



LBS Research Online

S Goodarzi, H Niles Perera and [D W Bunn](#)

The impact of renewable energy forecast errors on imbalance volumes and electricity spot prices
Article

This version is available in the LBS Research Online repository: <https://lbsresearch.london.edu/id/eprint/1186/>

Goodarzi, S, Niles Perera, H and [Bunn, D W](#)

(2019)

The impact of renewable energy forecast errors on imbalance volumes and electricity spot prices.

Energy Policy, 134 (110827).

ISSN 0301-4215

DOI: <https://doi.org/10.1016/j.enpol.2019.06.035>

Elsevier

<https://www.sciencedirect.com/science/article/pii/...>

Users may download and/or print one copy of any article(s) in LBS Research Online for purposes of research and/or private study. Further distribution of the material, or use for any commercial gain, is not permitted.

The Impact of Renewable Energy Forecast Errors on Imbalance Volumes and Electricity Spot Prices

Shadi Goodarzi^{a, 1}, H. Niles Perera^{b, c}, Derek Bunn^d

^a California State University, Fullerton, Mihaylo College of Business and Economics, CA 92831, USA

^b Institute of Transport & Logistics Studies, The University of Sydney, Darlington, NSW 2006, Australia

^c Department of Transport & Logistics Management, Faculty of Engineering, University of Moratuwa, Katubedda 10400, Sri Lanka

^d London Business School, Regent's Park, London NW1 4SA, UK

Abstract: This paper contributes to the general consideration of whether a policy of incentivising improved forecasts for renewable energy outputs, and making them more available in the daily electricity market, would be beneficial. Using data from the German electricity market, we investigate the effect of wind and solar energy forecasts errors on imbalance volumes and intraday spot electricity prices. We use ordinary least square regression, quantile regression and autoregressive moving averages to identify these relationships using variables that have a quarter-hourly data granularity. The results show a positive relationship between wind forecast errors and imbalance volumes. We find that wind forecast errors impact spot prices more than solar forecasting errors. Policy incentives to improve the accuracy and availability of renewable energy forecasts should therefore be encouraged.

Keywords: *electricity imbalance; electricity spot prices; renewable energy; forecast errors*

'Declarations of interest: none'.

1. Introduction

Since the emergence of liberalised electricity markets in the 1990s, policy interventions have regularly been sought to improve the efficiencies of market processes, for example to reduce transaction costs, encourage new entry and reduce consumer prices. From this perspective, there has been an increasing amount of attention on the intra-day and real-time ("balancing") markets, motivated in part by the influx of renewable generation and consumer engagement. When generators or retailers produce or consume differently in real-time compared to their advance notifications to the system operator, and compared to their forward contract positions, they will

¹ Corresponding author. E-mail address: sgoodarzi@fullerton.edu

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

generally be exposed to "imbalance" and "settlement" charges. With greater intra-day uncertainties, these costs have been rising for the market participants, creating financial distress (leading to market exits for new entrant retailers who fail to hedge effectively, e.g. Pigden, 2018), and the operational complexity has been adding to the costs of system operators.

As a consequence, in the EU, for example, new network code regulations for electricity balancing (Entso-e, 2017) have sought to harmonise and open-up the intraday and real time markets to greater competition, whilst the REMIT (Acer, 2014) legislations have required member states to move towards greater transparency in their wholesale markets. But, intra-day uncertainties continue to impose high risk management costs to the market participants (hedging and imbalance charges) as well as high transaction costs (collateral against settlement charges), and higher system operations costs incurred by the system operators. In GB, the energy regulator has recognised this issue somewhat and has directly incentivised the system operator to develop and publish more accurate demand forecasts to improve operations (Ofgem, 2018). The system operator is directly penalised or rewarded for the accuracy of its demand forecasts against targets within its regulatory framework.

In this research, we look more generally at this theme and estimate to what extent forecast errors on renewable energy production contribute to intra-day price increases and system imbalances. This analysis is therefore quite distinct from the many studies that have sought to model daily prices in terms of market fundamentals, such as actual demand levels and supply costs. We do not therefore seek to develop comprehensive explanatory or forecasting models, but look specifically at the impact of market uncertainty and the role of forecast errors in price formation. The policy implication of this motivation may be that incentives to improve and provide better forecasts to the market would be beneficial.

The structure of the paper is as follows. Section 2 provides a background to the focus upon Germany and reviews the relevant research. Section 3 discusses the data and explanatory variables of this study leading to the empirical analysis. Section 4 discusses the results. We conclude the paper presenting salient findings and discussion in Section 5.

2. Background

2.1 The German electricity market

We focus upon Germany since it is the largest electricity market within the European Union and has been at the forefront of the energy transition into renewables. Consumption was 595 Terra Watt hours (TWh) for the 2017 calendar year (Clean Energy Wire, 2018). Renewable energy sources (RES) have become fundamental to the German electricity market and their stochastic effects drive intraday trading (Cludius et al., 2014; Kiesel and Paraschiv, 2017). Cludius et al., (2014) report that renewable energy reduced prices through the merit-order effect (reduction in average price per unit of electricity due to rise in renewable energy supply introducing lower low marginal costs) by 6 Euros per Mega Watt hours (€/MWh) in 2010. Their calculations go on to show this reduction was 10 €/MWh in 2012 and 14 to 16 €/MWh in 2016. The trend in price reduction is evidently following the trend in renewable energy penetration.

The Energy Industry Act passed in 1998 fully liberalized the German energy market and the number of market participants active in the German electricity market now exceeds one thousand (German Trade & Invest, 2018). The system is run by four transmission systems operators. These TSOs are tasked with managing the supply to meet demand. In the event of surplus or shortage, they are expected to instantaneously balance the demand and supply using the capacity reserve (Graeber, 2014). Over 25% of the current energy mix of Germany is powered through renewable sources (see Table 1) (AG Energiebilanzen e.V., 2017). There is evidence of wind and PV energy satisfying up to 80% of Germany's energy demand on certain peak hours in 2014 (Martinot, 2015).

The European Energy Exchange AG (EEX) is the leading energy exchange in Central Europe. Its merger with Powernext SA of France in 2008 led to the formation of the European Power Exchange (EPEX SPOT). EPEX SPOT is 51% owned by EEX (both directly and indirectly) and the rest by the TSOs. EPEX SPOT deals with trading in Germany, France, the United Kingdom (UK), the Netherlands, Belgium, Austria, Switzerland and Luxembourg and represents on average 50% of the market share across these countries. Day-ahead trading refers to the midday auctions to clear a supply-demand equilibrium a day-ahead of the actual delivery. The intraday market starts operations at 3pm each day and trades up to 30 minutes prior to the start of the

traded 15 minute period (EEX AG, 2018; EPEX SPOT, 2018; Kiesel and Paraschiv, 2017). The day-ahead market allows participants to access the market, while the intraday trading allows them to adjust to the evolving demand and supply levels (Kiesel and Paraschiv, 2017).

Table 1: Germany's energy mix by source (%) (AG Energiebilanzen e.V., 2017)

Energy Source	2010	2011	2012	2013	2014
Coal	41.6	42.9	44.1	45.2	43.8
Nuclear	22.2	17.6	15.8	15.3	15.5
Natural gas	14.1	14.1	12.2	10.6	9.7
Oil	1.4	1.2	1.2	1.1	0.9
Renewable sources	16.5	20.1	22.6	23.7	25.8
Wind (onshore)	6.0	8.0	8.1	8.0	8.9
Wind (offshore)				0.1	0.2
Hydro power	3.3	2.9	3.5	3.6	3.1
Biomass	4.6	5.2	6.1	6.3	6.7
Photovoltaic (Solar)	1.9	3.2	4.2	4.9	5.7
Waste	0.7	0.8	0.8	0.8	1.0
Other sources	4.2	4.1	4.1	4.1	4.3

The intraday volume has grown in the last decade. This is mainly due to the wind production forecast errors, which leads market participants to trade close to delivery time to mitigate the ex costs that they may face by being out of balance (Aid et al., 2016). EPEX SPOT began trading intraday quarter hourly (15 minute) contracts in the German energy market in December 2014 (EEX AG, 2018; EPEX SPOT, 2018). According to German law, renewable energy needs initially to be traded day-ahead of actual consumption. Typically, the TSOs oversee this guaranteeing the supplier a feed-in-tariff. The production forecast for renewable energy has a horizon of up to 36 hours before delivery (Graeber and Kleine, 2013; Just and Weber, 2015). Evidently, forecasts are not without errors. Hence, the market allows the stakeholders to use the intraday market to balance the emerging differences between the forecast and the actual production. Studies on the mechanisms and the strategies for energy balancing have been conducted by Karakatsani and Bunn, (2008b), Möller, Rachev and Fabozzi, (2011) and Klæboe, Eriksrud and Fleten, (2013).

1
2
3
4 The cost of balancing demand with supply is becoming increasingly important as wind and PV
5 reaches high penetration rates (Baker et al., 2013), becoming a key concern for transmission
6 system operators (TSO) and regulators (Hu et al., 2015; K ok et al., 2016; Wu and Kapuscinski,
7 2013). Gross et al. (2006) suggest this cost is generally very low at low penetration levels but the
8 extra cost of managing intermittency is nonlinear and depends on different factors such as
9 location of electricity resources, and how the local electricity demand patterns match with
10 variability of electricity production from renewable sources (Ritchie, 2017).
11
12
13
14
15
16
17

18 The liquidity for intraday trading has been increasing in Germany, but nevertheless balancing the
19 system remains a challenge (Bueno-Lorenzo et al., 2013; Skajaa et al., 2015; Weber, 2010). This
20 becomes an issue when the generating fleet is insufficiently flexible because of longer ramping
21 constraints and slow start times (e.g. with some thermal power plants). A consequence is the
22 appearance of negative electricity wholesale prices during instances with excess supply (Kiesel
23 and Paraschiv, 2017). This is typical of a combination between low electricity demand and high
24 output from renewable sources displacing conventional capacity. Figure 1 and Figure 2 show the
25 electricity imbalance and the German EPEX SPOT price on an arbitrary day to illustrate this
26 phenomenon. The figure shows that the EPEX SPOT reaches negative prices multiple times.
27 Frictions in the market and the extent of the penetration of intermittent energy sources cause this
28 and lead to volatility clustering (Mandelbrot, 1997). Figure 3 indicates wind and photovoltaic
29 electricity forecast errors for the corresponding day.
30
31
32
33
34
35
36
37
38
39

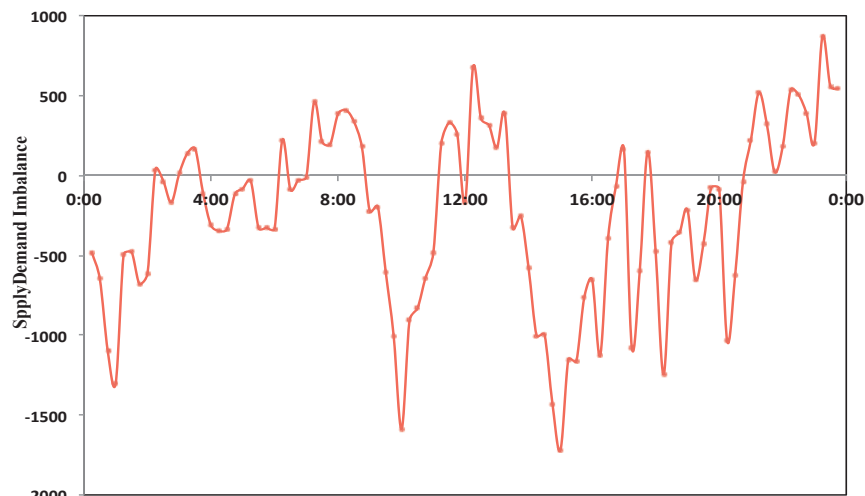


Figure 1: imbalance on a randomly selected day in 2014

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

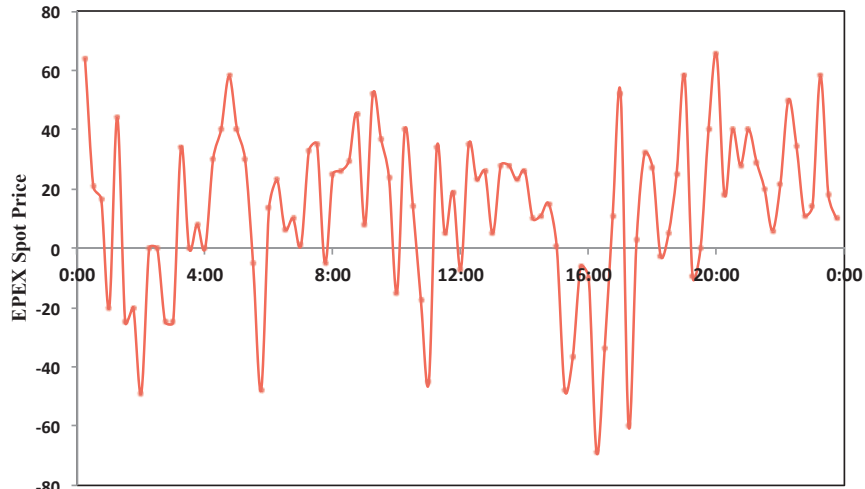


Figure 2: EPEX spot price on a randomly selected day in 2014

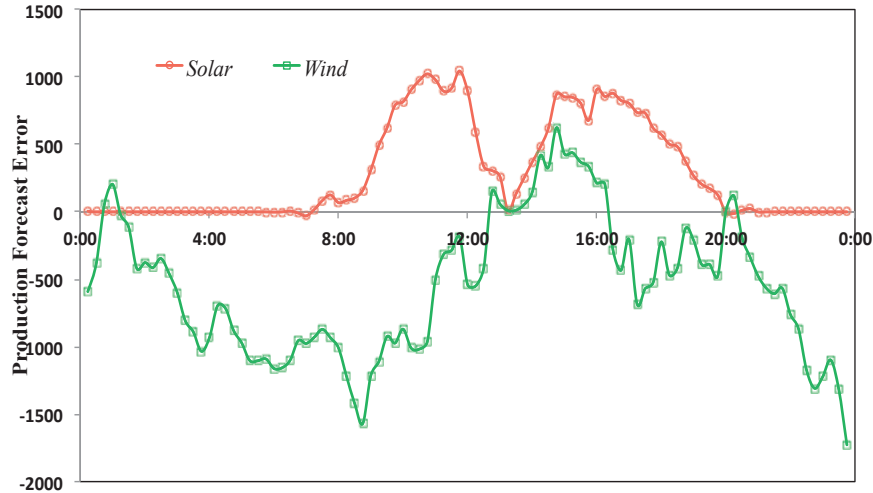


Figure 3: PV/wind production forecast error for a randomly selected day in 2014

Since the renewable energy suppliers are subsidized by the German Federal government, inefficiencies in balancing supply-demand are welfare costs to the consumer (Cludius et al., 2014). Understanding the role of forecast errors is therefore crucial not only for operational insights into the price formation, but also in indicating the potential benefits of improved forecasting services to the industry.

2.2 Background

Forecasting studies on electricity demand have a long history of methodological development. Taylor, (2003), Fan and Hyndman, (2012) and Quan, Srinivasan and Khosravi, (2014) have all modelled short-term electricity demand forecasts. But with market competition, load is no longer

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

the only variable that needs to be predicted and there is an increasing attention from researchers on electricity price modeling and forecasting (Garcia and Kirschen, 2004, Weron, 2014). Escribano, Ignacio Peña and Villaplana (2011) after adjusting for seasonality for daily equilibrium spot prices of eight electricity markets, examine the development of electricity prices in deregulated markets. They identify that equilibrium prices are mean-reverting, with volatility clustering and with jumps of time-dependent intensity. While Higgs, (2009) considers a generalized autoregressive conditional heteroskedasticity (GARCH) process to study electricity prices, Conejo et al. (2005) present a review of the time series analysis, neural networks and wavelet methods to predict the day-ahead market price. Nowotarski et al. (2014), provide more accurate forecasts by studying the use of forecast averaging in the context of day-ahead market electricity price.

Several researchers in the last decade analyzed the effects of incorporating wind energy in day-ahead and intraday markets on the price fluctuations (Barth et al., 2008; Swinand and O’Mahoney, 2015; Weber, 2010). Considering the production variability of both wind and PV, Hirth, (2015) studied the optimal share of these two technologies. Jónsson, Pinson and Madsen (2010) show the non-linear impact of wind energy forecasts on both day-ahead spot prices and their distributional characteristics.

There have been numerous prior works focusing on day-ahead electricity price forecasts (Clò et al., 2015; Jónsson et al., 2010; Karakatsani and Bunn, 2008b; Klæboe et al., 2013; Möller et al., 2011; Pape et al., 2016; Paraschiv et al., 2014). However, the emphasis on intraday market prices has been relatively scant. Weber (2010) provides an insightful study on how to absorb large amounts of wind energy to the intraday market. This study reviews market designs of France, Germany, Scandinavia and the UK. Most of the published research is on wind energy (Bueno-Lorenzo et al., 2013; Skajaa et al., 2015; Usaola and Moreno, 2009; Weber, 2010).

Whilst the literature has been ripe with works focusing on electricity spot prices, focus on electricity real-time imbalances has been relatively scant. Barth et al. (2008) emphasize the importance of regulating power costs considering actual scarcity with an eye on overall system imbalance. Aid, Gruet and Pham, (2016) develop a theoretical model to minimize the imbalance from residuals in electricity demand. They primarily focus on thermal power generation to

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

mitigate fluctuations in wind energy generations in their study. One study investigates the relationship between wind energy and supply-demand imbalance in the Spanish energy market (Bueno-Lorenzo et al., 2013). The paper however, focuses more on defining a new pricing scheme to design a more efficient electricity market.

From a methodological standpoint, regression has been widely used in forecasting intraday electricity prices. Autoregression has been used frequently to forecast intraday electricity prices (Panagiotelis and Smith, 2008; Pape et al., 2016; Ziel, 2016). Hagfors et al. (2016) use quantile regression in their study while Kiesel and Paraschiv, (2017) opt for reduced-form econometric analysis. Usaola and Moreno, (2009) and Bueno-Lorenzo, Moreno and Usaola, (2013) focus on revenue maximization by predicting wind energy inputs. Both these works focus extensively on imbalance and mitigating ancillary energy supply. Bueno-Lorenzo, Moreno and Usaola, (2013) introduce an optimal bidding strategy after analyzing data for 8 months. Skajaa, Edlund and Morales, (2015) develop algorithms in their study. Aïd, Gruet and Pham, (2016) approach their research using a linear quadratic control problem.

The geographic focus of these preceding works is spread narrowly. The Spanish (Bueno-Lorenzo et al., 2013; Usaola and Moreno, 2009) and the Danish electricity markets (Skajaa et al., 2015) have attracted considerable academic attention, although solely from the wind energy perspective. Elsewhere, Lisi and Edoli (2018) show that the sign of the zonal imbalance market markets is predictable, validated through out of sample backtesting, and based upon lagged imbalances and loads. Hagfors et al. (2016) focuses on electricity price forecasts for the UK. However, their study is not dedicated solely on intraday price forecasting or RES. Germany's intraday market has been subjected to numerous academic studies (Kiesel and Paraschiv, 2017; Pape et al., 2016). There have been studies that have focused on multiple countries. For instance, Ziel, (2016) focuses on forecasting electricity prices for Germany, Austria and the Netherlands. They extend this method to day-ahead forecasts for an out-of-sample study for Germany, Austria, Switzerland, Belgium, the Netherlands, Denmark. Sweden, Poland and Czech Republic. Australia has also been the subject of empirical focus on intraday electricity price forecasting (Panagiotelis and Smith, 2008).

Pape, Hagemann and Weber, (2016) and Kiesel and Paraschiv, (2017) provide the most relevant basis for this research. They use regression methods to forecast imbalance and electricity prices

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

for intraday markets. The impact from both wind and photovoltaic RES is considered in both their works. However, Pape, Hagemann and Weber, (2016)’s study is limited to hourly forecasts using data from two calendar years. They investigate both intraday prices and day-ahead prices. Their methodology is capable of capturing information variabilities across time. Kiesel and Paraschiv, (2017) focuses on quarter-hourly intraday prices using forecast errors for wind and photovoltaic energy. They build a link with volume of trades in the day-ahead market based on traditional electricity generation sources. Their results are achieved by analyzing intraday bidding data from EPEX SPOT. Kiesel and Paraschiv, (2017) uses regime switching to distinguish between high and low demand quotes. They also employ an indicator function to differentiate between positive and negative forecasting errors in renewables.

Pape, Hagemann and Weber, (2016) use expected prices from a fundamental model (Weron, 2014) and the price from the same hour of the last day/previous hour as explanatory variables. Kiesel and Paraschiv, (2017) considers the hourly day-ahead price, intraday price and volume of trades along with wind and photovoltaic forecast errors. Expected power plant availability, expected demand and control area balance are other factors considered in their model. The control area balance refers to “the sum of all balance group deviations of balance groups registered at the TSO and of the relevant balance groups owned by the TSO” (Kiesel and Paraschiv, 2017 pp. 80-81). Paraschiv, Fleten and Schürle, (2015) distinguishes between summer/winter, peak/off-peak hours. This is extended by Kiesel and Paraschiv, (2017) as they introduce a dummy variable that corresponds to the time of the day/season based on energy demand patterns in Germany. This dummy variable has eight distinct variables differentiated by the season and the peak/off-peak. Kiesel and Paraschiv, (2017)’s model yields R-squared values ranging between 28.76% and 37.99%, depending on the season and peak/off-peak segmentation.

Distinct from most of the previous research we do not seek to develop superior forecasting models for electricity imbalance volumes or spot prices in our study. Instead this research looks to estimate the effect of wind and solar electricity forecast errors on these variables. Unlike preceding studies, our research is solely based on the higher frequency, intra-day markets with a quarter hourly data granularity. This is an area where policies to encourage the provision of more timely, more accurate forecasts could be beneficial.

3. Method

We seek to model how RES (wind and PV) forecast errors affect the imbalance volume and EPEX Spot price. We also introduce two control variables, adaptive price response and adaptive imbalance response, in this study. These concepts are taken from Karakatsani & Bunn (2008) to measure the amount of market participant learning from the past events. In the absence of good forecasts, one would expect to see more adaptive behaviour in price formation.

3.1 Data and explanatory variables

This research is based on EPEX SPOT intraday quarter-hourly data for Germany for the 2014 calendar year (7 days a week). The variables we employ for this study are presented in Table 2. The descriptive statistics for these variables are presented in Table 3. Our data shows that during the year 2014, negative prices occurred 6.3% of the quarter hourly time periods observed. The data also shows that 49% of the time imbalances are positive, which is close to what one would expect (50%) if imbalance was to be unbiased, random forecast errors by the market participants. Following previous considerations of imbalance (Bueno-Lorenzo et al., 2013; Usaola and Moreno, 2009) and price (Kiesel and Paraschiv, 2017) we use variables that all have a quarter-hourly data granularity. As explained in Table 2, Adaptive Imbalance refers to the imbalance two-periods prior to delivery. The Adaptive Price refers to the EPEX SPOT price two-periods prior to delivery. The two-period lagged Realized Total Load is also considered. Since July 2015, energy trading in Germany is concluded 30 minutes (two trading periods) before the final delivery (EPEX SPOT, 2018). Kiesel and Paraschiv (2017) use the PV and wind forecasts in their model. We extend this and use the corresponding forecast errors from two periods prior to delivery.

We analyzed empirical price data of the German electricity market (Frauenhofer ISE, 2018). Our analysis identifies thirteen distinctly different price levels that could be differentiated as per seasonality and peak/off-peak periods of the day. This is an extension of the dummy variable introduced by Kiesel and Paraschiv (2017). The period between March 21 and September 21 are considered as summer while the rest are considered as winter for this study. The dummy variable categories are as follows;

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

- Summer
 - Morning pattern (peak) – 08:00 to 13:00
 - Afternoon trough (off-peak) – 13:00 to 14:00
 - Afternoon pattern (peak) – 14:00 to 18:00
 - Evening peak – 18:00 – 20:00 and 01:00 to 03:00
 - Evening descending pattern (off-peak) – 20:00 – 01:00
 - Early morning ascending pattern (off-peak) – 03:00 to 07:00
- Winter
 - Morning peak – 07:00 to 8:00
 - Morning pattern (peak) - 08:00 to 12:00
 - Afternoon trough (off-peak) – 12:00 to 13:00
 - Afternoon pattern (peak) – 13:00 to 17:00
 - Evening peak – 17:00 to 19:00 and 21:00 to 23:00
 - Descending pattern (off-peak) – 20:00 to 21:00 and 04:00 to 07:00
 - Night ascending pattern (off-peak) – 23:00 to 03:00

Table 2: Explanatory variables and their data granularity

Variable	Description	Data granularity
Imbalance (dependent variable)	The electricity supply-demand imbalance. It is positive when the electricity supply is less than the demand and the TSO needs to activate extra reserve.	Quarter-hourly
EPEX Spot price (dependent variable)	Wholesale electricity price.	Quarter-hourly
One Day Lagged Price	EPEX SPOT price for corresponding time slot one day prior to delivery.	Quarter-hourly
One Day Lagged Imbalance	Supply-demand imbalance for corresponding time slot one day prior to delivery.	Quarter-hourly
Adaptive Imbalance	Two-period-lagged value of imbalance.	Quarter-hourly
Adaptive Price	Two-period-lagged value of EPEX Spot price.	Quarter-hourly
Realized Total Load	Two-period lagged actual electricity load.	Quarter-hourly
PV Forecast Error	The actual electricity production by PV sources minus the forecasted amount.	Quarter-hourly

Wind Forecast Error	The actual electricity production by wind sources minus the forecasted amount.	Quarter-hourly
Seasonality & Peak Variable	Dummy variable based on season and peak/off-peak period of the day	Quarter-hourly

Table 3: Descriptive Statistics, N= 34616

Descriptive Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Realized Total Load	52178.41	8775.849	31281	73218	-0.0208	1.9222
Wind Forecast Error	-188.8289	1021.495	-5187.800	7802.800	0.5434	6.8133
PV Forecast Error	-68.87206	884.7721	-9794.500	4081.600	-1.9191	19.1649
Dependent Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
EPEX Spot Price	33.08333	23.92481	-200	398	0.6346	13.8410
Imbalance	-8.139229	532.3408	-3195.540	3772.265	0.02045	5.8623

We perform an augmented Dickey-Fuller test (ADF test) to test whether the variables are stationary. For all variables, we reject the null hypothesis of a unit root at a 1% significance levels, meaning that the data is stationary.

3.2 Econometric models

We present the following linear model that takes into consideration all the explanatory variables discussed in section 3.1.

$$\begin{aligned}
 \text{Imbalance} = & \alpha_1 + \alpha_2 \text{One Day Lagged Imbalance} + \alpha_3 \text{Adaptive Imbalance} \\
 & + \alpha_4 \text{Adaptive Price} + \alpha_5 \text{Realized Total Load}_{t-2} + \alpha_6 \text{PV forecast error} \\
 & + \alpha_7 \text{Wind forecast error} + \alpha_8 \text{Seasonality/Peak Variable} + \varepsilon
 \end{aligned}$$

$$\begin{aligned}
 \text{EPEX SPOT price} \\
 = & \beta_1 + \beta_2 \text{One Day Lagged Price} + \beta_3 \text{Adaptive Imbalance} \\
 & + \beta_4 \text{Adaptive Price} + \beta_5 \text{Realized Total Load}_{t-2} + \beta_6 \text{PV forecast error} \\
 & + \beta_7 \text{Wind forecast error} + \beta_8 \text{Seasonality/Peak Variable} + \varepsilon
 \end{aligned}$$

Estimating the tails of the EPEX Spot price and imbalance distributions are crucial risk considerations for the electricity market players. Quantile regression is an extension of ordinary least square regression that aims to estimate the median and quantiles of the response variables (Koenker and Bassett, 1978; Koenker and Hallock, 2001). Thus, it is a method that can provide

insightful solutions that explain tail characteristics (Koenker and Bassett, 1978). In this research using a range of regression models, OLS, Quantile 50, Quantile 05 and Quantile 95, we analyze the factors that affect the price and imbalance risks.

Table 4: OLS and quantile regression results, Dependent Variable: EPEX SPOT price, N=34614

Regressors	OLS Estimate (SE)	Tau=5% Estimate (SE)	Tau=50% Estimate (SE)	Tau=95% Estimate (SE)
One Day Lagged Price	0.277189**** (0.00453)	0.23812**** (0.00932)	0.30079**** (0.00453)	0.25011**** (0.00934)
Adaptive Imbalance	0.008583**** (0.00021)	0.00900**** (0.00035)	0.00795**** (0.00022)	0.00835**** (0.00052)
Adaptive Price	0.131492**** (0.00516)	0.14937**** (0.00504)	0.07371**** (0.00484)	0.13526**** (0.01240)
Realized Total Load	0.00058**** (0.00001)	0.00046**** (0.00003)	0.00056**** (0.00001)	0.00075**** (0.00003)
PV Forecast Error	-0.00228**** (0.00012)	-0.00148**** (0.00020)	-0.00206**** (0.00013)	-0.00457**** (0.00032)
Wind Forecast Error	-0.00336**** (0.00011)	-0.00326**** (0.00021)	-0.00338**** (0.00011)	-0.00351**** (0.00025)
Seasonality & Peak Variable	-0.10206** (0.03503)	0.04876* (0.07076)	-0.11108** (0.03628)	-0.22683** (0.08555)
R squared	0.333121			

Note: *p < .05, **p < .01, ***p < .001, ****p < .0001

Table 5: OLS and quantile regression results, Dependent variable = Imbalance, N=34615

Regressors	OLS Estimate (SE)	Tau=5% Estimate (SE)	Tau=50% Estimate (SE)	Tau=95% Estimate (SE)
One Day Lagged Imbalance	0.110355**** (0.00359)	0.12735**** (0.00846)	0.10708**** (0.00399)	0.10269**** (0.00855)
Adaptive Imbalance	0.75592**** (0.00394)	0.81492**** (0.00918)	0.73559**** (0.00443)	0.72922**** (0.00910)
Adaptive Price	-3.77761**** (0.09332)	-3.70965**** (0.19724)	-3.86624**** (0.10259)	-3.68606**** (0.18407)
Realized Total Load	0.003731**** (0.00024)	-0.00213*** (0.00055)	0.00288**** (0.00026)	0.01121**** (0.00054)
PV Forecast Error	-0.01206**** (0.00221)	-0.00839 (0.00530)	-0.01064*** (0.00276)	-0.02965**** (0.00536)
Wind Forecast Error	-0.02428**** (0.00194)	-0.04056**** (0.00468)	-0.01955**** (0.00218)	-0.01339** (0.00459)
Seasonality & Peak Variable	-3.43546**** (0.63238)	1.97508 (1.46663)	-4.37813**** (0.67260)	-8.04191**** (1.40177)
R squared	0.560604			

Note: *p < .05, **p < .01, ***p < .001, ****p < .0001

Based on autocorrelation and partial autocorrelation outputs we derived a ARMA where AR(1) and MA(1). Although the p values are significant, the Ljung Box value is significant which

1
2
3
4 suggests a correlation between the residuals. This suggests that there ARMA cannot clearly
5 explain the relationship between imbalance and the other variables. Given this the analysis
6 exhausted the use of ARMA to understand imbalance and its effects.
7
8
9

10 **4. Discussion**

11
12
13 Using OLS and different levels of quantile regression, we analyze the impact of PV and Wind
14 forecast production errors on imbalance and EPEX Spot Prices. We also studied the impact of
15 adaptation. The results show that adaptive price has a significantly positive effect on EPEX spot
16 price. This means that high spot prices persist in the market. The results from quantile
17 regressions show, this effect is higher in the tails of the distribution compared to the mean or
18 median. Therefore, extreme prices are more likely to impact the future price values.
19
20
21
22
23

24 In the study of EPEX Spot price, wind and PV production forecast errors are observed to have
25 significant negative effects. High production forecast errors for PV or wind means that the actual
26 electricity production from these sources is higher than what was initially forecasted. According
27 to the results, this leads to a lower electricity spot price, explained by the resulting surplus in
28 electricity. The results from different estimations show that whilst the effect of wind is similar
29 across the quantiles, for PV it increases steadily from the lower to the upper quantiles.
30
31
32
33
34

35 We also observe that adaptive imbalance has a significantly positive effect on the spot price. This
36 effect exists in mean and different quantile level estimations and it is increasing with the quantile
37 levels. This means that when imbalance is high in one period, an increase in price is likely. This
38 impact is higher when the prices are extremely high. Results of estimating imbalance show that,
39 adaptive imbalance has positive impacts on imbalance. This impact is higher in the lower
40 quantile level, which is the situation when there is excess supply in the balancing market.
41
42
43
44
45

46 The results of the quantile regression indicate that the realized total load has an interesting
47 relationship with the imbalance and the electricity price (see Figure 4 a and b). As the quantile
48 level increases, the coefficient of the realized total load increases. However, this relationship
49 appears not to be linear at the tails. Analysis of variance (ANOVA) shows that the coefficients
50 for the quantile level of $\tau = 5\%$ is significantly different to that of $\tau = 95\%$ ($p < 0.0001$). This
51 is further evident from the horizontal red line depicting the OLS coefficient and the dotted red
52 lines denoting the confidence intervals. The results suggest that when the realized total load is
53 high, the marginal cost to purchase electricity rises due to scarcity in supply.
54
55
56
57
58
59
60
61
62
63
64
65

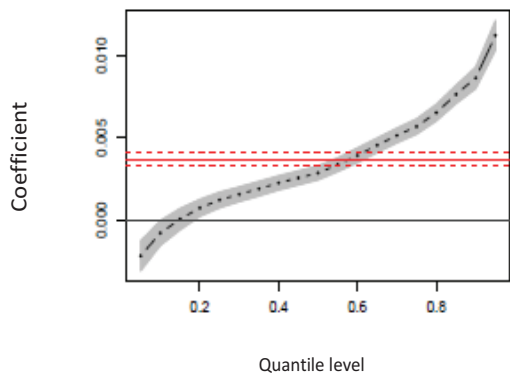
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

According to the results, both wind and PV production forecast errors have negative significant effects on imbalance. When the production forecast error is high, the electricity produced is more than the forecasted value. This surplus in energy leads to a lower imbalance. We also observe that Adaptive Price negatively affects the imbalance. This suggests that a higher spot price, is followed by excess electricity supply (i.e. when the EPEX spot price is high, intuitively it will attract more supply offering in the market).

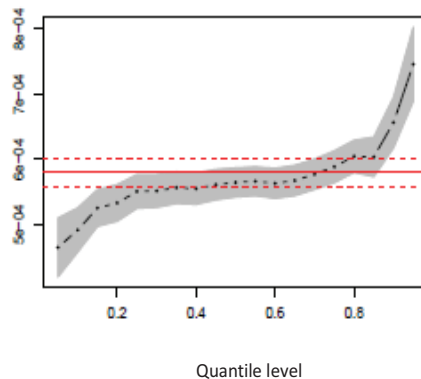
Further analysis using quantile regression indicates that the coefficient decreases for the solar forecast error as the quantile level increases (see Figure 4c and 4d). This reinforces that high and positive solar forecast errors have a stronger negative effect on the imbalance volume and spot price. The results from the wind forecast error provides interesting insights. The wind forecast error seems to mostly conform to the results from the OLS regression and has less impact on the spot price (see Figure 4e). However, quantile level for the wind forecast error has a positive relationship with the imbalance volume as per the results of the quantile regression (see Figure 4f). While negative wind forecast errors contribute to lower coefficients, positive wind forecast errors lead to higher coefficients in determining the imbalance volumes.

Improvements in wind forecasting are intuitively linked to more accurate predictions of the imbalance. Without improving its forecast accuracy, promoting wind energy would lead to many complications as it attains a larger portion of the electricity market. The uncertainty in supply would, if not well-forecast, necessitate the greater use of conventional peaking plant, such as gas turbine. Moreover, better forecasts should lead to a better managed system with lower real-time price volatility which would benefit all stakeholders of the electricity market.

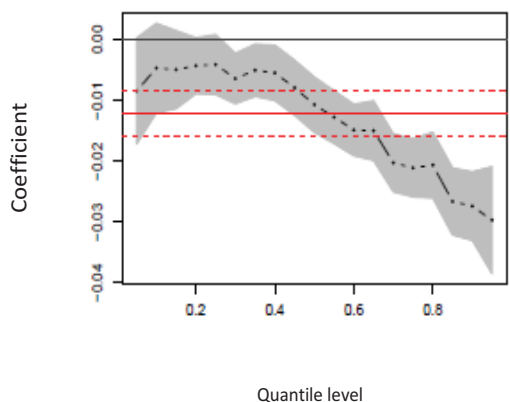
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65



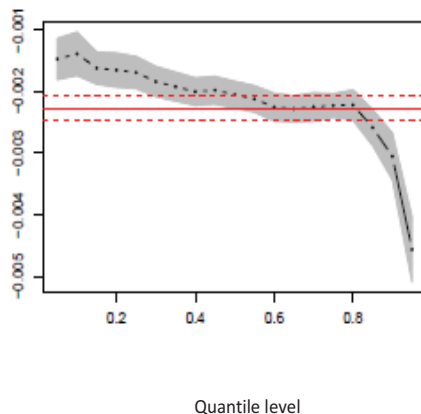
a) Quantile regression results for Realized Total Load on Imbalance



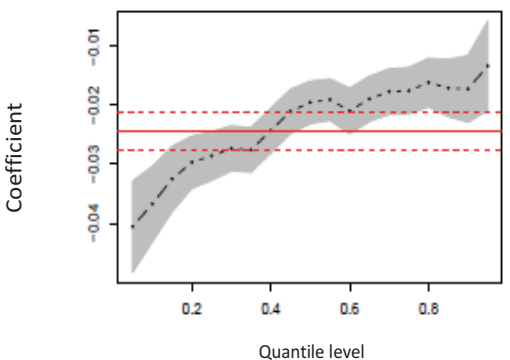
b) Quantile regression results for Realized Total Load on Spot Price



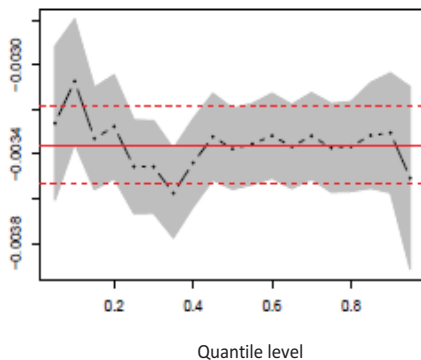
c) Quantile regression results for Solar Forecast Error on Imbalance



d) Quantile regression results for Solar Forecast Error on Spot Price



e) Quantile regression results for Wind Forecast Error on Imbalance



f) Quantile regression results for Wind Forecast Error on Spot Price

Figure 4. Quantile regression results for realized total load

5. Conclusions and Policy Implications

The renewable energy sector has grown rapidly over the past several decades buoyed by supportive policies and public pressure. Environmental benefits and low running costs have promoted their use despite the high capital costs required to install facilities. Evidence indicates that increased renewable energy inputs to the energy market creates complexities. The intermittency of electricity generation from renewable sources is a main cause for this. Despite recent advancements in accurately forecasting wind and PV energy generation, there remains room for improving forecast quality. This is especially true for wind forecasts. Due to the intermittency in wind and PV energy generation and inaccurate forecasts, balancing electricity supply with demand and the energy price are considerable.

We build on previous research to deliver a method to forecast real-time energy (supply-demand) imbalance and EPEX spot prices using quantile regression analysis using data from the German electricity spot market. The results of our study confirm that higher wind and PV production forecast errors decrease imbalance and the spot price. Our findings show that this relationship is more profound for wind energy forecast errors. However, the effects vary from the lower to the upper risk levels of the distributions. Evidently, improvements in forecast accuracy will reduce the volatilities of both spot price and imbalance volumes, and this would enhance welfare of producers, system operators and consumers. The findings outline the importance of improving forecast accuracy to ensure the smooth functioning of the electricity market.

It would not be unreasonable to envisage a requirement for system operators to be incentivised to provide more accurate wind and solar forecast to the market. Evidently forecasts are different from information, and they can be wrong. But the practice of system operators providing market indications is already widespread and, as noted in the Introduction, Ofgem (2018) has already incorporated an accuracy target into its regulatory regime for GB demand forecasts. This principle should be extended to the intraday market alongside the existing requirement for full system transparency, as in the EU REMIT legislation.

References

- Acer, 2104. REMIT Portal. <https://www.acer-remit.eu/portal/home>
- AG Energiebilanzen e.V., 2017. Bruttostromerzeugung in Deutschland ab 1990 nach Energieträgern [WWW Document]. URL https://ag-energiebilanzen.de/index.php?article_id=29&fileName=20171221_brd_stromerzeugung1990-2017.pdf (accessed 1.12.18).
- Aïd, R., Gruet, P., Pham, H., 2016. An optimal trading problem in intraday electricity markets. *Math. Financ. Econ.* 10, 49–85.
- Baker, E., Fowlie, M., Lemoine, D., Reynolds, S.S., 2013. The economics of solar electricity. *Annu. Rev. Resour. Econ.* 5, 387–426.
- Barth, R., Weber, C., Swider, D.J., 2008. Distribution of costs induced by the integration of RES-E power. *Energy Policy* 36, 3097–3105. <https://doi.org/10.1016/j.enpol.2008.03.039>
- Bueno-Lorenzo, M., Moreno, M.Á., Usaola, J., 2013. Analysis of the imbalance price scheme in the Spanish electricity market: A wind power test case. *Energy Policy* 62, 1010–1019. <https://doi.org/10.1016/j.enpol.2013.08.039>
- Clean Energy Wire, 2018. Germany’s energy consumption and power mix in charts [WWW Document]. URL <https://www.cleanenergywire.org/factsheets/germanys-energy-consumption-and-power-mix-charts> (accessed 9.2.18).
- Clò, S., Cataldi, A., Zoppoli, P., 2015. The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. *Energy Policy*. <https://doi.org/10.1016/j.enpol.2014.11.038>
- Cludius, J., Hermann, H., Matthes, F.C., Graichen, V., 2014. The merit order effect of wind and photovoltaic electricity generation in Germany 2008-2016 estimation and distributional implications. *Energy Econ.* 44, 302–313. <https://doi.org/10.1016/j.eneco.2014.04.020>
- Conejo, A.J., Contreras, J., Espínola, R., Plazas, M.A., 2005. Forecasting electricity prices for a day-ahead pool-based electric energy market. *Int. J. Forecast.* 21, 435–462. <https://doi.org/10.1016/j.ijforecast.2004.12.005>
- EEX AG, 2018. EEX AG [WWW Document]. URL <https://www.eex.com/en/about/eex/eex-ag> (accessed 2.10.18).
- Entso-e, 2017, Electricity Balancing. https://electricity.network-codes.eu/network_codes/eb

1
2
3
4 EPEX SPOT, 2018. ABOUT EPEX SPOT [WWW Document]. URL
5 https://www.epexspot.com/en/company-info/about_epex_spot (accessed 2.10.18).
6
7
8 Escribano, A., Ignacio Peña, J., Villaplana, P., 2011. Modelling electricity prices: International
9 evidence. *Oxf. Bull. Econ. Stat.* 73, 622–650. <https://doi.org/10.1111/j.1468-0084.2011.00632.x>
10
11 Fan, S., Hyndman, R.J., 2012. Short-term load forecasting based on a semi-parametric additive
12 model. *IEEE Trans. Power Syst.* 27, 134–141.
13
14 Fan, S., Hyndman, R.J., 2011. The price elasticity of electricity demand in South Australia.
15 *Energy Policy* 39, 3709–3719.
16
17 Frauenhofer ISE, 2018. Energy Charts [WWW Document]. URL [https://www.energy-](https://www.energy-charts.de/price.htm)
18 [charts.de/price.htm](https://www.energy-charts.de/price.htm)
19
20 Garcia, M.P., Kirschen, D.S., 2004. Forecasting system imbalance volumes in competitive
21 electricity markets, in: *Power Systems Conference and Exposition. IEEE PES*, pp. 1805–1812.
22
23 Germany Trade & Invest, 2018. The German Electricity Market - A Brief Overview [WWW
24 Document]. URL [https://www.gtai.de/GTAI/Navigation/EN/invest,t=the-german-electricity-](https://www.gtai.de/GTAI/Navigation/EN/invest,t=the-german-electricity-market--a-brief-overview,did=622868.html)
25 [market--a-brief-overview,did=622868.html](https://www.gtai.de/GTAI/Navigation/EN/invest,t=the-german-electricity-market--a-brief-overview,did=622868.html) (accessed 2.10.18).
26
27 Graeber, D.R., 2014. *Handel mit Strom aus erneuerbaren Energien*, 1st ed. Springer Gabler,
28 Wiesbaden.
29
30 Graeber, D.R., Kleine, A., 2013. The combination of forecasts in the trading of electricity from
31 renewable energy sources. *J. Bus. Econ.* 83, 409–435.
32
33 Gross, R., Heptonstall, P., Anderson, D., Green, T., Leach, M., Skea, J., 2006. *The costs and*
34 *impacts of intermittency*. UK Energy Research Centre, London.
35
36 Hagfors, L.I., Bunn, D., Kristoffersen, E., Staver, T.T., Westgaard, S., 2016. Modeling the UK
37 electricity price distributions using quantile regression. *Energy* 102, 231–243.
38
39 <https://doi.org/10.1016/j.energy.2016.02.025>
40
41 Higgs, H., 2009. Modelling price and volatility inter-relationships in the Australian wholesale
42 spot electricity markets. *Energy Econ.* 31, 748–756. <https://doi.org/10.1016/j.eneco.2009.05.003>
43
44 Hirth, L., 2015. The Optimal Share of Variable Renewables: How the Variability of Wind and
45 Solar Power affects their Welfare-optimal Deployment. *Energy J.* 36, 149–184.
46
47 Hu, S., Souza, G.C., Ferguson, M.E., Wang, W., 2015. Capacity Investment in Renewable
48 Energy Technology with Supply Intermittency: Data Granularity Matters! *Manuf. Serv. Oper.*
49 *Manag.* 17, 480–494.
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

- 1
2
3
4 Jónsson, T., Pinson, P., Madsen, H., 2010. On the market impact of wind energy forecasts.
5 Energy Econ. <https://doi.org/10.1016/j.eneco.2009.10.018>
6
7
8 Just, S., Weber, C., 2015. Strategic behavior in the German balancing energy mechanism:
9 incentives, evidence, costs and solutions. J. Regul. Econ. 48, 218–243.
10
11 Karakatsani, N. V., Bunn, D.W., 2008a. Intra-day and regime-switching dynamics in electricity
12 price formation. Energy Econ. <https://doi.org/10.1016/j.eneco.2008.02.004>
13
14 Karakatsani, N. V., Bunn, D.W., 2008b. Forecasting electricity prices: The impact of
15 fundamentals and time-varying coefficients. Int. J. Forecast.
16
17 <https://doi.org/10.1016/j.ijforecast.2008.09.008>
18
19 Kiesel, R., Paraschiv, F., 2017. Econometric analysis of 15-minute intraday electricity prices.
20 Energy Econ. 64, 77–90. <https://doi.org/10.2139/ssrn.2671379>
21
22 Klæboe, G., Eriksrud, A.L., Fleten, S.E., 2013. Benchmarking time series based forecasting
23 models for electricity balancing market prices. Energy Syst. 6, 43–61.
24
25 <https://doi.org/10.1007/s12667-013-0103-3>
26
27 Koenker, R., Bassett, G., 1978. Regression Quantiles. Econometrica 46, 33.
28
29 <https://doi.org/10.2307/1913643>
30
31 Koenker, R., Hallock, K.F., 2001. Quantile Regression. J. Econ. Perspect. 15, 143–156.
32
33 Kök, A.G., Shang, K., Yücel, Ş., 2016. Impact of Electricity Pricing Policies on Renewable
34 Energy Investments and Carbon Emissions. Manage. Sci. 64, 131–148.
35
36 Lijesen, M.G., 2007. The real-time price elasticity of electricity. Energy Econ. 29, 249–258.
37
38 Lisi, F. and Edoli, E., 2018. Analyzing and Forecasting Zonal Imbalance Signs in the Italian
39 Electricity Market. *The Energy Journal*, 39(5).
40
41
42
43
44
45
46 Mandelbrot, B.B., 1997. The variation of certain speculative prices, in: *Fractals and Scaling in*
47 *Finance*. Springer, New York, pp. 371–418.
48
49 Martinot, E., 2015. How is Germany Integrating and Balancing Renewable Energy Today?
50 [WWW Document]. URL [http://www.martinot.info/renewables2050/how-is-germany-](http://www.martinot.info/renewables2050/how-is-germany-integrating-and-balancing-renewable-energy-today)
51 [integrating-and-balancing-renewable-energy-today](http://www.martinot.info/renewables2050/how-is-germany-integrating-and-balancing-renewable-energy-today) (accessed 1.31.18).
52
53
54 Möller, C., Rachev, S.T., Fabozzi, F.J., 2011. Balancing energy strategies in electricity portfolio
55 management. Energy Econ. 33, 2–11. <https://doi.org/10.1016/j.eneco.2010.04.004>
56
57
58
59
60
61
62
63
64
65

1
2
3
4 Nowotarski, J., Raviv, E., Trück, S., Weron, R., 2014. An empirical comparison of alternative
5 schemes for combining electricity spot price forecasts. *Energy Econ.* 46, 395–412.
6
7 <https://doi.org/10.1016/j.eneco.2014.07.014>
8
9
10 Ofgem, 2018. Policy decision on the Electricity System Operator regulatory and incentives
11 framework from April 2018. <https://www.ofgem.gov.uk/publications-and-updates/policy->
12 [decision-electricity-system-operator-regulatory-and-incentives-framework-april-2018.](https://www.ofgem.gov.uk/publications-and-updates/policy-)
13
14 Panagiotelis, A., Smith, M., 2008. Bayesian density forecasting of intraday electricity prices
15 using multivariate skew t distributions. *Int. J. Forecast.* 24, 710–727.
16
17 <https://doi.org/10.1016/j.ijforecast.2008.08.009>
18
19 Pape, C., Hagemann, S., Weber, C., 2016. Are fundamentals enough? Explaining price variations
20 in the German day-ahead and intraday power market. *Energy Econ.*
21
22 <https://doi.org/10.1016/j.eneco.2015.12.013>
23
24 Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead
25 electricity prices. *Energy Policy.* <https://doi.org/10.1016/j.enpol.2014.05.004>
26
27 Paraschiv, F., Fleten, S.E., Schürle, M., 2015. A spot-forward model for electricity prices with
28 regime shifts. *Energy Econ.* 47, 142–153. <https://doi.org/10.1016/j.eneco.2014.11.003>
29
30 Pigden, K. 2018 Snowdrop Energy transfers all customers to Nabuh Energy. Utilityweek 20
31 October 2018. <https://utilityweek.co.uk/snowdrop-energy-transfers-customers-nabuh-energy/>
32
33 Quan, H., Srinivasan, D., Khosravi, A., 2014. Short-term load and wind power forecasting using
34 neural network-based prediction intervals. *IEEE Trans. Neural Networks Learn. Syst.* 25, 303–
35 315.
36
37 Ritchie, E.J., 2017. The Cost Of Wind And Solar Intermittency [WWW Document]. *Forbes.*
38 URL <https://www.forbes.com/sites/uhenergy/2017/01/24/the-cost-of-wind-and-solar->
39 [intermittency/#5b33bf6668de](https://www.forbes.com/sites/uhenergy/2017/01/24/the-cost-of-wind-and-solar-) (accessed 4.30.18).
40
41
42 Roozbehani, M., Dahleh, M.A., Mitter, S.K., 2012. Volatility of Power Grids Under Real-Time
43 Pricing. *IEEE Trans. Power Syst.* 27, 1926–1940.
44
45 Skajaa, A., Edlund, K., Morales, J.M., 2015. Intraday Trading of Wind Energy. *IEEE Trans.*
46 *Power Syst.* 30, 3181–3189. <https://doi.org/10.1109/TPWRS.2014.2377219>
47
48 Swinand, G.P., O’Mahoney, A., 2015. Estimating the impact of wind generation and wind
49 forecast errors on energy prices and costs in Ireland. *Renew. Energy* 75, 468–473.
50
51 <https://doi.org/10.1016/j.renene.2014.09.060>
52
53
54
55
56
57
58
59
60
61
62
63
64
65

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Taylor, J.W., 2003. Short-term electricity demand forecasting using double seasonal exponential smoothing. *J. Oper. Res. Soc.* 54, 799–805.

Usaola, J., Moreno, M.Á., 2009. Optimal bidding of wind energy in intraday markets, in: 2009 6th International Conference on the European Energy Market, EEM 2009. <https://doi.org/10.1109/EEM.2009.5207179>

Weber, C., 2010. Adequate intraday market design to enable the integration of wind energy into the European power systems. *Energy Policy* 38, 3155–3163. <https://doi.org/10.1016/j.enpol.2009.07.040>

Weron, R., 2014. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *Int. J. Forecast.* 30, 1030–1081. <https://doi.org/10.1016/j.ijforecast.2014.08.008>

Wu, O.Q., Kapuscinski, R., 2013. Curtailing Intermittent Generation in Electrical Systems. *Manuf. Serv. Oper. Manag.* 15, 578–595.

Ziel, F., 2016. Forecasting Electricity Spot Prices Using Lasso: On Capturing the Autoregressive Intraday Structure. *IEEE Trans. Power Syst.* 31, 4977–4987. <https://doi.org/10.1109/TPWRS.2016.2521545>