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

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ABSTRACT

This paper contributes to the general consideration of whether a policy of incentivising system operators to improve the quality and market availability of forecasts for renewable energy outputs 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 subsequent spot electricity prices. We use ordinary least squares regression, quantile regression and autoregressive moving averages to identify these relationships using variables that have a quarter-hourly data granularity. The results show that higher wind and solar forecast errors increase the absolute values of imbalance volumes and that these can pass through into higher spot prices. We find that wind forecast errors in Germany impact spot prices more than solar forecasting errors. Policy incentives to improve the accuracy and availability of renewable energy forecasts by the system operators should therefore be encouraged.

1. Introduction

Since the emergence of liberalized 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. Extending such efficiency-driven interventions is the theme of this paper, but these policies have to be viewed alongside other structural interventions associated with policies towards a low carbon economy (e.g. through feed-in tariffs, renewable portfolio standards, or auctions to support new renewable technologies). Whilst some of these structural policies were successfully designed and implemented, there are examples of where they needed to be modified or even withdrawn. In Spain, for example, due to an expensive level of feed-in tariffs, the government had to withdraw retrospectively support for renewables when the global financial crisis required drastic cuts in public spending (Goodarzi et al., 2018). Klessmann et al. (2008) studied different market designs and documented how Germany, Spain, and the UK moved legislation towards different support mechanisms for the energy transition. For example, all responsibility for output, balancing and grid integration of renewable energies was originally placed on the Transmission System Operator in Germany, whilst in the UK, although benefitting from some price support, renewable electricity producers had to compete within the market. Other policy legislation in the EU has been more harmonized, especially with respect to market-wide, efficiency-driven interventions. The REMIT directive for example (Acer, 2014) has introduced market transparency platforms which require generators to make all production information available to the market as soon as possible, and the coupling of the day ahead and intraday wholesale trading arrangements across countries has reduced transaction costs. In this paper, we suggest there are benefits if transparency could go further.

In particular, in the context of market efficiency considerations, attention has been increasing on the 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 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 and leading to market exits for retailers who fail to hedge effectively, (Pigden, 2018; Tribe, 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

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regulations for electricity balancing (Entso-e, 2017) have sought to harmonise and open-up the intraday and real time markets to greater competition and transparency. 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. This is an interesting precedent and suggests greater interest by a regulatory authority not just on the timely provision of market-sensitive information by market participants, but also the greater provision of the most accurate forecasts that the independent system operators are able to develop. This is not a trivial challenge, involving more than an improvement in forecasting techniques, as a substantial amount of renewable energy resources are increasingly being embedded in the system at end-use level, not as metered generation on the transmission system and, as such, production data is more elusive.

In this research we therefore look more generally at this theme and estimate to what extent forecast errors on renewable energy production contribute to intra-day price increases and the size of the system imbalances. This analysis is therefore quite distinct from the many studies that have sought to model daily prices in terms of market fundaments, such as actual demand levels and supply costs. We do not therefore seek to develop comprehensive explanatory or forecasting models. For renewable energies, the intraday market is most relevant since it supports the trading up to gate closure when the latest information and forecasts can be used to adjust prospective imbalance exposures (Klessmann et al. (2008)). Thus, we do not consider the energy futures market and their forward prices, as these are used to hedge against the day ahead or intraday prices, not imbalance exposures (Ketterer, 2014; Wozabal et al., 2016).

This research specifically investigates the impact of market uncertainty and the role of forecast errors in price and imbalance formation. The paper provides both an original and significant contribution to research, mainly through the use of high-frequency data related to considerations of whether a policy of facilitating improved forecasts for renewable energy outputs, and making them more available in the daily electricity market, would be beneficial. Thus the policy implication of this research is related to greater market transparency on production and the market efficiency gains from facilitating better forecasts of renewable energy production.

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. 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 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.

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 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 and 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 min prior to the start of the traded 15 min 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).

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 (Aïd et al., 2016). EPEX SPOT began trading intraday quarter hourly (15 min) contracts in the German energy market in December 2014 (EEX AG, 2018; EPEX SPOT, 2018). The production forecast for renewable energy has a horizon of up to 36 h 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 (2008a), Möller et al. (2011) and Klæboe et al. (2013).

The cost of balancing demand with supply is becoming increasingly

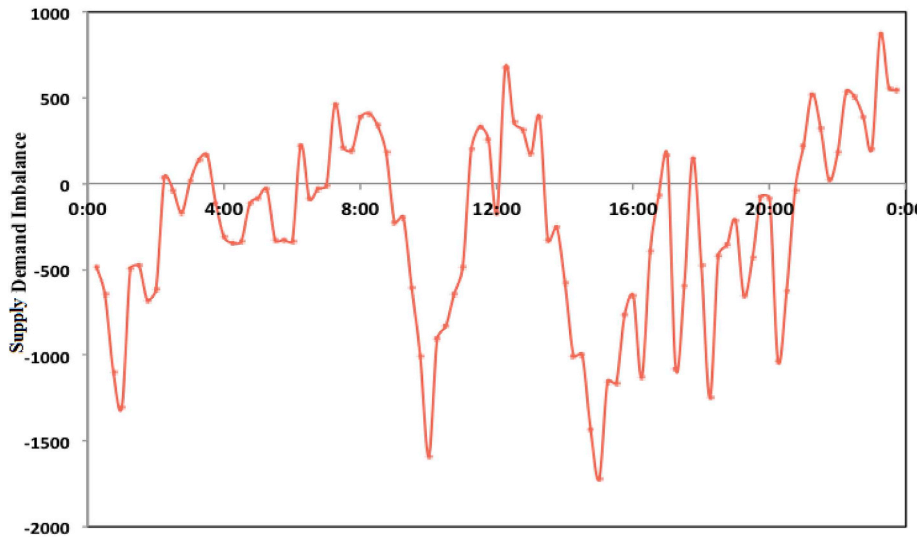


Fig. 1. Imbalance on a randomly selected day in 2014.

important as wind and PV reaches high penetration rates (Baker et al., 2013), becoming a key concern for transmission system operators (TSO) and regulators (Hu et al., 2015; Kök et al., 2016; Wu and Kapuscinski, 2013). Gross et al. (2006) suggest this cost is generally small at low penetration levels but the extra cost of managing intermittency is nonlinear and depends on different factors such as location of electricity resources, and how the local electricity demand patterns match with variability of electricity production from renewable sources (Ritchie, 2017).

The liquidity for intraday trading has been increasing in Germany, but nevertheless balancing the system remains a challenge (Bueno-Lorenzo et al., 2013; Skajaa et al., 2015; Weber, 2010). This becomes an issue when the generating fleet is insufficiently flexible because of longer ramping constraints and slow start times (e.g. with some thermal power plants). A consequence is the appearance of negative electricity wholesale prices during instances with excess supply (Kiesel and Paraschiv, 2017). This is typical of a combination between low electricity demand and high output from renewable sources displacing conventional capacity. Fig. 1 and Fig. 2 depict the electricity imbalance (MW) and the German EPEX SPOT price (€/MWh) on an arbitrary day to illustrate these effects. As Fig. 1 shows, the supply/demand imbalance is fluctuating between positive and negative values, where negative (positive) occurs when electricity supply is higher (lower) than the electricity demand. Fig. 2 shows that the EPEX SPOT reaches negative prices many times, the acceptability of which is rather controversial. Frictions in the market and the extent of the penetration of intermittent energy sources cause this and lead to volatility clustering (Mandelbrot, 1997). Fig. 3 shows wind and photovoltaic electricity forecast errors (MW) for the corresponding day. As the Figure indicates, the production forecast error for both wind and solar can have both positive and negative values. Negative and positive values of production forecast error occur when the forecasted electricity generation is lower and higher, respectively, than the actual generation from that source.

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

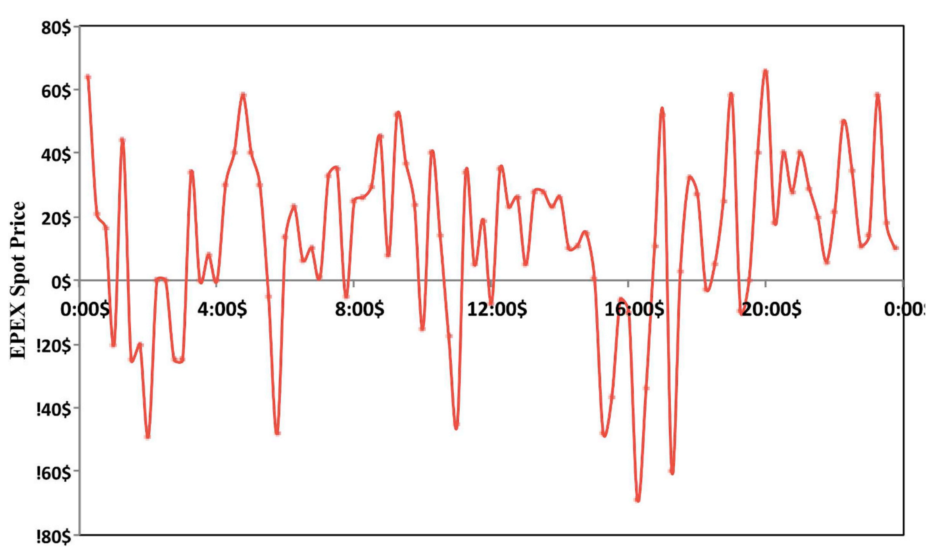


Fig. 2. EPEX spot price on a randomly selected day in 2014.

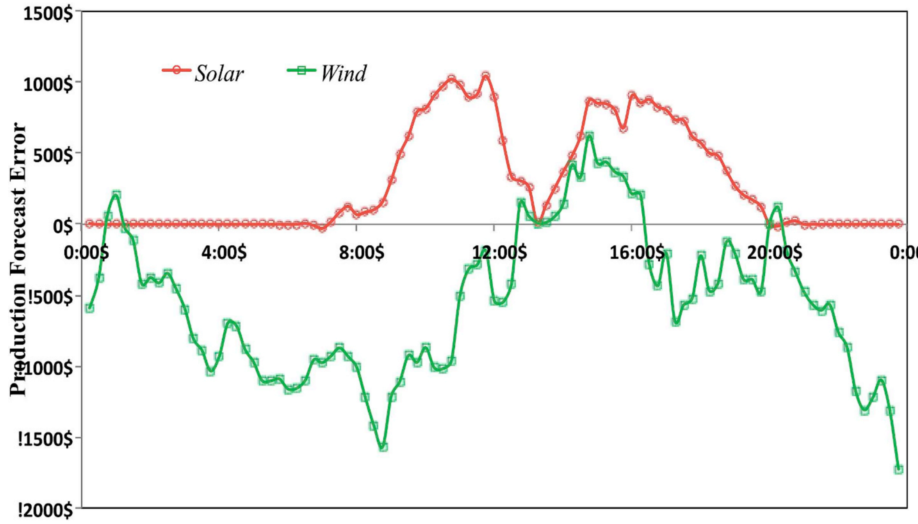


Fig. 3. PV/wind production forecast error for a randomly selected day in 2014.

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 et al. (2014) have all modelled short-term electricity demand forecasts. But with market competition, load is no longer the only variable that needs to be predicted and there is an increasing attention from researchers on electricity price modelling and forecasting (Garcia and Kirschen, 2004; Weron, 2014). Escribano et al. (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. Aïd, 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 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 et al. (2013) focus on revenue maximization by predicting wind energy inputs. Both these works focus extensively on imbalance and mitigating ancillary energy supply. Bueno-Lorenzo et al. (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 et al. (2016) and Kiesel and Paraschiv (2017) provide the most relevant basis for this research. They use regression methods to forecast imbalance and electricity prices for intraday markets. The impact from both wind and photovoltaic RES is considered in both their works.

However, Pape et al. (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 et al. (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 and Bunn (2008a) 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 min (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 different price levels. These could be differentiated as per seasonality (winter/summer) 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. Based on empirical data from the Frauenhofer ISE (2018), we also observe ascending and descending patterns that sandwich the peak demand periods. The dummy variable categories are as follows;

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

Table 2
Explanatory variables (Variables are measured at quarter-hourly intervals).

Variable	Description
Imbalance (dependent variable) (MW)	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, and negative otherwise.
EPEX Spot price (dependent variable) (€/MWh)	Wholesale electricity price.
One Day Lagged Price (€/MWh)	EPEX SPOT price for corresponding time slot one day prior to delivery.
One Day Lagged Imbalance (MW)	Supply-demand imbalance for corresponding time slot one day prior to delivery.
Adaptive Imbalance (MW)	Two-period-lagged value of imbalance.
Adaptive Price (€/MWh)	Two-period-lagged value of EPEX Spot price.
Realized Total Load (MW)	Two-period lagged actual electricity load.
PV Forecast Error (MW)	The actual electricity production by PV sources minus the forecasted amount.
Wind Forecast Error (MW)	The actual electricity production by wind sources minus the forecasted amount.
Seasonality & Peak Variable	Dummy variable based on season and peak/off-peak period of the day

Table 3
Descriptive statistics, N = 34616.

Descriptive Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Realized Total Load (MW)	52178.41	8775.849	31281	73218	−0.0208	1.9222
Wind Forecast Error (MW)	−188.8289	1021.495	−5187.800	7802.800	0.5434	6.8133
PV Forecast Error (MW)	−68.87206	884.7721	−9794.500	4081.600	−1.9191	19.1649
Dependent Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
EPEX Spot Price (€/MWh)	33.08333	23.92481	−200	398	0.6346	13.8410
Imbalance (MW)	−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 models that take into consideration all the explanatory variables discussed in section 3.1. The two equations are estimated independently from each other despite sharing a set of common explanatory variables. The evident time lags, the fact that spot trading closes two periods before the imbalances are determined, as well as the specification that neither of the dependent variables act as explanatory variables in the other equation, reduces endogeneity, concerns. The paper focuses predominantly on how forecast errors of RES impacts imbalance and the EPEX SPOT price, hence justifying the dependent variables in the reduced-form, linear models presented below.

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

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

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 squares 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

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

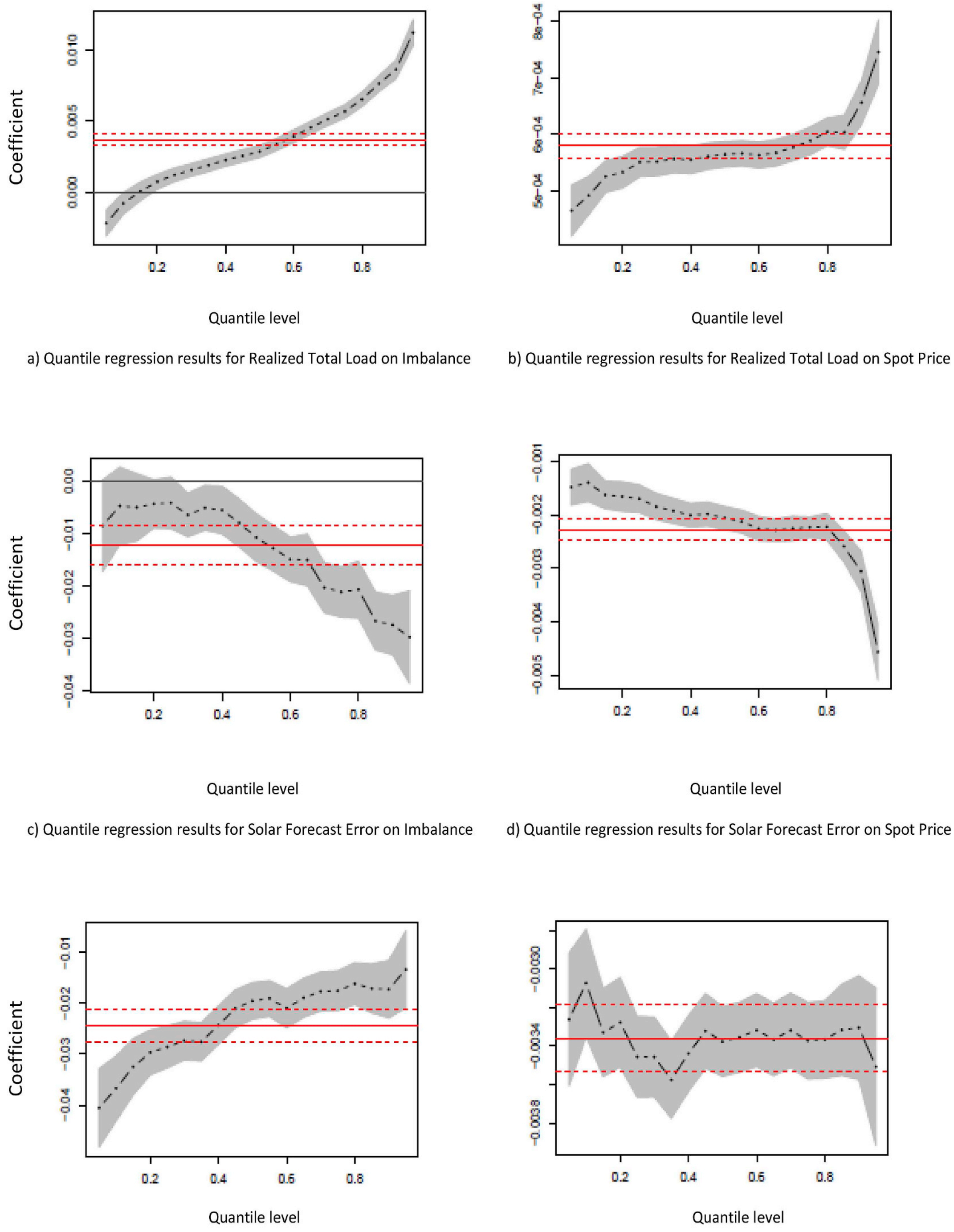
Regressors	OLS Estimate (SE)	Tau = 5% Estimate (SE)	Tau = 50% Estimate (SE)	Tau = 95% Estimate (SE)
One Day Lagged Price	0.277189**** (0.00453)	0.23812**** (0.00932)	0.30079**** (0.00453)	0.25011**** (0.00934)
Adaptive Imbalance	0.008583**** (0.00021)	0.00900**** (0.00035)	0.00795**** (0.00022)	0.00835**** (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.



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

Fig. 4. Quantile regression results.

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 (Tables 4 and 5).

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 suggests a correlation between the residuals. This suggests that ARMA cannot clearly explain the relationship between imbalance and the other variables. Thus, this analysis shows the inadequacy of ARMA to understand imbalance and its effects (please refer to Appendix A for detailed results).

4. Discussion

In the study of EPEX Spot price, the most interesting effects are the impacts of adaptation. The results (Table 4) show that adaptive imbalance and adaptive price have significantly positive effects on EPEX spot price. This means that high spot prices persist in the market and that imbalances pass through into market prices. The results from quantile regressions show this effect is higher in the tails of the distribution compared to the mean or median. Therefore, extreme imbalances and prices have relatively higher impacts on price risk. In particular, this means that when imbalance is highly positive in one period, an increase in price is likely to follow. This impact is higher when the prices are extremely high or low.

The explanatory variables wind and PV production forecast errors for EPEX spot are observed to have significant negative effects, but these are descriptive features and do not have predictive value. Recall that these forecasts are day ahead and that EPEX spot is determined 30mins before real-time delivery. Thus, high (low) production forecast errors for PV or wind means that the actual electricity production from these sources is higher (lower) than what was initially forecasted day ahead and inevitably the intraday prices will have adjusted downwards (upwards).

Load intuitively has a positive sign and is significant. The results of the quantile regression indicate that the realized total load has an interesting relationship with the imbalance and the electricity price (see Fig. 4 a and b). As the quantile level increases, the coefficient of the realized total load increases. However, this relationship appears not to be linear at the tails. Analysis of variance (ANOVA) shows that the coefficients for the quantile level of tau = 5% is significantly different to that of tau = 95% ($p < 0.0001$). This is further evident from the horizontal red line depicting the OLS coefficient and the dotted red lines denoting the confidence intervals. The results suggest that when the realized total load is high, the marginal cost to purchase electricity rises due to scarcity in supply.

Regarding Imbalances, both wind and PV production forecast errors have negative significant effects on imbalance. Thus, when the production forecast error is high, the electricity produced is more than the forecasted value. This surplus in energy leads to a negative imbalance. Negative imbalances therefore require the system operator to curtail production elsewhere. The reverse holds for negative forecast errors. Note that wind forecast errors will primarily be of concern at high wind speeds which will be more associated with excess supply, negative imbalances and thereby more pronounced at the lower rather than the higher quantiles, as observed in Table 5. Wind forecast errors have a stronger effect than solar, except at the high quantile. Solar mostly serves the non-peak demand whilst wind errors are distributed across the day and in Germany this includes the evening peak where imbalances are likely to be higher. Hence the generally larger impact of wind. 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).

Improvements in wind and solar forecasting therefore intuitively linked to more accurate predictions of the imbalance. Reducing the absolute level of imbalances will reduce costs for participants and system operations. Moreover, as the results show, forecast errors have significant impact on subsequent spot price levels as imbalances have a lagged effect. Therefore, better wind and solar forecasts should lead to a better managed system with lower real-time costs and market price variations to the benefit all stakeholders in the electricity market.

Evidently the empirical support for these insights has come from our detailed modelling of the German market. We believe that whilst the implications are generalizable, as balancing and settlement is pervasive to all liberalized power market trading, the scale of impact evidently depends upon the degree of penetration of wind and solar. Germany is one of the leaders and to that extent our results may be predictive of what may yet become an issue elsewhere, but many other markets already have similar issues. For the EU in particular, the German market arrangements are the basis for greater harmonization in balancing across the whole single market of electricity, progressively involving all member states.

5. Conclusions and policy implications

The renewable energy sector has grown rapidly since the beginning of this century, 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 transparency to the market.

We build on previous research to deliver a method to model real-time energy (supply-demand) imbalance and EPEX spot prices using quantile regression analysis using applied to data from the German electricity spot market. The results of our study confirm that larger wind and PV production forecast errors increase the absolute levels of imbalance and that larger imbalances influence subsequent spot prices. Our findings show that this relationship is more influential for wind energy forecast errors. However, the effects vary from the lower to the upper risk levels of the distributions.

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. Improving forecasts is not simply a matter of using better techniques; data on wind and solar production embedded in the system at the end-user level is often obscure or not available in a timely manner to the system operators. Thus, regulatory intervention on this matter would involve issues of greater data transparency the behaviour of end-users.

Such a recommendation should be considered alongside incentives for storage. Evidently, storage operations can help the system, operator to balance the system. Thus, Cai et al. (2015) suggest that with gradually decreasing costs of battery storage systems, they can be more helpful to the short-term balancing of electricity supply and demand, and therefore reduce the costs of wind and solar prediction uncertainties. Also, Anderson and Leach (2004) and Dufo-López et al. (2009), argue that substantial sources of renewable energy such as solar and wind make storage systems crucial and, furthermore, Bitaraf et al. (2015) explicitly suggest how energy storage systems can decrease the impact of wind power forecast error. Nevertheless, many storage operators need daily forecasts of price spreads and imbalance requirements to optimize their operations, and so the emergence of storage is unlikely to dilute the value of daily forecasts.

Acknowledgment

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Appendix A. ARMA Output

```
ARIMA Model: Imbalance

Estimates at each iteration


                      Iteration         SSE        Parameters
                        0  9725938124  0.100   0.100  -6.530
                        1  5820542286  0.250  -0.050  -5.445
                        2  4764958143  0.400   0.006  -4.358
                        3  3784016439  0.550   0.040  -3.271
                        4  3093203853  0.700   0.059  -2.184
                        5  2820675556  0.850   0.070  -1.097
                        6  2818986520  0.862   0.070  -1.018
                        7  2818982317  0.862   0.070  -1.015
                        8  2818982307  0.862   0.070  -1.015

Relative change in each estimate less than 0.0010


Final Estimates of Parameters

                      Type        Coef  SE Coef       T      P
                      AR   1    0.8625   0.0032  266.98  0.000
                      MA   1    0.0702   0.0064   11.03  0.000
                      Constant  -1.015    1.430   -0.71  0.478
                             Mean        -7.38    10.40


Number of observations:  34520
Residuals:    SS =  2818969182 (backforecasts excluded)
              MS =  81669   DF = 34517


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

                     Lag             12      24      36      48
                     Chi-Square  3614.0  4392.4  4775.0  5172.6
                     DF               9      21      33      45
                     P-Value      0.000   0.000   0.000   0.000
```

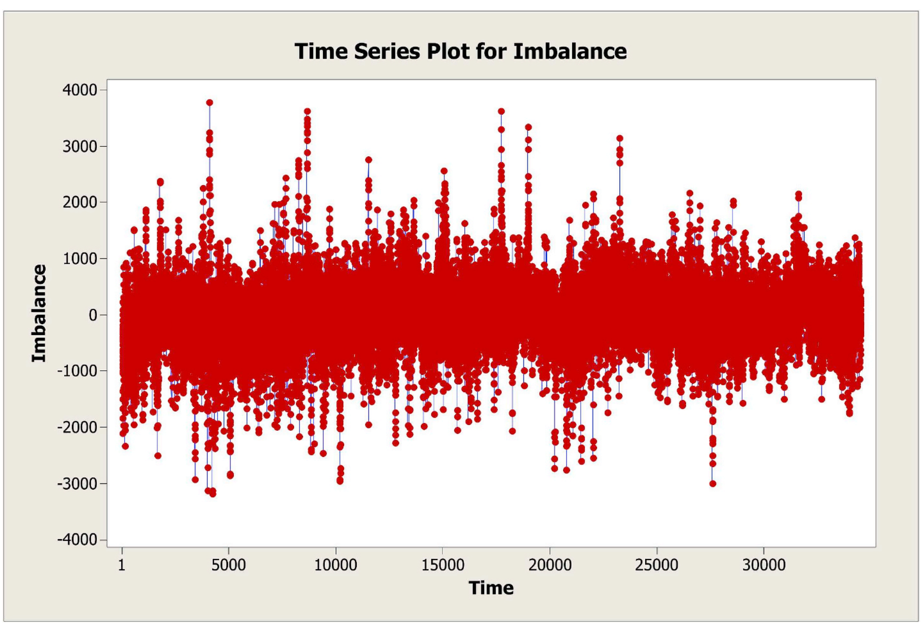

Fig. 5. Time series plot for imbalance

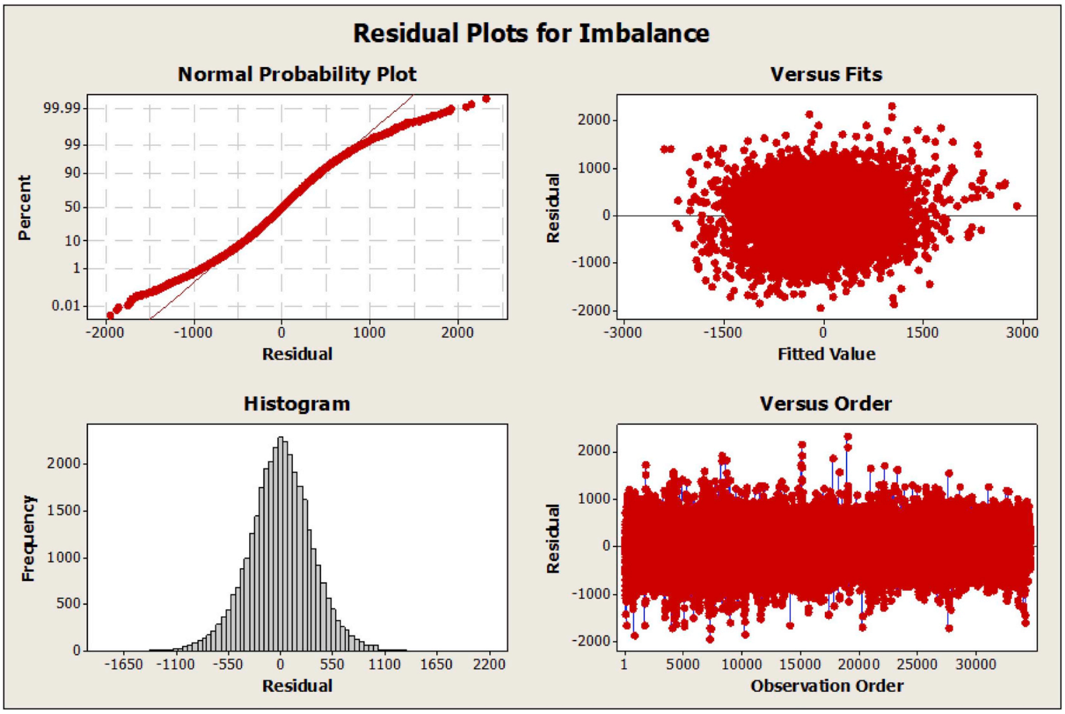

Fig. 6. Residual plots for imbalance

Declarations of interest

None.

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