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**ECONOMETRIC ANALYSIS OF 15-MINUTE INTRADAY
ELECTRICITY PRICES**

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Econometric analysis of 15-minute intraday electricity prices

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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 fundamental model. A unique data set of 15-minute intraday prices and intraday-updated forecasts of wind and photovoltaic has been employed and price bids are modelled by prior information on fundamentals. 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 energy, forecasting model

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1 **1. Introduction**

2 Trading in the intraday electricity markets increased rapidly since the
 3 opening of the market. This may be driven by the need of photovoltaic and
 4 wind power operators to balance their production forecast errors, i.e. de-
 5 viations between forecasted and actual production. Evidence for this is a
 6 jump in the volume of intraday trading as the direct marketing of renewable
 7 energy was introduced. Furthermore, there may be a generally increased in-
 8 terest in intraday trading activities due to proprietary trading. We study the
 9 structure of intraday trading of electricity and identify the price-driving fac-
 10 tors. Our main goal is to identify market fundamental factors that influence
 11 the bidding behavior in the 15-minute intraday market at European Power
 12 Exchange (EPEX).

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

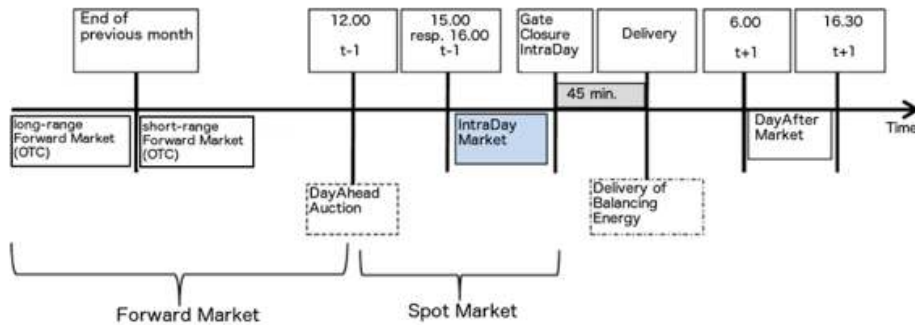


Figure 1: Timing Electricity Trading

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

21 According to the Equalization Mechanism Ordinance (ger.: Verordnung
 22 zur Weiterentwicklung des bundesweiten Ausgleichsmechanismus, abbr.:

23 AuglMechV) all electricity generated by renewable sources has to be traded
24 day-ahead. This is usually done by the transmission system operator (TSO)
25 with the plant operator receiving a legally guaranteed feed-in-tariff. From
26 2012 on the inclusion of a market premium led direct marketers within the
27 feed-in premium support scheme to enter the market as well. Trading of elec-
28 tricity from a renewable energy source is based on forecasts which may have
29 a horizon of up to 36 h (taking some data-handling into account). To correct
30 errors in forecasts the AusglMechV requires the marketers of renewable en-
31 ergy to use the intraday market to balance differences in actual and updated
32 forecasts. Intraday trading starts at 3 pm and takes place continuously until
33 up to 45 min (by 2015 this was shortened to 30 min) before the start of the
34 traded quarter-hour. As forecasts change regularly, marketers may sell and
35 buy the same contract at different times during the trading period.

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

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

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

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

60 Recent studies of the intraday high-frequency electricity prices at EPEX

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

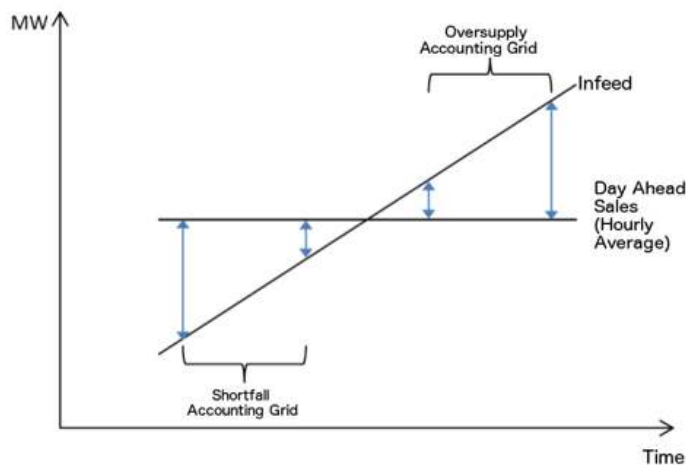


Figure 2: Quarter Hour Ramps

71 [8] and [9] used the ex-post published wind infeed data to explain ex-ante
 72 their impact on the day-ahead market. These are publicly available data
 73 from the Transparency Platform EPEX. However, the actual infeed is only
 74 known ex-post and therefore it cannot be used directly to explain the price
 75 formation on the intraday market. In fact, the intraday market participants
 76 have access to updated forecasts of wind. In our study, we will extend the
 77 existing literature by taking into account the intraday updated forecasts for
 78 wind and PV, which have been supplied by EWE Trading GmbH.

79 Each day, hourly day-ahead electricity prices are revealed around 2 pm
 80 at EPEX (see [23]). At the same time, market participants have access to
 81 forecasts for wind and PV published by each Transmission System Operator
 82 (TSO) in 15-minute intervals for the next day. However, wind and PV fore-

83 casts are updated frequently during the trading period. Thus, at the time
84 when market participants place their bids for a particular intraday delivery
85 period (hour, quarter of hour), updated information about the forecasting
86 errors of renewables becomes available. In consequence, also deviations be-
87 tween the intraday prices and the day-ahead price for a specific hour are
88 expected to occur. Our main research question is, thus, to which extent do
89 market participants change their bidding behavior when new information on
90 wind and PV forecasts becomes available. We will employ a unique data set
91 of the latest forecasts of wind and PV available at the time of the bid.

92 Our analysis is twofold: Firstly, we derive an asymmetric fundamental
93 model for the difference between the last price bid for a certain quarter
94 of hour and the day-ahead price for that hour. We distinguish between
95 summer/winter, peak/off-peak hours. We test for asymmetric behavior of
96 prices to forecasting errors of renewable energy dependent on the demand
97 quote regime and further investigate the typical jigsaw pattern of intraday
98 prices. Thus, we identify a seasonality shape that provides traders important
99 information about the time of the day when they can bid, dependent on their
100 demand/supply profiles. Furthermore, the effect of volume of trades/market
101 liquidity are investigated. Secondly, we are interested in the bidding behavior
102 of market participants in the intraday electricity market, continuous bidding.
103 We thus analyse the continuous trades and disentangle the effect of market
104 fundamentals dependent on the time of the day. The econometric model is
105 replicated for several traded hourly quarters, in different time of the day.
106 In particular, we are interested to see how delta bid prices change when
107 new information becomes available in the intraday renewable forecasts for
108 wind and PV. We look at the trade-off between autoregressive terms and
109 fundamental factors impacting the intraday price formation process.

110 Our contribution to the existing literature is twofold: we use ex-ante fore-
111 casts of fundamental variables and employ high-frequency, namely quarter-
112 hourly intraday prices.

113 **2. Model architecture**

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

- 118 1. The traditional capacity planned for the day-ahead satisfies the ex-
119 pected demand for a certain hour;
- 120 2. There is a certain demand quote uncovered by the planned capacity.

121 Thus, in scenario 2, negative forecasting errors of wind and PV will increase
122 faster the intraday prices than in scenario 1, due to the excess demand pres-
123 sure. Viceversa, in scenario 1, positive forecasting errors in renewables will
124 put pressure on traditional suppliers to reduce the production, since renew-
125 ables are fed into the grid with priority (on average 20% of electricity pro-
126 duction in Germany is wind and PV based). Thus, prices will decrease faster
127 than in scenario 2, where the excess of renewables (positive updated fore-
128 casts) will balance out the excess demand. Therefore, in the context of a
129 threshold model, we investigate whether there is an asymmetric adjustment
130 of the intraday prices to forecasting errors in renewables, dependent on the
131 demand quote regime (proportion of the forecasted demand for electricity
132 in the planned traditional capacity for the day-ahead). The location of the
133 threshold in the demand quote is estimated and this gives an indication of the
134 bidding behavior in the intraday market. Market participants can compare
135 the identified threshold value to the forecasted demand quote for a certain
136 hour to identify the market regime and to further define a bidding strategy.
137 Employing the demand quote as threshold variable is supported by the lit-
138 erature as several papers have found that total electricity demand influences
139 price behaviour strongly. In [14] it is shown that the ratio between wind and
140 conventional power production affects the electricity price most (the so-called
141 wind penetration). [19] identify the residual load, the electricity demand that
142 needs to be met by conventional power, as an important variable.

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

149 In a first part of our analysis we aim at a model for the difference between
150 the last intraday bid price for a certain quarter of an hour and the day-ahead
151 price for that specific hour. As a prerequisite for our modeling approach, we
152 investigate the typical jigsaw pattern of the 15-minute intraday prices and
153 control for seasonality. Figures 3, 4, 5 show the long-term mean of last prices

154 and average prices bid for a certain quarter of an hour between 01/01/2014–
155 01/07/2014. During the day, the jigsaw pattern is mainly explained by the
156 following situation: Renewable energy providers sell day-ahead the full hour
157 (average of all quarters). During morning (evening) hours the sun goes up
158 (down) so in the first quarter there is a buy-pressure on them as they are
159 not able to produce the hourly average. On the other hand, in the fourth
160 quarter they produce too much and have to sell.

161 We also found a persistent jigsaw pattern of prices during off-peak hours.
162 This is driven by the production design of fossil power plants (supply side:
163 when it starts low and ends high) or power-intensive industry (demand side:
164 when it starts high and ends low).

165 A reason for that may be inter-temporal restrictions in using fossil plants.
166 In addition to fuel costs, these plants have ramp-up and ramp-down costs,
167 which prevent plant operators from shutting down plants in case of drops in
168 demand or starting up plants in case of spikes in demand. The short-term
169 marginal costs from this may dominate fuel costs.

170 3. Data

171 As motivated in section 2, for the analysis we employed historical day-
172 ahead and intraday electricity prices for 15-minute products in the continuous
173 trading system between 01/01/2014–30/06/2014. As fundamental variables
174 selected in this study we refer to demand forecast, power plant availability,
175 intraday updated forecasts for wind and photovoltaic, volume trades in the
176 continuous trading, and the control area balance. The latter represents the
177 corresponding use of balancing power in the balancing market¹. In partic-
178 ular, the control area balance corresponds to the sum of all balance group
179 deviations of balance groups registered at the transmission system operator
180 and of the relevant balance groups owned by the transmission system oper-
181 ator (e.g. EEG, grid losses, unintentional deviation)². In Tables 1 and 2 we
182 give an overview of the data sources and their frequency, respectively.

¹As 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.

²see <http://www.tennettso.de>

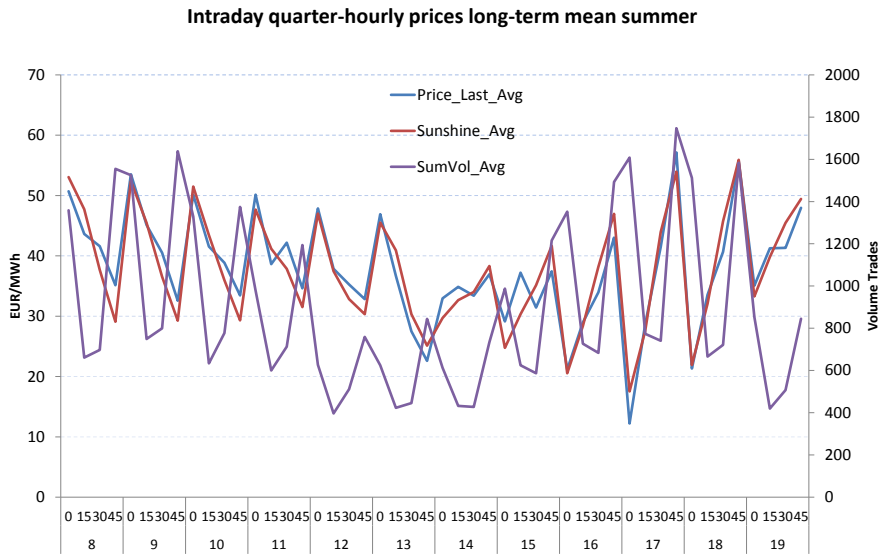
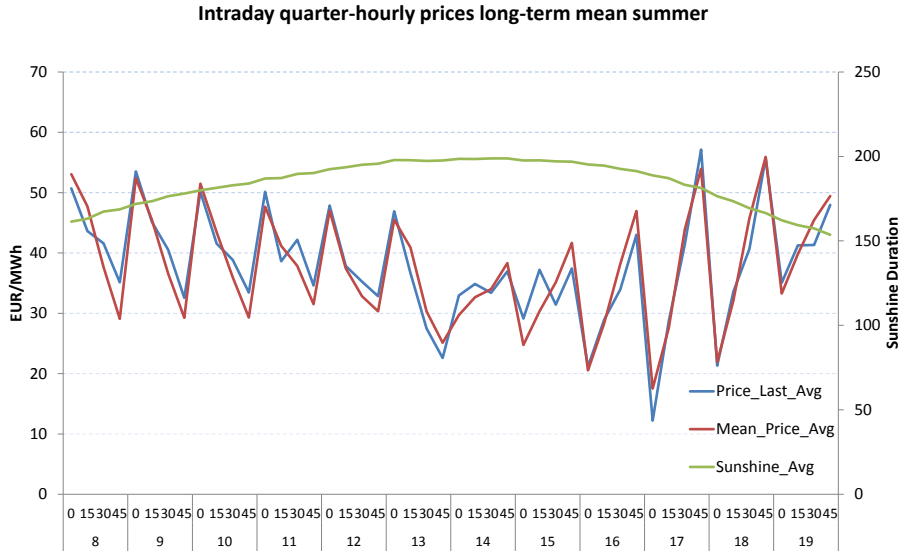


Figure 3: Seasonality pattern of the last prices and average prices bid for a certain quarter of an hour during the peak hours in summer. The right axes show the sunshine duration and the sum of volumes traded.

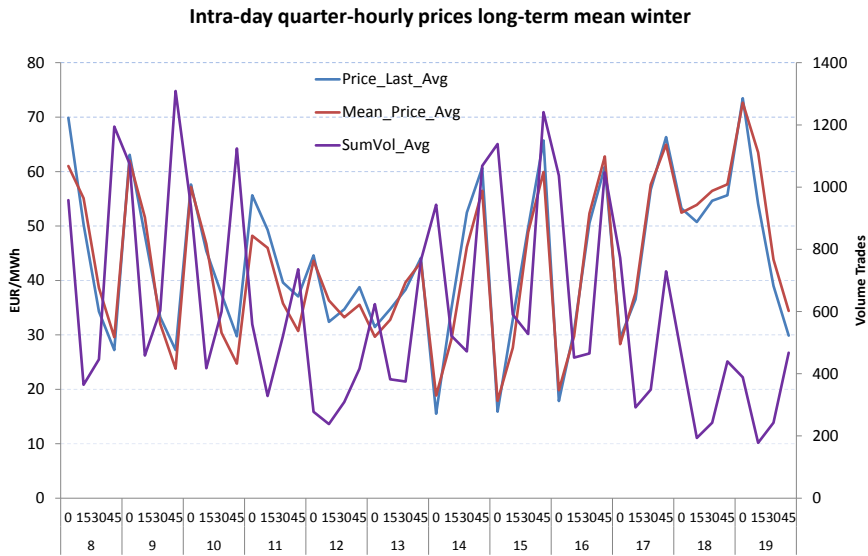
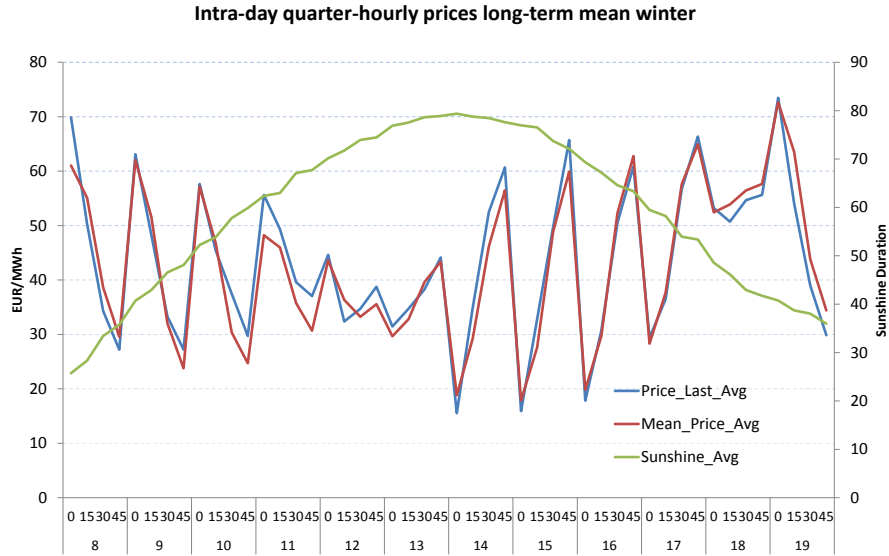


Figure 4: Seasonality pattern of the last prices and average prices bid for a certain quarter of an hour during the peak hours in winter. The right axes show the sunshine duration and the sum of volumes traded.

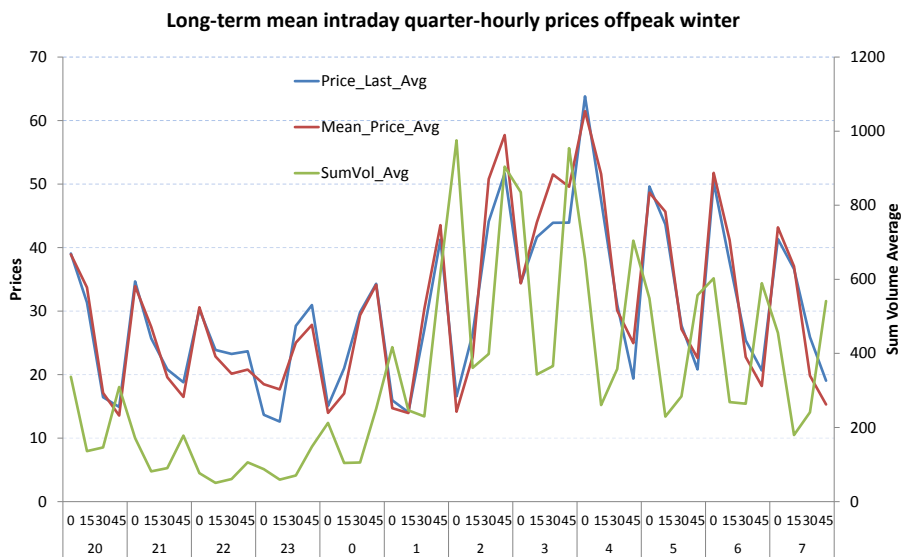
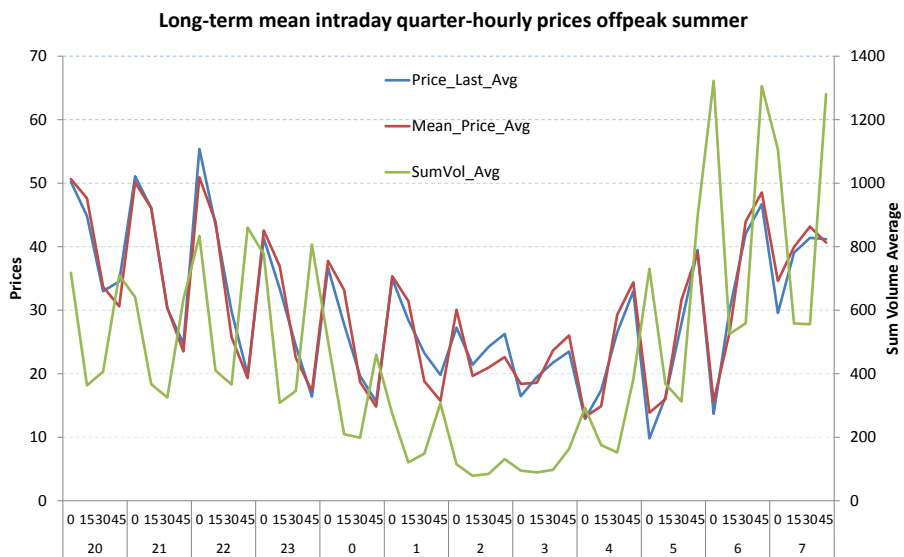


Figure 5: Seasonality pattern of the last prices and average prices bid for a certain quarter of an hour during the off-peak hours in summer and winter, respectively. The right axis shows the sum of volumes traded.

Variable	Description	Data Source
units		
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 in-feed of wind electricity into the grid	EWE TRADING GmbH http://www.ewe.com/en/
PV Forecast MW	Sum of intraday forecasted in-feed 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.tennetso.de

Table 1: Overview of fundamental 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 fundamental variables

183 4. Methodology

184 4.1. Threshold model specification

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

$$y_i = \theta_1' x_i + \varepsilon_i, \quad \omega_i \leq \tau, \quad (1)$$

$$y_i = \theta_2' x_i + \varepsilon_i, \quad \omega_i > \tau, \quad (2)$$

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

188 Our observed sample is $\{y_i, x_i, \omega_i\}_{i=1}^n$, where y_i represent the dependent
 189 variable and x_i is an m -vector of independent variables. The *threshold vari-*
 190 *able* ω_i may be an element of x_i and is assumed to have a continuous dis-
 191 tribution. To write the model in a single equation³, we define the dummy
 192 variable $d_i(\tau) = \mathbf{1}[\omega_i \leq \tau]$, where $\mathbf{1}[\cdot]$ is the indicator function and we set
 193 $x_i(\tau) := x_i d_i(\tau)$. Furthermore, let $\lambda_n' = \theta_2' - \theta_1'$ denote the threshold effect.
 194 Thus, equations (1) and (2) become:

$$y_i = \theta' x_i + \lambda_n' x_i(\tau) + \varepsilon_i \quad (3)$$

195 In order to simplify the threshold estimation procedure, we rewrite equa-
 196 tion (3) in matrix notation. We define the vectors $Y \in \mathbb{R}^n$ and $\varepsilon \in \mathbb{R}^n$
 197 by stacking the variables y_i and ε_i , and the $n \times m$ matrixes $X \in \mathbb{R}^{n \times m}$ and
 198 $X(\tau) \in \mathbb{R}^{n \times m}$ by stacking the vectors x_i' and $x_i(\tau)'$. Then (3) can be written
 199 as:

$$Y = X\theta + X(\tau)\lambda_n + \varepsilon \quad (4)$$

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

202 4.2. Hansen's grid search to locate the most likely threshold

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

$$S_n(\theta, \lambda, \tau) = (Y - X\theta - X(\tau)\lambda)'(Y - X\theta - X(\tau)\lambda) \quad (5)$$

be the sum of squared errors function. Then, by definition, the LS estima-
 tors $\hat{\theta}, \hat{\lambda}, \hat{\tau}$ 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

³see Hansen (2000)

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 $\hat{\theta}(\tau)$ and $\hat{\lambda}(\tau)$ by regression of Y on $X(\tau)^* = [XX(\tau)]$. 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.,

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

208 To test the hypothesis $H_0 : \tau = \tau_0$, a standard approach is to use the like-
 209 hood 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:

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

210 5. Fundamental modeling of intraday prices

211 We examine whether deviations between the intraday and day-ahead
 212 prices for a certain quarter of a hourly delivery period are caused by market
 213 fundamentals. Deviations between the intraday and the day-ahead prices are
 214 caused by the fluctuant renewable energy which must be fed into the grid
 215 with priority. Thus, at the time when market participants place their bids for
 216 a certain delivery period intraday, they update their information about the
 217 forecasted wind and PV for the relevant quarter of an hour. Wind and PV
 218 power operators must balance out their production forecast errors and devi-
 219 ations from the day-ahead price are expected to occur. Forecasting errors of
 220 renewables are thus expected to cause deviations between the intraday and
 221 day-ahead prices. Their impact on prices, however, should not be judged in
 222 isolation, but dependent on the demand quote, meaning the extent at which
 223 forecasted demand for a certain hour is covered by the traditional capacity
 224 planned in the day-ahead market.

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

230 *5.1. Modeling deviations of last prices from the day-ahead price*

231 In the first part of our analysis, we analyze the differences between the
232 historical last prices bid for a certain 15-minute delivery period in the intra-
233 day market and the day-ahead price for the corresponding hour. We used
234 historical last prices sorted for quarter-hourly products between 01/01/2014–
235 30/06/2014. As market fundamentals we include positive/negative forecast-
236 ing errors in wind and PV, defined as deviations between the latest forecast
237 available at the time when the last prices are observed and the day-ahead
238 available forecasts. The last prices for a certain delivery period are placed
239 in the market not later than 30 minutes before the delivery period starts⁴.
240 At this time, market participants can also forecast the volume in the bal-
241 ancing market, namely positions that could not be filled in the intra-day
242 market. These positions are defined by the Transmission System Operators
243 as “control area balances”⁵.

244 We derive the forecasts of the control area balance on an autoregressive
245 model.⁶ Historical control area balances are therefore modeled by an autore-
246 gressive model, as shown in Table 3. The order of lags has been identified
247 by examining the autocorrelation function and we further performed Akaike
248 (AIC) and Bayesian (BIC) information criteria to select the best model⁷.
249 We found that the control area balances for a certain 15-minute delivery pe-
250 riod can be forecasted based on the last 8 observations (up to 2 hours ago).
251 Forecasts based on this model are further included in our model estimation.

252 The demand quote is defined as:

$$DemandQuote_t = DemandForecast_t / PPA_{dt} \quad (6)$$

253 where d is the day-ahead and t one hour in day d .

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

⁵see <http://www.tennettso.de>

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

⁷Results are available upon request

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.

254 In Tables 4 and 5 we show descriptive statistics of the selected input
255 variables. We distinguish between summer/winter, peak/off peak hours (as
256 shown in [23]). We observe that, independent on the season, on average the
257 intraday last price for 15-minute delivery periods is below the day-ahead price
258 for the corresponding hour. Furthermore, the difference becomes larger and
259 more volatile for off-peak than for peak hours and in winter than in summer.
260 The control area balances are, on average, negative in winter and turn into
261 positive in summer.

262 On average, the demand quote is higher and more volatile during peak
263 than in off-peak hours, which makes the planning of traditional capacity for
264 the day ahead more difficult.

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

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

272 • **Summer peak**

273 – We introduce one Dummy variable for each of the Q1–Q4 quarters
274 for the interval 08:00–13:00 (*Morning pattern*)

275 – We introduce one Dummy variable for each of the Q1–Q4 quarters
276 for the interval 14:00–18:00 (*Afternoon pattern*)

277 • **Winter peak**

278 – We introduce one Dummy variable for each of the Q1–Q4 quarters
279 for the interval 08:00–12:00 (*Morning pattern*)

280 – We introduce one Dummy variable for each of the Q1–Q4 quarters
281 for the interval 13:00–17:00 (*Afternoon pattern*)

282 • **Summer off-peak**

283 – We introduce one Dummy variable for each of the Q1–Q4 quarters
284 for the interval 20:00–01:00 (*Evening descending pattern*)

285 – We introduce one Dummy variable for each of the Q1–Q4 quarters
286 for the interval 03:00–07:00 (*Early morning ascending pattern*)

287

• **Winter off-peak**

288

– 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*)

289

290

– We introduce one Dummy variable for each of the Q1–Q4 quarters for the interval 23:00–03:00 (*Night, ascending pattern*)

291

292

The model specification reads:

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

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

293

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296

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 the renewables.

297

5.2. *Model for the continuous trades for quarter-hourly products*

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In the second part, we examine the continuous trades for several quarter-hourly products. Thus, we are interested to see how delta bid prices change when new information on wind and PV for a certain delivery period of interest becomes available intraday. We are interested in the bidding behavior of market participants in the intraday electricity market as influenced by

303 market fundamentals. In particular, we are interested to see how delta bid
 304 prices for a certain quarter of an hour change when new information on the
 305 forecasts for wind and PV becomes available. We look at the trade-off be-
 306 tween autoregressive terms and fundamental factors impacting the intraday
 307 price formation process.

308 The model specification reads:

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

309 The examination of autocorrelation function of price changes for a cer-
 310 tain quarter of an hour shows that the first 3 lags of price changes should
 311 be selected in the autoregressive part of the model. Changes in the wind,
 312 $\Delta Wind_t^{ID}$, and in the PV, ΔPV_t^{ID} , are real time updated forecasts, avail-
 313 able at the time when the bids are placed.⁸ $Volume_t^{ID}$ is the volume trade
 314 at the time when the price change is observed. The bids for a certain quarter
 315 of an hour do not occur at equal time intervals in the continuous bidding.
 316 In fact, market participants start bidding around 4 pm, after the day-ahead
 317 prices are published at EPEX and continuous trades go up to 45 minutes
 318 before the beginning of the delivery period. Thus, the time steps between
 319 consecutively placed bids are not equal, but can vary from some seconds to
 320 several hours. We take into account this time discontinuity by including in
 321 our list of explanatory variables the control variable $\sqrt{\Delta t}$.

322 In Tables 6 and 7 we show descriptive statistics for the price changes and

⁸Results are available upon request

323 volume trades for the 15-minute continuous trading for delivery periods in
324 different times of the day. We observe that the volatility of intraday price
325 changes increases continuously between the morning quarter of hours (H7Q1)
326 up to noon (H12Q4) and decreases again towards the evening (quarters of
327 hour 18). Thus, the higher the demand, the larger the average price changes
328 in the continuous trading. The volume of trades is on average the highest
329 and more volatile for the first and last quarters of each one of the investigated
330 hours, independent on the time of the day.

331 **6. Empirical results**

332 *6.1. Modeling deviations of last prices from the day-ahead price*

333 The model shown in Equation (7) has been estimated for the historical
334 differences between the last prices and the day-ahead prices separately for
335 winter and summer and we further distinguished among peak (8 am and
336 8 pm) and off-peak hours. This approach is justified by the different price
337 levels in summer compared to the winter time and by the different demand
338 profiles during peak and off-peak hours (see [23] for an extensive discussion
339 on the seasonality of electricity prices).

340 The overall OLS estimation results for each case study are shown in Ta-
341 ble 8. We further tested for a threshold effect in the demand quote in each
342 case. The threshold variable is the demand quote and the threshold loca-
343 tion is estimated using the methodology described in section 4.2. All model
344 parameters in Equations (7) are allowed to vary among regimes. We found
345 evidence for significant threshold effect only in the case of winter peak case
346 study. Results are available in Table 9.

347 Throughout all variables are significant and show the expected sign (see
348 Table 8). Dummy variables which explain the jigsaw pattern are statisti-
349 cally significant and their inclusion still allows significant marginal effects of
350 fundamental variables on delta prices. The coefficients of positive/negative
351 forecasting errors in wind and PV are significant at 1% significance level.
352 Positive forecasting errors of wind/PV signal market participants more ca-
353 pacity available in the market than planned. This will have a decreasing effect
354 on the residual demand and will further decrease last price bids. Viceversa,
355 when updated forecasts signal less infeed from renewables than planned in
356 the day ahead (negative forecasting errors), market participants will increase
357 their bid prices intraday accordingly.

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

364 We observe that the coefficient of demand quote is negative during the off-
365 peak regimes, but it turns into positive during peak hours. In both summer
366 and winter regimes, the mean value of demand quote in the off-peak hours is
367 slightly below one, touching a maximum of 1.291 and 1.178, respectively (as
368 shown in Tables 4 and 5). Thus, on average, the traditional capacity planned
369 in the market covers the expected demand for the day-ahead. However,
370 higher levels of demand quote (up to a maximum observed in off-peak of
371 about 1.2), power producers plan less capacity for the day ahead, due to
372 a higher expectation of renewables infeed in the market. It is known that
373 in the night hours extreme wind infeed has been empirically observed (see
374 [23]). The input from renewable energies is expected to be, on average, 20%
375 of the total input production mix in Germany (see [22]). Renewables will
376 be fed with priority into the grid, decreasing the residual demand. This
377 will imply further that price bids in the intraday market will be in the less
378 convex area of the merit order curve, thus market participants will bid lower
379 prices intraday. This assumption is confirmed by the negative sign of the
380 coefficients of demand quote in the off-peak hours winter/summer, as shown
381 in Table 8.

382 In summer peak, descriptive statistics show that on average, the demand
383 quote exceeds 1.2. Thus, power producers plan less capacity in the market,
384 given the volatile infeed from photovoltaic in peak hours. However, demand
385 quotes above 1.2 reflect the situation where the 20% expected infeed from
386 renewables will not suffice and there will be still high residual demand in the
387 market. This will have an increasing effect on intraday prices in general and
388 on the last prices in particular, which is confirmed by the positive sign of the
389 coefficient of demand quote. This is reflected in the high maximum spreads
390 between the last prices and day-ahead prices observed in summer peak, as
391 shown in Table 5.

392 We found no significant threshold effect in the demand quote in summer-
393 related case studies and in winter off-peak. This shows that in those seasons,
394 market participants adjust linearly last prices (and implicitly the spreads
395 last prices-day-ahead prices) to market fundamentals. However, in winter

396 peak time we found evidence for asymmetric behavior (see Table 9). Thus,
397 a threshold in the demand quote was found significant at the level of 1.058.
398 In the regime of low levels of demand quote (regime 1, < 1.058), we observe
399 that coefficients are generally not statistically significant. That is, power
400 producers have low expectation of renewable infeed in the day-ahead, and in
401 consequence plan sufficient traditional capacity to satisfy expected demand.
402 However, when demand levels are high, thus in regime 2, delta prices adjust
403 linearly to forecasting errors in renewable energy, to control area balances
404 and to demand quote. An increase in demand quote in this regime will
405 suppress bid prices in the intraday market, since again higher demand quote
406 levels reflect a high expectation of infeed from renewable energies, which
407 will lower the price level. The coefficient of control area balances is positive
408 and significant. This reflects two situations: if there is high infeed from
409 renewables in the market, negative forecasts of control area balances will
410 suppress the intraday last prices. By contrary, in the presence of high demand
411 quote not fully covered by renewables infeed, positive forecasts in control area
412 balances will increase intraday price bids.

413 The model can be used to forecast the last prices submitted for a certain
414 quarter of one hour intraday. This is based on a rigorous forecasting model
415 for the control area balances. This model is highly relevant for practitioners:
416 the main goal of market participants is to clear their positions in the day-
417 ahead and intraday markets and avoid participating in the more expensive
418 balancing market.

419 *6.2. Model for the continuous trades for quarter-hourly products*

420 We estimated the model specification shown in Equation (8) for each one
421 of the following delivery periods: hour 7 (quarters 1–4), hour 12 (quarters
422 1–4) and hour 18 (quarters 1–4). We aim at analysing whether the impact
423 of fundamentals on the bidding behavior depends on the time of the day.
424 Thus, we analyse representative delivery periods within one day: morning,
425 noon peak and (for winter evening) peak. In Tables 10, 13 and 15 we show
426 the overall estimation without threshold of the model shown in Equation (8)
427 applied to data sorted for hours 7, 12 and 18, respectively, quarters 1–4. In
428 the lower panel of the tables we show a benchmark, where we estimated the
429 model without fundamental variables. We further tested for threshold effect
430 in the demand quote in all case studies and found significant threshold effect
431 as shown in Tables 11 and 12 for the four quarters of hour 7, and in Tables 14

432 and 16 for each quarter of hours 12 and 18, respectively. The threshold values
433 are significant, accordingly to the likelihood ratio test, as discussed in section
434 4.1. The graphs and calculations corresponding to each threshold values are
435 available upon request. We have tested for threshold significance also in the
436 other fundamental variables, but no conclusive results were obtained.

437 By comparing the values of the R^2 between the lower and upper panels in
438 Tables 10, 13 and 15, we observe that in the model where market fundamen-
439 tals are considered, the R^2 s increases. The increase becomes more obvious
440 for the quarters of hour 12, where market fundamentals help increasing the
441 explanatory power of the model by up to 4 times.

442 By examining Tables 10 and 13 we observe that during morning (quar-
443 ters 1–4 hour 7) and evening (quarters 1–4 hour 18), market participants
444 adjust their intraday bids to lagged price changes, which replace the role of
445 fundamental variables. Thus, during morning and evening updated forecasts
446 of wind and photovoltaic become less relevant. However, the coefficients of
447 fundamental variables become significant during noon (see Table 13). This
448 can be due to the fact that over noon there is a high demand for electricity
449 in the market and in the same time it is more difficult to optimally plan
450 capacity, given the highly volatile infeed from photovoltaic and wind. Thus,
451 the effect of market fundamentals increases with an increased expected share
452 from renewable energy. In this context, updated forecasts in wind and PV
453 available at the time of the bid become highly relevant information for market
454 participants who adjust their bids accordingly. Negative forecasting errors in
455 wind and PV will increase intraday prices, while positive forecasting errors
456 in renewables will have a suppressing effect on prices.

457 In particular, by examining the threshold model applied to price changes
458 for quarters 1–4 of hour 12 we can conclude an asymmetric adjustment to
459 forecasting errors in renewables (see Table 14). In both quarters 1 and 2 the
460 coefficients of wind forecasting errors (positive/negative) are not significant
461 in regime 1 (of low demand quote), but they turn significant in regime 2.
462 Similarly, in the fourth quarter of hour 12 the coefficient of negative fore-
463 casting errors of wind and of positive forecasting errors of PV are significant
464 only in the second regime of the demand quote. These situations justify the
465 choice of demand quote as threshold variable: in the high regime of the de-
466 mand quote, thus, when there is excess demand uncovered by the planned
467 traditional capacity in the market, forecasting errors of renewables influence
468 the bidding behavior in the intraday market. Interestingly, for quarter 3 of
469 hour 12 we observe however a higher speed of adjustment of price changes to

470 forecasting errors from renewables in the lower demand quote regime than
471 in regime 2. However, this can be due to the fact that less than 10% of the
472 overall observations are concentrated in regime 1.

473 As already mentioned, the results of the threshold model applied to obser-
474 vations in hours 7 and 18 (Tables 11 and 16) show that the role of forecasting
475 errors of renewables for the morning and evening quarters drops. Still, posi-
476 tive forecasting errors in PV will decrease prices in quarter 4 of hour 7 in
477 regime 2, which reflects the ramping up effect of the sun. By contrary, during
478 quarters 1–3 of hour 18, negative forecasting errors of wind will increase price
479 changes intraday in the same high regime of the demand quote. In addition,
480 negative forecasting errors of PV increase intraday prices in the first quarter
481 of hour 18. After this quarter, however, the role of forecasting errors of PV
482 drops, showing the ramping down effect of the sun.

483 We observe that the coefficient of volume of trades is significant only for
484 quarter 4 of hour 7 (see Table 10) and has a negative sign. This pattern
485 is again observed in the threshold model for hour 7 (see Table 11). When
486 we allow for threshold effect in the demand quote, the coefficient of volume
487 trades for quarter 4 of hour 7 is significant and has a negative sign in regime
488 1, when the demand quote is below 1.415 (see Tables 11). The observations
489 in regime 1 are further split into two regimes, as shown in Table 12, where
490 a second threshold has been found significant when the demand quote is at
491 1.178. In the low regime, with demand quote below 1.178, we observe again
492 that the coefficient of volume of trades is statistically significant and has a
493 negative sign. For the last quarter of hour 7 the intraday price is below the
494 average price bid for hour 7 in the day ahead due to the sun ramping up
495 effect. This becomes apparent in the jigsaw pattern shown in Figures 3 and
496 4. Thus, the volume of trades in quarter 4 of hour 7 corresponds to the supply
497 side market participants who need to lower their conventional output, due
498 to an excess of infeed from PV. This has a suppressing effect on the intraday
499 prices. By contrary, the coefficient of volume trades becomes positive and
500 significant in quarter 2 of hour 7 in the second sample split for this case study
501 (see Table 12). Thus, when the demand quote exceeds 1.145, demand side
502 volume of trades will further increase intraday prices.

503 The same pattern of coefficients of volume of trades holds also for the
504 results concerning quarters 1–4 for hour 12. The coefficient is significant and
505 has a positive sign for the first quarter and turns into negative in quarter 4
506 in the overall OLS estimation and in the upper regime of the demand quote,
507 as shown in Tables 13 and 14, respectively. However, for hour 18 this effect is

508 reverted. As shown in Tables 15 and 16, the coefficient of volume of trades is
509 significant and has a negative sign for the first quarter of hour 18 and turns
510 into positive in the last quarter. This reflects the sun ramping down effect,
511 which causes the jigsaw pattern for the evening hours: the intraday price for
512 quarter 1 is below the average price bid in the day ahead for the respective
513 hours and it ends above it for quarter 4 (as shown in Figures 3 and 4). Thus,
514 in quarter 1 there is an excess of capacity and supply side volume of trades
515 will lower intraday prices. The opposite will happen for the last quarter of
516 evening hours.

517 **7. Conclusion**

518 In this study, we investigate the bidding behavior in the intraday electric-
519 ity market, in the context of a fundamental model. In particular, we shed
520 light on the impact of the updates in the forecasting errors of wind and pho-
521 tovoltaic (PV) on the 15-minute electricity price changes in the continuous
522 bidding. We employ a unique data set of the latest forecasts of wind and PV
523 available to traders prior to the placements of their price bids intraday. To
524 our knowledge, this is the first study in the literature which models intra-
525 day prices based on prior information on fundamentals. We further control
526 for the demand/supply disequilibria, volume of trades, forecasts of control
527 area balances and model the typical jigsaw seasonality pattern of 15-minute
528 prices.

529 Our analysis is twofold. We firstly propose a forecasting model for the
530 changes between last prices bid intraday for a certain quarter of one hour
531 and the corresponding day-ahead price for that hour. This is highly relevant,
532 since market participants are mainly interested in squeezing their positions
533 in the day-ahead or intraday markets and avoid to need the control area
534 balancing market. Secondly, a fundamental model for the price changes in
535 the continuous bidding is derived. We found clear evidence that the bidding
536 behavior is influenced by forecasting errors in renewables, available at the
537 time of the bid. In particular, intraday prices increase in negative forecasting
538 errors, while positive forecasting errors have a suppressing effect on prices.

539 We account for both linear and asymmetric adjustments of price changes
540 of market fundamentals. The asymmetries are driven by the threshold vari-
541 able demand-quote. The location of the threshold show market participants
542 the proportion in which the expected demand is covered by the planned

543 traditional capacity in the day-ahead market. Dependent whether the mar-
544 ket is in the lower/upper regime of the demand-quote, market participants
545 can intuitively form expectations about the expected infeed from renewable
546 energies, wind and PV, in the market and adjust their bids accordingly.
547 Our model disentangles the effect of market fundamentals dependent on the
548 regime of the demand quote and further dependent of the time of the day.
549 Tangentially, market fundamentals influence more the bidding behavior in
550 the middle of the day than during mornings and evenings. There is an asym-
551 metric adjustment of electricity prices with respect to both volume of trades
552 and forecasting errors in renewables. Namely, in the high regime of the de-
553 mand quote, where there is too little planned traditional capacity in the
554 day-ahead market, market participants incorporate the information of the
555 latest available forecasting errors of renewables in their bids. This effect is
556 more obvious for the mid-day quarters, but less obvious during morning and
557 evening hours.

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

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Table 4: Descriptive statistics of the differences between the historical last prices for 15-minute delivery periods and the day-ahead price and of fundamental 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 fundamental 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 5: Descriptive statistics of the differences between the historical last prices for 15-minute delivery periods and the day-ahead price and of fundamental 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 fundamental 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 6: 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	H12Q3	H12Q4	H18Q1	H18Q2	H18Q3	H18Q4
Mean	0.002	0.003	0.007	0.008	0.007	0.008	0.007	0.008	0.004	0.000	0.008	0.002
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	62.000	51.000	74.290	84.980	74.290	84.980	84.980	84.980	110.990	55.900	84.000	112.120
Minimum	-73.900	-71.700	-101.680	-73.790	-101.680	-73.790	-282.000	-247.340	-91.900	-68.000	-85.990	-112.120
Std. Dev.	5.306	6.335	6.284	6.404	6.284	6.404	6.906	7.249	6.167	5.988	6.350	6.939
Skewness	-0.288	-0.940	-0.507	0.732	-0.507	0.732	-14.328	-8.138	2.275	-0.358	-0.087	-1.551
Kurtosis	29.557	22.154	35.209	31.139	35.209	31.139	584.780	291.760	68.092	24.433	28.764	58.012
Jarque-Bera	143358.300	75254.870	210973.800	161306.400	210973.800	161306.400	68932280.000	16994366.000	865012.600	93434.750	134859.800	616793.700
Probability	0.000	0.000	0.000	0.000	0.000	0.000	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	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-38.895	-36.297	-27.598	-37.781	-27.598	-37.781	-39.001	-41.789	-0.000	0.000	-39.001	-41.789
Critical value: 1% level	-3.431	-3.432	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431	0.000	0.000	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	0.000	0.000	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	0.000	0.000	-2.567	-2.567
	H12Q3	H12Q4	H18Q1	H18Q2	H18Q3	H18Q4						
Mean	0.006	0.002	-0.004	0.000	0.000	0.002	0.006	0.000	0.000	0.000	0.000	0.002
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	89.000	120.000	110.990	55.900	110.990	55.900	84.000	112.120	110.990	55.900	84.000	112.120
Minimum	-180.000	-92.000	-91.900	-68.000	-91.900	-68.000	-85.990	-112.120	-91.900	-68.000	-85.990	-112.120
Std. Dev.	8.011	6.576	6.167	5.988	6.167	5.988	6.350	6.939	6.167	5.988	6.350	6.939
Skewness	-3.725	0.754	2.275	-0.358	2.275	-0.358	-0.087	-1.551	2.275	-0.358	-0.087	-1.551
Kurtosis	121.892	55.360	68.092	24.433	68.092	24.433	28.764	58.012	68.092	24.433	28.764	58.012
Jarque-Bera	2883104.000	557458.100	865012.600	93434.750	865012.600	93434.750	134859.800	616793.700	865012.600	93434.750	134859.800	616793.700
Probability	0.000	0.000	0.000	0.000	0.000	0.000	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	4876.000	4876.000	4876.000	4876.000	4876.000	4876.000
ADF test t-Statistic	-53.756	-72.044	-46.798	-33.827	-46.798	-33.827	-49.234	-26.363	-46.798	-33.827	-49.234	-26.363
Critical value: 1% level	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431	-3.431	0.000	0.000	-3.431	-3.431
Critical value: 5% level	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	-2.862	0.000	0.000	-2.862	-2.862
Critical value: 10% level	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	-2.567	0.000	0.000	-2.567	-2.567

Table 7: 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

Table 8: 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)
<i>Rsquared</i>	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.

Table 9: Winter peak, threshold estimation results. Threshold variable: Demand Quote

Threshold estimation (threshold variable DemandQ)				
Dependent variable Delta Last Price- Price Dahd				
Threshold value	Regime 1		Regime 2	
	<= 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)
<i>Rsquared</i>	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.

Table 10: Estimation results hour 7, Quarters 1–4, global OLS without threshold, entire sample

OLS estimation of the model including fundamental 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)
<i>Rsquared</i>	5.989%		10.930%		7.333%		9.481%	
No. Obs.	6979		4873		4977		7175	
OLS estimation of the autoregressive model, excluding fundamental 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)
<i>Rsquared</i>	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 11: Estimation results hour 7, Quarters 1–4, First Sample Split

Dependent variable Delta Price		H7Q1		H7Q2		H7Q3		H7Q4	
		Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Regime 1									
Threshold value		<= 1.161*		<= 0.757*		<= 0.828*		<= 1.415*	
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)
DeltaWindIntraP	0.000	(0.000)		-0.056*	(0.018)	-0.134*	(0.025)	-0.001	(0.001)
DeltaWindIntraN	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)
<i>Rquared</i>	6.081%			67.460%		63.497%		9.053%	
No. Obs.	4090			82		111		6984	
Regime 2									
Threshold value		> 1.161*		> 0.757*		> 0.828*		> 1.415*	
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)
DeltaWindIntraP	-0.002**	(0.001)		0.000	(0.000)	-0.001	(0.001)	-0.052	(0.036)
DeltaWindIntraN	-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)
<i>Rquared</i>	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= $\sqrt{\Delta t}$; DeltaWindIntraP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table 12: Estimation results hour 7, Quarters 2,4, Second Sample Split. For Quarter 2 the second regime identified in the first sample split (Table 11) has been further checked for threshold effect. For Quarter 4 the observations in regime 1 (Table 11) have been further checked for threshold effect.

Dependent variable Delta Price				
Regime 1				
	H7Q2		H7Q4	
Threshold value	<= 1.145*		<= 1.178*	
	Coeff	Std. err.	Coeff	Std. err.
Co	-4.367	(3.103)	-2.411	(1.412)
DeltaPrice1	-0.431*	(0.041)	-0.287*	(0.036)
DeltaPrice2	-0.242*	(0.032)	-0.180*	(0.023)
DeltaPrice3	-0.132*	(0.029)	-0.082*	(0.019)
DemandQuote	4.051	(2.847)	2.224	(1.284)
Volume	-0.014	(0.013)	-0.019*	(0.007)
SqrTimeStep	1.178	(1.807)	4.501*	(1.694)
DeltaWindIntrP	-0.001*	(0.000)	-0.001	(0.001)
DeltaWindIntrN	-0.001	(0.001)	0.000	(0.001)
DeltaPVIntraP	0.000	(0.002)	-0.001	(0.001)
DeltaPVIntraN	0.001	(0.001)	0.002	(0.002)
<i>Rsquared</i>	18.171%		9.526%	
No. Obs.	2175		4605	
Regime 2				
	H7Q2		H7Q4	
Threshold value	> 1.145*		> 1.178*	
	Coeff	Std. err.	Coeff	Std. err.
Co	-0.826	(2.130)	3.845	(4.117)
DeltaPrice1	-0.227*	(0.045)	-0.168*	(0.042)
DeltaPrice2	-0.102*	(0.029)	-0.091*	(0.028)
DeltaPrice3	-0.058**	(0.023)	-0.090	(0.047)
DemandQuote	0.536	(1.724)	-3.034	(3.344)
Volume	0.043*	(0.012)	-0.013	(0.011)
SqrTimeStep	-2.138	(1.950)	1.134	(3.719)
DeltaWindIntrP	0.000	(0.001)	-0.002**	(0.001)
DeltaWindIntrN	0.000	(0.001)	0.001	(0.003)
DeltaPVIntraP	0.001	(0.001)	0.006	(0.004)
DeltaPVIntraN	0.003*	(0.001)	-0.005*	(0.001)
<i>Rsquared</i>	7.361%		19.427%	
No. Obs.	2576		1665	

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

OLS estimation of the model including fundamental 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)
<i>R</i> squared	7.296%		4.705%		7.011%		8.411%	
No. Obs.	6859		5449		6558		7931	

OLS estimation of the autoregressive model excluding fundamental 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)
<i>R</i> squared	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= $\sqrt{\Delta t}$; DeltaWind-IntrP/N=positive/negative forecasting errors in wind; DeltaPVIntraP/N=positive/negative forecasting errors in PV.

Table 14: Estimation results hour 12, Quarters 1–4, First Sample Split

Dependent variable Delta Price									
Regime 1									
	H12Q1		H12Q2		H12Q3		H12Q4		
Threshold value	<= 1.245*		<= 1.245*		<= 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)	
<i>Rsquared</i>	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)	
<i>Rsquared</i>	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 15: Estimation results hour 18, Quarters 1–4, global OLS without threshold

OLS estimation of the model including fundamental 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)
<i>R</i> squared	11.135%		8.929%		8.048%		7.037%	
No. Obs.	8507		5982		6162		8936	

OLS estimation of the autoregressive model excluding fundamental 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)
<i>R</i> squared	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.

Table 16: 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)
<i>R</i> squared	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)
<i>R</i> squared	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.