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AUTHORS

Andreas Knaut

Martin Paschmann

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Institute of Energy Economics at the University of Cologne (EWI)
www.ewi.uni-koeln.de

Institute of Energy Economics
at the University of Cologne (EWI)

Alte Wagenfabrik
Vogelsanger Str. 321a
50827 Köln
Germany

Tel.: +49 (0)221 277 29-100
Fax: +49 (0)221 277 29-400
www.ewi.uni-koeln.de

CORRESPONDING AUTHOR

Martin Paschmann
Institute of Energy Economics at the University of Cologne (EWI)
martin.paschmann@ewi.uni-koeln.de

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Andreas Knaut[a], Martin Paschmann[a]

[a] *Institute of Energy Economics, University of Cologne, Vogelsanger Strasse 321a, 50827 Cologne, Germany.*

Abstract

Analyzing commodity market dynamics, we observe that price volatility increases with reduced contract duration. In this paper, we derive a theoretical model depicting the price formation in two markets with altering product granularity. Supplemented by empirical evidence from German electricity markets for hourly and quarter-hourly products, we find that the high price volatility is triggered by restricted participation of suppliers in the market for quarter-hourly products as well as by sub-hourly variations of renewable supply and demand. Welfare implications reveal efficiency losses of EUR 96 million in 2015 that may be reduced if markets are coupled.

Keywords: commodity markets, price volatility, sequential market organization, short-term market dynamics, electricity market interaction, short-term price formation

JEL classification: C13, C51, D44, D47, L94, Q21, Q41

1. Introduction

Prices in commodity markets mostly reveal high price volatility, especially when contracts are settled close to physical delivery. This is particularly applicable to energy commodities such as oil, gas or electricity (Regnier, 2006). Moreover, electricity markets have additional characteristics that favor high price volatility. First, demand and supply have to be balanced at each point in time. Second, there is only limited potential to store large quantities of energy, especially in the short run. The increasing intermittent electricity generation from renewable energies, which are prone to forecast uncertainty and highly fluctuating feed-in profiles, has

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Email addresses: `andreas.knaut@ewi.uni-koeln.de, +49 221 277 29 306` (Andreas Knaut), `martin.paschmann@ewi.uni-koeln.de, +49 221 277 29 300` (Martin Paschmann)

increased the need of short-term trading opportunities. This has lead to an establishment of new trading opportunities on the exchange where market participants are granted the option to trade products with shorter contract duration close to the point of physical delivery. In these markets, electricity is traded first with hourly and afterwards with quarter-hourly contract duration. Price variations between the respective products can be huge. Figure 1 illustrates the price volatility observed in first, the German day-ahead auction for hourly products and second, the intraday auction for quarter-hourly contracts on an exemplary day[1]. As both auctions are cleared in rapid succession, 12:00 day-ahead and 15:00 intraday, one day before physical delivery, the information of participants is almost identical. Nevertheless, Figure 1 seems puzzling as we observe an apparently systematic price pattern. Prices for quarter-hourly products fluctuate around the previously settled prices in the day-ahead auction and are much more volatile. In this paper, we derive a fundamental explanatory approach in order to model the price relations observed.

Since price signals in short-term electricity markets may reflect an additional need for electricity market flexibility or indicate an inefficient market design, it is important to gain a deeper understanding of the underlying drivers. In this paper, we therefore develop a theoretical framework to model the price formation in the day-ahead and intraday auction and empirically validate it for the German market.

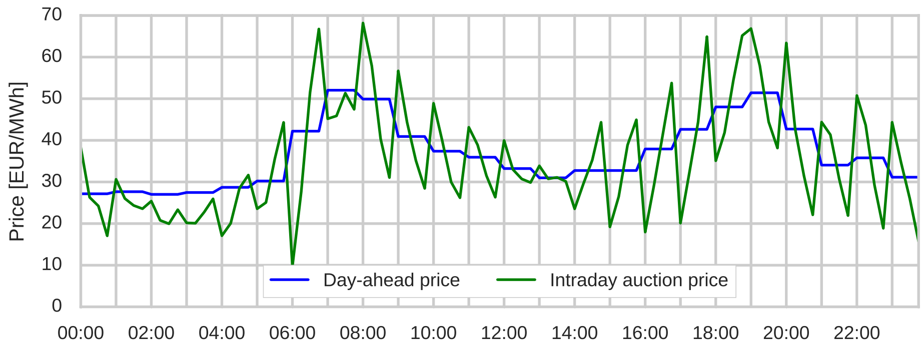

Figure 1: Exemplary price time series of German short-term electricity markets

Research into sequential market design and price volatility has a long history. In general, the paper at hand builds on the literature in the field of sequence economies. More precisely, the literature has emphasized the importance of sequential market organization in order to allocate commodities efficiently. A large and growing body of literature has investigated the interaction of sequential markets such as Green (1973) and Veit et al. (2006). Pindyck (2001) analyzes the short-term dynamics of commodity markets as well as prices

[1]This is the 13th of March 2015.

and Pindyck (2004) depicts the impact of volatility on commodity prices. Closely related, Kawai (1983) derives a model in order to explain the impact of future trading on spot market dynamics. Electricity markets represent a special subset of commodity markets and previous research into sequential electricity markets has focused on short-term trading opportunities on the exchange. Against this backdrop, von Roon and Wagner (2009) as well as Borggrefe and Neuhoff (2011) outline the importance of functioning short-term markets in order to deal with the increasing share of renewable energies in the German power supply system and the corresponding forecast uncertainty. Ito and Reguant (2016) and Knaut and Obermüller (2016) focus on strategic behavior in sequential short-term electricity markets. Their main findings are that, under restricted market entry and imperfect competition, a systematic price premium analogous to Bernhardt and Scoones (1994) may occur in the first market stage. Additionally, there is a vast body of literature investigating the price formation in short-term electricity markets based on forecasting techniques such as time series analysis or artificial neural networks (Karakatsani and Bunn (2008),Hagemann (2013),Weron (2014), Kiesel and Paraschiv (2015)).

We analyze the price formation in sequential short-term electricity markets based on a fundamental approach. To the best of our knowledge there is no prior literature with focus on the fundamental interaction of sequential markets with differing product granularities. It has to be stressed that we neglect the influence of uncertainty due to rapid succession of both investigated markets. Rather to the contrary, we derive a theoretical model illustrating that the high volatility of quarter-hourly intraday prices is mainly driven by two aspects. First, the main purpose of trading in the intraday auction is to balance sub-hourly variations of demand and renewable generation. Second, we find an average increase of the quarter-hourly gradient of the supply curve compared to the day-ahead auction due to restricted participation in the intraday auction. We apply an empirical analysis of historical price data and validate our theoretical considerations. Furthermore, we quantify the increase of the supply curve gradients. Based on the respective estimates, we relate restricted participation in the intraday auction to welfare losses of about EUR 96 million in 2015. Since the increasing share of renewable electricity generation which goes hand in hand with further need of trading 15-minute contracts may not be accompanied by sufficient additional German electricity market flexibility, counter-measures addressing restricted market participation in the intraday auction such as market coupling should be urged.

The paper is structured as follows. First, we briefly depict the price formation in the markets of interest (Section 2). We then address our main research questions by conducting empirical analyses that are outlined in Section 3. We use historical price data for the intraday auction in Germany. Finally, conclusions are drawn in Section 4.

2. Price Formation in the Day-Ahead and Intraday Auction

Electricity is traded sequentially at various points in time. Trading opportunities increase closer to the time of physical delivery and the contract duration for different products decreases. Figure 2 depicts the time line of trading for the German wholesale electricity market. Trading on the exchange starts with futures that are traded for yearly, quarterly, monthly or weekly time intervals. These markets are mainly used for risk hedging purposes and financial trading. In contrast, in the day-ahead auction physical electricity is traded at hourly time intervals. The respective auction is held at noon (12:00), one day before physical delivery. Historically, the day-ahead price has been the most important reference price for all electricity market participants. At the end of 2014, the intraday auction has been implemented which is settled at 3pm and first allows for trading 15-minute contracts. As a consequence, market participants are now able to balance sub-hourly variations of supply and demand. Subsequently, trading is organized in a continuous intraday market, where trade takes place on a first-come-first-serve basis via an open order book. Gate closure is 30 minutes before physical delivery and the respective products include hourly as well as 15-minute contracts. The continuous intraday market is mainly used to balance forecast errors based on updated information until delivery. The end of the intraday trading period marks the end of electricity trading in the wholesale market.

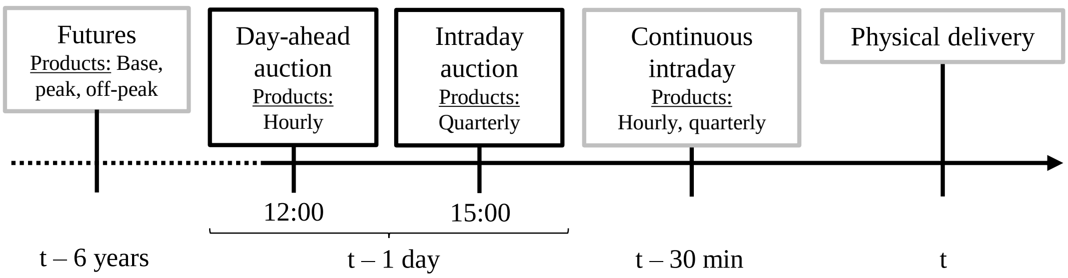

Figure 2: Sequence of trading in wholesale markets

In this paper, we focus on the interaction of the day-ahead and intraday auction. Both markets are settled in rapid succession and differ in terms of product granularity (hourly/quarter-hourly). Since the intraday auction is settled three hours after the day-ahead auction, we consider new information to be negligible between both market stages. Based on additional empirical evidence, we abstract from the impact of forecast errors that are expected to rather influence continuous intraday trade. In contrast, we find that the relation of prices in both markets under consideration is mainly driven by restricted participation in the intraday auction. This may especially be the case since participation in the intraday auction is restricted to a national level and cross-border trade is not possible. Markets with quarter-hourly contracts are not coupled within the internal European electricity market in contrast to the hourly day-ahead auction. Additional reasons for restricted participation in the intraday auction may also be a lack of short-term flexibility regarding different types of conventional power plants, additional costs of market entry, and a slow adjustment of market participants to newly emerging trading opportunities. Our explanatory approach that aims at modeling the price formation in the intraday auction is consequently based on restricted participation as the main driver of the price relations under consideration.

2.1. Theoretical Model

We use a stylized theoretical model in order to depict the market interaction as well as the price formation in the day-ahead and intraday auction. In general, we consider two types of suppliers (restricted and unrestricted) which interact in two markets (day-ahead and intraday auction) that differ in terms of product granularity and participation. Both types of suppliers participate in the market for hourly products, which can be regarded as the day-ahead auction. In the second market (intraday auction) products are traded with shorter contract duration and only unrestricted suppliers are able to participate. More precisely, the common product that can be supplied by both types of suppliers is further split into n different sub-products in the intraday auction which are identified by $\tau \in 1, 2, ...n$.

Consumers demand a varying quantity D_τ in each time interval τ. The demand is satisfied under perfect competition by both restricted and unrestricted suppliers. Both suppliers operate generation plants with increasing marginal costs of generation. The unrestricted suppliers offer the quantity q^u_τ reflecting the production level in τ that results from supply in both markets. The respective total costs are $C_u(q^u_\tau)$. In contrast, the restricted players are not able to participate in the sub-hourly market and do not vary their production level along the time intervals τ. Thus, the respective supply is kept constant at a level of q^r over n time intervals. The total costs for the restricted players in time interval τ amount to $C_r(q^r)$. Due to rapid succession of both market settlements, we assume information in both markets to be identical. As the quantities of both types of suppliers are chosen under perfect competition, we formulate the following optimization problem minimizing the total costs of electricity generation such that supply meets demand.

$$\min z = \sum_\tau [C_u(q^u_\tau) + C_r(q^r)] \tag{1}$$

$$\text{s.t.} \qquad D_\tau = q^u_\tau + q^r \qquad \forall t. \tag{2}$$

In order to derive an optimal solution, we transform the problem into its Lagrangian representation by introducing the shadow prices p_τ:

$$\mathbb{L} = \sum_t \left[C_u(q_\tau^u) + C_r(q^r) + p_\tau(D_\tau - q_\tau^u - q^r) \right]. \tag{3}$$

Applying the Karush-Kuhn-Tucker conditions, we derive the necessary conditions that characterize the cost minimal solution. We get the optimal quantities q_τ^u and q^r as well as the respective shadow prices p_τ.

$$\frac{\partial \mathbb{L}}{\partial q^r} = \sum_\tau \left[C_r'(q^r) - p_\tau^* \right] = 0 \qquad \rightarrow C_r'(q^r) = \frac{\sum_\tau p_\tau^*}{n} \tag{4}$$

$$\frac{\partial \mathbb{L}}{\partial q_\tau^u} = C_u'(q_\tau^u) - p_\tau^* = 0 \qquad \rightarrow p_\tau^* = C_u'(q_\tau^u). \tag{5}$$

Due to illustration purposes, we apply the general model to a framework assuming linear marginal cost functions of both restricted and unrestricted suppliers. However, the following considerations could analogically be applied to different types of supply functions. Exemplary linear marginal cost functions are displayed in Figure 3. We formulate the respective marginal cost functions for both suppliers as

$$\text{Restricted suppliers:} \qquad C_r'(q^r) = a_0 + a_1^r q^r \tag{6}$$

$$\text{Unrestricted suppliers:} \qquad C_u'(q_\tau^u) = a_0 + a_1^u q_\tau^u, \tag{7}$$

where a_0 is the offset, a_1^r is the gradient of the restricted supply curve and a_1^u is the gradient of the unrestricted supply curve.[2] Adding both functions horizontally we attain the aggregate supply function as

$$C'(q) = a_0 + \frac{a_1^r a_1^u}{a_1^r + a_1^u} q = a_0 + a_1 q, \tag{8}$$

with $a_1 = \frac{a_1^r a_1^u}{a_1^r + a_1^u}$ being the gradient of the aggregate supply function. We now solve the linear model with respect to optimal quantities and prices.

Proposition 1. *The average price over all periods ($\overline{p}$) is determined by the intersection of the aggregate supply function (including restricted as well as unrestricted suppliers) and the average demand ($\overline{D}$)*

$$\overline{p} = a_0 + a_1 \overline{D}. \tag{9}$$

Proof. Making use of the linear marginal cost functions, we can plug in (5) and (2) into (4). As a result, we get

$$a_0 + a_1^r q^{r*} = \frac{1}{n} \sum_\tau a_0 + a_1^u (D_\tau - q^{r*}). \tag{10}$$

Defining the average demand over n periods as $\overline{D} = \frac{\sum_\tau D_\tau}{n}$ and solving for q^{r*}, we obtain the quantity

[2] We assume the offset (a_0) of both marginal cost functions to be identical. This implies that the first marginal production units of restricted and unrestricted suppliers are identical in terms of costs. In electricity markets this may for example be nuclear power plants.

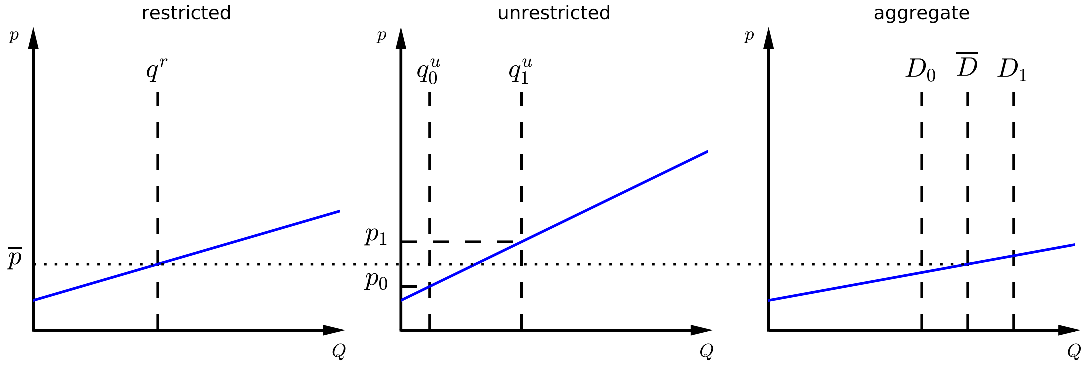

Figure 3: Marginal cost functions of restricted and unrestricted suppliers and the resulting aggregate marginal cost function

that is produced by the restricted suppliers as

$$q^{r*} = \frac{\overline{D} a_1^u}{a_1^r + a_1^u}. \tag{11}$$

Furthermore, based on (4), the average price $\overline{p} = \frac{\sum_\tau p_\tau}{n}$ is determined by the marginal generation costs of the restricted suppliers. By plugging in the result for q^{r*}, we obtain the average price as the previously calculated aggregate marginal cost function for the average demand $(\overline{D})$ in (9). □

The average price $\overline{p}$ may be regarded as the settlement price in the first market where both types of suppliers are able to participate. In a next step, we derive the prices for each time period τ that are settled in the second market where only unrestricted suppliers are participating.

Proposition 2. *The price in each time period τ depends on the difference between the average demand and the demand in each time period τ (D_τ) as well as the gradient of the unrestricted supply curve.*

$$p_\tau^* = a_0 + a_1 \overline{D} + (D_\tau - \overline{D}) a_1^u = \overline{p} + (D_\tau - \overline{D}) a_1^u \tag{12}$$

Proof. Based on the previously derived quantity q_r from (11) and (2) in (5), we obtain

$$p_\tau^* = a_0 - \frac{(a_1^u)^2}{a_1^r + a_1^u} \overline{D} + a_1^u D_\tau. \tag{13}$$

Here the first term is the offset of the aggregate supply function (a_0). Furthermore, we make use of the following equation

$$\frac{(a_1^u)^2}{a_1^r + a_1^u} = a_1^u - \frac{a_1^u a_1^r}{a_1^r + a_1^u} = a_1^u - a_1 \tag{14}$$

and introduce the gradient of the aggregate supply function (a_1). By inserting the term into (13) and reformulating, we obtain (12).

□

The optimal prices and quantities relate to the second-best outcome, given that restricted suppliers are not able to change their production level at a temporal resolution τ. If the restricted suppliers were able to adjust their production level, efficiency would be increased.

Proposition 3. *The welfare loss due to restricted participation is given by*

$$\Delta W_\tau = W_\tau^{eff} - W_\tau^{ineff} = \frac{1}{2}(a_1^u - a_1)(\overline{D} - D_\tau)^2 \geq 0. \tag{15}$$

Proof. Since we assume a perfectly inelastic demand, we derive welfare implications based on cost considerations. Assuming restricted participation of some suppliers, the total costs to satisfy demand in period t amount to

$$\begin{aligned} C^{ineff}(D_\tau) &= C_u(q_\tau^u) + C_r(q^r) \\ &= a_0(D_\tau - q^{r*}) + \frac{(a_1^u)^2}{2}(D_\tau - q^{r*})^2 + a_0 q^{r*} + \frac{(a_1^r)^2}{2}(q^{r*})^2. \end{aligned} \tag{16}$$

The efficient outcome could be achieved if both suppliers were able to adjust their production level in each time period τ without restrictions. As a result, this would lead to costs that are determined by plugging in D_τ into the aggregate supply function (8).

$$C^{eff}(D_\tau) = a_0 + \frac{a_1^r a_1^u}{a_1^r + a_1^u} D_\tau. \tag{17}$$

Analyzing the difference between costs in the efficient and inefficient cases and inserting the result from (11), we get the total deadweight loss defined as

$$\begin{aligned} \Delta W_\tau &= C^{ineff}(D_\tau) - C^{eff}(D_\tau) \\ &= \frac{1}{2a_1^r + 2a_1^u}\left(\overline{D}^2 (a_1^u)^2 - 2\overline{D}(a_1^u)^2 D_\tau + (a_1^u)^2 D_\tau^2\right). \end{aligned} \tag{18}$$

By rewriting and simplifying we finally obtain (15). □

Welfare losses from restricted participation essentially depend on first the difference between the gradient of the supply curve of unrestricted suppliers and the aggregate supply function($a_1^u - a_1$), and second the volatility of demand ($\overline{D} - D_\tau$). We thus identify two major drivers of welfare losses and derive the following relations. First, if fewer suppliers are participating in both markets, this will increase the gradient a_1^u and lead to an increase in welfare losses. Second, the higher the volatility of demand in time periods τ, the higher the overall welfare losses.

The consumers that determine the inelastic demand and suppliers are affected in different ways.

Proposition 4. *Compared to the case of unrestricted participation, restricted participation leads to losses in consumer surplus and producer surplus of restricted suppliers. Producer surplus of unrestricted suppliers increases.*

Proof. See Appendix.1. □

In the Appendix we derive that consumer surplus is significantly reduced compared to the efficient outcome. The respective consumer losses are twice as high as the total welfare losses ($2\Delta W = 2\sum_{\tau=1}^{n} \Delta W_\tau$). On the opposite side, suppliers altogether profit from the inefficiency. Taking a closer look at the distributional effects between restricted and unrestricted suppliers, we infer that only unrestricted suppliers face a higher surplus if market participation is restricted. The surplus of restricted suppliers is lower compared to the efficient case.

2.2. Application to Intraday Auction Prices

Applying the previous model to real-world electricity market dynamics, we are able to depict the fundamental causal relations that drive the price relations between the German day-ahead and intraday auction. Therefore, it is first necessary to comment on some basic assumptions made in the stylized theoretical framework.

In the context of electricity market analyses, the demand side is most commonly modeled using the term residual demand. We follow this approach and define the residual demand as total demand minus the electricity generation from wind and solar power $D_t^{res} = D_t - Wind_t - Solar_t$. Renewable energies are characterized by short-term marginal costs close to zero and the respective electricity generation corresponds to the availability of wind and solar power at each point in time. Trade in electricity markets is performed by balancing responsible parties which are responsible to balance supply and demand within their balancing group. Since balancing group operators have the incentive to be balanced in each time interval to avoid penalties, the residual demand is expected to drive the level of trade volumes in electricity spot markets. Furthermore, in the existing literature evidence is given that demand in electricity markets can be assumed to be rather price inelastic, especially in the short-run (Lijesen, 2007; Knaut and Paulus, 2016). Within our model, we thus do not consider any price elasticity of demand.

The residual demand is supplied by conventional generation units with increasing marginal costs depending on the underlying energy carrier. In our model we assume the marginal costs functions to be linear. As far as the day-ahead auction is concerned, we clearly observe a rather linear relation of residual demand and the respective prices in historical data (for more details see Section Appendix.2). In contrast, the structure of the intraday auction supply curve may vary in individual hours since the underlying market dynamics are crucially depending on the day-ahead market clearing point. However, within the scope of this paper, we use an aggregate explanatory approach that focuses on general price relations. We find empirical evidence that these relations can be adequately mapped based on the assumption of linear relations. Further details are given in the empirical part of this paper.

In general, the assumption of perfect competition seems approximately appropriate for the German day-ahead and intraday markets [3].

[3]See the findings of the Monitoring Report by the German regulator (Bundesnetzagentur and Bundeskartellamt, 2015).

We additionally assume a simultaneous decision of restricted and unrestricted suppliers regarding their production quantities. In reality, however, the settlement of the day-ahead and intraday auction is determined in sequential order and the unrestricted suppliers reflect the subset of all suppliers that are able to participate in both markets. Based on a continuous interaction of all market participants, we assume an absence of arbitrage opportunities between both markets following general economic theory (see, e.g., Harrison and Kreps (1979) and Delbaen and Schachermayer (1994)). More precisely, sequential markets should exhibit identical average price levels under the following conditions (Mercadal, 2015):

- First, prices should be transparent, unambiguous and accessible to each market participant.
- Second, prices should refer to identical products and the respective products should be perfect substitutes. More precisely, they should be valid for electricity supply at the same point in time.
- Third, prices should be based on the same and latest available information.

The three conditions are crucial in order to expect mean price equivalence between the day-ahead and intraday auction. Going into detail, trade in both auctions is processed on the exchange and information transparency is given at each point in time. Sequential settlement goes hand in hand with day-ahead prices being reference prices for bids in the subsequent intraday auction. Furthermore, there is no discrimination of individual players. As a consequence, we claim that the first condition is met. Second, intraday auction products combined represent perfect substitutes for day-ahead contracts. Additionally, contracts in both auctions refer to the physical delivery of electricity. As a consequence, the second condition is valid as well. Finally, the day-ahead and intraday auction are settled in rapid succession. Forecast errors that appear until delivery are rather balanced within continuous intraday trade that starts after the intraday auction gate closure. We have tested and validated these assumptions empirically. To sum up, we suggest that the three conditions as listed above are valid regarding day-ahead and intraday auction market dynamics. In fact, a descriptive analysis of historical price data reveals that the average day-ahead and intraday auction prices equal within our period of observations (see Section 3.1). Based on the previous considerations, we equate the hourly average price in Equation (12) and the hourly day-ahead auction price.

2.3. Illustrative Insights Derived From the Theoretical Model

Based on our theoretical model, we gain insights into the price relations in markets with low and high product granularity with restricted participation. For the case of the day-ahead and intraday auction this means that hourly products are further divided into quarter-hourly products ($\tau \in 1, 2, 3, 4$). We illustrate the respective implications for an exemplary hour in Figure 4 and describe the price formation in more detail. The day-ahead supply curve reflects the aggregate marginal cost function ($C'(q)$) since market participation is considered to be unrestricted. In contrast, the gradient of the intraday auction supply curve equals the gradient of the supply curve of unrestricted producers (a_1^u). As we model intraday auction prices as deviations from the respective day-ahead prices, we can project this gradient into the day-ahead market clearing point according to Equation (12). Differences between the quarter-hourly and hourly mean of the residual demand ($(D_\tau - \overline{D})$) are now transferred into movements along the 15-minute supply curve and result in quarter-hourly intraday auction prices.

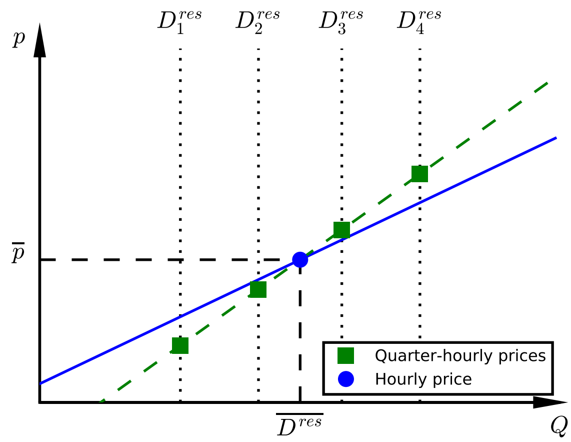

Figure 4: Supply and demand in the hourly and quarter-hourly market

When we transfer these relations to subsequent hours as depicted in Figure 5, one can observe a distinct pattern of prices. Prices for quarter-hourly products fluctuate around the respective prices for hourly contracts as illustrated by the green price time series. If the participation in the intraday auction would not be restricted, gradients of the supply curve would be equal in both markets and prices would follow the curve of the fictitious quarter-hourly residual demand level as marked in blue.

Based on Figure 5, we observe three typical price movements. First, for an increasing residual demand, prices in the first quarter-hour are significantly lower compared to the respective ones in the last quarter-hourly time interval of the hour. Second, with a decreasing demand, the opposite is the case. Third, a flat demand profile leads to a low price variation.

So far, the model suggests that the high price volatility in sequential electricity markets is mainly driven by two aspects. First, quarter-hourly prices are driven by quarter-hourly deviations of the residual demand from the respective hourly means. Second, the high volatility of prices stems from restricted participation of some suppliers which results in an inclination of the supply curve from the first (hourly) to the second

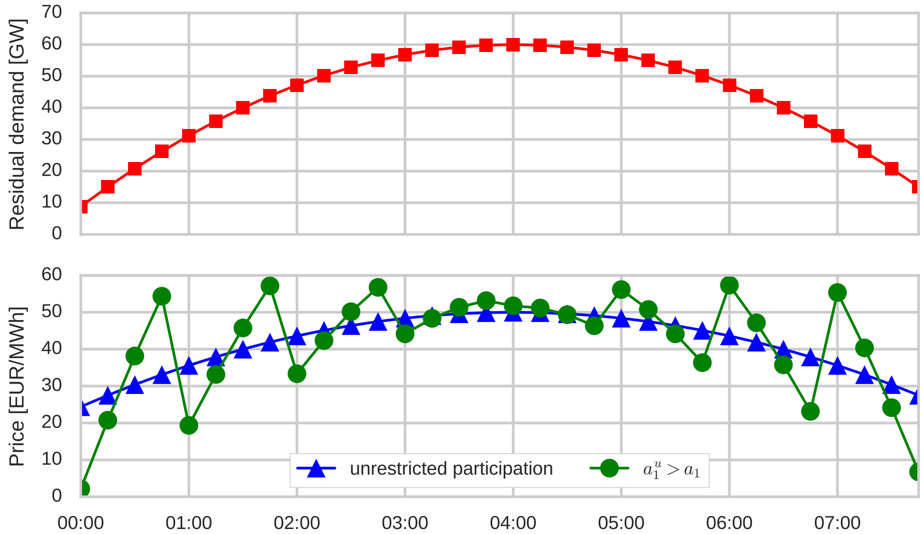

Figure 5: Exemplary profile of a residual demand and the resulting pattern for quarter-hourly product prices

market stage (quarter-hourly) ($a_1^u > a_1$).

3. Empirical Analysis

By analyzing the time period from January 2015 to the end of February 2016, we are able to test the applicability of our theoretical model with respect to historical data. Furthermore, we intend to quantify the inclination of the supply curve between the day-ahead and intraday auction and gain insights on welfare implications. We first give a short overview over the historical data used, then describe our estimation approach and ,finally, we depict and evaluate our empirical results.

3.1. Data

This section gives an overview on relevant data included in the empirical estimation and the respective references. Due to the recent implementation of the intraday auction on 9 December 2014, the analysis includes data from January 2015 until the end of February 2016.

A detailed list of all variables that are used in the empirical analyses in the following sections is presented in Table 1. The table includes a brief explanation for each variable and the symbols that we use in order to depict our empirical models and the respective estimation equations. Additionally, Table 2 provides information on the most relevant descriptive statistics.

Price data for German electricity markets can be obtained from the European Power Exchange (EPEX, 2016). Trades in the day-ahead and intraday auction take place one day before physical delivery and are

Symbol	Label	Variable	Measure	Reference
p_t^{ida}	id auction price	Uniform settlement price for a 15-minute product in the German intraday auction	EUR/MWh	EPEX (2016)
p_t^{da}	day-ahead price	Hourly German day-ahead auction price	EUR/MWh	EPEX (2016)
D_t^{res}; $\overline{D^{res}}_t$	residual demand 15 residual demand 60	Day-ahead forecast for the residual demand in a 15-minute period and the respective hourly mean (ex-ante value)	GW	EEX (2016) , ENTSO-E (2016)
ΔD_t^{res}	residual demand deviation	Difference of the 15-minute residual demand and the respective hourly mean	GW	EEX (2016) , ENTSO-E (2016)
$Solar_t$; $\overline{Solar}_t$	solar power 15 solar power 60	Day-ahead forecast for the 15-minute solar power and the respective hourly mean (ex-ante value)	GW	EEX (2016)
$\Delta Solar_t$	solar power deviation	Difference of the 15-minute solar power and the respective hourly mean	GW	EEX (2016)
$Wind_t$; $\overline{Wind}_t$	wind power 15 wind power 60	Day-ahead forecast for the 15-minute wind power and the respective hourly mean (ex-ante value)	GW	EEX (2016)
$\Delta Wind_t$	wind power deviation	Difference of the 15-minute wind power and the respective hourly mean	GW	EEX (2016)
D_t; $\overline{D}_t$	load 15; load 60	Day-ahead forecast for the 15-minute load and the respective hourly mean (ex-ante value)	GW	ENTSO-E (2016)
ΔD_t	load deviation	Difference of the 15-minute load and the respective hourly mean	GW	ENTSO-E (2016)

Table 1: List of variables and references

based on expectations for the level of demand and generation from wind and solar power. Forecasts for renewable generation are provided by the four German transmission system operators (TSOs) who are in charge of the reliable operation of the power system. We make use of the day-ahead forecasts for wind and solar power based electricity generation published on the transparency platform of the European Energy Exchange (EEX, 2016).

Variable	N[4]	Mean	Std.Dev.	Min	25%	Median	75%	Max
id auction price	38,640	30.9	14.8	-164.5	21.7	30.5	40.1	464.4
day-ahead price	38,640	30.9	12.8	-80.0	23.9	29.9	38.8	99.8
residual demand 15	38,640	41.7	11.0	6.3	34.2	41.6	49.6	70.6
residual demand 60	38,640	41.7	11.0	6.3	34.2	41.6	49.6	70.6
residual demand deviation	38.6	0.0	0.9	-9.1	-0.4	0.0	0.4	9.5
solar power 15	38,640	3.6	5.8	0.0	0.0	0.1	5.4	25.8
solar power deviation	38,640	0.0	0.5	-6.0	0.0	0.0	0.0	4.5
wind power 15	38,640	9.6	7.6	0.2	3.7	7.4	13.9	33.6
wind power deviation	38,640	0.0	0.2	-1.6	-0.1	0.0	0.0	4.5
load 15	38,640	55.0	9.9	31.7	46.7	54.5	64.1	76.2
load deviation	38,640	0.0	0.8	-8.3	-0.4	0.0	0.4	9.5

Table 2: Descriptive Statistics

In addition to forecasts on the renewable energy feed-in, the four TSOs generate and publish load forecasts. Load is commonly considered as the best proxy for electricity demand and is therefore used within the framework of our empirical analysis.[5] We use load data that is published on the transparency platform of the European Network of Transmission System Operators for Electricity (ENTSO-E, 2016).

3.2. Empirical Estimations

We apply a multistage approach in order to analyze the validity of our underlying theoretical model empirically. In more detail, we are first interested in the applicability of the model with respect to historical prices observed in the intraday auction. Several robustness checks are made. Second, we set up an empirical approach that allows us to derive conclusions on the fundamental relation of the gradient of the aggregate supply curve in the day-ahead market and the supply curve of unrestricted suppliers in the subsequent intraday auction with quarter-hourly contract duration.

3.2.1. Empirical Framework

As outlined above, the econometric approach adopted within this paper aims at depicting the price formation for quarter-hourly products in the intraday auction. The general estimation procedure is formulated

[5]More information on load can be found in Schumacher and Hirth (2015)

in Equation (19):

$$p_t = X'_{i,t}\,\beta_i + \nu + \epsilon_t$$
$$\text{with } \epsilon_t \sim\ N\,(0, \sigma^2), \tag{19}$$

where p_t denotes the quarter-hourly price in period $t = 1, 2, ..., T$. $X'_{i,t}$ includes the exogenous variables of the model, namely the hourly day-ahead price as well as the quarter-hourly deviation of the residual demand from its respective hourly mean value. We consider the intercept ν being the estimated constant assuming that the underlying supply function is time-invariant. ϵ_t denotes the error term. In order to choose a suitable estimation methodology, we first test for basic assumptions that would be required if applying Ordinary Least Squares Regression techniques. These are standard assumptions such as predetermination or exogeneity of regressors and $p_t, X_{i,t}$ being ergodic and jointly stationary.

Beginning with stationarity, we apply two different statistical tests for unit roots. The respective results of an Augmented Dickey Fuller test and a Phillips-Perron test are depicted in detail in Appendix.3. The statistics clearly reject the assumption of non-stationary processes. This is especially plausible because we only include data for a limited period of observations. During these 14 months the underlying drivers of demand and supply as well as prices in the markets of interest only changed slightly. These are ,e.g., fuel prices and the share of renewable power plants. A significant time trend is not identified.

By using forecasted data, we guarantee exogeneity of the residual demand by construction. We furthermore conduct a Durbin-Wu-Hausman test in order to control for the exogeneity of the day-ahead auction price. The test results reject the assumption of exogeneity [6] and we thus use a Two-Stage Least Squares (2SLS) Regression Analysis including the hourly average of the residual demand as an instrument for the day-ahead price. The hourly residual demand is the main driver of demand in the day-ahead auction and thus is highly correlated with the respective prices ($Cov(X_{i,t}, Z_{i,t}) \neq 0$, where $Z_{i,t}$ is the instrument). This assumption is supported by the first stage regression results giving clear empirical evidence for a strong instrument. Additionally, we argue that our underlying estimation approach directly accounts for the exclusion restriction ($Cov(Z_{i,t}, \epsilon_t) = 0$). All information from the first market that can be expected to influence quarter-hourly product prices in the second market is incorporated by the inclusion of the day-ahead price. Finally, we use robust standard errors in order to account for heteroscedasticity.

3.2.2. Empirical Validation

In a first step, the aim of our empirical analysis is to validate the theoretical model as depicted in Section 2.1. Based on the model Equation (12) and according to Section 3.2, we apply Equation (20) using

[6] In more detail, the test suggests that $Cov(X'_{i,t}, \epsilon_t) \neq 0$

a Two-Stage Least Squares Regression:

$$\begin{aligned} p_t^{ida} &= \beta_1 \cdot p_t^{da} + \beta_2 \cdot (D_t^{res} - \overline{D^{res}}_t) + \nu + \epsilon_t \\ &= \beta_1 \cdot p_t^{da} + a_1^u \cdot \Delta D_t^{res} + \nu + \epsilon_t. \end{aligned} \tag{20}$$

The difference between the residual demand on a quarter-hourly and hourly level (*residual demand deviation* (ΔD_t^{res})) is included as the main explanatory variable. Besides, the day-ahead auction price for hourly products (*day-ahead price* (p_t^{da})) is used. We use forecast values for the residual demand as trading decisions in the day-ahead and intraday auction are made under uncertainty. The coefficient β_2 can be interpreted as the gradient of the unrestricted supply curve (a_1^u).

The resulting estimates are depicted in column (1) of Table 3. Additionally, we conducted further robustness checks and show the respective results in columns (2) - (3). The latter tests will be explained in more detail below.

The estimates in column (1) of Table 3 indicate that our theoretical model is applicable to actual price relations observed in the intraday and day-ahead auction. We observe an adjusted R^2 that is close to 85% and thus a large part of the variance of intraday auction prices can be explained by the model. Additionally, the t-values of the coefficients validate that the difference in prices is influenced significantly by the deviation of the residual demand on a quarter-hourly level from its hourly mean. Furthermore, the estimated coefficient with respect to the day-ahead auction price is close to one, as suggested by the model. Thus, the regression results confirm the validity of day-ahead auction prices as reference prices for intraday auction prices. If we estimate the model without an intercept, the coefficient of the day-ahead price even equals one. [7].

The estimated coefficient for *residual demand deviation* reveals a positive sign and can be interpreted as the gradient of the supply curve in the intraday auction. The positive coefficient means that a positive deviation of the residual demand leads to an increase of quarter-hourly prices compared to the respective hourly day-ahead price. This causal relation is in line with our theoretical model assumptions. The average absolute value for *residual demand deviation* amounts to 0.370 GW and can be transferred into an absolute price difference of 3.7 EUR/MWh. Thus, the causal relations that have been revealed lead to the high volatility of intraday auction prices we observe.

In a next step, we are interested in the robustness of the results. One underlying assumption of our model considers identical gradients of the supply curve for a positive as well as a negative deviation of the residual demand. More precisely, we assume a linear relation of prices and quantities in the intraday auction

[7]In more detail, the respective estimation results show a coefficient for *day-ahead price* that is 0.998 and a robust standard error of 0.0001

	Dependent variable: id auction price ($p^{ida}_{q,t}$)		
Explanatory variable	IV (1)	IV (2)	IV (3)
day-ahead price (p^{da}_t)	0.94***	0.94***	0.94***
	(0.003)	(0.003)	(0.003)
residual demand deviation (ΔD^{res}_t)	7.80***		
	(0.11)		
positive residual demand deviation		7.96***	
		(0.26)	
negative residual demand deviation		7.65***	
		(0.18)	
wind power deviation ($\Delta Wind_t$)			-9.38***
			(0.21)
solar power deviation ($\Delta Solar_t$)			-10.08***
			(0.08)
load deviation (ΔD_t)			6.0***
			(0.12)
intercept (ν)	1.99***	1.91***	2.10***
	(0.10)	(0.14)	(0.10)
observations	38,640	38,640	38,640
adj. R^2	0.84	0.84	0.85
F	46,650	33,840	30,390

Notes to Table 3: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. The term *positive residual demand deviation* in column (2) is constructed using a dummy variable that equals one if the residual demand deviation is positive. The term *negative residual demand deviation* is constructed using a dummy variable that equals one if the residual demand deviation is negative. Due to indication of endogeneity of *day-ahead price* we use *residual demand deviation 60* as instrumental variable and apply a 2SLS Regression. In general, we use data from January 2015 until the end of February 2016.

Table 3: Regression estimates for intraday auction price data

reflecting the underlying supply curves. We test this assumptions by distinguishing between positive and negative differences of the residual demand in the regression (*positive residual demand deviation* and *negative residual demand deviation*). The respective results are shown in column (2) of Table 3. The coefficients for the positive and negative residual demand deviation only exhibit slight differences. However, the overall picture strongly supports the hypothesis of a continuous linear relation between supply and prices in the intraday auction [8].

In order to gain additional insights with respect to the different drivers of the residual demand, we conduct an additional regression. The results are displayed in column (3). Here, we decompose the residual demand deviation into its three elements *wind power deviation*, *solar power deviation* and *load deviation*. The respective estimates reveal variations as has to be expected since high variations of wind and solar power as well as load do not fully coincide. For illustration purposes, electricity generation from solar power is only present in distinct hours when the sun is shining. As a consequence, when disentangling the individual drivers, we measure the average coefficient of the quarter-hourly supply curve only in a subset of hours. Based on these considerations, different coefficients for solar power, wind power and load are not surprising. On the contrary, it is rather important to evaluate whether the signs of the coefficients match the underlying causal relations. A positive deviation of the renewable energy generation implies oversupply which in turn causes lower prices in the intraday auction. In line, the respective coefficients are negative whereas the coefficient for load is positive. Looking at the value distribution of solar and wind power as well as load, it is revealed that the volatility of intraday auction prices is mainly driven by the quarter-hourly variation of load. However, very high differences in prices can also result from a high gradient of solar power generation [9]. Besides these explicitly outlined robustness tests, additional insights into seasonality, alternative hypotheses, and the methodological approach are given in Appendix.5. To sum up, we find model validity and robustness of our findings.

3.2.3. Econometric Analysis of the Supply Curve Gradients

As a further part of the empirical analysis, we conduct a comparative analysis for the gradients of the supply curve in the day-ahead and intraday auction. The theoretical model as formulated in Section 2.1 suggests that the high price volatility is triggered by restricted participation which leads to differing supply curve gradients. This section aims at giving empirical evidence supporting this hypothesis. In order to do so, the day-ahead spot market price in Equation (20) is substituted by the hourly residual demand according

[8]We also tested for deviant types of relations such as quadratic ones but found no empirical evidence for applicability.
[9]For more details see Appendix.4.

to Equation (9). The purpose is to estimate a_1 as a proxy for the gradient of the aggregate supply curve. We thus obtain Equation (21):

$$p_t^{ida} = a_1 \cdot \overline{D^{res}}_t + a_1^u \cdot \Delta D_t^{res} + \xi + \epsilon_t, \tag{21}$$

where the constant intercept of the hourly supply curve is shifted into the constant ξ and the error-term of the estimation equation. Again, we use forecast values for the construction of the hourly and quarter-hourly residual demand in order to circumvent endogeneity. Based on these considerations, we apply an Ordinary Least Squares Regression using robust standard errors. The empirical results indicate explanatory power and a significant impact of the respective explanatory variables. We observe a slight decrease of the adjusted R^2 due to a loss of information by using a less informative variable ($\overline{D^{res}}_t$ instead of p_t^{da}). Furthermore, we are now able to comment on the average difference of the aggregate and unrestricted supply curve by comparing the coefficients a_1 and a_1^u. The estimation results are depicted in column (1) of Table 4. The estimated coefficient for the impact of the quarter-hourly residual demand deviation (*residual demand deviation*) on intraday auction prices is more than eight times higher than the influence of the hourly residual demand (*residual demand 60*) on the proxy for day-ahead spot prices.

Dependent variable: id auction price ($p_{q,t}^{ida}$)	
Explanatory variable	OLS
hourly residual demand ($D_{h,t}^{res}$)	0.94***
	(0.004)
residual demand deviation ($\Delta D_{q-h,t}^{res}$)	7.8***
	(0.12)
intercept (ξ)	-8.2***
	(0.18)
observations	38,640
adj. R^2	0.70
F	24,440

Notes to Table 3: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from July 2013 until the end of July 2015.

Table 4: Regression estimates for intraday auction price data (2)

Based on the estimates for the gradients of the aggregate and unrestricted supply curve (a_1 and a_1^u), we are now able to estimate the welfare losses as derived in Equation (15). In 2015 the total welfare losses from restricted participation amounted to EUR 96 million. When taking a closer look at the distributional effects, as derived in Appendix.1, consumer surplus is reduced by EUR 192 million. On the supply side, the surplus of unrestricted producers is increased by EUR 107 million and surplus of restricted suppliers is reduced by EUR 11 million compared to the efficient case of unrestricted participation.

We note that these calculations do not include actual costs of market entry and thus have to be regarded as an upper bound for the welfare and distributional effects from restricted participation. Since a lack of market coupling is one driver of restricted participation, we may regard German power plant operators as the unrestricted suppliers. In this case, the German suppliers profit from non-coupled markets. In contrast, power plant operators in neighboring countries and German consumers suffer from the lack of market coupling. As the implementation of cross-border trade of 15-minute and even shorter contracts is planned for 2017 (Cross-Border Intraday Market Project XBID), welfare losses may decrease in the future. However, ensuring sufficient cross-border intraday capacities as well as an efficient coupling mechanism are crucial pillars that should be urged by policy makers.

4. Conclusion

After identifying a concurrence of strongly increasing price volatility and shortened contract duration in German short-term electricity markets, we derive a theoretical model to illustrate the respective price formation based on a fundamental approach. We consider two markets that are characterized by altering product granularity and a change in the set of suppliers along the sequential market settlement. We apply our model to the German day-ahead and intraday auction that allow for trading hourly and quarter-hourly products respectively. Our empirical results clearly indicate validity of our theoretical considerations. More precisely, we find that the high price volatility that is observed in historical price data basically is triggered by two factors. First, the variability of demand and renewable electricity generation causes a need for the trade of sub-hourly contracts. Second, we find that the supply curve in the intraday auction inclines compared to the day-ahead auction due to restricted market participation. Based on our estimates, we relate restricted intraday auction participation to welfare losses that amounted to EUR 96 million in 2015.

The main findings presented within the scope of this paper provide a better understanding of sequential markets with restricted participation and differing product granularity. An identification and classifications of reasons why the current spot market design reveals inefficiencies is indispensable in order to derive appropriate strategies of how to reduce such welfare losses. This is extremely important since the increasing share of renewable energies will lead to additional needs for sub-hourly short-term trade and thus may increase efficiency losses if the short-term flexibility potential provided in the electricity markets of interest is not increasing accordingly. Policy makers should tackle issues related to intraday market participation. Above all, a market opening may be a first step towards a more efficient market outcome. Against this backdrop, the Cross-Border Intraday Market Project planning to implement cross-border intraday trade with 15-minute and potentially even lower contract duration by 2017, is expected to make trading needs stemming from renewable electricity generation and flexibility offered in electricity markets more compatible. Our results show that this will reduce welfare losses. However, the provision of sufficient cross-border intraday capacity as well as the implementation of an efficient coupling mechanism should be urged.

On a more micro-economic level, a fundamental understanding of the price relations in the markets of interest can be transferred into price forecasts and may be used in order to evaluate the future market development. Market participants need to understand long-term drivers of price spreads in short-term electricity markets in order to assess investment decisions with respect to more flexible generation units. As of today, an exemplary profitability calculation for a battery storage unit revealed that the price volatility observed does not allow for a profitable operation.

Finally, since we observe the respective price patterns not only in electricity markets, it would be worthwhile to analyze the applicability of the model to further market settings e.g. for commodities such as gas, coal or oil. However, due to the market structures being fundamentally different we leave this open for future research.

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Appendix

Appendix.1. Proof of Proposition 4 on Distributional Effects

Proof. Before taking a closer look into the distributional effects that result from restricted participation, we first derive the respective surplus of consumers and producers. We therefore consider consumers being price inelastic up to a certain threshold where the electricity price exceeds the value of lost load (VOLL). We link the VOLL to the price p^{VOLL} which marks the upper limit of the willingness-to-pay regarding electricity consumption (this definition is analogous to Knaut and Obermüller (2016)). On the supply side, the producer surplus is determined by the difference of the unique market price and the marginal costs of electricity generation of each producer.

In the case of restricted participation ($ineff$) the consumer (CS) and producer surplus (PS) in each period t are calculated as

$$CS_\tau^{ineff} = p^{VOLL} D_\tau - \overline{p}\overline{D} - p_\tau(D_\tau - \overline{D}) \tag{.1}$$
$$PS_\tau^{ineff} = \overline{D}\overline{p} + (D_\tau - \overline{D})p_\tau - C^{ineff}(D_\tau). \tag{.2}$$

If all suppliers were able to supply at resolution t, the efficient outcome (eff) would lead to the following consumer and producer surplus

$$CS_\tau^{eff} = (p^{VOLL} - p_\tau^{eff})D_\tau \tag{.3}$$
$$PS_\tau^{eff} = p_t^{eff} D_t - C(D_\tau). \tag{.4}$$

The price in the efficient case ($p_\tau^{eff} = a_0 + a_1 D_\tau$) directly depends on the aggregate marginal cost function . The difference in consumer and producer surplus can therefore be derived as

$$\begin{aligned}\Delta CS_t &= CS_\tau^{eff} - CS_\tau^{ineff} \\ &= (a_1^u - a_1)(\overline{D} - D_\tau)^2 + a_1\overline{D}(\overline{D} - D_\tau) \\ &= 2\Delta W_\tau + a_1\overline{D}(\overline{D} - D_\tau)\end{aligned} \tag{.5}$$

$$\begin{aligned}\Delta PS_\tau &= PS_\tau^{eff} - PS_\tau^{ineff} \\ &= -\frac{1}{2}(a_1^u - a_1)(\overline{D} - D_\tau)^2 - a_1\overline{D}(\overline{D} - D_\tau) \\ &= -\Delta W_\tau - a_1\overline{D}(\overline{D} - D_\tau).\end{aligned} \tag{.6}$$

We insert the previously derived welfare losses ΔW_τ for both the change in consumer and producer surplus. Summing up over the n time periods, this results in

$$\Delta CS = \sum_{t=1}^{n} \Delta CS_\tau = 2\sum_{\tau=1}^{n} \Delta W_\tau + a_1\overline{D}\underbrace{\sum_{\tau=1}^{n}(\overline{D} - D_\tau)}_{=0} = 2\sum_{\tau=1}^{n} \Delta W_\tau \geq 0 \tag{.7}$$

$$\Delta PS = \sum_{\tau=1}^{n} \Delta PS_\tau = -\sum_{\tau=1}^{n} \Delta W_\tau - a_1\overline{D}\underbrace{\sum_{\tau=1}^{n}(\overline{D} - D_\tau)}_{=0} = -\sum_{\tau=1}^{n} \Delta W_\tau \leq 0. \tag{.8}$$

The consumer surplus decreases due to restricted participation in the second market. It is twice as high as the overall welfare losses. In contrast, the producers face an increasing surplus. The respective increase amounts to the total sum of welfare losses along all time periods. As these considerations differ across restricted and unrestricted suppliers, we now analyze the respective surplus in more detail. In the inefficient case we get the following relations

$$PS_\tau^{r,ineff} = \overline{p}q^r - C^r(q^r) \tag{.9}$$

$$PS_\tau^{u,ineff} = \overline{p}(q_\tau^u) + p_\tau(D_\tau - \overline{D}) - C^u(q_\tau^u). \tag{.10}$$

In the efficient case the respective surplus would be as follows.

$$PS_\tau^{r,eff} = p_\tau^{eff} q_\tau^{r,eff} - C^r(q_\tau^{r,eff}) \tag{.11}$$

$$PS_\tau^{u,eff} = p_\tau^{eff}(q_\tau^{u,eff}) - C^u(q_\tau^{u,eff}). \tag{.12}$$

We derive the optimal quantities supplied by restricted and unrestricted suppliers in the efficient case based on the aggregate supply function.

$$q_\tau^{r,eff} = \frac{a_1^u}{a_1^r + a_1^u} D_\tau \tag{.13}$$

$$q_\tau^{u,eff} = \frac{a_1^r}{a_1^r + a_1^u} D_\tau. \tag{.14}$$

For restricted suppliers we now derive the difference in surplus.

$$\Delta PS_\tau^r = PS_\tau^{r,eff} - PS_\tau^{r,ineff} \tag{.15}$$

$$= \frac{1}{2} a_1 (1 - \frac{a_1}{a_1^u})(D_\tau^2 - \overline{D}^2). \tag{.16}$$

Summing up over all time periods, we can further simplify the expression.

$$\Delta PS^r = \sum_{\tau=1}^{n} \Delta PS_\tau^r = \frac{1}{2} a_1 \underbrace{(1 - \frac{a_1}{a_1^u})}_{\geq 0} \underbrace{\sum_{\tau=1}^{n}(D_\tau^2 - \overline{D}^2)}_{Var(D_\tau) \geq 0} \geq 0. \tag{.17}$$

Since the variance of demand is always positive, we conclude that restricted suppliers have a lower surplus in the inefficient case. In a next step, we derive the difference in surplus for unrestricted suppliers. As we have already derived the difference in surplus for all suppliers and the respective one for restricted suppliers, we just derive the following expression.

$$\Delta PS^u = \underbrace{\Delta PS}_{\leq 0} - \underbrace{\Delta PS^r}_{\geq 0} \leq 0. \tag{.18}$$

To sum up, we prove that restricted participation leads to a reduction in consumer surplus. On the other hand, unrestricted suppliers face a higher surplus in the inefficient case whereas restricted suppliers suffer from such restriction. □

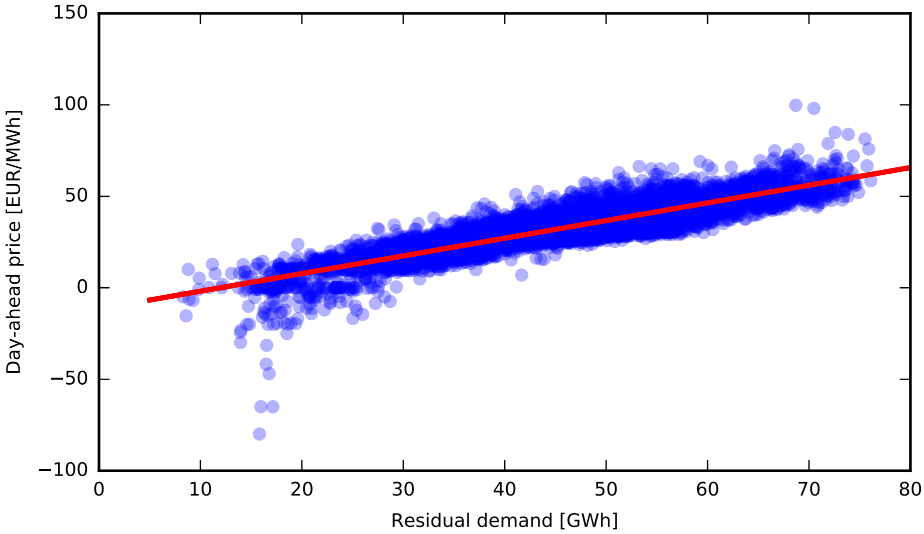

Figure .6: Relation of day-ahead quantities and prices in 2015

Appendix.3. Unit Root Tests

	Augmented Dickey Fuller (Levels)			Philipps-Perron Test (Levels)		
Variable	statistic	p-value	lags	statistic	p-value	lags
id auction price	-17.50	0.00	55	-152.25	0.00	55
day ahead price	-17.30	0.00	55	-18.65	0.00	55
residual demand 60	-13.15	0.00	53	-15.18	0.00	53
residual demand deviation 15	-40.19	0.00	55	-492.70	0.00	55
residuals (ϵ)	-17.42	0.00	54	-204.50	0.00	54

Notes to Table .5: We apply both, an Augmented Dickey Fuller test and a Phillips-Perron test for unit roots (Dickey and Fuller, 1979) (Phillips and Perron, 1979). The latter test uses Newey-West standard errors in order to account for serial correlation. The null hypothesis of both is that there is a unit root in the respective period of observation. We use the Akaike Information Criterion (AIC) in order to determine the optimal lag lengths. However, the AIC results are ambiguous for some variables and tend do indicate using as many lags as tested for. In these cases we use the Schwert rule of thumb and consider a leg length of 55 (Schwert, 1989). We prefer making a slight error due to including too many lags since Monte Carlo experiments suggest that this procedure is preferable to including too few lags. In order to give evidence for the robustness of our results, we repeat the tests for different lag lengths. Within the scope of the Augmented Dickey Fuller test, we extend the basic test of a random walk against a stationary autoregressive process by including a drift and trend term. As far as the listed results are concerned, we decide whether to include a trend or constant by checking the significance of the trend/constant parameters at a 5% significance threshold. The parameter *residuals* refers to the estimation results for equation 20 using a 2SLS regression.

Table .5: Unit root tests

Appendix.4. Detailed Results: Intraday Auction

Descriptive statistics allow us to comment on the relative importance of the individual impact factors that have been identified within our empirical estimations. We are especially interested in their individual impact on intraday auction prices. Against this backdrop, in terms of average values, the impact of differences in the renewable energy feed-in is relatively small compared to the price differences that result from the quarter-hourly load profile. We use the 25 percent and 75 percent quantiles in order to illustrate this effect. The respective values of the quarter-hourly differences of wind power amount to deviations of +45 MW and -45 MW. At the same time, the absolute effect on prices is about 0.6 EUR/MWh. Likewise, a typical solar power deviation of minus 30 MW or plus 30 MW would mean an absolute price deviation of 0.6 EUR/MWh. On the other hand, the 25 percent quantile of the quarter-hourly load difference is characterized by a threshold value of about 270 MW. The respective absolute price effect in the intraday auction amounts to 3 EUR/MWh. However, it has to be mentioned that apart from average effects extremes play an important role in order to explain the price volatility of interest. More precisely, a solar power deviation of plus or minus 1200 MW that occurs in less than five percent of all periods could lead to differences between intraday and day-ahead auction prices of 18 EUR/MWh whereas the same effect for the wind power deviation just amounts to 3 EUR/MWh. Apart from that, a 95 percent quantile threshold value of 920 MW for the load deviation can be transferred into a price difference of 10.5 EUR/MWh. To sum up, this reveals that the price volatility in intraday auction prices is mainly driven by differences between solar power and load on an hourly and sub-hourly level.

Appendix.5. Additional Information with Respect to Robustness, Alternative Hypotheses, and Methodological Variation

Besides explicitly outlined robustness checks, further variations of the basic estimation procedure were evaluated in order to get further insights into the underlying causal relations of short-term price formation in electricity markets. First, the four specific 15-minute intervals of each hour are addressed via a dummy variable in order to analyze whether the estimated coefficients for the quarter-hourly deviation of the residual demand from its hourly mean differ significantly across the 15-minute time intervals of each hour. The estimation results depict that the respective coefficients only differ slightly at a level of approximately ten percent. However, due to a small absolute difference we value the sub-hourly variation of coefficients as negligible. Second, the intra-day variation of the coefficients for the 15-minute residual demand deviation is analyzed by referring to each specific hour of a day via a dummy variable. The results only give slight evidence for significant intra-day deviation in hour two. Thus,we conclude that the causal relations are robust against intra-day variation. Third, the causal relations in winter and summer basically are the same. In a next step, we want to comment on additional impact factors that may influence quarter-hourly intraday auction prices and thus should be listed in order to complete our explanatory approach. First, we analyze the impact of forecast errors. In more detail, forecast errors reveal after day-ahead gate closure and are balanced within subsequent intraday trade. However, continuous intraday trade is assumed to be more favourable to balance these forecast errors. This is due to both, market design and gate closure closer to physical delivery. In line with these considerations, we find empirical evidence that the impact of forecast errors on intraday auction prices is insignificant. Additionally, strategic behavior could have impact on the price formation of interest. Based on Bundesnetzagentur and Bundeskartellamt (2015) we reject this hypothesis. Finally, our empirical approach is based on crucial assumptions with regard to exogeneity and stationarity of data. However, a simple Ordinary Least Squares Regression and the 2SLS Regression basically provide identical estimates. Furthermore, an application of a Vector Error Correction Model after an initial test for cointegration of the respective variables gives additional evidence for significance of the included parameters.