Econometric analysis of 15-minute intraday electricity prices

Rüdiger Kiesel[a,*], Florentina Paraschiv[b,1,**]

[a] *Chair for Energy Finance, University of Duisburg-Essen, Universitätsstrasse 12, D-45117 Essen, Germany*
[b] *Institute for Operations Research and Computational Finance, University of St. Gallen, Bodanstrasse 6, CH-9000, St. Gallen, Switzerland*
[c] *Norwegian University of Science and Technology (NTNU), Faculty of Economics and Management, NTNU Business School, Klbuveien 72, NO-7030, Trondheim, Norway*

Abstract

The trading activity in the German intraday electricity market has increased significantly over the last years. This is partially due to an increasing share of renewable energy, wind and photovoltaic, which requires power generators to balance out the forecasting errors in their production. We investigate the bidding behaviour in the intraday market by looking at both last prices and continuous bidding, in the context of a reduced-form econometric analysis. A unique data set of 15-minute intraday prices and intraday-updated forecasts of wind and photovoltaic has been employed. Price bids are explained by prior information on renewables forecasts and demand/supply market-specific exogenous variables. We show that intraday prices adjust asymmetrically to both forecasting errors in renewables and to the volume of trades dependent on the threshold variable demand quote, which reflects the expected demand covered by the planned traditional capacity in the day-ahead market. The location of the threshold can be used by market participants to adjust their bids accordingly, given the latest updates in the wind and photovoltaic forecasting errors and the forecasts of the control area balances.

Keywords: intraday electricity prices, bidding behavior, renewable energies

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[**]Corresponding author: Florentina Paraschiv, florentina.paraschiv@ntnu.no.

1. Introduction

Trading in the intraday electricity markets increased rapidly since the opening of the market. This may be driven by the need of photovoltaic and wind power operators to balance their production forecast errors, i.e. deviations between forecasted and actual production. Evidence for this is a jump in the volume of intraday trading as the direct marketing of renewable energy was introduced. Furthermore, there may be a generally increased interest in intraday trading activities due to proprietary trading. Our main goal is to identify explanatory variables, specific to the electricity intraday market, that influence the bidding behavior in the 15-minute intraday market at the European Power Exchange (EPEX).

Along the basic timeline of electricity trading activities, see Figure 1, the intraday activities relate mostly to further adjustments of positions after the closure of the day-ahead market.

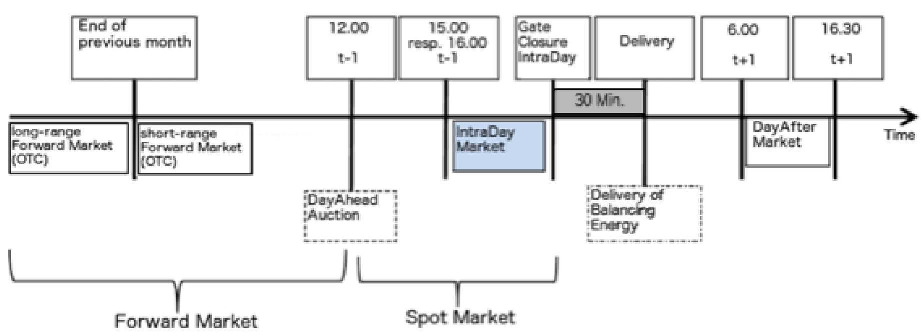


Figure 1: Timing Electricity Trading

While day-ahead trading offers the possibility to correct the long-term production schedule (build on the forward markets) in terms of hourly production schedule of power plants (Delta Hedging) and to adjust for the residual load profiles on an hourly basis, the increasing share of renewable energy sources (wind, solar) in electricity markets requires a finer adjustment.

According to the Equalization Mechanism Ordinance (ger.: Verordnung zur Weiterentwicklung des bundesweiten Ausgleichsmechanismus, abbr.: AuglMechV) all electricity generated by renewable sources has to be traded day-ahead. This is usually done by the transmission system operator (TSO) with the plant operator receiving a legally guaranteed feed-in-tariff. From 2012 on the inclusion of a market premium led direct marketers within the feed-in premium support scheme to enter the market as well. Trading of electricity from a renewable energy source is based on forecasts which may have a horizon of up to 36 h (taking some data-handling into account). To correct errors in forecasts the AusglMechV requires the marketers of renewable energy to use the intraday market to balance differences in actual and updated forecasts. Intraday trading starts at 3 pm and takes place continuously until up to 30 min before the start of the traded quarter-hour. As forecasts change regularly, marketers may sell and buy the same contract at different times during the trading period.

After the closure of the intraday market balancing energy has to be used to close differences between available and forecasted electricity. As a smaller number of power plants are used for balancing energy the merit-order curve is steeper than that in the intraday market. Thus on average larger prices are paid and marketers aim at minimising this difference, see [5]. In addition, TSOs may impose sanctions on marketers who frequently require balancing energy.

Balancing energy is supplied by generators with the necessary flexibility to balance the market. In case generation is below demand positive balancing energy is used, otherwise negative balancing energy. [6] and [13] contain a detailed description of the integration of renewable energy in electricity markets and the regulatory requirements and we refer the reader to these sources for further information.

The day-ahead market (spot market) and the balancing markets have been investigated extensively. For example, [22] show that the day-ahead price formation process at EPEX depends on the interaction/substitution effect between the traditional production capacity (coal, gas, oil) with the fluctuant renewable energies (wind and photovoltaic (PV)). Further empirical studies on intraday/balancing markets include [1], [16]. Also, [18] studies strategic behaviour linking day-ahead and balancing markets.

An investigation in the merit-order effect is given by [2], who find that electricity generation by wind and PV has reduced spot market prices considerably by 6 €/MWh in 2010 rising to 10 €/MWh in 2012. They also show that merit order effects are projected to reach 14-16 €/MWh in 2016.

Recent studies of the intraday high-frequency electricity prices at EPEX are [8] and [9] who look at liquidity effects and forecast determinants on a hourly basis. Also, [3] considers trading strategies to minimise costs from imbalances for both PV and wind, but generates price changes in terms of a reduced-form model (using a stochastic process). The focus lies in developing a trading strategy for a given setting, and not on explaining the relevant price process. Several studies have discussed the effects of prognosis errors for wind generation (see [15] and [20]). As Figure 2 suggests, a PV production introduces quarter-hour ramps quite naturally. In addition, changes in forecasts of renewable energy production require a timely correction of day-ahead positions. However, photovoltaic has not been investigated so far.

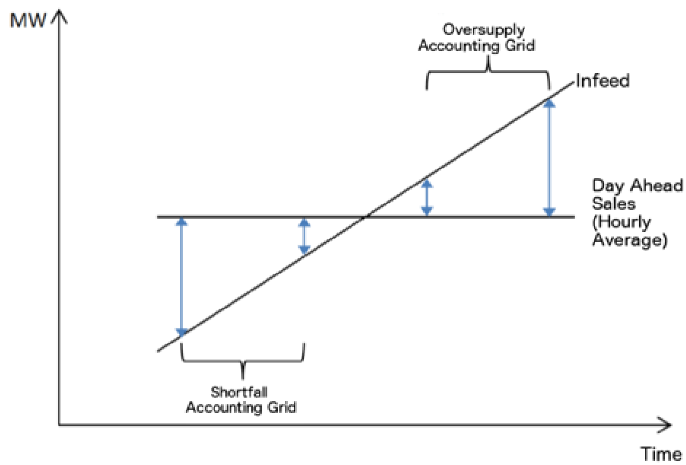


Figure 2: Quarter Hour Ramps

[8] and [9] used the ex-post published wind infeed data to explain ex-ante their impact on the day-ahead market. These are publicly available data from the Transparency Platform EPEX. However, the actual infeed is only known ex-post and therefore it cannot be used directly to explain the price formation on the intraday market. In fact, the intraday market participants have access to updated forecasts of wind. In our study, we will extend the existing literature by taking into account the intraday updated forecasts for wind and PV, which have been supplied by EWE Trading GmbH.

Each day, hourly day-ahead electricity prices are revealed around 2 pm at EPEX (see [23]). At the same time, market participants have access to forecasts for wind and PV published by each Transmission System Operator (TSO) in 15-minute intervals for the next day. However, wind and PV forecasts are updated frequently during the trading period. Thus, at the time when market participants place their bids for a particular intraday delivery period (hour, quarter of hour), updated information about the forecasting errors of renewables becomes available. In consequence, also deviations between the intraday prices and the day-ahead price for a specific hour are expected to occur. Our main research question is, thus, to which extent do market participants change their bidding behavior when new information on wind and PV forecasts becomes available. We will employ a unique data set of the latest forecasts of wind and PV available at the time of the bid.

Our analysis is twofold: Firstly, we analyse the difference between the *last price* bid for a certain quarter of hour and the day-ahead price for that hour. We distinguish between summer/winter, peak/off-peak hours. We test for asymmetric behavior of prices to forecasting errors of renewable energy dependent on the demand quote regime and investigate further the typical zigzag pattern of intraday prices. Thus, we identify a seasonality shape that provides traders important information about the time of the day when they can bid, dependent on their demand/supply profiles. Furthermore, the effect of volume of trades/market liquidity is investigated. Secondly, we are interested in the bidding behavior of market participants in the continuous intraday electricity market. We thus analyse the *continuous* trades and disentangle the effect of explanatory variables dependent on the time of the day. The econometric analysis is replicated for several traded hourly quarters, at different time of the day. In particular, we are interested to see how delta bid prices change when new information becomes available in the intraday renewable forecasts for wind and PV. We look at the trade-off between autoregressive terms and the market-related exogenous variables impacting the intraday price formation process.

Our contribution to the existing literature is twofold: *we use ex-ante forecasts of wind and photovoltaic* and employ *high-frequency intraday prices for specific quarter hours*. Overall, our paper aims at understanding historically the continuous bidding in the intraday market, and proposes a one-period reduced-form forecasting model based on exogenous variables which are observed by market participants at the time of the bid. We show that estimation results are stable over time, but it is highly relevant to reestimate the ecponometric model separately for summer/winter, peak/off-peak periods. We used as benchmark an autoregressive model and show that the price formation process is rather driven by market-specific explanatory variables, especially for mid-day delivery periods. The list of explanatory variables includes expected demand, an aggregate index for the power plant availability including traditional capacity planned day-ahead, the volume of trades, control area balances, and intraday updated forecasting errors of wind and photovoltaic. This is the first study which includes ex-ante updates in forecasting errors of renewable energies. This study proves that intraday updated forecasts of wind and PV impact the bidding behavior: we show that market participants access updated forecasts in renewables to have more private information and thus to bid more accurately.

The rest of the paper is organized as follows: In Section 2 we explain the modeling assumptions. Sections 3 and 4 show the data used as input and a theoretical representation of our concept. Section 5 proceeds with the formulation of our reduced-form econometric analysis. Results and their interpretation are given in Section 6 and Section 7 concludes.

2. Theoretical considerations

Our main assumption is that the electricity intraday price formation process depends on how much traditional capacity has been allocated in the day-ahead market and in which proportion it covers the forecasted demand. Let us consider two possible market regimes:

1. The traditional capacity planned for the day-ahead satisfies the expected demand for a certain hour;

2. There is a certain demand quote uncovered by the planned capacity.

Thus, in scenario 2, negative forecasting errors of wind and PV will increase faster the intraday prices than in scenario 1, due to the excess demand pressure. Viceversa, in scenario 1, positive forecasting errors in renewables will put pressure on traditional suppliers to reduce the production, since renewables are fed into the grid with priority (on average, 20% of electricity production in Germany is wind and PV based). Thus, prices will decrease faster than in scenario 2, where the excess of renewables (positive updated forecasts) will balance out the excess demand. Therefore, in the context of a threshold model, we investigate whether there is an asymmetric adjustment of the intraday prices to forecasting errors in renewables, dependent on the demand quote regime (proportion of the forecasted demand for electricity in the planned traditional capacity for the day-ahead). The location of the threshold in the demand quote is estimated and this gives an indication of the bidding behavior in the intraday market. Market participants can compare the historically derived threshold value to the currently computed forecasted demand quote for a certain hour to identify the market regime and to further define a bidding strategy.

Employing the demand quote as threshold variable is supported by the literature as several papers have found that total electricity demand influences price behaviour strongly. In [14] it is shown that the ratio between wind and conventional power production affects the electricity price most (the so-called wind penetration). [19] identify the residual load, the electricity demand that needs to be met by conventional power, as an important variable.

To include the trading volume as explanatory variable is also supported by the literature, as e.g. [6] find that the forecast balancing costs in intraday trading are linked to the trading volume. This is in line with earlier papers, such as [17] and [4], who estimate asymmetric GARCH models and include traded electricity volume in the variance equation to study its impact on price volatility.

In a first part of our analysis, we examine the difference between the last intraday bid price for a certain quarter of an hour and the day-ahead price for that specific hour. As a prerequisite for our analysis, we investigate the typical zigzag pattern of the 15-minute intraday prices and control for seasonality. Figures 3 and 4 show the long-term mean of last prices and average prices bid for a certain quarter of an hour between 01/01/2014–01/07/2014 for peak and off peak hours, respectively. During the day, the zigzag pattern is mainly explained by the following situation: Renewable energy providers sell day-ahead the full hour (average of all quarters). In the first part of the day, up to 1400, as the sun goes up, there is a buy-pressure on them in the first quarter as they are not able to produce the hourly average (see Figure 3, upper graph). On the other hand, in the fourth quarter they produce too much and have to sell. By contrary, in the second part of the day (between 1400–2000) the ramping down effect of the sun determines a sell-pressure in the first quarter, which turns into buy-pressure in the last quarter. The buy/sell pressure becomes obvious in the evolution of volume of trades (see Figure 3, lower graph): we observe that the volume of trades is highest during the first and last quarters of each peak hour, reflecting demand/supply side pressures.

We also found a persistent zigzag pattern of prices during off-peak hours (between 2000–0800), as shown in Figure 4. This is driven by the production design of fossil power plants (supply side: when it starts low and ends high) or power-intensive industry (demand side: when it starts high and ends low). A reason for that may be inter-temporal restrictions in using fossil plants. In addition to fuel costs, these plants have ramp-up and ramp-down costs, which prevent plant operators from shutting down plants in case of drops in demand or starting up plants in case of spikes in demand. The short-term marginal costs from this may dominate fuel costs.

The typical zigzag seasonality pattern of intraday quarter-hourly prices will be corrected by dummy variables in the econometric model specification.

3. Input variables: definition and data sources

As motivated in section 2, for the analysis we employed historical day-ahead and intraday electricity prices for 15-minute products in the continuous trading system between 01/01/2014–30/06/2014. As explanatory variables selected in this study we refer to demand forecast, power plant availability, intraday updated forecasts for wind and photovoltaic, volume of trades in the continuous trading, and the control area balance. The latter represents the corresponding use of balancing power in the balancing market[1]. In particular, the control area balance corresponds to the sum of all balance group deviations of balance groups registered at the Transmission System Operator and of the relevant balance groups owned by the transmission system operator (e.g. EEG, grid losses, unintentional deviation)[2]. In Tables 1 and 2 we give an overview of the data sources and their frequency, respectively.

4. Asymmetric econometric model for intraday prices

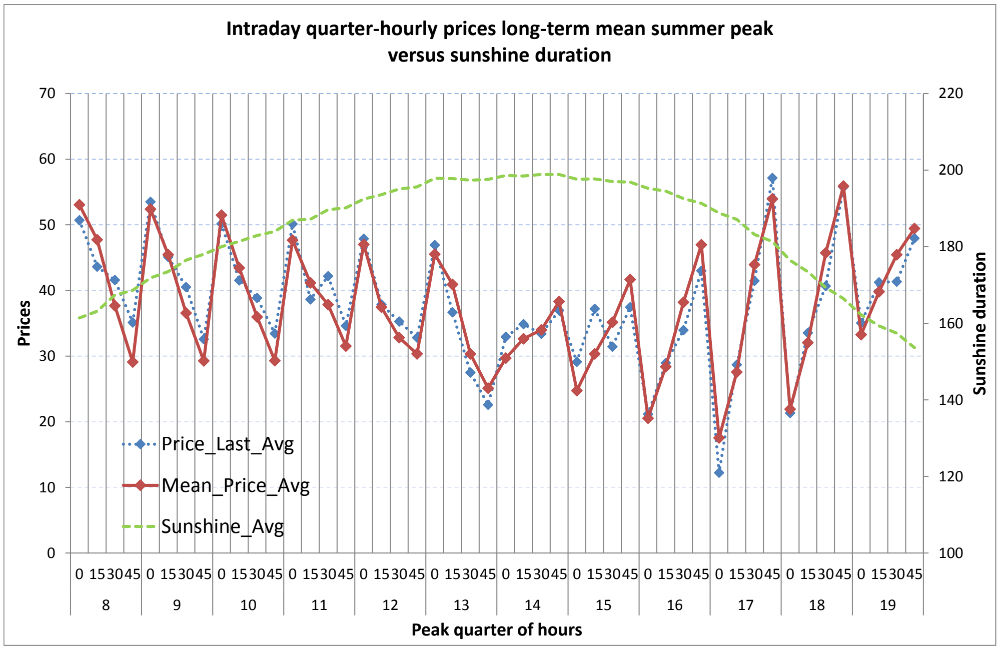
4.1. Threshold model specification

The technical specification of our model follows [21] and reads:

$$y_i = \theta_1^{'} x_i + \varepsilon_i, \quad \omega_i \leq \tau, \tag{1}$$

[1]As balance group deviations are not immediately available online the control area balance is calculated on the basis of the corresponding use of balancing power. The published data are values from operating measurements that are adjusted by measurement corrections if necessary. The actual settlement-relevant data can be retrieved under the prices for grid balancing.

[2]see http://www.tennettso.de



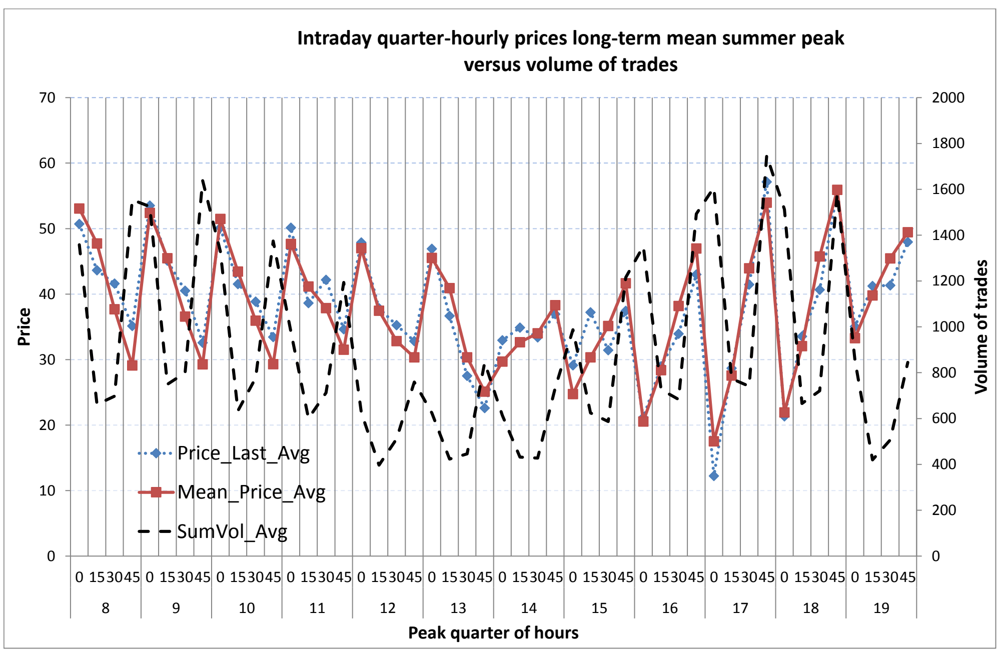


Figure 3: Seasonality pattern of the last prices and average prices bid for a certain quarter of an hour during the peak hours in summer. The right axes show the sunshine duration (upper graph) and the sum of volumes traded (lower graph).

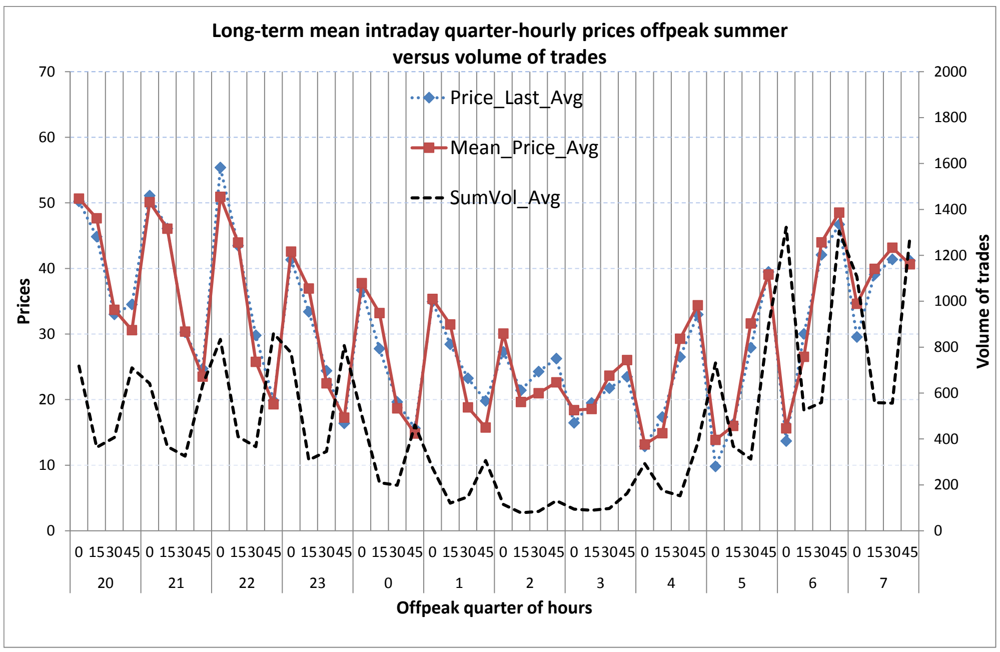


Figure 4: Seasonality pattern of the last prices and average prices bid for a certain quarter of an hour during the off-peak hours in summer. The right axis shows the sum of volumes traded.

Variable units	**Description**	**Data Source**
Day-ahead Price EUR/MWh	Market clearing price for a certain hour in the day-ahead auctions (Phelix)	European Power Exchange (EPEX) `https://www.epexspot.com/en/`
Intraday Price EUR/MWh	Intraday electricity prices for 15-minute products in the continuous trading	European Energy Exchange Transparency Platform: `http://www.eex-transparency.com/de`
Intraday Volume Trades MWh	Intraday volume trades for 15-minute products in the continuous trading	European Energy Exchange Transparency Platform: `http://www.eex-transparency.com/de`
Wind Forecast MW	Sum of intraday forecasted infeed of wind electricity into the grid	EWE TRADING GmbH `http://www.ewe.com/en/`
PV Forecast MW	Sum of intraday forecasted infeed of PV electricity into the grid	EWE TRADING GmbH `http://www.ewe.com/en/`
Expected Power Plant Availability MW	Ex-ante expected power plant availability for electricity production on the delivery day (daily granularity), daily published at 10:00 am	European Energy Exchange & transmission system operators: `ftp://infoproducts.eex.com`
Expected Demand MW	Demand forecast for the relevant hour on the delivery day	European Network of Transmission System Operators (ENTSOE): `https://transparency.entsoe.eu/`
Control area balance MW	Balancing market margins, available ex-post for a certain delivery period	Transmission system operators: `http://www.50Hertz.com`, `http://www.amprion.de`, `http://www.transnetbw.de`, `http://www.tennettso.de`

Table 1: Overview of **explanatory** variables used in the analysis

Variable	**Daily**	**Hourly**	**quarter-hourly**
Day-ahead Price		×	
Intraday Price			×
Intraday Volume Trades			×
Wind Forecast			×
PV Forecast			×
Expected Power Plant Availability	×		
Expected Demand		×	
Control area balance			×

Table 2: Data granularity of **explanatory** variables

$$y_i = \theta_2^{'} x_i + \varepsilon_i, \quad \omega_i > \tau, \tag{2}$$

where ω_i is the threshold variable used to split the sample into two regimes. The random variable ε_i is a regression error.

Our observed sample is $\{y_i, x_i, \omega_i\}_{i=1}^n$, where y_i represent the dependent variable and x_i is an m-vector of independent variables. The *threshold variable* ω_i may be an element of x_i and is assumed to have a continuous distribution. To write the model in a single equation[3], we define the dummy variable $d_i(\tau) = \mathbf{1}[\omega_i \leq \tau]$, where $\mathbf{1}[\cdot]$ is the indicator function and we set $x_i(\tau) := x_i d_i(\tau)$. Furthermore, let $\lambda_n^{'} = \theta_2^{'} - \theta_1^{'}$ denote the threshold effect. Thus, equations (1) and (2) become:

$$y_i = \theta' x_i + \lambda_n' x_i(\tau) + \varepsilon_i \tag{3}$$

In order to simplify the threshold estimation procedure, we rewrite equation (3) in matrix notation. We define the vectors $Y \in \mathbb{R}^n$ and $\varepsilon \in \mathbb{R}^n$ by stacking the variables y_i and ε_i, and the $n \times m$ matrixes $X \in \mathbb{R}^{n\times m}$ and $X(\tau) \in \mathbb{R}^{n\times m}$ by stacking the vectors x_i' and $x_i(\tau)'$. Then (3) can be written as:

$$Y = X\theta + X(\tau)\lambda_n + \varepsilon \tag{4}$$

The regression parameters are $(\theta, \lambda_n, \tau)$ and the natural estimator is least squares (LS).

4.2. Hansen's grid search to locate the most likely threshold

To determine the location of the most likely threshold, we will apply Hansen's grid search. In the implementation of this threshold estimation procedure, we follow [11] and [12]. This paper develops a statistical theory for threshold estimation in the regression context. As mentioned in the previous section, the regression parameters are $(\theta, \lambda_n, \tau)$. Let

$$S_n(\theta, \lambda, \tau) = (Y - X\theta - X(\tau)\lambda)'(Y - X\theta - X(\tau)\lambda) \tag{5}$$

be the sum of squared errors function. Then, by definition, the LS estimators $\hat{\theta}, \hat{\lambda}, \hat{\tau}$ jointly minimize (5). For this minimization, τ is assumed to be restricted to a bounded set $[\underline{\tau}, \bar{\tau}] = \Omega$. The LS estimator is also the MLE when ε_i is i.i.d. $N(0, \sigma^2)$. Following [11], the computationally easiest method to obtain the LS estimates is through concentration. Conditional on τ, equation (4) is linear in θ and in λ_n, yielding the conditional OLS estimators $\hat{\hat{\theta}}(\tau)$

[3]see Hansen (2000)

and $\hat{\lambda}(\tau)$ by regression of Y on $X(\tau)^* = [X X(\tau)]$. The concentrated sum of squared errors function is

$$S_n(\tau) = S_n(\hat{\theta}(\tau), \hat{\lambda}(\tau), \tau) = Y'Y - Y'X(\tau)^*(X(\tau)^{*'}X(\tau)^*)^{-1}X(\tau)^{*'}Y,$$

and $\hat{\tau}$ is the value that minimizes $S_n(\tau)$, i.e.,

$$\hat{\tau} = \operatorname{argmin} S_n(\tau)$$

To test the hypothesis $H_0 : \tau = \tau_0$, a standard approach is to use the likelihood ratio statistic under the auxiliary assumption that ε_i is i.i.d. $N(0, \sigma^2)$. Let

$$LR_n(\tau) := n\frac{S_n(\tau) - S_n(\hat{\tau})}{S_n(\hat{\tau})}.$$

The likelihood ratio test of H_0 is to reject for large values of $LR_n(\tau_0)$. Using the $LR_n(\tau)$ function, asymptotic p-values for the likelihood ratio test are derived:

$$p_n = 1 - \left(1 - \exp(-1/2 \cdot LR_n(\tau_0)^2)\right)^2.$$

5. Analysis of intraday prices

We examine whether intraday prices in the continuous bidding system are caused by market-specific variables. As already mentioned earlier in this study, marketers of renewable energy use the intraday market to balance out differences between actual/updated forecasts of wind and PV. Indeed, discussions with energy traders revealed that at the time of the bid market participants have private access to the freshest weather forecasts for a certain quarter of an hour (delivery period) and use this information for adjusting their bids accordingly. Intuitively, this adjustment causes deviations between the intraday and day-ahead prices for a certain delivery period. An understanding of these deviations is furthermore important for strategic bidding.

The impact of forecasting errors in renewables on intraday prices should however not be judged in isolation, but dependent on the demand quote, meaning the extent at which forecasted demand for a certain hour is covered by the traditional capacity planned in the day-ahead market. Keeping in mind that renewables are fed with priority into the electricity grid, accordingly, more or less traditional capacity is planned (and more or less demand gap or demand quote is realized). Thus, intuitively, the higher the expectation from the renewables in the market day-ahead, the higher the demand quote: power producers plan overall less traditional capacity, since the residual demand is expected to be covered by wind/PV infeed.

As discussed in section 2, dependent on the demand quote regime, thus, if there is excess demand or not in the market, positive and negative forecasting errors in wind and PV are expected to have different impact on price deviations. In the context of a threshold model specification, where the threshold variable is the demand quote, we will examine these dynamics.

5.1. Analysing deviations of last prices from the day-ahead price

In the first part of our analysis, we analyze the differences between the historical last prices bid for a certain 15-minute delivery period in the intra-day market and the day-ahead price for the corresponding hour. We used historical last prices sorted for quarter-hourly products between 01/01/2014–30/06/2014. As exogenous variables we include positive/negative forecasting errors in wind and PV, defined as deviations between the latest forecast available at the time when the last prices are observed and the day-ahead available forecasts. The last prices for a certain delivery period are placed in the market not later than 30 minutes before the delivery period starts[4]. At this time, market participants also forecast the volume in the balancing market, namely positions that could not be filled in the intra-day market. These positions are defined by the Transmission System Operators as "control area balances"[5].

We derive the forecasts of control area balances based on an autoregressive model.[6] Results are shown in Table 3. The order of lags has been identified by examining the autocorrelation function and we further performed Akaike (AIC) and Bayesian (BIC) information criteria to select the best model[7]. We found that the control area balances for a certain 15-minute delivery period can be forecasted based on the last 8 observations (up to 2 hours ago). Forecasts based on this model are further included in our estimation.

The demand quote is defined as:

$$DemandQuote_t = DemandForecast_t / PPA_{dt} \tag{6}$$

[4]Since 16th July, 2015, EPEX Spot will shorten the lead time from 45- to 30 minute before delivery (see European Power Exchange (EPEX) `https://www.epexspot.com/en/`).

[5]see `http://www.tennettso.de`

[6]Discussions with traders revealed that this is a common praxis in the industry.

[7]Results are available upon request

where d is the day-ahead and t one hour in day d. $DemandForecast_t$ is the demand forecast for the relevant hour t on the delivery day d overall Transmission System Operators (source ENTSOE[8]). Based on the expected demand, power producers plan traditional capacity day-ahead. The PPA is the ex-ante expected power plant availability for electricity production on the delivery day (daily granularity), daily published at 10:00 am (see Table 1 for the exact data sources). These data exclude the renewable capacity and include only the traditional plants[9]. EPEX publishes data on installed and available capacities. Although these publications are voluntary, participating companies have tripled in 2010 and by the end of the year represented 89% of all relevant companies (see [22]). Thus, the numbers provided can be considered a reasonable approximation for the entire market. We use ex-ante demand quote as explanatory variable to take into account to which extent the expected demand for electricity for the day-ahead is covered by the planned traditional capacity.

In Tables A.10 and A.11 we show descriptive statistics of the selected input variables. We distinguish between summer/winter, peak/off peak hours (as shown in [23]). We observe that, independent on the season, on average the intraday last price for 15-minute delivery periods is below the day-ahead price for the corresponding hour. Furthermore, the difference becomes larger and more volatile for peak than for off-peak hours and in winter than in summer. The control area balances are, on average, negative in winter and turn into positive in summer. On average, the demand quote is higher and more volatile during peak than in off-peak hours.

To test for stationarity we perform an augmented Dickey-Fuller test (ADF test). For all variables we reject the null hypothesis of a unit root at a 95% significance level meaning that the data is stationary.

As shown in Figures 3 and 4, there is a clear zigzag seasonality in the last prices, independent of the season. Based on the information of the long-term dynamics of historical last prices, we control for the seasonal pattern by introducing dummy variables as follows:

- **Summer peak**

[8]European Energy Exchange & Transmission System Operators

[9]The PPA includes: coal, gas, lignite, oil, pumped-storage, run-of-the-river, seasonal-store and uranium planned capacity day-ahead.

Table 3: Autoregressive model for control area balances

Dependent Variable: Balances				
Method: Least Squares				
Included observations: 2535 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.551*	6.228	2.978	0.002
Balances(-1)	0.818	0.019	41.195	0
Balances(-2)	0.055	0.025	2.160	0.031
Balances(-3)	-0.072	0.025	-2.809	0.005
Balances(-4)	0.162	0.025	6.359	0
Balances(-5)	-0.132	0.025	-5.166	0
Balances(-6)	-0.013	0.025	-0.543	0.586
Balances(-7)	-0.004	0.025	-0.185	0.852
Balances(-8)	0.047	0.019	2.369	0.017
R-squared	0.727	Mean dependent var		131.686
Adjusted R-squared	0.726	S.D. dependent var		577.588
S.E. of regression	301.8479	Akaike info criterion		14.261
Sum squared resid	2.30E+08	Schwarz criterion		14.281
Log likelihood	-18067.2	Hannan-Quinn criter.		14.268
F-statistic	844.035	Durbin-Watson stat		1.998
Prob(F-statistic)	0			

The order of lags has been identified by examining the autocorrelation function and we further performed Akaike (AIC)and Bayesian (BIC) information criteria to select the best model.

- We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 08:00–13:00 (*Morning pattern*)
- We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 14:00–18:00 (*Afternoon pattern*)

- **Winter peak**
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 08:00–12:00 (*Morning pattern*)
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 13:00–17:00 (*Afternoon pattern*)
- **Summer off-peak**
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 20:00–01:00 (*Evening descending pattern*)
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 03:00–07:00 (*Early morning ascending pattern*)
- **Winter off-peak**
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 20:00–21:00 and 04:00–07:00 (*Descending pattern*)
  - We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 23:00–03:00 (*Night, ascending pattern*)

The model specification reads:

$$
\begin{aligned}
(P_t^{ID} - P_t^{Dahd})^h = {} & c^h + \beta^h ControlAreaBalance_t \mathbf{1}_t^h + \theta^h DemandQuote_t \mathbf{1}_t^h \\
& + k^{hn}(Wind_t^{ID} - Wind_t^{Dahd})\mathbf{1}_t^h \mathbf{1}_t^n + k^{hp}(Wind_t^{ID} - \\
& - Wind_t^{Dahd})\mathbf{1}_t^h \mathbf{1}_t^p + k^{hn}(PV_t^{ID} - PV_t^{Dahd})\mathbf{1}_t^h \mathbf{1}_t^n \\
& + k^{hp}(PV_t^{ID} - PV_t^{Dahd})\mathbf{1}_t^h \mathbf{1}_t^p + \sum_{j=1}^{8} \delta_j^h DQ_j
\end{aligned}
$$

$$
\begin{aligned}
(P_t^{ID} - P_t^{Dahd})^l = {} & c^l + \beta^l ControlAreaBalance_t \mathbf{1}_t^l + \theta^l DemandQuote_t \mathbf{1}_t^l \\
& + k^{ln}(Wind_t^{ID} - Wind_t^{Dahd})\mathbf{1}_t^l \mathbf{1}_t^n + k^{lp}(Wind_t^{ID} - \\
& - Wind_t^{Dahd})\mathbf{1}_t^l \mathbf{1}_t^p + k^{ln}(PV_t^{ID} - PV_t^{Dahd})\mathbf{1}_t^l \mathbf{1}_t^n \\
& + k^{lp}(PV_t^{ID} - PV_t^{Dahd})\mathbf{1}_t^l \mathbf{1}_t^p + \sum_{j=1}^{8} \delta_j^l DQ_j
\end{aligned} \tag{7}
$$

As threshold variable, the demand quote splits the data in two regimes: high/sufficient demand quote (“h”) or low (“l”). The indicator function $\mathbf{1}_t^{p/n}$ further distinguishes in each regime between positive/negative forecasting errors in renewables.

5.2. Analysis of the continuous trades for quarter-hourly products

In the second part, we examine the continuous trades for several quarter-hourly products. In particular, we are interested to see how delta bid prices for a certain quarter of an hour change when new information on the forecasts for wind and PV becomes available. We look at the trade-off between autoregressive terms and market-specific factors impacting the intraday price formation process.

The model specification reads:

$$
\begin{aligned}
(\Delta P_t^{ID})^h = {} & c^h + \alpha_1^h \Delta P_{t-1}^{ID} \mathbf{1}_t^h + \alpha_2^h \Delta P_{t-2}^{ID} \mathbf{1}_t^h + \alpha_3^h \Delta P_{t-3}^{ID} \mathbf{1}_t^h \\
& + k_w^{hn}(\Delta Wind_t^{ID})\mathbf{1}_t^h \mathbf{1}_t^n + k_w^{hp}(\Delta Wind_t^{ID})\mathbf{1}_t^h \mathbf{1}_t^p \\
& + k_{PV}^{hn}(\Delta PV_t^{ID})\mathbf{1}_t^h \mathbf{1}_t^n + k_{PV}^{hp}(\Delta PV_t^{ID})\mathbf{1}_t^h \mathbf{1}_t^p \\
& + \gamma^h DemandQuote_t^{Dahd} \mathbf{1}_t^h + \epsilon^h Volume_t^{ID} \mathbf{1}_t^h + \beta_h \sqrt{\Delta t}
\end{aligned}
$$

$$
\begin{aligned}
(\Delta P_t^{ID})^l = {} & c^l + \alpha_1^l \Delta P_{t-1}^{ID} \mathbf{1}_t^l + \alpha_2^l \Delta P_{t-2}^{ID} \mathbf{1}_t^l + \alpha_3^l \Delta P_{t-3}^{ID} \mathbf{1}_t^l \\
& + k_w^{ln} (\Delta Wind_t^{ID}) \mathbf{1}_t^l \mathbf{1}_t^n + k_w^{lp} (\Delta Wind_t^{ID}) \mathbf{1}_t^l \mathbf{1}_t^p \\
& + k_{PV}^{ln} (\Delta PV_t^{ID}) \mathbf{1}_t^l \mathbf{1}_t^n + k_{PV}^{lp} (\Delta PV_t^{ID}) \mathbf{1}_t^l \mathbf{1}_t^p \\
& + \gamma^l DemandQuote_t^{Dahd} \mathbf{1}_t^l + \epsilon^l Volume_t^{ID} \mathbf{1}_t^l + \beta_l \sqrt{\Delta t}
\end{aligned} \tag{8}
$$

The examination of autocorrelation function of price changes for a certain quarter of an hour shows that the first 3 lags of price changes should be selected in the autoregressive part of the model. Changes in the wind, $\Delta Wind_t^{ID}$, and in the PV, ΔPV_t^{ID}, are real time updated forecasts, available at the time when bids are placed.[10] $Volume_t^{ID}$ is the volume trade at the time when the price change is observed. The bids for a certain quarter of an hour do not occur at equal time intervals in the continuous bidding. In fact, market participants start bidding around 4 pm, after the day-ahead prices are published at EPEX and continuous trades go up to 30 minutes before the beginning of the delivery period. Thus, the time steps between consecutively placed bids are not equal, but can vary from some seconds to several hours. We take into account this time discontinuity by including in our list of explanatory variables the control variable $\sqrt{\Delta t}$.

In Tables A.12 and A.13 we show descriptive statistics for the price changes and volume of trades for the 15-minute continuous trading for delivery periods at different times of the day. We observe that the volatility of intraday price changes increases continuously between the morning quarter of hours (H7Q1) up to noon (H12Q4) and decreases again towards the evening (quarters of hour 18). Thus, the higher the demand, the larger the average price changes in the continuous trading. The volume of trades is on average the highest and most volatile for the first and last quarters of each one of the investigated hours, independent on the time of the day. This explains the sell/buy pressure, as explained in Section 2.

[10]Results are available upon request

6. Estimation results and interpretation

6.1. Analysis of the deviations of last prices from the day-ahead price

Equation (7) has been estimated for the historical differences between the last prices and the day-ahead prices separately for winter and summer and we further distinguished between peak (8 am and 8 pm) and off-peak hours. This approach is justified by the different price levels in summer compared to the winter time and by the different demand profiles during peak and off-peak hours (see [23] for an extensive discussion on the seasonality of electricity prices).

As a preliminary analysis, we estimated the model without allowing for a threshold effect, to assess whether there is a linear adjustment of intraday (last) prices to exogenous variables. The overall OLS estimation results for each case study are shown in Table 4.

Throughout all variables are significant and show the expected sign (see Table 4). Dummy variables which explain the zigzag pattern are statistically significant and their inclusion still allows significant marginal effects of the other explanatory variables on delta prices. The coefficients of positive/negative forecasting errors in wind and PV are significant at 1% significance level. Positive forecasting errors of wind/PV signal market participants more capacity available in the market than planned. This will have a decreasing effect on the residual demand and will further decrease last price bids. Viceversa, when updated forecasts signal less infeed from renewables than planned in the day ahead (negative forecasting errors), market participants will increase their bid prices intraday accordingly.

At the time of the last price bids, market participants do not know yet the real control area balances, but forecasts of those are used in practice. This is reflected in the coefficients of balances forecasts which are statistically significant in all case studies and have a positive sign. Higher control area balances are a signal of excess demand which has not been yet balanced out in the intraday market, and this will be reflected in higher intraday last prices.

We observe that the coefficient of demand quote is negative during the off-peak regimes, but it turns into positive during peak hours. The mean value of demand quote in the *off-peak hours* is slightly below one, touching a maximum of 1.291 and 1.178, respectively (as shown in Tables A.10 and A.11). Thus, on average, the traditional capacity planned in the market covers the expected demand for the day-ahead. In Figure 5, the upper graph illustrates such a theoretical case, where the demand quote is 1. However, at higher levels of demand quote (up to a maximum observed in off-peak hours of about 1.2), power producers plan less capacity for the day ahead, due to a higher expectation of renewables infeed in the market (see Figure 5, lower graph).[11]. That means, less expensive capacity is planned, which situates the prices in the less convex area of the merit order. The input from renewable energies is expected to be, on average, 20% of the total input production mix in Germany (see [22]). Renewables will be fed with priority into the grid, decreasing the residual demand and thus market participants will bid lower prices intraday. This assumption is confirmed by the negative sign of the coefficients of demand quote in the off-peak hours winter/summer, as shown in Table 4.

For the *peak hours* descriptive statistics show that on average, the demand quote exceeds 1.2 (see Table A.11), which means that there is more than 20% of the expected demand uncovered by the planned traditional capacity. Thus, power producers plan less capacity in the market, given a high market expectation for renewables infeed in peak hours. We illustrate graphically this situation in Figure 6, lower graph. However, demand quotes above 1.2 reflect the situation where the 20% expected infeed from renewables will not suffice and there will be still high residual demand in the market. This will have an increasing effect on intraday prices in general and on the last prices in particular, which is confirmed by the positive sign of the coefficient of demand quote (see Table 4)[12].

We further tested for a threshold effect in the demand quote in each case. The threshold variable is the demand quote and the threshold location is estimated using the methodology described in section 4.2. All model parameters in Equations (7) are allowed to vary among regimes. We found evidence for significant threshold effect only in the case of winter peak case study. Results are available in Table 5.

We found no significant threshold effect in the demand quote in summer-related case studies and in winter off-peak. This shows that in those seasons, market participants adjust linearly last prices (and implicitly the spreads last prices-day-ahead prices) to our market-specific explanatory variables. However, in winter peak time we found evidence for asymmetric behavior (see

[11]It is known that in the night hours extreme wind infeed occur (see [23]).

[12]This is reflected in the high maximum spreads between the last prices and day-ahead prices observed in summer peak, as shown in Table A.11.

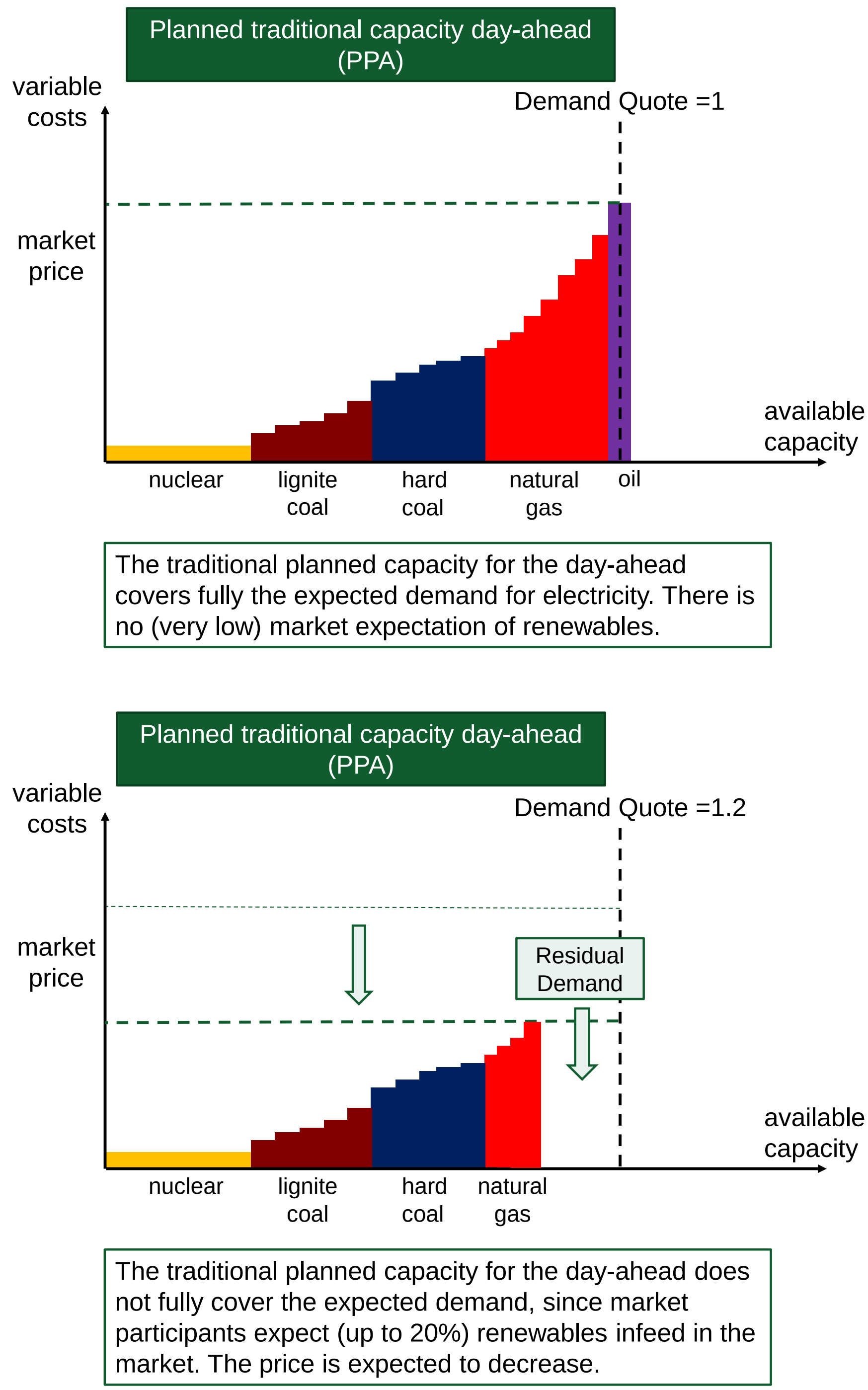


Figure 5: Theoretical example explaining the impact of ex-ante demand quote on intraday electricity prices.

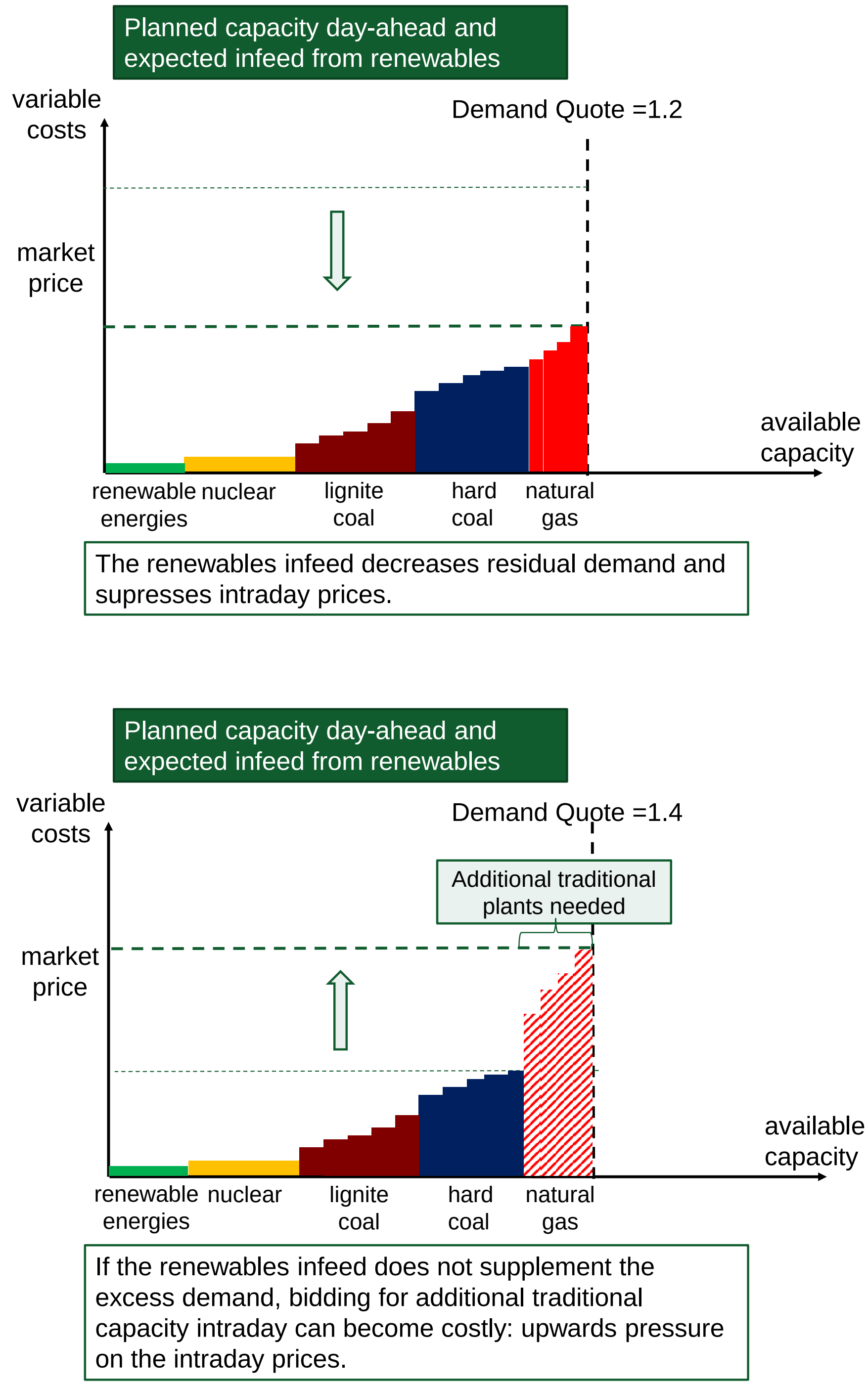


Figure 6: Theoretical example explaining the impact of ex-ante demand quote on intraday electricity prices (continuation).

Table 5). Thus, a threshold in the demand quote was found significant at the level of 1.058. In the regime of low levels of demand quote (regime 1, < 1.058), we observe that coefficients are generally not statistically significant. That is, power producers have low expectation of renewable infeed in the day-ahead, and in consequence plan sufficient traditional capacity to satisfy expected demand. However, when demand levels are high, thus in regime 2, delta prices adjust linearly to forecasting errors in renewable energy, to control area balances and to demand quote. An increase in demand quote in this regime will furthermore suppress bid prices in the intraday market, since again higher demand quote levels reflect a high expectation of infeed from renewable energies, which will lower the price level. The coefficient of control area balances is positive and significant. This reflects two situations: if there is high infeed from renewables in the market, negative forecasts of control area balances will suppress the intraday last prices. By contrary, in the presence of high demand quote not fully covered by renewables infeed, positive forecasts in control area balances will increase intraday price bids.

Our results can be used to forecast the last prices submitted for a certain quarter of one hour intraday. This is based on a rigourous forecasting model for the control area balances. The insights of our econometric analysis are highly relevant for practitioners: the main goal of market participants is to clear their positions in the day-ahead and intraday markets and avoid participating in the more expensive balancing market.

6.2. Analysis of continuous trades for quarter-hourly products

In this section, we show the impact of explanatory variables on the (continuous) bidding behavior. We checked for both linear and asymmetric adjustment of intraday price changes to explanatory variables, dependent on the time of the day. We therefore replicated the analysis to different delivery periods (peak/off-peak) corresponding to different demand profiles: quarters 1–4 of hours 7, 12 and 18 have been investigated. The estimation results of (OLS) linear estimation, without threshold, of Equation (8) are shown in Table 6, B.14 and B.15. The main threshold estimation results following the specification in Equation (8) are shown in Tables 7–9. In all cases the demand quote has been found to be the only significant threshold variable.[13]

[13]The threshold values are significant, accordingly to the likelihood ratio test, as discussed in section 4.1. The graphs and calculations corresponding to each threshold values

Table 4: Estimation results of the model shown in Equation 7. Global OLS without threshold

Dependent variable Delta Last Price- Price DayAhedd								
	Summer off-peak		**Summer peak**		**Winter off-peak**		**Winter peak**	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	7.388*	(1.971)	-20.956*	(6.128)	14.469*	(4.762)	-9.015	(10.354)
DemandQ	-7.438*	(2.159)	10.929**	(4.852)	-12.715*	(4.605)	-0.354	(8.728)
Balancing	0.007*	(0.001)	0.008*	(0.001)	0.014*	(0.001)	0.009*	(0.001)
DeltaWindP	-0.005*	(0.001)	-0.002**	(0.001)	-0.003*	(0.001)	-0.003*	(0.001)
DeltaWindN	-0.007*	(0.001)	-0.012*	(0.001)	-0.004*	(0.001)	-0.004*	(0.001)
DeltaPVP	–	–	-0.003*	(0.001)	–	–	-0.003*	(0.001)
DeltaPVN	–	–	-0.004*	(0.001)	–	–	-0.005*	(0.001)
DQ1M	10.170*	(1.112)	10.022*	(1.462)	-4.561*	(1.729)	23.808*	(2.340)
DQ2M	3.515*	(1.144)	2.192	(1.507)	-5.094*	(1.717)	11.336*	(2.148)
DQ3M	-6.519*	(1.122)	-1.486	(1.463)	-3.148	(1.704)	2.740	(2.207)
DQ4M	-10.454*	(1.139)	-6.031*	(1.622)	-1.187	(1.719)	-0.548	(2.296)
DQ1A	-13.845*	(1.219)	-8.111*	(1.539)	3.114	(1.848)	-6.098*	(2.173)
DQ2A	-6.852*	(1.229)	0.268	(1.374)	-0.948	(1.802)	3.203	(2.016)
DQ3A	0.349	(1.161)	3.458**	(1.341)	-4.578**	(1.793)	16.773*	(2.118)
DQ4A	4.842*	(1.203)	13.132*	(1.451)	-4.568**	(1.825)	25.588*	(2.294)
Rsquared	35.43%		37.99%		28.76%		36.63%	
No. Obs.	2543		2483		2447		2363	

Standard errors are shown in parenthesis. * and **, denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. DemandQ=Demand Quote defined in Equation (6); Balancing=control area balances; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV; DQ1M–DQ4M=Dummies for the four quarters of each morning hours (where morning defines the first part of the day: 0800–1400); DQ1A–DQ4A=Dummies for the four quarters of each afternoon hours (where afternoon defines the second part of the day: 1400–2000)

Table 5: Winter peak, threshold estimation results. Threshold variable: Demand Quote

Threshold estimation (threshold variable DemandQ)				
Dependent variable Delta Last Price- Price Dahd				
	Regime 1		**Regime 2**	
Threshold value	<= 1.058		> 1.058	
	Coeff	Std. Err.	Coeff	Std. Err.
Co	-48.973*	(15.527)	63.563*	(22.987)
DemandQ	26.810**	(12.806)	-61.545*	(19.412)
Balancing	0.003	(0.002)	0.010*	(0.001)
DeltaWindP	-0.004	(0.003)	-0.002**	(0.001)
DeltaWindN	-0.006**	(0.003)	-0.004*	(0.001)
DeltaPVP	-0.003	(0.002)	-0.004*	(0.001)
DeltaPVN	-0.006*	(0.001)	-0.006*	(0.001)
DQ1M	41.322*	(8.710)	21.500*	(2.324)
DQ2M	21.880*	(7.985)	10.443*	(2.129)
DQ3M	4.806	(7.948)	3.682	(2.205)
DQ4M	2.266	(8.284)	0.298	(2.329)
DQ1A	-8.175	(7.420)	-1.367	(2.340)
DQ2A	8.898	(7.325)	3.440	(2.207)
DQ3A	30.651*	(7.536)	12.192*	(2.235)
DQ4A	45.249*	(7.616)	17.453*	(2.369)
Rsquared	48.61%		35.93%	
No. Obs.	652		1711	

Standard errors are shown in parenthesis. * and **, denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. DemandQ=Demand Quote defined in Equation (6); Balancing=control area balances; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV; DQ1M–DQ4M=Dummies for the four quarters of each morning hours (where morning defines the first part of the day: 0800–1400); DQ1A–DQ4A=Dummies for the four quarters of each afternoon hours (where afternoon defines the second part of the day: 1400–2000)

In Table 6 we benchmarked our results by a version excluding the market-specific variables (see lower panel). By comparing the values of the R^2 between the lower and upper panels we observe that at noon market-specific exogenous variables increase the explanatory power of the model by up to 4 times. This effect is however less obvious in the case of morning and evening peak quarter-hourly products (see Tables B.14 and B.15).

More specifically, results reveal that during morning and evening the information from lagged price changes become more relevant for the price formation process than exogenous variables. However, the market-specific exogenous variables become significant during noon (see Table 6). This can be due to the fact that over noon, given the high demand for electricity in the market, the merit order (MO) curve is usually very steep, since more expensive plants are on use. Thus, market participants become more sensitive to market-specific variables, in particular to forecasting errors of renewable energies, given their low marginal costs of production. Negative forecasting errors in wind and PV would further increase the steepness of the MO, which leads to increased intraday prices, while positive forecasting errors in renewables will have a suppressing effect on prices.

In Table 8 we allow for threshold effect in the demand quote for quarters 1–4 of hour 12. Similarly to the results in section 6.1, a threshold has been found significant when the demand quote is around 1.2, which allows a nice interpretation, given the 20% expected infeed from renewables in the German power market. Given this expectation, less traditional plants are planned day-ahead (see Figures 5 and 6). Also in this case, we conclude an asymmetric adjustment of intraday price changes to forecasting errors of wind and PV, dependent on the demand quote regime. In particular, results reveal that market participants adjust their intraday bids to updated forecasts moreover in the high demand quote regime. Thus, when there is a high expected infeed from renewables day-ahead, market participants follow updated forecasted errors in wind and PV and incorporate this information in adjusting their bids accordingly intraday. This effect becomes more obvious for noon hours, when the demand is high and the MO is usually steeper than during morning and evening hours. Thus, Tables 7 and 9 show that the role of forecasting errors of renewables for the morning and evening quarters drops, independent

are available upon request. We have tested for threshold significance also in the other explanatory variables, but no conclusive results were obtained.

of the demand quote regime.

Still, during morning and evening delivery periods (Tables 7 and 9) we observe that market related variables help explaining the zigzag pattern of intraday prices: positive forecasting errors in PV decrease prices in quarter 4 of hour 7 in regime 2, which reflects the *ramping up effect of the sun*. By contrary, forecasting errors of wind and PV impact intraday prices in the first 3 quarters of hour 18. After this quarter, however, the role of forecasting errors of PV drops, showing the *ramping down effect of the sun*.

Results reveal further evidence for the ramping up/down effects of the sun, reflected in the sign of the volume of trades. We observe that the corresponding coefficient is significant only for quarter 4 of hour 7 (see Table B.14) and has a negative sign. This pattern is again observed in the threshold model for hour 7 (see Table 7) in regime 1, when the demand quote is below 1.415 (see Tables 7). For the last quarter of hour 7 the intraday price is below the average price bid for hour 7 in the day-ahead due to the sun ramping up effect, reflecting an oversupply of the accounting grid (see Figure 2). However, for hour 18 this effect is reverted. As shown in Tables B.15 and 9, the coefficient of volume of trades is significant and has a negative sign for the first quarter of hour 18 and turns into positive in the last quarter. This reflects the sun ramping down effect, which causes the zigzag pattern for the evening hours: the intraday price for quarter 1 is below the average price bid in the day-ahead for the respective hour (oversupply of the accounting grid) and it ends above it for quarter 4, reflecting shortfalls in the accounting grid.

Table 6: Estimation results hour 12, Quarters 1–4, global OLS without threshold

OLS estimation of the model including all exogenous variables

Dependent variable Delta Price

	H12Q1		**H12Q2**		**H12Q3**		**H12Q4**	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	-0.558	(0.672)	-0.674	(0.977)	-0.111	(0.765)	-0.032	(0.799)
DeltaPrice1	-0.175**	(0.086)	-0.167*	(0.043)	-0.207*	(0.038)	-0.140*	(0.020)
DeltaPrice2	-0.071**	(0.032)	-0.040	(0.023)	-0.077**	(0.036)	-0.079*	(0.020)
DeltaPrice3	-0.102	(0.060)	-0.018	(0.017)	-0.039	(0.021)	-0.020	(0.013)
DemandQuote	0.109	(0.499)	0.408	(0.755)	0.156	(0.578)	0.088	(0.635)
Volume	0.053*	(0.019)	0.012	(0.009)	-0.012	(0.009)	-0.013**	(0.006)
SqrTimeStep	0.423	(1.570)	1.868	(1.365)	1.010	(1.348)	1.683	(1.853)
DeltaWindIntrP	-0.001*	(0.000)	-0.001	(0.001)	-0.001*	(0.000)	-0.001*	(0.000)
DeltaWindIntrN	-0.001*	(0.000)	-0.001	(0.001)	-0.001	(0.001)	-0.002**	(0.001)
DeltaPVIntraP	-0.002**	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)	-0.004*	(0.001)
DeltaPVIntraN	0.000	(0.001)	-0.001	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)
Rsquared	7.296%		4.705%		7.011%		8.411%	
No. Obs.	6859		5449		6558		7931	

OLS estimation of the autoregressive model excluding market-specific exogenous variables

Dependent variable Delta Price

	H12Q1		**H12Q2**		**H12Q3**		**H12Q4**	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.006	(0.077)	0.004	(0.099)	0.005	(0.092)	0.003	(0.066)
DeltaPrice1	-0.172*	(0.012)	-0.167*	(0.014)	-0.206*	(0.012)	-0.137*	(0.011)
DeltaPrice2	-0.065*	(0.012)	-0.041*	(0.014)	-0.077*	(0.013)	-0.078*	(0.011)
DeltaPrice3	-0.099*	(0.012)	-0.018	(0.014)	-0.041*	(0.012)	-0.019	(0.011)
Rsquared	3.715%		2.733%		4.219%		2.187%	
No. Obs.	6859		5449		6558		7931	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table 7: Estimation results hour 7, Quarters 1–4, First Sample Split

Dependent variable Delta Price								
	H7Q1		**H7Q2**		**H7Q3**		**H7Q4**	
Regime 1								
Threshold value	<= 1.161∗		<= 0.757∗		<= 0.828∗		<= 1.415∗	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.765	(1.365)	16.416*	(7.688)	-16.689	(13.279)	-1.561**	(0.822)
DeltaPrice1	-0.184*	(0.036)	-0.155**	(0.073)	-0.221*	(0.083)	-0.255*	(0.030)
DeltaPrice2	-0.193*	(0.038)	-0.187*	(0.044)	-0.087	(0.085)	-0.169*	(0.020)
DeltaPrice3	-0.098*	(0.022)	-0.005	(0.051)	-0.075	(0.057)	-0.086*	(0.017)
DemandQuote	-0.844	(1.253)	-21.980**	(10.706)	19.229	(17.252)	1.416**	(0.700)
Volume	0.010	(0.007)	0.044	(0.108)	-0.061	(0.053)	-0.018*	(0.006)
SqrTimeStep	0.054	(1.959)	1.370	(9.574)	44.873*	(12.333)	3.820**	(1.571)
DeltaWindIntrP	0.000	(0.000)	-0.056*	(0.018)	-0.134*	(0.025)	-0.001	(0.001)
DeltaWindIntrN	0.000	(0.001)	-0.013	(0.017)	0.014**	(0.007)	0.001	(0.001)
DeltaPVIntraP	0.001	(0.002)	0.001	(0.013)	0.007	(0.024)	0.003*	(0.001)
DeltaPVIntraN	0.000	(0.001)	0.012	(0.011)	0.011	(0.008)	0.000	(0.001)
Rsquared	6.081%		67.460%		63.497%		9.053%	
No. Obs.	4090		82		111		6984	
	H7Q1		**H7Q2**		**H7Q3**		**H7Q4**	
Regime 2								
Threshold value	> 1.161∗		> 0.757∗		> 0.828∗		> 1.415∗	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.388	(1.305)	-0.368	(1.062)	-0.172	(1.095)	-58.038	(120.183)
DeltaPrice1	-0.233*	(0.050)	-0.318*	(0.031)	-0.236*	(0.035)	-0.363*	(0.135)
DeltaPrice2	-0.081	(0.049)	-0.156*	(0.022)	-0.109*	(0.020)	-0.231*	(0.088)
DeltaPrice3	-0.047	(0.025)	-0.084*	(0.019)	-0.081*	(0.018)	-0.093**	(0.047)
DemandQuote	-0.210	(1.023)	0.302	(0.904)	-0.096	(0.914)	39.713	(83.769)
Volume	0.004	(0.006)	0.014	(0.009)	0.002	(0.009)	-0.035	(0.039)
SqrTimeStep	-3.034	(1.930)	-0.905	(1.372)	4.528*	(1.291)	43.401*	(17.220)
DeltaWindIntrP	-0.002**	(0.001)	0.000	(0.000)	-0.001	(0.001)	-0.052	(0.036)
DeltaWindIntrN	-0.001	(0.001)	0.000	(0.000)	0.000	(0.001)	-0.006	(0.036)
DeltaPVIntraP	0.001	(0.002)	0.001	(0.001)	0.000	(0.001)	-0.029*	(0.004)
DeltaPVIntraN	0.001	(0.001)	0.002**	(0.001)	-0.001	(0.001)	-0.027	(0.055)
Rsquared	10.094%		10.659%		7.349%		47.604%	
No. Obs.	2889		4791		4850		191	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table 8: Estimation results hour 12, Quarters 1–4, First Sample Split

Dependent variable Delta Price								
Regime 1								
	H12Q1		**H12Q2**		**H12Q3**		**H12Q4**	
Threshold value	<= 1.245*		> 0.757*		<= 1.146*		<= 1.197*	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	-0.669	(1.982)	-0.693	(3.302)	0.421	(2.418)	0.365	(3.418)
DeltaPrice1	-0.202	(0.118)	-0.126*	(0.043)	-0.191**	(0.075)	-0.108*	(0.031)
DeltaPrice2	-0.065	(0.043)	-0.042**	(0.021)	-0.142	(0.085)	-0.082**	(0.040)
DeltaPrice3	-0.099	(0.078)	-0.010	(0.018)	-0.023	(0.078)	-0.030	(0.017)
DemandQuote	0.163	(1.685)	0.518	(2.798)	0.036	(2.104)	-0.378	(3.069)
Volume	0.070**	(0.028)	0.022	(0.012)	-0.007	(0.029)	0.003	(0.016)
SqrTimeStep	-1.363	(2.119)	-0.205	(1.886)	-9.905	(5.560)	0.880	(2.436)
DeltaWindIntrP	0.000	(0.001)	0.000	(0.001)	0.005*	(0.002)	-0.001	(0.001)
DeltaWindIntrN	-0.001	(0.001)	-0.001	(0.001)	-0.006*	(0.001)	0.002	(0.002)
DeltaPVIntraP	-0.003*	(0.001)	-0.003*	(0.001)	-0.007**	(0.003)	-0.002	(0.002)
DeltaPVIntraN	0.001	(0.001)	-0.001	(0.001)	-0.002	(0.002)	-0.003*	(0.001)
Rsquared	9.155%		3.806%		27.371%		7.764%	
No. Obs.	3911		3052		487		2438	
Regime 2								
	H12Q1		**H12Q2**		**H12Q3**		**H12Q4**	
Threshold value	> 1.245*		> 0.757*		> 1.146*		> 1.197*	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.125	(1.349)	-1.036	(1.809)	-0.037	(0.928)	0.405	(0.944)
DeltaPrice1	-0.094**	(0.040)	-0.256*	(0.060)	-0.208*	(0.040)	-0.155*	(0.022)
DeltaPrice2	-0.108	(0.040)	-0.046	(0.053)	-0.072	(0.038)	-0.075	(0.020)
DeltaPrice3	-0.099**	(0.043)	-0.035	(0.035)	-0.039	(0.022)	-0.011	(0.018)
DemandQuote	-0.216	(0.965)	0.630	(1.304)	0.065	(0.693)	-0.163	(0.692)
Volume	0.018**	(0.008)	-0.006	(0.013)	-0.012	(0.010)	-0.021*	(0.006)
SqrTimeStep	1.140	(1.439)	3.942**	(1.758)	2.263	(1.191)	-0.097	(1.700)
DeltaWindIntrP	-0.002*	(0.000)	-0.002**	(0.001)	-0.001*	(0.000)	-0.001	(0.001)
DeltaWindIntrN	-0.001*	(0.000)	-0.002**	(0.001)	-0.001	(0.001)	-0.002**	(0.001)
DeltaPVIntraP	0.000	(0.001)	-0.001	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)
DeltaPVIntraN	-0.001	(0.001)	-0.002**	(0.001)	-0.001	(0.001)	-0.004*	(0.001)
Rsquared	8.868%		10.760%		6.590%		11.624%	
No. Obs.	2948		2397		6071		5493	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table 9: Estimation results hour 18, Quarters 1–4, First Sample Split

Dependent variable Delta Price

Regime 1

	H18Q1		**H18Q2**		**H18Q3**		**H18Q4**	
Threshold value	<= 0.915∗		<= 1.221∗		<= 1.219∗		<= 1.442∗	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	46.694	(152.240)	0.020	(2.024)	-5.932*	(2.012)	-0.481	(1.031)
DeltaPrice1	-0.510*	(0.116)	-0.258*	(0.035)	-0.252*	(0.032)	-0.198*	(0.037)
DeltaPrice2	-0.284*	(0.105)	-0.197*	(0.030)	-0.154*	(0.028)	-0.088*	(0.022)
DeltaPrice3	-0.137	(0.086)	-0.079**	(0.031)	-0.111*	(0.029)	-0.148*	(0.049)
DemandQuote	-52.391	(170.802)	0.296	(1.758)	4.995*	(1.757)	0.142	(0.855)
Volume	-0.051	(0.085)	-0.038*	(0.008)	0.041*	(0.008)	0.035*	(0.005)
SqrTimeStep	6.124	(19.295)	-1.137	(1.179)	-0.772	(1.032)	-3.303*	(1.266)
DeltaWindIntrP	0.019	(0.026)	0.000	(0.000)	-0.001*	(0.000)	0.000	(0.000)
DeltaWindIntrN	-0.027	(0.020)	-0.001	(0.001)	0.000	(0.000)	-0.001	(0.001)
DeltaPVIntraP	-0.340	(0.224)	0.038	(0.052)	-0.006	(0.014)	-0.053	(0.032)
DeltaPVIntraN	0.159	(0.321)	0.024	(0.029)	-0.036	(0.045)	0.086	(0.106)
Rsquared	30.618%		8.668%		8.109%		6.356%	
No. Obs.	133		3571		3553		8776	

Regime 2

	H18Q1		**H18Q2**		**H18Q3**		**H18Q4**	
Threshold value	> 0.915∗		> 1.221∗		> 1.219∗		> 1.442∗	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.460	(0.670)	0.944	(2.590)	-1.882	(3.752)	-10.224	(43.509)
DeltaPrice1	-0.181*	(0.025)	-0.284*	(0.064)	-0.247*	(0.061)	0.008	(1.892)
DeltaPrice2	-0.161*	(0.035)	-0.095*	(0.039)	-0.171*	(0.055)	-0.090	(0.990)
DeltaPrice3	-0.119*	(0.023)	-0.098*	(0.035)	-0.106*	(0.029)	-0.011	(0.992)
DemandQuote	-0.165	(0.526)	-0.568	(1.970)	1.163	(2.876)	-39.818	(57.807)
Volume	-0.025*	(0.004)	-0.008	(0.012)	0.042*	(0.014)	0.156	(0.506)
SqrTimeStep	-0.212	(1.319)	-3.076	(1.815)	0.507	(1.533)	-48.774	(122.258)
DeltaWindIntrP	0.000	(0.000)	-0.001	(0.001)	0.000	(0.001)	0.000	(0.043)
DeltaWindIntrN	-0.003*	(0.001)	-0.002**	(0.001)	-0.002*	(0.000)	0.204	(0.301)
DeltaPVIntraP	0.012	(0.009)	-0.010	(0.015)	-0.019	(0.014)	0.332	(7.980)
DeltaPVIntraN	-0.014**	(0.007)	-0.008	(0.013)	0.005	(0.031)	-2.765	(8.155)
Rsquared	11.003%		11.252%		9.295%		25.624%	
No. Obs.	8299		2411		2397		160	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWindIntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

7. Conclusion

In this study, we investigate the bidding behavior in the intraday electricity market, in the context of a reduced-form econometric analysis. In particular, we shed light on the impact of updated forecasting errors of wind and photovoltaic (PV) on the 15-minute electricity price changes in the continuous bidding. We employ a unique data set of the latest forecasts of wind and PV available to traders prior to the placements of their price bids intraday. To our knowledge, this is the first study in the literature which models intraday prices based on prior information on weather forecasts. We further control for the demand/supply disequilibria, volume of trades, forecasts of control area balances and model the typical zigzag seasonality pattern of 15-minute prices.

Our analysis is twofold. We firstly study the changes between last prices bid intraday for a certain quarter of an hour and the corresponding day-ahead price. This is highly relevant, since market participants are mainly interested in squeezing their positions in the day-ahead or intraday markets and avoid ending into the control area balancing market. Secondly, we analysed the price changes in the continuous bidding. We found clear evidence that the bidding behavior is influenced by forecasting errors in renewables, available at the time of the bid. Intuitively, intraday prices increase in negative forecasting errors, while positive forecasting errors have a suppressing effect on prices.

We account for both linear and asymmetric adjustments of price changes to market-specific explanatory variables. The asymmetries are driven by the threshold variable demand quote. This shows market participants the proportion in which the expected demand is covered by the planned traditional capacity in the day-ahead market. Our analysis disentangles the effect of exogenous variables dependent on the regime of the demand quote and further dependent on the time of the day. Tangentially, demand/supply variables and weather forecasting errors influence more the bidding behavior in the middle of the day than during mornings and evenings. There is an asymmetric adjustment of electricity prices with respect to both volume of trades and forecasting errors in renewables. Namely, in the high regime of the demand quote, where there is too little planned traditional capacity in the day-ahead market, traders incorporate the information of the latest available forecasting errors of renewables in their bids with a higher speed. This effect is more obvious for the mid-day quarters, but less obvious during morning and evening hours. Thus, the historically derived threshold in the demand quote for a specific delivery period is a highly relevant information for strategically bidding in the intraday market. The actual demand quote can be compared to the historical threshold value and, dependent whether the market is in the low/high demand quote regime, market participants can us our insights for one-period forecasts accordingly.

The identification of regimes in the demand quote helps also to disentangle the demand/supply side volume of trades. In the regime of high demand quote, demand-side volume of trades have an increasing effect on prices. Vice versa, supply-side volumes have a suppressing effect on intraday prices, which becomes obvious in the low regime of the demand quote.

Outlook

Our analysis sheds light on the bidding behavior historically speaking and offers a solid basis for one-period forecast of last intraday prices and continuous bids. Since all variables used as input can be computed based on the information available at the time of the bid (demand quote, updated forecasts in renewables), the econometric model can be used for forecasting the (next) continuous bid. We prove the superiority of this econometric model specification over the classical AR model representation. As this is the first study which employs intraday-updated renewables forecasts, it is certainly the most realistic representation existing in the literature up to present. Practitioners use in reality updated forecasted errors as private information to bid more accurately in the intraday electricity market. In this context, our one-period proposed reduced-form forecasting model is highly relevant for both academics and practitioners.

Appendix A. Descriptive statistics

Table A.10: Descriptive statistics of the differences between the historical last prices for 15-minute delivery periods and the day-ahead price and of exogenous variables at the time of the last bid during the winter time (01/01/2014–01/04/2014), for working days Monday–Thursday.

Winter Monday to Thursday, peak hours							
	DeltaPriceLast	ControlAreaBalance	DemandQuote	DeltaWindN	DeltaWindP	DeltaPVN	DeltaPVP
Mean	-0.379	-158.279	1.155	-484.003	264.214	-301.559	373.034
Median	-0.640	-163.671	1.165	-125.000	0.000	0.000	0.000
Maximum	299.290	3697.952	1.266	0.000	5180.000	0.000	4188.000
Minimum	-101.970	-3012.049	0.649	-4165.000	0.000	-7557.000	0.000
Std. Dev.	26.738	713.387	0.069	781.715	626.864	849.927	710.205
Skewness	1.514	0.447	-3.316	-2.313	4.584	-4.660	2.380
Kurtosis	15.535	5.940	20.110	8.346	29.278	29.969	8.695
Jarque-Bera	16956.260	962.823	34334.330	5095.960	78971.970	83011.470	5615.863
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2447.000	2447.000	2447.000	2447.000	2447.000	2447.000	2447.000
ADF test t-Statistic	-7.653	-12.988	-7.208	-5.731	-6.318	-8.844	-11.928
CV 1% level	-3.433	-3.433	-3.433	-3.433	-3.433	-3.433	-3.433
CV 5% level	-2.863	-2.863	-2.863	-2.863	-2.863	-2.863	-2.863
CV 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567
Winter Monday to Thursday, off–peak hours							
	DeltaPriceLast	ControlAreaBalance	DemandQuote	DeltaWindN	DeltaWindP	DeltaPVN	DeltaPVP
Mean	-1.088	-150.579	0.934	-393.945	256.662	na	na
Median	-0.300	-136.937	0.908	-88.000	0.000	na	na
Maximum	152.810	2320.693	1.178	0.000	4670.000	na	na
Minimum	-110.350	-2139.298	0.634	-4012.000	0.000	na	na
Std. Dev.	20.224	456.092	0.122	632.799	488.188	na	na
Skewness	0.342	-0.017	0.178	-2.512	3.500	na	na
Kurtosis	5.129	4.620	1.981	10.353	21.523	na	na
Jarque-Bera	510.016	267.770	118.916	8087.061	39977.890	na	na
Probability	0.000	0.000	0.000	0.000	0.000	na	na
Observations	2447.000	2447.000	2447.000	2447.000	2447.000	na	na
ADF test t-Statistic	-7.812	-14.549	-8.909	-6.764	-9.406	na	na
CV 1% level	-3.433	-3.433	-3.433	-3.433	-3.433	na	na
CV 5% level	-2.863	-2.863	-2.863	-2.863	-2.863	na	na
CV 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	na	na

We treat separately peak hours (from 08:00–20:00), as shown in panel 1 and off-peak hours (20:00–08:00), panel 2. The exogenous variables include: "DeltaPriceLast" = Difference between the historical last prices for 15-minute delivery periods and the day-ahead prices for the corresponding hour; "ControlAreaBalance"=Historical balancing market volumes for the corresponding hour; "DemandQuote"=The quote of demand in the power plant availability, as defined in Equation 6; "DeltaWindN/P" and "DeltaPVN/P" represent changes in the forecasts of renewables, wind and photovoltaic, between the time of the last price bid and the forecast available at 2 o'clock in the previous day

Table A.11: Descriptive statistics of the differences between the historical last prices for 15-minute delivery periods and the day-ahead price and of exogenous variables at the time of the last bid during summer time (01/04/2014–01/07/2014), for working days Monday–Thursday.

Summer Monday to Thursday, peak hours							
	DeltaPriceLast	ControlAreaBalance	DemandQuote	DeltaWindN	DeltaWindP	DeltaPVN	DeltaPVP
Mean	-0.060	130.313	1.259	-329.796	190.448	-357.785	314.296
Median	-1.730	99.908	1.249	-56.000	0.000	0.000	0.000
Maximum	255.710	3494.669	1.467	0.000	2473.000	0.000	2900.000
Minimum	-56.820	-1829.939	1.082	-3027.000	0.000	-4726.000	0.000
Std. Dev.	22.892	577.670	0.080	507.571	344.782	676.016	599.469
Skewness	3.888	0.855	0.373	-1.921	2.403	-2.896	2.186
Kurtosis	33.493	6.619	2.486	6.411	9.573	12.964	7.247
Jarque-Bera	104929.000	1697.612	86.909	2796.685	7026.268	14074.430	3935.850
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2543.000	2543.000	2543.000	2543.000	2543.000	2543.000	2543.000
ADF test t-Statistic	-6.875	-12.907	-3.433	-7.132	-9.796	-9.485	-10.162
Critical value: 1% level	-3.433	-3.433	-2.663	-3.433	-3.433	-3.433	-3.433
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862
Critical value: 10% level -2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	
Summer Monday to Thursday, off–peak hours							
	DeltaPriceLast	ControlAreaBalance	DemandQuote	DeltaWindN	DeltaWindP	DeltaPVN	DeltaPVP
Mean	-0.619	72.547	0.979	-245.913	179.044	na	na
Median	0.020	82.760	0.955	0.000	9.000	na	na
Maximum	82.910	2286.065	1.291	0.000	2142.000	na	na
Minimum	-65.010	-1454.723	0.714	-2569.000	0.000	na	na
Std. Dev.	16.148	447.547	0.137	448.846	288.142	na	na
Skewness	0.087	0.182	0.210	-2.449	2.453	na	na
Kurtosis	4.130	3.800	1.941	8.926	10.916	na	na
Jarque-Bera	138.469	81.799	137.655	6262.849	9189.520	na	na
Probability	0.000	0.000	0.000	0.000	0.000	na	na
Observations	2543.000	2543.000	2543.000	2543.000	2543.000	na	na
ADF test t-Statistic	-7.402	-13.318	-8.048	-6.784	-9.466	na	na
Critical value: 1% level	-3.433	-3.433	-3.433	-3.433	-3.433	na	na
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	na	na
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	na	na

We treat separately peak hours (from 08:00–20:00), as shown in panel 1 and off-peak hours (20:00–08:00), panel 2. The **explanatory variables** include: “DeltaPriceLast” = Difference between the historical last prices for 15-minute delivery periods and the day-ahead prices for the corresponding hour; “ControlAreaBalance”= Historical balancing market volumes for the corresponding hour; “DemandQuote”= The quote of demand in the power plant availability, as defined in Equation 6; “DeltaWindN/P” and “DeltaPVN/P” represent changes in the forecasts of renewables, wind and photovoltaic, between the time of the last price bid and the forecast available at 2 o'clock in the previous day

Table A.12: Descriptive statistics of the intraday price changes between two consecutive bids for the 15-minute delivery periods in the continuous trading. We selected 4 delivery periods during morning (H7Q1–4), noon peak (H12Q1–4) and evening peak (H18Q1–4) quarter of hours.

	H7Q1	H7Q2	H7Q3	H7Q4	H12Q1	H12Q2
Mean	0.002	0.003	0.007	0.008	0.007	0.008
Median	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	62.000	51.000	74.290	84.980	80.000	67.690
Minimum	-73.900	-71.700	-101.680	-73.790	-282.000	-247.340
Std. Dev.	5.306	6.335	6.284	6.404	6.906	7.249
Skewness	-0.288	-0.940	-0.507	0.732	-14.328	-8.138
Kurtosis	29.557	22.154	35.209	31.139	584.780	291.760
Jarque-Bera	143358.300	75254.870	210973.800	161306.400	68932280.000	16994366.000
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-38.895	-36.297	-27.598	-37.781	-39.001	-41.789
Critical value: 1% level	-3.431	-3.432	-3.431	-3.431	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567

	H12Q3	H12Q4	H18Q1	H18Q2	H18Q3	H18Q4
Mean	0.006	0.002	-0.004	0.000	0.008	0.002
Median	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	89.000	120.000	110.990	55.900	84.000	112.120
Minimum	-180.000	-92.000	-91.900	-68.000	-85.990	-112.120
Std. Dev.	8.011	6.576	6.167	5.988	6.350	6.939
Skewness	-3.725	0.754	2.275	-0.358	-0.087	-1.551
Kurtosis	121.892	55.360	68.092	24.433	28.764	58.012
Jarque-Bera	2883104.000	557458.100	865012.600	93434.750	134859.800	616793.700
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-53.756	-72.044	-46.798	-33.827	-49.234	-26.363
Critical value: 1% level	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567

Table A.13: Descriptive statistics of the volume trades between two consecutive bids for the 15-minute delivery periods in the continuous trading. We selected 4 delivery periods during morning (H7Q1–4), noon peak (H12Q1–4) and evening peak (H18Q1–4) quarter of hours.

	H7Q1	H7Q2	H7Q3	H7Q4	H12Q1	H12Q2
Mean	15.048	8.213	8.394	14.029	10.004	6.976
Median	12.000	5.000	5.200	10.200	5.000	2.500
Maximum	150.000	60.600	70.000	100.000	234.900	75.000
Minimum	0.100	0.100	0.100	0.100	0.100	0.100
Std. Dev.	12.897	8.876	8.856	12.525	11.770	9.735
Skewness	1.455	1.823	1.820	1.414	2.979	2.177
Kurtosis	7.696	7.159	7.485	6.062	33.388	8.574
Jarque-Bera	6201.308	6215.672	6778.603	3528.371	194828.900	10163.740
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-33.183	-30.176	-24.859	-34.669	-37.050	-28.199
Critical value: 1% level	-3.431	-3.432	-3.431	-3.431	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567
	H12Q3	H12Q4	H18Q1	H18Q2	H18Q3	H18Q4
Mean	8.975	11.606	13.690	8.480	8.136	12.688
Median	4.200	6.300	10.000	4.100	4.000	9.000
Maximum	100.000	100.000	179.000	95.500	195.600	200.000
Minimum	0.100	0.100	0.100	0.100	0.100	0.100
Std. Dev.	11.145	12.917	13.546	10.368	10.328	13.099
Skewness	1.845	1.661	1.788	1.960	3.200	2.842
Kurtosis	7.007	6.717	10.450	7.533	30.815	26.207
Jarque-Bera	6026.335	5050.212	13874.880	7295.622	165508.500	115984.000
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-26.156	-25.007	-34.258	-33.775	-31.587	-37.025
Critical value: 1% level	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567

Appendix B. OLS estimation without threshold, morning and evening delivery periods

Table B.14: Estimation results hour 7, Quarters 1–4, global OLS without threshold, entire sample

OLS estimation of the model including all explanatory variables

Dependent variable Delta Price

	H7Q1		H7Q2		H7Q3		H7Q4	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.288	(0.645)	-0.450	(0.965)	-1.392	(1.139)	-1.102	(0.858)
DeltaPrice1	-0.208*	(0.030)	-0.320*	(0.032)	-0.244*	(0.035)	-0.281*	(0.033)
DeltaPrice2	-0.157*	(0.032)	-0.159*	(0.021)	-0.121*	(0.027)	-0.175*	(0.020)
DeltaPrice3	-0.084*	(0.017)	-0.080*	(0.018)	-0.084*	(0.019)	-0.086*	(0.016)
DemandQuote	-0.300	(0.543)	0.381	(0.829)	0.966	(0.965)	1.011	(0.736)
Volume	0.008	(0.005)	0.015	(0.009)	0.001	(0.009)	-0.020*	(0.006)
SqrTimeStep	-0.833	(1.420)	-1.212	(1.359)	4.101*	(1.319)	4.127*	(1.547)
DeltaWindIntrP	0.0001	(0.0002)	0.0002	(0.0002)	-0.001	(0.001)	-0.001	(0.001)
DeltaWindIntrN	-0.001*	(0.0001)	0.0001	(0.0002)	0.0002	(0.001)	0.001	(0.001)
DeltaPVIntraP	0.0001	(0.001)	0.001	(0.001)	0.0002	(0.001)	0.002	(0.002)
DeltaPVIntraN	0.001	(0.001)	0.002**	(0.001)	-0.001	(0.001)	0.000	(0.001)
Rsquared	5.989%		10.930%		7.333%		9.481%	
No. Obs.	6979		4873		4977		7175	

OLS estimation of the autoregressive model, excluding the market-specific explanatory variables

Dependent variable Delta Price

	H7Q1		H7Q2		H7Q3		H7Q4	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	0.004	(0.061)	0.005	(0.086)	0.010	(0.086)	0.007	(0.072)
DeltaPrice1	-0.207*	(0.012)	-0.321*	(0.014)	-0.243*	(0.014)	-0.276*	(0.012)
DeltaPrice2	-0.158*	(0.012)	-0.159*	(0.015)	-0.119*	(0.014)	-0.175*	(0.012)
DeltaPrice3	-0.083*	(0.012)	-0.080*	(0.014)	-0.085*	(0.014)	-0.082*	(0.012)
Rsquared	5.055%		9.718%		6.170%		8.085%	
No. Obs.	6979		4873		4977		7175	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWind-IntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table B.15: Estimation results hour 18, Quarters 1–4, global OLS without threshold

OLS estimation of the model including all explanatory variables
Dependent variable Delta Price

	H18Q1		H18Q2		H18Q3		H18Q4	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	-0.156	(0.809)	0.068	(0.941)	-1.861	(0.980)	-1.160	(1.087)
DeltaPrice1	-0.206*	(0.032)	-0.276*	(0.036)	-0.254*	(0.033)	-0.214*	(0.036)
DeltaPrice2	-0.163*	(0.033)	-0.149*	(0.025)	-0.173*	(0.030)	-0.105*	(0.023)
DeltaPrice3	-0.131*	(0.024)	-0.090*	(0.024)	-0.101*	(0.020)	-0.149*	(0.045)
DemandQuote	0.324	(0.642)	0.186	(0.772)	1.274	(0.806)	0.708	(0.908)
Volume	-0.025*	(0.004)	-0.028*	(0.006)	0.041*	(0.007)	0.037*	(0.005)
SqrTimeStep	0.143	(1.319)	-1.628	(1.062)	-0.233	(0.921)	-3.565*	(1.258)
DeltaWindIntrP	0.000	(0.000)	0.000	(0.000)	-0.001*	(0.000)	0.000	(0.000)
DeltaWindIntrN	-0.003*	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
DeltaPVIntraP	0.011	(0.009)	-0.006	(0.013)	-0.004	(0.011)	-0.055	(0.033)
DeltaPVIntraN	-0.014**	(0.007)	0.004	(0.011)	-0.012	(0.027)	0.087	(0.105)
Rsquared	11.135%		8.929%		8.048%		7.037%	
No. Obs.	8507		5982		6162		8936	

OLS estimation of the autoregressive model excluding **the market-specific explanatory** variables
Dependent variable Delta Price

	H18Q1		H18Q2		H18Q3		H18Q4	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Co	-0.005	(0.058)	-0.001	(0.073)	0.005	(0.082)	0.005	(0.078)
DeltaPrice1	-0.201*	(0.011)	-0.276*	(0.013)	-0.252*	(0.013)	-0.207*	(0.010)
DeltaPrice2	-0.163*	(0.011)	-0.146*	(0.013)	-0.170*	(0.013)	-0.100*	(0.011)
DeltaPrice3	-0.131*	(0.011)	-0.088*	(0.013)	-0.098*	(0.013)	-0.144*	(0.010)
Rsquared	6.099%		7.715%		7.247%		5.859%	
No. Obs.	8507		5982		6162		8936	

Standard errors are shown in parenthesis. *, and ** denote a test statistic is statistically significant at the 1% and 5% level of significance, respectively. The interpretation of variables is: DeltaPrice(x)=lagged price changes 1–3; DemandQuote=demand quote; Volume=volume of trades; SqrTimeStep=$\sqrt{\Delta_t}$; DeltaWind-IntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

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