Analysis of the Fundamental Predictability of Prices in the British Balancing Market

Derek W. Bunn[1], John N. Inekwe and David MacGeehan

Abstract—**This research analyses the non-linear and complex effects of drivers of system imbalance prices in the GB electricity market. Unlike day-ahead prices, the balancing settlement prices are comparatively under-researched, yet their importance is growing with greater market risks. The fundamental drivers of these prices are analysed over 2016-2019. The result of a non-linear modelling approach reveals that system imbalance price exhibits a regime-switching behaviour, driven by weather and demand forecast errors, as well as other system effects. Surprisingly, balancing prices are predictable out of sample and a regime switching specification is more accurate than a linear model for prediction.**

***Index Terms*— Electricity Imbalance Prices; Balancing Market; Regime-switching; Forecasting**

I. INTRODUCTION

ELECTRICITY System Operators have always been faced with the task of balancing the real-time production and consumption of power to ensure that the load stays close to the target frequency. With liberalisation, market mechanisms are increasingly being implemented to provide these required balancing services on a competitive basis. In these situations, the System Operator (SO) becomes the counterparty to bids and offers from market participants, who are competing to provide the balancing services. Furthermore, it is the market participants themselves who cause the need for the balancing power, as they inevitably deviate to some extent in real time from their prior production and consumption nominations to the SO. To the extent that the participants' nominations reflect their rational ex ante expectations of actual production and consumption during delivery periods, their ex post imbalance volumes (ie, metered deviations from nominations) should be surprises. Furthermore, the participants' exposures to balancing costs will depend both upon their imbalance volumes and the imbalance prices applied according to the balancing market design. As balancing costs are increasing with the penetration of renewables and distributed resources [1, 2, 3, 4], forecasting imbalance prices is of material interest to participants in their risk management. Yet, if imbalance volumes are surprises, and imbalance prices flip from positive to negative depending upon the sign of the net market imbalances, then imbalance prices should be unpredictable, especially in a mature and liquid market. We test this efficiency conjecture by seeking to estimate and backtest a forecasting model for the British imbalance prices. The GB balancing market is a good test, having started in 2001, it is one of the most mature.

In contrast to the day ahead wholesale prices, the forecasting of balancing prices has not been researched so extensively. We contribute to methodology in this context and investigate the role of market transparency for improving predictability. We find that balancing prices are predictable and offer some comments on the implication of this for trading and risk management. A further contribution of the research is in the application of adaptive regime switching methods. The benefits of this class of nonlinear methods have been controversial, with various researchers having suggested that it is hard to outperform linear models, but with imbalance prices switching signs over time, this application turns out to be a successful case for regime-switching models.

The analysis was applied to the daily data of 48 half hour delivery periods in the British electricity market during 2016 - 2019. Britain reformed its electricity trading in 2001 to include a balancing market and that has since evolved through various market design changes, most notably in 2015, which is why we do not go back further. We use the entire sample for a descriptive analysis to understand the effects of potential drivers of price formation with Markov switching regressions. Then we consider out-of-sample forecasting using rolling window estimation. The use of the Markov non-linear approach outperforms a linear comparator.

The paper is organised as follows. Section 2 gives an overview of studies relating to imbalance prices. Section 3 describes the British balancing mechanism and electricity price behaviour. Section 4 presents the data and forecasting methodology. In Section 5 the results are presented, and Section 6 concludes.

II. RESEARCH ON BALANCING SYSTEMS

A balancing system includes a set of economic and technical arrangements that are used to ensure or restore short-term power balances [1]. Two economic mechanisms are involved: the balancing mechanism (for the SO to acquire balancing power) and the imbalance settlement system (to clear participant imbalances financially). One of the earliest studies by Just and Weber [5] examines the pricing of reserves and the interdependencies between markets for spot electricity and secondary reserve capacity. Vandezande, Meeus, Belmans, Saguan and Glachant [6] examine the design of balancing markets in Europe taking into account the increasing wind power penetration. The Nordic balancing system is surveyed in Kristiansen [7]. A framework for policy-makers is provided in van der Veen and Hakvoort [8] with the aim of identifying the relevant performance criteria and design variables that are relevant in the design and analysis of European balancing markets. Möller, Rachev and Fabozzi [9] study the balancing

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energy strategies in electricity portfolio management. In the analysis of bidding strategies for retailers with flexible demands, Song and Amelin [62] show the extent to which larger imbalances may be to the detriment of profits.

Thus, while various studies have focused on the design of the balancing market [56-60], the forecasting of its price movements is under-researched [61-63]. Marneris, Roumkos, and Biskas [57] present a study on balancing market integration in the European region, while Wu and Zhou [59] recommend a dual pricing mechanism for balancing markets. Kraft, Keles, and Fichtner [61] identify the advantages of both neural and econometric approaches for forecasting balancing prices. In [13] the difficulty for forecasting balancing prices in the Nordic system was demonstrated. A theoretical model by Aïd, Gruet and Pham [29] aims at minimising the imbalance from electricity demand residuals, using thermal power generation to mitigate fluctuations in wind energy outputs. In the Spanish energy market, Bueno-Lorenzo, Moreno and Usaola [30] investigate the relationship between supply-demand imbalance and wind energy, whilst Garcia and Kirschen [31] found no clear linear relationship between imbalance volumes and other market variables. However, more recent studies than [31] have found some determinants of imbalance volumes and prices. Based upon lagged imbalances and loads, Lisi and Edoli [32] show that the sign of the zonal imbalance markets in Italy is predictable. Ocker and Ehrhart [33] provide the evidence that the German generators orientate their offers towards previous auction prices and that they coordinate on prices above the competitive levels. More general studies on electricity markets have mainly focused on predicting day-ahead electricity prices [9-16] as well as intra-day and related trading aspects [17-28]. In particular, Pape, Hagemann and Weber [14] find that a large part of electricity price variance is explainable by fundamental modelling.

The impact of renewables on the balancing mechanism is receiving increasing attention. Kiesel and Paraschiv [19] use German quarter-hourly intraday electricity prices to assess the effect of intraday updated forecasting errors of wind and photovoltaic production on intraday prices. They show that intraday prices adjust asymmetrically to both the volume of trades and forecasting errors in renewables. Thus, prior information on renewables' forecasts, as well as demand/supply exogenous variables are explanatory. Mureddu and Meyer-Ortmanns [34] find that prices have skewed distributions because of renewable effects. A study by Goodarzi, Perera and Bunn [35] find that higher wind and solar forecast errors increase the absolute values of imbalance volumes and that these can pass through into higher spot electricity prices. They find that in Germany, solar forecasting errors impact spot prices less than wind forecast errors.

From the background of this research, we provide an extension to these existing studies by analysing the nonlinear determinants of imbalance prices and, most importantly, their potential predictability.

III. GB Balancing Price Formation and Behaviour

The British Balancing Mechanism operates on 30 minute intervals ("Settlement Periods", SP) during which forward commitments are delivered and over which imbalance volumes are settled. An hour prior to each SP all participants must notify the SO of their expected physical positions for the SP, ie what they expect to generate or consume during that half-hour. This point is known as "gate-closure" and at this point all flexible generators (or demand side aggregators) also inform the SO of their offers/bids to increase/reduce generation (or reduce/increase demand). Based upon these offers and bids, the SO produces an order book and throughout the settlement period continuously accepts the most economic bids and offers to balance the system and ensure the system frequency remains at 50Hz. In practice many offers and bids are accepted on a minute by minute basis to control the balancing. In Figure 1, we see the sequence of accepted bids and offers over three SPs in 2018. Since there are 48 SPs in a day, the periods 8, 9 and 10 refer to 4am, 4.30am and 5am. Within each SP the sequence of progressively accepting higher offers and lower bids appears to be economically efficient. But then each settlement period is an episode and the process tends to repeat, as shown. This suggests that the episodic nature of the settlement period balancing is inducing potential predictability. Hence the reason for our predictability conjecture.

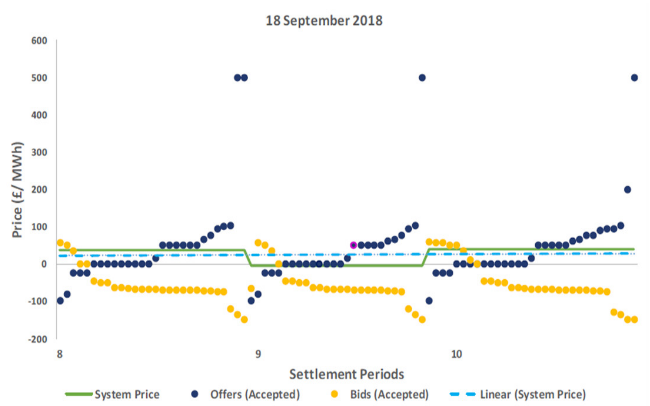

Figure 1: Accepted bids and offers over three settlement periods in 2018. Data from Elexon: www.elexon.co.uk

Evidently, the system requires the balancing services because individual participants are deviating from the nominations that they made at gate-closure, most significantly from demand forecasting error but also due to the variable production from renewables. The costs that the SO incurs in balancing should at least partially be recovered from pricing the extent to which individual participants are out of balance. Thus, there is a System Imbalance Price which each participant will pay on its imbalance volume (the difference between ex ante nomination and ex post metered volumes in the SP). This System Imbalance Price is computed, in GB, as the marginal cost to the SO in each SP. To get the marginal cost, the SO derives the Net Imbalance Volume for each SP as the net amount of offer and bid volumes accepted over the 30mins. Thus, if the system is short, the SO will be accepting more offers than bids, and the Net Imbalance Volume (NIV) will be positive. NIV will be negative conversely if the system is long (eg more wind production than anticipated). The System Imbalance Price will be the marginal offer accepted at a positive NIV, or marginal bid paid at a negative NIV. Offers will be higher than the marginal generation cost of participants, whilst bids will be lower than the marginal generation costs; otherwise generators would not place those offers and bids for increasing or reducing output. Bids will be lower than marginal cost for a generator because if accepted it would allow the generator to fulfil its forward commitment (contract) by buying power from the system and reducing its own output. Thus the System Imbalance Price will be higher or lower than marginal costs according to whether the system is short or long in each period. Figure 2 shows System Imbalance Prices against NIVs for all SPs in September 2019. The negative values result from subsidised facilities, such as wind, whose marginal cost of production is not zero but the negative value of the subsidy paid for their production.

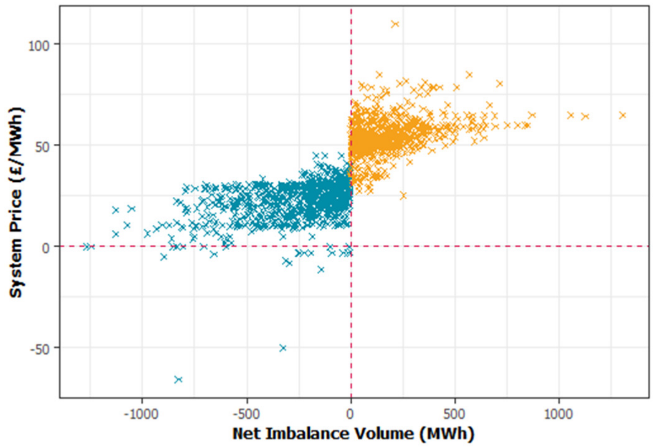

Figure 2. System Imbalance Price (£/MWh) against NIV for July 2019. Source: Elexon (www.elexon.co.uk)

All of this means that if a participant is out of balance in the opposite direction to the system, it may be profitable. For example, if a generator is short, ie it is producing less than it nominated, and the system is long, it may pay an imbalance price less than its marginal cost of production. Since its nomination reflected a forward sale, in this case it may be able to fulfil its sale at less than its marginal cost of production, Conversely it can profit by being long against a short market. The economic intuition is that in both cases the participant is helping the system by being out of balance in the opposite direction to the system, and therefore should benefit. The implication of this is that there is an incentive for participants to forecast the system imbalance and seek to be out of balance in the opposite direction. There is strong evidence this is happening in GB, and indeed that the regulatory authority tolerates it.

This speculative trading against the direction of NIV became possible after November 2015 when the trading rules changed to the new system. Figure 3 shows that since 2015 there has been a steady increase in the growth of trading against NIV by the non-physical (speculating) market participants in particular. Furthermore, from April 2019, a further market rule change allows participants to trade after gate closure, throughout the hour prior to the SP. They cannot change their nominations to the SO but they can adjust their trading positions. Figure 4 shows how the volume of intraday trading increased following this rule change. Presumably this allows speculation on System Imbalance to be closer to real time as well as helping participants adjust to their own forecast errors

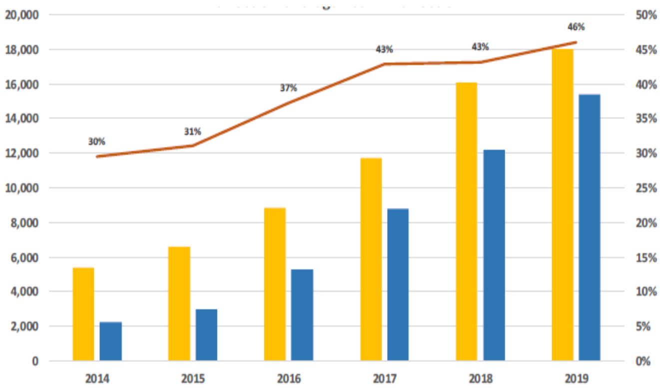

Figure 3. The Increase in Trading Against NIV in GB. Left scale is daily NIV with light bars in NIV direction, dark bars against NIV direction; right scale is % against direction of NIV. (Source: Elexon, www.elexon.co.uk)

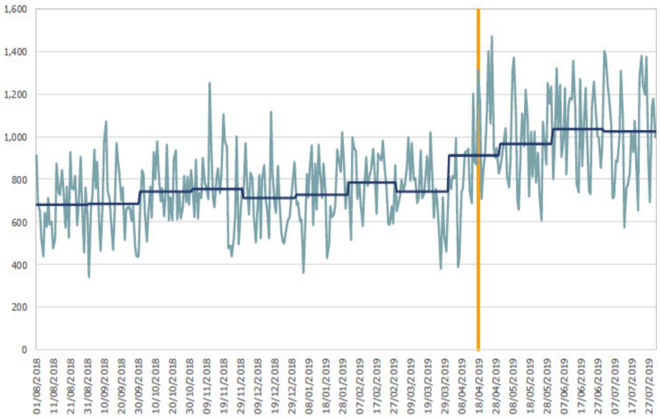

Figure 4: Market Intraday Volume, with monthly averages and step change after April 2019. (Source: www.elexon.co.uk)

As a consequence of this, 30% of the intraday trading in 2019 was within that final hour before real time, and 55% within two hours of the real time SP. The anecdotal evidence above suggests that much of that may be derived from the attraction of seeking to forecast the System Imbalance Prices and speculatively arbitrage against them. This raises the question of how it might be possible to forecast the imbalance prices, and, in particular, whether useful forecasts can be specified through models of transparent market fundaments.

IV. Forecasting System Imbalance Prices

We therefore analyse the predictability of the system balancing prices. Recalling Figure 2, there is a clear attraction to consider a regime-switching model, as there are distinct empirical densities according to whether NIV is positive or negative. This is quite a different application of regime-switching to that which has previously appeared in the electricity price modelling and forecasting research. Typically researchers have been attracted to regime switching models to capture the recurrent episodes of scarcity in power markets manifesting price spikes and high volatility. The intuition has been that power price modelling reverts between two regimes, one characterising regular behaviour and the other scarcity. Markov regime switching can model this with essentially two distinct regression equations representing the regimes and a transition probability matrix driving the switches from one regime to the other. Thus, the existence of regime shifts in the price formation process was identified in [12], theoretically motivated by the multiple equilibria in electricity identified in auction theory [36, 37]. Following its econometric foundations [38-41], there have been many applications of Markov regime switching in electricity price modelling [42-50]. However, despite its in-sample fitting successes, whether it offers a robust accuracy advantages in out-of-sample forecasting has been doubted (see the discussion in [51]). Thus, one of the modelling questions in this research is to see if this is a case study in which regime-switching outperforms a linear comparator.

We implement an extension of the conventional Markov regime-switching model of Hamilton [39, 54, 55] to allow for time varying probabilities. The regime-switching regression with two regimes can be specified as:

$$P_t = X'_t \beta_{R_t} + \varepsilon_t \,, \qquad (1)$$

where $\varepsilon_t \sim N(0, \sigma^2_{R_t})$. P_t is the system price on day t and in load period k, (for simplicity, the subscript k is omitted), R_t is a latent regime state variable at time t, indicating one of two regimes. X_t is a vector of regressors at time t, β_{R_t} is the regime dependent vector of regression coefficients, $\sigma^2_{R_t}$ is the regime-dependent, error variance. The time-varying transition probability between the two regimes is specified through a logistic function to depend upon a lagged exogenous variable, in our case, NIV two periods earlier. The two period lag provides market participants time to act on the latest information revealed to the market.

V. DATA

The GB data were obtained from the Balancing Mechanism Reporting Service (BMRS) provided by ELEXON (www.elexon.co.uk), extracted using the Application Programming Interface (API) function of BMRS to query a range of market metrics. The sampling period was specified from 1st July 2016 to 30th June 2019, providing 3 years of historical data for developing and testing the statistical model. There are 48 data points per day, each representing an SP, resulting in a total of 52,560 data points within each time series.

The variables selected for the model can be categorised as either market state measures (System Price, Net Imbalance Volume), demand and supply forecast errors (Wind Error, Solar Error, Demand Error), or scarcity indicators in the supply and availability of power volumes (De-rated Margin, NONBM, Inter Delta). Descriptions of the variables are in Table I, together with their anticipated effects on system imbalance prices. Each variable has data available within the forecast lead time of two periods, or is composed from real-time out-turn data and day-ahead forecasts that are readily available ahead of the forecast lead time. This is a more extensive set of fundamental variables than is often reported in research on electricity price forecasting. Note that SO actions that relate to operational factors such transmission constraints, voltage control, etc, are not included in the energy balancing calculations, and so we do not have to consider them in the price modelling. Some of the slower moving fundamentals such as gas and coal prices are not included as they will be picked up in the lagged price variable. Thus, imbalance prices are modelled and forecast entirely from short-term market information available to the market.

TABLE I: DESCRIPTIONS OF VARIABLES

Variable	Description
System Price (*£/MWh*)	System Price is the dependent variable and we also use lags of two periods and beyond as predictive variables. *We expect lagged effects to be positive on price.*
Net Imbalance Volume (*MWh*)	Net Imbalance Volume is the sum of all energy balancing buy and sell actions, netted to give the overall system energy imbalance for each settlement period. A positive value represents a shortage of power in the market, and a negative value represents a surplus of power. *We expect lagged effects to be positive on price.*
De-Rated Margin (*MW*)	De-Rated Margin is the difference between the combined generation forecast and the capacity requirement for the market. It is a measure of how much spare generation capacity is available within the power network, ie an inverse measure of scarcity. *We expect lagged effects to be negative on price.*
Wind Error (*MW*)	Wind Error is the difference between actual total wind generation, including onshore and offshore assets, within each settlement period and the day-ahead forecast made the night before. This variable is a measure of the error in the day-ahead wind generation forecast
Solar Error (*MW*)	Solar Error is the difference between actual solar generation within each settlement period and the day-ahead forecast made the previous day. It is a measure of the error in the day-ahead solar generation forecast
NONBM (*MWh*)	The Non-Balancing Mechanism Short Term Operating Reserve (STOR) is the volumes instructed by the system operator within each settlement period to either increase generation or reduce demand on pre-contracted terms with market participants. These are volumes outside of the balancing mechanism
Inter Delta (*MWh*)	Inter Delta is the change in interconnector import-export netted volumes between subsequent settlement periods, summed across five major UK interconnectors. It is a measure of the short-term change in power market volume supplied from outside of the UK
Demand Error (*MW*)	Demand Error is the difference between initial national demand out-turn for the settlement period and the day-ahead national demand forecast made the previous day. National demand figures include transmission losses but exclude interconnector flows, station transformer demand and pumped storage demand. This variable is a measure of the error in the day-ahead national demand forecast

As in Karakatsani and Bunn [12], the logarithmic transformation of electricity prices is not used. Using the level series is reasonable since the statistical price properties which are of interest in the study could be masked by the transformation, and the effects of fundamentals might become restricted to an exponential form, though other monotonic relationships are desirable

Time series checks on all variables confirmed stationarity with Augmented Dickey-Fuller and Phillips–Perron unit root tests, and for the System Price series, the Bai and Perron [53] test of multiple breaks indicated multiple regimes. Figure 5 shows the System Price time series, with is spikey episodes, volatility clustering and occasional negative prices.

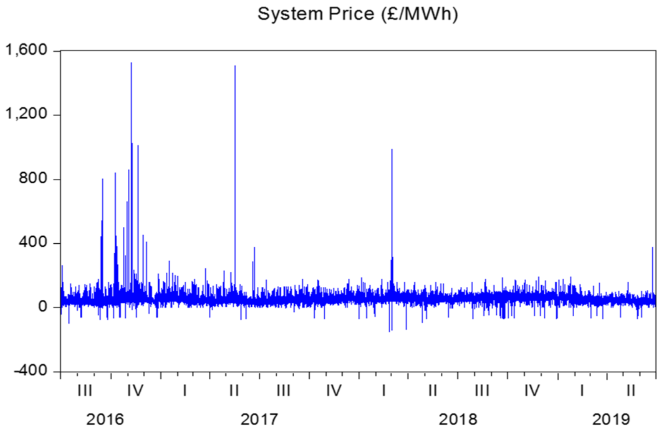

Figure 5: System Prices 2016-2019

VI. Model Performance

In Table 2 we report the results of the in-sample model as estimated in EViews. Note all exogenous variables are lagged by 2 to reflect market information availability.

Table 2: In-sample 2-Regime Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
WINDERROR(-2)	-2.58E-05	1.36E-05	-1.907351	0.0565
SOLARERROR(-2)	-0.000161	3.54E-05	-4.558716	0.0000
NONBM(-2)	0.000177	0.000225	0.786973	0.4313
NET_IMBALANCE_VOLUME__MWH_(-2)	0.000296	4.32E-05	6.845599	0.0000
INTERDELTA(-2)	5.93E-05	3.64E-05	1.628586	0.1034
DRM_1H(-2)	-0.000108	4.59E-06	-23.50407	0.0000
DEMANDERROR(-2)	4.80E-05	2.42E-05	1.987092	0.0469
C	53.56324	0.232599	230.2815	0.0000
AR(2)	0.405136	0.005306	76.35553	0.0000
LOG(SIGMA)	3.154714	0.004069	775.2741	0.0000
Regime 2				
WINDERROR(-2)	-1.26E-05	8.98E-06	-1.398399	0.1620
SOLARERROR(-2)	-0.000203	2.77E-05	-7.312905	0.0000
NONBM(-2)	0.000655	0.000213	3.069159	0.0021
NET_IMBALANCE_VOLUME__MWH_(-2)	-0.000537	3.21E-05	-16.72509	0.0000
INTERDELTA(-2)	0.000115	1.87E-05	6.136785	0.0000
DRM_1H(-2)	-9.76E-05	4.25E-06	-22.97483	0.0000
DEMANDERROR(-2)	0.000108	1.71E-05	6.303402	0.0000
C	53.29524	0.231590	230.1274	0.0000
AR(2)	1.000238	0.000336	2977.509	0.0000
LOG(SIGMA)	-0.182689	0.011919	-15.32798	0.0000
Transition Matrix Parameters				
P11-C	1.292509	0.016829	76.80172	0.0000
P11-NET_IMBALANCE_VOLUME__MWH_(-2)	0.000753	4.92E-05	15.29360	0.0000
P21-C	-0.411702	0.019307	-21.32368	0.0000
P21-NET_IMBALANCE_VOLUME__MWH_(-2)	0.001242	5.00E-05	24.85150	0.0000

We observe that all signs are as expected and generally all variables have high significance. By examination, Regime 1 corresponds to positive NIV, and we observe that the negative coefficient for lagged NIV in Regime 2 is associated with negative NIVs, and so our sign expectations remain consistent. Interestingly wind forecast error is significant at 5.6% in regime 1 and only at 16.2% in regime 2. This significance is weaker than expected and may imply that wind generators are able to hedge their risks, particularly for negative NIV when they may be curtailing. Likewise Non BM reserve is only significant in negative NIV, perhaps because of its more selective use for turn-down operation. The transition matrix parameters refer to a logistic regression on lagged NIV and the main take-away is the strong significance. In other words lagged NIV is a strong driver of regime-switching in the price formation model. The RMSE for this model is 19.29 and the Pseudo R-Sq is 38%.

The inclusion of extra lags were significant but weakened the significance of some of the exogenous variables and only provided a tiny improvement in the RMSE to 19.27. As for the linear benchmark with extra lags, this offered comparable, very slightly better, fit with an RSq of 39% and RMSE of 18.98, but lower significance for the exogenous variables (see Table 3)

Table 3: In-sample Linear Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WINDERROR(-2)	0.000157	0.000112	1.394160	0.1633
SOLARERROR(-2)	-0.005351	0.000437	-12.23887	0.0000
NONBM(-2)	0.006212	0.002923	2.125380	0.0336
NET_IMBALANCE_VOLUME__MWH_(-2)	0.009928	0.000488	20.34777	0.0000
INTERDELTA(-2)	0.002531	0.000271	9.337105	0.0000
DRM_1H(-2)	-0.000728	3.93E-05	-18.51082	0.0000
DEMANDERROR(-2)	0.002614	0.000283	9.246473	0.0000
C	58.59794	0.637716	91.88726	0.0000
AR(2)	0.433722	0.009314	46.56515	0.0000
AR(3)	0.020829	0.007201	2.892406	0.0038
AR(4)	0.036499	0.006551	5.571328	0.0000
AR(5)	0.096626	0.007075	13.65689	0.0000
Root MSE	18.98426	R-squared		0.392549

We also compared with a Linear GARCH(1,1) model to include volatility. Regime-switching captures volatility clustering to some extent, as there is a different variance term in each regime, but a GARCH model is a conventional benchmark. The In-sample GARCH fit is shown in Table 4.

Table 3: In-sample Linear GARCH(1,1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
WINDERROR(-2)	0.000118	9.35E-05	1.257558	0.2086
SOLARERROR(-2)	-0.004756	0.000373	-12.75347	0.0000
NONBM(-2)	0.003932	0.002199	1.788210	0.0737
NET_IMBALANCE_VOLUME__MWH_(-2)	0.006996	0.000355	19.72302	0.0000
INTERDELTA(-2)	0.001690	0.000239	7.077209	0.0000
DRM_1H(-2)	-0.000570	4.18E-05	-13.63591	0.0000
DEMANDERROR(-2)	0.002019	0.000242	8.332364	0.0000
C	53.69590	0.785296	68.37667	0.0000
AR(2)	0.386298	0.007068	54.65518	0.0000
AR(3)	0.105567	0.006595	16.00836	0.0000
AR(4)	0.051107	0.006100	8.378899	0.0000
AR(5)	0.090805	0.005960	15.23626	0.0000
Variance Equation				
C	94.53048	5.335302	17.71793	0.0000
RESID(-1)^2	0.373924	0.012552	29.78964	0.0000
GARCH(-1)	0.371616	0.023797	15.61641	0.0000
R-squared	0.385224	Mean dependent var		48.32822

Whilst the volatility terms are clearly very significant, the fundamental drivers of the mean equation are similar, as expected with GARCH modelling, and the RSq is the same as the regime switching at 38%. Whilst GARCH models provide better representations of heteroskedasticity and the coefficient estimates, they rarely improve the mean forecasts.

Overall, we would argue that the regime-switching in-sample model is satisfactory in its structural interpretation and gives clearer insight on the relative impact of the plausible exogenous variables of the two regimes for positive and negative Imbalance price formation. The two period lags indicate potential predictability but this needs to be confirmed with out of sample back-testing.

To do this we looked at the final 4,000 observations in 2019, estimated the regime switching and linear models on the first 2,000 observations of these and then successively forecast one period ahead with rolling re-estimation throughout the final 2,000 out-of-sample observations. The forecasting results are in Table 4:

Table 4: Out-of-sample Backtest Comparison

Model	Regime Switching	Linear
RMSE Out of Sample	14.7	15.4

The RMSE for the regime switching is clearly superior to the linear benchmark. Note these RMSEs are lower than the in – sample since, from Figure 1, it is clear that 2019 is less volatile than data at the beginning of the time series in 2016. It is the comparative performance, however, that is important as evidence that out-of-sample prediction with regime switching can outperform a linear model with the same explanatory variables.

We do however recognise that our results may not generalise to more highly volatile periods. With this in mind, we re-estimated the model on the years 2017-2019 and then forecast the more data in 2016 as if it were following. The forecasting results are shown in Table 5 and again confirm the regime-switching superiority.

Table 5: Backtest on 2016

Model	Regime Switching	Linear
RMSE	22.1	24.5

For greater comparability with the rolling re-estimation used for Table 4, we selected close to 2000 observations January-February 2017 for estimating the regime switching, linear and GARCH models and then successively forecast one period ahead with rolling re-estimation throughout the 2,000 out-of-sample observations in November and December 2016, as if they were following. The results are shown Table 6.

Table 6: Rolling Backtest on Nov-Dec 2016

Model	Regime Switching	Linear	**GARCH**
RMSE	20.8	23.0	23.4

These again confirm the benefit of regime switching. In fact the performance is proportionally better over this more volatile period; perhaps not unexpected as regime switching is often advocated for data with episodes of unusually high (or low) values. However, regardless of the relative performance of the regime switching, one of the main contributions is to show that balancing prices are indeed predictable through a fundamental model with a fully intuitive structure.

Finally, we observe the ability of the predictors to forecast positive or negative imbalance prices in Table 5. Over the period 1st of April 2019 to 30th of June 2019, the percentage correct prediction of both positive and negative prices is 99.5%. The model has about 0.4% false-positive predictions and 1% false-negative predictions.

Table 7: In Sample Counter Factual Classification of Forecast Values

	Observation	Percent	Cumulative
Correct	4,346	99.50	99.50
False Positive	18	0.41	99.91
False Negative	4	0.09	100.00

VII. Conclusions

The GB balancing mechanism represents a mature and active market, evolving since 2001. One would therefore expect the balancing market to have become efficient and that the imbalance volumes would be surprises, predictable, at best, by adaptive noise-following heuristics. This is what happens elsewhere, for example, with technical traders in the highly efficient global stock markets. As a consequence of market efficiency, if it exists, the imbalance prices should therefore be hard to predict from intuitive fundamentals. However, we show that the imbalance prices do reflect the fundamental drivers of wind, solar and demand forecast errors, scarcity variables, lagged prices and lagged imbalance volumes. The lagged autoregressive influence is also significant and adds to the predictability. Thus, we find strong evidence of fundamental predictability, as specified through an intuitive model. We also find that this is a good application area for regime switching, whose forecasts perform better than linear and GARCH benchmark models. Elsewhere in electricity price forecasting, the evidence for the superiority of regime switching over linear models has been mixed.

Reflecting upon this modelling evidence, it is understandable why there are profitable speculators on the British balancing market. Informal evidence with traders is that machine learning techniques are increasingly being used.to predict and optimise speculative trading strategies in the balancing market. Our research indicates that such approaches are likely to reflect fundamental econometric relationships as well as adaptive heuristics.

All of which raises the question of why the balancing market should be sustainably predictable, for such a mature and liquid market. We conjecture that predictability appears to be induced by the episodic nature of the settlement periods in which SO actions are repeated. Recall Figure 1. Evidently different market arrangements with shorter settlement periods, or less transparent and timely release of information would reduce predictability. But that is not the regulatory intent in GB. Indeed, the regulatory body sees benefits in allowing participants to forecast, self-hedge and attempt to take actions which benefit themselves and the overall system balance.

VIII. References

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