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Cost Pass-through in the British Wholesale Electricity Market

Previously published as "**Cost Pass-through in the British Wholesale Electricity Market: Implications of Brexit and the ETS reform**"

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Abstract

Cost pass-through (CPT) rates give a useful perspective of market competition. This article studies how input costs of electricity generation are passed through to the wholesale price in Great Britain between 2015 and 2018. Our empirical results fail to reject the null hypothesis of 100% CPT rates for gas costs and EUA prices (and coal costs for most hours), suggesting a competitive British wholesale electricity market in most hours. We observe a higher CPT rate for coal costs in peak and off-peak periods. This is due to coal plants usually bidding at rates somewhat lower than marginal costs during off-peak periods in order to dispatch at their minimum load to avoid the costs of shutting down and starting back up. Instead, during peak periods the rate of capacity utilisation is high and marginal coal plants tend to exercise their market power, resulting in a higher CPT rate for coal costs. We extend the argument by assessing coal plants' bidding and find evidence of coal plants exercising market power in hours with high residual demand, generating extreme prices.

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1 Introduction

Similarly to most European wholesale electricity markets,[1] Great Britain (GB) has a small number of firms providing most of the country's electricity generation (EC, 2015). For a long time, the six largest British electricity generation companies provided nearly 70% of all electricity generated nationally.[2] CMA (2016) calculates that in 2015, the Herfindahl-Hirschman Index (HHI) in GB's wholesale electricity market was 1,269, suggesting a concentrated market. The company with the largest market share contributed to about a quarter of GB's total generation, with two thirds of its energy supply coming from nuclear, which generally runs at baseload with high-load factors. About 3.5% of the company's energy supply came from coal and 9.3% from gas.

The market structure of the British wholesale electricity market raises concerns of market power as it is highly profitable for the largest electricity generator to raise prices for their marginal units, which are most typically gas- or coal-powered plants. Competition in the wholesale market promotes lower electricity bills for consumers, while market power tends to make electricity more expensive (Green and Newbery, 1992).

Policymakers often rely on the Cost Pass-Through (CPT) rate to measure market competition since it is a measure of the degree to which a change in costs determines a change in prices (CMA, 2016; Ofgem, 2018).[3] An increase in the input cost raises the marginal cost of electricity generation, but generators may absorb some of the increase by marking up their offer by a smaller or larger amount if the market is imperfectly competitive, depending on the shape of the residual demand (i.e. total demand minus renewable output) curve. The CPT would then differ from 100%. However, given that consumers are inelastic to wholesale electricity prices in the short-run (Cl et al., 2015), a CPT rate that is significantly different from 100% would cast doubt on the assumption of a competitive electricity market (CMA, 2016).

In estimating the CPT, we first apply a Vector Error Correction (VEC) model and use daily data to estimate the long-run effects of fuel and carbon costs on wholesale electricity prices. The effect of fuel (i.e. coal or gas) costs is then divided by the share of hours during which the corresponding technology supplies electricity at the margin, and the effect of carbon costs is divided by the Marginal Emission Factor (MEF) of electricity generation. The ratios are therefore the estimated CPT for fuel and carbon costs. If our estimated CPT rates are significantly different from 100% we find evidence supporting a competitive electricity market. However, it is also worth noting that it is possible to find the average daily CPT rates to be close to 100%, although rates may vary between peak and off-peak periods, indicating the existence of market power during different realised levels of demand.

We do not reject the hypothesis that gas costs and carbon prices were entirely passed on to the British wholesale electricity price. When removing electricity price outliers we do not reject the hypothesis of a 100% CPT rate. However, when the outliers are not removed, the

[1] The wholesale market for electricity is one where generators sell their electricity to retail companies. The latter then sell the electricity to homeowners and businesses in the retail market.

[2] See https://www.ofgem.gov.uk/data-portal/wholesale-electricity-generation-market-shares-company-2018-gb.

[3] An alternative could be to estimate the pass-through elasticity, which informs about the percentage increase in prices arising from a 1% increase in costs.

estimated CPT rate for coal costs is substantially greater than 100%, confirming that extreme prices are due to the marginal coal plants exercising market power. Therefore, one of the main contribution of this article is to identify whether market power exists in the wholesale electricity market, which generators have market power, and how and when do they exercise it.

Another contribution is to enrich the literature on heterogeneous CPT. We find evidence that coal CPT rate is higher in peak compared to off-peak periods, which is in agreement with the argument that electricity generators tend to implement different bidding strategies over different hours of the day (e.g. Jouvet and Solier, 2013; Fabra and Reguant, 2014). One possible reason for this is that during off-peak periods coal plants are mostly operating at minimum load, hence the generator is incentivised to bid at a lower price level to avoid the costs of shutting down and starting back up. We also extend this argument by investigating marginal plants' (coal plants in this case) bidding based on the reduced form estimates and marginal market shares. From our results we infer that their off-peak bids are mainly subject to coal costs, while their peak bids depend on both coal and carbon costs.

The rest of the article is structured as follows. Section 1.1 describes how the wholesale electricity market operates, while Section 1.2 discusses conventional measures of market power in electricity markets. Section 2 provides a review of related literature, Section 3 describes the data, and Section 4 details the econometric method applied in this article and the associated validity tests. Section 5 reports and analyses the results whilst conclusions are drawn in Section 6.

1.1 The British wholesale electricity markets

In Great Britain, wholesale electricity trading can take place bilaterally or via exchanges. By far the majority of electricity is traded through contracts covering timescales (i.e., markets) ranging from several years ahead to close to real-time. Among those markets, the day-ahead market is considered to be the most liquid and efficient among all, delivering a trusted market that sets bidding zone prices for the next 24 hours.

In the day-ahead market, at the demand side electricity retailers submit hourly prices they are willing to pay for specific demand one day in advance, and their offers are arranged from the highest to the lowest, formulating the demand curve. On the supply side, generators submit their hourly bids for a specified quantity of electricity that they are willing to supply. For each hour, bids from electricity generators are then arranged into a merit order from the cheapest to the most expensive, constructing the electricity supply curve. Figure 1 shows an estimate of the marginal cost curve for GB's conventional generation plant in Q2 2016, with carbon emission costs included.[4] Figure 1 shows an estimate of the marginal cost curve for GB's conventional generation plant in Q2 2016, with carbon emission costs included. It should be noted that, when the market is perfectly competitive the merit order curve should be identical to the marginal cost

[4]For simplicity, we use the same thermal efficiency for the same types of power plants. The carbon emission costs include both EUA price and the Carbon Price Support (CPS). In GB, carbon-intensive generators are also subject to an additional GB-only carbon price known as the CPS. As the CPS was fixed at £18/tCO_2 since 2015 Q2, the time when our analysis begin, we ignore its impact on GB's wholesale electricity price. To find estimates of the CPT rate of the CPS, see Guo and Newbery (2020).

curve and we would have complete CPT. Otherwise, we may observe the CPT rate deviating from 100%. The area between the two vertical dotted lines denotes the range in which the residual demand lies (in that quarter).

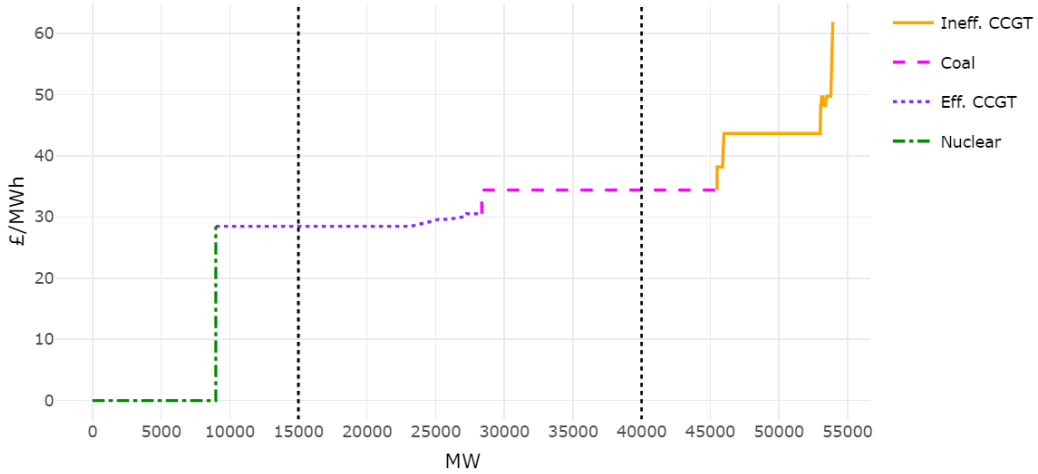

Figure 1: Merit order for GB's conventional generation plant, Q2 2016

Source: BEIS *Quarterly Energy Prices* at https://www.gov.uk/government/statistical-data-sets/prices-of-fuels-purchased-by-major-power-producers and Entso-e Transparency platform.

From Figure 1, if the market is competitive, coal-fired power plants are considered to be the marginal plant during peak hours. However, Chyong et al. (2020) find that during 2015-2017 in GB, despite the marginal cost for coal plants being higher than for Combined Cycle Gas Turbines (CCGTs), in peak hours CCGTs are directly[5] responding to about 60% of marginal demand changes, and about 70% of marginal wind changes. This is because CCGTs have higher flexibility of operation (compared to coal plants). Therefore, even if coal plants were to be more expensive at margin than CCGTs, both types of plants could act as the marginal supplier.

Because of the highly inelasticity (short-run) of the demand curve, for each hour the wholesale price is only set by the marginal supplier. Furthermore, because the costs of coal and gas plants are mainly determined by the underlying fuel (coal or natural gas) and the carbon emissions costs, in a perfectly competitive market, the wholesale electricity price should also be determined by them.

Fossil fuels are traded internationally, hence fuel costs of electricity generation are mostly affected by the global energy market. Carbon emission costs, on the other hand, refer to the EU allowance (EUA) prices from the EU Emissions Trading System (ETS) launched in 2005. As the main instrument to reduce greenhouse gas (GHG) emissions from energy-intensive sectors, the EU ETS works on the "cap and trade" principle: a cap is set by the EU to limit the total amount of GHG that to be emitted, and companies can trade individual emission allowances

[5]Indirectly, the numbers should be higher as imports and pumped storage may also come from CCGT plants.

(i.e. EUAs) with one another. The cap is reduced over time so that total emissions fall. Companies must surrender a sufficient number of allowances to cover all of their emissions, or they face hefty fines. See Ellerman et al. (2016) for a detailed introduction to the EU ETS.

Figure 2: EU ETS carbon price, 2008-2018

Source: Weekly averaged EUA prices from Sandbag at sandbag.org.uk/carbon-price-viewer/.

If the carbon emission cost is sufficiently high, it should discourage carbon-intensive generation and promote clean energy investments. Figure 2 plots the dynamic of the EUA price since 2008, when the price peaked at almost £24/tCO_2. The 2008 economic crisis and the inflow of carbon credits from the outside EU further decreased the ETS price, resulting in consistent low EUA prices during 2011-2017, providing wrong signals on carbon savings and low-carbon investments. Major reforms took effect since 2013 when the EU ETS entered Phase III. The most significant changes were the introduction of an EU-wide cap (instead of some country-wide caps)[6] on emissions and a progressive shift towards auctioning of allowances instead of the initial free allocation scheme. Since 2021, the EU ETS has formally entered Phase IV that replaces the fixed cap with one that is based on past and future market outcomes. Perino (2018) argues that the new character of the ETS would have retroactive impacts on GHG abatement from overlapping policies.

In 2014, the European Commission proposed a Market Stability Reserve (MSR) for the EU ETS, which was then formally implemented in January 2019. The aim was to correct the large surplus of allowances and make the electricity system more resilient to imbalances between the EUA supply and demand, to increase the carbon price and provide a working signal on the externality cost of CO_2 emissions. In February 2018, the EU Council approved the reform of the EU ETS for the period after 2020.[7] Because banking on (from the past) and borrowing (from the future) the EUA price is allowed, the MSR had made carbon-intensive sectors stock

[6]The original country-wide cap is considered to be time consuming, complex and not sufficiently transparent or harmonised.

[7]The reform includes increasing the pace of emissions cuts, doubling the number of allowances to be placed in the MSR between 2019-2023, and building a new mechanism to limit the validity of allowances in reserve from 2023 onwards.

more 2018 EUAs for 2019, tripling the EUA price from £8/tCO_2 in January 2018 to £25/tCO_2 in December 2018 (as Figure 2 shows). During the period of study, the EUA price experienced a drastic incline, bringing an ideal test bed for the CPT of EUA prices. A more detailed review on the formulation of the EUA price is given by Hintermann et al. (2016).

1.2 Measures of market power

The fundamental measure of market power is the price-cost margin, which is the degree to which prices exceed marginal costs (Borenstein et al., 1999). However, measuring price-cost margins is difficult for electricity industries because costs are usually private information for electricity generation companies.

Some most common measures of market power include the Herfindahl-Hirschman Index (HHI), market shares and market concentration. HHI is calculated by squaring companies' market shares and adding up the resulting numbers. This is done to give large companies greater weight, as a large market share owned by one firm could have a negative impact on competition. On the other hand, market shares inform us about the size of a company relative to the rest of the market, while market concentration examines the extent to which a market is dominated by only a few firms. However, HHI, market shares and market concentration may not fully explain market power, as many other factors can affect the degree of competition within an industry, such as the incentive of producers and the price elasticity of demand (Borenstein et al., 1999).

Pivotality analysis is also widely adopted (Ofgem, 2017). It examines whether at least 1 megawatt (MW) of the company's generation is required by the system to meet demand. The lack of competition for that additional MW of supply allows the firm to exercise its market power by increasing electricity prices by a greater amount than it otherwise would. However, models falling in this category consider the impact of individual firms, hence require data with much higher resolution, most of which is not publicly available.

Finally, cost pass-through (CPT) is one of the most popular and effective tool to access market power in economic literature. It measures the impact of changes in input costs on prices. As first argued by Dupuit (1995) and Jenkin (1872), under perfect competition, a tax burden is split among consumers and producers. In this article, "tax burden" may refer to a change in the EUA or the fossil fuel prices. In electricity markets, as electricity demand is highly inelastic, the tax burden would be mostly, if not all, paid by consumers in a competitive market.[8] Put another way, a CPT rate of 100% is consistent with the notion of a competitive wholesale electricity market. In our case, CPT can be estimated via investigating the relationship between input costs and the wholesale price. Our empirical work focuses on a wide range of CPT, which inform the welfare implications of various types of price discriminations and imperfect competition.

[8]Here we assume the demand response is negligible in the GB electricity system during the period of study as demand is inelastic in the short-run (Cl et al., 2015). In a future world where demand response play a non-negligible in the electricity system, the CPT in a competitive market would be lower than 100%.

2 Literature Review

Studies working on the theory of CPT include but is not limited to Bulow and Pfleiderer (1983), Seade (1985), and more recently Weyl and Fabinger (2013) and Reguant (2014). Most empirical works focused on how the EUA cost passes through to electricity prices in the context of the EU ETS. An early work from Sijm et al. (2006) find that the carbon price CPT varied between 60% and 100% in the German and Dutch wholesale electricity markets, though at the time, most of the emission allowances were freely allocated. As an extension, Zachmann and von Hirschhausen (2008) find that the CPT was higher when the carbon price is rising than falling. Castagneto Gissey (2014) uses the year-ahead data for four European countries during 2008-2012 to show that the CPT ranged between 88% and 137%, with GB among the most cost-reflective in a small sample of European markets. In contrary, Jouvet and Solier (2013), in using different data and methodology, find that the estimated CPT was insignificantly different from zero for most of the EU countries involved in their study, especially during the second phase of the ETS.

The structure of electricity systems can be different for different countries, resulting in different degrees of CPT of EUA prices. Honkatukia et al. (2008) find a CPT of 75-95% in Finland during Phase I. Hintermann (2016) finds it to be 81-111% in Germany during Phases I and II. Bariss et al. (2016), in studying Phase I and II, find that a €1/MWh increase in the ETS price was associated with an increase in the Nordic and Baltic electricity prices by €0.55/MWh and €0.67/MWh, respectively. Finally, Bunn and Fezzi (2008) study the UK during Phase I, and argue that on average, a 1% shock in carbon prices was translated into a 0.42% shock in the British electricity price.

Many studies also find that some higher CPT rates were usually associated with high demand and the utilisation rate of generation capacity (Sijm et al., 2006; Honkatukia et al., 2008; Jouvet and Solier, 2013; Fabra and Reguant, 2014). This is because it is costly for fossil generators to shut down and start up again, hence generators are more likely to bid a lower price (than the marginal costs) during off-peak hours in order to maximise the overall profit. On the other hand, the utilisation rate of generation capacity is high during peak periods, then potentially, fossil-fuelled generators that provide marginal supply could exercise market power by submitting bids higher than their marginal costs.

The CPT of other forms of carbon taxes can also be found in the literature. Examples include the Australian Emissions Trading Scheme (Nazifi, 2016; Maryniak et al., 2019), the British Carbon Price Support (Guo and Newbery, 2020), and California's CO_2 cap-and-trade programme (Woo et al., 2017).

Several studies consider prices on other pollutants. For example, Kolstad and Wolak (2003) consider how firms used NO_x prices to exercise market power in the electricity market of California, finding evidence that firms respond differently to environmental cost shocks relative to shocks in other marginal costs. Fowlie et al. (2016) study firms' responses in the NO_x Budget Program, and conclude that the degree of emission cost internalisation was depending on the degree to which the production was subsidised.

Fuel prices CPT are usually the by-products of carbon prices CPT, especially in literature

published in the past decade. Hintermann (2016) finds that fuel prices were passed through to electricity prices more evenly than carbon prices in Germany. A similar result is also reported by Fabra and Reguant (2014), who argue that Spanish firms did not pass on fuel prices to the same degree as allowance costs. One reason for this might be the presence of transaction costs and long-term contracts for fuels, hence the authors conclude that spot prices did not perfectly represent firms' opportunity costs related to fuel consumption. Castagneto Gissey (2014) finds that the British coal and gas CPT in 2007-2012 were 90% and 112%, respectively, and that the CPT was greater for the fuel type that was more often used for generation. Ahamada and Kirat (2018) focus on France and Germany during ETS Phase II, arguing that coal-fired units were more often the price-setting marginal units. The CMA (2016) studies the degree to which fuel prices passed through to retail electricity prices. The study had substantial competition policy implications for the British retail electricity sector which was shown to exhibit market power.

However, there is limited literature looking into CPT of EU ETS carbon costs during Phase III, where the UK power sector obtained their allowances exclusively via auctioning. Furthermore, unlike most literature that focuses on the carbon price CPT, this article investigates a wide range of CPTs, including CPT of gas costs, coal costs, and carbon prices, and whether they are consistent with the notion of a competitive British wholesale electricity market. We use a cointegration approach to estimate long-run relationships between the input costs (i.e. gas costs, coal costs, and carbon prices) of electricity generation and the British wholesale electricity price during 2015-2018, and then estimate the marginal emission factor (MEF) of the GB electricity system. The MEF is then used in conjunction with the earlier estimated long-run relationships to estimate the CPT rate

3 Data

To study the impact of input costs of electricity generation on the British wholesale electricity price (thereafter, wholesale price), the variables of interests include coal and gas costs, carbon prices, as well as the wholesale price. The hourly GB day-ahead electricity price (in Sterling) is considered to be an efficient proxy for the wholesale price, and is collected from the Entso-e Transparency Platform. We use the EU ETS closing spot price as the proxy for the daily EUA price, which is converted from Euro to Sterling using the daily exchange rate. As a proper proxy for gas costs, the daily National Balancing Point gas price (in Sterling) comes from the InterContinental Exchange (ICE) and is converted from £p/therm to £/MWh$_e$ (i.e. Pounds per Megawatt hour of electricity) assuming a Lower Heating Value efficiency for CCGTs of 54.5%.[9] For coal costs, the daily Newcastle Coal Futures price is collected from ICE in $ /metric ton, and is also converted to £/MWh$_e$, using the daily exchange rate between the US dollar and Sterling, assuming an average thermal efficiency for the GB coal-fired power plants of 35.6%.[10] Given these variables, we can directly study the relationship between input costs and electricity prices.

[9] 1 (UK) therm is equivalent to 29.31 kWh$_{th}$. Under the Lower Heating Value efficiency of 54.5%, 1 (UK) therm is equivalent to 15.97(=29.31×54.5%) kWh$_e$.

[10] Thermal efficiencies for coal and CCGT plants are taken from Chyong et al. (2020).

It is noteworthy that to cover the logistics costs of fossil fuels, we adjust both coal and gas costs based on the quarterly "Average prices of fuels purchased by the major UK power producers" published by the Department for Business, Energy & Industrial Strategy (BEIS),[11] in which the logistics costs are included. Specifically, we aggregate the daily coal and gas costs by quarters of each year, which are then subtracted from the BEIS quarterly data, and the differences represent the (quarterly) logistics costs of coal and gas. Next, we sum up the logistics costs and the daily coal and gas costs to obtain the adjusted coal and gas costs.

Our data ranges from 1st April 2015[12] to 31st December 2018. As coal costs, gas costs, and EUA prices are only available on workdays, any missing observations on weekends and holidays are replaced by the most adjacent observation.

As the wholesale price is determined one-day ahead, our control variables include the day-ahead forecast of GB's renewable generation and residual demand (demand, thereafter),[13] as well as GB's nuclear generation. The forecast of GB's renewable (wind and solar) generation and domestic demand comes from the Entso-e Transparency Platform. Besides, nuclear generation can also affect the wholesale price because when nuclear generators are under maintenance or suffering from outages, fossil fuel needs to backup the deficit, resulting in a higher wholesale price. Due to data unavailability, we use the actual daily nuclear generation as a proxy for the day-ahead forecast of nuclear generation. We do this because nuclear power plants are highly inflexible and serve baseload power in GB, meaning that the actual nuclear generation can potentially be very close to its day-ahead forecast.

Table 1: Summary Statistics, Day-ahead Markets

Variable	Abbr.	Unit	Obs.	Mean	S. D.	Min.	Max.
GB day-ahead Prices	P_t^{GB}	£/MWh	1371	46.23	10.98	28.12	170.15
Coal Costs	P_t^{COAL}	£/MWh$_e$	1371	24.38	5.85	12.59	33.78
Gas Costs	P_t^{GAS}	£/MWh$_e$	1371	28.57	5.63	16.90	45.11
EUA Prices	P_t^{EUA}	£/ tCO_2	1371	7.52	4.58	3.34	22.83
GB day-ahead Renew. Gen.	R_t^{GB}	GW	1371	6.10	2.76	1.03	14.94
GB day-ahead Res. Demand	D_t^{GB}	GW	1371	33.95	4.15	24.73	45.26
GB Nuclear Gen.	N_t^{GB}	GW	1371	7.34	0.67	4.69	8.83

Summary statistics for all variables that deliver the baseline result are provided in Table 1, where all hourly data is averaged to daily means. Figure 3 presents the 28-day moving averages of the wholesale price, coal and gas costs, as well as the ETS price during the period of study. It suggests strong comovements between fuel costs and the wholesale price, and between the ETS price and wholesale price.

[11] From https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/437428/qep321_1_.xls.

[12] The British Carbon Price Support (CPS) was raised from £9.55/tCO_2 to £18.08/tCO_2 on 1st April 2015 and has been stabilised since then. This may influence GB electricity prices. In the empirical part, we start our analysis from 1st April 2015, such that the CPS is fixed during the period of study, and is excluded from our regression analysis.

[13] Recall that the residual demand is defined as total electricity load minus renewable generation.

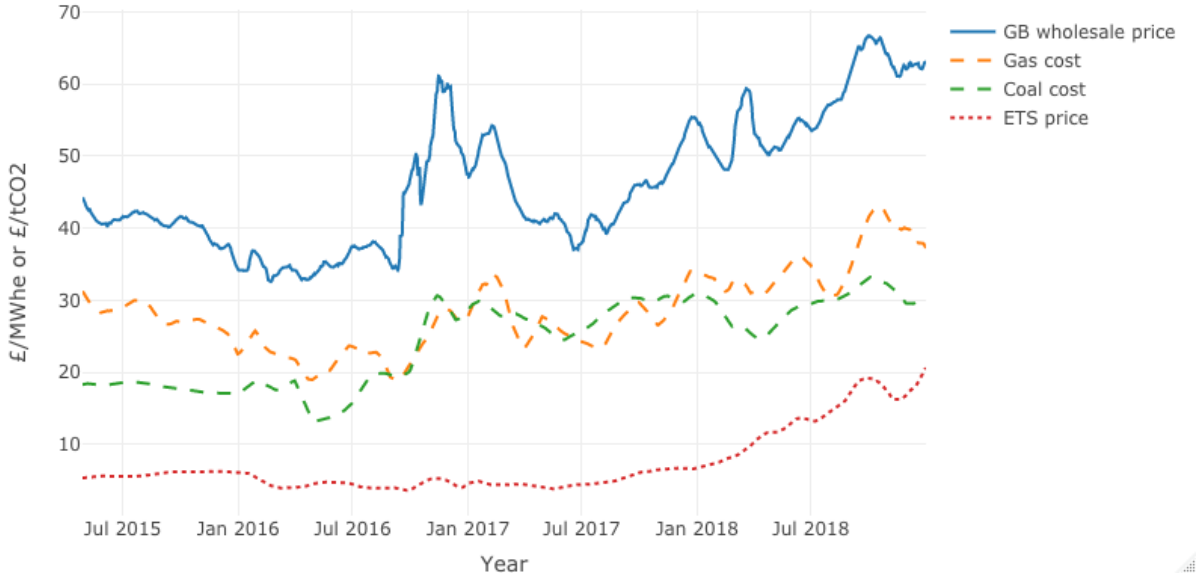

Figure 3: Coal and gas costs and wholesale prices, April 2015 - December 2018

4 Econometric Model

We implement Vector Error Correction (VEC) models to study the relationship between the wholesale price and input costs of electricity generation. The same model has been widely adopted in literature studying the CPT in energy markets, as it effectively captures both short-run and long-run relationships among variables of interest (e.g. Bunn and Fezzi, 2008; Mohammadi, 2009; Alexeeva-Talebi, 2011; Freitas and Da Silva, 2013; Delft and Oeko-Institut, 2015; Fell et al., 2015).

Endogeneity can be an issue when interactions between fuel costs and the wholesale price play a critical role in the wholesale price formation (Knittel and Roberts, 2005). This also applies to the relationship between the wholesale price and carbon prices. Fortunately, the VEC model can effectively deal with endogeneity as it allows us to treat not only the wholesale price but also input costs as endogenous.

Our VEC model specification takes the following form:

$$!\boldsymbol{y}_t = \boldsymbol{"}(\boldsymbol{\#}^{!}\boldsymbol{y}_{t"\ 1}) + \sum_{i=1}^{p"\ 1} \boldsymbol{\$}_i\, !\boldsymbol{y}_{t"\ i} + \boldsymbol{B}\boldsymbol{z}_t + \boldsymbol{C}\boldsymbol{d}_t + \boldsymbol{u}_t, \tag{1}$$

where t represents days, $!$ is the first-different operator, and $\boldsymbol{y}_t$ is an $m \times 1$ vector of dependent variables. In the baseline regression reported in Section 5.1, $\boldsymbol{y}_t$ includes the daily averaged wholesale price (P_t^{GB}), coal costs (P_t^{COAL}), gas costs (P_t^{GAS}), and EUA price (P_t^{EUA}). In Section 5.3-5.5, however, we vary the specification of the VEC model for robustness checks and extension analysis. All variables in $\boldsymbol{y}_t$ are $I(1)$ time series processes (i.e., time series with unit roots, tested in Appendix Table A.3) and are cointegrated with one cointegration equations (tested in Appendix Table A.4).

$\boldsymbol{"}$ and $\boldsymbol{\#}$ are $m \times r$ matrices of full column ranks, and we will test $\boldsymbol{\#}^{!}\boldsymbol{y}_{t"\ 1} \sim I(0)$ to show

that the endogenous variables are cointegrated and $\#^{\prime}\boldsymbol{y}_{t"\ 1}$ is the $r \times 1$ vector of cointegration relations. " is known as measures the speed of convergence when the system deviates from its long-run equilibrium. " and # can be identified by setting one of the parameters in # to 1. In our case, the coefficient for $P^{\mathrm{GB}}_{t"\ 1}$ is set to 1. $\$_i$ consists of coefficients capturing the short-run (SR) relationships among endogenous variables.

$\boldsymbol{z}_t$ is a vector of stationary, or $I(0)$ exogenous stochastic variables, including the day-ahead forecast of electricity demand (D^{GB}_t) and renewable generation (R^{GB}_t), as well as nuclear generation (N^{GB}_t). $\boldsymbol{d}_t$ is a vector of deterministic variables containing a time-invariant constant term, a deterministic trend, and day-of-week and quarterly time dummies. $\boldsymbol{B}$ and $\boldsymbol{C}$ are coefficient matrices. Finally, $\boldsymbol{u}_t$ is an $m \times 1$ vector of unobserved error terms, and is assumed to be stochastically independent, or $\boldsymbol{u}_t \sim (\mathbf{0}, \%_u)$.

We implement the Akaike Information Criterion to determine the lag lengths (p) for dependent variables, and the suggested optimal lag length is $p = 4$. One may also argue that setting $p = 4$ does not fully capture the weekly seasonality of wholesale prices, hence in Section 5.3, we set $p = 8$ as a robustness check so that the weekly seasonality is well captured.

5 Results

This section presents and discusses the regression results for the proposed VEC model and its variations, and calculates the CPT of coal costs, gas costs, and carbon prices to the wholesale price. Precisely, Section 5.1 presents the baseline result where we remove and replace extreme prices, and discusse the impact of input costs of electricity generation on the wholesale price. Section 5.2 estimates the marginal responses of coal and gas generation to electricity demand, which are then used, alongside with the baseline result from Section 5.1, to further calculate the CPT.

Extension analysis is conducted in Sections 5.3-5.5. In Section 5.3, we report robustness checks by varying regression specifications. In Section 5.4, we extend the regression analysis by considering within-day heterogeneous effects (peak and off-peak), and explain the reason for different CPT rates during different periods of the day. Finally, by playing with the definition of outliers, Section 5.5 investigates which fuel types that own and exercise market power in specific hours.

5.1 Baseline results

Extreme wholesale prices in the day-ahead market may occur in events such as nuclear outages and extremely cold days with high demand and low renewable supply. Including extreme prices in our regression analysis may have some substantial effects on our estimates, resulting in misinterpretation of the relationship between input costs and the wholesale price. To deal with this issue, we define an upper/lower threshold for outliers as the sample mean plus/minus & times the standard deviation. Any wholesale prices greater/smaller than the upper/lower threshold are then replaced by the upper/lower threshold. In the baseline regression, we set & = 1.96; while in Section 5.5, we discuss cases where & = 2.58 and & = ', with the latter representing not

dealing with extreme prices and directly applying the VEC model.[14] Figure 4 shows the kernel density estimates of the wholesale price, with observations greater than £200/MWh excluded. The dotted and dashed vertical lines represent the upper and lower bounds when & = 1.96 and & = 2.58, respectively. It is straightforward that the outliers replaced are mostly extremely high prices. Further investigation shows that outliers are usually accompanied by high demand, low renewable energy supply, and sometimes nuclear outages.

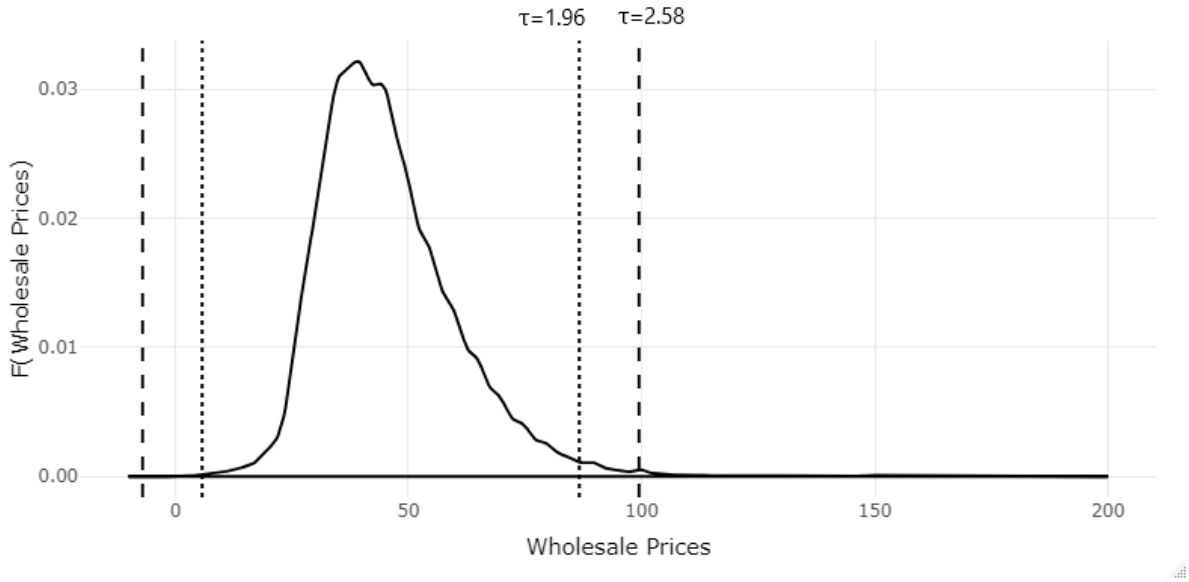

Figure 4: Kernel density estimates of the GB wholesale price, £/MWh

Figure 5 presents some selected impulse responses from estimating specification (2).[15] Impulse responses trace the evolution of all variables in $\boldsymbol{y}_t$ in reaction to a shock in a single variable. From the first row of Figure 5, over time, the responses of the wholesale price to input costs are significant, suggesting that these input costs Granger cause the wholesale price. However, from the second row we find no evidence that the wholesale price Granger causes coal costs, gas costs and EUA prices.

Table 2 reports the baseline regression results from specification (1). The numbers in the "Long-run Dynamics" panel are estimates of **#** and the corresponding standard errors that examine the long-run relationships between the wholesale price and input costs. It is noteworthy that as all endogenous variables are at the same side of the regression, the estimates in negative values refer to positive relation between the wholesale price and the associated input cost. Table 2 shows that in the long-run,[16] a £1/MWh$_e$ increase in coal costs (P_t^{COAL}) is associated with a £0.40/MWh$_e$ increase in the wholesale price; a £1/MWh$_e$ increase in gas costs (P_t^{GAS}) would on average raise the wholesale price by £0.77/MWh$_e$; and a £1/tCO_2 increase in EUA prices corresponds to a £0.36/MWh$_e$ increase in the wholesale price. All coefficients are statistically

[14]When $\tau = 1.96$, we remove and replace less than 2% of the hourly observations; when $\tau = 1.96$, we remove and replace less than 1% of the hourly observations.

[15]The complete impulse responses are available upon request.

[16]As the day-ahead electricity market is considered to be liquid, in this article "long-run" refers to several days after the price shock.

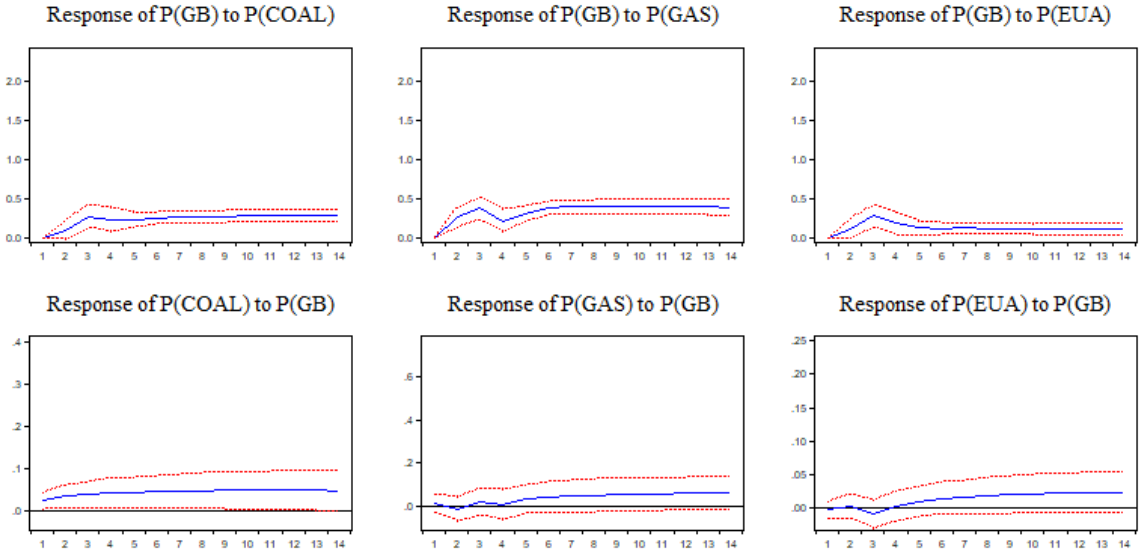

Figure 5: Impulse Response Functions among Variables

significant at the 0.1% level.

Table 2: Structural VEC Model Results

Long-run Dynamics					
Const.	$P_{t"1}^{GB}$	Trend	$P_{t"1}^{COAL}$	$P_{t"1}^{GAS}$	$P_{t"1}^{EUA}$
-9.425	1.000	-0.002	-0.396$^{\#\#\#}$	-0.766$^{\#\#\#}$	-0.364$^{\#\#\#}$
			(0.079)	(0.071)	(0.091)

Short-run Dynamics				
	$!P_t^{GB}$	$!P_t^{COAL}$	$!P_t^{GAS}$	$!P_t^{EUA}$
$EC_{t"1}$	-0.329$^{\#\#\#}$	0.005	0.013	0.005
	(0.022)	(0.004)	(0.009)	(0.003)
Const.	-5.567$^{\#\#\#}$	0.170	0.080	-0.122
	(1.291)	(0.226)	(0.494)	(0.147)
Trend	0.002$^{\#\#\#}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
D_t^{GB}	0.207$^{\#\#\#}$	-0.010	-0.0098	0.002
	(0.029)	(0.005)	(0.011)	(0.003)
R_t^{GB}	-0.377$^{\#\#\#}$	0.001	-0.006	0.006
	(0.023)	(0.004)	(0.009)	(0.003)
N_t^{GB}	-0.198$^{\#}$	0.021	0.013	0.000
	(0.087)	(0.015)	(0.033)	(0.010)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The "Short-run Dynamics" panel reports the short-run relationships between exogenous and endogenous variables. It is noteworthy that not all short-run relation is reported in Table 2, such as $\$_i$ in specification (1) that captures the short-run relation among endogenous variables, as

well as C that estimates the effect of deterministic dummy variables on endogenous variables, both of which are presented in Table A.1 in the Appendix. The coefficients of error correction (EC), $EC_{t"\ 1}$, are estimates of " in specification (1), which measure the speed of convergence to long-run equilibrium. Our results suggest that if the wholesale price diverges from the long-run equilibrium on day t due to unexpected market shocks, then on day $t+1$, about 33% of that disequilibrium is dissipated before the next time period, and 67% remains. If there is no further shock on day $t+1$, then on day $t+2$ about 33% of the remaining (67% of) disequilibrium would be adjusted and dissipated; and so forth. Put another way, 95% of the disequilibrium will be dissipated after eight days of the initial shock. Our estimation results also suggest that the wholesale price is positively affected by electricity demand (D_t^{GB}) and negatively affected by renewable (R_t^{GB}) and nuclear (N_t^{GB}) supply, consistent with conventional intuitions.

5.2 Cost pass-through

In Section 5.1, we estimate the long-run relationship between input costs and the wholesale price using daily data. This means that we are studying the variation of electricity price daily averages. If gas costs are fully passed through to the daily-averaged wholesale price, we would expect a £1/MWh$_e$ increase in gas costs to raise the wholesale price by s^{GAS}, the percentage of time that CCGTs are operating as the marginal fuel. Therefore, to estimate the CPT of gas cost, we will need to estimate s^{GAS} first. Similarly, to estimate the CPT of coal costs, we need to first estimate s^{COAL}, the percentage of time that coal plants are supplying at margin. As we are interested in estimating how the input costs are passed onto the daily averaged electricity prices, we must estimate how a change in demand would change electricity generation from different fuel types at the daily level. Therefore, inspired by Chyong et al. (2020) and Staffell (2017), we apply the following regression specifications to derive the marginal plants.

$$!\,Coal_t = \ "_0 + \ "_1\,!\,Wind_t + \ "_2\,!\,Demand_t + (!_{\mathbf{COAL}}\boldsymbol{X_t} +)_t^{\mathrm{COAL}}, \tag{2}$$

$$!\,CCGT_t = \#_0 + \#_1\,!\,Wind_t + \#_2\,!\,Demand_t + (!_{\mathbf{CCGT}}\boldsymbol{X_t} +)_t^{\mathrm{CCGT}}, \tag{3}$$

$$!\,PS_t = *_0 + *_1\,!\,Wind_t + *_2\,!\,Demand_t + (!_{\mathbf{PS}}\boldsymbol{X_t} +)_t^{\mathrm{PS}}, \tag{4}$$

$$!\,Import_t = +_0 + +_1\,!\,Wind_t + +_2\,!\,Demand_t + (!_{\mathbf{IMPORT}}\boldsymbol{X_t} +)_t^{\mathrm{IMPORT}}, \tag{5}$$

$$!\,Hydro_t = \ ,_0 + \ ,_1\,!\,Wind_t + \ ,_2\,!\,Demand_t + (!_{\mathbf{HYDRO}}\boldsymbol{X_t} +)_t^{\mathrm{HYDRO}}. \tag{6}$$

Recall that t represents days and ! is the first-difference operator.[17] $Coal_t$, $CCGT_t$, PS_t, $Import_t$ and $Hydro_t$ respectively denote electricity generated from coal, CCGTs, pumped storage, imports, and hydro power. On the right hand side, $Demand_t$ denotes residual demand of electricity and $Wind_t$ denotes wind supply, both of which are exogenous. $\boldsymbol{X_t}$ contains day-of-week dummy

[17] Chyong et al. (2020) and Staffell (2017) use half-hourly data to run the regression. Here, to be consistent with the VEC model, we aggregate the data into daily terms. Since, as we will discuss later, electricity from pumped storage and imports may also come from fossil fuelled power plants, aggregating the data from hourly to daily weakens the role of pumped storage and imports in response to demand changes, providing more accurate estimates of the impact of demand changes on fossil fuelled generation.

variables. The slope coefficients for $!Demand_t$ estimate the percentage of time that the corresponding fuel (i.e. the left-hand-side variable) responds to demand changes or in other words, operates at margin.

It is noteworthy that we take the first difference of different types of fuel generation not because those variables are non-stationary; instead, taking the first difference allows us to capture how different fuel types respond to changes in demand and renewable generation. From another perspective, our method can be thought of as treating the first-differenced variables as cross-sectional instead of time series variables. One can argue that serial correlation may arise, but that should not affect the consistency of the estimates.

Table 3: Estimating Marginal Fuels, 1 April 2015 - 31 December 2018

	Dependent Variables				
	$!Coal_t$	$!CCGT_t$	$!PS_t$	$!Import_t$	$!Hydro_t$
(Intercept)	-20.840	93.570	$-18.115^{\#}$	-52.545	-6.980
	(47.332)	(52.353)	(8.787)	(39.668)	(4.502)
$!Wind_t$	$-0.138^{\#\#\#}$	$-0.799^{\#\#\#}$	$-0.013^{\#\#\#}$	$-0.021^{\#}$	$-0.011^{\#\#\#}$
	(0.012)	(0.014)	(0.002)	(0.010)	(0.001)
$!Demand_t$	$0.237^{\#\#\#}$	$0.708^{\#\#\#}$	$0.017^{\#\#\#}$	$0.029^{\#}$	$0.003^{\#}$
	(0.016)	(0.018)	(0.003)	(0.013)	(0.002)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.539	0.926	0.163	0.169	0.129
Num. obs.	1370	1370	1370	1370	1370

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: the half-hourly generation-by-fuel-type data comes from Elexon Portal. As the negative values in the columns "import" and "pumped storage" (PS) are missing, we replace the "import" column by the data from the National Grid (NG) Electricity System Operator (ESO), and replace the "pumped storage" by aggregating the PS data from the Elexon P114 data set, which gives half-hourly generation for each Balancing Mechanism Unit.

Table 3 lists the estimation results of (2)-(6). We find that CCGTs respond to at least 71% of demand changes if none of the (marginal) supply from imports and pumped storage are from CCGTs. This number raises to 75% if we assume that all of the (marginal) supply from imports and pumped storages comes from CCGTs. Given Tables 2 and 3, the 95% confidence interval for the gas CPT rate is [89%,128%] in the former case, and [83%,120%] in the latter case.[18,19] Therefore, in any scenarios, we fail to reject the hypothesis that gas costs are fully passed through to the wholesale price.

[18]For the former case, the range of the confidence interval is between $(0.766 \pm 1.96 \times 0.071)/0.708$, where 0.071 is the standard error for the estimated long-run relationship between gas costs and the wholesale price, and 1.96 is the critical value at 5% significance level. For the latter case, the confidence interval ranges between $(0.766 \pm 1.96 \times 0.071)/0.754$.

[19]Note that the standard errors for the partial effects of demand on different fuel types are negligible, hence are ignored in our CPT calculations throughout the article. For example, in the former case if both standard errors are considered, then under the assumption that the two estimates are uncorrelated, the standard error for the CPT rate is $\sqrt{0.766^2/0.708^2 \cdot (0.071^2/0.766^2 + 0.018^2/0.708^2)} = 0.104$. Therefore, the 95% confidence interval is [88%,129%], very close to [89%,128%] in the text.

Similarly, we can estimate the CPT of coal costs. Table 3 shows that coal responds to at least 24% of demand changes if none of the supply from imports and pumped storage comes from coal plants. If, however, we assume that coal generators supply all imports and pumped storage, coal responds to 29% of demand changes. In the former case, we marginally reject the hypothesis that coal costs are fully passed on to the wholesale price at 5% significance level; while in the latter case, we fail to reject the hypothesis at 5% significance level. At 1% significance level, the hypothesis can not be rejected in either case. Precisely, the 99% confidence interval for the coal CPT is [81%,253%] in the former case, and [70%,220%] in the latter case. The ranges are much greater than those for gas CPT because the numerator for calculating the CPT (i.e. s^{COAL}) is small. In fact, if at least 9% of the supply from imports and pumped storages comes from coal plants,[20] we would not reject the hypothesis of 100% coal CPT at 5% significance level.[21]

It is straightforward to show that a 100% EUA price CPT requires that the estimated long-run relationship between EUA prices and the wholesale price is not significantly different from the Marginal Emission Factor (MEF) of the GB electricity supply. The MEF measures the tonnes of CO_2 emissions from an additional 1 MWh of electricity produced at margin. We can calculate the MEF of GB during the period of study with the formula:

$$\widehat{\text{MEF}} = EF_{\text{COAL}} \cdot \hat{\#}_2 + EF_{\text{CCGT}} \cdot \hat{\#}_2 + EF_{\text{PS}} \cdot \hat{\#}_2 + EF_{\text{IMPORT}} \cdot \hat{\#}_2, \tag{7}$$

where $\hat{\#}_2$, $\hat{\#}_2$ and $\hat{\#}_2$ are estimates reported in Table 3, "$\wedge$" refers to estimates, and EF is the abbreviation of "Emission Factor". We set $EF_{\text{COAL}} = 0.871\text{tCO}_2/\text{MWh}$ and $EF_{\text{CCGT}} = 0.337\text{tCO}_2/\text{MWh}$, consistent with Chyong et al. (2020). The values of EF_{PS} and EF_{IMPORT} depend on our assumption on which fuel types supply imports and pumped storages. In extreme scenarios, if we assume all imports and pumped storages come from CCGTs, the MEF is 0.461 tCO_2/MWh; if we assume all imports and pumped storages come from coal plants, the MEF is 0.485 tCO_2/MWh.[22] Either way, comparing 0.364 from Table 2 with the MEFs, we fail to reject the null that EUA prices are fully passed through to the wholesale price.

Finally, Table 4 lists the estimated CPT from different types of inputs for electricity generation, as well as the associated standard errors. Note that under different assumptions about where the imported and stored electricity comes from, the CPT rates might be different.

5.3 Robustness checks

Table 5 shows the regression results to be discussed in Section 5.3-5.5. To save space, we only report the long-run dynamics and EC terms.

[20] This is very likely to be the case given that during the period of study, coal was the marginal fuel in the island of Ireland and the Netherlands who are directly incterconnected with GB.

[21] From the regression results in Table 3, about 4.6% of the marginal demand is answered by imports and pumped storages. Then, if there is an additional 0.4%($= 9\% \times 4.6\%$) of marginal demand answered by coal, in total coal plants respond to 24.1% of the marginal demand. 24.1%=0.241 equals to the lower bound of the 95% confidence interval of the estimate 0.396(s.e.=0.079) in Table 2.

[22] Our estimates of the MEF are consistent with Chyong et al. (2020).

Table 4: Estimated Cost Pass-through for Different Types of Inputs

	Gas Costs (P^{GAS})	Coal Costs (P^{COAL})	EUA Prices (P^{EUA})
CPT†	108.2%	139.9%	75.1%
	(17.1%)	(27.9%)	(19.7%)
CPT‡	101.6%	167.1%$^{\#}$	79.0%
	(0.94%)	(33.3%)	(18.8%)

* refers to estimated CPT significantly different from 1 at the 5% level.

† Assuming that all imported and stored electricity comes from coal plants.

‡ Assuming that all imported and stored electricity comes from CCGTs.

Table 5: Robustness Check

	(i) EXOG.	(ii) $p = 8$	(iii) LOG	(iv) OFF-PEAK	(iv) PEAK	(v) τ =2.58	(vi) τ =∞
Long-run Dynamics							
P^{GB}_{t-1}	1.000	1.000	1.000			1.000	1.000
$P^{GB,OFF}_{t-1}$				1.000			
$P^{GB,PEAK}_{t-1}$					1.000		
P^{COAL}_{t-1}	-0.386***	-0.430***	-0.263***	-0.116**	-0.615***	-0.447***	-0.668***
	(0.081)	(0.094)	(0.041)	(0.082)	(0.090)	(0.085)	(0.159)
P^{GAS}_{t-1}	-0.750***	-0.766***	-0.390***	-0.921***	-0.556***	-0.766***	-0.625***
	(0.072)	(0.085)	(0.046)	(0.074)	(0.080)	(0.076)	(0.141)
P^{EUA}_{t-1}	-0.366**	-0.339***	-0.105***	-0.247***	-0.554***	-0.442***	-0.514***
	(0.093)	(0.109)	(0.019)	(0.095)	(0.103)	(0.098)	(0.182)
Trend	0.002	0.002	0.000	-0.006	0.001	-0.002	0.000
Const.	-9.913	-8.895	-1.452	-3.713	-13.746	-8.226	-8.425
Short-run Dynamics							
	ΔP^{GB}_t	$\Delta \log P^{GB}_t$	ΔP^{GB}_t	$\Delta P^{GB,OFF}_t$	$\Delta P^{GB,PEAK}_t$	ΔP^{GB}_t	ΔP^{GB}_t
EC_{t-1}	-0.330***	-0.272***	-0.337***			-0.352***	-0.422***
	(0.022)	(0.024)	(0.023)			(0.023)	(0.033)
EC^{OFF}_{t-1}				-0.416***			
				(0.028)			
EC^{PEAK}_{t-1}					-0.340***		
					(0.024)		

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

In delivering the baseline result (Sections 5.1), we treat input costs as endogenous. However, fuel prices are determined by the international market, and EUA prices are set by all participants in the EU ETS. As a result, a single country like GB may have little influence on fuel costs and EUA prices. This raises concerns of input costs being weakly exogenous. Weakly exogeneity can be tested by applying the Wald test to the VEC specification (1), with the null hypothesis being that the EC parameters for input costs (i.e., the second to forth param-

eters of ") are jointly zero. The test result suggests that coal costs, gas costs, as well as EUA prices are indeed weakly exogenous,[23] indicating that a structural VEC model (Pesaran, 2015) that restricts the associated EC parameters to zeros might be a better option.

Regression (i) in Table 5, therefore, treats all input costs as weakly exogenous and apply the structural VEC model. The regression result is similar to that in the baseline case, suggesting that even though the VEC model might be less efficient than the structural VEC model, the efficiency loss is negligible. Therefore, the analysis in Sections 5.1-5.2 is still valid.

Regression (ii) sets $p = 8$, so that the weekly seasonality is captured not only by the day-of-week dummy variables but also by the autoregressive terms. Although choosing a higher order of lags may result in high standard errors, the effect is expected to be negligible due to our large sample size. When $p = 8$, the long-run relationships are consistent with those shown in Table 2.

Regression (iii) takes log of the wholesale price, coal and gas costs, EUA prices, as well as the control variables, hence studies the (long-run) elasticities of the wholesale price with respect to input costs. The result shows that in the long-run, a 1% increase in coal costs is associated with a 0.26% increase in the wholesale price. Note that from Table 1, the average coal cost is £24.38/MWh$_e$, and the average wholesale price is £46.23/MWh. Then, the regression result suggests that if the average coal cost is increased by £0.24/MWh$_e$ (1% of the average), the wholesale price will raise by £0.12/MWh (0.26% of the average). Equivalently, the wholesale price would be raised by £0.50/MWh following a £1/MWh$_e$ increase in the coal price. This is not significantly different from the baseline result.

Similarly, a 1% increase in gas costs is associated with a 0.39% increase in the wholesale price. Given the average gas cost and wholesale price in Table 1, if the average gas cost has been raised by £1/MWh$_e$, the wholesale price would on average increase by £0.63/MWh$_e$, which is also not significantly different from the baseline estimate.

Regression (iii) also shows that a 1% increase in EUA prices is associated with a 0.11% increase in the wholesale price. Given the average EUA price and wholesale price in Table 1, a £0.08/tCO_2 increase in EUA prices is associated with a £0.05/MWh increase in the wholesale price. The estimated impact is slightly higher than the estimates from Table 2,[24] but given the estimated MEFs of the GB electricity market in Section 5.2, we still could not reject the null that in the long-run, EUA prices are fully passed through to the wholesale price.

5.4 Peak *v.s.* off-peak

To investigate whether the CPT varies in different periods of the day, Regression (iv) separates a day into peak (07:00-23:00, WET/WEST) and off-peak (23:00-07:00, WET/WEST) periods.[25] In Regression (iv), the daily average wholesale price (P_t^{GB} in $\boldsymbol{y}_t$) is replaced by the daily

[23] $\chi^2_{(3)} = 6.98$ with p-value 0.07.

[24] 0.05/0.08=0.63 against 0.46.

[25] Figure A.1 presents the average daily electricity demand curve in GB during the period of study. The two dashed vertical lines separate the day into peak and off-peak periods. The demand between peak and and off-peak periods is substantially different, indicating the validity of how we separate the day. The results are not sensitive to the definition of peak and off-peak hours.

average peak and off-peak wholesale prices ($P_t^{\text{GB,OFF}}$ and $P_t^{\text{GB,PEAK}}$), hence in Regression (iv) endogenous variables are $\boldsymbol{y}_t = (P_t^{\text{GB,OFF}}, P_t^{\text{GB,PEAK}}, P_t^{\text{COAL}}, P_t^{\text{GAS}}, P_t^{\text{EUA}})^{!}$. The Johansen cointegration tests suggest two cointegrating equations in Regression (iv) (See Appendix A.4), which is intuitive because we are expecting one cointegratng equation for peak periods, and another for off-peak periods.

Regression (iv) suggests the long-run relationship between input costs and the wholesale price do vary in different periods of the day. Specifically, gas costs have more substantial effects on the wholesale price during off-peak than peak periods. On the other hand, coal costs have more substantial effect on the wholesale price during peak than off-peak periods.

To estimate the CPT for different periods of the day, we need to first estimate the marginal responses of coal and gas generation to demand changes in peak and off-peak periods. The results are reported in Table A.2. Then, if we assume half of the electricity supply from pumped storages and imports comes from coal and another half comes from natural gas,[26] the CPT rates for coal are 48% during off-peak periods and 221% during peak periods, significantly different from a hypothesis of 100% CPT rates; the CPT rates for gas are 124% during off-peak periods and 78% during peak periods, not significantly different from 100%; the CPT rates for the EUA price are 53% during off-peak periods and 115% during peak periods, with the off-peak estimate significantly different from 100%.

We find heterogeneous CPT rates for different periods of the day, especially for coal costs. The different CPT rates indicate that coal plants are bidding differently between peak and off-peak periods.

During off-peak periods, the utilisation rate of generation capacity is low, meaning that if a coal plant bids according to its marginal cost, the system would dispatch other cheaper power plants to meet the off-peak demand. If that happens, the coal plant will have to shut down during the off-peak. As it is costly for fossil plants to shut down during off-peak and restart during peak, failing to operate during off-peak would result in a much higher total cost. Given this, a better strategy for the coal plant is to bid a lower price in off-peak to secure supplying the minimum load.

During peak periods, the utilisation rate of generation capacity is high. Then, GB's largest electricity generator (who owns substantial high nuclear capacity and some non-negligible amount of the more expensive coal plants) may exercise market power to bid at rates greater than marginal costs. By doing this, their coal plants make up their losses from off-peak bidding.

As we could not reject the hypothesis that gas costs are always fully passed through to the wholesale price, it might be reasonable to assume that the CCGTs always bid according to its marginal costs (carbon costs included) of electricity generation. Under this assumption, we can use the result from Regression (iv) to further investigate the bidding strategy for coal plants. Specifically, the following formula should hold:

$$CPT^{\text{EUA}} = \frac{CPT^{\text{EUA,GAS}} \times EF^{\text{GAS}} \times s^{\text{GAS}} + CPT^{\text{EUA,COAL}} \times EF^{\text{COAL}} \times s^{\text{COAL}}}{MEF} \tag{8}$$

[26] As pumped storage and import only respond to about 5% of demand changes, this assumption has negligible effects on the estimated CPT rates.

where CPT^{EUA} denotes the EUA price CPT, and $CPT^{\text{EUA},i}$ for $i \in \{\text{COAL},\text{GAS}\}$ denotes the EUA price CPT for a specific type of power plant. EF^i denotes the emission factor for fuel type i and recall s^i represents the percentage of the time that fuel type i supplies at the margin. Equation (8) simply tells that the CPT of EUA prices of the electricity market should be equal to the weighted average of the degree to which the EUA price is passed on to coal and gas generators' day-ahead biddings.

Regression (iv) in Table 5 provides estimates of CPT^{EUA} for both peak and off-peak periods, Table A.2 provides estimates of s^i and MEF, for both periods, and EF^i are pre-defined (see Section 5.2). Under the assumption that $CPT^{\text{EUA,GAS}} = 100\%$, we can estimate $CPT^{\text{EUA,COAL}} = -3\%$ for off-peak periods and $CPT^{\text{EUA,COAL}} = 130\%$ for peak periods.

The above calculation indicates that the bidding strategy for coal plants is that when bidding for the off-peak supply, they completely ignore the EUA price markups (and ignore 100%-48%=52% of the coal costs markups). In peak periods when coal plants can exercise market power, they would bid at some rates substantially higher than their marginal costs — marking up about 221% of coal costs and 130% of EUA prices. One reason might be that similar to the CPT for coal costs, in off-peak the degree that the EUA price is passed on to coal plants' bidding is also small, resulting in statistically insignificant estimates.

5.5 Extreme pricing

Recall that for regressions in previous subsections, to deal with extreme prices, we define the upper/lower threshold for outliers as the sample mean plus/minus & = 1.96 times the standard deviation. Any observations (of the wholesale price) greater/smaller than the upper/lower thresholds are then replaced by the upper/lower threshold. In this subsection, we vary the value of & and examine whether the CPT varies with &.

We first reset & = 2.58. As such, a much smaller proportion of the wholesale price is defined as outliers and are removed and replaced. The results are reported in Table 5 as Regression (v). Next, we reset & = ', meaning that all outliers remain in the regression analysis, and the results are reported in Table 5 as Regression (vi).

We observe a much stronger long-run relationship between coal costs and the wholesale price as & gets larger, resulting in much higher CPT rates for coal costs. Specifically, when & = 2.58, the point estimate of the coal CPT is 179%; when & = ', the number raises to 267%.[27]

On the other hand, the long-run relationship between gas costs and the wholesale price is more resistant to outliers. We can estimate that when & = 2.58, the gas CPT is 105%; when & = ', it is 91%, both are not significantly different from 100%.

The above results suggest that for some specific hours, coal plants can exercise market power, resulting in extreme prices. This is not surprising given that in GB, the biggest electricity generation company owns significant baseload capacity (i.e., nuclear) and some coal plant capacity, hence it is highly beneficial for the company from an increase in the wholesale price.

[27] This is calculated under the assumption that half of the supply from pumped storage and imports comes from coal plants, same for the estimates on the CPT rates for gas costs.

Put another way, the company has a strong incentive to raise the wholesale price when bidding at the wholesale market for its marginal plants (i.e. the coal plants that the company owns). On the other hand, it is coal plants that exercise market power instead of CCGTs because in GB, electricity from coal is more expensive than gas, hence coal plants may exercise market power when the total supply approaches the capacity limit. Another possible reason for the existence of (local) market power is that there is serious congestion in the transmission lines on the Scottish border, while GB has only one single price zone.

Finally, note that coal is more carbon intensive than gas. When coal plants exercise market power, their bidding strategy is to substantially mark up both coal and carbon costs (i.e. the EUA price), resulting in a greater impact of EUA prices on the wholesale price.

6 Conclusions

This paper assessed the degree to which major input costs of electricity generation were passed through to the wholesale electricity price in Great Britain during the period 2015-2018. We failed to reject the hypothesis that gas costs and EUA prices were fully passed through to the electricity price. After removing extreme prices and aggregating hourly wholesale prices into daily aggregates, we also could not reject the hypothesis of a 100% Cost Pass-Through (CPT) rate for coal costs. Our results suggest a functioning competitive British wholesale electricity market. However, we found evidence of coal plants exercising market power in hours with high residual demand. This indicates that policy measures are needed to reduce the incidence of market power at peak times with a view to shield consumers from higher bills.

We also examined the heterogeneity of CPT between peak and off-peak periods. The CPT rates for coal costs are higher during peak, relative to off-peak, periods. This derives from the substantial cost attached to coal plants needing to shut down during off-peak periods and start up at peak times, hence it is more cost-effective to for them to bid rates that are somewhat lower than the marginal costs at off-peak times in order to maximise overall profits. During peak periods the utilisation rate of generation capacity is high so coal plants can exercise market power by bidding rates that exceed marginal costs. We used our econometric results to extend this argument showing that, during off-peak periods, coal plants' bids are only based on coal costs while, during peak periods, coal plants' bids vary with both coal costs and carbon prices.

In Great Britain the retail market is dominated by six vertically integrated energy companies. This creates major barriers to market entry and raises concerns about the effects of an oligopolistic market structure on consumers. To this end, the Competition and Market Authority (CMA) concluded in a recent report that vertical integration did not produce anti-competitive price effects (CMA, 2016).

Our analysis did not cover 2019 and beyond, or years where GB electricity generators were affected by major uncertainty around the payable carbon price and the terms of exit from the European Union. Future work should therefore be aimed at investigating the impact of politico-economic uncertainty on electricity generating firms' bidding decisions. If uncertainty were to have deviated generators' bidding outcomes from their optimal strategies, the market would be

considered less efficient, resulting in deadweight losses and increased consumer bills. Policies to limit intra-daily market power remain critical to achieve affordable electricity prices for consumers, especially if Brexit were to reduce competition and increases domestic generators' price-setting ability.

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A Appendix

A.1 Structural VEC Model Results, Table 2 Cont'd

Table A.1 presents the short-run dynamics that Table 2 did not report.

Table A.1: Structural VEC Model Results, Table 2 Cont'd

Short-run Dynamics				
	ΔP_t^{GB}	ΔP_t^{COAL}	ΔP_t^{GAS}	ΔP_t^{EUA}
ΔP_{t-1}^{GB}	-0.226^{***}	0.000	-0.025^{*}	-0.003
	(0.028)	(0.005)	(0.011)	(0.003)
ΔP_{t-2}^{GB}	-0.175^{***}	0.001	-0.003	-0.008^{**}
	(0.026)	(0.005)	(0.010)	(0.003)
ΔP_{t-3}^{GB}	-0.120^{***}	0.000	-0.018^{*}	-0.002
	(0.024)	(0.004)	(0.009)	(0.003)
ΔP_{t-1}^{COAL}	-0.022	-0.012	0.062	0.055^{**}
	(0.158)	(0.028)	(0.060)	(0.018)
ΔP_{t-2}^{COAL}	0.289	0.044	0.063	-0.024
	(0.158)	(0.028)	(0.061)	(0.018)
ΔP_{t-3}^{COAL}	0.029	0.045	0.108	-0.003
	(0.159)	(0.028)	(0.061)	(0.018)
ΔP_{t-1}^{GAS}	0.112	0.022	-0.041	0.080^{***}
	(0.074)	(0.013)	(0.028)	(0.008)
ΔP_{t-2}^{GAS}	0.059	-0.007	-0.007	-0.011
	(0.076)	(0.013)	(0.029)	(0.009)
ΔP_{t-3}^{GAS}	-0.200^{*}	-0.004	0.016	0.004
	(0.076)	(0.013)	(0.029)	(0.009)
ΔP_{t-1}^{EUA}	0.277	0.018	-0.087	0.016
	(0.240)	(0.042)	(0.092)	(0.027)
ΔP_{t-2}^{EUA}	0.860^{***}	0.019	-0.036	0.016
	(0.239)	(0.042)	(0.091)	(0.027)
ΔP_{t-3}^{EUA}	0.071	0.026	-0.067	-0.042
	(0.231)	(0.040)	(0.088)	(0.026)
Monday	2.057^{***}	0.085^{*}	0.163	-0.004
	(0.243)	(0.043)	(0.093)	(0.028)
Tuesday	1.198^{***}	0.071	0.182	-0.007
	(0.263)	(0.046)	(0.101)	(0.030)
Wednesday	1.233^{***}	0.056	0.090	-0.013
	(0.260)	(0.046)	(0.100)	(0.030)
Thursday	1.292^{***}	0.051	0.141	0.039
	(0.256)	(0.045)	(0.098)	(0.029)
Friday	0.760^{***}	0.036	0.103	-0.002
	(0.238)	(0.042)	(0.091)	(0.027)
Saturday	0.175	0.041	0.076	0.026
	(0.209)	(0.037)	(0.080)	(0.024)
Q1	-0.400^{*}	-0.025	0.014	-0.010
	(0.175)	(0.031)	(0.067)	(0.020)
Q2	0.381^{*}	-0.050	0.022	0.011
	(0.196)	(0.034)	(0.075)	(0.022)
Q3	0.930^{***}	-0.045	0.017	0.023
	(0.218)	(0.038)	(0.083)	(0.025)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

A.2 Estimating the Marginal Emission Factor of GB

Table A.2 separates the data into peak and off-peak periods, and estimates the marginal responses of different fuel types to demand changes by applying regressions (2)-(6).

Table A.2: Estimating Marginal Fuels, Peak *v.s* Off-peak

OFF-PEAK PERIODS					
	Dependent Variables				
	$!Coal_t$	$!CCGT_t$	$!PS_t$	$!Import_t$	$!Hydro_t$
(Intercept)	13.879	$106.333^{\#}$	$-32.912^{\#\#\#}$	$-75.732^{\#}$	-8.088
	(46.349)	(51.498)	(9.260)	(37.291)	(4.736)
$!Wind_t$	$-0.152^{\#\#\#}$	$-0.798^{\#\#\#}$	$-0.011^{\#\#\#}$	-0.008	$-0.012^{\#\#\#}$
	(0.012)	(0.013)	(0.002)	(0.010)	(0.001)
$!Demand_t$	$0.221^{\#\#\#}$	$0.723^{\#\#\#}$	$0.007^{\#}$	$0.037^{\#\#}$	$0.005^{\#\#}$
	(0.015)	(0.017)	(0.003)	(0.012)	(0.002)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.518	0.919	0.129	0.188	0.127
Num. obs.	1370	1370	1370	1370	1370
PEAK PERIODS					
	Dependent Variables				
	$!Coal_t$	$!CCGT_t$	$!PS_t$	$!Import_t$	$!Hydro_t$
(Intercept)	-85.985	68.295	-3.117	10.793	-7.501
	(56.569)	(65.384)	(14.395)	(52.175)	(6.005)
$!Wind_t$	$-0.115^{\#\#\#}$	$-0.773^{\#\#\#}$	$-0.017^{\#\#\#}$	$-0.070^{\#\#\#}$	$-0.012^{\#\#\#}$
	(0.013)	(0.015)	(0.003)	(0.012)	(0.001)
$!Demand_t$	$0.253^{\#\#\#}$	$0.685^{\#\#\#}$	$0.046^{\#\#\#}$	0.004	$0.006^{\#\#}$
	(0.016)	(0.019)	(0.004)	(0.015)	(0.002)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.543	0.926	0.542	0.128	0.169
Num. obs.	1370	1370	1370	1370	1370

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

A.3 Validity Test Statistics

We use the Augmented Dickey-Fuller (ADF) and the KwiatkowskiPhillipsSchmidtShin (KPSS) tests to test the existence of a unit root in the dependent variables. The ADF test uses Auto-Regression (AR) regressions to examine whether a time series variable is non-stationary, while KPSS is a reversed version that uses stationarity as the null hypothesis. The ADF test has very low power (against $I(0)$ alternatives that are close to being $I(1)$), while KPSS has a high possibility of Type I errors (i.e. it tends to over-reject the null hypothesis). Based on this, whenever the two tests give controversial results, the time series is more likely to be an $I(0)$ process.

Table A.3: Unit Root Tests

	ADF tests#				KPSS tests		
Variables	Lags	Stat.	p-value	Results##	Stat.	p-value	Results##
levels							
GB day-ahead Prices	21	−0.91	0.79	I(1)	0.52	<0.01	I(1)
Coal Prices	3	−1.27	0.64	I(1)	0.29	<0.01	I(1)
Gas Prices	8	−1.88	0.34	I(1)	0.62	<0.01	I(1)
EUA Prices	14	1.96	1.00	I(1)	1.02	<0.01	I(1)
GB Renew. Gen	17	−4.40	0.00	I(0)	0.19	<0.05	I(1)
GB Demand	23	−2.51	0.11	I(1)	0.10	>0.10	I(0)
GB Nuclear Gen.	1	−7.35	0.00	I(0)	0.41	<0.01	I(1)
first differences							
! GB day-ahead Prices	20	−10.17	0.00	I(0)	0.01	>0.10	I(0)
! Coal Prices	2	−19.63	0.00	I(0)	0.06	>0.10	I(0)
! Gas Prices	7	−15.53	0.00	I(0)	0.04	>0.10	I(0)
! EUA Prices	23	−7.46	0.00	I(0)	0.07	>0.10	I(0)
! GB Renew. Gen	17	−14.75	0.00	I(0)	0.08	>0.10	I(0)
! GB Demand	22	−8.09	0.00	I(0)	0.04	>0.10	I(0)
! GB Nuclear Gen.	11	−14.37	0.00	I(0)	0.01	>0.10	I(0)

* test with constant and trend terms

** suggested results at 5% significant level

The unit root test results are shown in Table A.3. The lag lengths for the test specifications are selected by the Akaike Information Criterion (AIC), where the upper bound for the optimal lag length is determined by the Schwert criterion. Our ADF test results fail to reject the null that all dependent variables in $\boldsymbol{y}_t$ in (1) are $I(1)$ processes, whereas the KPSS tests suggest that these variables are not $I(0)$. Therefore, we can safely conclude that all variables in $\boldsymbol{y}_t$ are non-stationary.

The ADF and KPSS tests give contrasting results about the order of integration for the GB day-ahead renewable generation and electricity demand, and the GB nuclear generation. Because of the aforementioned reason — the ADF test suffers from low power, while the KPSS is vulnerable in front of Type I errors — the three variables are treated as stationary processes.

The validity for the VEC model requires the dependent variables to be cointegrated. The Johansen cointegration tests work on the canonical correlation of $!\boldsymbol{y}_t$ and $\boldsymbol{y}_{t"\ 1}$. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of m (the number of sequences in $!\boldsymbol{y}_t$) cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors. The results in Table A.4 indicate one cointegrating equation in the proposed VEC model (1), with both tests conducted at the 5% significant level.

A.4 Johansen tests results for Regressions (iii) and (iv)

Tables A.5 reports the Johansen cointegration tests for the VEC model specifications discussed in Sections 5.4, respectively. It suggests two cointegration equations.

Table A.4: Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.##
None#	0.03951	83.31	55.25	0.00
At most 1	0.01490	28.31	35.01	0.22
At most 2	0.00566	7.91	18.40	0.69
At most 3	0.00013	0.17	3.84	0.68

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.##
None#	0.03951	54.94	30.82	0.00
At most 1	0.01490	20.45	24.25	0.15
At most 2	0.00566	7.74	17.15	0.63
At most 3	0.00013	0.17	3.84	0.68

* denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (1999) p-values.

Table A.5: Cointegration Tests for Regression (iii), Peak *v.s.* Off-peak

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.##
None#	0.05676	162.56	79.34	0.00
At most 1#	0.03903	82.91	55.25	0.00
At most 2	0.01494	28.66	35.01	0.20
At most 3	0.00583	8.14	18.40	0.67
At most 4	0.00013	0.17	3.84	0.68

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.##
None#	0.05676	79.65	37.16	0.00
At most 1#	0.03903	54.26	30.82	0.00
At most 2	0.01494	20.52	24.25	0.14
At most 3	0.00583	7.97	17.15	0.61
At most 4	0.00013	0.17	3.84	0.68

* denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (1999) p-values.

A.5 Figure Appendix

Figure A.1 plots the average daily residual demand in the British electricity market during the period of study.

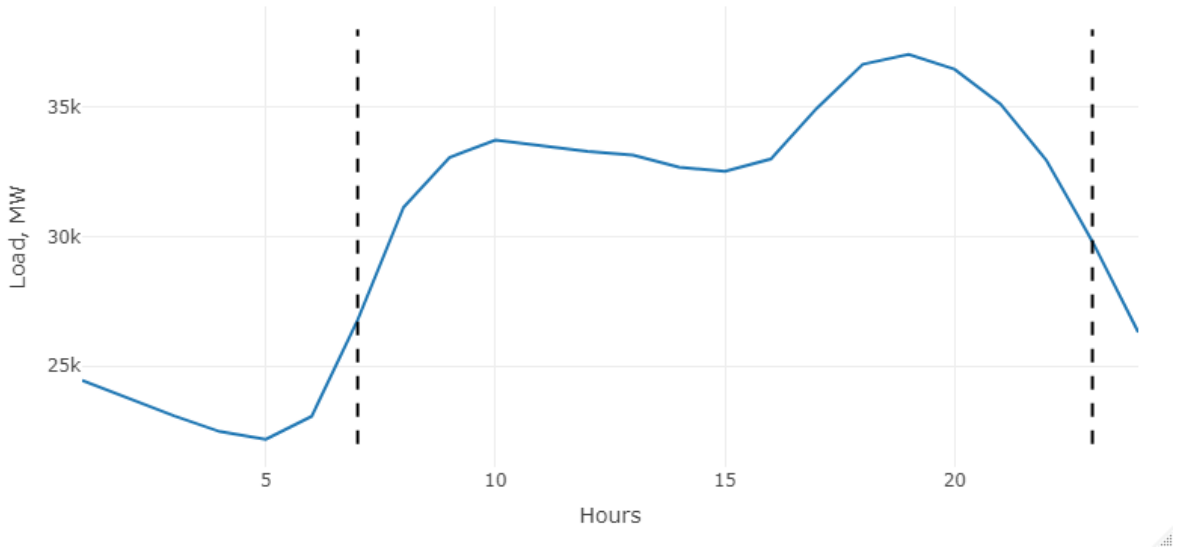

Figure A.1: The Average Daily Residual Demand Curve, 2015-2018