Cost Pass-through in the British Wholesale Electricity Market: Implications of Brexit and the ETS reform

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JEL Classification	L13, Q48, D41, H23, C32

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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 (European Commission, 2015). In 2018, the six largest British electricity generation companies provided nearly 70% of all electricity generated nationally,[2] leading to concerns of market power, or a lack of market competition at the wholesale level. Retailers buy electricity from the wholesale market and then resell it to consumers. Wholesale costs, which are costs incurred to generate and sell wholesale electricity, are the greatest component of electricity bills in GB, consisting of about a third of a typical electricity bill (Ofgem, 2018). Competition in the wholesale market promotes lower electricity bills for consumers, while market power tends to make electricity more expensive (Green and Newbery, 1992).

Competition in the wholesale market can be measured using price-cost margins, market shares and market concentration (Borenstein et al., 1999), or by running a pivotality analysis (Ofgem, 2017). However, these measures fail to consider how fuels costs, including those from carbon emissions, affect the wholesale price. To consider the impact of fiscal policies or unexpected policy shocks on domestic consumers, policymakers often rely on cost Pass-Through Rates (PTRs) since these can measure the degree to which a change in costs determines a change in prices (Ofgem, 2018; CMA, 2016).[3]

The wholesale electricity market is typically seen as consistent with Cournot competition (see e.g. Lundin and Tangerås, 2017; Gal et al., 2017; Dressler, 2016; Willems et al., 2009; Willems, 2002; Andersson and Bergman, 1995), a subtype of oligopolistic competition where generators compete on the amount of output they will produce, as opposed to the price they will set. In homogeneous goods settings, under Cournot competition, as the number of firms in the market increases, the cost PTR has been shown to converge to 100% (RBB Economics, 2014). In other words, a PTR of about 100% indicates a competitive wholesale electricity market (CMA, 2016).

[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] 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 cost.

Political events and reforms in the United Kingdom (UK) and the European Union (EU) could strongly influence the cost of energy to producers and hence to consumers. First, the UK voted to leave the EU in 2016. This leads to widespread political and economic uncertainty, and a substantially weaker Sterling. With half of domestically-consumed natural gas imported from the Continent, and gas setting the British electricity price most of the time (Ofgem, 2018), the cost of energy for British consumers is exposed to exchange rate fluctuations. Second, as EU carbon emission Allowance prices (EUA prices, or the price of CO_2 set in the Emission Trading System, ETS) have been too low to deliver the desired levels of emission reductions, the EU Commission (EC) reformed the ETS by creating a Market Stability Reserve (MSR). The MSR came into effect in January 2019 and intends to cancel surplus allowances, tighten the carbon market and increase the EUA price (EU Commission, 2015). Higher carbon prices encourage cleaner electricity generation across Europe. From Table 2, we observe that, since late 2017, anticipation of the reform's start has driven an EUA price rally. The Brexit referendum and introduction of the MSR resulted in substantial changes in Sterling exchange rates and carbon prices (respectively), providing an ideal test-bed for studying cost PTRs.

Unlike most empirical papers, which focus on carbon cost pass-through, our paper investigates a wide range of key PTRs, in particular from fuel and carbon prices, and exchange rates, and whether this is consistent with the notion of a competitive British wholesale electricity market. Our investigation is conducted both theoretically and empirically.

From a theoretical standpoint, we also contribute to the theory of competition. We show that the carbon price PTR should be equal to the ratio between the partial effect of carbon prices on electricity prices and the Marginal Emission Factor (MEF) of the electricity system. We formally prove this to be the case by linking a Cournot competition model with the underlying wholesale market structure and associated PTR. We also show that a 100% fuel-price PTR should be interpreted as "a £1/MWh$_e$ increase in the fuel price associated with a £s^{FUEL}/MWh increase in the wholesale electricity price", where s^{FUEL} denotes the total share of the type of fuel plants at marginal supply. These interpretations are generally ignored in the related empirical literature as most of the studies use thermal unit-level data to estimate the PTR directly (see, most notably, Fabra and Reguant, 2014; Sijm et al., 2011). However, in our paper, these interpretations cannot be ignored as we employ the much cruder "generation by fuel type" dataset, which is typically widely-available in the public domain.

Empirically, we use econometrics to estimate long-run relationships between the input cost of electricity generation and the GB wholesale electricity price during 2015-2018. We do not reject the null that gas prices, carbon prices, and exchange rates are entirely passed through to the British wholesale electricity prices. We find heterogeneous PTRs for different times of the day and days of the week. We argue this occurs due to electricity generators exercising different bidding strategies over different periods of the day. We further this by showing generators' profit-maximising bidding strategy: the off-peak bids are mainly based on fuel costs, while those at peak depend on both fuel and carbon costs. Finally, assuming that the wholesale cost has been fully passed through to the domestic electricity bill,[4] we use the econometric results to estimate how the Brexit referendum and MSR have affected British electricity bills. We also anticipate how the GB wholesale electricity price would react following the UK's departure from the EU without a deal.

The rest of the paper is structured as follows. Section 1.1 briefly describes how the wholesale electricity market works, Sections 1.2 and 1.3 provide background information regarding the Brexit referendum and ETS reform. Section 2 builds up the theoretical foundation for cost pass-through in the wholesale electricity market, while Section 3 provides a review of related literature. Section 4 details the empirical methodology, Section 5 reports our results, while Section 6 discusses policy implications. Conclusions are drawn in Section 7.

1.1 The GB wholesale electricity markets

In Great Britain, wholesale electricity trading can take place bilaterally or via exchanges. However, by far the majority of electricity is traded through contracts covering timescales (markets) ranging

[4]This is a standard simplifying assumption that is typically used to assess the pass through rate of wholesale costs into electricity prices. Another reason for this assumption is that most suppliers in GB are also generators, which makes it likely for the pass- through rate to be at or close to 100%.

from several years ahead to close to real-time. Among those markets, the day-ahead (DA) market has proven its efficiency, delivering a trusted market which sets bidding zone prices for the next 24 hours.

In the DA market, the supply side consists of generators who submit their hourly bids for a specified quantity of electricity to supply at a specified price. 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. On 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 price to the lowest, formulating the demand curve. For each hour, the intersection of the supply and demand curves determines the DA price. As demand increases, more expensive generation units are dispatched, resulting in higher electricity prices.

Generators' bidding functions are usually determined by the marginal cost of electricity generation, which are mainly given by the underlying fuel prices (coal or natural gas) and the carbon emission cost. The GB carbon-intensive generators are subject to additional carbon prices than other European countries — they pay an EU-wide carbon price (EU ETS) and a GB-only carbon tax known as the Carbon Price Support (CPS). [5] On the other hand, the exchange rate (particularly between Sterling and Euro) plays a crucial role in setting electricity prices, because GB is importing about a half of the natural gas consumption from the Continent and the trading currency with its continental neighbours is Euro.

The merit order theory of electricity supply suggests that the electricity price is set by the dispatched power plants with the highest marginal cost. However, during 2015-2017 in GB, despite that the marginal cost for coal plants is higher than that for Combined Cycle Gas Turbines (CCGTs), CCGTs are directly[6] responding to about 60% of marginal demand changes, and about 70% of wind changes (Chyong et al., 2020). In other words, CCGTs are the marginal fuel for GB during the period, thanks to their much higher flexibility (than coal plants). Similar results are reported in Castagneto Gissey et al. (2018), who found natural gas was the marginal fuel 65% of

[5]The CPS started from £4.95/tCO_2 in April 2013 and has been held fixed at £18.08/tCO_2 since April 2015.

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

the hours in 2017. Given this, natural gas is potentially the fuel type that sets the DA wholesale electricity price most of the time.

1.2 The Brexit referendum

In a referendum held in June 2016, the UK has voted to withdraw from the EU and is expected to abandon the bloc by February 2020 formally. At the time of writing, the EU has allowed a further extension of Brexit up to 31 January 2020, and an election has been called, resulting in a greater level of uncertainty.

An instantaneous effect of voting to leave the EU is the drastic decline in the GBP/EUR exchange rate, shown in Figure 1. The steep depreciation resulted from expectations of capital outflows, a depressed investment outlook, and severe political instability.

Figure 1: GBP/EUA historical exchange rate, 2015-2018. The vertical dotted line indicates the EU withdrawal referendum date.

Source: investing.com

The drastic decline in the value of Sterling could strongly affect the UK economy. The Bank of England (2018) estimated that a 5% depreciation adds almost 1% to the price of consumer goods.

Forbes et al. (2018) studied the implications of the Brexit vote. They found that the exchange rate PTR is relatively large in response to domestic monetary policy shocks but relatively small in response to domestic demand shocks. Their work helps explain why PTRs vary over time, such as why Sterling's post-crisis depreciation led to a sharper increase in prices than expected, and Sterling's recent appreciation has had a more muted effect. Voting to leave also resulted in high inflations after 2017, which has cost an extra of £404 a year on an average British household (Breinlich et al., 2018). The UK stock market index (FTSE100) fell by about 4%, with companies most exposed to the UK and EU markets suffering the most significant share price falls (Davies and Studnicka, 2017).

As for the energy sector, Castagneto Gissey et al. (2018) estimated that the exchange rate depreciation had increased the cost of inputs to power and gas supply, translating into an average household's bill increasing by £35 for electricity and £40 for gas the year after the referendum. More generally, the falling exchange rate is expected to have profound consequences throughout the energy value chain, with impacts on upstream oil and gas production and downstream generation and distribution (PwC, 2016).

Since 1996, the EU's Internal Energy Market has required countries to adopt wide-ranging policy measures — addressing issues such as energy market access, transparency and regulation, consumer protection, supporting interconnection, and ensuring adequate levels of energy supply — in an integrated fashion.[7] The benefits of European electricity market integration are large and well documented (Newbery et al., 2016), and so are the specific benefits to the UK's energy system (Pöyry, 2016).

In the near future, leaving the EU could trigger regulatory changes that could significantly affect how the British energy system works. Those impact, both positive and negative, include but not limited to: leaving the EU ETS and replacing the EUA by a domestic Carbon Emission Tax (CET), but leaving the CPS as an additional generation fuel tax, uncoupling interconnectors from the day-ahead cross-border electricity trading,[8] and changing the role of interconnectors in

[7] https://www.europarl.europa.eu/factsheets/en/sheet/45/internal-energy-market

[8] From 4 February 2014, GB is coupled with France and the Netherlands. Market coupling ensures that the lower-

capacity auctions.[9] As a result, the UK's energy cost may be substantially affected.

1.3 The ETS reform

The EU Emissions Trading System (ETS) was launched in 2005 as the EU's main instrument to reduce its greenhouse gas 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 greenhouse gases that to be emitted, and companies can trade individual emission allowances (EU Allowances, EUA) with one another. Participants in the EU ETS can also buy international credits from global emission-saving projects external to the ETS. The cap is reduced over time so that the total emission falls. Companies must surrender a sufficient number of allowances to cover all of their emissions, or they face hefty fines.

If the carbon price is sufficiently high, it should discourage carbon-intensive generation and promote clean energy investment. As shown in Figure 2, the price peaked at almost £24/tCO_2 in 2008, while the freely allocated permits led to a large surplus of low-priced permits and a gradually crashing EUA price. The 2008 economic crisis and the inflow of carbon credits from outside the EU further decreased the ETS price, which was then remained low during 2011-2017, providing wrong signals on carbon saving or low-carbon investment. In order to meet the EU's target of reducing its greenhouse gas emissions by 40% by 2030 (relative to the 1990 level), reforming the ETS becomes a necessity.

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) on emissions and a progressive shift towards auctioning of allowances instead of the initial free allocation

price market would always import from the higher-price market day-ahead. Due to the different time zones, uncoupling means that traders have to anticipate the GB price when bidding for the cross-border trading for the next day, resulting in uneconomical trading.

[9] Capacity Markets usually takes the form of forward contracts that last between one and three years, and are determined through an auction mechanism. Under the current scheme, generators are offered financial incentives to ensure that power plants are ready to provide emergency back-up when needed. The first British Capacity Auction (T-4) for delivery in 2018 was concluded on 18 December 2014 at a clearing price of £19.40/kW/year. However, On 15 November 2018, the EU's General Court issued a judgement annulment, depriving the capacity payment that the GB capacity market participants expected to receive.

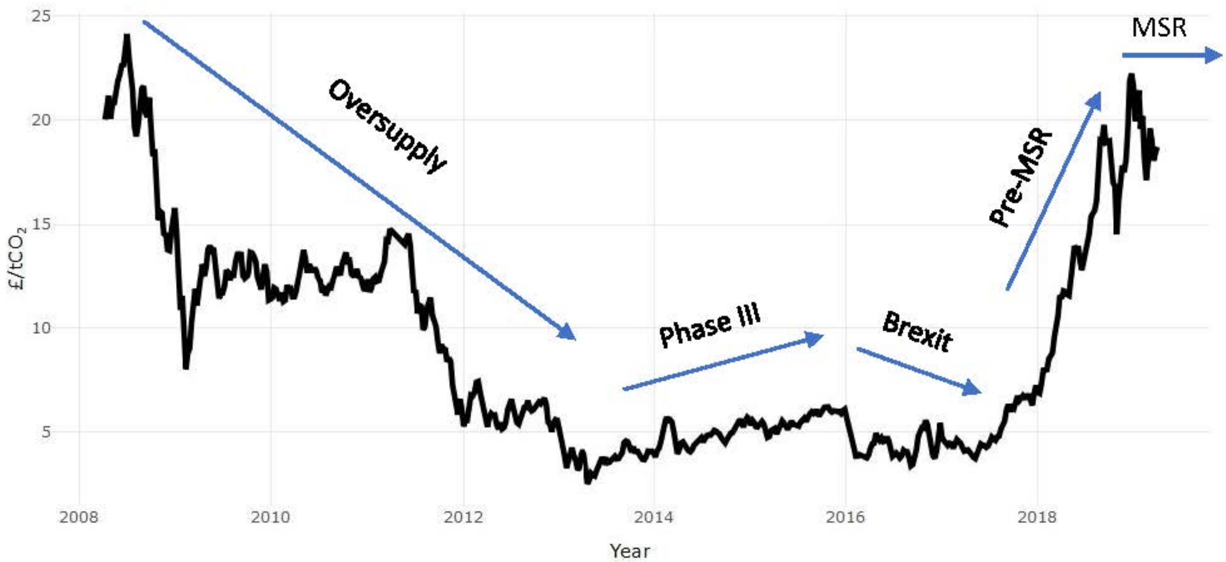

Figure 2: EU ETS carbon price, 2012-2018

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

scheme. Phase III resulted in some gradual inclines in the EUA prices until 2016, when the market again experienced a drastic decline, followed by the Brexit referendum.[10] However, it is worth mentioning that the downward arrow around 2016 does not entirely attribute to Brexit — other factors such as changes in the relative fuel price may also interact with the carbon price.[11]

In 2014, the EC proposed a Market Stability Reserve (MSR) for the EU ETS, which was then 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, which includes increasing the pace of emissions cuts,[12] doubling the number of allowances to be

[10]Facing the risks of a no-deal Brexit, the UK operators and traders with EUAs in their account may eventually lose the registry access. As a result, UK operators are motivated to sell/transfer their allowances, resulting in a surplus in the EUA supply and a reduction in the EUA price.

[11]Since 2016, due to the higher relative prices, coal has become the more expensive fuel than gas. The gas supplying the base load for major EU countries would potentially lower the demand of EUAs.

[12]The overall number of emission allowances will decline at an annual rate of 2.2% from 2021 onwards, compared to 1.74% currently.

placed in the MSR between 2019-2023,[13] and building a new mechanism to limit the validity of allowances in reserve from 2023 onwards.

As Figure 2 shows, the public anticipation of the start of the MSR has tripled the EUA price from £8/tCO_2 in January 2018 to £25/tCO_2 in December 2018. Perhaps surprisingly, the actual operation of the MSR did not further raise the EUA price during the first quarter of 2019, but the picture will be more precise as the reform moves forward.

The consistently low EUA price since 2011 did not generate the required low carbon investments, leading the UK government to introduce the Carbon Price Support (CPS) in 2013. CPS is a GB-only[14] carbon tax that tops up the ETS price, levied on domestic power generators which is not replicated by other European countries.[15] The CPS has been fixed at £18.08/tCO_2 since April 2015 until the fiscal year 2020-2021.

The UK government is considering long term options for carbon pricing following Brexit. A report from the Department for Business, Energy & Industry Strategy (BEIS, 2019) states that, should the UK leave the EU without a deal, the UK will introduce a Carbon Emissions Tax (CET) to replace the ETS share of total £/tCO_2 carbon prices in order facilitate the achievement of the UK's legally binding carbon reduction commitments under the Climate Change Act. The tax rate for 2019 would be £16/tCO_2, and the rate for 2020 will be announced in Budget 2019. Meanwhile, the CPS would remain in place in a no-deal scenario.

2 Competition and 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

[13] Between the first five years of its operation (2019-2023), the MSR will hold back 24% of the allowances in circulation, doubled from its regular feeding rate of 12%, which will be restored as of 2024.

[14] Northern Ireland belongs to the Irish Single Electricity Market with the Republic of Ireland. The Irish government declined to replicate the CPS, making it a GB-only carbon tax.

[15] However, some interest has been shown by other countries to adopt a national CPS. On 4 June 2019, the Dutch government proposed a Carbon Price Floor on its domestic CO_2 emissions by its electricity producers from January 2020. The proposed price for 2020 is €12.30/tCO_2, and would raise to €31.90/tCO_2 in 2030.

difficult for the electricity industry because costs are usually private information for the producers.

The most common measures of market power are market shares and market concentration. Market shares inform us about the size of a company relative the rest of the market, while market concentration indicates the extent to which a market is dominated by only a few firms. However, it is not always the case that market shares and market concentration can fully explain market power, as many other factors can affect the degree of competition within an industry (Borenstein et al., 1999). In the case of electricity, a homogeneous good, consumers can easily consume a substitute, so producers with high market share may not be able to exercise their dominant position.

Pivotality analysis is also widely adopted (Ofgem, 2017) and helps to assess how relevant each firm is in meeting electricity demand. Pivotality analysis determines whether the power stations owned by a particular company are needed to meet demand in a particular period. In other words, 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 would allow the firm to exercise its market power by increasing electricity prices more 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 are not publicly available.

Our work focuses on a wide range of cost PTRs, which inform the welfare implications of various types of price discriminations and imperfect competition (Fabra and Reguant, 2014; Pless and Benthem, 2019). Below in Section 2.1, we build a simple game theory model for (industry-level) cost pass-through under the assumption of Cournot competition, to derive the relationship between PTR and market competition. Then in Section 2.2, we link the model with the nature of the wholesale electricity market and define what a 100% PTR means in the relationship between the input cost and the wholesale electricity price.

2.1 Cost Pass-through: an economic theory

Suppose an industry consists of a set of $N = \{1, 2, ..., n\}$ firms who face a common inverse demand curve $p(Q)$, where Q denotes the total output. $p(Q)$ is assumed to be negatively related to Q, hence $p'(Q) < 0$. Firm $i \in N$ chooses how much output q_i to sell to the market to maximise its profit $\phi(q_i)$:

$$\max_{q_i} \quad \phi(q_i) = q_i \cdot p(q_i + Q_{-i}) - c_i(q_i) - t_i \cdot q_i, \tag{1}$$

where the first term, $q_i \cdot p(q_i + Q_{-i})$, denotes the revenue for firm i from selling quantity q_i. Q_{-i} denotes the amount of output from all other firms and is taken as given, therefore $Q_{-i} = Q - q_i$. $c_i(q_i)$ is the cost function for firm i. Finally, t_i is a cost shifter for firm i. For example, t_i could be the EUA price on each unit of electricity generated from the firm.

Taking the first order condition of (1), firm i sets $q_i = q_i^*$ to satisfy

$$q_i^* \cdot p'(q_i^* + Q_{-i}) + p(q_i^* + Q_{-i}) - c_i'(q_i^*) - t_i = 0. \tag{2}$$

Aggregating across all firms gives

$$\sum_{i \in N} q_i^* \cdot p'(q_i^* + Q_{-i}^*) + \sum_{i \in N} p(q_i^* + Q_{-i}^*) - \sum_{i \in N} c_i'(q_i^*) - \sum_{i \in N} t_i = 0, \tag{3}$$

where Q_{-i}^* denotes the optimal output from all other firms. Under market equilibrium, $q_i^* + Q_{-i}^* = Q^*$, where Q^* denotes the equilibrium total output. Then a simplified version of (3) can be expressed as

$$Q^* \cdot p'(Q^*) + n \cdot p(Q^*) - \sum_{i \in N} c_i'(q_i^*) - \sum_{i \in N} t_i = 0, \tag{4}$$

where $p(Q^*) = p^*$ denotes the equilibrium price.

Applying the implicit function theorem on (4) and differentiating with respect to $\bar{t} = \frac{1}{n} \sum_{i \in N} t_i$, the average cost shifter across the whole industry, and assuming the cost function $c_i(q_i)$ to be linear with q_i, such that $c''(q_i^*) = 0$, we have

$$(n+1) \cdot p'(Q^*) \cdot \frac{dQ^*}{d\bar{t}} + Q^* \cdot p''(Q^*) \cdot \frac{dQ^*}{d\bar{t}} - n = 0. \tag{5}$$

Rearranging, we obtain $dQ^*/d\bar{t}$, the change in the equilibrium total output following a change in the average cost shifter, as

$$\frac{dQ^*}{d\bar{t}} = \frac{n}{(n+1)\cdot p'(Q^*) + Q^*\cdot p''(Q^*)} \tag{6}$$

Knowing that the equilibrium price $p^* = p(Q^*)$ is a function of the equilibrium total output Q^* hence $dp^*/dQ^* = p'(Q^*)$, we can derive the rate of cost pass-through for the industry under Cournot competition as

$$\begin{aligned}\frac{dp^*}{d\bar{t}} &= p'(Q^*)\cdot\frac{dQ^*}{d\bar{t}}\\ &= \frac{n\cdot p'(Q^*)}{(n+1)\cdot p' + Q^*\cdot p''(Q^*)}\\ &= \frac{n}{(n+1) + Q^*\cdot p''(Q^*)/p'(Q^*)}.\end{aligned}$$

Letting $\xi = -Q^*\cdot p''(Q^*)/p'(Q^*)$ denote a measure of the curvature of inverse demand, namely the elasticity of slope of inverse demand, then the PTR is

$$\frac{dp^*}{d\bar{t}} = \frac{n}{(n+1)-\xi}. \tag{7}$$

When $n = 1$, the PTR under Cournot competition becomes the case of monopoly. When n is large, the Cournot case converges to the perfect competition result. Under the assumption of a (locally) linear market demand curve,[16] ξ equals to zero and the PTR would only depend on the number of firms in the industry, which converges to 100% as n becomes large.

Other forms of expressions of PTR can be found in Pfleiderer (1983), Seade (1985) and more recently Weyl and Fabinger (2013), though their models might be based on different market structures.

[16] It is commonly agreed that the electricity demand curves are inelastic (i.e., a large $|p'(Q^*)|$) with low curvature (i.e., a small $|p''(Q^*)|$), meaning that ξ in the electricity market is close to 0.

2.2 Cost pass-through in wholesale electricity markets

This paper examines the cost pass-through of coal and gas price, the carbon price, and the exchange rate to the GB wholesale electricity price. Depending on which exact PRT we are investigating, the interpretation on the average cost shifter $\bar{t}$ can be different.

It is important to notice that not all electricity generators in the market should be included in the set of firms N. As the wholesale price is set by marginal fuels, N should only consist of power plants that can activity set the wholesale price, including coal and CCGT plants, imports, pumped storage, and hydro plants.[17] In Appendix 7.1, we show how N is empirically determined.

2.2.1 The EUA pass-through

The linkage between the EUA price PTR and the Cournot competition model is straightforward. Suppose t_i in (1) represents the carbon price from EUA for firm i. Then, the EUA cost for coal plants would be $t_{\text{COAL}} = EF_{\text{COAL}} \cdot p^{\text{EUA}}$, and for CCGT plants would be $t_{\text{CCGT}} = EF_{\text{CCGT}} \cdot p^{\text{EUA}}$, where EF denotes the emission factor (EF) for different fuel types and p^{EUA} denotes the EUA price in £/tCO$_2$. Because hydro plants emit zero CO$_2$, then $t_{\text{HYD}} = EF_{\text{HYD}} \cdot p^{\text{EUA}} = 0$.

The EF for pumped storage (PS) depends on which fuel types is supplying at margin when pumping/charging. For GB, it is mostly likely to be the more flexible CCGTs and/or the more expensive coal-fired power plant. Denoting the EF for pumped storage as EF_{PS}, $t_{\text{PS}} = EF_{\text{PS}} \cdot p^{\text{EUA}}$.

In addition to domestic fossil plants and PS, any changes in electricity demand can also be met by imports, through trading in cross-border electricity interconnectors. Despite that electricity imported from the European Continent and the Island of Ireland may come from various of fuel sources, the British System Operator imports at the foreign wholesale prices, which is set by the foreign marginal plants. In other words, the EUA cost for import would be $t_{\text{FR}} = MEF_{\text{FR}} \cdot p^{\text{EUA}}$ from France, $t_{\text{NL}} = MEF_{\text{NL}} \cdot p^{\text{EUA}}$ from the Netherlands, and $t_{\text{IR}} = MEF_{\text{IR}} \cdot p^{\text{EUA}}$ from the island

[17] As nuclear and renewable power plants enjoy a close-to-zero marginal cost, they are regarded as base load — (almost) always producing at their maximum available output. Therefore, it is commonly agreed that nuclear and renewable power plants are not capable of setting wholesale prices through actively changing their productivity. Other fuels such as oil and Open Cycle Gas Turbines (OCGTs) barely operate, hence negligible.

of Ireland,[18] where MEF denotes the Marginal Emission Factor (MEF) for a particular country. Then,

$$\bar{t}^{\text{EUA}} = \frac{1}{n_1 + n_2} \left(\sum_{i_1 \in N_1} EF_{i_1} \cdot p^{\text{EUA}} + \sum_{i_2 \in N_2} MEF_{i_2} \cdot p^{\text{EUA}} \right),$$

where $N_1 = \{1, ..., n_1\}$ consists of fossil plants, hydro, and pumped storage companies, $N_2 = \{n_1 + 1, ..., n_1 + n_2\}$ represents the set of firms biding for cross-border electricity trading. The value of EF_{i_1} has to be within the set of $\{EF_{\text{COAL}}, EF_{\text{CCGT}}, EF_{\text{HYD}}, EF_{\text{PS}}\}$, and the value of MEF_{i_2} has to be within the set of $\{MEF_{\text{FR}}, MEF_{\text{NL}}, MEF_{\text{IR}}\}$.

By definition, $N = N_1 \cup N_2$, $\emptyset = N_1 \cap N_2$, and $n = n_1 + n_2$. A full PTR of the EUA cost requires the marginal effect of the EUA price on the wholesale price to be close $\bar{t}^{\text{EUA}}$, which is also known as the MEF for GB.

2.2.2 Fuel prices pass-through

Now suppose the gas price for a particular short period is $p^{\text{CCGT}} = \bar{p}^{\text{CCGT}} + p_{\varepsilon}^{\text{CCGT}}$, where $\bar{p}^{\text{CCGT}}$ denotes the average gas price during the whole period of studying and $p_{\varepsilon}^{\text{CCGT}}$ denotes the price that deviates from its average. In other words, any changes in the gas price is due to changes in $p_{\varepsilon}^{\text{CCGT}}$.

For simplicity, we assume $c_{\text{CCGT}}(q_{\text{CCGT}}) = \bar{p}^{\text{CCGT}} \cdot q_{\text{CCGT}} + C$, where C represents a fixed cost such as the wear and tear on the machine. If all other input costs, including coal price, carbon price, and the exchange rate are held constant, then in (1), t_i can be interpreted as the gas-price shifter $p_{\varepsilon}^{\text{CCGT}}$.

Note that any changes in $p_{\varepsilon}^{\text{CCGT}}$ will have influence not only on CCGTs, but also on other fuel sources, in particular imports and PS. This is because importand PS that respond to demand changes may also come from (foreign or domestic) CCGTs. Then

$$\bar{t}^{\text{CCGT}} = s^{\text{CCGT}} \cdot p_{\varepsilon}^{\text{CCGT}},$$

where s^{CCGT} is the total share of CCGTs that sets the wholesale electricity price, when the fuel

[18] GB is also connected with Belgium since 31 January 2019, which is not within the period of studying.

sources that supply import and PS at margin are taken into consideration. A full PTR of the gas price would require the marginal effect of gas price on the wholesale price to be close to the share of CCGTs at margin, s^{CCGT}.

Using the same logic, the coal price PTR can be expressed as

$$\bar{t}^{\mathrm{COAL}} = s^{\mathrm{COAL}} \cdot p_{\varepsilon}^{\mathrm{COAL}},$$

where s^{COAL} is a mirror image of s^{CCGT}.

2.2.3 The exchange rate pass-through

The impact of the exchange rate on the wholesale electricity price may not be reflected in the Cournot competition model. Although the exchange rate would affect both fuel and carbon prices, the empirical analysis in Section 5 estimates the effect of exchange rate on the wholesale price *conditional on* the fuel and carbon prices, whose values are taken in Sterling. Under the scenario of a full PTR, a 1% depreciation in Sterling relative to Euro would result in a 1% increase in the GB wholesale price.

3 Literature Review

Most studies calculating PTRs focused on carbon emission allowance cost pass-through to electricity prices in the context of the EU ETS. An early work done by Sijm et al. (2006) find that the CO_2 cost PTR varies between 60% and 100% for German and Dutch wholesale electricity markets, though at the time, most of the emission allowances are freely allocated. As an extension of Sijm et al. (2006), Zachmann and Von Hirschhausen (2008) find that the PTR is higher when the CO_2 price is rising than falling. Castagneto Gissey (2014) uses the year-ahead data for four European countries during 2008-2012, to show that the PTRs ranged between 88% and 137%, with GB among the most cost-reflective in a sample of European markets. Jouvet and Solier (2013), however, find that the estimated PTRs are insignificantly different from zero for most of the EU countries studied, especially during the second phase of the EU ETS. The contrary results from the two studies might be different estimation methodologies and data applied.

The structure of electricity systems can be different for different countries, resulting in heterogeneous CO_2 PTRs, even under the same ETS. Honkatukia et al. (2008) find a PTR 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) also study Phase I and II, and 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, finding that a 1% shock in carbon prices translates on average into a 0.42% shock in UK electricity prices.

Many studies also found higher PRTs is associated with high demand and the utilisation rate of generation capacity (Sijm et al., 2006; Honkatukia et al., 2008; Jouvet and Solier, 2013; Hintermann; Fabra and Reguant, 2014). However, literature fails to give persuasive intuition on why this is the case. We intend to fill this gap.

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

Several studies consider markets for 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 (2010) studies firms' responses in the NO_x Budget Program, finding that the degree of emission cost internalisation depends on the degree to which the production was subsidised.

Fuel price PTRs are usually the by-products from studies on carbon price pass-through, especially in literature during the past decade. Hintermann (2016) finds that fuel prices are 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 do not pass on fuel prices to the same degree as allowance costs. They consider that a reason for this is the presence of transaction costs and long-term contracts for fuels and conclude that spot prices do not perfectly represent firms' opportunity costs related to fuel use.

Castagneto Gissey (2014) finds that the British coal- and gas-price PTRs in 2007-2012 were 90% and 112%, respectively, with PTRs the largest for the fuel type that was more often used for generation. Ahamada and Kirat (2018) study France and Germany during ETS Phase II, finding that coal-fired units are more often the price-setting marginal units, a factor which they find explains the higher PTR of coal prices. The CMA (2016) studies pass-through of fuel prices to retail electricity prices. The study has substantial competition policy implications for a UK retail electricity sector which was shown to exhibit market power.

Finally, literature regarding the impact of exchange rates on wholesale electricity prices is surprisingly limited. The Ontario Energy Board (2008) emphasises that the exchange rate influences Canadian electricity prices by affecting the fuel price and the electricity price from the neighbouring US market. Castagneto Gissey and Green (2014) study a sample of European electricity markets during the 2008 financial crisis and find that the exchange rate affected electricity prices in their volatility but did not have a significant effect in their levels. A more recent study finds that in the long-run, electricity prices would increase by 0.56% following a 1% increase in the real exchange rate in Ghana (Adom et al., 2018).

4 Methods

We use econometrics to study how would the GB day-ahead (DA) wholesale electricity price react when there are changes in the input costs of electricity generation (i.e., fuel prices, carbon prices, and exchange rates) during the period of 2015-2018. We begin by introducing the data used in this study and proceed by covering the underlying model and related technical considerations.

4.1 Data

All data ranges from 1st April 2015[19] to 31st December 2018, and hourly data is averaged to daily means. The hourly GB DA wholesale electricity price (i.e. the spot market price, in Sterling) is collected from the Entso-e Transparency Platform (TP). The daily National Balancing Point (NBP) gas price (in Sterling) comes from the InterContinental Exchange (ICE) and is converted from £p/therm to £/MWh$_e$ assuming a Lower Heating Value (LHV) efficiency for CCGTs of 54.5%.[20] The daily coal price, from CME Globex in \$ /short ton, is converted to £/MWh$_e$, using the daily GBP/USD exchange rate, assuming an average thermal efficiency for the GB coal-fired power plants of 35.6%.[21] Note that coal prices in the US can be different from that consumed by GB generators, mainly because of different transportation costs. We, therefore, adjust the US daily coal price data based on the UK quarterly coal price data from the Department for Business, Energy & Industrial Strategy (BEIS).[22,23] The daily EUA price is the EU ETS closing spot price and is converted from Euro to Sterling using the daily exchange rate.[24]

The DA forecasts of GB renewable (wind and solar) generation and domestic demand come from the Entso-e TP.[25] Besides, when nuclear generators are under maintenance or suffering from outages, fossil fuel needs to backup the deficit, which affects the wholesale price. Due to data unavailability, we use the actual daily nuclear generation as a proxy for the DA forecast of nuclear generation.[26] Table 1 provides summary statistics for all variables involved in the preliminary

[19] 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. The impact of the British CPS on the GB electricity market is discussed in detail in Chyong et al. (2020) and Guo et al. (2019).

[20] 1 (UK) therm is equivalent to 29.31 kWh$_{th}$. Under the LHV efficiency of 54.5%, 1 (UK) therm is equivalent to 15.97(=29.31×54.5%) kWh$_e$.

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

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

[23] We aggregate the daily data into quarterly, subtract from the BEIS data, and adjust the daily data by adding this quarterly averaged margin to each day.

[24] Note that the coal price, gas price, EUA price, and the exchange rate are only available for weekdays; hence, we use the most adjacent value as a proxy for any missing value.

[25] The "generation forecast for wind and solar" and the "day-ahead forecast on total load".

[26] 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 DA forecast.

regression analysis (Section 5.1).

Table 1: Summary Statistics, Day-ahead Markets

Variable	Unit	Mean	S. D.	Min.	Max.
GB DA Prices	£/MWh	46.24	10.98	28.12	170.15
Coal Prices	£/MWh$_e$	24.16	5.80	13.34	33.69
Gas Prices	£/MWh$_e$	34.06	7.50	20.29	54.46
EUA Prices	£/ tCO_2	7.52	4.58	3.34	22.83
GBP/EUR XR	£/ €	1.21	0.10	1.08	1.44
GB Renew. Gen.	GW	6.10	2.76	1.03	14.94
GB Demand	GW	33.95	4.15	24.73	45.26
GB Nuclear Gen.	GW	7.34	0.67	4.69	8.83

4.2 Vector Error Correction Model

We implement the Vector Error Correction Model (VECM) to study the impact of fuel prices, carbon prices, and exchange rates on the British wholesale electricity price. The same model has been widely used in studying the cost pass-through in the energy market (see, e.g., Alexeeva-Talebi, 2011; CE Delft and Oeko-Institut, 2015; Freitas and Da Silva, 2013; Bunn and Fezzi, 2008; Mohammadi, 2009; Fell et al., 2015), as it effectively captures both short-run and long-run relationships among variables of interest.

Furthermore, when estimating the impact of input costs on the wholesale electricity price, endogeneity can become an issue when interactions between fuel prices and wholesale prices play a critical role in the wholesale price formation (Knitell and Roberts, 2005). This also applies to the relationship between wholesale prices and carbon prices, and between wholesale prices and exchange rates, suggesting that all variables representing the input cost for generating electricity have the potential to be endogenous. The VECM allows us to treat both wholesale electricity prices and input costs as endogenous.

We start from introducing the Vector Auto-Regressive (VAR) model, and then transform the VAR into the VECM model. Given the daily averaged GB day-ahead price (P_t^{GB}), coal and gas prices (P_t^{COAL} and P_t^{GAS}), EUA price (P_t^{EUA}), and GBP/EUR exchange rate (e_t)[27] are all $I(1)$ time

[27] An alternative would be using the GBP/USD exchange rate, but the result suggests that the GBP/USD exchange

series processes (i.e., time series with unit roots, tested in Table 7), the VAR model can be expressed as:

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{B}\boldsymbol{z}_t + \boldsymbol{C}\boldsymbol{d}_t + \boldsymbol{u}_t \tag{8}$$

where t represents days, $\boldsymbol{y}_t = (P_t^{\mathrm{GB}}, P_t^{\mathrm{COAL}}, P_t^{\mathrm{GAS}}, P_t^{\mathrm{EUA}}, e_t)'$ is an $m \times 1$ vector of dependent variables, here $m = 5$. $\boldsymbol{z}_t$ is a vector of stationary, or $I(0)$ exogenous stochastic variables, and $\boldsymbol{d}_t$ 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. A VAR model captures dynamic interactions among the dependent variables, where $\boldsymbol{A}_i$'s are $m \times m$ coefficient matrices measuring the impact of lagged values of the dependent variables on their current values. Finally, $\boldsymbol{u}_t$ is an $m \times 1$ vector of unobserved error terms, and is assumed to be stochastically independent, or $\boldsymbol{u}_t \sim (\boldsymbol{0}, \boldsymbol{\Sigma}_u)$.

The process in (8) is stable if the dependent variables have a common stochastic trend(s) in the sense that a linear combination(s) of them are $I(0)$. If the common trend(s) exists, the dependent variables are cointegrated. In this case, a VECM specification of (8) is preferable because it explicitly underpins the cointegration relationships. Rearranging (8) we obtain the VECM form:

$$\Delta \boldsymbol{y}_t = \boldsymbol{\Pi} \boldsymbol{y}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{y}_{t-i} + \boldsymbol{B}\boldsymbol{z}_t + \boldsymbol{C}\boldsymbol{d}_t + \boldsymbol{u}_t. \tag{9}$$

Here $\boldsymbol{\Pi} = -(\boldsymbol{I} - \sum_{i=1}^{p} \boldsymbol{A}_i)$ and $\boldsymbol{\Gamma}_i = -(\boldsymbol{A}_{i+1} + \cdots + \boldsymbol{A}_p)$ for $i = 1, \ldots, p-1$.

As $\boldsymbol{\Pi}\boldsymbol{y}_{t-1}$ is the only term in (9) containing $I(1)$ variables, it must be stationary to ensure that the error term in (9) is also stationary. Now suppose $\boldsymbol{\Pi}\boldsymbol{y}_{t-1} \sim I(0)$, then in the case where $Rank(\boldsymbol{\Pi}) = m$, $\boldsymbol{\Pi}$ is nonsingular and invertible, and $\boldsymbol{y}_{t-1} = \boldsymbol{\Pi}^{-1}\boldsymbol{\Pi}\boldsymbol{y}_{t-1} \sim I(0)$.[28] This contradicts the earlier assumption that $\boldsymbol{y}_t$ are $I(1)$ processes, therefore we must have $Rank(\boldsymbol{\Pi}) = r < m$ in order to obtain cointegration.

We can then re-write $\boldsymbol{\Pi}$ as $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $m \times r$ matrices of full column ranks.

rate has insignificant impact on the GB electricity price.

[28] Multiplying an $I(0)$ vector by some matrix (with all entries being constant) results in an $I(0)$ vector.

Then $\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha}(\boldsymbol{\beta}'\boldsymbol{y}_{t-1}) \sim I(0)$, and (9) can be re-written as

$$\Delta \boldsymbol{y}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}'\boldsymbol{y}_{t-1}) + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{y}_{t-i} + \boldsymbol{B}\boldsymbol{z}_t + \boldsymbol{C}\boldsymbol{d}_t + \boldsymbol{u}_t, \tag{10}$$

where $\boldsymbol{\beta}'\boldsymbol{y}_{t-1} \sim I(0)$,[29] and $\boldsymbol{\beta}'\boldsymbol{y}_{t-1}$ is the $r \times 1$ vector of cointegration relations, known as the long-run (LR) relationships. $\boldsymbol{\alpha}$ is known as the vector of error correction (EC) coefficients, which represent the speed to convergence when the system deviates from its long-run equilibrium. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can be identified by setting one of the parameters in $\boldsymbol{\beta}$ to 1. In our case, the coefficient for P_{t-1}^{GB} is set to 1. $\boldsymbol{\Gamma}_i$'s in (10) consist of coefficients capturing the short-run (SR) relationships.

Recall that in equation (10), the input costs are treated as endogenous. However, one may argue that fuel and carbon prices are mainly determined by the European and world markets, while a single country like GB can have little influence on the fuel price (Guo et al., 2019). If this is the case, treating fuel prices as exogenous may improve estimation efficiency. This ambiguity on whether variables representing input costs should be treated as endogenous suggests to implement tests for (weak) exogeneity and to use the test results to formulate specifications for the VECM.

Exogeneity can be tested in a VECM specification as (10), with the null hypothesis being that the EC parameters (i.e., the second to fifth parameters of α) are jointly significantly different from zero. If we fail to reject the null, then the corresponding variables should be treated as weakly exogenous.

In this case, a structural VAR (or structual VECM) model would be preferable (Pesaran, 2015), where $\boldsymbol{y}_t = (\boldsymbol{y}_t^{\star\prime}, \boldsymbol{x}_t{}')'$, where $\boldsymbol{y}_t^{\star}$ and $\boldsymbol{x}_t$ are endogenous and weakly exogenous variables, respectively whose dimensions are $m_y \times 1$ and $m_x \times 1$ and we have $m_y + m_x = m$. In (9), $\mathbf{\Pi} = (\mathbf{\Pi}_{y^\star}, \mathbf{\Pi}_x)'$, where $\mathbf{\Pi}_{y^\star}$ and $\mathbf{\Pi}_x$ are $m_y \times m$ and $m_x \times m$ matrices, respectively. $\boldsymbol{x}_t$ being weakly exogenous means that $\mathbf{\Pi}_x{}' = 0$.

[29] Because $\boldsymbol{\alpha}$ is full rank, then pre-multiplying the $I(0)$ vector $\boldsymbol{\alpha}(\boldsymbol{\beta}'\boldsymbol{y}_{t-1})$ by a vector $(\boldsymbol{\alpha}'\boldsymbol{\alpha})^{-1}\boldsymbol{\alpha}'$, we obtain $\boldsymbol{\beta}'\boldsymbol{y}_{t-1} \sim I(0)$.

4.3 Validity Tests

This subsection provides results for unit root tests, lays out the criteria for determining the optimal lag length, specifies tests for cointegration, and reports results for the weakly exogeneity test. Only test results are reported and the detailed test statistics can be found in Appendix 7.2.

Cointegration only exists among nonstationary variables. Therefore, before implementing the Johansen cointegration tests, one should confirm that the variables in $\boldsymbol{y}_t$ (i.e. fuel prices, carbon prices, and exchange rates) are nonstationary.

The unit root tests suggest that all variables in $\boldsymbol{y}_t$ are nonstationary, and the variables in $\boldsymbol{z}_t$ (i.e. forecasts of electricity demand, renewable generation, and nuclear generation) are stationary. Further, the Johansen cointegration tests indicate one cointegration equation in the proposed VECM in (10). We implement the Akaike Information Criterion to determine the lag lengths for dependent variables, and the optimal lag length is $p = 4$, or 3 lags for the VECM in (10).

Finally, we conduct the test for weak exogeneity of coal and gas prices, EUA prices, as well as exchange rates, as illustrated in the end of Section 4.2. The test shows that the parameters of interest are not statistically different from zero, suggesting treating those variables as weakly exogenous.[30]

5 Results

In this section, unless specified, "wholesale price" refers to the GB day-ahead wholesale electricity price. Section 5.1 analyses preliminary linear results on the impact of input costs of electricity generation on the wholesale price, thereby calculating the corresponding PTRs. We assume that the impacts are homogeneous between weekdays and weekends, and between peak and off-peak. In Section 5.2, we vary the regression specification to conduct robustness checks, and split the data by peak and off-peak (weekdays and weekends). We give intuition on why PTRs are heterogeneous with time.

[30] $\chi^2_{(3)} = 1.52$ with p-value 0.82.

5.1 Preliminary Results

Recall that the tests for weak exogeneity reported in Section 4.3 suggest that we should treat coal and gas prices, EUA prices, and GBP/EUR exchange rates as weakly exogenous. By restricting the corresponding error correction (EC) parameters to zero, Table 2 reports the regression result for the structural VECM.

Table 2: VEC Model Results

Long-run Dynamics						
Const.	P_{t-1}^{GB}	Trend	P_{t-1}^{COAL}	P_{t-1}^{GAS}	P_{t-1}^{EUA}	e_{t-1}
-82.044	1.000	0.007	-0.075	-0.831***	-0.461**	53.314***
			(0.150)	(0.090)	(0.165)	(9.232)

Short-run Dynamics		Weakly Exogenous Variables			
	ΔP_t^{GB}	$\Delta P_t^{\mathrm{COAL}}$	$\Delta P_t^{\mathrm{GAS}}$	$\Delta P_t^{\mathrm{EUA}}$	Δe_t
EC_{t-1}	-0.553***	—	—	—	—
	(0.036)	—	—	—	—
Const.	-14.261***	0.210	-0.282	-0.180	-0.003
	(3.391)	(0.180)	(0.439)	(0.147)	(0.004)
Trend	0.003***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_t^{GB}	0.522***	-0.004	0.004	0.004	0.000
	(0.077)	(0.004)	(0.010)	(0.003)	(0.000)
R_t^{GB}	-0.597***	-0.004	-0.003	0.005	0.000
	(0.058)	(0.003)	(0.008)	(0.003)	(0.000)
N_t^{GB}	-0.449*	-0.007	0.014	0.000	0.000
	(0.227)	(0.012)	(0.029)	(0.010)	(0.000)

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

In the long-run, *ceteris paribus*, a fall in the GBP/EUR exchange rate by 1,000 basis point (i.e. a 0.1 reduction) is associated with an increase in the wholesale price by £5.33/MWh. Given the 2015-2018 average wholesale price in Table 1, under the null hypothesis of 100% exchange rate PTR, a 0.1 change in the GBP/EUR exchange rate is supposed to be associated with a £4.62/MWh($= 46.23 \times 0.1$) opposite change in the wholesale price. Since the estimated £5.33/MWh(s.e.=0.92) is not statistically significantly different from £4.62/MWh, we do not reject the null.

Our results also show that in the long-run, a £1/MWh$_e$ increase in the gas price is associated with a £0.83/MWh$_e$ increase in the wholesale price. Based on our analysis in Section 2.2, a full pass-through of gas price would require the long-run relation to be statistically close to the proportion of CCGTs as marginal fuels, when the proportion of imports and pumped storage that comes from CCGTs are also taken into account. We replicate Chyong et al. (2020) and Staffell (2017) to estimate the marginal fuel of GB during the period of studying (Apr. 2015 - Dec. 2018), and found that CCGTs respond to at least 60% of demand changes under the assumption that none of the supply from imports and pumped storage (PS) are from CCGTs. This number raises to 78% if we assume that the supply from imports and PS are entirely from CCGTs. Appendix 7.1 gives estimation details and further discussions. Given this, the 99% confidence interval for the gas price PRT to the wholesale price is [100%,177%] in the former case, and [77%,136%] the the latter case.[31] In other words, in any scenario, we fail to reject the null that the gas price PTR is statistically significantly different from 100% at 1% significant level. In fact, if at least 31% of the supply from imports and PS comes from CCGTs, we would not reject the null at 5% significant level.[32]

The long-run relationship between coal and wholesale prices is not significantly different from zero. Furthermore, the estimate suffers from a large standard error, probably because of low variation in coal prices during the past few years. As a result, the estimation is not informative, and we are unable to make a credible discussion about the PTR of coal.[33]

A £1/tCO_2 increase in the EUA price corresponds to a £0.46/MWh increase in the wholesale electricity price. As discussed and proved in Section 2.2, a 100% EUA price PTR requires that the estimated long-run relationship between the EUA price and the wholesale electricity price to

[31] For the former case, the confidence interval is calculated from $(0.83 \pm 2.58 \times 0.09)/0.60$, where 0.09 is the corresponding standard error and 2.58 is the critical value at 1% significant level. For the latter case, it is calculated from $(0.83 \pm 2.58 \times 0.09)/0.78$.

[32] From the regression results in Appendix 7.1, about 18% of the marginal demand is answered by imports and PS. 31% of the 18% means that there is an additional 5.5% of marginal demand is answered by CCGTs, making gas plants answering a total of 65.5% of marginal demand. In this case, 0.655 is the lower bound of the 95% confidence interval of the estimate 0.831(s.e.=0.090) in Table 2.

[33] However, the estimation result itself, as least, do not reject the null hypothesis that the coal price pass-through is 100%.

be close to the Marginal Emission Factor (MEF) of the GB electricity supply. From our replicated results in Appendix 7.1, during the period of studying, the MEF for the GB electricity supply is between 0.429 and 0.525 tCO_2/MWh.[34] Either way, we fail to reject the null that the EUA price has a 100% PTR.

The coefficients for the EC term estimate the speed of convergence to long-run equilibrium. Precisely, if the wholesale price diverges from the long-run equilibrium on the day t due to unexpected market shocks, then on the day $t+1$, about 55% of that disequilibrium is dissipated before the next time period, and 45% remains. If there is no further shock on the day $t+1$, then on that day, about 55% of the remaining disequilibrium would be adjusted and dissipated; and so forth.

Finally, the estimation result also suggests that the wholesale price is positively affected by electricity demand and negatively affected by renewable and nuclear supply.

5.2 Robustness Check and Extension

In section 5.2.1, we report robustness checks by varying regression specifications of the preliminary regression used in Section 5.1. In Section 5.2.2-5.2.3, we extend the regression analysis by considering heterogeneous effects within days (peak and off-peak) and across days (weekdays and weekend). Finally, in Section 5.2.4 we explain the reason that the PTRs can be different for different time of the day and different days of the week.

Table 3 shows the regression results discussed in the subsection, with only the long-run dynamics and the EC terms reported.

5.2.1 Robustness check

Regression (i) removes the weak exogeneity assumption in Table 2. The regression results are still to those the preliminary case, which verifies the fact that treating those variables as weakly exogenous would not generate bias. Instead, it delivers more efficient estimators.

[34] This is calculated under two extreme cases where we assume that the supply from imports and PS is either entirely from CCGTs, or entirely from coal-fired power plants.

Table 3: Robustness Check

	(i)	(ii)	(iii)		(iv)	
	ENDOG.	LOG	OFF-PEAK	PEAK	W.DAY	W.END
Long-run Dynamics						
P_{t-1}^{GB}	1.000	1.000				
$P_{t-1}^{\mathrm{GB,OFF}}$			1.000			
$P_{t-1}^{\mathrm{GB,PEAK}}$				1.000		
$P_{t-1}^{\mathrm{GB,W.DAY}}$					1.000	
$P_{t-1}^{\mathrm{GB,W.END}}$						1.000
P_{t-1}^{COAL}	-0.106	-0.040	0.202**	-0.214	-0.128	0.035
	(0.149)	(0.045)	(0.081)	(0.224)	(0.211)	(0.108)
P_{t-1}^{GAS}	-0.812***	-0.599***	-0.897***	-0.796***	-0.822***	-0.900***
	(0.089)	(0.042)	(0.049)	(0.134)	(0.129)	(0.066)
P_{t-1}^{EUA}	-0.451***	-0.090***	0.041	-0.711***	-0.655***	-0.309**
	(0.164)	(0.023)	(0.089)	(0.246)	(0.241)	(0.123)
e_{t-1}	49.945***	1.145***	15.224***	71.884***	69.610***	34.317***
	(9.201)	(0.141)	(5.001)	(13.783)	(13.422)	(6.847)
Trend	0.006	0.091	-0.005	0.000	-0.008	0.014
Const.	-77.520	-104.760	-47.124	-2.901	-25.767	-105.003
Short-run Dynamics						
	ΔP_t^{GB}	$\Delta \log P_t^{\mathrm{GB}}$	$\Delta P_t^{\mathrm{GB,OFF}}$	$\Delta P_t^{\mathrm{GB,PEAK}}$	$\Delta P_t^{\mathrm{GB,W.DAY}}$	$\Delta P_t^{\mathrm{GB,W.END}}$
EC_{t-1}	-0.552***	-0.573***				
	(0.037)	(0.033)				
EC_{t-1}^{OFF}			-0.559***			
			(0.033)			
EC_{t-1}^{PEAK}				-0.542***		
				(0.038)		
$EC_{t-1}^{\mathrm{W.DAY}}$					-0.748***	
					(0.059)	
$EC_{t-1}^{\mathrm{W.END}}$						-0.930***
						(0.069)
Test for Weakly Exogeneity						
p-values	—	$p = 0.63$	$p = 0.82$		$p = 0.27$	

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

Regression (ii) takes the log of all price variables,[35] and estimates the elasticities of the wholesale price relative to the input costs. The result shows that in the long-run, a 1% increase in the gas price is associated with a 0.6% increase in the wholesale price. Note that from Table 1, the average gas price is £34.06/MWh$_e$, and the average wholesale price is £46.24/MWh. Then, the regression result suggests that if the average gas price is increased by £0.34/MWh$_e$ (1% of the average), the wholesale price will raise by £0.28/MWh (0.6% of the average). Alternatively, the wholesale price would be raised by £0.82/MWh following a £1/MWh$_e$ increase in the gas price, close to the result in Table 2.

Regression (ii) also shows that a 1% increase in the EUA price is associated with a 0.09% increase in the wholesale price. From Table 1, the average EUA price was £7.52/tCO$_2$. Hence a £0.75/tCO$_2$ (10% of the average) increase in the EUA price is associated with a £0.42/MWh (0.9% of the average) increase in the wholesale price. The impact is slightly higher than the estimates from Table 2,[36] but we still could not reject the null that the EUA price has been fully passed through to the wholesale price in the long-run.

A final insight from regression (ii) is that if the GBP/EUR exchange rate falls by a thousand basis points (or by 0.1), one would expect the wholesale price to rise by 11.45%, or equivalently, by £5.29/MWh on average. Again, this is close to the estimator from the preliminary case in Table 2, and we do not reject the null that the exchange rate variation has been fully passed-through to the wholesale price.

5.2.2 Peak *v.s.* off-peak

In order to investigate whether the PTR depends on the underlying period of the day, Regression (iii) distinguishes between peak (07:00-23:00, WET/WEST) and off-peak (23:00-07:00, WET/WEST) periods.[37] We calculate the daily average peak and off-peak wholesale prices to replace P_t^{GB} in $\boldsymbol{y}_t$ (in (8)), hence we have $\boldsymbol{y}_t = (P_t^{\mathrm{GB,OFF}}, P_t^{\mathrm{GB,PEAK}}, P_t^{\mathrm{COAL}}, P_t^{\mathrm{GAS}}, P_t^{\mathrm{EUA}}, e_t)'$. In other words, we use one

[35] Wholesale prices, coal and gas prices, and EUA prices.
[36] 0.42/0.75=0.56 against 0.46.
[37] The results are not sensitive to the definision of peak and off-peak hours.

structural VECM to estimate peak and off-peak effects simultaneously. The Johansen cointegration tests suggest two cointegrating equations in Regression (iii),[38] which is intuitive because one would expect one cointegratng equation for peak periods, and another for off-peak periods.

The result from regression (iii) suggests that the time of the day has little impact on the long-run relationship between fuel prices and the wholesale price. Instead, it has some more substantial influences on the long-run effects of the EUA price on the wholesale price — during off-peak periods, the effect is insignificantly different from zero, while during peak periods, the estimate is 54% greater than the estimate from the preliminary case (Table 2). (Recall that in the preliminary case, we estimate the average pass-through rate over peak and off-peak.) Consequently, this gives a 0% EUA price PTR for off-peak periods, while a greater-than-100% EUA price PTR for peak periods.

The exchange rate PTRs for peak and off-peak periods are also different. Given that the average wholesale price during the period of study is £38.59/MWh and £50.06/MWh for off-peak and peak periods, respectively, the exchange rate PTR is 40%(s.e.=23%) for off-peak periods and 135%(s.e.=28%) for peak periods.

Finally, we fail to reject the null that the rates of adjustment (for the wholesale price towards long-run equilibrium) are identical between peak and off-peak. Specifically, off-peak prices converge to their long-run equilibrium (EC_{t-1}^{OFF}) at a rate of 55.9%, while peak prices converge to their long-run equilibrium (EC_{t-1}^{PEAK}) at a rate of 54.2%.

5.2.3 Weekdays *v.s.* weekends

Regression (iv) investigates heterogeneous PTRs between weekdays and weekends. To do this, we first separate the wholesale price into two subsets based on weekdays and weekends. This, however, creates gaps in each of the time series. To deal with this issue, we then aggregate both time series from daily to weekly and construct two time-series sequences with weekly frequency — one representing weekdays and the other representing weekends. We also aggre-

[38]See Appendix 7.3 for test statistics.

gate the daily data of fuel and carbon prices, exchange rates, as well as other exogenous variables to weekly data,[39] and then construct the VECM, where vector of dependent variables $\boldsymbol{y}_t = (P_t^{\text{GB,W.DAY}}, P_t^{\text{GB,W.END}}, P_t^{\text{COAL}}, P_t^{\text{GAS}}, P_t^{\text{EUA}}, e_t)'$. Similar to Regression (iii), the Johansen cointegration test suggests two cointegrating equations in Regression (iv),[40] one for weekdays and the other for weekends. The lag length for the level model (8), suggested by AIC, is set to 1. This is not surprising because in this case, t represents weeks instead of days.

The result shows that weekdays and weekends have little impact on the long-run relationship between fuel and wholesale prices. However, its impact on the long-run relationship between carbon and wholesale prices, as well as the long-run relationship between exchange rates and wholesale prices are significant. Specifically, a £1/tCO_2 increase in the EUA price would on average raise the wholesale price by £0.66/MWh during weekdays, but by £0.31/MWh during weekends. Provided the estimates of the MEFs for the GB electricity supply for weekdays and weekends in Appendix 7.1, the point estimate of the EUA price PTR during weekdays is 150% if the entire supply from imports and PS comes from CCGTs, or 121% otherwise. The point estimate of the EUA price PTR during weekends is 73% if the entire supply from imports and PS comes from CCGTs, or 58% if it entirely comes from coal. The difference is non-negligible, though none of the estimates is statistically significantly different from 100%.

The exchange rate PTRs are also different between weekdays and weekends. Given that the average wholesale price is £47.00/MWh during weekdays and £44.29/MWh during weekends, the exchange rate PTR is 148%(s.e.=28%) for weekdays and 78%(s.e.=15%) for weekends. Similar to the EUA case, although none of the estimates suggests that the exchange rate PTR is significantly different from 100%, the result does suggest the PTRs are significantly different between weekdays and weekends.

Finally, because one lag in the weekly data is equivalent to seven lags in the daily data, the speed of convergence to the long-run equilibrium is substantially higher using the weekly relative

[39] The fuel prices, carbon prices, exchange rates are only available for weekdays, as the trading platforms are closed during weekends. Therefore, the aggregation for those variables are the weekday averages.

[40] See Appendix 7.3 for details of the test result.

to the daily data.

5.2.4 Heterogeneity in the cost pass-through: A discussion

In Sections 5.2.2 and 5.2.3, we show heterogeneity in the carbon price and exchange rate PTRs for different time of the day, and different day of the week. The intuition for the heterogeneous PTRs between peak and off-peak is that it is costly for fossil plants to shut down during off-peak and restart during peak. Instead, fossil plants are usually running at minimum load during off-peak and ramp-up to deliver when demand and price rise, achieved by deploying different bidding strategies between peak and off-peak.

During off-peak periods, the utilisation rate of generation capacity is low, meaning that if a CCGT plant bids according to its marginal cost, the system would dispatch other cheaper power plants to meet the off-peak demand. If that is the case, the CCGT plant will have to shut down during the off-peak, resulting in much higher total cost. Given this, a better strategy for the CCGT plant is probably to have the off-peak bids lower than its marginal cost, ensuring it to supply at the minimum load during the off-peak.

During peak periods, the utilisation rate of generation capacity is high, meaning that the CCGTs can exercise market power to bid at some rates higher than the marginal costs. The CCGTs would have a strong incentive to do so because otherwise, their overall profit would most likely to be negative due to the off-peak loss.

Our estimation results in Regression (iii) suggests that the bidding strategy for fossil plants, especially CCGT plants,[41] is that when bidding for the off-peak supply, they completely ignore the EUA price markups, and ignore some of the exchange rate markups. It also suggests that the CCGTs would take gas price markup into full consideration when bidding for both peak and off-peak periods. This is not surprising as gas price constitutes about 70% of the marginal cost of electricity generation from a CCGT plant.[42] During peak periods, however, the CCGTs would over-count the input costs from EUA and exchange rate markups, to compensate losses from the

[41] Recall that CCGTs set the DA electricity price over 80% of the time.

[42] This is roughly estimated from Table 1, by dividing the average gas price by the average GB DA price.

off-peak operation.

The same logic applies to the heterogeneous PTRs between weekdays and weekends. Electricity demand is lower during weekends than weekdays.[43] To avoid shutting down during weekends, fossil plants, especially CCGTs, would lower their bids during weekends, and compensate their losses through bidding at higher rates during weekdays. Similar to the within-day heterogeneity (peak *v.s.* off-peak), our result from Regression (iii) suggests that when bidding for the weekend supply, the CCGTs would fully count in gas price markups and ignore some of the carbon price and the exchange rate markups. During weekdays, the CCGTs would bid at prices higher than the marginal cost, to compensate the losses from weekends.

6 Policy Implication

Recall the preliminary estimation result in Table 2 shows that a £1/tCO_2 increase in the EUA price is associated with a £0.46/MWh increase in the GB DA wholesale electricity price. It also shows that a 0.1 increase in the GBP/EUR exchange rate is associated with a £5.33/MWh increase in the DA wholesale electricity price.

As shown in Figure 1, the GBP/EUR exchange rate fell after the Brexit referendum from an average of 1.29 (1 Jan 2016 - 23 Jun 2016) to an average of 1.17 (24 Jun 2016 - 31 Dec 2016). Our estimation shows that, conditional on fuel and carbon prices, the exchange rate depreciation has raised average electricity prices by £6.40/MWh. Assuming that electricity retailers entirely pass through their wholesale costs to retail prices (and domestic tariffs), and given that the total GB electricity load in 2017 was about 300 TWh,[44] we conclude that the referendum led to an increase in GB electricity bills by £1.9 billion in 2017. Given that domestic users (GB households) consumed 35% of the country's total electricity consumption,[45] and that in 2017 there were 26.4

[43] During the period of studying, the electricity load during peak periods is 35.14 GW, and that during off-peak periods is 30.98 GW.

[44] Aggregated from the half-hourly actual electricity load from ENTSO-E Transparency Platform.

[45] https://www.statista.com/statistics/550592/uk-electricity-consumption-by-final-users/.

million GB households,[46] the electricity bill for an average household in GB has been increased by an additional £25.2 in 2017, or a 4.1% increase in the average bill.[47]

At the time of writing, although the EU has allowed a further extension of Brexit to 31 January 2020, a general election has been called, and the future of Brexit remains uncertain. In a worst-case scenario, a no-deal Brexit is expected to further lower the GBP/EUR exchange rate to 1.03,[48] or by 0.1 relative to the 2018 average level. Our estimations show this would, on average, further raise the electricity price by £5.33/MWh. On the back of this, a no-deal Brexit would further raise the total electricity bill in GB by £1.6 billion/year, or £21.2/household/year.[49]

Finally, anticipating the introduction of the Market Stability Reserve (MSR) resulted in a drastic increase in average EUA prices, which climbed from £5.16/tCO_2 in 2017 to £14.14/tCO_2 in 2018. The £9/tCO_2 increase in the EUA price is associated with a £4.13/MWh rise in the GB day-ahead electricity price. Assuming the wholesale cost has been fully passed through to retail prices, anticipation of the MSR has raised the GB electricity bill by about £1.2 billion in 2018. About £420 million of this has been transferred to domestic users, corresponding to a £15.9 per year average increase in the typical household's annual electricity bill. This is equivalent to 2.6% of the average bill in 2018.

7 Conclusion

This paper assessed how major generation costs have been passed through to electricity prices. We started by contributing to the theoretical literature on market competition by using a simple Cournot competition model to show that the carbon price PTR equals the ratio between the partial effect of carbon prices on electricity prices and the Marginal Emission Factor (MEF) of the wider electricity system.

[46] https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/adhocs/005374totalnumberofhouseholdsbyregionandcountryoftheuk1996to2015

[47] https://www.statista.com/statistics/421318/uk-average-annual-domestic-standard-electricity-bills/.

[48] https://www.poundsterlinglive.com/gbp-live-today/12114-pound-to-euro-and-dollar-barclays-forecasts.

[49] These are approximations using 2017 data for the total GB electricity demand and the total number of British households.

We then used empirical econometrics to investigate the long-run relationships between the input cost of electricity generation and the British wholesale electricity price during 2015-2018. Based on the theoretical foundations set out, we estimated the PTR in the British wholesale electricity market. Among our results, we failed to reject the null that the gas price, carbon price, and the GBP/EUR exchange rate have been fully passed through to the electricity price, indicating a functioning competitive GB electricity wholesale market.

We also examine heterogeneity of the PTR between peak and off-peak periods hours, as well as between weekdays and weekends. Cost PTRs are found to be higher when electricity demand and generation capacity utilisation rates are high, which occurs during peak as opposed to off-peak periods, and during weekdays compared to weekends. We argue this is because it is costly for fossil generators to shut down and then start up again, hence generators are more likely to bid lower than their marginal costs rate during off-peak hours in order to maximise overall sales. On the other hand, the utilisation rate of generation capacity is high during peak periods, indicating that fossil-fuelled generators are able to exercise market power, in which case they will bid higher than its marginal costs when supplying at peak. We use our econometric results to extend this analysis, showing that during off-peak periods, fossil plants' bids are mainly based on fuel costs, while during peak periods, they vary with both fuel and carbon costs.

The study also considered how the 2016 Brexit referendum and the introduction of the EU's Market Stability Reserve have affected electricity prices in GB. We estimated that the referendum resulted in an average increase in GB electricity wholesale prices of £6.40/MWh. In other words, the vote has led to an increase in electricity costs for the average British household by £25.2 in 2017, corresponding to a 4.1% rise. We also estimated that a no-deal Brexit could further increase the GB electricity wholesale price by £5.33/MWh, which corresponds to an addition of £21.2/year to the average household's annual bill. Finally, the MSR is also shown to increases GB electricity prices, which it does by cancelling surplus carbon emission allowances. The MSR has resulted in a £4.13/MWh increase in the GB electricity price in 2018. This means that an average GB household would need to pay £15.9 (or 2.6%) on top of its current electricity bill due to the associated increase in the EU carbon price.

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Appendix

7.1 Estimating the Marginal Emission Factor of GB

To estimate the marginal fuel of the GB electricity supply, we replicate Chyong et al. (2020) and Staffell (2017) and run the following regressions:

$$\Delta Coal_t = \alpha_0 + \alpha_1 \Delta Wind_t + \alpha_2 \Delta Demand_t + \boldsymbol{\theta'_{Coal} X_t} + \varepsilon_t^{Coal},$$

$$\Delta CCGT_t = \beta_0 + \beta_1 \Delta Wind_t + \beta_2 \Delta Demand_t + \boldsymbol{\theta'_{CCGT} X_t} + \varepsilon_t^{CCGT},$$

$$\Delta PS_t = \gamma_0 + \gamma_1 \Delta Wind_t + \gamma_2 \Delta Demand_t + \boldsymbol{\theta'_{PS} X_t} + \varepsilon_t^{PS},$$

$$\Delta Import_t = \delta_0 + \delta_1 \Delta Wind_t + \delta_2 \Delta Demand_t + \boldsymbol{\theta'_{Import} X_t} + \varepsilon_t^{Import},$$

$$\Delta Hydro_t = \zeta_0 + \zeta_1 \Delta Wind_t + \zeta_2 \Delta Demand_t + \boldsymbol{\theta'_{Hydro} X_t} + \varepsilon_t^{Hydro},$$

where Δ denotes taking the first different, and $\boldsymbol{X_t}$ contains half-hourly dummy variables.

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.

7.2 Validity Test Statistics

We use the Augmented Dickey-Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to determine the existence of a unit root in the dependent variables. The ADF test uses Auto-Regression (AR) regressions to determine whether a time series variable is non-stationary, while KPSS is a reversed version which 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, the two tests give

Table 4: Estimating Marginal Fuels

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	89.369^{***}	164.669^{***}	-324.716^{***}	64.180^{***}	6.421^{***}
	(5.109)	(8.574)	(5.322)	(7.507)	(1.304)
$\Delta Wind_t$	-0.125^{***}	-0.676^{***}	-0.123^{***}	-0.053^{***}	-0.017^{***}
	(0.005)	(0.008)	(0.005)	(0.007)	(0.001)
$\Delta Demand_t$	0.190^{***}	0.602^{***}	0.119^{***}	0.059^{***}	0.021^{***}
	(0.001)	(0.003)	(0.002)	(0.002)	(0.000)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.444	0.805	0.467	0.102	0.308
Num. obs.	64469	64469	64469	64469	64469

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

different results, the time series is more likely to be an $I(0)$ process.

The unit root test results are shown in Table 7. All ADF tests contain a constant term and a trend term, therefore they test whether the dependent variables are trend stationary. 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 (1989) criterion. Our ADF test results fail to reject the null that all dependent variables in $\boldsymbol{y}_t$ in (8) 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 DA 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 lag lengths for dependent variables, p in (8), are determined by the AIC. As Table 8 shows, the optimal lag length is $p = 4$, or 3 lags for the VECM in (10).

As discussed in Section 4.2, the validity for the VECM requires the dependent variables to be cointegrated. The Johansen (1991) cointegration tests work on the canonical correlation of $\Delta\boldsymbol{y}_t$ and $\boldsymbol{y}_{t-1}$. The trace test tests the null hypothesis of r cointegrating vectors against the alternative

Table 5: Estimating Marginal Fuels, Peak *v.s* Off-peak

PEAK PERIODS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	-222.677^{***}	184.696^{***}	190.981^{***}	-175.384^{***}	10.767^{***}
	(7.526)	(11.910)	(6.914)	(10.345)	(2.147)
$\Delta Wind_t$	-0.141^{***}	-0.670^{***}	-0.124^{***}	-0.042^{***}	-0.022^{***}
	(0.006)	(0.009)	(0.005)	(0.008)	(0.002)
$\Delta Demand_t$	0.204^{***}	0.599^{***}	0.094^{***}	0.068^{***}	0.026^{***}
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.468	0.809	0.246	0.116	0.319
Num. obs.	43263	43263	43263	43263	43263

OFF-PEAK PERIODS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	48.208^{***}	172.591^{***}	-246.820^{***}	34.742^{***}	-8.260^{***}
	(5.154)	(9.936)	(6.736)	(8.816)	(0.722)
$\Delta Wind_t$	-0.090^{***}	-0.689^{***}	-0.118^{***}	-0.081^{***}	-0.006^{***}
	(0.007)	(0.014)	(0.010)	(0.013)	(0.001)
$\Delta Demand_t$	0.146^{***}	0.611^{***}	0.200^{***}	0.029^{***}	0.005^{***}
	(0.003)	(0.005)	(0.004)	(0.005)	(0.000)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.378	0.794	0.619	0.078	0.243
Num. obs.	21206	21206	21206	21206	21206

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

Table 6: Estimating Marginal Fuels, Weekdays *v.s* Weekends

WEEKDAYS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	115.033^{***}	162.257^{***}	-377.204^{***}	90.157^{***}	7.026^{***}
	(6.269)	(10.305)	(6.065)	(9.278)	(1.572)
$\Delta Wind_t$	-0.126^{***}	-0.683^{***}	-0.116^{***}	-0.056^{***}	-0.015^{***}
	(0.005)	(0.009)	(0.005)	(0.008)	(0.001)
$\Delta Demand_t$	0.209^{***}	0.564^{***}	0.116^{***}	0.080^{***}	0.022^{***}
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.471	0.820	0.512	0.125	0.311
Num. obs.	45658	45658	45658	45658	45658

WEEKENDS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	62.984^{***}	67.212^{***}	-185.153^{***}	50.585^{***}	12.262^{***}
	(8.743)	(14.967)	(10.205)	(12.439)	(2.370)
$\Delta Wind_t$	-0.118^{***}	-0.666^{***}	-0.138^{***}	-0.047^{***}	-0.022^{***}
	(0.008)	(0.013)	(0.009)	(0.011)	(0.002)
$\Delta Demand_t$	0.182^{***}	0.590^{***}	0.137^{***}	0.060^{***}	0.027^{***}
	(0.003)	(0.005)	(0.003)	(0.004)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.383	0.780	0.463	0.101	0.324
Num. obs.	18811	18811	18811	18811	18811

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

Table 7: Unit Root Tests

Variables	ADF tests*				KPSS tests		
	Lags	Stat.	p-value	Results**	Stat.	p-value	Results**
levels							
GB DA Prices	20	−3.24	0.08	I(1)	0.36	<0.01	I(1)
Coal Prices	0	−1.82	0.69	I(1)	0.31	<0.01	I(1)
Gas Prices	0	−2.46	0.35	I(1)	0.62	<0.01	I(1)
EUA Prices	14	0.22	1.00	I(1)	1.02	<0.01	I(1)
GBP/EUR XR	4	−1.99	0.60	I(1)	0.86	<0.01	I(1)
GB DA Renew. Gen	17	−5.67	0.00	I(0)	0.19	<0.05	I(1)
GB DA Demand	23	−2.66	0.25	I(1)	0.10	>0.10	I(0)
GB Nuclear Gen.	1	−7.73	0.00	I(0)	0.41	<0.01	I(1)
first differences							
ΔGB DA Prices	19	−13.02	0.00	I(0)	0.00	>0.10	I(0)
ΔCoal Prices	0	−37.37	0.00	I(0)	0.10	>0.10	I(0)
ΔGas Prices	7	−15.37	0.00	I(0)	0.06	>0.10	I(0)
ΔEUA Prices	23	−8.00	0.00	I(0)	0.07	>0.10	I(0)
ΔGBP/EUR XR	3	−20.32	0.00	I(0)	0.04	>0.10	I(0)
ΔGB DA Renew. Gen	17	−14.75	0.00	I(0)	0.08	>0.10	I(0)
ΔGB DA Demand	22	−8.08	0.00	I(0)	0.04	>0.10	I(0)
ΔGB 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

Table 8: AIC for Lag Lengths

Criterion	Lag Lengths						
	1	2	3	4	5	6	7
AIC	-13.02	-13.17	-13.15	-13.22*	-13.20	-13.19	-13.17

* optimal lag length suggested by AIC.

hypothesis of m (the number of sequences in $\Delta\mathbf{y}_t$) 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 9 indicate one cointegrating equation in the proposed VECM (10), and both tests are conducted at the 5% significant level.

Table 9: Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.14812	269.14	79.34	0.00
At most 1	0.01644	49.99	55.25	0.13
At most 2	0.01182	27.34	35.01	0.26
At most 3	0.00798	11.08	18.40	0.38
At most 4	0.00009	0.13	3.84	0.72

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.14812	219.14	37.16	0.00
At most 1	0.01644	22.66	30.82	0.35
At most 2	0.01182	16.25	24.25	0.39
At most 3	0.00798	10.96	17.15	0.32
At most 4	0.00009	0.13	3.84	0.72

* denotes rejection of the hypothesis at the 0.05 level.

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

7.3 Johansen tests results for Regressions (iii) and (iv)

Tables 10 and 11 report the Johansen cointegration test for the VECM specification discussed in Sections 5.2.2 and 5.2.3, respectively. Both tables suggest two cointegration equations.

Table 10: 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*	0.20132	515.91	107.35	0.00
At most 1*	0.10959	208.61	79.34	0.00
At most 2	0.01636	49.93	55.25	0.14
At most 3	0.01187	27.39	35.01	0.26
At most 4	0.00795	11.06	18.40	0.38
At most 5	0.00011	0.15	3.84	0.70

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.20132	307.30	43.42	0.00
At most 1*	0.10959	158.68	37.16	0.00
At most 2	0.01636	22.54	30.82	0.36
At most 3	0.01187	16.33	24.25	0.39
At most 4	0.00795	10.92	17.15	0.32
At most 5	0.00011	0.15	3.84	0.70

* denotes rejection of the hypothesis at the 0.05 level.

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

Table 11: Cointegration Tests for Regression (iv), Weekdays *v.s.* Weekends

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.51475	293.41	107.35	0.00
At most 1*	0.42186	153.13	79.34	0.00
At most 2	0.09995	46.83	55.25	0.22
At most 3	0.08100	26.40	35.01	0.31
At most 4	0.04737	10.02	18.40	0.48
At most 5	0.00309	0.60	3.84	0.44

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.51475	140.28	43.42	0.00
At most 1*	0.42186	106.30	37.16	0.00
At most 2	0.09995	20.43	30.82	0.52
At most 3	0.08100	16.39	24.25	0.38
At most 4	0.04737	9.41	17.15	0.45
At most 5	0.00309	0.60	3.84	0.44

* denotes rejection of the hypothesis at the 0.05 level.

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