by 15% against both the US dollar and the Euro. The impact of the referendum on exchange rates thereby appears to correspond almost exactly to the increase of 5.7% in retail electricity prices from 2016 to 2017. The referendum was also linked to an increase in electricity wholesale price volatility by 50%. This was likely due to the volumes of Sterling to US dollars traded in the year after relative to before the vote. An additional factor may have been the degree of uncertainty prevailing in the energy sector as well as other sectors of the economy.

5 Methods

Much of the research involving the estimation of pass-through rates regress price on marginal cost and use several controls. However, this approach fails to recognise that the volatility of electricity prices is time-varying. This can largely bias results since not using such an approach would effectively imply that volatility is constant over time, which is clearly not the case (see Figure 13). We therefore employ a Generalised Autoregressive Conditionally Heteroscedastic (GARCH) approach to address this issue.

The remainder of this section is structured as follows. Section 5.1 describes the wide range of data used in this study. Section 5.2 relates to the determination of the marginal shares attributed to the different fuel-intensive electricity generators, which are used in Section 5.3 to calculate the pass-through rates.

5.1 Data

We used several data types to derive the insights in this report and estimated numerous models. Electricity generation and thermal efficiencies of fuel-intensive plants were used to calculate the shares at margin. Fuel and imbalance prices and volumes were employed to model electricity prices and derive pass-through rates. The data is introduced hereafter, and their stationarity properties analysed, where appropriate.

The countries under examination were selected based on the level of Gross Domestic Product (GDP) to consider the largest EU countries, in addition to Norway, which was considered to provide comparison with Castagneto Gissey (2014). The study covered 2008-2012, so the sample period for the fuel cost pass-through analysis in the present work was chosen as 2012-2017 to examine the remaining timeframe up to present. The periods under study vary based on the underlying analysis, covering several years up to present, and were dictated by data availability. These are considered in Section 5.1.7.

5.1.1 Data used for marginal shares analysis

5.1.1.1 Electricity generation

Electricity produced from each of the generation technologies, in MWh, was collected for each of the examined electricity markets, and were extracted from the following sources:

- Great Britain: Electric Insights (2018);
- France: RTE (2018);
- Germany: EEX (2018);
- Spain: REE (2018);
- Italy, Netherlands and Norway: ENTSO-E (2018).

5.1.1.2 Thermal efficiencies

For GB, efficiencies were taken from BEIS (2017). For other countries, no standard data on fleet-average efficiency was available. Efficiencies were estimated based on the mix of plant age and type within each country's fleet, based on the method and data from Wilson and Staffell (2018). Coal capacity was divided by fuel type: hard coal, soft coal (sub-bituminous) and lignite; and by the class of steam generator: ultra-supercritical, supercritical and subcritical. Gas capacity was divided into combined-cycle and single-cycle. Standard efficiency values for each technology class and age were based on global averages from the International Energy Agency (IEA, 2017). For validation, these values were also calculated for GB and the US and gave good agreement (within ±3% relative error) to the reported efficiencies from BEIS (2017) and Bloomberg New Energy Finance (2017), respectively. Efficiencies for some countries varied by year, but by small amounts. For the period 2012–2017, we recorded a standard deviation of up to 0.8% for gas and 0.3% for coal.

Table 5 depicts thermal efficiencies for coal, gas and oil, for each country, as averages for the full period under analysis. Due to data availability, we assumed that oil efficiencies for all countries were the same as for GB and that gas and coal efficiencies for Norway were the same as in Germany.

Market	**Gas**	**Coal**	**Oil**
GB	51.7%	35.4%	23.9%
DE	47.2%	37.3%	23.9%
FR	48.1%	35.1%	23.9%
IT	50.0%	38.2%	23.9%
ES	51.5%	35.1%	23.9%
NL	49.6%	38.3%	23.9%
NO	47.2%	37.3%	23.9%

Table 5. Thermal efficiencies of carbon intensive units by country, expressed as averages over 2012–2017.

5.1.2 Time series data used in regression analyses

Table 6 reports the descriptive statistics for the daily time series of financial data used in our regressions. Prices for all markets except GB were natively in EUR/MWh so were converted to GBP/MWh using exchange rate data from Bloomberg (2018). All data is inclusive of weekdays only.

Type	Variable	Mean	Std. Dev.	Min.	Max.
Electricity price (£/MWh)	GB	44.64	8.27	15.64	116.52
	DE	38.82	12.10	8.38	100.42
	FR	46.10	15.41	7.11	367.60
	IT	50.76	12.62	19.66	114.43
	ES	39.14	10.76	0.67	174.27
	NL	37.81	8.76	12.98	82.93
	NO	29.58	12.48	4.53	119.32
Fuel prices	GB natural gas (£/MWh)	17.26	4.23	7.24	36.21
	GB natural gas (p/therm)	50.57	12.39	21.21	106.12
	Western Europe natural gas (£/MWh)	17.22	4.13	9.00	41.52
	Western Europe natural gas (p/therm)	50.45	12.10	26.36	121.68
	Coal (£/MWh)	10.19	2.61	5.33	16.14
	Coal (£/t)	82.95	21.22	43.40	131.40
	Oil (£/MWh)	19.64	7.52	6.55	32.28
	Oil (£/barrel)	31.10	11.91	10.38	51.11
Carbon price (£/t)	ETS carbon	7.93	3.58	2.70	34.87
	GB carbon	6.86	7.22	-0.23	18.20
National imbalances	Imbalance price (£/MWh)	46.68	11.16	11.33	236.33
	Imbalance cost (£)	287,991.50	435,794.10	-1,252,438.00	2,572,117.00
Firm-level imbalance costs (£)	Drax	259.25	989.62	-11,272.69	6,830.40
	EDF	-76.04	1,005.69	-12,460.87	12,478.75
	SSE	620.12	2,497.79	-10,561.39	16,434.25
	RWE	-288.15	1,010.73	-4542.18	12,921.88
	Centrica	-0.01	0.02	-0.11	0.16
	Distribution-connected (aggregated)	845.81	8,827.94	-20,677.77	55,250.41
Exchange rate (ratio)	EUR to GBP	1.23	0.08	1.08	1.44
	USD to GBP	1.49	0.14	1.21	1.72

Table 6. Descriptive statistics of price time series data used in regression analyses.

5.1.3 Electricity and fuel prices

5.1.3.1 Electricity prices

The data to be explained by means of our econometric analyses are the electricity prices. We use daily baseload electricity day-ahead prices (£/MWh) from 7 European electricity wholesale markets: APX (GB), EEX (DE), Powernext (FR), GME (IT), OMIP (ES), EPEX (NL), and NordPool (NO). This data is from Bloomberg (2018). Daily data was used instead of hourly data because day-ahead prices depend on costs to generators incurred at least the previous day and using hourly data would have meant over-specifying the electricity price models with an excessive number of lags, potentially masking the impact of generation costs.

Another option would have been the use of one-year forward price data, as in Castagneto Gissey (2014). One year-ahead forward data would have enabled the analysis of electricity prices without the contamination by demand changes on a daily basis inherent in close-to-real-time prices, which long-period forward prices are hardly affected by. However, the presence of a substantial amount of missing data points for many of the European data shifted our focus on day-ahead prices. A sound analysis using day-ahead price data was possible because we considered several key explanatory variables, including indicators of electricity demand (loads), variable renewable generation, and numerous other data, presented earlier, which would not have been considered upon use of forward data. It can perhaps be argued that the use of day-ahead data is more appropriate because it contains substantially wider information than forward prices.

Most of the electricity prices are based on day-ahead auctions, whereas APX UK uses continuous bilateral trading until shortly before real time. Moreover, GB prices are formed every half hour, as opposed to all other countries, which are hourly markets.

Market	**Mean electricity price (£/MWh)**		**Electricity price variance (squared £/MWh)**	**Market**
IT	50.73		175.77	FR
FR	45.81		157.28	IT
GB	44.64		151.88	NO
ES	39.08		144.51	DE
DE	38.79		106.92	ES
NL	37.78		75.76	NL
NO	29.54		56.93	GB

Table 7. **Daily electricity price means and variances for the examined markets during 2012–2017, from largest to lowest. Compared to Table 6, electricity prices are here presented free of outliers.**

Table 7 shows the electricity prices for each market in order of mean and variance. While Table 6 presented the raw data, the electricity prices are here presented free of outliers, defined as values exceeding the mean by six standard deviations.[21] The highest mean electricity prices (in GBP) during the period 2012-17 were recorded in Italy (on average, ca. £51/MWh), followed by France (£46/MWh) and the United Kingdom (£44/MWh). The lowest prices are instead those of Norway, most probably due to their relatively low marginal costs, a consequence of the nearly exclusive use of hydropower for baseload generation.

[21] We accordingly censored 3, 0, 2, 0, 1, 0, and 1 outlier for GB, DE, FR, IT, ES, NL, and NO, respectively.

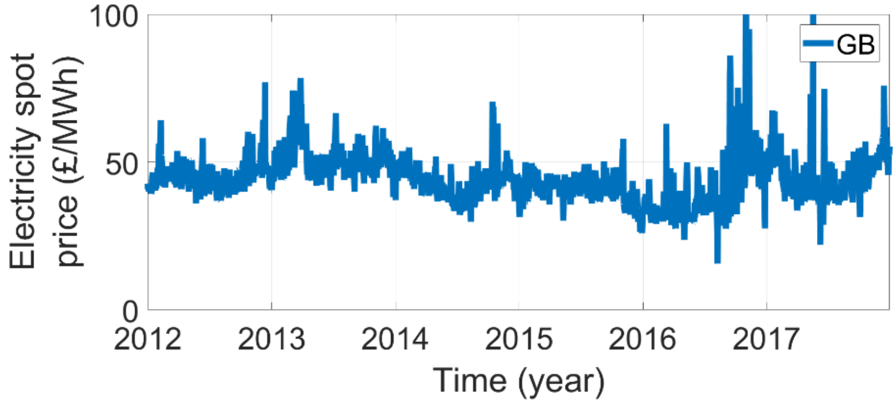

Figure 13. **Electricity day-ahead price in GB during 2012–2017. Outliers are shown for reference purposes only.**

The largest electricity price volatility occurred in France and Italy. The GB electricity price, shown in Figure 13, displays one of the highest means in Europe but also the lowest volatility. Figure 14 depicts the electricity day-ahead prices between 2012 and 2017.

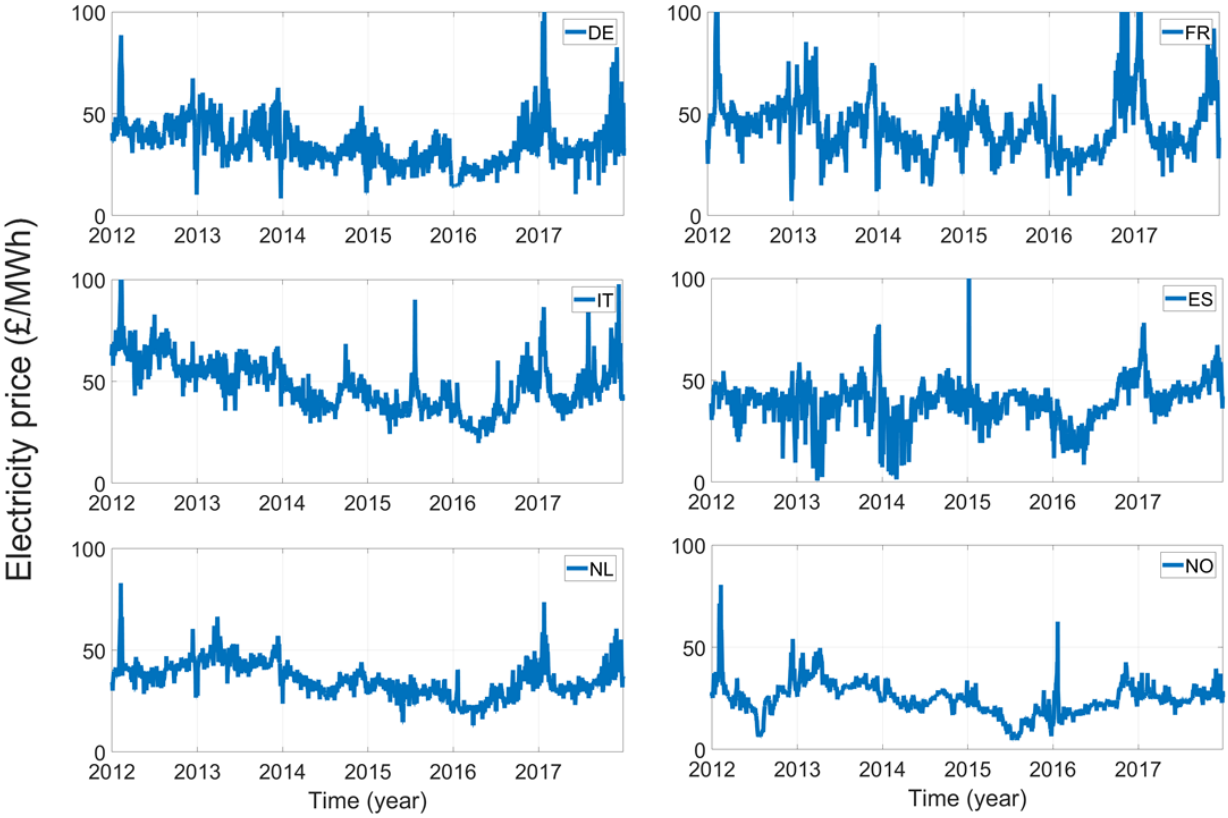

Figure 14. **Electricity day-ahead prices of the examined European markets between 2012 and 2017. Outliers are shown for reference purposes only.**

5.1.3.2 Fuel prices

To explain the electricity prices based on the main fuel costs involved in electricity generation we used natural gas, coal, oil and carbon dioxide emission allowance prices. Fuel prices were all extracted as daily data from Bloomberg (2018).[22]

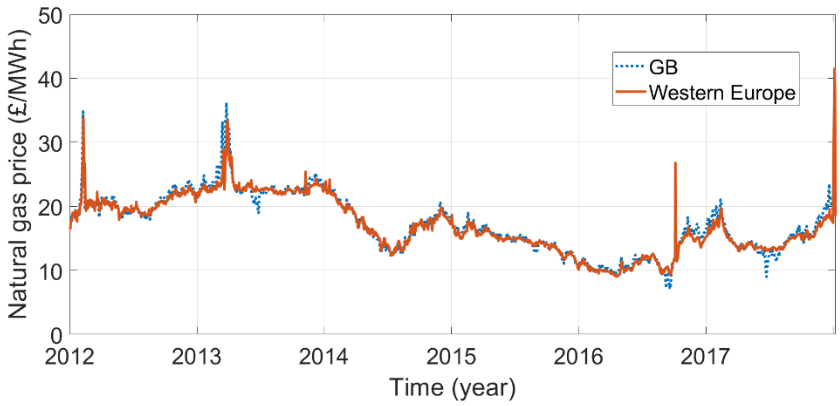

Figure 15. Natural gas day-ahead prices in GB and Western Europe. Outliers are shown for reference purposes.

The natural gas day-ahead price data are from some of the major European natural gas trading hubs. Since gas prices in Western Europe tend to be closely related, as they are formed in areas which are more closely linked, we used the EEX natural gas NCG price for European countries, which derives from the Title Transfer Facility, NetConnect and Gaspool. For GB we used the National Balancing Point (NBP) price since GB gas prices tend to assume a slightly different behaviour compared to prices in Western Europe. This is also appropriate for Norway, given that it as a major gas supplier in Europe. Norway exports its gas mainly to Germany, but also to the UK and slightly less to France. Figure 15 shows these gas prices between 2012 and 2017 along with their strong similarities.

For the coal price, we refer to the day-ahead price of the internationally traded commodity classified as coal CIF API2, or the Generic CIF ARA steam coal price, delivered to the Dutch ARA region, which represents a European coal price benchmark. It is inclusive of cost, insurance and freight. Figure 16 shows the coal price between 2012 and 2017. The record fall in global coal consumption, driven by the low oil price, is reflected by the steep fall in the coal price occurred in 2016. This was followed by a steep rise, which was attributed to the increase in Chinese coal consumption (Reuters, 2017).

[22] We checked for the possibility that data extracted from Bloomberg was statistically significantly different from ICIS day-ahead price data. We found that the data was not significantly different at the 1% level.

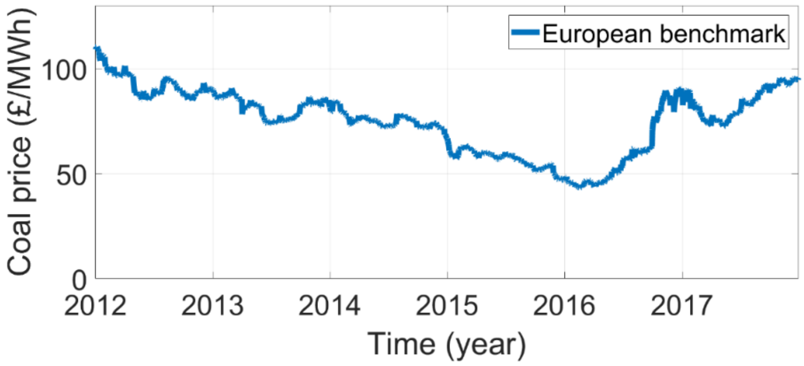

Figure 16. European coal day-ahead price benchmark.

As the EU ETS carbon price had remained broadly stable at around €5/tCO2 for various years, the use of carbon intensive generation, including coal, failed to fall during those years, and led to concerns of insufficient low-carbon investments. [23] The carbon price floor was introduced on 1 April 2013 to underpin the carbon price at a level that drives low carbon investment, which the EU ETS had not achieved. This is a UK Government policy which increases the EU ETS carbon price by a level given by the UK's Carbon Price Support, which is shown as the difference between the UK and EU ETS carbon prices in Figure 17. This difference grew from £5/t in 2013 to £18/t in 2017, with the total UK carbon price rising from £5/t in 2013 to nearly £30/t in 2017.

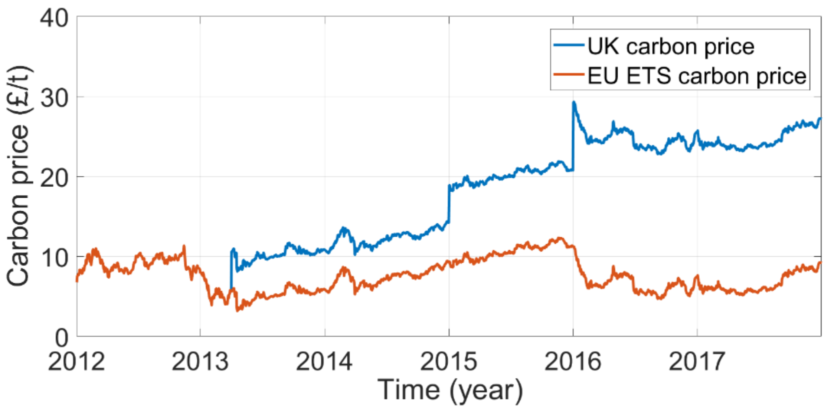

Figure 17. UK and EU ETS carbon price.

We use the European and UK carbon prices: the EU ETS carbon price and the UK carbon price floor, both deriving from Bloomberg (2018). These are employed in the respective models for European countries and GB.

The oil price refers to the price of Brent Crude, a trading classification of sweet light crude oil that serves as a major benchmark price for worldwide purchases of oil. Brent Crude is extracted from the North Sea.

[23] The generous rounds of free allocations of permits which continued until the end of Phase II, or 2012, resulted in the EU carbon market crashing. In addition, the general economic outlook in Europe, which originated from the 2008 financial crisis, meant the carbon price crashed again during Phase II. The carbon price was very low and led to increased incentives for carbon intensive units, particularly coal-fired plants as shown by the increased profitability of coal-fired generation in Castagneto Gissey (2014).

A single plot of the GB data on prices and the major fuel input costs, including carbon costs is shown in Figure 18 and is shown from 2000 to 2018. The circled timeframe corresponds to the period 2012 to 2017, which this study considers.

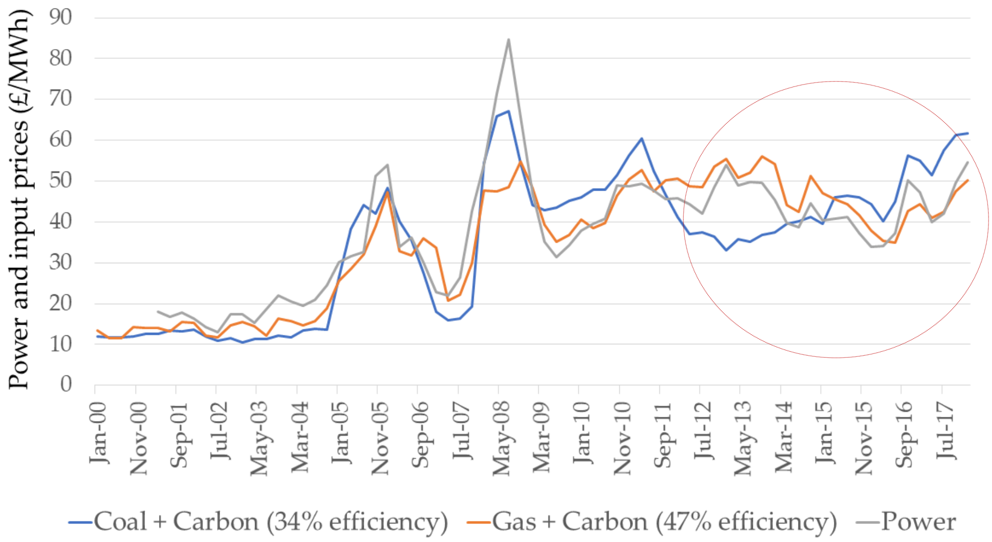

Figure 18. Power and input prices inclusive of carbon costs from 2000 and during 2012-2017 (circled).

5.1.4 National and firm-level imbalance costs

Energy imbalance prices (£/MWh) and the national energy imbalance volume (MWh) were provided by Ofgem and are from Neta Reports (2018). We calculated the national imbalance cost (£) as the energy imbalance price times the national energy imbalance volume. The national imbalance cost is depicted in Figure 19, along with the imbalance price (£/MWh) and volume (MWh).

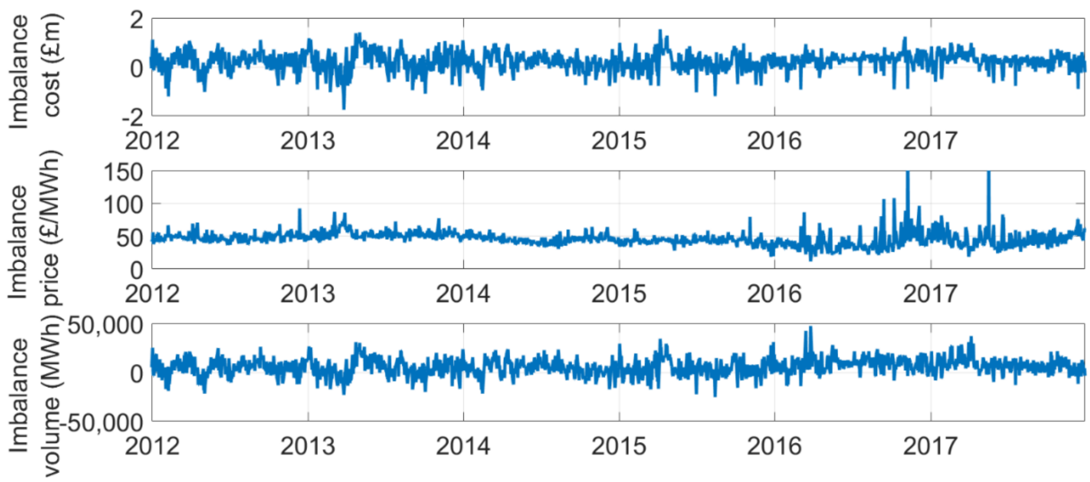

Figure 19. Daily national imbalance cost, volume, and prices, between 2012–2017. Time (years) is on the x-axis.

Energy imbalance charges (£) were provided by Elexon (2018) and relate to each BMU Party representing the five largest GB electricity generators of EDF, RWE, Centrica, Drax and SSE. We were also provided with data representing the aggregate imbalance charge for distribution-connected firms. The imbalance costs relative to these entities are reported in Figure 20 and summarised in Table 8.

Firm-level imbalance costs (£)	Mean	Std. Dev.	Min.	Max.
Distribution-connected (aggregated)	845	8,827	-20,677	55,250
SSE	620	2,497	-10,561	16,434
Drax	259	989	-11,272	6,830
Centrica	-0.01	0.02	-0.11	0.16
EDF	-76	1,005	-12,460	12,478
RWE	-288	1,010	-4,542	12,921

Table 8. Descriptive statistics for daily imbalance costs at firm level, in order from the largest to smallest.

Table 8 ranks the firm-level imbalance costs from positive to negative. It is interesting to note how, out of the firms with the largest generation market shares, the largest imbalance payments seem to be made by the firms with relatively low market shares, whereas the largest sums are paid to the largest firms. This suggests that the largest firms are the creditors of the imbalance market whereas the smallest ones are debtors of the market.

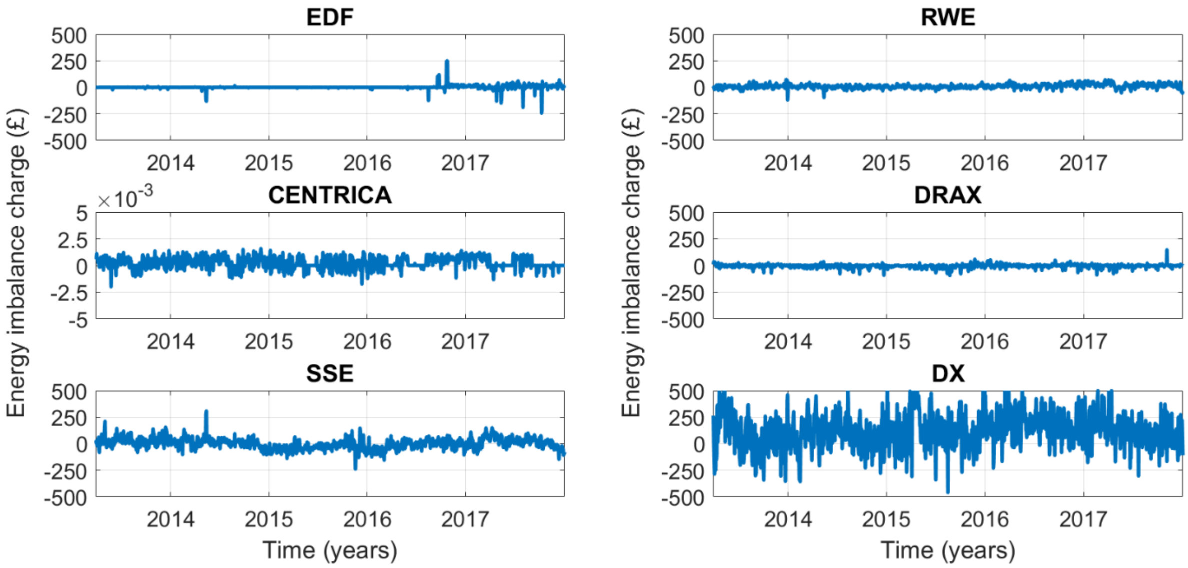

Figure 20. Mean daily imbalance costs relative to each of the largest 5 GB generators and distribution-connected firms, between 2012 and 2017. These charges are illustrated as daily means of half-hourly data. The y-axis scale for Centrica is different to better illustrate the very low charges incurred by their generation account.

Figure 20 graphically shows the energy imbalance costs for each of the largest 5 GB generators as well as for distribution-connected firms, whereas Figure 21 illustrates their energy imbalance volumes, between 2012 and 2017. While RWE and EDF have the largest negative imbalance positions, with absolute daily means between £76 and £288, Centrica has a marginally negative position. SSE, Drax and distribution-connected firms instead share the most positive energy imbalance positions with daily mean values between £259 and £845. The largest standard deviations are those of distribution-connected firms, as well as SSE and RWE.

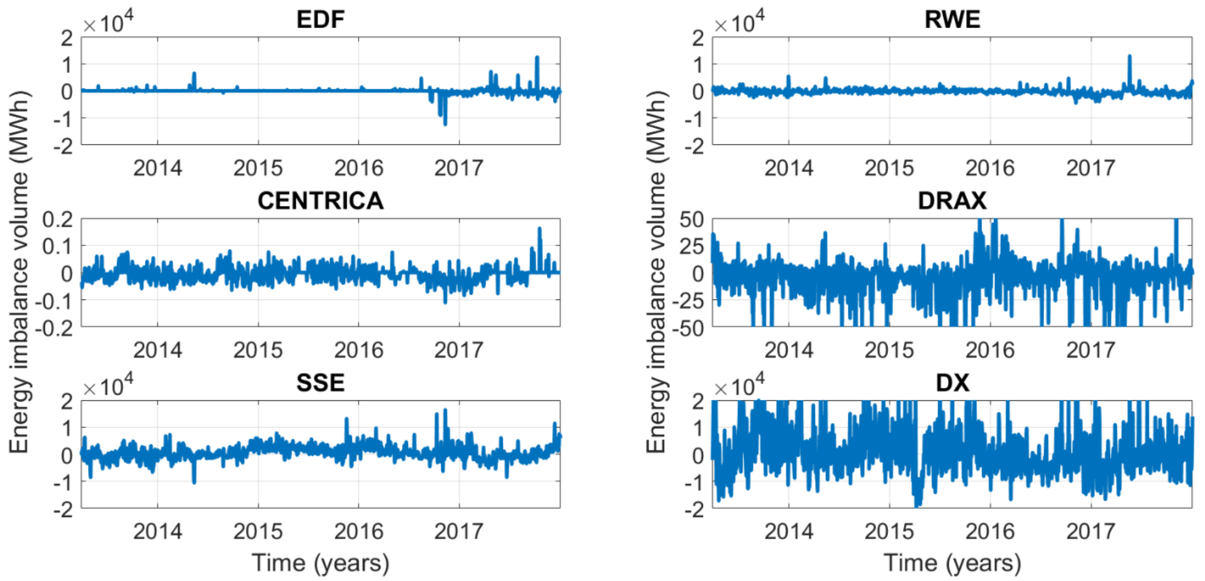

Figure 21. Imbalance volumes of the Big 5 and distribution-connected firms, between 2012 and 2017. Time in years is shown on the x-axis. These volumes are illustrated as daily means of half-hourly data. The y-axis scales for Centrica and Drax are different to better illustrate the low volumes traded through their generation accounts.

5.1.5 Control variables

Because we are using daily day-ahead electricity prices, which are affected by changes in demand, we employ load as a key control variable. Load data, in MW, was extracted from European Network of Transmission System Operators (ENTSO-E)[24] Power Statistics (ENTSO-E, 2018). Controlling for load is one way to control for daily changes in electricity demand and serves to ensure that factors such as temperature are accounted for. For example, changes in temperature are likely to be reflected in greater heating and cooling demand, which would in turn be reflected in electricity consumption.

We additionally account for changes in renewable generation from variable supplies. Variable renewable electricity (VRE) generation includes supplies such as on- and off-shore wind, tidal and solar energy and represents an important variable in the determination of electricity wholesale prices since changes in VRE generation have the potential to increase the volatility of electricity prices. This volatility is often smoothed by burning fossil fuels, particularly gas, which fills in the gaps in supply deriving from the use of variable renewables. Not accounting for VRE generation would bias the estimations of coefficients in the electricity price equations. VRE generation derives from several official sources.[25]

A Capacity-weighted Interconnector Flow index (CIF Index) was used to account for international electricity exchanges. This index is here introduced for the first time and is

[24] ENTSO-E represents 43 electricity transmission system operators from 36 countries across Europe.

[25] This data was taken from the OpenMod data platform and derives from: 50Hertz, APG, ENTSO-E Transparency, ENTSO-E Data Portal and Power Statistics, Energinet.dk, Svenska Kraftnaet, Amprion, TransnetBW, RTE, CEPS, PSE, TenneT, BNetzA and netztransparenz.de, and is available at: https://data.open-power-system-data.org/time_series/.

defined as the sum of the electricity price differentials with interconnected markets weighted by the relative interconnector capacity. For example, the CIF Index for GB is defined as:

$$\boldsymbol{CIF(t) = 2(p_{GB}(t) - p_{FR}(t)) + 1(p_{GB}(t) - p_{NL}(t)) + 0.5(p_{GB}(t) - p_{NIRL}(t)) + 0.5(p_{GB}(t) - p_{ROI}(t)),} \quad \text{[Eq. 1]}$$

where p is the electricity price level. Eq. 1 reflects GB's 2GW interconnector to France (IFA), 1GW to the Netherlands (BritNed) and the two 500MW interconnectors to Northern Ireland (Moyle) and the Republic of Ireland (East West). GB tends to import from France (via IFA) and The Netherlands (BritNed), and exports to Northern Ireland (via Moyle) and the Republic of Ireland (East-West) (POST, 2018). Exports via Moyle and East-West only make up a very small fraction of total electricity flows in GB.[26]

5.1.6 Transformations

All cost data is used with at least a one-period (day) lag, depending on whether additional lags improved the fit of our models because day-ahead prices are based on costs borne one day, or more, in advance. All other data is contemporaneous to the electricity price.

Stationarity is a key data property required to conduct an econometric analysis using data with stochastic trends. The distribution tests (Table A4) and unit root tests (Table A5) of the daily first-differenced series are reported in the Appendix. By examining the sample autocorrelations, partial autocorrelations, and by performing unit root tests, we concluded that some of the data were non-stationary in levels, so all data were differenced and used with the same order of integration. While mean first differences are generally small, the relative standard deviations are larger by an order of several magnitudes. The distributions of the first differences suggest high positive skewness and high positive kurtosis, which are demonstrated by the highly significant Jarque-Bera test results.

After differencing, the time series data to be used in the econometric analyses were found to be free of autocorrelations. We used the Augmented Dickey-Fuller (ADF) unit root tests, which test the null hypothesis that a time series is I(1) against the alternative that it is trend-stationary I(0), with the underlying assumption that the dynamics in the data have an Auto-Regressive Moving Average (ARMA) structure. The ADF test results, shown in Table A5, reject the hypothesis of a unit root in the first differenced series at the 5% significance level, suggesting that the series are stationary. Moreover, the Box-Pierce Q-statistics do not reject autocorrelations up to 20 orders in the series, so are serially autocorrelated and subject to time-varying volatility, which justifies the use of GARCH modelling.

5.1.7 Periods under analysis

The described econometric analyses relate to four different time periods partly because of the number of different analyses performed and partly due to different availabilities of data for fuel and imbalance costs.

[26] Due to data quality and availability issues, we only considered CIF for GB to be a function of the French and Dutch electricity prices. This is unlikely to affect our results since almost the entirety of electricity flows to and from GB derive or are directed toward these countries.

The time periods under analysis are specified as follows:

- The fuel marginal shares analysis was performed for the period 01/01/2012 to 31/12/2017;
- the fuel and imbalance cost econometric analyses accounted for the period 01/02/2012 to 31/12/2017;
- the imbalance cost firm-level analysis considered all data relative to the period 04/04/2013 to 31/12/2017;
- finally, the analysis of the impact of the June 2016 referendum on the GB electricity price accounted for identical sample periods before and after 23 June 2016 in order to provide the most accurate possible results from the analysis.

5.2 Fuel shares at the margin

In European day-ahead electricity wholesale markets, generators submit their bids to supply a specified quantity of electricity at a specified price one day in advance of delivery. These are arranged into a merit order – giving rise to the next day's electricity supply curve – from the cheapest to the most expensive source based on marginal cost. In real time, as the level of demand varies, electricity prices are determined by simple equation of the supply and demand curves with units dispatched accordingly. Price spikes often occur if demand is high relative to supply, during a shortage of generation, or due to excess demand. The former may occur for many reasons, such as unexpected equipment outages and, increasingly, errors in forecasted renewable output, which typically arise when it is unusually cold or hot. If not driven by unmanipulated market conditions, price spikes could be an indication of market abuse (Ofgem, 2017).

Given the nature of modern day-ahead electricity wholesale markets, the lowest-merit power technologies[27] are those that set the electricity price when they are dispatched. These technologies are said to be at the margin and, the more they are at the margin, the more they set the electricity price.

An initial step toward deriving and understanding the pass-through rates of fuel prices is therefore to determine which fuels are most often at the margin. Hence, we set out to calculate the share of hours each year in which three types of generators – fired by coal, gas and oil – are at the margin.[28]

The marginal share for each type of generator in each year was calculated as the ratio between the first difference of a technology's output and the *hourly* first difference[29] of overall electricity demand; in other words, this is the amount that technology's output changes from one hour to the next relative to the change in overall demand. For example, if demand increases by 1000 MW and output from gas-fired generators increased by 600 MW, gas provided 60% of the

[27] These are the plants with the highest marginal cost.

[28] We henceforth refer to these as the relevant technology's 'share at the margin' or 'marginal share'.

[29] A first difference is here defined as a change from an hour to the next. Most electricity markets in Europe run on an hourly basis, while the GB market runs every half-hour. For consistency, we therefore focus on hourly changes.

marginal generation in that period. We do not calculate the average of this ratio across all hours, as the result would be heavily influenced by extreme values.[30] It is more robust to perform a simple Ordinary Least Squares (OLS) regression of the change in each generator's output against the change in demand and take the slope to be the marginal share. For example, if demand increases by 10 MW in a given hour but coal increases by 1000 MW, not considering this bias means including a ratio of +100 in the result.[31]

It is important to clean the data of outliers before performing the calculation since data reporting errors and anomalies are common in such real-world datasets, and these could compromise the results. Our cleaning filter excludes any periods where the change in a variable is greater than 12 standard deviations away from the mean change across all periods, thus excluding them from the regression. Four clearly erroneous data points below 10,000 MW demand were removed for the 2017 GB demand series. After compiling the data this way and then running a simple filter to objectively clean outliers, we performed a regression on the change in coal, oil and gas generation versus the demand change.

5.3 Cost reflectivity: pass-through rates and asymmetric effects

The contribution of gas to higher overall electricity prices across Europe is a result of the combination of gas price increases and the requirement of gas plants to run more often. The increasing price of hard coal also led to increasing electricity prices across some European countries. The lower shares of renewable energy in southern markets in combination with the higher shares of coal in Eastern European countries and Germany fostered the difference in electricity prices between northern and southern countries (Jones *et al.*, 2018).

5.3.1 Determinants of electricity prices

Electricity wholesale prices are mostly influenced by supply-side drivers, such as the structure of the power generation mix; the difference between generated power over the amount that is required domestically; and the availability of power imports and exports, especially in countries that rely on interconnectors. Other factors may also be at play, such as carbon prices, network charges and possibly also imbalance costs. If present, market abuse or market power may also have substantial impacts on prices.

The demand side is affected by people's behaviour, such as demands for appliances, lighting and heating; the structure of the country's economy, particularly the share of heavy industry and services; and the technology mix used to provide services, especially heating, which also brings in dependence on temperature and possibly other weather conditions. In the longer

[30] For example, demand could increase by 10 MW while coal increases by 500 MW (and other technologies decrease output). This would yield a 5000% marginal ratio, which would bias the average.

[31] Both the regression and an hour-by-hour division would generally give the same result but would differ if one has a large number of data points (in our case, it is 17,500 half-hours per year) with a few extreme outliers. For example, if it is the middle of the night and demand changed by only 1 MW, yet gas output increased by 100 MW and coal decreased by 99 MW. You now have a marginal share of 10000% gas. The problem we found was that just one hour with this result is enough to increase the annual marginal share of gas by one percentage point (e.g. from 55% to 56%), so this did not feel robust.

term, electricity demand may also be heavily affected by regulation, such as energy efficiency policies (EU Commission, 2014b).

The major costs that tend to drive the wholesale electricity price is the wholesale price of the fuels used for generation, particularly those most often at the margin. Hence, the carbon price is likely to also be a major driver in carbon-intensive electricity systems. Yet even in countries where electricity generation is completely dominated by renewable resources, such as Norway with 97% hydro generation, electricity prices can also be reliant on coal or gas prices, since these fuels represent the opportunity cost, or 'shadow price', of the water used for hydro generation.

Other directly observable major costs to generators are imbalance costs[32] and network charges. While imbalance charges may be accounted for via the relevant bids in the imbalance market, they might also end up being internalised into electricity wholesale prices. As for network costs, these include distribution and transmission charges, which are fixed in GB and other major European electricity systems.

Econometric analysis is needed to understand how the cost of inputs to generation tend to be passed through to consumers via wholesale prices. For an econometric analysis to be applicable it is necessary that these costs vary over time. The major generation costs from which a pass-through rate can be derived are fuel prices, including carbon prices, and imbalance costs, which are time-varying by nature. In 2016, fuel prices constituted 31% of average domestic end-use electricity prices in GB (Ofgem, 2017). Imbalance costs are typically unforeseen, so we consider whether previously incurred imbalance costs are subsequently passed through to prices.

We study the pass-through rates of fuel prices for: GB, Germany, France, Italy, Spain, the Netherlands and Italy, during 2012–2017. Our analysis of imbalance cost pass-through only covers the GB market, for which we will additionally investigate the impact of the largest five generators. The generating process behind the formation of electricity wholesale prices in each of these markets relies on accurately modelling the costs of generation following an analysis of the generation technology mix, which we explore next.

[32] Generators may generate more or less energy than they have sold, and customers may consume more or less energy than their supplier has purchased on their behalf. Similarly, traders may buy more or less energy than they have sold. These parties are players of the balancing market known as Balancing Mechanism Unit parties (BMUs). They are referred to as being 'in imbalance' and the 'energy imbalances' – or the energy generated or consumed that is not covered by contracts – have been bought or sold from or to the National Grid Transmission System. Before November 2015, two 'cash-out' prices, or 'energy imbalance prices' (the System Buy Price, SBP, and the System Sell Price, SSP), were used to settle these differences. A single System Price came into effect thereafter Elexon (2017).

5.3.2 Generation mix by country

5.3.2.1 Great Britain

Figure 22 depicts the electricity generation shares by technology in GB. Given that electricity demand depends on the wider energy system, we also report the total primary energy supply and total final consumption in these markets relative to each of the main technologies. Note this excludes renewables, which are fuelled for instance by wind and sunshine.

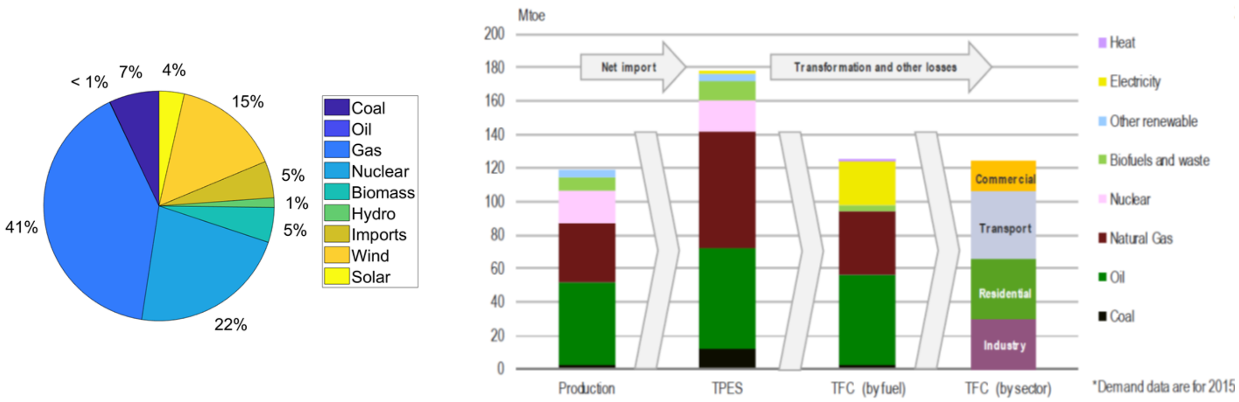

Figure 22. Generation shares in 2017 GB (left panel) and energy system transformation in the UK (right panel), using data from 2016. Source: Left panel: Authors' representation based on data from BEIS (2018); Right panel: adapted from IEA (2017). Key: *TPES = Total Primary Energy Supply; TFC = Total Final Consumption.

Electricity in GB is widely produced by burning fossil fuels, most of which comes from natural gas (40% in 2017) and coal (9%) (BEIS, 2018), whereas oil accounts for only 0.4% of total generation. The volume of electricity generated by coal and gas-fired power stations varies every year, and some generators tend to switch between the two depending on those fuels' prices (i.e. their differential) plus their carbon cost.[33]

About 22% of GB electricity derives from nuclear fission reactors. Renewable energy – including hydro, wind, and solar – made up just below 25% of electricity generation in 2017, the largest ever share for GB.[34] Figure 23 shows how UK electricity generation changed over the last years as more renewables entered the mix. For example, the increasing use of flexible generation via gas is a result of an increasing generation by means of variable renewables.

[33] Generators in GB paid the European Union Emission Trading System (EU ETS) carbon price until 1 April 2013, when the Carbon Price Floor was introduced, which acts as a premium top-up to the EU ETS price (Wilson and Staffell, 2018).

[34] The UK aims to meet its EU target of generating 30% of electricity from renewable sources by 2020.

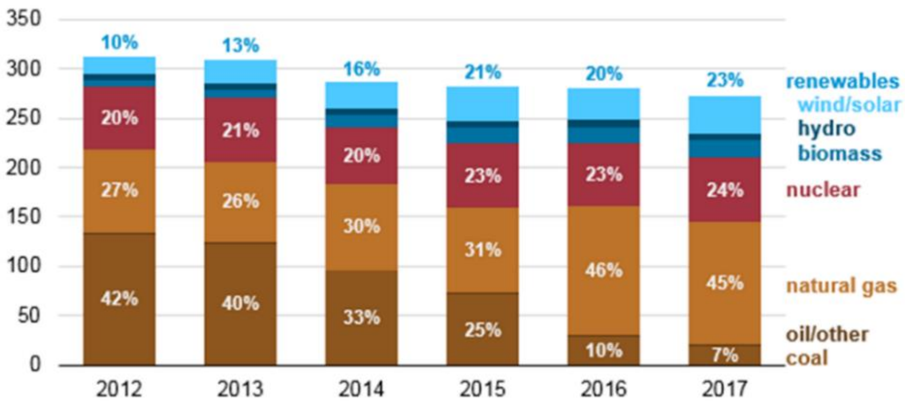

Figure 23. Electricity technology mix in the UK between 2012 and 2017 (in TWh). Source: (EIA, 2018).

The UK is interconnected to the electricity systems of France, the Netherlands and Ireland, through which flows <2% of total generation. In 2015, the UK was a net importer from France and the Netherlands with total net imports of nearly 14 TWh and 8 TWh respectively, which accounted for 6% of electricity supplied in 2015. Total net exports to Ireland amounted to only 0.9 TWh (Energy UK, 2018).

5.3.2.2 Other major European electricity markets

Figure 24 reports the generation shares for each technology in the examined European markets of Germany, France, Italy, Spain, the Netherlands, and Norway, whereas Figure 25 provides the levels of total primary energy supply and final consumption in these markets by technology.

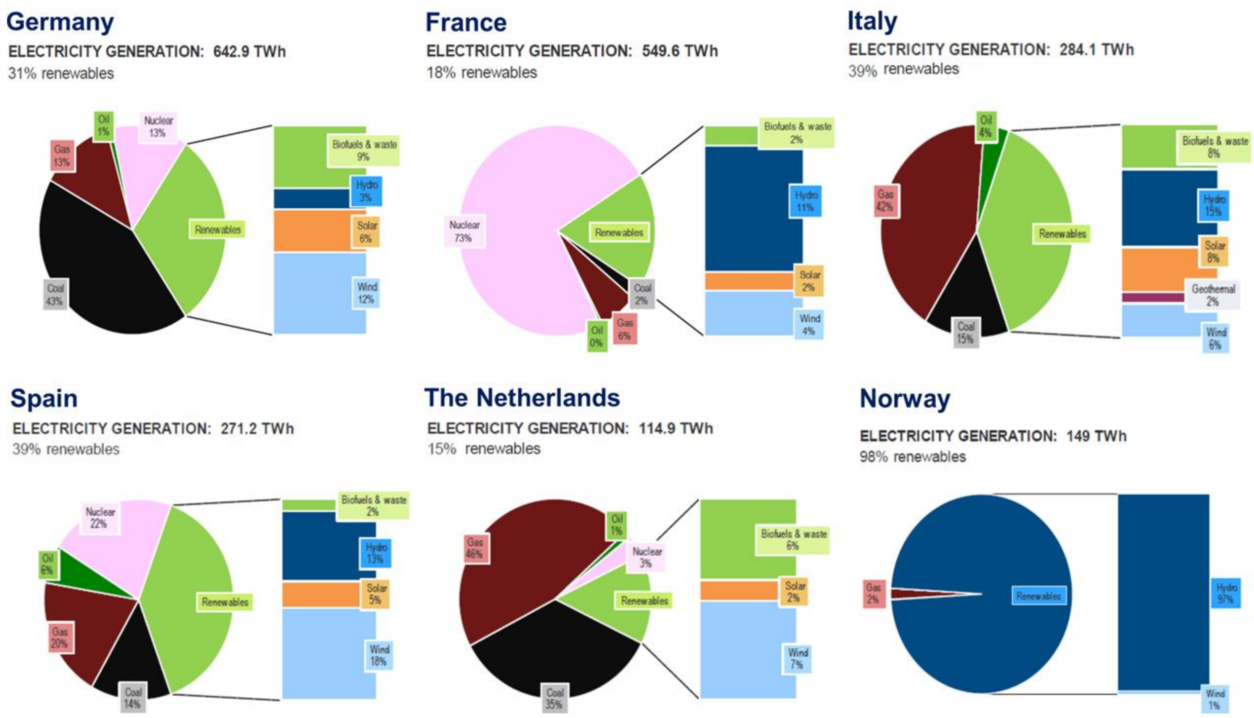

Figure 24. Electricity technology mix in Germany, France, Italy, Spain, the Netherlands, and Norway, in 2016. Source: Adapted from IEA (2016).

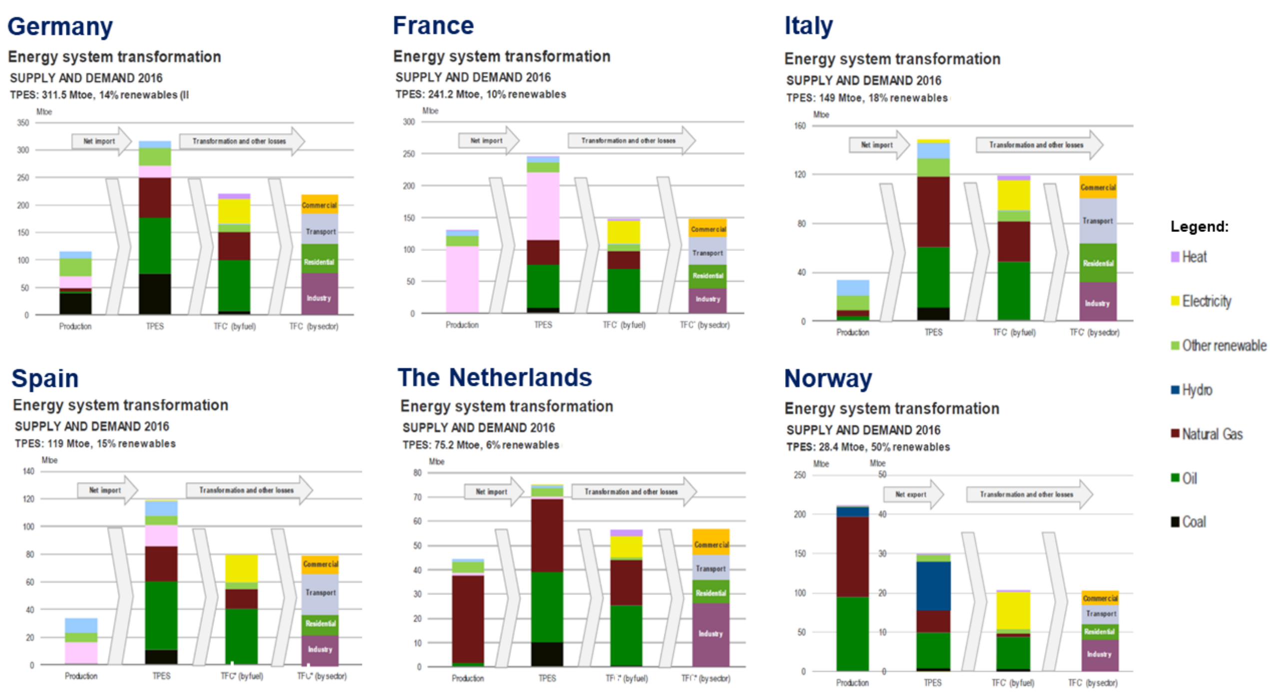

Figure 25. Energy system transformation and demands by technology in Germany, France, Italy, Spain, the Netherlands, and Norway, in 2016. Demand used for TFC is from 2015. Key: *TPES = Total Primary Energy Supply; TFC = Total Final Consumption. Source: Adapted from IEA (2016).

Germany is the most intensive in coal-fired generation (53% of the total electricity mix in 2016) of the examined countries, as indicated in Figure 24 using data from IEA (2016). It also burns a substantial amount of gas (13%), but very little oil (1%). Germany also uses 31% renewables, of which most comes from wind (12%).

France uses very small amounts of coal (2%) and gas (6%) in electricity production, which is dominated by nuclear power (73%). France only uses <1% of oil for electricity generation. In 2016, roughly 18% of electricity in France came from renewables, particularly from hydro (11%).

Italian electricity generation is dominated by gas (42%), with coal (15%) also playing a substantial role. Oil-fired generation stands at 4%. Renewables account for 39% of total electricity generation, which mostly derives from hydro (15%) as well as solar and biofuels (both 8%).

The Spanish electricity market also burns considerable amounts of fossil fuels, particularly gas (20%), as well as coal (14%). Oil still makes up 6% of total generation, which represents the highest share of oil-fired generation among the major European electricity markets. Renewables provide 39% of total generation, with most coming from wind (18%), hydro (13%) and solar (5%).

Electricity generated in the Netherlands is still very carbon intensive, with fossil fuels accounting for 82% of total generation. Gas provides 46% of total generation, whereas coal and oil supply 35% and 1%, respectively. Renewables represent 15% of total electricity generated in 2016, with most deriving from wind (7%), as well as biofuels and waste (6%).

Norway produces 98% of its electricity using renewables, of which most comes from hydro (97%), whereas wind is accountable for only 1% of total generation. The share of gas is only 2%. Local prices could also be set by the electricity imports from neighbouring countries as well as by the opportunity cost of not exporting electricity (Castagneto Gissey, 2014). This information will feed into our expectations of the electricity price model parameters, outlined in Section 5.3.7.

5.3.3 Modelling electricity prices

The study of how generation costs are marginally internalised into electricity prices requires deriving the coefficient of variation of the electricity prices with respect to changes in these costs. To do so, it is essential to explicitly model electricity prices using an econometric model which accounts for the time-varying nature of the variance of electricity prices. We therefore employ a GARCH approach, a type of modelling which relates to a family of models first introduced by Engle (1982) and later improved by Bollerslev (1986). In simple terms, this entails defining a stochastic equation for the conditional mean as well as the conditional variance (or volatility) of electricity prices, which well suits the stylised fact that prices are affected by recurrent spikes and an often-unpredictable behaviour. We follow the methodology set out in Castagneto Gissey (2014).

5.3.3.1 GARCH modelling

The simplest type of GARCH model is the GARCH(1,1) model. This is a model where the conditional mean of a time series, in our case the electricity price, is generally defined as an Auto-Regressive Moving Average (ARMA) and the conditional variance is modelled as the weighted sum of past squared residuals, and autoregressive terms of the variance itself, with weights decreasing as we go further back in time. The GARCH framework was initially developed to account for empirical regularities in financial data, which have several characteristics in common, including:

1. Non-stationary price levels with stationary returns or differences and the possibility of fractionally internalised series;
2. returns or differences series usually display little or no autocorrelation;
3. sometimes non-linear relationships between subsequent observations;
4. volatility clustering;
5. rejection of normality in favour of some long-tailed distribution;
6. potentially, the presence of a leverage effect, by which prices tend to be negatively correlated with volatility changes;
7. co-movement of the volatility of different prices (Rossi, 2004), with the latter accounting for endogeneity.[35]

[35] The properties of GARCH processes are: stationarity, ergodicity, geometric ergodicity, existence of moments of the extended-GARCH, consistence and asymptotic normality of likelihood estimators, among others. Additional information about GARCH is provided in Nana *et al.* (2013).

In a regression of price on marginal cost, the regression coefficient on cost is the cost pass-through rate. Yet differencing is warranted due to concerns about non-stationarity.[36] This means that we instead regress the *change* in the electricity price (ΔP) on the *change* in the marginal cost (ΔMC). We therefore interpret the pass-through rate of fuel prices and imbalance costs into electricity prices as the fraction of the change in the electricity price that is made up by the change in the marginal cost (i.e., dΔP/dΔMC). We proceed by using the first differences of the electricity prices (the explained variable) as well as those of various generation costs (the explanatory variables) and other determinants (the controlled variables).

The values of skewness and kurtosis presented in Appendix Tables A1 and A4 suggest that many of the distributions of the level series used in this study exhibit lepto- or platy-kurtosis. We ensure that the first differences of the series are stationary, which is consistent with the principles of GARCH modelling (see Appendix Table A5), and that series are used based on the same order of differencing for ease of interpretability of results.

Modelling the first differences of electricity prices and their volatility involves two procedures. The first entails specifying an ARMA(p,q) model for the conditional mean, requiring the use of various diagnostic tests on the residuals. The second is the specification of a GARCH (p,q) model for the conditional variance, similarly followed by other diagnostic tests; see Castagneto Gissey and Green (2014). The electricity price series are appropriate for an investigation using heteroscedastic volatility models given that their first differences are serially autocorrelated and display time-varying volatility. Inspection of the differenced prices suggested how these series display the property of volatility clustering.

We abandoned the possibility of transforming the series into natural logs both because electricity prices can take negative values and since it would have likely implied a reduction of the volatility magnitude observed in the electricity prices, which could have disguised the explored statistical links; see Karakatsani and Bunn (2008). Seasonality is a critical issue to be considered when analysing electricity price data. We accounted for seasonality by using Boolean indicators, for three out of four seasons to avoid multicollinearity.

5.3.3.2 Conditional mean and variance

We formulate the following basic specification for the conditional mean model, which we apply to explain the first differences of GB and European daily electricity prices, y_t, and specify as:

$$\boldsymbol{y_t} = \boldsymbol{a_0} + \boldsymbol{ARMA(p,q)} + \Omega_i \mathbf{g}(\boldsymbol{\sigma^2_{t-i}}) + \boldsymbol{\omega X_{t-w}} + \boldsymbol{\varepsilon_t}, \qquad \text{[Eq. 2]}$$

where p and q are the optimal lag orders of the Autoregressive (AR) and Moving Average (MA) terms, which are selected based on the Bayesian Information Criterion (BIC); a_0 is the intercept; and ε_t is the error term. Depending on the model fit, an ARCH-in-mean function, $g(\sigma^2_{t-i})$, with coefficient to be estimated Ω_i, may also be included to account for potential changes in the variance σ^2_{t-i} that could affect the price mean. The lag order of this term, i, is optimally selected using the same information criteria. X_{t-w} is a vector of explanatory variables,

[36] In addition, it is important to ensure the use of variables that have the same order of integration.

with each described by a coefficient ω to be estimated. Given that day-ahead prices are based on costs from one day prior to the current day t, variables in X_{t-w} that represent costs (fuel prices and imbalance costs) are represented with $w = 1$, whilst contemporaneous variables (variable renewable generation) are included with $w = 0$. The vector of explanatory variables includes some or all of the following variables, depending on whether adding the variables improved the model:

- total load (in MW), to account for changes in temperature and demand on a daily basis;
- fuel wholesale day-ahead prices, including coal, gas and oil prices (in £/MWh) and carbon emission allowance prices (£/Mt), to account for the pure marginal cost of fuels;
- imbalance prices (£/MWh) or costs (£), both at a national and firm-level to account for additional variable prices and costs that might be marginally reflected by electricity prices[37];
- in addition, we included the imbalance costs (£) for each of the largest five and distribution-connected generators, to understand how national and firm-level imbalance costs affect the electricity price;
- variable renewable generation (MW), to control for changes in variable generation, which could alter prices and the use of flexible technologies;
- the GBP exchange rates against the EUR and USD, included as part of the foreign currency-denominated explanatory variables, to account for appreciation or depreciations in currencies, and to reflect economic situations[38];
- an interconnection flow index, which we defined as the sum of electricity price differentials with interconnected markets, weighted by the capacity of the relevant interconnector[39];
- Boolean indicators for all countries included three seasons (winter, fall, spring), to account for seasonal variations in electricity prices. Additional Boolean indicators for GB included: one to account for possible variations following the June 2016 fall in exchange rates; an additional indicator to account for the change in the imbalance price formula occurred in 2015; as well as one to account for the step change in imbalance prices deriving from the use of the generation and supplier accounts by one unnamed BMU Party (Elexon, 2017) to more accurately model the imbalance price pass-through rate, if it exists.

[37] Imbalance costs are considered only for GB in a dedicated analysis of imbalance cost pass-through.
[38] These exchange rates are used to convert the prices of internationally traded commodities to GBP and for the analysis of the post-EU referendum changes in GB electricity prices.
[39] This index is used for well interconnected countries, defined as those with electricity interconnection as percentage of installed electricity production capacity conforming to the EU target of at least 10% (EU Commission, 2015).

The GARCH process (Bollerslev, 1986) is represented by:

$$\mathbf{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\sigma}_t^2 = \boldsymbol{\theta}_0 + \mathbf{A}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon}) + \mathbf{B}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon})^2 + \boldsymbol{\gamma}_1 \boldsymbol{J}_{t-w}. \quad \text{[Eq. 3]}$$

The benchmark model is the GARCH (1,1) conditional variance model, which is also an autoregressive process since it depends on past variance terms (σ_{t-i}^2). This model can be specified as:

$$\boldsymbol{\sigma}_t^2 = \boldsymbol{\theta}_0 + \sum_{i=1}^{q} \boldsymbol{\alpha}_i \boldsymbol{\varepsilon}_{t-i}^2 + \sum_{i=1}^{p} \boldsymbol{\beta}_i \boldsymbol{\sigma}_{t-i}^2 + \boldsymbol{\gamma}_1 \boldsymbol{J}_{t-w} \quad \text{[Eq. 4]}$$

where θ_0 is an intercept; α_i, β_i, and γ_1 are coefficients to be estimated; ε_{t-i}^2 are past squared error terms associated with the conditional mean equation reported as Eq. 2; and J_{t-w} is a vector containing the variance of the same explanatory variables specified in the conditional mean equation, with the lags of these (w) specified in the same way as in Eq. 2. These include the variance of fuel prices and imbalance costs. The conditional variance also includes the same Boolean indicators applied for the electricity price mean equation. The terms ε_{t-i}^2 and σ_{t-i}^2 specify the lags squared residuals and one-period lagged variance, respectively. For GARCH(1,1), $i = 1$. Note how, if $A(\cdot) = B(\cdot) = 0$, the model collapses to a linear regression.

The model assumes that $\theta_0 > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$, as well as $\alpha_i + \beta_i < 1$, for the process to be well-defined and stable (non-explosive). The value estimated for β_i enables for an assessment of the persistence of shocks. An absolute value of $\beta_i < 1$ ensures the properties of stationarity and ergodicity for our models. The GARCH model assumes that h responds in a symmetric fashion to the innovations to one-period lagged volatility. Different specifications of the GARCH model are fitted to the data and the most parsimonious model is selected using BIC and based on pseudo log-likelihood (Hajizadeh *et al.*, 2012; Javed and Mantalos, 2013).

We use the COMPASS model, presented in Section 5.3.4, which has the advantage that it selects the best-fit model out of the GARCH family of model specifications. We consider several GARCH specifications, such as the simple asymmetric ARCH (SAARCH) model; the threshold ARCH (TARCH) model; the asymmetric ARCH (AARCH) model; the nonlinear ARCH model (NARCH); the exponential GARCH (EGARCH) model; the power ARCH (PARCH) model; the threshold power (TPARCH) model; the asymmetric power ARCH (APARCH) model; the nonlinear power ARCH (NPARCH) model; and the power GARCH (PGARCH) model. These vary the conditional mean and variance equations as follows.

The following specifications add to $A(\cdot)$, with α_i, β_i, and ξ_i representing parameters to be estimated (Stata, 2013):

Model	**Terms added to A(·)**
ARCH	$A(\cdot) = A(\cdot) + \alpha_{1,1}\varepsilon_{t-1}^2 + \alpha_{1,2}\varepsilon_{t-2}^2 + \cdots$
GARCH	$A(\cdot) = A(\cdot) + \alpha_{2,1}\sigma_{t-1}^2 + \alpha_{2,2}\sigma_{t-2}^2 + \cdots$
SAARCH	$A(\cdot) = A(\cdot) + \alpha_{3,1}\varepsilon_{t-1} + \alpha_{3,2}\varepsilon_{t-2} + \cdots$
TARCH	$A(\cdot) = A(\cdot) + \alpha_{4,1}\varepsilon_{t-1}^2(\varepsilon_{t-1} > 0) + \alpha_{4,2}\varepsilon_{t-2}^2(\varepsilon_{t-2} > 0) + \cdots$
AARCH	$A(\cdot) = A(\cdot) + \alpha_{5,1}(\lvert\varepsilon_{t-1}\rvert + \gamma_{5,1}\varepsilon_{t-1})^2 + \alpha_{5,2}(\lvert\varepsilon_{t-2}\rvert + \gamma_{5,2}\varepsilon_{t-2})^2 + \cdots$
NARCH	$A(\cdot) = A(\cdot) + \alpha_{6,1}(\varepsilon_{t-1} + \kappa_{6,1})^2 + \alpha_{6,2}(\varepsilon_{t-2} + \kappa_{6,2})^2 + \cdots$

If the EGARCH model is used, the basic conditional variance model fit is:

$$\mathbf{lnVar}(\boldsymbol{\varepsilon}_t) = \mathbf{ln}\boldsymbol{\sigma}_t^2 = \boldsymbol{\theta}_0 + \mathbf{A}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon}) + \mathbf{B}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon})^2 + \mathbf{C}(\mathbf{ln}\boldsymbol{\sigma}, \mathbf{z})^2 + \boldsymbol{\gamma}_1 \boldsymbol{J}_{t-w}, \qquad \text{[Eq. 5]}$$

where $z_t = \varepsilon_t/\sigma_t$. $A(\cdot)$ and $B(\cdot)$ are inserted as indicated above, but now add to $\ln\sigma_t^2$ as opposed to σ_t^2. The term $C(\cdot)$ is given by:

Model	Terms added to $\mathbf{C}(\cdot)$
EARCH	$C(\cdot) = C(\cdot) + \alpha_{7,1}z_{t-1} + \gamma_{7,1}(\lvert z_{t-1}\rvert - \sqrt{2/\pi}) + \alpha_{7,2}z_{t-2} + \gamma_{7,2}(\lvert z_{t-2}\rvert - \sqrt{2/\pi}) + \cdots$
EGARCH	$C(\cdot) = C(\cdot) + \alpha_{8,1}ln\sigma_{t-1}^2 + \alpha_{8,2}ln\sigma_{t-2}^2$

If instead the PARCH, TPARCH, APARCH, NPARCH, or PGARCH specifications are selected, the basic model fit is given by the following conditional mean and variance equations:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{ARMA}(\boldsymbol{p}, \boldsymbol{q}) + \Omega_i \mathbf{g}(\boldsymbol{\sigma}_{t-i}^2) + \boldsymbol{\omega X}_{t-w} + \boldsymbol{\varepsilon}_t, \qquad \text{[Eq. 6]}$$

$$\{\boldsymbol{Var}(\boldsymbol{\varepsilon}_t)\}^{\frac{\phi}{2}} = \boldsymbol{\sigma}_t^{\boldsymbol{\phi}} = \boldsymbol{\theta}_0 + \mathbf{A}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon}) + \mathbf{B}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon})^2 + \mathbf{D}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon}) + \boldsymbol{\gamma}_1 \boldsymbol{J}_{t-w}, \qquad \text{[Eq. 7]}$$

where ϕ is a parameter to be estimated; $A(\cdot)$ and $B(\cdot)$ are as above, but now add to σ_t^{ϕ}. $\mathrm{D}(\cdot)$ is specified as follows:

Model	Terms added to $\mathbf{D}(\cdot)$
PARCH	$D(\cdot) = D(\cdot) + \alpha_{9,1}\varepsilon_{t-1}^{\phi} + \alpha_{9,2}\varepsilon_{t-2}^{\phi} + \cdots$
TPARCH	$D(\cdot) = D(\cdot) + \alpha_{10,1}\varepsilon_{t-1}^{\phi}(\varepsilon_{t-1} > 0) + \alpha_{10,2}\varepsilon_{t-2}^{\phi}(\varepsilon_{t-2} > 0) + \cdots$
APARCH	$D(\cdot) = D(\cdot) + \alpha_{11,1}(\lvert\varepsilon_{t-1}\rvert + \gamma_{11,1}\varepsilon_{t-1})^{\phi} + \alpha_{11,2}(\lvert\varepsilon_{t-2}\rvert + \gamma_{11,2}\varepsilon_{t-2})^{\phi} + \cdots$
NPARCH	$D(\cdot) = D(\cdot) + \alpha_{12,1}\lvert\varepsilon_{t-1} - \kappa_{12,1}\rvert^{\phi} + \alpha_{12,2}\lvert\varepsilon_{t-2} - \kappa_{12,2}\rvert^{\phi} + \cdots$
PGARCH	$D(\cdot) = D(\cdot) + \alpha_{13,1}\sigma_{t-1}^{\phi} + \alpha_{13,2}\sigma_{t-2}^{\phi} + \cdots$

COMPASS maximises model fit based on BIC out of the GARCH family of models reported above and accordingly adds terms to A, C, and D. The type of GARCH model therefore varies according to the estimation at hand in order to yield the best-fitting model. To derive our results, the GARCH model AR(1)-GARCH(1,1) tended to be the most widely used model due to its parsimony and high performance relative to other more complicated models. Results therefore relate to this model specification unless otherwise stated or implied.

5.3.4 Calculation of cost reflectivity and pass-through rates

The challenge with the concept of 'cost reflectivity' is that it risks muddling two possible inferences associated to the relationship between electricity prices and the relevant costs borne by generators. Where P refers to the electricity price level and MC stands for the marginal cost of electricity production using a certain generation technology, these two concepts are: (i) the ratio P/MC, i.e., what fraction of price is made up by marginal cost, which relates to profit margin, defined as (P-MC)/P; and (ii) the ratio dP/dMC, i.e., what fraction of the cost change is passed through to the electricity price. This is the rate of cost pass-through, which we consider here. It should thereby be noted that the link between (i) and (ii) is, in general, surprisingly weak and context-dependent (Ritz, 2015).

A 100% pass-through rate, under wide assumptions, represents proof of some degree of market power. While a 100% pass-through is consistent with perfect competition it is also consistent with a monopolistic or oligopolistic market, so cannot constitute a demonstration of any particular competition mode (Ritz, 2015). Reaching additional conclusions about the precise degree of competition would require more detailed structural modelling of the underlying demand and supply conditions.

5.3.4.1 Fuel prices

The main aim of this work is to consider how fuel prices tend to be internalised into the electricity wholesale price. We explicitly model the pass-through rates of gas, coal, and oil wholesale prices. These are based on the marginal change in the electricity price associated with a unit rise in the given fuel price. As emphasised in Castagneto Gissey (2014), it is critical to adjust this change by the thermal efficiency and share at the margin of the plant type in question. The pass-through rate ρ_f of the price of fuel type f is therefore calculated as:

$$\rho_f = \frac{\omega_f \upsilon_f}{\vartheta_f}, \qquad \text{[Eq. 8]}$$

where ω_f is the marginal change in the electricity price y_t associated with a unit rise in the price of fuel f; υ_f is the thermal efficiency of the type of generation plant burning fuel f, whereas ϑ_f is the share at the margin of plant type f. Given that the terms in the numerator and denominator are all expressed as ratios, ρ_f is in percentage terms. Thermal efficiencies and shares at the margin for each of the plants are covered in Sections 5.1 (Data) and 2.3 (Results), respectively. The annual pass-through rates are normalised to the full period rate to eliminate any small sample bias that may arise from the use of daily data.[40]

5.3.4.2 Carbon cost

The COMPASS-2 model is an evolution of the COMPASS[41] model first introduced by Castagneto Gissey (2014) in that it selects the best-fit GARCH model for the purpose of deriving robust pass-through rates. The study calculated the pass-through rate of the carbon cost into electricity prices by estimating the GARCH conditional mean coefficient, or the derivative of the electricity price with respect to the carbon price (ω_{carbon}), divided by the 'theoretical' value of the carbon cost (TCC), as:

$$\rho_f = \frac{\omega_{carbon}}{TCC}. \qquad \text{[Eq. 9]}$$

[40] In case the relevant fuel price coefficient in the electricity price conditional mean equation is not statistically significant at the 5% level in the full period analysis, the full period pass-through rate is calculated as the mean of the significant annual pass-through rates.

[41] More information on the electricity generation COMpetitiveness model for the derivation of carbon cost PASS-through rates (COMPASS) can be found by visiting http://www.ucl.ac.uk/energy-models/models/compass. This model is Copyright © 2016 Castagneto Gissey; it was used in Castagneto Gissey (2014) and was licensed to Ofgem for this work. The model was updated to include a GARCH model selection algorithm and became the COMPASS-2 model, now owned by Ofgem.

The theoretical carbon cost (TCC), which can be seen as the effective carbon intensity of coal and gas-fired generation, is given by the sum of the carbon intensities of gas- (0.35 $kgCO_2/GJ$) and coal-fired generation (0.9) times their average shares in electricity generation at the margin, and is specified as:

$$\mathbf{TCC} = \mathbf{0.35}\zeta_{gas} + \mathbf{0.9}\zeta_{coal}, \quad \text{[Eq. 10]}$$

where ζ_{gas} and ζ_{coal} are the coal and gas average shares at the margin in the electricity market. The former is given by the efficiency of gas times the GARCH coefficient on the gas price, which is the marginal change in the electricity price given a unit change in the gas price, or ω_{gas}. Similarly, the latter is calculated as the efficiency of coal times the GARCH coefficient on the coal price, in other words the marginal change in the electricity price given a unit change in the coal price, or ω_{coal}. These are formulated as:

$$\zeta_{gas} = \tau\omega_{gas} \quad \text{[Eq. 11]}$$

and

$$\zeta_{coal} = \tau\omega_{coal}. \quad \text{[Eq. 12]}$$

The efficiency of gas, τ_G, slightly varies across markets as well as, by some degree, on an annual basis,[42] but is typically close to 0.53. The efficiency of coal, τ_C, is known to vary more widely across countries (European Environment Agency, 2013). Thermal efficiencies are specified in Section 5.1.1.2.

As ω_{carbon} approaches the 'theoretical' carbon price value (TCC), the marginal rate at which the carbon price is internalised into the price of electricity approaches the perfect cost reflectivity threshold of 100%. Values >100% suggest a positive degree of market power (Ritz, 2015), while values <100% mean that costs are internalised less than proportionately. For an analysis of carbon cost pass-through rates that considers emissions trading and other factors, see Sijm *et al.* (2012).

5.3.4.3 Imbalances

Prior to 5 November 2015, the GB imbalance market was characterised by a dual price: a system buy price and a system sell price (Endco, 2015), which applied to short and long positions, respectively. After this date, the system sell price and system buy price became equal as a single system price (Ofgem, 2015).

We model three variations of the pass-through rate applied to the cost of imbalances: (a) relative to the national imbalance cost ('cost-plus'); (b) relative to the imbalance cost at the firm-level; and (c) relative to the imbalance price (arbitrage). More information on these rates is provided hereafter:

(a) *National imbalance costs* are derived as the imbalance price (£/MWh) times the national imbalance volume (MWh), for each hour, so are expressed in Sterling. The pass-

[42] Thermal efficiencies by plant type were collected for each year and country. See section 5.1.1.2 for more information about thermal efficiencies.

through rate of the national imbalance cost into the electricity price, is then simply given by the change in the electricity price, y_t, per unit increase in the imbalance cost.

(b) The *firm-level imbalance cost* was provided for each of the largest five GB generators as well as for distribution-connected firms as a whole. Similarly to (a), the pass-through rate of the firm-level imbalance costs into the electricity price, is given by the change in the electricity price, y_t, per unit increase in the firm-level imbalance cost.

(c) The pass-through rate of the *imbalance price* into the electricity price is given by the first derivative of the electricity price with respect to the derivative of the imbalance price. It represents the marginal change in the electricity price from a unit rise in the price of imbalances. This rate is expressed as a percentage given it represents the ratio of two terms measured in £/MWh.

5.3.5 Asymmetric cost internalisation effects

An 'asymmetric' response occurs when electricity prices rise more strongly, or quickly, following an increase in an input's cost, than they fall following a corresponding reduction in the input cost.[43] However, note that from a policy perspective, knowing the cost pass-through patterns in a market does *not* allow for profound inferences on the intensity of competition. It rather simply informs our understanding of the patterns of cost internalisation. In practice, the mode of competition is unknown, and knowledge of pass-through patterns has been shown not to help identify it (Ritz, 2015).

We were tasked to consider whether the input costs examined in this work, or fuel and imbalance prices, and national and firm-level imbalance costs, can be said to have been associated with asymmetric responses in the electricity price. We perform this exercise for each market and focus on the full period under study as well as the years 2016 and 2017.

We employ the Simple Asymmetric ARCH model (SAARCH), which specifies the conditional mean as in Eq. 2 and the conditional variance as:

$$\boldsymbol{\sigma_t^2} = \boldsymbol{\theta_0} + \mathbf{A}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon}) + \mathbf{B}(\boldsymbol{\sigma}, \boldsymbol{\varepsilon})^2 + \boldsymbol{\gamma_1 J_{t-w}}, \qquad \text{[Eq. 13]}$$

where $A(\cdot)$ is specified as:

$$\boldsymbol{A}(\cdot) = \boldsymbol{A}(\cdot) + \boldsymbol{\alpha_{3,1}\varepsilon_{t-1}} + \boldsymbol{\alpha_{3,1}\varepsilon_{t-2}} + \cdots \qquad \text{[Eq. 14]}$$

The asymmetric terms are contained in $A(\cdot)$ and, adding these terms makes the standard ARCH and GARCH models respond asymmetrically to positive and negative innovations. Specifying this term alongside the ARCH and GARCH terms provides the SAARCH model described by Engle (1990). Each of the input costs will be used independently as explanatory variables in the conditional mean and variance models of the electricity price. For example, if

[43] It is often argued that good news and bad news do not have the same effect on financial data. There are many theories which suggest that positive and negative innovations vary in their impact. For example, for risk-averse investors, a large unanticipated drop in the market more likely leads to higher volatility than a large unanticipated increase (Black, 1976; Nelson, 1991).

the SAARCH term were recorded as statistically significant and negative, it would imply that positive shocks have resulted in smaller increases in volatility than negative shocks of the same absolute magnitude. In addition, it must then be recalled that the volatility, depending on the presence of ARCH-in-mean terms or, more simply, the innovations, will feed into the conditional mean of the electricity price via past residuals or variance depending on the specification of GARCH-in-mean term.

5.3.6 Causal impacts of generation costs

To improve the quality of our inference we perform an analysis of Granger-causality, a statistical concept of causality based on prediction. According to Granger (1969), if a signal (in our case, imbalance prices) Granger-causes another signal (the electricity price), then past values of that signal should contain information that helps predict the electricity price above and beyond the information contained in past values of the electricity price alone. It is important to perform such tests to abandon the possibility of interaction based on spurious correlations. This is a likely possibility since electricity and imbalance prices often move with the same variables, so may appear to be correlated even when there is no substantive relationship between the two.

A Vector Autoregressive (VAR) model is used as the benchmark for the Granger-causality tests, which will determine whether causality runs from these the imbalance price toward the electricity price. VAR modeling approach, first introduced by Sims (1980), is able to provide an accurate representation of the dynamic behavior of a system of variables. Yet its main drawback entails the economic interpretability of its parameter estimates. These are hence not interpreted, with the associated marginal changes in the electricity prices being obtained from the respective GARCH analysis. In fact, the VAR coefficients only represent reduced form model parameters because the instantaneous interactions of the endogenous variables are not explicitly modeled but are included in the covariance matrix of the residuals; see Cooley and LeRoy (1985) and Bunn and Fezzi (2008). The VAR model is formalised as:

$$\boldsymbol{y_{t=}A_1 y_{t-1}} + \cdots + \boldsymbol{A_n y_{t-n} B x_t} \qquad \text{[Eq. 15]}$$

where, y_t is the endogenous variable (the electricity price) and x_t is a vector of exogenous variables, which are specified in the same way as presented in Section 5.3.3.2; $A_1 \dots A_n$ and B are matrices containing the coefficients to be estimated; and t is a vector of innovations which can be simultaneously correlated but which are uncorrelated with their own lagged values and uncorrelated with all variables on the right-hand side of Eq. 15. The Akaike information criteria were used to determine the most appropriate lag lengths of the explanatory variables used in the model. The conditional maximum likelihood estimator is used as estimator for the coefficient matrix and is consistent and asymptotically efficient. This involves employing the Kronecker product as well as the vectorisation of the matrix containing the endogenous variables.

Granger causality represents the dependency relationships between two time series and is used to reveal the causal relationships between pairs of variables under study.[44] This test specifies that, if two series $\{X_t, Y_t \geq 1\}$ are strictly stationary, $\{Y_t\}$ Granger-causes $\{X_t\}$ if past and current values of Y embody further information regarding the future values of X. If $F_{X,t}$ and $F_{Y,t}$ denote the relevant information set of past values of both X_t and Y_t, at time t, $\{Y_t\}$ is said to Granger-cause $\{X_t\}$ if the following condition is satisfied:

$$(\boldsymbol{Y_{t+1}}, \dots, \boldsymbol{Y_{t+k}}) \,|(\boldsymbol{F_{X,t}}, \boldsymbol{F_{Y,t}}) \sim (\boldsymbol{Y_{t+1}}, \dots, \boldsymbol{Y_{t+k}}) \mid \boldsymbol{F_{X,t}}, \qquad \text{[Eq. 16]}$$

where '~' denotes distribution equivalence between both sides of the equation. Assuming that $X_t^{l_X} = (X_{t-\ell X+1}, \dots, X_t)$ and that $Y_t^{l_Y} = (Y_{t-\ell Y+1}, \dots, Y_t)$ represent the lag vectors, where $\ell_X, \ell_Y \geq 1$, the null hypothesis states that realised values of $X_t^{l_X}$ embed further evidence on Y_{t+1}, beyond that present in $Y_t^{l_Y}$ (Karagianni and Pempetzoglou, 2013).

Because we have specified the conditional variance of the electricity prices in the different GARCH models as depending on the values of costs from the previous period (day) and considering that the Granger causality test would entail studying the causality interface between the current electricity price and the one-period lagged of the cost and price variables, the latter variables are included in this analysis as contemporaneous. The results from this test will inform about whether causality runs from the imbalance to the electricity price and will complement our GARCH analysis.

5.3.7 Model parameter expectations

The Netherlands, Italy and GB are especially intensive in gas-fired electricity generation, as indicated by shares in total generation of at least 40% (see Figure 24). These models are therefore expected to yield the largest coefficients for the relationship between electricity prices and natural gas prices. Spain (20%) and Germany (13%) also have relatively high gas shares, so similar considerations also apply. France, on the other hand, uses relatively small fractions of gas (6%) with electricity production instead largely based on nuclear power. The same applies to Norway, which only uses a tiny fraction of gas (2%) for electricity generation. Thus, we would expect gas and coal prices to have a relatively small impact on the electricity prices of Norway and France. Yet Norway can be reliant on fossil fuel prices as generation fired by fossil fuels represents the opportunity cost of present hydro-generation.

Generation from coal is widely prevalent in Germany and the Netherlands, which still produce 43% and 35% of their electricity using coal, respectively. Italy (15%), Spain (14%) and GB (9%) also have noteworthy shares of coal, so are expected to display at least some dependency of their electricity prices to changes in the coal price. Oil, on the other hand, is mainly used in Spain (6%), whereas other examined markets only employ 1% or less of coal-fired generation in total electricity production. We therefore do not expect oil to be an important driver of electricity prices, even in the model of Spanish prices.

[44] This is a bivariate test based on a multivariate model. Yet causality may also be studied based on a system of interconnected variables using Granger-Causal Dynamic Complex Networks (GCDCN). The GCDCN model was introduced to study the co-movements of a system of energy prices by Castagneto-Gissey *et al.* (2014).

Local prices may also be set by the electricity imports from neighbouring countries as well as by the opportunity cost of not exporting. This should be particularly true for highly interconnected countries such as the Netherlands, which has high interconnection capacity relative to generating capacity compared to other examined countries. In an analogous way, electricity prices should reflect the use of the employed carbon-intensive units of coal and gas and should therefore imply lower magnitudes of effect for France and Norway compared to Germany, the Netherlands, Italy, GB and Spain, which generate more carbon-intensive electricity. We expect these hypotheses to also be qualitatively valid when modelling the conditional variances, although magnitudes may be larger when viewed in terms of volatility transmission between variables.

The degree to which imbalance costs are factored into electricity prices in advance will depend on the extent to which these costs are foreseen. If unforeseen, we would therefore not be surprised should imbalance costs not be statistically significant. Alternatively, our analysis may detect imbalance costs as statistically significant, but small in magnitude. This may be a consequence of either these costs being somewhat internalised into prices, or perhaps more simply it might be caused by the influence of common factors. If the former were to be the case, we would expect the magnitude of effect to be small. GB imbalance costs typically represent 1–6% of annual revenues at minimum (Baringa, 2013), so assuming perfectly competitive markets where costs equal revenues, and that imbalance costs are passed through via wholesale prices, we would expect a minimum pass-through rate of 3%.[45]

[45] All averages used to represent the marginal shares and the pass-through rates relate to estimates that are statistically significant at the 5% significance level, with missing data censored from any computed averages. This measure was taken to ensure the robustness of the calculated averages.

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7 Author biographies

This project brings together an experienced team with a track record of working across disciplines to advise electricity market policy through the application of state-of-the-art econometrics and energy modelling techniques. It combines expertise from UCL and Imperial College London.

Dr Giorgio Castagneto Gissey (UCL – Principal Investigator) is a Senior Research Associate in Energy Economics and Policy. He has published on European electricity market competition and on the impacts of policy incentives in EU electricity and gas markets, on some of the most recognized energy economics and policy journals. A lead author of EPSRC-funded publications on electricity market, regulatory and policy barriers to the deployment of energy storage technologies in the UK electricity markets, he led a study which was used by the Mexican government as a case study of barriers to storage in the UK. He is the lead developer of COMPASS, and GCDCN, which are models concerning market power in electricity markets and market integration and have been used by Ofgem and the U.S. FERC, respectively.

He is Research Co-I on the EPSRC-funded RESTLESS project (~£1.75m), leading on the economics of energy storage. He is Research Co-I and Acting PI on the 'Value of Interconnection in a Changing Electricity System' (ICE) project, a project recently funded by RCUK and InnovateUK (~£1m), concerning the impacts of Brexit on the GB and European wholesale electricity systems and aiming to provide a system-wide business case for interconnectors in GB and Ireland between 2020 and 2050. His proposal was endorsed by Ofgem, BEIS, National Grid, ENTSO-E, National Infrastructure Commission, House of Commons, the Scottish and Welsh Governments, as well as numerous private institutions, such as Transmission Investment, Scottish Power, and many more.

He has provided expert advice to Ofgem and BEIS on many occasions about potential policies to internalise storage in electricity markets, and to the consultancy Arup, on request of the Mexican Government. He advised the U.S. FERC in relation to electricity network modelling. He was an adviser to BEIS for their UK's Industrial Strategy Roundtable and also to the Energy Saving Trust for the Community Energy Storage Roundtable. He worked at UCL as a Teaching Fellow in Economics and Business, teaching many courses in advanced econometrics at all academic levels, and held positions at Imperial College, the Italian Ministry of the Economy and Finance, and National Research Council. He recently founded the UCL Energy & Resource Economics Group. He led the econometric analysis of electricity cost pass-through and marginal fuels in this project.

Prof. Michael Grubb (UCL – Co-Investigator) is Professor of Energy and Climate Policy. He has substantial experience in the study of competition in electricity markets and has published influential papers on the topic. His research and experience have grouped broadly around four main themes: (1) Carbon pricing and emissions trading systems, including the design of the EU ETS and industrial competitiveness; (2) Energy systems and low carbon innovation, with emphasis upon the innovation process in the energy sector, particularly in relation to renewable sources and the design of support systems; (3) International climate change responses more broadly including the UNFCCC negotiations, the Kyoto Protocol and its Mechanisms, and the wider challenges of international cooperation; and, (4) Internalisation of renewable electricity sources into electricity systems. He has published numerous leading papers on power system modelling. He previously served as Chair of the UK Panel of Technical Experts on Electricity Market Reform, and a member of the CCC. An interdisciplinary researcher on the economics and policy of energy and climate change, he is PI on numerous projects, such as the ~£3m Green-Win project. Founding editor-in-chief of the journal Climate Policy, he was previously: Senior Advisor to Ofgem; Senior Research Associate at the University of Cambridge; Chair of the international research organization Climate Strategies; Chief Economist at the Carbon Trust; Professor at Imperial College London; Head of Energy and Environment at Chatham House. He is author of eight books, numerous research articles and publications on competition policy, and a Lead Author for several reports of the IPCC on mitigation, including the IPCC Fourth Assessment Report.

Dr Iain Staffell (Imperial College London – Co-Investigator) is Senior Lecturer in Sustainable Energy at the Centre for Environmental Policy. He is a multi-disciplinary scientist holding degrees in Physics, Chemical Engineering and Economics. He leads the Electric Insights project, an interactive website and quarterly report on the supply, demand, price and environmental impacts of Britain's electricity. His research on electricity markets and renewables has advised the European Commission, the IEA, BEIS, National Grid and Australian electricity market operator. He has authored two books and fifty papers across the sphere of natural sciences, engineering, economics and policy.

Dr Paolo Agnolucci (UCL – Co-Investigator) is Senior Lecturer in Environmental and Energy Economics at the UCL Institute for Sustainable Resources. He has strong interest in the application of quantitative methods in fields including energy and the environment. He worked in the private sector and have acted as a consultant to several institutions and private clients, especially the European Commission and the Department for Energy and Climate Change. He has a PhD in Economics from Birkbeck College and a MSc in Environmental and Natural Resource Economics from UCL.

Prof. Paul Ekins OBE (UCL – Co-Investigator) is Professor of Resources and Environmental Policy and Director of the UCL Institute for Sustainable Resources. He is also Deputy Director of the UK Energy Research Centre, and the UKERC Co-Director leading on its Energy Resources theme. He was awarded an OBE in the UK's New Year's Honours List for services to environmental policy. In 1994, Paul Ekins received a Global 500 Award 'for outstanding environmental achievement' from the United Nations Environment Programme. He is a member of Ofgem's high-level Sustainable Development Advisory Group and was Chairman of the Government-funded National Industrial Symbiosis Programme (NISP), the UK's most successful programme to improve resource productivity. In addition, he is a member of UNEP's International Resource Panel; a Fellow of the Energy Institute; a Senior Consultant to Cambridge Econometrics; and he leads UCL's participation in the EPSRC SUPERGEN consortium on hydrogen fuel cells and on bioenergy research. From 2002-2008, he was a Member of the Royal Commission on Environmental Pollution. From 1997-2005, he was a specialist adviser to the Environmental Audit Committee of the House of Commons, from 2003-2007 was a Member of the Government's Sustainable Energy Policy Advisory Board, and in 2007 was a Specialist Adviser to the Joint Parliamentary Committee on the Climate Change Bill. He has extensive experience consulting for business, government and international organisations, which has included over 50 projects and consultancies over the last ten years, and many advisory positions. He has also been a consultant to the Government's Sustainable Development Commission, and an adviser to the UK Government's Advisory Committee on Business and the Environment and Round Table on

Sustainable Development and has been a frequent contributor to His Royal Highness the Prince of Wales' annual course for senior executives on business and the environment at the University of Cambridge, and the Cambridge Programme for Sustainability Leadership. Since 2003, he has been a member, and is now Chairman, of the Judging Panel, UK Ashden Sustainable Energy Awards, and he is on the Judging Panel of the Rushlight and Rosenblatt New Energy Awards. He was a member in 2010-11 of two Ministerial Advisory Panels, on the Green Deal (DECC) and on the Natural Environment White Paper (DEFRA), and is on the Advisory Board of DECC's Energy Efficiency Deployment Office. In 2011 he was appointed Vice-Chairman of the DG Environment Commissioner’s High-Level Economists Expert Group on Resource Efficiency and a member of the European Commission's high-level European Resource Efficiency Platform. He will contribute toward the analysis of the trade-offs between electricity prices and electricity system sustainability.

8 Appendix

8.1 Data

Variable	Skewness	Kurtosis	Normality
GB electricity price	0.00	0.00	0.00
DE electricity price	0.00	0.00	0.00
FR electricity price	0.00	0.00	0.00
IT electricity price	0.00	0.10	0.00
ES electricity price	0.00	0.00	0.00
NL electricity price	0.00	0.30	0.00
NO electricity price	0.00	0.00	0.00
GB gas price	0.00	0.29	0.00
Western Europe gas price	0.00	0.00	0.00
Coal price	0.00	0.00	0.00
Oil price	0.00	0.00	0.00
ETS carbon price	0.00	0.09	0.00
UK carbon price	0.04	0.00	0.00
Drax imbalance charge	0.95	0.00	0.00
EDF imbalance charge	0.00	0.00	0.00
SSE imbalance charge	0.00	0.00	0.00
RWE imbalance charge	0.00	0.00	0.00
Centrica imbalance charge	0.00	0.00	0.00
Distribution-connected imbalance charge	0.00	0.00	0.00
Imbalance volume (national)	0.79	0.00	0.00
Imbalance price	0.00	0.00	0.00
Imbalance cost (national)	0.00	0.00	0.00
EUR to GBP exchange rate	0.00	0.0006	0.00
USD to GBP exchange rate	0.00	0.00	0.00

Table A1. Distribution tests on time series level data, including skewness, kurtosis and normality. The values reported are p-values and indicate statistical significance when under the 0.05 level.

Variable	ADF test statistic	ADF P-value	PP Z(Rho)	PP Z(t)	PP P-value
GB electricity price	-9.88	0.00	-631.58	-19.76	0.00
DE electricity price	-8.34	0.00	-268.70	-12.24	0.00
FR electricity price	-9.45	0.00	-352.06	-14.18	0.00
IT electricity price	-6.26	0.00	-178.59	-9.93	0.00
ES electricity price	-8.31	0.00	-336.19	-13.93	0.00
NL electricity price	-7.13	0.00	-208.43	-10.71	0.00
NO electricity price	-5.23	0.00	-77.27	-6.35	0.00
GB gas price	-3.52	0.04	-23.99	-3.57	0.03
Western Europe gas price	-3.87	0.01	-50.83	-5.11	0.00
Coal price	-1.01	0.94	-2.34	-0.91	0.96
Oil price	-2.19	0.50	-7.13	-2.20	0.49
ETS carbon price	-1.49	0.83	-7.01	-1.69	0.76
GB carbon price	-1.35	0.88	-3.69	-1.37	0.87
Drax imbalance charge	-27.68	0.00	-1,109.09	-28.70	0.00
EDF imbalance charge	-22.81	0.00	-725.83	-22.74	0.00
SSE imbalance charge	-19.54	0.00	-678.55	-20.60	0.00
RWE imbalance charge	-19.71	0.00	-639.92	-20.24	0.00
Centrica imbalance charge	-25.55	0.00	-1,085.65	-27.30	0.00
Distribution-connected imbalance charge	-23.95	0.00	-904.97	-24.99	0.00
Imbalance volume (national)	-27.56	0.00	-1,348.73	-29.43	0.00
Imbalance price	-28.59	0.00	-1,499.00	-31.03	0.00
Imbalance cost (national)	-27.55	0.00	-1,335.86	-29.32	0.00
EUR to GBP exchange rate	-1.34	0.61	-3.91	-1.28	0.64
USD to GBP exchange rate	-1.01	0.75	-2.14	-0.97	0.77

Table A2. Unit root tests for stationarity on time series level data with 3 lags. These are the traditional Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests for stationarity of time series data.

Variable	Mean	SD	Min	Max
GB electricity price	0.01	6.81	-70.80	73.76
DE electricity price	0.00	5.88	-34.67	53.26
FR electricity price	-0.01	9.70	-220.35	250.23
IT electricity price	-0.01	5.39	-38.37	32.76
ES electricity price	0.01	6.89	-124.53	132.30
NL electricity price	0.00	3.89	-20.38	21.95
NO electricity price	-0.02	3.11	-33.51	57.96
UK gas price	0.00	0.60	-10.35	4.83
Western Europe gas price	0.00	0.92	-19.53	15.00
Coal price	0.01	0.91	-7.65	7.90
Oil price	0.00	0.84	-5.29	3.09
ETS carbon price	0.00	0.27	-3.11	3.01
GB carbon price	0.00	0.32	-3.11	8.53
Drax imbalance charge	1.69	1,222.16	-11,119.31	6,767.77
EDF imbalance charge	-0.62	1,096.05	-15,586.93	11,336.17
SSE imbalance charge	2.98	2,433.38	-14,930.02	15,505.00
RWE imbalance charge	0.59	989.57	-12,247.70	10,664.92
Centrica imbalance charge	0.00	0.03	-0.16	0.16
Distribution-connected imbalance charge	-12.26	9,888.97	-54,894.78	61,368.05
Imbalance volume (national)	-2.77	9,301.01	-36,988.04	39,942.88
Imbalance price	0.01	11.91	-139.23	190.82
Imbalance cost (national)	-113.39	452,720.40	-2,171,039.00	2,002,905.00
EUR to GBP exchange rate	-0.000049	0.0066	-0.079	0.03
USD to GBP exchange rate	-0.00015	0.0081	-0.12	0.04

Table A3. Mean, standard deviation, minimum and maximum of first differences of time series level data.

Variable	Skewness	Kurtosis	Normality
GB electricity price	0.07	0.00	0.00
DE electricity price	0.00	0.00	0.00
FR electricity price	0.00	0.00	0.00
IT electricity price	0.31	0.00	0.00
ES electricity price	0.00	0.00	0.00
NL electricity price	0.30	0.00	0.00
NO electricity price	0.00	0.00	0.00
GB gas price	0.00	0.00	0.00
Western Europe gas price	0.00	0.00	0.00
Coal price	0.00	0.00	0.00
Oil price	0.18	0.00	0.00
ETS carbon price	0.15	0.00	0.00
GB carbon price	0.00	0.00	0.00
Drax imbalance charge	0.00	0.00	0.00
EDF imbalance charge	0.00	0.00	0.00
SSE imbalance charge	0.00	0.00	0.00
RWE imbalance charge	0.00	0.00	0.00
Centrica imbalance charge	0.45	0.00	0.00
Distribution-connected imbalance charge	0.17	0.00	0.00
Imbalance volume (national)	0.43	0.00	0.00
Imbalance price	0.00	0.00	0.00
Imbalance cost (national)	0.34	0.00	0.00
EUR to GBP exchange rate	0.00	0.00	0.00
USD to GBP exchange rate	0.00	0.00	0.00

Table A4. Distribution tests on first-differences of time series level data.

Variable	ADF test statistic	ADF P-value	PP Z(Rho)	PP Z(t)	PP P-value
GB electricity price	-47.61	0.00	-2,787.91	-69.71	0.00
DE electricity price	-42.90	0.00	-2,466.09	-56.73	0.00
FR electricity price	-41.56	0.00	-2,625.91	-61.57	0.00
IT electricity price	-44.69	0.00	-2,581.45	-60.92	0.00
ES electricity price	-46.30	0.00	-2,652.03	-63.86	0.00
NL electricity price	-43.08	0.00	-2,468.17	-56.91	0.00
NO electricity price	-37.59	0.00	-2,351.51	-52.69	0.00
GB gas price	-33.37	0.00	-2,124.41	-46.75	0.00
Western Europe gas price	-31.87	0.00	-1,907.05	-42.04	0.00
Coal price	-31.76	0.00	-2,020.19	-44.50	0.00
Oil price	-36.96	0.00	-2,416.52	-54.30	0.00
ETS carbon price	-34.76	0.00	-2,316.47	-51.43	0.00
GB carbon price	-49.15	0.00	-2,725.03	-67.60	0.00
Drax imbalance charge	-46.02	0.00	-1,170.51	-60.99	0.00
EDF imbalance charge	-52.28	0.00	-1,352.18	-71.32	0.00
SSE imbalance charge	-48.86	0.00	-1,270.10	-64.11	0.00
RWE imbalance charge	-59.98	0.00	-1,515.98	-88.63	0.00
Centrica imbalance charge	-53.28	0.00	-1,359.48	-76.26	0.00
Distribution-connected imbalance charge	-67.90	0.00	-2,226.98	-97.86	0.00
Imbalance volume (national)	-68.37	0.00	-2,212.22	-103.69	0.00
Imbalance price	-67.69	0.00	-2,224.98	-96.75	0.00
Imbalance cost (national)	-67.26	0.00	-2,257.02	-90.36	0.00
EUR to GBP exchange rate	-37.345	0.00	-1,354.335	-37.313	0.00
USD to GBP exchange rate	-26.023	0.00	-652.104	-25.966	0.00

Table A5. Unit root tests for stationarity on first differences of time series level data. Lags=1.

8.2 Results

8.2.1 Average coal and gas shares at the margin 2012–2017

	Gas	Coal
GB	51.7%	35.4%
DE	47.2%	37.3%
FR	48.1%	35.1%
IT	50.0%	38.2%
ES	51.5%	35.1%
NL	49.6%	38.3%
NO	<1%	<1%

Table A6. Shares at the margin of coal and gas during 2012 to 2017 for all the examined European markets. Oil is excluded as *all* countries have shares for oil of less than 1%.

8.2.2 Full period analysis

8.2.2.1 Fuel cost analysis

Variable	GB		DE		FR		IT		ES		NL		NO	
	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p
Load	0.0002 (0.00003)	<0.0001	0.00002 (0.00001)	0.069	0.0002 (0.00002)	<0.0001	0.0001 (0.00001)	<0.0001	0.0001 (0.00002)	<0.0001	0.0002 (0.00004)	<0.0001	0.0005 (0.00004)	<0.0001
Gas price	1.319 (0.106)	<0.0001	0.676 (0.209)	0.001	0.563 (0.250)	0.024	0.511 (0.112)	<0.0001	0.064 (0.062)	0.297	1.311 (0.132)	<0.0001	0.253 (0.104)	0.015
Coal price	0.085 (0.055)	0.126	0.078 (0.091)	<0.0001			0.082 (0.071)	0.249	0.0025 (0.084)	0.976	-0.033 (0.042)	0.419	0.034 (0.037)	0.353
Oil price							-0.020 (0.072)	0.785			0.0373 (0.036)	0.297	0.037 (0.034)	0.282
Carbon price	0.219 (0.130)	0.091	0.078 (0.092)	0.394	0.078 (0.103)	0.447	-0.118 (0.247)	0.632	0.194 (0.222)	0.380	0.377 (0.153)	0.014	0.113 (0.103)	0.273
Imbalance price	0.023 (0.015)	0.138	-0.072 (0.088)	0.415	0.301 (0.270)	0.264								
Variable renewable generation	-0.0009 (0.00009)	<0.0001	0.375 (0.265)	0.157	-0.0016 (0.0001)	<0.0001	-0.0012 (0.0001)	<0.0001	-0.001 (0.00004)	<0.0001	-0.002 (0.0001)	<0.0001	-0.004 (0.0006)	<0.0001
Interconnection index											1.863 (0.086)	<0.0001		
Winter	-0.009 (0.022)	0.682	-0.066 (0.086)	0.443	-0.170 (0.140)	0.227			-0.097 (0.093)	0.295	-0.046 (0.021)	0.025	-0.127 (0.072)	0.076
Fall	-0.022 (0.023)	0.356	0.140 (0.078)	0.072	0.137 (0.116)	0.238			0.064 (0.061)	0.292	0.040 (0.020)	0.046	-0.008 (0.050)	0.868
Spring	0.066 (0.022)	0.003	-0.031 (0.060)	0.604	-0.145 (0.118)	0.217			0.092 (0.066)	0.164	-0.018 (0.019)	0.334	-0.132 (0.055)	0.017
Constant	-0.027 (0.016)	0.077	0.006 (0.041)	0.883	0.119 (0.082)	0.148	-0.026 (0.027)	0.333	0.039 (0.036)	0.275	-0.003 (0.012)	0.826	0.039 (0.032)	0.228
ARMA														
AR (L1)	0.251 (0.059)	<0.0001	0.499 (0.076)	<0.0001	0.291 (0.093)	0.002	0.327 (0.040)	<0.0001	0.450 (0.061)	<0.0001	0.502 (0.048)	<0.0001	0.542 (0.096)	<0.0001
MA (L1)	-0.940 (0.030)	<0.0001	-0.861 (0.062)	<0.0001	-0.623 (0.080)	<0.0001	-0.781 (0.031)	<0.0001	-0.773 (0.050)	<0.0001	-0.939 (0.027)	<0.0001	-0.672 (0.083)	<0.0001

Table A7(a). Conditional mean models of European electricity prices between 2012 and 2017. One, two and three asterisks indicate statistical significance at the 10%, 5% and 1% significance levels.

Variable	GB		DE		FR		IT		ES		NL		NO	
	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p	Coefficient (Std. error)	p
Load	0.0002 (0.0001)	0.126	0.00002 (0.00006)	0.686	0.0002 (0.00006)	0.003	0.00006 (0.00004)	0.109	-0.0002 (0.00009)	0.008	0.00009 (0.0001)	0.400	0.001 (0.0001)	<0.0001
Gas price	0.238 (0.391)	0.543	0.175 (0.068)	0.010	0.272 (0.099)	0.006	0.262 (0.116)	0.024	0.194 (0.125)	0.120	0.376 (0.064)	<0.0001	0.317 (0.083)	<0.0001
Coal price	0.307 (0.101)	0.002	0.252 (0.323)	0.436	-0.068 (0.299)	0.821	-0.131 (0.169)	0.438	-0.342 (0.168)	0.042	-0.092 (0.069)	0.184	-0.212 (0.190)	0.263
Oil price	-0.179 (0.172)	0.299	-0.405 (0.539)	0.453	-0.065 (0.160)	0.685			0.071 (0.254)	0.781	0.037 (0.079)	0.634	-0.046 (0.136)	0.733
Carbon price	-0.480 (0.457)	0.293	-0.102 (0.636)	0.873	-0.129 (0.398)	0.745			0.578 (0.932)	0.535	0.216 (0.249)	0.386	-0.238 (0.286)	0.404
Imbalance price	0.023 (0.006)	<0.0001												
Variable renewable generation	-0.0003 (0.0001)	0.035	0.0001 (0.00004)	0.002	0.00003 (0.00027)	0.924	0.0002 (0.0002)	0.398	0.00009 (0.00008)	0.261	-0.0003 (0.0003)	0.341	-0.002 (0.003)	0.523
Interconnection index											-0.600 (0.054)	<0.0001		
Winter	0.019 (0.177)	0.915	0.029 (1.153)	0.980	0.157 (0.284)	0.580			1.281 (0.381)	0.001	0.434 (0.144)	0.003	0.653 (0.327)	0.046
Fall	0.156 (0.174)	0.369	1.008 (0.384)	0.009	-0.0323 (0.212)	0.876			0.605 (0.330)	0.067	0.167 (0.130)	0.200	0.162 (0.219)	0.460
Spring	-0.011 (0.163)	0.948	0.109 (0.363)	0.763	0.039 (0.216)	0.855			0.798 (0.331)	0.016	0.179 (0.132)	0.176	0.642 (0.198)	0.001
Constant	-0.013 (1.319)	0.992	-0.666 (0.564)	0.238	0.903 (0.424)	0.033	1.098 (0.250)	<0.0001	-1.318 (0.559)	0.018	0.254 (0.156)	0.104	-1.383 (0.296)	<0.0001
ARCH														
ARCH (α_1)			0.170 (0.045)	<0.0001	0.284 (0.050)	<0.0001	0.303 (0.047)	<0.0001	0.259 (0.049)	<0.0001	0.136 (0.031)	<0.0001	0.376 (0.069)	<0.0001
GARCH (β_1)			0.799 (0.044)	<0.0001	0.634 (0.045)	<0.0001	0.615 (0.040)	<0.0001	0.739 (0.042)	<0.0001	0.463 (0.064)	<0.0001	0.524 (0.066)	<0.0001
NPARCH (α_1)	0.128 (0.053)	0.016												
NPARCH_k	-0.908 (0.622)	0.144												
PGARCH (β_1)	0.750 (0.169)	<0.0001												
SAARCH (γ_1)							0.603 (0.195)	0.002	-0.267 (0.151)	0.077				
$\sum(\alpha_1+\beta_1)$	0.878		0.969		0.918		0.918		0.998		0.599		0.899	
LL	-5681.75		-5964.63		-6050.11		-5796.08		-5531.21		-4607.71		-4046.39	
AIC	11417.50		11977.26		12148.22		11636.17		11112.43		9269.429		8142.79	
BIC	11569.52		12112.40		12283.35		11760.04		11253.20		9421.464		8283.56	
Wald χ^2	3410.73		802.58		396.36		2131.73		1402.22		4112.22		274.05	
Prob> χ^2	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
Q (l)	2.162	0.141	10.987	0.052	60.235	0.064	67.399	0.062	139.514	0.084	5.78	0.123	73.36	0.060

Table A7(b). Conditional variance models of European electricity prices between 2012 and 2017. One, two and three asterisks indicate statistical significance at the 10%, 5% and 1% significance levels.

8.2.2.2 Balancing cost analysis without firms (arbitrage)

Variable	**GB**	
	Coefficient (Std. error)	p
Load	0.0002 (0.00003)	<0.0001
Gas price	1.319 (0.106)	<0.0001
Carbon price	0.219 (0.129)	0.091
Imbalance price	0.0229 (0.0154)	0.138
Variable renewable generation	-0.0009 (0.00009)	<0.0001
Winter	-0.009 (0.0217)	0.682
Fall	-0.0218 (0.024)	0.356
Spring	0.066 (0.022)	0.003
Constant	-0.028 (0.016)	0.077
AR (L1)	0.251 (0.060)	<0.0001
MA (L1)	-0.941 (0.030)	<0.0001

Table A8(a). Conditional mean of GB electricity price.

Variable	**GB**	
	Coefficient (Std. error)	p
Load	0.0002 (0.0001)	0.126
Gas price	0.238 (0.391)	0.543
Coal price	0.307 (0.101)	0.002
Oil price	-0.179 (0.172)	0.299
Carbon price	-0.480 (0.457)	0.293
Imbalance price	0.023 (0.006)	<0.0001
Variable renewable generation	-0.0003 (0.0001)	0.035
Winter	0.019 (0.177)	0.915
Fall	0.156 (0.174)	0.369
Spring	-0.011 (0.163)	0.948
Constant	-0.013 (1.319)	0.992
ARCH		
NPARCH	0.128 (0.053)	0.016
NPARCH_k	-0.909 (0.622)	0.144
PGARCH	0.750 (0.170)	<0.0001
$\sum(\alpha_1 + \beta_1)$	0.878	
LL	-5681.748	
AIC	11417.5	
BIC	11569.52	
Wald χ^2	3410.73	
Prob> χ^2	<0.0001	
Q (l)	0.141	

Table A8(b). Conditional variance of GB electricity price.

8.2.2.3 Balancing cost analysis with firms (arbitrage)

Variable	**GB**	
	Coefficient (Std. error)	p
Load	0.0001 (0.0004)	<0.0001
Gas price	1.336 (0.139)	<0.0001
Carbon price	0.098 (0.141)	0.489
Imbalance price	0.052 (0.020)	0.011
Variable renewable generation	-0.0009 (0.00008)	<0.0001
Winter	0.017 (0.034)	0.611
Fall	-0.049 (0.039)	0.206
Spring	0.020 (0.034)	0.546
Dummy 2015	-0.061 (0.023)	0.010
Drax	0.0002 (0.0001)	0.103
EDF	-0.0003 (0.0003)	0.215
SSE	-0.0007 (0.00006)	0.306
RWE	0.0002 (0.0002)	0.200
Centrica	-10.115 (5.137)	0.049
DX	0.0002 (0.00002)	<0.0001
Constant	0.014 (0.023)	0.541
AR (L1)	0.166 (0.058)	0.004
MA (L1)	-0.911 (0.025)	<0.0001

Table A9(a). Conditional mean model.

Variable	GB	
	Coefficient (Std. error)	p
Gas price	1.404 (0.875)	0.109
Variable renewable generation	-0.0002 (0.0001)	0.015
Constant	1.015 (1.756)	0.563
ARCH		
NPARCH	0.095 (0.092)	0.302
NPARCH_k	-0.134 (1.098)	0.903
PGARCH	0.744 (0.144)	<0.0001
$\sum(\alpha_1 + \beta_1)$	0.839	
LL	-3373.262	
AIC	6798.525	
BIC	6931.614	
Wald χ^2	4254.33	
Prob> χ^2	<0.0001	
Q (l)	0.169	

Table A9(b). Conditional variance model.

8.2.2.4 Balancing cost analysis without firms (cost-plus)

Variable	GB	
	Coefficient (Std. error)	p
Load	0.0002 (0.00003)	<0.0001
Gas price	1.292 (0.094)	<0.0001
Carbon price	0.219 (0.116)	0.059
Imbalance cost	-0.000001 (0.0000002)	<0.0001
Variable renewable generation	-0.0009 (0.00008)	<0.0001
Winter	-0.007 (0.022)	0.765
Fall	-0.019 (0024)	0.429
Spring	0.062 (0.023)	0.006
Constant	-0.028 (0.016)	0.079
AR (L1)	0.223 (0.047)	<0.0001
MA (L1)	-0.934 (0.025)	<0.0001

Table A10(a). Conditional mean model.

Variable	**GB**	
	Coefficient (Std. error)	p
Load	0.0001 (0.0001)	0.329
Gas price	0.294 (0.500)	0.557
Coal price	0.309 (0.094)	0.001
Oil price	-0.219 (0.175)	0.210
Carbon price	-0.544 (0.313)	0.082
Imbalance cost	-0.0000007 0.0000004	0.083
Variable renewable generation	-0.0003 (0.0002)	0.084
Winter	-0.044 (0.194)	0.819
Fall	0.142 (0.183)	0.437
Spring	0.0007 (0.183)	0.997
Constant	-0.118 (1.069)	0.912
ARCH		
NPARCH	0.126 (0.048)	0.009
NPARCH_k	-0.712 (0.563)	0.206
PGARCH	0.769 (0.127)	<0.0001
$\sum(\alpha_1 + \beta_1)$	0.895	
LL	-5567.928	
AIC	11389.86	
BIC	11541.88	
Wald χ^2	3754.20	
Prob> χ^2	<0.0001	
Q (l)	0.575	

Table A10(b). Conditional variance model.

8.2.2.5 Balancing cost analysis with firms (cost-plus)

Variable	**GB**	
	Coefficient (Std. error)	p
Load	0.0001 (0.00003)	<0.0001
Gas price	1.405 (0.137)	<0.0001
Carbon price	0.128 (0.151)	0.396
Imbalance cost	0.0000007 (0.0000002)	0.004
Variable renewable generation	-0.0009 (0.00008)	<0.0001
Winter	0.014 (0.032)	0.661
Fall	-0.049 (0.035)	0.165
Spring	0.018 (0.032)	0.581
Dummy 2015	-0.064 (0.022)	0.003
Drax	0.0002 (0.0001)	0.079
EDF	-0.0003 (0.0002)	0.156
SSE	-0.00006 (0.00006)	0.301
RWE	0.00002 (0.0002)	0.213
Centrica	-9.600 (4.938)	0.052
DX	0.0002 (0.00002)	<0.0001
Constant	0.017 (0.022)	0.427
AR (L1)	0.232 (0.047)	<0.0001
MA (L1)	-0.922 (0.024)	<0.0001

Table A11(a). Conditional mean model.

Variable	GB	
	Coefficient (Std. error)	p
Gas price	1.701 (0.595)	0.004
Variable renewable generation	-0.0002 (0.00009)	0.010
Constant	1.453 (1.704)	0.394
ARCH		
NPARCH	0.077 (0.060)	0.197
NPARCH_k	-0.003 (1.042)	0.998
PGARCH	0.742 (0.109)	<0.0001
$\sum(\alpha_1+\beta_1)$	0.819	
LL	-3374.923	
AIC	6801.846	
BIC	6934.936	
Wald χ^2	4859.55	
Prob> χ^2	<0.0001	
Q (l)	0.229	

Table A11(b). Conditional variance model.

8.2.3 Annual analysis (GB)

8.2.3.1 Fuel cost analysis

8.2.3.1.1 Gas prices

Year	GB
2012	1.295
2013	1.554
2014	0.857
2015	1.439
2016	1.640
2017	1.360

Table A12. GARCH conditional model coefficients for the NBP gas price, by year. Where available, coefficients were significant at the 5% or 1% significance levels.

8.2.3.2 Balancing cost analysis

8.2.3.2.1 Imbalance price and national imbalance cost

Year	Imbalance price	National imbalance cost
2012	N/A	-0.000001
2013	0.007	-0.000001
2014	N/A	-0.000003
2015	N/A	N/A
2016	0.051	-0.000001
2017	N/A	-0.000001

Table A13. GARCH conditional mean model coefficients for GB. Where available, coefficients were significant at the 5% or 1% significance levels.

8.2.3.2.2 Firm-level imbalance cost

Variable	2014		2015		2016		2017	
	Coefficient (Std error)	p	Coefficient (Std error)	p	Coefficient (Std error)	p	Coefficient (Std error)	p
Load	0.0001 (0.0001)	0.174	2.67e-06 (0.0001)	0.977	0.0001 (0.00004)	0.031	0.0002 (0.00006)	0.001
Gas	0.963 (0.400)	0.016	1.885 (0.377)	<0.0001	2.463 (0.244)	<0.0001	1.634 (0.164)	<0.0001
Imb_Prvol	-1.32e-06 (2.17e-06)	0.545	-2.30e07 (1.97e-06)	0.907	8.54e-07 (2.15e-06)	0.692	-1.15e-06 (1.38e-06)	0.405
Drax	0.0002 (0.0002)	0.436	0.0003 (0.0002)	0.172	0.00007 (0.0003)	0.821	0.00007 (0.0002)	0.755
Edf	0.0003 (0.0009)	0.767	0.0047 (0.002)	0.012	-0.00078 (0.0003)	0.010	-0.0003 (0.0001)	0.040
Sse	-0.0001 (0.0002)	0.549	-0.00002 (0.0001)	0.856	0.0001 (0.0001)	0.456	0.00008 (0.0001)	0.485
Rwe	0.00007 (0.0008)	0.934	0.0004 (0.0004)	0.349	0.0004 (0.0003)	0.245	0.0002 (0.0002)	0.312
Centr	6.139 (26.158)	0.814	-5.713 (9.013)	0.526			-0.329 (8.948)	0.971
Aof	-0.00004 (0.00009)	0.646	0.00003 (0.00009)	0.750	0.0001 (0.00008)	0.111	0.0001 (0.00005)	0.047
Constant	-0.0218 (0.054)	0.687	0.016 (0.020)	0.425	0.028 (0.007)	<0.0001	0.018 (0.014)	0.207
AR (L1)	0.309 (0.272)	0.256	0.222 (0.101)	0.028	0.175 (0.050)	<0.0001	0.037 0.048	0.444
MA (L1)	-0.911 (0.227)	<0.0001	-0.957 (0.018)	<0.0001	-1.007 (0.003)	<0.0001	-1.008 (0.009)	<0.0001

Table A14(a). GARCH conditional mean model coefficients with GB firms' imbalance costs as explanatory variables. Where available, coefficients were significant at the 5% or 1% significance levels.

Variable	2014		2015		2016		2017	
	Coefficient (Std error)	p	Coefficient (Std error)	p	Coefficient (Std error)	p	Coefficient (Std error)	p
Gas	0.748 (0.350)	0.033	-0.0005 (0.0001)	<0.0001				0.004
Vreg	-3.90e-07 (0.0017)	1.000			-0.0003 (0.00008)	<0.0001		
Constant	1.665 (0.735)	0.023	1.146 (0.251)	<0.0001	2.729 (1.257)	0.030		0.001
ARCH								
ARCH (α_1)	0.188 (0.116)	0.106	0.138 (0.057)	0.015	0.001 (0.0002)	<0.0001	N/A	0.226
GARCH (β_1)	0.467 (0.236)	0.048	0.422 (0.094)	<0.0001			N/A	<0.0001
EGARCH (γ_1)					0.734 (0.074)	<0.0001		0.464
$\sum(\alpha_1+\beta_1)$	0.655		0.560		0.735			
LL	-704.38		-667.36		-807.21		-762.58	
AIC	1446.76		1370.73		1648.42		1553.17	
BIC	1514.42		1434.82		1708.95		1603.021	
Wald χ^2	338.17		6050.45		313874.29		27949.91	
Prob> χ^2	<0.0001		<0.0001		<0.0001		<0.0001	
Q (20)	14.87	0.783	20.76	0.410	116.98	0.063	19.12	0.514

Table A14(b). GARCH conditional variance model coefficients with GB firms' imbalance costs as explanatory variables. Where available, coefficients were significant at the 5% or 1% significance levels. 'N/A' for the 2017 ARCH and GARCH coefficients indicates that the best model estimated could estimate such terms, reducing the model to a and was therefore a simple ARMA model.

8.2.4 Asymmetric cost internalisation analysis

8.2.4.1 Gas prices

Year	GB	DE	FR	IT	ES	NL	NO
2012–2017	N/A	N/A	0.070	0.456	N/A	N/A	N/A
2016	N/A	-	-	-	-	-	-
2017	N/A	-	-	-	-	-	-

Table A15. Coefficient of asymmetric effect in the electricity price from gas prices as detected using SAARCH modelling. A '-' sign indicates that the asymmetric effect was not investigated; 'N/A' means that the asymmetric effect was absent. We only considered the presence of asymmetric effects for GB for the years 2016 and 2017 since this evidence was required due to relevance in relation to Ofgem's upcoming State of the Energy Market Report.

8.2.4.2 Coal prices

Year	GB	DE	FR	IT	ES	NL	NO
2012–2017	0.346	N/A	-0.323	N/A	-	-	-
2016	N/A	-	-	-	-	-	-
2017	N/A	-	-	-	-	-	-

Table A16. Coefficient of asymmetric effect in the electricity price from coal prices as detected using SAARCH modelling. A '-' sign indicates that the asymmetric effect was not investigated; 'N/A' means that the asymmetric effect was absent. We only considered the presence of asymmetric effects for GB for the years 2016 and 2017 since this evidence was required due to relevance in relation to Ofgem's upcoming State of the Energy Market Report.

8.2.4.3 Imbalance costs

Year	Imbalance price	National imbalance cost
2014–2017	0.394	-0.986
2016	N/A	N/A
2017	N/A	N/A

Table A17(a). Coefficient of asymmetric effect in the GB electricity price from the imbalance price and national imbalance costs as detected using SAARCH modelling.

Year	EDF	RWE	Centrica	Drax	SSE	DX
2016	N/A	N/A	N/A	N/A	N/A	N/A
2017	N/A	N/A	0.042	N/A	N/A	N/A

Table A17(b). Coefficient of asymmetric effect in the GB electricity price from the firm-level imbalance costs as detected using SAARCH modelling.

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