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Fundamental and speculative shocks, what drives electricity prices?

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Abstract—In the paper, Structural Vector Autoregressive models (SVAR) are used to identify fundamental and speculative shocks, in the UK electricity market. The structural shocks are identified via short run restrictions, which are imposed on the matrix of instantaneous effects. In the research, two main types of shocks are considered: fundamental shocks, which result from unexpected changes of demand, supply and generation costs and speculative shocks, which are associated solely with electricity prices. The results indicate that speculative shocks play an important role in the price setting process. Although they account for a significant part (from 30% to 95%) of the price volatility, I do not find evidence that the influence differs between peak and off-peak hours. When fundamental shocks are considered, some dependence between their effects on electricity prices and periods of the day is confirmed. For example, the impact of wind supply shocks on electricity prices is significantly stronger during the peak hours than during the off-peak hours. Moreover, the supply shocks become a major source of electricity price volatility during the peak hours. Finally, it is confirmed that shocks associated with generation costs (prices of fuels) don't have any instantaneous effect on the electricity prices.

Index Terms—Electricity spot prices, Structural analysis, Vector autoregression,

I. INTRODUCTION

ELECTRICITY is a very unusual commodity. The electricity demand depends strongly on the weather conditions and the business cycle. At the same time, it is price inelastic, which means that it responds weakly to price changes. Moreover, electricity cannot be economically stored but the power system stability requires that there is a constant balance between production and consumption [1], [2]. As the result, electricity prices are very volatile and difficult to forecast. Market players face not only a volume risk but also a price movements risk [3], [4].

So far, most of the literature has focused on forecasting the wholesale electricity prices. Overall, many different modeling approaches have been proposed, including cost-based (or production cost), equilibrium (or game theoretic), fundamental (or structural), quantitative (or reduced form), statistical and artificial intelligence-based models [4]. There is no agreement, which forecasting scheme is the most efficient and suitable for electricity prices (see [5], [6] for a comprehensive review of forecasting methods). Recently, some new approaches, which

aims at combining different forecasting methods of electricity prices, have been proposed ([7]).

Therefore, it is important to understand economic mechanisms, which make the forecasting process so difficult. A Structural VAR modeling approach allows to decompose forecast errors of electricity prices into structural innovations, which can be related to particular economic activities. This approach may help to answer questions of the sources of unexpected price changes.

A few papers have addressed the issue of structural modeling of electricity prices. [8], [9] and [10] applied the structural VECM models to energy markets. The prime interest of [8] is evaluation of a hypothesis of inelastic demand. Therefore, in the article, a two equation model of electricity prices and demand is used. The parameters are calibrated to the PJM market. [9] focuses on the UK electricity market and the interactions between carbon and electricity prices. In [10], the US market is modeled and relations between the electricity prices and fuel costs are analyzed. None of these articles incorporates the growing importance of renewable energy sources.

The EU climate policy 3×20 ([11]) obligated the EU member countries to improve the energy efficiency, reduce the CO_2 emission and increase the share of energy coming from renewable resources by 20%. Therefore most of the EU countries try to shift the generation from conventional (coal and gas) into wind, solar or water power plants. Hence, the market participants face a new kind of risk, associated with unexpected changes of electricity supply from these new energy sources. It is not clear, how important are these new types of shocks and how they affect the final electricity prices.

The aim of the paper is to analyze the UK electricity market and to decompose the electricity price forecast errors into structural innovations. Three fundamental (wind generation, demand and gas price) shocks and one speculative shock are identified. The approach allows to compare the importance of particular innovations and their influence on the price level. The analysis are focused on demand and wind supply shocks, because they are associated with a recent discussion on the demand-side management and the generation from renewable resources.

The final question concerns the differences of the price setting mechanisms between the peak and off-peak hours. It is

well known, that the behavior of electricity prices changes over the day. During the morning and late evening hours, the prices are much lower and less volatile than during the peak hours. The paper attempts to verify, if these differences result from behavior of fundamental variables or rather reflect different attitudes of market agents.

The article is structured as follows. Section II introduces an econometric model and discusses identification schemes used to estimate structural parameters. Section III presents the results of SVAR models applied separately to peak and off-peak hours. Finally, in Section IV I conclude and indicate directions of further research.

II. THE MODEL

In this research, a structural vector autoregression model (SVAR) is used, in order to estimate and evaluate effects of structural shock on electricity spot prices. This methodology was introduced by [12] and [13] and applied by many authors, particularly in macroeconomic analysis. It allows to give economic interpretation to shocks, which influence endogenous variables of interest. In a classical VAR model, with a deterministic component, the endogenous variables are modeled as follows

$$y_t = Ax_t + \sum_{i=1}^p \Theta_i y_{t-i} + \varepsilon_t \quad (1)$$

where y_t is a $(K \times 1)$ vector of endogenous variables and x_t is $(M \times 1)$ vector of deterministic variables. The parameter A is a $(K \times M)$ matrix and Θ_i 's are $(M \times M)$ matrices. Residuals, ε_t , are described by a $(K \times 1)$ vector. Although, the residuals are assumed not to be autocorrelated, they can be contemporaneously correlated. Therefore, they are often called forecast errors and don't have any direct economic interpretation.

A VAR model could be, in principle, viewed as a reduced form of a structural model. In the literature, a few types of structural models have been discussed (see [14] for detailed discussion). Here, I use so called B-model, which assumes that forecast errors are a linear combination of independent, structural shocks. The model may be written as follows

$$y_t = Ax_t + \sum_{i=1}^p \Theta_i y_{t-i} + Bu_t \quad (2)$$

where u_t 's are $(K \times 1)$ vectors of independent structural shocks with a diagonal variance-covariance matrix, $\Sigma_u = \Lambda$. The B matrix is called an instantaneous effect matrix and describes the contemporaneous relationship between structural shocks and endogenous variables. Due to linear relation between the forecast and structural errors, the following identity holds

$$\Sigma_\varepsilon = B' \Lambda B \quad (3)$$

It is often assumed that Λ is an identity matrix I_K . Here, I allow the variances of structural innovations to vary. In the same time, I restrict the diagonal elements of the B matrix to be equal to 1. I prefer this definition of the matrices B

and Λ because it is more convenient for model comparison. It normalizes the responses of endogenous variables and enables comparison of shock variances.

The reduced form VAR model can be easily estimated with a ML method. In the same time, the structural VAR cannot be directly applied because it is not identifiable. This means that the reduced form doesn't provide sufficient information to estimate all of parameters of the structural form. In particular, the structural model has $KM + pK^2 + K(K-1) + K$ parameters and the reduced form only $KM + pK^2 + K(K+1)/2$ parameters. Hence, in order to identify the model, at least $K(K-1)/2$ restrictions need to be imposed.

Different possible restrictions have been proposed in the literature. It is common to identify structural innovations, u_t , directly from the reduced form residuals, by imposing zero restriction on the B matrix. If the economic theory provides sufficient justification, a lower/upper triangular form of the B matrix can be assumed (e.g. [15]). It should be underlined that other zero restrictions on the B matrix are also possible.

Our modeling approach is based on a reduced form VAR model describing four endogenous variables: electricity prices (P_t), gas prices (G_t), total demand/production of electricity (D_t) and the electricity production from wind (W_t). Additionally, four exogenous variables are included in the model: a dummy for a day type - X_t , the length of the day (which is a proxy of yearly seasonality) - L_t , forecasted demand (published by National Grid) - FD_t and forecasted wind production (also published by National Grid) - FW_t . The temperature is not included, as information about the forecasted temperature is already contained in the forecasted demand and forecasted wind production.

Defining $y'_t = [W_t, D_t, G_t, P_t]$ and $x'_t = [1, X_t, L_t, FP_t, FW_t]$, the structural VAR system can be written as

$$y_t = Ax_t + \sum_{i=1}^p \Theta_i y_{t-i} + Bu_t \quad (4)$$

In the model, it is assumed that there are three fundamental shocks and one speculative shock. The fundamental innovations correspond with unexpected shocks affecting demand, supply and generation costs. Because the production in conventional power plants is scheduled in some advance, I focus here on production from renewable resources (wind), which is difficult to control and therefore fluctuates a lot. In the research, the following instantaneous relationships between innovations and endogenous variables are assumed:

- The wind supply shock, u_{1t} , can affect all of the fundamental variables
- The demand shock, u_{2t} , may influence all variables apart from production from wind
- The gas price shock, u_{3t} , doesn't have any instantaneous effect on neither demand nor wind supply. The assumption is in line with [8], which showed that the quantity of electricity sold in the market is not affected by current gas prices.

- The speculative shock, u_{4t} , is the one, which influences only electricity prices. This identifying assumption reflects the fact that the demand is contemporaneously inelastic (see [8]) and that electricity prices don't have any instantaneous effect on gas prices ([9]).

Hence, I restrict the B matrix to be lower triangular

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ * & 1 & 0 & 0 \\ * & * & 1 & 0 \\ * & * & * & 1 \end{bmatrix} \quad (5)$$

This means that responses of selected variables to particular innovations are unity. The variables are: W_t for the wind supply shock u_{1t} , D_t for the demand shock u_{2t} , G_t for the gas price shock u_{3t} and P_t for the speculative shock u_{4t} . The diagonal parameters of the variance-covariance matrix Λ

$$\Lambda = \begin{bmatrix} * & 0 & 0 & 0 \\ 0 & * & 0 & 0 \\ 0 & 0 & * & 0 \\ 0 & 0 & 0 & * \end{bmatrix} \quad (6)$$

are assumed to be positive. This means that 6 restrictions are imposed, which is sufficient to identify the structural form of the model (4).

III. RESULTS

A. Data

In this research, I focus on the British electricity market. In this market, agents can trade electricity through power exchanges. The most popular exchange in the UK is APX. It publishes electricity spot prices, which are often considered as the reference spot prices. The daily spot price is computed as an average of 48 half-hourly prices (for details see www.apxende.com). On the basis of intra-day prices, two other price measures are constructed: peak and off-peak price indexes. The first one is an average of prices for peak hours (from 07:00 to 19:00) and the second one is an average of prices of all remaining periods (from 00:00 to 7:00 and from 19:00 to 00:00). Additionally, National Grid provides information about the forecasted demand, the forecasted production from wind and realized production of electricity, with division into different fuel types. The data is published for half-hourly periods and allows computation of average values over peak and off-peak hours. All the data used in this research is transformed into natural logarithms to reduce variability.

The data spans the period from 01.01.2010 to 31.12.2012. Although, the longer sample is also available, I decide to estimate models with the data describing only last two years (731 days) to ensure model stability. If the longer sample was used, I would have to cope with changes of the market structure, which result mainly from the increase of popularity of renewable energy sources (such as wind).

TABLE I
LAG ORDER SELECTION BASED ON THE AIC CRITERIA

Model	Hours	Lag order
Model 1	peak	1
Model 2	off-peak	8

B. Model specification

At the beginning, the stationarity of the data is analyzed. Since the data exhibits a strong seasonal pattern, the deterministic variables X_t and L_t are included in the testing procedure. These variables are proxies for weakly and yearly seasonality. The ADF tests, with 7 and 14 lags, reject the null of nonstationarity for all the endogenous variables and hence I assume that the data is stationary. This result is not surprising because the research focuses on a relatively short and homogenous time period. On contrary, Fezzi and Bunn ([8]), who analyzed the PJM market in years 2002-2003, didn't find any evidence in favor of stationarity. The differences can be explained the fact that [8] didn't control for the yearly seasonality and included only daily dummies in their testing procedure.

In order to compare the effects of structural shocks between the peak and off-peak hours, two separate models are estimated. The first one, includes the peak prices and uses information about production and demand in these hours. The second one, describes relations between variables during the off-peak hours. The number of lags in both models is selected by the AIC information criterion and presented in Table I.

C. Model results

The estimates of the contemporaneous effect matrices, B , and estimates of standard deviations of structural shocks, $diag(\sqrt{\Lambda})$, are presented in Table II.

The results lead to the following conclusions. First, as expected, a positive wind supply shock, u_{1t} , has a negative impact on electricity prices. The marginal cost of production from renewable resources is much lower than the marginal cost of production in conventional power plants. Hence, an unexpected rise of production from wind should decrease the final electricity price. The strength of the influence varies between models. The responses of electricity prices to the supply shock are -0.485 and -0.139 for peak and off-peak hours, respectively. The significance of these parameters is tested for different significance levels $\alpha = 1\%, 5\%, 10\%$. The results indicate that the response in the off-peak hours is insignificant (even at $\alpha = 10\%$), whereas in peak hours it is significant at $\alpha = 1\%$.

On the contrary, a positive shock to the demand, u_{2t} , leads to an increase of electricity prices. It is a natural consequence of a demand-supply price setting mechanism. The normalized responses to the demand shock are 0.025 and 0.030 and are both significantly different from zero. A closer look at the results suggests that the responses don't differ across day periods (when standard deviations of parameters: 0.006 and 0.006, are taken into account).

TABLE II
THE ESTIMATES OF THE THE CONTEMPORANEOUS EFFECTS MATRIX, B ,
FOR MODEL 1 AND MODEL 2

Model 1 (Peak hours)				
B	1	0	0	0
	-1.281***	1	0	0
	1.401***	0.015	1	0
	-0.485***	0.025***	0.000	1
$diag(\sqrt{\Lambda})$	0.283 (0.0086)	0.016 (0.0004)	0.013 (0.0003)	0.094 (0.0025)
Model 2 (Off-peak hours)				
B	1	0	0	0
	1.024	1	0	0
	-0.179	-0.022	1	0
	-0.139	0.030***	0.001	1
$diag(\sqrt{\Lambda})$	0.147 (0.0041)	0.014 (0.0003)	0.013 (0.0003)	0.092 (0.0021)

Note: The ML estimates of the unrestricted elements of the B matrices: *, ** and *** indicate parameters, which are significantly different from 0 at the significance levels 10%, 5% and 10%, respectively; standard deviations of the parameters $diag(\sqrt{\Lambda})$ are presented in parenthesis. Models are specified in Table I.

TABLE III
THE INPUT OF STRUCTURAL SHOCKS TO THE VARIANCE OF ELECTRICITY
PRICES

	u_{1t}	u_{2t}	u_{3t}	u_{4t}
Model 1	0.6822	0.0000	0.0000	0.3177
Model 2	0.0465	0.0000	0.0000	0.9535

Note: Models are specified in Table I.

Second, it can be noticed that the generation cost shock doesn't influence contemporaneously the electricity prices for both peak and off-peak hours. The estimates of corresponding elements of the B matrices are close to zero and are insignificant. This outcome is in line with earlier results of [8] and [16], which indicate that changes in gas prices affect the electricity prices, on PJM and German markets, with some delay.

Finally, let analyze the the standard deviations, $diag(\sqrt{\Lambda})$, of structural disturbances. It can be noticed that the first two fundamental shocks varies more during the peak hours than off-peak hours. Their standard deviations are 0.283 and 0.016 in peak hours and 0.147 and 0.014 in off-peak hours. When estimation errors of these parameters are taken into account, the outcomes suggest that the differences are significant. On the contrary, when the variances of gas price and speculative shocks are analyzed, there are no evidence that they differ across day periods. It is particularly interesting, when the responses to speculative shocks are compared. The results indicate that bidding strategies of market participants are in some way consistent over the whole day and equally difficult to predict.

Based on the estimated models, the input of structural shocks to the variance of electricity prices can be estimated. The results are presented in Table III. It can be noticed that the speculative shocks account only for 32% of the variance of

the electricity price in the peak hours. In the same time, they are responsible for as much as 96% of the variance in the off-peak hours. It confirms that there are major differences in price setting mechanisms between the peak and off-peak hours. The differences are also revealed by the input of the fundamental shocks to the electricity price variances. The wind supply shocks have almost no effect on the variance of the off-peak hours (their share is less than 5%). For the peak hours, they account for more 68% of the variance and are the most important source of the price variability.

IV. CONCLUSIONS

In this research, structural (fundamental and speculative) shocks influencing electricity prices are identified via a Structural VAR (SVAR) model. When the fundamental innovations are considered, three shocks are distinguished: a wind supply shock, a demand shock and a gas prices shock. The speculative shock is defined as the one, which influences only the electricity prices.

The results indicate that not all of the fundamental shocks have contemporaneous effect on electricity prices. There are no evidence that electricity prices respond instantaneously to unexpected changes of gas prices. This result is in line with earlier finding of [8]. In the same time, the outcomes indicate that the wind supplies shock and demand shocks play an important role in the price setting process.

The differences of responses between the peak and off-peak hours are analyzed by compering models based on these two day periods. Some shocks, such as demand and the speculative shocks, have similar variances and effects on electricity prices in both, peak and off-peak hours. On the contrary, wind supply shocks (its variance and strength of influence) differ a lot between these two periods of a day. The wind supply shocks have a relatively small variance in off-peak hours and don't effect directly the electricity prices. In the same time, during the peak hours, they have a much larger variance and their influence on electricity prices is significant. As the result, the wind supply shocks become a major source of electricity price volatility during the peak hours.

The findings confirm that there are significant differences in price setting mechanism between the peak and off-peak hours. This article underlines the importance of wind supply shocks, particularly during the peak hours. This result may encourage researchers to improve forecasts of wind supply of electricity. A reduction of the variance of the wind supply shock could lead to a fall of the variance of electricity prices and hence limit the risk associated with the price volatility.

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