Energy Economics 54 (2016) 376–387

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Are fundamentals enough? Explaining price variations in the German day-ahead and intraday power market

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ARTICLE INFO

Article history:
Received 11 April 2015
Received in revised form 23 December 2015
Accepted 30 December 2015
Available online 14 January 2016

JEL classification:
Q41

Keywords:
Intraday market for electricity
Fundamental price modeling

ABSTRACT

European electricity market participants are encouraged to balance intraday deviations from their day-ahead schedules via trades in the intraday market. Together with the increasing production of variable renewable energy sources (RES), the intraday market is gaining importance. We investigate the explanatory power of a fundamental modeling approach explicitly accounting for must-run operations of combined heat and power plants (CHP) and intraday peculiarities such as a shortened intraday supply stack. The fundamental equilibria between every hour's supply stack and aggregated demand in 2012 and 2013 are modeled to yield hourly price estimates. The major benefits of a fundamental modeling approach are the ability to account for non-linearities in the supply stack and the ability to combine time-varying information consistently. The empirical results show that fundamental modeling explains a considerable share of spot price variance. However, differences between the fundamental and actual prices persist and are explored using regression models. The main differences can be attributed to (avoided) start up-costs, market states and trading behavior.

1. Introduction

Scarcities of electricity in day-ahead and intraday markets are reflected in the publicly observable prices on power exchanges. The prices of unobserved bilateral trades will not deviate systematically from exchange prices because traders have the option to trade either on the exchange or bilaterally. They will not trade in one market if trading in the other yields a higher profit. To support the decision making of producers, consumers and traders, various modeling and forecasting approaches for electricity spot prices have been developed.[1] According to Weron (2014), fundamental models form a prominent day-ahead price modeling category. Other modeling approaches are game theoretic models (Batlle and Barquín, 2005; Ventosa et al., 2005), technical analysis and expert systems, econometric-stochastic models (Bowden and Payne, 2008; Cuaresma et al., 2004; Huisman and Mahieu, 2003; Keles et al., 2012; Ketterer, 2014; Kian and Keyhani, 2001; Kristiansen, 2012; Misiorek et al., 2006; Nogales et al., 2002; Paraschiv et al., 2015) and artificial intelligence models (Cruz et al., 2011). Fundamental models are in line with the standard economic theory that prices in competitive markets result from the equilibrium of demand and supply. The day-ahead market price then equals the marginal costs of the last operating power plant that is needed to satisfy demand (Borenstein et al., 2002; Joslow and Kahn, 2001; Karakatsani and Bunn, 2008a, 2010; Möst and Genoese, 2009; Müsgens, 2006; Weigt and Hirschhausen, 2008).

For the German intraday market, no results from a fundamental modeling approach have been published so far, and only a few explicit intraday price models exist compared to the day-ahead pricing literature. Hagemann (2015) uses a multiple linear regression model to investigate the influence of intraday price determinants in Germany and explains that intraday supply side shocks may have different price effects. Selasinsky (2014) visualizes the causal relationship between German intraday prices and unforeseen intraday changes of the residual load in a contour diagram. Furió et al. (2009) analyze the price convergence between the Spanish day-ahead and intraday market from 2000 to 2005 and find significant price differences between both markets. Further intraday literature covers trading strategies of agents who balance wind power forecast errors (Bueno-Lorenzo et al., 2013; Chaves-Ávila et al., 2013; Henriot, 2014; Morales et al., 2010; Moreno et al., 2012) and research on market design and liquidity (Borggrefe and Neuhoff, 2011; Furió and Lucia, 2009; Hagemann and Weber, 2013; Weber, 2010).The major strength of a fundamental modeling approach are the ability to account for non-linearities in the supply stack and the ability to combine time-varying information such as fuel and

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[1] Spot markets are the latest possibility to trade electricity before physical delivery. Commonly important energy exchanges in Europe define that the spot market includes the day-ahead and the intraday market.

http://dx.doi.org/10.1016/j.eneco.2015.12.013
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CO_2 prices or renewable feed-in consistently. Furthermore fundamental approaches are flexible in the sense that existing models can be integrated for certain fundamental factors (e g. wind forecasting tools). By applying Monte Carlo simulations, insights into future spot price dynamics under various future demand and supply scenarios are possible. Therefore the first objective of this work is to develop a fundamental model to explain current day-ahead and intraday market prices in Germany. Fundamental models differ concerning the applied methodology and the forecasting target. Approaches to modeling the supply and demand side based on time series and econometrics are developed by different authors, e. g., Eydeland and Wolyniec (2003) or Lyle and Elliott (2009) aim to find prices from derivatives. The following works are comparable to our work because hourly electricity spot prices are modeled: Gonzáles et al. (2012) and Karakatsani and Bunn (2010), who forecast electricity spot prices for the British market; Vehviläinen and Pyykkönen (2005), who forecast electricity spot prices in the Nordic market; and Cartea and Villaplana (2008), who forecast electricity spot prices for PJM and the British and the Nordic markets. A recent work using a time series approach including a supply stack model was developed by Liebl (2013). Fundamental modeling including inter-temporal restrictions of plant operation and using optimization techniques is done by Ellersdorfer et al. (2008) or Hirschhausen et al. (2007) for the German market and by Borenstein et al. (2002) for the Californian market. More recently, Graf and Wozabal (2013) published a work with a similar approach for the German day-ahead market. Publications basing their fundamental modeling on the representation of power plants' variable costs are used to investigate strength, competitiveness or strategic behavior in power markets. Usually their focus is not on electricity price forecasting but, instead, on identifying differences between prices predicted by the marginal cost theory and actual prices. Müsgens (2005) uses an advanced fundamental model for more than one region but only with marginal costs based on a monthly time resolution. Schwarz and Lang (2006) apply a similar modeling approach, focusing on Germany and assessing the hourly marginal costs to investigate price mark-ups as well as fly-ups. In line with this research stream, the second objective of this work is to explain differences between the prices predicted by the supply stack model and the prices actually observed. Using multiple linear regression models, the price difference is tested for influences from (i) (avoided) start up-costs, (ii) different market states and (iii) trading behavior.

This paper contributes to theoretical intraday pricing literature as follows. The fundamental model for the intraday market is presumably the first application of this modeling approach to explain intraday prices. The fundamental modeling approach is modified to account for intraday market peculiarities. These peculiarities include a limited technical flexibility of conventional power plants to adjust their generation within short intraday lead-times. Furthermore, the supply stack from the day-ahead planning is divided into scheduled and unscheduled conventional power plants. Scheduled power plants may act as intraday purchasers (intraday demand curve) and unscheduled power plants as sellers (intraday supply curve) of electricity in the intraday market. This paper also contributes to academic literature by including a representation for must-run electricity production from combined heating and power production facilities (CHP) and a detailed consideration of scheduled and unscheduled power plant unavailabilities.

This research paper has practical relevance. First, the fundamental models developed may be used for very short term price forecasting and may thus reduce the high level of uncertainty in both day-ahead and intraday markets. Trading in intraday markets requires frequent re-optimizations due to the constant improvements of information quality after the day-ahead scheduling, e. g., wind and solar power predictions, load forecasts or unscheduled power plant outages. In the light of the Regulation on Wholesale Energy Market Integrity and Transparency (REMIT) in Europe a fundamental price estimate may provide competitive reference prices and thus help to evaluate effects of an increased electricity market transparency (Nijman, 2012). Second, the hedging activities, e. g. from power plant operations for their electricity production or from retail companies for their electricity consumption start several years before delivery in long-term markets and end in the day-ahead market. A fundamental modeling approach may ensure a consistent planning and representation of electricity markets during this process and also during final balancing in the intraday market.[2] Third, the ability to understand and predict intraday price volatility may be used to optimize unit commitment and increase revenues from the operation of flexible power plants such as hydro pump storages, gas turbines or modern hard coal power plants.

The remainder of this paper is organized as follows. In section two, overviews of the German day-ahead, intraday and balancing markets are given. In the third section, the fundamental and regression models for the day-ahead and intraday markets are presented. Section four contains the description of the data set and an overview of the empirical results. Afterwards, a discussion of the model results and an explanation of limitations follows. Finally, section five contains the conclusion.

2. The German power market

Because electricity is not economically storable in relevant quantities, a balance of supply and demand is required at all times to maintain system stability. In Germany, this continuous equilibrium is ensured through a sequence of interdependent wholesale markets. The day-ahead market closes at 12 pm on the day before delivery. In this market, participants may trade electricity with physical delivery on the next day either anonymously on a trading platform of the European Power Exchange (EPEX Spot) or bilaterally over the counter (OTC). In terms of trading volumes, the day-ahead auction of the EPEX Spot is the most important spot market for Germany with a total trading volume of approximately 245 TWh for years 2012 and 2013.[3] Here, supply and demand bids are matched in a uniform pricing auction to obtain a market clearing price and quantity for each of the 24 hours of the next day. According to Viehmann (2011), the exchange based and the bilateral day-ahead markets show trading volumes in the same order of magnitude in Germany. The day-ahead market is of great importance for the integration of variable renewable energy sources (RES) because market participants forecast the expected production profile (e. g., for wind and solar power plants) for the next day and sell those expected quantities in the day-ahead market.

After the gate closure of the day-ahead market at 12 pm on the day before delivery, trading continues from 3 pm on the day before delivery until 45 min before physical delivery on the electronic intraday platform of the EPEX Spot. Here, market participants are encouraged to self-balance unforeseen deviations from their day-ahead schedules. The German intraday market is a continuous and order driven market. Incoming limit buy and sell orders are stored in the limit order book and executed as soon as the buy price exceeds the sell price or vice versa. In contrast to limit orders, market orders are executed immediately at the best available market price. A large fraction of intraday trades stem from the increasing production of variable renewable energy sources. Market participants that are responsible for the marketing of wind and solar power may trade the quantity difference between the profile sold day-ahead and the more precise intraday forecast values in the intraday market to self-balance their portfolios. This quantity difference is called forecast error. The German intraday trading volumes have been constantly increasing from 1.4 TWh in 2007 to 16 TWh in 2012 and to 20 TWh in 2013. Trading volumes are much higher in the day-ahead market than in the intraday market. Hence the intraday market is of minor importance for trading and hedging but of higher

[2] Furthermore, from a macroeconomic perspective, the fundamental modeling approach may enable to assess price effects of market couplings by including foreign imports and exports.

[3] The German and the Austrian markets are treated as one market area by the EPEX Spot and thus the trading volume is reported together for both countries.

importance for system security. Any trade in the intraday market may contribute to reduce the activation of control energy through the TSOs.

After the gate closure of the intraday market, the four TSOs in Germany – 50 Hertz Transmission GmbH, Amprion GmbH, TenneT TSO GmbH and TransnetBW GmbH – use the previously contracted control energy to level out demand and supply in real time and maintain the grid frequency at 50 hertz. In Germany, control energy is classified into primary, secondary and tertiary reserves. The three types of control energies have different activation times and durations of operation.[4] Individual market participants are charged ex-post for imbalances they cause. Therefore, they will generally try to avoid the use of control energy for two reasons. The first reason is that, in Germany, using balancing services is always more expensive than self-balancing on the intraday market (BNA, 2012). The second reason is that the TSOs may impose sanctions on market participants that cause many imbalances by abrogating their balancing contract.

3. Methodology

3.1. A fundamental modeling approach for electricity spot prices

In competitive markets, prices are expected to correspond to the intercept of demand and supply. The supply curve in electricity markets is represented by all available power plant capacities sorted in ascending order according to their short run marginal costs. In a perfectly competitive market, the marginal costs of the last running plant for a certain delivery period (e. g. hour) set the electricity price. In the absence of market power, this bidding strategy ensures maximum profits of suppliers in one-shot auctions with marginal pricing (David and Wen, 2000; Ventosa et al., 2005; Weigt and Hirschhausen, 2008). This bidding strategy is represented by a fundamental model. Fundamental models are often referred to as production cost, supply stack or merit order models, as in Burger et al. (2004); Weber (2005); Weron (2014).

A formal description of the fundamental model used for the day-ahead market is provided by the set of Equations (Eqs. 1 to 6). The novelties are a detailed treatment of scheduled and unscheduled unavailabilities as well as the inclusion of electricity production from must-run facilities. For the intraday model, the capacity constraint in Eq. (4) is replaced by Eq. (7) to account for intraday peculiarities[5]:

$$C_t = \sum_{pl} c_{pl,t} = \sum_{pl} \left[\left(p_{fuel,t} + p_{CO2,t} \cdot \varepsilon_{fuel} \right) \cdot h_{pl} + c^{other}_{pl,t} \right] \cdot y_{pl,t} \rightarrow \min \quad (1)$$

$$D_t = \sum_{pl} y_{pl,t} \quad (2)$$

The objective function (1) minimizes the operational costs at a total power plant output $y_{pl,t}$ multiplied by the marginal costs per power plant. The marginal costs include the fuel prices $p_{fuel,t}$ and emission certificate prices $p_{CO2,t}$ multiplied by the emission intensity for each fuel type ε_{fuel}. The sum is multiplied by the plant heat rate h_{pl} and adjusted by other variable costs $c^{other}_{pl,t}$, such as fuel transport costs. Eq. (2) balances supply and demand.[6] The power plant with the highest marginal costs needed to satisfy demand is referred to as marginal plant ($margpl_t$). The operational costs of $margpl_t$ determine the fundamental prices for the day-ahead market (DAP^{fund}_t).

The supply stack is the linkage between operational costs and the installed capacity K_{pl}. The installed capacity is adjusted by scheduled $\Upsilon^{sched}_{fuel,t}$ and unscheduled power plant unavailabilities $\Upsilon^{unsched}_{fuel,t}$ on an hourly time resolution. Due to the data availability and simplification, the plant availability is assumed to be identical within each fuel type.

$$\upsilon_{fuel,t} = 1 - \frac{\Upsilon^{sched}_{fuel,t} + \Upsilon^{unsched}_{fuel,t}}{\sum_{pl=fuel} K_{pl}} \quad (3)$$

For the day-ahead and the intraday models, different power plant availabilities $\upsilon_{fuel,t}$ are relevant. In both markets scheduled and unscheduled unavailabilities influence the prices. Depending on the time of occurrence, unforeseen power plant outages can be substituted with purchases in the day-ahead market, but they can be traded in the intraday market if they occur after the day-ahead gate closure and before the delivery period (Hagemann and Weber, 2013). Eq. (4) provides the capacity constraint for the day-ahead market including the plant availability $\upsilon^{DA}_{fuel,t}$ in the day ahead market.

$$y^{DA}_{pl,t} \leq K_{pl} \cdot \upsilon^{DA}_{fuel,t} - y^{CHP}_{pl,t} \quad (4)$$

The available capacity is reduced by must-run production obligations $y^{CHP}_{pl,t}$ related to combined heating and power production (CHP). This must-run production is directly deduced from electricity demand (cf. Eq. (6)). CHP must-runs are considered via a proportional distribution per fuel type as described in Eq. (5).

$$y^{CHP}_{pl,t} = y^{CHP}_{fuel,year} \cdot f(temp_t) \frac{K^{CHP}_{pl} \cdot \upsilon_{fuel,t}}{\sum_{pl=fuel} \left[K^{CHP}_{pl} \cdot \upsilon_{fuel,t} \right]} \quad (5)$$

The capacity of must-run power plants $K^{CHP}_{pl,fuel}$ includes CHP power plants with one and two degrees of freedom in their operations. The former have no variability of their electricity production if heating demand occurs in their system. The latter have some flexibility, yet still there is still a minimum electricity production accompanying heat delivery. CHP heat demand includes both a temperature dependent share, notably from residential heating, and a non-temperature dependent share related notably to industrial CHP plants that have to deliver process heat. To account for both, the electricity production from must-run CHP facilities is modeled by a stepwise functional relationship $level_{chp} = f(temp_t)$ between the hourly average temperature ($temp_t$) and level of must-run utilization ($level_{chp}$). The non-temperature dependent electricity production is represented by a minimum level of utilization that is not undercut (see Fig. 1).

Demand in the model is considered as residual load D_t given by Eq. (6). The residual load represents the gross national load L_t after the deduction of renewable feed-in, considering foreign trade balance and reserve power demand.

$$D_t = L_t - W_t - S_t + Ex_t - Im_t + RE^{pos}_t - \sum_{pl} y^{CHP}_{pl,t} \quad (6)$$

The must-run electricity production from CHP plants is subtracted from the electricity demand because the obligation to cover the heat demand is assumed to cause the marginal costs of electricity production to equal zero. Similarly, the fluctuating renewable feed-in (Wind W_t and Solar S_t) is subtracted because the marginal costs are zero or close to zero. An increase in production (supply) implies a reduction in demand from conventional plants and vice versa. As long as only a national market is modeled, the load data has to be corrected by exports and imports of electricity (Graf and Wozabal, 2013; Schwarz and Lang, 2006).

[4] More detailed presentation of the German balancing mechanisms can be found in Flinkerbusch and Heuterkes (2010); Möller et al. (2011).

[5] Indices to differentiate between the day-ahead (DA) and intraday (ID) market models are used only if symbols are exclusively used for one of the models. All variables without a notation are either the same for both models (e. g. heat rate) or can be used with DA or ID information (e. g. wind) dependent to the model.

[6] Eq. (2) holds for $0 \leq D_t \leq K_{pl,fuel} \cdot \upsilon_{fuel,t}$. When $D_t \leq 0$ (negative residual load), the resulting prices are set to −10€ per MWh, indicating that power plant operators accept negative bids to stay online. When $D_t \geq K_{pl,fuel} \cdot \upsilon_{fuel,t}$, the resulting prices are assumed to be equal to $\max(c_{pl,t})$. Resulting quantities of undersupply can be interpreted as reserve energy demand.

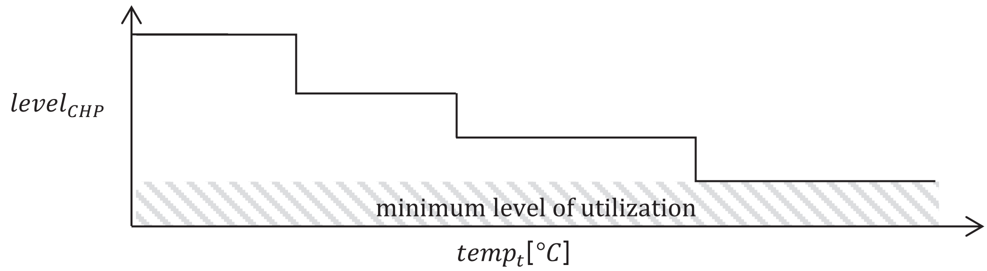

Fig. 1. Schematic relation to model must-run CHP electricity production ($level_{chp}$).

Exports from a country Ex_t increase the residual demand while imports Im_t reduce it.[7] Plant capacity is not available for the spot market if it is committed in the reserve power market (Just and Weber, 2008). Consequently positive primary and secondary reserve demand RE_t^{pos} are added to the load data.[8]

3.2. Fundamental modeling of intraday prices

Either intraday prices can be modeled directly as the equilibrium price at the intercept of intraday supply and demand (as done in this paper) or the deviation of intraday prices from day-ahead prices can be modeled as done by Hagemann (2015). Therefore, the set of equations for the intraday model is basically equal to the one described in Section 3.1. The differences are that intraday instead of day-ahead information is used and that Eq. (4) is adjusted to account for fundamental peculiarities of the intraday market.

First, based on the day-ahead market results, the supply stack is separated into a lower part with operating power plants that are able to decrease the scheduled power output and an upper part with non-operating unscheduled power plants that may be started up or increase their scheduled power output (see Fig. 2). For the identification of the marginal power plant ($margpl_{DA}$) we compare two approaches and label them $IDP1^{fund}$ and $IDP2^{fund}$. In the first approach ($IDP1^{fund}$) we identify the marginal power plant within the fundamental day-ahead market model at the intersection between the supply and demand curves. In the second approach ($IDP2^{fund}$) we identify the marginal power plant by comparing the actual day-ahead price with the modeled supply stack.[9] The whole intraday supply stack ($y_{pl,t}^{ID}$) is the concatenation of the intraday down-ramping ($y_{pl,t}^{ID,Down}$) and up-ramping part ($y_{pl,t}^{ID,Up}$). Second, the intraday supply curve is shortened to consider inflexibilities and shorter lead times.

The capacity constraints for the intraday market are then given by Eq. (7), which is derived from Eq. (4) and incorporating the former defined variables for installed capacities $K_{pl,fuel}$, intraday unavailabilities $\upsilon_{fuel,t}^{ID}$, the correction for must-run production $y_{pl,t}^{CHP}$ and the occupancy level of the marginal plants production $y_{margpl,t}^{DA}$.

$$y_t^{ID} = \begin{cases} \left(K_{pl,fuel} \cdot \upsilon_{fuel,t}^{ID} - y_{pl,t}^{CHP} - y_{margpl,t}^{DA}\right) \cdot s_{up}, & pl < margpl \\ \left(K_{pl,fuel} \cdot \upsilon_{fuel,t}^{ID} - y_{pl,t}^{CHP} + y_{margpl,t}^{DA}\right) \cdot s_{down}, & for\ pl \geq margpl \end{cases} \tag{7}$$

The upper part of the intraday supply stack includes all power plants that may be scheduled for delivery in the intraday market. Those power plants allow a dispatch in the short run and have marginal costs above the day-ahead price. Inflexible or partly inflexible power plants have limited ramping potential and imply a steeper slope of the supply curve. The factor s_{up} determines the extent of shortening the upper part of the intraday supply stack in the model. The lower part of the intraday supply stack consists of all operating power plants after day-ahead scheduling. The lower part of the intraday supply stack is restricted by limited down-ramping flexibilities of operating power plants. These limitations mostly stem from the power plants specific minimum stable operation limit (Nicolosi, 2010). Furthermore power plants which operate to deliver negative reserve power represent additional must-run capacities in the intraday market. They cannot be ramped down because then they could not deliver negative reserve power. The reduction of intraday down-ramping capacity in the model is determined by the factor s_{down} to shorten the lower part of the intraday supply stack.

Some factors affect the slope of the entire intraday supply stack (upper and lower part). First, shorter lead times for power plant dispatches can make flexibility restrictions of conventional power plants binding. Second, not all power plant owners and sales companies are able to participate in the intraday market or have a 24/7 intraday shift desk because a 24/7 shift work is economically beneficial only for larger companies. Third, redispatch interventions from the TSOs can influence the slope of the intraday supply stack. The TSOs monitor the status of the grid and require redispatch from power plants if some transmission lines are overloaded.

The deviation between the intraday and the day-ahead residual load (forecast error FE_t) determines whether up-ramping or down-ramping capacity in the intraday market is needed. In the fundamental model, all intraday deviations are aggregated. The residual load in the intraday market differs from the residual load in the day-ahead market because of forecast deviations for variable renewable energy sources (RES) and for load.

$$FE_t = D_t^{ID} - D_t^{DA} \tag{8}$$

Market participants may sell or buy the quantity difference in the intraday market to minimize their balancing costs. Negative deviations result from less electricity load or additional production from RES in the intraday market. On the contrary, positive deviations result from additional electricity load or less RES production. Moreover, unplanned power plant outages may increase intraday demand. The availability factor of power plants in the intraday market $\upsilon_{fuel,t}^{ID}$ is on average lower than in the day-ahead market $\upsilon_{fuel,t}^{DA}$ because of unscheduled unavailabilities that occur after day-ahead gate closure.

3.3. Identifying price impacts beyond pure supply stack effects

In addition to the marginal costs of operating plants, other factors may influence the observed electricity prices. Therefore, multiple linear regression models are developed subsequently to test the explanatory

[7] For the day-ahead price formation, the day-ahead cross border schedules are relevant. For the intraday market model, we use the day-ahead data as well due to data quality limitations from the physical flows and the fact that physical cross boarder flows do not necessarily influence intraday prices. Physical cross border flows are likely to follow physical limitations (e. g. loop-flows) instead of commercial trading flows.

[8] Positive minute reserve is not considered in the model because it is provided by peak power plants with high marginal costs. These power plants are out of the money and do not influence the marginal price. Negative balancing energy is not considered because it is delivered by operating plants (or demand).

[9] By using the fundamental model to determine the marginal plant, the errors from the day-ahead market model are carried on. In case the actual day-ahead price is used, an error can occur if the actual day-ahead prices differ from the theoretic fundamental prices.

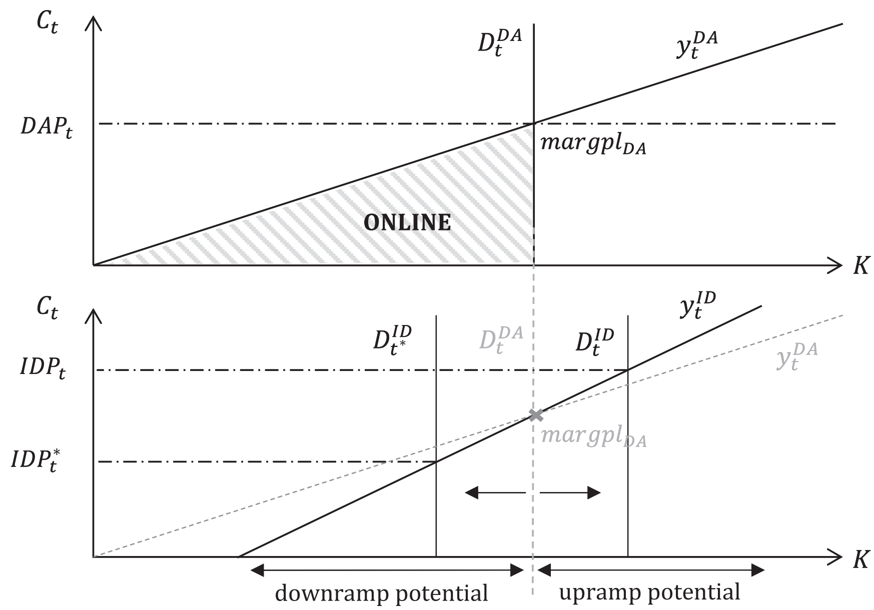

Fig. 2. Day-ahead versus intraday market price from a supply stack model.

power of other spot price determinants beyond those included in the fundamental model. Apart from the fundamental price, the regression models capture the influence of (i) (avoided) start-up costs, (ii) market state variables and (iii) trading behavior.

3.3.1. (Avoided) start-up costs

Ramping constraints due to base and mid load plant inflexibilities can lead to differences between actual and fundamental prices. According to Nicolosi (2010), must-run obligations of power plants due to operational constraints such as minimum and maximum down-times or start-up times (Troy et al., 2010) may cause those differences.[10] Furthermore prices may be influenced by limitations to changes in unit commitment during intraday trading or by (avoided) start-up costs. In a series of hours, if only single hours show prices below the marginal costs of an inflexible base load plant, the operators may not be able or willing to ramp down the power plant. This may lead to very low or even negative spot market prices.[11] The Ramp variables (Eqs. 9 to 10) are designed to capture the price effects due to conventional power plant ramping costs and inflexibilities.

$$\mathrm{Ramp}_t^{\mathrm{Up}} = \left| \left(\mathrm{D_t} - \frac{\sum_{i=1}^{H} \mathrm{D}_{t-i}}{\mathrm{H}} \right)^{+} \right| \tag{9}$$

$$\mathrm{Ramp}_t^{\mathrm{Down}} = \left| \left(\mathrm{D_t} - \frac{\sum_{i=1}^{H} \mathrm{D}_{t-i}}{\mathrm{H}} \right)^{-} \right| \tag{10}$$

In periods with an increasing residual load, start-up costs of conventional power plants are expected to increase day-ahead and intraday prices above the levels predicted by the fundamental model. In periods with a decreasing residual load, power plant inflexibilities are expected to increase the sales in the spot market and decrease prices below the levels predicted by the fundamental model. Because one can expect different price effects during downward and upward ramping periods, two different regressors are modeled. They are calculated as the absolute difference between the current and average residual demand of the last H hours.

3.3.2. Market state variables

Furthermore, different market states may explain deviations between the fundamental and observed prices. For the definition of market states, various indicators can be found in the literature about regime switching models for energy prices (Bierbrauer et al., 2004; Erlwein et al., 2010; Huisman and Mahieu, 2003; Janczura and Weron, 2009). In this work, we focus on markets states related to supply scarcities. Different works investigate scarcity factors and model their influence on spot price. Aïd et al., 2013 include a 'margin capacity,' the difference between current demand and installed capacity, to explain the differences between marginal costs and spot prices. Voronin et al., 2014 and Sensfuß et al., 2008 use a 'supply–demand-index,' which is the ratio between idle capacity and demand to investigate scarcity mark-ups. Price mark-ups may occur if market participants committed most of their generating output before the spot market starts so that the short term supply in the day-ahead and intraday market is scarce.

Table 1
Data sources.[a]

Data	Source	Product
Load	ENTSO-E	-
Demand (Energy Supplied)	IEA Statistics	-
Spot prices	EPEX-Spot	Info-User (EOD)
Coal Price	Energate.de	API#2 Front year
CO_2	EEX	EU-CO_2-Emission Allowances
Gas price	Spectron	TTF-Day-Ahead
Wind and Solar feed-in	EEX Transparency data service	Info-Vendor
Unavailability's	EEX Transparency data service	Info-Vendor
Cross Boarder Flow	ENTSO-E.net	D-1 Commercial Schedule
Power plant information	EWL database (based on Platts, etc.)	-
Electricity production from CHP	BMWi and Destatis	

[a] Fuel prices are either spot market or front year future prices for coal, gas, emission and oil. Lignite, uranium, biomass, waste and other fuel prices are based on cost estimates.

[10] Other approaches to include start-up costs can be found in Müsgens (2005) or Schwarz and Lang (2006)

[11] Within the marginal cost framework, prices that are higher than the marginal costs may be demanded even in the absence of abusive market power and strategic behavior. In addition to start-up costs, the peak load pricing concept may explain price mark-ups. It states that peak load plants require more than their marginal costs in order to recover their fixed costs Crew et al. (1995).

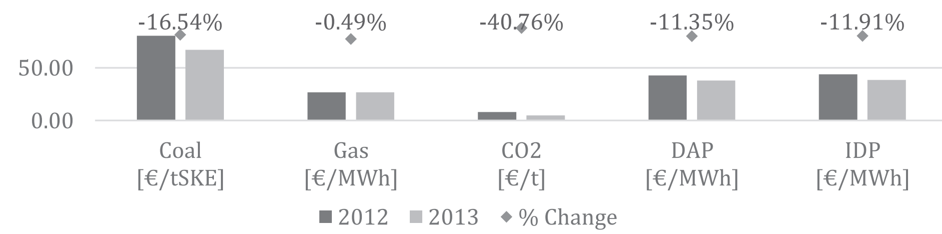

Fig. 3. Yearly average of coal, gas, CO_2, day-ahead and intraday prices 2012 and 2013 (Data sources see Table 1).

If the excess supply is low, temporal quantity retentions may occur in the intraday market as well. In our work, we use the 'load supply ratio' (LSR) as the measure for scarcity in the energy system. To obtain the LSR, the relation between the residual demand and total available capacity is calculated. Two variables are constructed to capture a market state with capacity scarcity and one with capacity excess. Capacity scarcity is deemed to occur when the LSR exceeds the mean LSR plus one standard deviation. Conversely, a LSR lower than the mean LSR minus one standard deviation then indicates a market state with excess capacity.

$$LSR_t = \frac{D_t}{\sum_{pl} K_{pl} \cdot \upsilon_{fuel,t} - y^{CHP}_{pl,t}} \tag{11}$$

3.3.3. Trading behavior

Finally, traders tend to use the present or past price information to forecast future prices. In the day-ahead market, the so called similar day-approach states that the future prices can be calculated using previous prices which are corrected by changes of fundamental influences (Weron, 2006). For models with hourly resolution, a similar hour-approach is suitable. Weron and Misiorek, 2008 and Kristiansen, 2012 find significant influences of the day-ahead price of the same delivery hour of the previous two days and the previous week on the present price. In electricity systems with a high penetration of wind and solar power feed-in, changing weather conditions have a significant influence on the wind and solar power production and, thus, on the day-ahead prices (Sensfuß et al., 2008). Quickly changing day-ahead prices may reduce the explanatory power of past days. Therefore, only the autoregressive term for the same hour of the previous day is included in the day-ahead regression model. Intraday traders are likely to include the price information of the previous hour in their trading decisions because intraday trading happens continuously. Therefore, the price of the preceding hour is included in the intraday regression model. Apart from trading behavior, the autoregressive variables may capture autocorrelated fundamental influences that are not directly observable and, hence, not included in the model. The complete regression models are specified in Eq. (12) for the day-ahead and in Eq. (13) for the intraday model:

$$\begin{aligned} DAP_t = {} & c_1 + c_2 \cdot DAP^{fund}_t + c_3 \cdot Ramp^{DA,Up}_t + c_4 \cdot Ramp^{DA,Down}_t \\ & + c_5 \cdot LSR^{DA}_{low,t} + c_6 \cdot LSR^{DA}_{high,t} + c_7 \cdot DAP_{t-24} + \varepsilon_t \end{aligned} \tag{12}$$

$$\begin{aligned} IDP_t = {} & c_1 + c_2 \cdot IDP2^{fund}_t + c_3 \cdot Ramp^{ID,Up}_t + c_4 \cdot Ramp^{ID,Down}_t \\ & + c_5 \cdot LSR^{ID}_{low,t} + c_6 \cdot LSR^{ID}_{high,t} + c_7 \cdot IDP_{t-1} + \varepsilon_t \end{aligned} \tag{13}$$

DAP_t and IDP_t denote the day-ahead and intraday price in delivery hour t, c_1 is the constant term, c_i with $i = (2,..,7)$ is the regression coefficients and ε_t is the independently and identically distributed error term.[12]

4. Empirical analysis

4.1. Data

Because of the continuous trading in the intraday market, more than one price for one delivery hour is observed. In this study we employ the quantity weighted hourly average intraday price since it includes information about all trades for one delivery hour and contains less outliers than, e. g., the last trade price. The data for the fundamental model is collected from the sources indicated in Table 1.

Figs. 3 and 4 given an impression about the evolution of prices and other input data from the fundamental model for the time period being investigated (2012 till 2013). The changes in these data influence the fundamental price estimates.

The hourly load data from ENTSO-E is defined as the 'hourly average active power absorbed by all installations connected to the transmission network or to the distribution network' (entsoe.eu, 2014). Those hourly load values do not match the domestic supply data provided by the IEA. Because the consumption and the energy produced from all power plants in a system always have to be in balance, the hourly load values from ENTSO-E are adjusted to fit the domestic supply data provided by IEA statistics. The adjustment of the hourly load data is done on a monthly basis to account for the yearly seasonality. A base load consumption for each month, e. g., from industries´ or power plants´ own use, is added proportionally. Furthermore grid losses are included over a quadratic function of the total consumption.

Official data about electricity production from CHP power plants are available with a yearly time resolution. The hourly CHP electricity production per fuel type is then determined using Eq. (5). The temperature data are taken as the average temperature of main metropolitan areas in Germany (Düsseldorf, Stuttgart, Munich and Berlin). The must-run utilization levels in the model are defined as indicated in Table 2.[13]

The extent of the shortening of the intraday supply stack is not easily determined as it results from the interactions of different factors. Based on the considerations from Section 3.2, we find a reasonable shortening of the supply stack in the upper and lower part by setting the factor in Eq. (7) for s^{up} to 0.5 and s^{down} to 0.4.

The sources for the regression model data are depicted in Table 3.

4.2. Fundamental model results

Key results of the fundamental models are presented in Table 4. The naïve benchmark uses the price information of the same hour on the previous similar day (e. g. previous weekday for other weekdays or last weekend day for weekends, see Conejo et al., 2005). The naïve benchmark already explains a remarkable share of the day-ahead (47%) and intraday (32%) price variance. The basic intraday model ($IDP1^{fund}$) determines the marginal plant within the model, as done in the day-ahead model (DAP^{fund}), and accounts for intraday peculiarities. Both achieve quite remarkable results, explaining 65 and 66% of the price variances, respectively. Using the day-ahead price to determine

[12] Since the results for $IDP2^{fund}$ are significantly better than those from $IDP1^{fund}$ (see Section 4.2) and for better legibility we further focus on a single regression model for the intraday market based on $IDP2^{fund}$. We additionally evaluated a regression model based on $IDP1^{fund}$ but it does not deliver additional insights.

[13] The typical heating threshold in Germany where households start to heat is 15 degrees. Above 15 degrees, must-run obligations due to heat constraints are relevant only for CHP plants that deliver heat to industrial processes, for example.

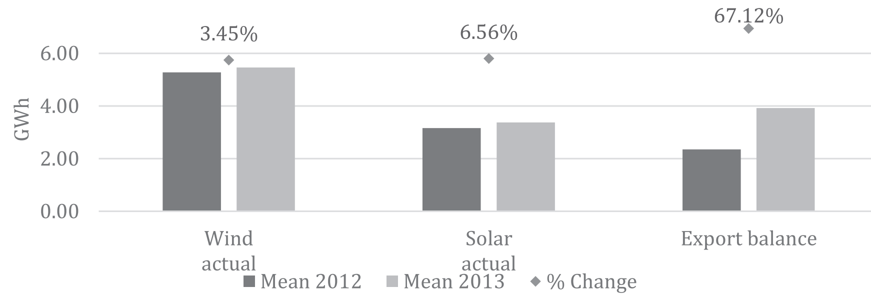

Fig. 4. Yearly average quantities for renewable forecast and actual feed-in as well as the export balance in 2012 and 2013 (Data sources see Table 1).

the marginal plant for the intraday model (IDP2^{fund}) further improves the model fit, as indicated by an R^2 of 0.74. The point forecasts of the DAP and IDP model are on average too high as indicated by the positive mean errors. This is partly because the simple fundamental models struggle to reproduce negative prices, and negative prices cannot fall beyond all limits (see Section 3.1 and footnote 6). Another possible explanation are the fuel price assumptions. Notably, for coal, the fuel qualities used by power plants in Germany may differ from the reference grade (API#2), and, thus, coal prices may be lower than the reference prices used here. Moreover, the commodity prices used in the model might be an upper boundary, since the normal backwardation argument implies that companies with long term contracts for fuels will pay prices below the spot prices on average.

The point forecast errors vary for different hours of a day (Fig. 5). IDP1^{fund} carries on the ME from the DAP model. IDP2^{fund} shows almost no ME at all, but the MAE still shows a daily structure, mainly caused by the structure of the original price time series, leading to MAEs between 4.8 and 9.1 EUR/MWh. The RMSE, which gives more weight to extreme forecast deviations, is high for hours 1 to 8 compared to the MAE measures (See Fig. 5.).

The price distribution of the fundamental price estimates is not smooth (Fig. 6). The steps in the probability density function indicate fuel switches in the model. This can be explained by the assumption that all power plants of one fuel type acquire the fuel for exactly the same price. In reality, supply contracts with different conditions exist.

4.3. Regression model results

The overall results of the regression models in Table 5 indicate adjusted R^2 values between 0.72 for the day-ahead and 0.91 for the intraday regression models, which indicate improvements in the model fit compared to the pure fundamental models. The high F-Statistics imply that the identified determinants exert a significant impact on the price. In order to statistically compare the predictive accuracy we perform a test procedure proposed by Diebold and Mariano (1995). Based on the loss differential defined as the difference between squared forecast errors, the null hypothesis of no difference in the accuracy of the compared forecasts is rejected at a 0.01 significance level, concluding that the day-ahead and intraday regression models significantly improve the forecast accuracy compared to their corresponding fundamental model.[14] The Durbin-Watson statistics indicate a positive autocorrelation in the regression residuals of the day-ahead model. Generally, a positive autocorrelation in the residuals violates the assumption that the regression residuals are independently distributed and may lead to biased standard error estimates and thus biased statistical significances of the regression coefficients.[15] Consequently, the day-ahead regression parameters are estimated using the heteroscedasticity and autocorrelation consistent Newey-West procedure (Wooldridge, 2009). This affects only the significance but not the size of the regression coefficients.

The unstandardized regression coefficients and their significance levels are summarized in Table 6. All price determinants except the LSR^{High} and the Ramp^{Down} have a significant impact in all regression models. The explanatory variables have been tested for multicollinearity. Most variance inflation factors show only moderate values between 1.21 and 4.74 (O'brien, 2007). Thus multicollinearity should not bias the regression slope estimators of those factors. Within the day-ahead regression model, the autoregressive variable DAP(−24) has a centered variance inflation factor of 9.44, which is critical. Nevertheless, the variable is kept within the model.

Significances are computed using standard errors obtained through the Newey-West procedure. Significances at the 0.01 level are labeled with ***, while significances at the 0.05 level are labeled with **and at the 0.1 level with *. For our applications, H from Eqs. (9)-(10) is set to four.[16]

We account for possible endogeneity by choosing explanatory variables that are exogenous from a theoretical perspective (cf. Karakatsani and Bunn, 2008b). Additionally, all exogenous variables are aggregated measures across all plants and/or demand that further reduce endogeneity concerns. Quantitatively, we use standard statistical test for endogeneity (Hausman, 1978) for the final models (see Appendix 0, Tables 7 and 8). At this point it should be noted that similar to Karakatsani and Bunn (2008b) the Hausman test for the intraday model shows that for the two market state variables (high and low load supply ratio which are designed to capture extreme prices) the instrument variable estimates in the two stage least squares regression are more sensitive than OLS estimates. This might be due to the fact that it is a delicate issue to find suitable instrument variables for dummy variables and given the limited data available in high (hourly) time resolution. Anyhow we conclude that unobserved fundamental price determinants are captured by the autoregressive variable and

[14] We performed the test by accounting for autocorrelation in the loss differential up to a lag of 48 h.

[15] The autocorrelation structures from the day-ahead and intraday model without the autoregressive component c_7 in Eqs. (12) and (13) are similar and do not provide further insights into the intraday weighted average price formation. More detailed investigations of the autocorrelation structure are promising if one is to focus on price formation for single transactions in the continuous intraday trading.

[16] It was also tested whether ramping costs may stretch over longer time horizons (6, 12 or 24 h), but the specification with 4 h has by far the highest explanatory power. One explanation may be that for the spot price formation, only start-up costs from peak and middle load plants are relevant. Base load plants typically run long periods without interruption. Spot price reductions in single consecutive hours may be caused by avoided start-up costs of base load plants.

Table 2
Must-run utilization level depended on the average temperature.

Average temperature	< 7.5 °C	7.5–10 °C	10–12.5 °C	12.5–15 °C	> 15 °C
Must-run level	100%	90%	80%	70%	35%

thus endogeneity does not bias our intraday regression model results. For the day-ahead regression model, the share of unexplained variance (28%) together with a positive autocorrelation in the residuals indicate that fundamental price determinants are omitted in the regression model. The Hausman test results reveal possible endogeneity for the start-up costs variables, the market scarcity and the autoregressive variable. However, a comparison of the TSLS with the OLS results reveal that the signs and magnitude of the regression coefficients do not change considerably.

4.4. Discussion

The results obtained indicate that a simple supply stack model based on fundamental information is able to explain a large share of the price variance in current day-ahead and intraday markets. Thus, fundamental factors are the main drivers for both day-ahead and intraday markets for electricity (0.653 and 0.663 R^2). The intraday model fit improves when the fundamental intraday price is determined based on the day-ahead price (see Table 4). For day-ahead markets, our results are line with earlier studies, e. g. Ellersdorfer et al. (2008) report the MAE for a fundamental modeling approach of the German day-ahead market price for each year between 2002 and 2006. Apart from the year 2004 (MAE 5.70 EUR/MWh), their MAE (8.13–13.18 EUR/MWh) exceeds the one from our day-ahead model (6.28 EUR/MWh) for the years 2012 and 2013. Graf and Wozabal (2013) develop a fundamental model to explain German day-ahead market prices in 2010 and focus on the consideration of pump storages and must-run capacities. Similar to our results, a graphical comparison reveals that the hourly average prices from the model come close to the average observed prices but tend to be flatter. The differences between actual prices and prices predicted by the fundamental model can mainly be attributed to (i) (avoided) startup-costs, (ii) the impact of different market states, (iii) trading behavior and (iv) data inaccuracies. Considering those price determinants in addition to the fundamental model results increase the adjusted R^2 to 0.717 for the day-ahead and to 0.908 for the intraday model. Gonzáles et al. (2012) show that for the British APX power market in 2008 a hybrid model consisting of a fundamental and a smooth transition regression model is able to capture 78% of the daily price variance. Even though Gonzáles et al. (2012) are not forecasting hourly but daily prices and their econometric model is substantially different from ours, the paper demonstrates that combinations of fundamental with econometric models capture price variances well.

First, the results of the statistical analysis support the first hypothesis that fundamental market peculiarities such as (avoided) startup-costs also have an impact on prices. When the residual load is increasing, conventional power plants are ramped up, and start-up costs arise. If the current residual load value is by one GWh higher than the average of the past four values, the day-ahead and intraday prices are significantly higher in both markets by 0.408 EUR/MWh and 0.676 EUR/MWh, respectively. When the residual load of the current hour is below the average residual load of the prior four hours, must-run obligation and power plant inflexibilities encourage power plant owners to market power plants below their marginal costs, which causes day-ahead and intraday prices to fall by 0.035and 0.295(EUR/MWh)/GWh, respectively. The ramp down variable for the day-ahead market is not statistically significant. Thus, downward ramps in the residual load do not further decrease the fundamentally expected day-ahead price. This implies that the effect of avoided start-up costs is already captured by the must-run obligations within the fundamental model. Avoided start-up costs and price mark-ups for the provision of flexibility occur in the intraday market. This may be explained by balancing requirements in the intraday market.

Second, different market states are also found to have a significant impact on spot prices. E. g. in line with Karakatsani and Bunn (2010) or Aïd et al. (2013), our data analysis discovers price impacts due to scarcity in the German market. We measure system scarcity by the LSR and has different impacts on day-ahead and intraday market prices. In hours where the available supply capacity strongly exceeds the residual demand (low LSR), day-ahead and intraday prices are, on average,

Table 3
Overview regressors and data sources in the regression models.

Coefficient	Variable Name	Description	Source
c_1	-	Constant	-
c_2	DAP and IDP^{fund}	Prices calculated in the fundamental model	Fundamental model
c_{3-4}	Ramp	Dummy for changes in residual load	Own calculations
c_{5-6}	LSR	Dummy for low/high LSR	Fundamental Model
c_7	DAP_{t-24}/IDP_{t-1}	Price from the same hour of the last day/previous hour	EPEX Spot

Table 4
Descriptive statistics and point forecast error from spot prices for the period from 01.01.2012 until 31.12.2013. Day-ahead forecast data for the day ahead model and actual values for the intraday model. Notations in the table: Standard Deviation (SD), Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) (bold = best results, underlined = does not pass the naive test).

	DAP	DAP Naïve	DAP^{fund}	IDP	IDP Naïve	$IDP1^{fund}$	$IDP2^{fund}$
Min.	−221.99	−221.99	6.79	−270.11	−270.11	6.79	−10.00
Max.	210.00	210.00	93.78	272.95	272.95	111.07	242.36
Mean.	40.19	41.25	41.55	41.01	41.97	42.37	41.24
SD	17.77	17.26	13.43	19.18	18.87	14.79	18.15
ME		1.06	1.35		0.96	1.36	0.22
MAE		8.21	6.28		10.84	7.26	6.37
RMSE		12.96	10.47		15.84	11.01	9.70
R^2		0.4680	0.6532		0.3183	0.6628	0.7442

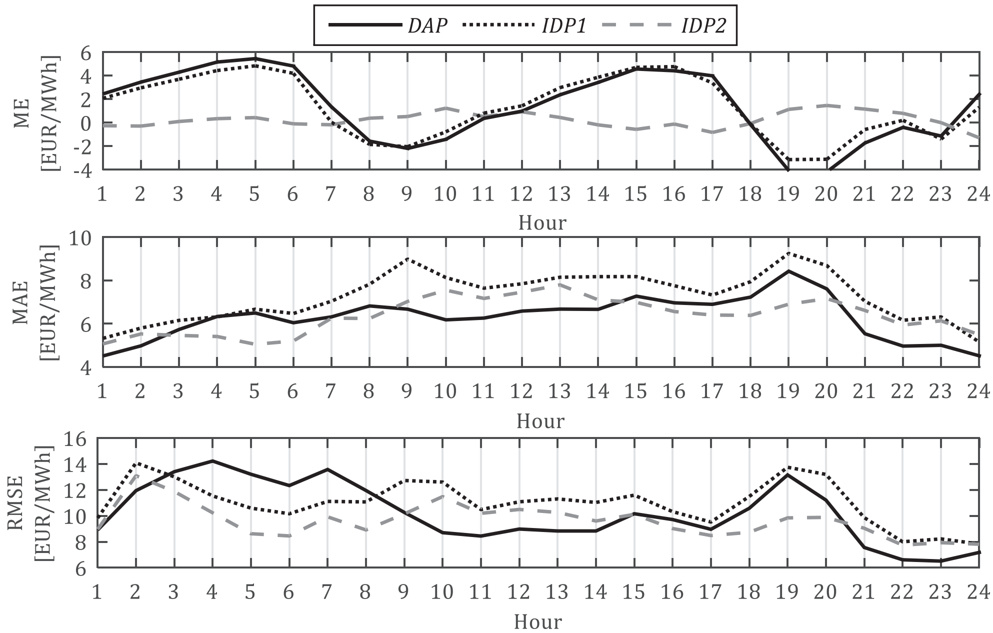

Fig. 5. ME, MAE and RMSE per hour for the three fundamental models.

3.917 (EUR/MWh)/GWh and 1.217 (EUR/MWh)/GWh lower than predicted by the fundamental model. Market participants are willing to bid at lower prices to be selected for supply. During hours where the available supply capacities are scarce and hardly exceed the demand (high LSR), intraday prices tend to be 0.973(EUR/MWh)/GWh higher, on average.[17] This indicates that, in hours with intraday supply scarcity, market participants try to increase profits by demanding higher prices than predicted by the fundamental model. In contrast, market participants in the day-ahead market are, on average, unable to obtain higher prices when supply is scarce, probably due to stronger competition and regulatory oversight.

Third, the empirical results underline that traders use the present or past price information to forecast future prices and adjust their trading strategy accordingly. The autoregressive variables included in the regression models have a positive and significant influence. The regression coefficient of the AR(1) variable in the intraday regression model is larger than the regression coefficient of the AR(24) variable in the day-ahead model. The autocorrelation of unobserved fundamental influences may be stronger between two subsequent hours than between the same hour of two different days.

Obviously, the simple fundamental modeling approach used here shows some simplifications compared to the reality, which can explain the remaining unexplained variance in the regression models. The fundamental model is consistent with the one shot auction used in day-ahead markets but may fail to capture the full dynamics of trading decisions in the continuous intraday market. In particular, the fundamental model approach implicitly assumes that forecasts errors are aggregated per hour and traded once. Under consideration of portfolio internal matching of intraday position (Hagemann, 2015) and liquidity costs (e.g., price impact costs), market participants may prefer to trade nothing in the intraday market or do so in several steps with only partial quantities (Henriot, 2014).[18] All analyses are limited by imperfect data availability. For example, it remains unclear to what extent wind, solar and load forecast errors are actually balanced within the producers' portfolios or not identified at all e.g., because of poor forecasting performances and thus not traded in the intraday market.

5. Conclusion and outlook

The paper provides the first detailed empirical evidence on the explanatory power of supply stack models for the German intraday market. A simple fundamental model with carefully selected input data and appropriate calibration is found to explain approximately 75% of the observed intraday price variance. The fundamental models yield significantly better price estimates when market peculiarities such as must-run obligations are considered, e.g., due to CHP constraints or intraday market peculiarities such as shorter lead times of power plants. Furthermore, the results indicate that it is beneficial to use the day-ahead price information to improve the intraday forecasts.

Remaining differences between the prices predicted by the fundamental model and observed prices may be explained to some extent by (avoided) startup-costs, market states and trading behavior. Startup-costs of conventional power plants cause day-ahead and intraday prices to rise above the prices predicted by the fundamental model. On the contrary, must-run obligations and power plant inflexibilities set an incentive for power plant owners to keep power plants in operation in the intraday market, which may lead to sales below the short run marginal costs, thus decreasing intraday prices. In the day-ahead market, avoided start-up costs are already appropriately considered in the fundamental model via must-run restrictions. Furthermore, market states have significant price impacts. In times of

[17] The LSR-variable is significant only if it is separated in extreme low and high scenarios and if outliers are not excluded from the time series. The applied outlier treatment follows the recommendation by Janczura et al. (2013) to replace all values that deviate more than three times the standard deviation from the mean by the mean plus/minus three times the standard deviation.

[18] Another weakness of the fundamental model is its implicit assumption that all power plants are perfectly flexible. Consequently, the model assumes that power plant owners will immediately ramp their power plants down as soon as prices fall below their marginal costs. Due to the inflexibilities of base load plants and must-run restrictions, this assumption is quite strong.

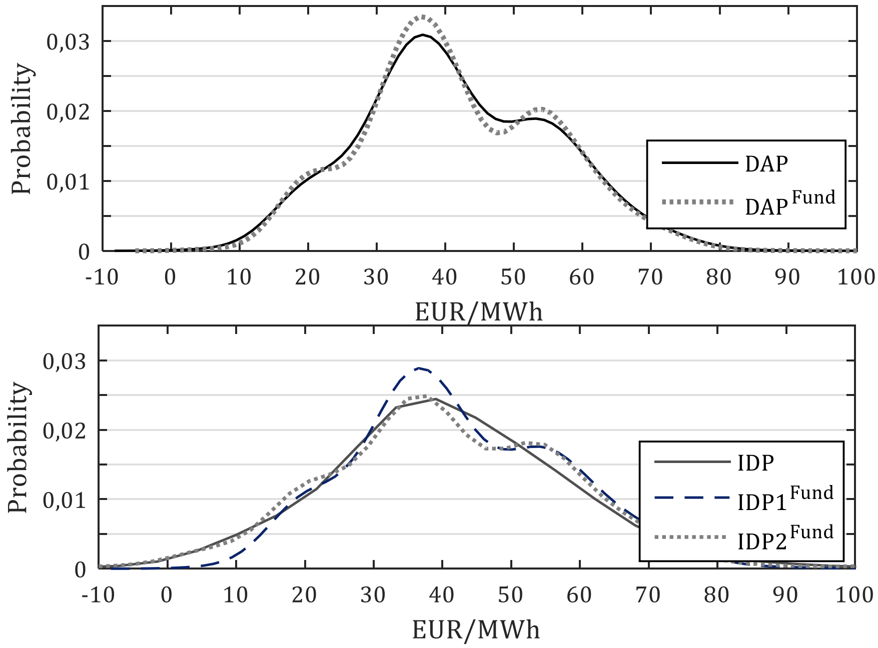

Fig. 6. Probability density function of actual and fundamental prices.

excess supply, power plant owners are willing to bid at prices below their marginal costs to be appointed for delivery. On the contrary, capacity scarcity leads to significant price increases but only in intraday prices. Moreover, the results indicate that traders use past price information to predict prices in the day-ahead and intraday markets and to trade accordingly.

Further research may focus on improving the intraday price model. The results of the present fundamental models already show that the consideration of power plant inflexibilities and must run-restrictions via a shortened offer stack improve the model fit. Advanced approaches to cope with inflexibilities may further improve the modeling of intraday market prices, e.g., varying the extent to which the intraday supply stack is shortened in each hour of the day. Another topic for further research is the analysis of the interdependencies between interconnected national intraday markets.

Table 5
Overall results of the multiple linear regression models.

	Day-Ahead	Intraday
R-squared	0.7175	0.9082
Adjusted R-squared	0.7174	0.9082
F-statistic	7412.78	28,910.81
Probability (F-statistic)	0	0
Mean dependent variable	40.22	41.01
S.D. dependent variable	17.76	19.18
Durbin-Watson statistic	0.36	1.54
Observations	17,520	17,543

Table 6
Regression coefficients of the multiple linear regression models.

	Day-Ahead	Intraday
Intercept	−2.314	1.602***
$Price^{fund}$	0.778***	0.249***
$Ramp^{Up}$	0.408***	0.676***
$Ramp^{Down}$	−0.035	−0.295***
LSR^{Low}	−3.971***	−1.217***
LSR^{High}	0.655	0.973***
DAP_{t-24}	0.251***	-
IDP_{t-1}	-	0.693***

Appendix A

Table 7
Hausman test results with instrument variables for the intraday regression models.

	Difference in J-stats	df	Probability
French day-ahead price as instrument for the fundamental intraday price	0.44844	1	0.5031
Intraday sell volume as instrument for avoided startup costs	0.070625	1	0.7904
Intraday buy volume as instrument for startup costs	1.641774	1	0.2001
Negative minute reserve volumes as instrument for low load supply ratios	4.720179	1	0.0298
Positive minute reserve volumes as instrument for high load supply ratios	25.96517	1	0
Electricity load of the same hour of the previous day as instrument for IDP(−1)	0.12526	1	0.7234

Table 8
Hausman test results with instrument variables for the day-ahead regression models.

	Difference in J-stats	df	Probability
Price for negative reserve power as instrument for fundamental day-ahead price	0.454279	1	0.5003
Intraday sell volumes as instrument for avoided startup costs	24.07709	1	0
Intraday buy volume of the previous hour as instrument for startup costs	8.35159	1	0.0039
Price for negative reserve power of the previous hour as instrument for low load supply ratios	0.906194	1	0.3411
Price for positive reserve power as instrument for high load supply ratios	437.6176	1	0
Load of the same hour of the previous day as instrument for DAP(−24)	222.3514	1	0

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