Trading Room Seminar

Analysing the Bid-Ask-Spread of the German Intraday Power Market with a Trade Indicator Model

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List of Abbreviations

EPEX	European Power Exchange
MO	Market Order
LO	Limit Order
ID	Intraday
RES	Renewable energy sources
MRR	Structural Model by Madhavan et al. (1997)
TtM	Time to Maturity
Qx	Quarter x
St. Dev.	Sample Standard Deviation

List of Symbols

p_t	Transaction Price
x_t	Indicator Variable
s_t	Bid-Ask Spread
s_t^{eff}	Effective Bid-Ask Spread
u_t	Ex post Asset Value (Midprice)
r_t	Share of Asymmetric Information on implied Bid-Ask-Spread
θ	Impact of Order Flow Innovation
ϕ	Impact of Transaction Costs
ρ	Autocorrelation of x_t
α	Constant
λ	$P[x_t = 0]$

1 Introduction

Due to the increasing share of renewable energy sources (RES) the need for short term portfolio optimization to avoid balancing energy costs rises. Therefore, the intraday power trading is getting more and more popular and important over the last years. This trend is shown in the rising number of trades and trading volumes in the European Power Exchange (EPEX) SPOT intraday market. Another factor for the increasing utilization of intraday trading is the higher granularity of the traded products. Operators of conventional power plants can optimize their day-ahead traded power plant schedule. The traditional unit commitment planning is typically on an hourly scale but with the help of quarter-hourly products market participants can reduce the deviation between produced energy and demand.

Furthermore the forecasting errors of the fluctuating RES lead to more volatile prices and price spikes which makes intraday trading interesting even for traders who do not operate renewable energy power plants themselves. With regard to the increasing relevance of intraday trading the deep understanding of the intraday market structure and the price formation is of highest importance, both for practitioners and researchers.

This paper aims to improve the understanding of the intraday price dynamics and market structure. For achieving this, the intraday price will be modelled with a structural model introduced by Madhavan et al. (1997) (MRR-model), which utilizes a trade indicator variable to estimate the price movements. Like Madhavan et al. (1997) it is assumed that two main components are responsibly for the price dynamic in the intraday market: Public information shocks and the trading process itself, due to market frictions and imperfections. It is expected that both effects lead to price revisions from traders, but are highly interested in the impact of the individual components. Hence the implied bid-ask spread of the model will be decomposed and the percentage provided, for which asymmetric information is responsible for the bid-ask spread in the EPEX SPOT intraday market in the model framework.

The model will be fitted to data from EPEX SPOT, which includes all events occurred in the intraday market from the second quarter 2015 and second quarter 2016. The realised bid-ask spread will be computed from the original data and compared with the implied bid-ask spread by the MRR-model.

The term paper is structured as follows: Chapter two gives an overview of the intraday market in Germany and the used data from EPEX SPOT. Chapter three introduces the applied model and provides the theoretical background. Chapter four describes briefly the implementation and estimation of the model and presents and interprets the modelling results. Chapter five summarizes the results and provides an outlook for further research.

2 Intraday Power Market in Germany

In this section the considered market will be described and special properties will be stated. Also the used data basis will be presented.

2.1 Organizational Background - EPEX SPOT

In this paper the EPEX SPOT intraday power market for Germany is focused. When intraday market is mentioned in the following, precisely the named EPEX SPOT intraday power market is referred.

EPEX SPOT was established as a joint venture between the power markets of EEX and Powernext in the year 2008/2009, as described in EPEX SPOT A (2017). Today it covers day-ahead as well as intraday markets for Germany/Austria, France, Netherlands, Switzerland and United Kingdom. In 2016 about 529 TWh were traded on these markets with 468 TWh on the day-ahead markets and 62 TWh intraday. A more detailed market overview of market participants and exchange history is given in EPEX SPOT A (2017).

The intraday market for Germany consists of a 15-Minute Intraday Call Auction and continuous trading. The auction takes place every day at three pm and offers 96 traded products (every quarter-hour) to bundle liquidity at the beginning of the intraday trading. The continuous intraday trading is available full-time (24/7) all year and starts every day for the next day at three pm. Since 2015-07-16 the lead time is 30 minutes (so products can be traded till 30 minutes before delivery) and available products are quarter-hours, full hours and block contracts as stated in EPEX SPOT A (2017). The daily trading scheme at the EPEX SPOT is shown in Figure 1.[1]

This term paper concentrates on the continuous intraday trading. To sell or buy electricity

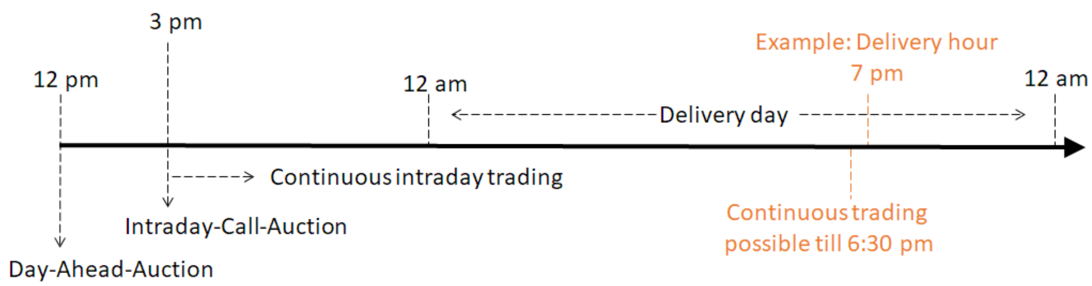

Figure 1: Daily EPEX SPOT Intraday Trading Procedure (in dependence to EPEX SPOT A (2017))

on the continuous market the participant can submit different orders which are directly executed if a match occurs. An order generally carries the information if the participant wants

[1] All used figures and graphs in this paper are self created

to buy or sell, the price and the quantity, as well as some optional information (”iceberg”, ”linked or fill”, ”good for session” etc. see EPEX SPOT B (2017) for more information). Furthermore, it can be distinguished between limit and market orders. Limit orders (LO) are getting placed in the order book and remain there, till they get executed or cancelled (neglecting special cases like ”good till date”), whereas market orders (MO) will not enter the order book. Limit orders get executed just at their limit price or at better ones. Market orders get directly matched and executed if possible. A buy market order is therefore matched with a sell limit order and vice versa. The detailed price matching is described in EPEX SPOT B (2017). Therefore, limit orders supply liquidity to the market and market orders demand liquidity, because limit orders can be seen as offers to buy or sell and market orders just remove limit orders from the order book. The order book includes all sorted limit orders and gets continuously updated. The price of the best (lowest) sell limit order in the order book is called the ask-price and the price of the best (highest) buy limit order is called the bid-price. The difference between the ask and the bid is called the bid-ask spread and can be interpreted as the cost of trading or in another way the profit for the market maker.

2.2 Special Properties and Price Structure

Figure 3 shows all intraday prices for hour 12 (delivery from 11 am till 12 am) on 2015-04-05 and on 2016-04-05. Figure 2 shows the daily mean intraday prices for every hour of the second quarter 2015 and 2016 (dates and the hour were arbitrary chosen for illustration purposes).

Three important characteristics can be seen in these plots: The liquidity increases with decreasing time to maturity, there are significant outliers in the daily means and the different hours have various price levels (the hours are represented through different colors in Figure 2).

Pape et al. (2016) explained fundamentally the unsteady prices during the trading period through the forecasting errors for energy production and other fundamental factors. Since for example the weather forecast (which highly influences the expected infeed from RES) is similar for every market participant, the occurring forecast error is similar, too. Hence, if greater errors appear many participants want to buy or sell electricity at the same time to avoid balancing energy costs and the price reaches a higher level (less RE-infeed than expected) or converges to zero or even gets negative (more RE-infeed than expected). But not all price spikes can be explained by this argumentation, because the prices show regularly outliers which do not follow or start a trend, but instantly return to the previous price level. An example for this pattern is given in Figure 4.

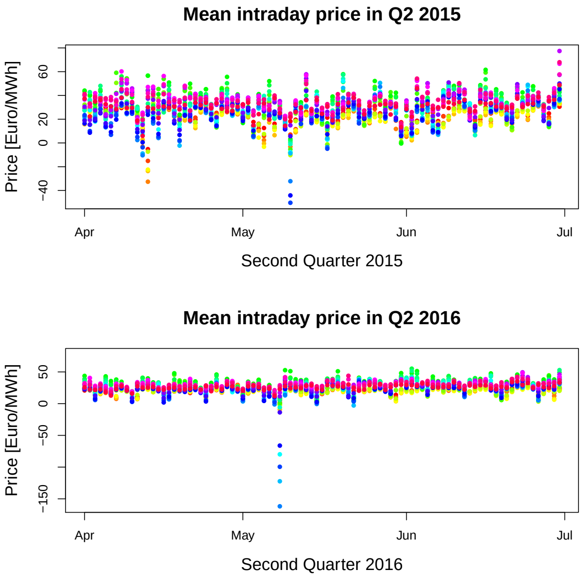

Figure 2: Daily Mean of Intraday Prices for all Hours in Q2 2015/2016

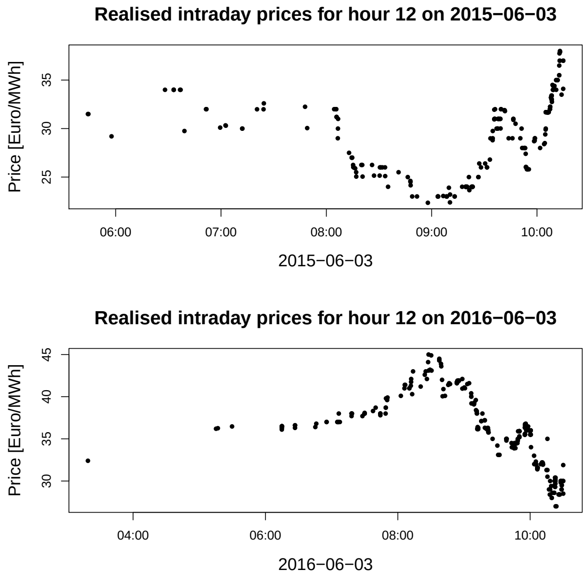

Figure 3: Transaction Intraday Prices in Hour 12 on 2015/2016-06-03

But Pape et al. (2016) found positive results by explaining the intraday prices with a

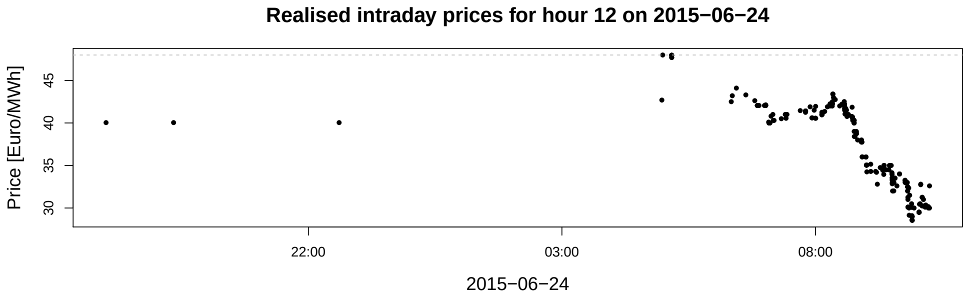

Figure 4: Intraday Price Outlier - Hour 12 - 2015-06-24

fundamental model and stated that the remaining unexplained part could be attributed to start-up-costs, market states and trading behaviour. Though Hagemann & Weber (2013) rejected a completely fundamental model to explain price formation and found evidence for a trading model, which is based on trading behaviour.

Figure 5 shows the average bid-ask spread over all days of the second quarter 2015 and 2016 for every hour. The spread seems to drop with decreasing time to maturity. For most hours a slightly w-shaped pattern can be stated. The higher values in the first hours of trading correspond to the low liquidity at the beginning of the trading period (compare to figure 16 in the appendix). And as expected with increasing liquidity the bid-ask spread shrinks. Therefore, the slightly rising values near to the delivery time are not intuitively explainable, since this is averagely the time with the highest number of trades. Hence, further aspects have to be considered to explain this structure. The presented model in this paper aims to help quantifying the effects which lead to this observed bid-ask-spread.

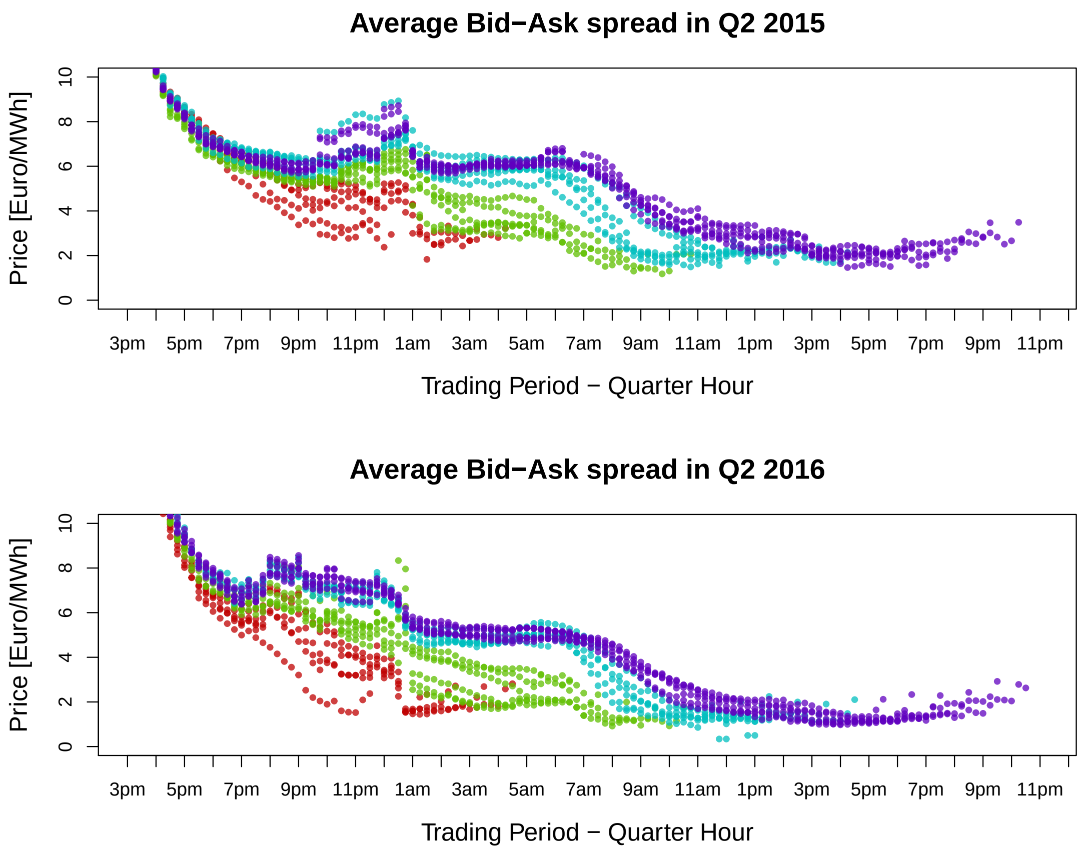

Figure 5: Average Bid-Ask Spread over all Days in Q2 2015/2016 for all Hours

2.3 Database

The used database is indirectly provided by the EPEX SPOT and includes all events which occurred in the EPEX SPOT intraday power market for Germany from 2015-04-01 till 2015-06-30 and 2016-04-01 till 2016-06-30. Every event consists of a specific time stamp (millisecond resolution) and the order information (delivery date, LO/MO, buy/sell, price, volume, order-ID).

3 Structural Model by Madhavan et al.

Madhavan et al. (1997) introduced their model with an application on NYSE stocks. Because of slightly different market assumptions we have to adapt the model to the application on intraday power markets. First, we clarify the model background and explain the different parameters. After that we consider the differences between the markets and present the application in the German power market.
The model aims to describe quote-driven markets in which the market maker supplies liquidity. But even in an order-driven market, the limit order book can be seen as as central market maker, as Mizrach & Otsubo (2013) described. Thus the sum of market participants who supply liquidity is generally called market maker in the following.

3.1 Model Background

Modelling the bid-ask spread of liquid markets two model types are common, which get compared in Huang & Stoll (1997). Covariance models[2] use the observed serial autocovariance from the intraday prices to explain the price dynamic, whereas structural indicator models[3] utilize a trade indicator variable and determine their model coefficients by regression. Huang & Stoll (1997) show that both model types are equivalent. However, there are many different models regarding the considered coefficients and input data like Mizrach & Otsubo (2013), Hamm (2011), Hagstroemer et al. (2016), Ryu (2016).
Madhavan et al. (1997) assume that the bid-ask spread mainly emerges from:

1. Asymmetric information / adverse selection costs
2. Inventory carrying costs
3. Order processing costs

Whereas inventory costs and order processing costs are combined as transaction costs and dealt with as one factor since both are straight additional costs for the market maker. The transaction costs impact his price setting only temporary (thus they are called transitory costs in some literature).
The concept behind the model is that Madhavan et al. differ between asset value (also called midprice) and asset price (transaction price) and assume that the market maker sets his bid and ask symmetrically around the post trade expected asset value within the distance of his transaction costs (which include trading fees, inventory costs, risk bearing and so on). The change in the post trade expected asset value is dependent on public information shocks and the innovation in order flow. In this case order flow innovation represents asymmetric

[2] Like Roll (1984)
[3] Like Glosten & Harris (1988)

information, since it is accepted that there are informed traders and every new trade holds possibly new information. To put it in other words when an informed market participant trades, he probably will make profit because of his information advantage. This profit due to informed trading is on the other side loss for the market maker and is from this perspective called adverse selection cost. Because the amount of order flow innovation as well as the sign of the transaction costs depend on the trade direction, they can be expressed in relation to the indicator variable, which enables a simple and neat model.
More formal lets denote p_t the intrady price from transaction t. In the MRR-model the indicator variable x_t is defined by [4]:

$$x_t = \begin{cases} 1 & \text{if } p_t \text{ is buyer initiated} \\ 0 & \text{if } p_t \text{ lies inside the spread} \\ -1 & \text{if } p_t \text{ is seller initiated} \end{cases} \tag{1}$$

The probability that a trade occurs inside the spread is defined as

$$\lambda = \mathrm{P}(x_t = 0) \tag{2}$$

and if it is assumed that seller and buyer-initiated trades have the same probability it follows

$$\mathrm{E}[x_t = 1] = \mathrm{E}[x_t = 2] = 0 \tag{3}$$

$$\mathrm{var}[x_t] = (1 - \lambda) \tag{4}$$

The asset value u_t depends on public information and order flow, noted as:

$$u_t = u_{t-1} + \theta(x_t - \mathrm{E}[x_t|x_{t-1}]) + \epsilon_t \tag{5}$$

where ϵ_t represents the public information shock and is assumed to be independent and identically distributed (i.i.d) with $\bar{\epsilon} = 0$ and $\mathrm{var}[\epsilon] = \sigma^2$. $\theta(x_t - \mathrm{E}[x_t|x_{t-1}])$ describes the whole revision in belief due to order flow innovation, whereas $(x_t - \mathrm{E}[x_t|x_{t-1}])$ is the order flow innovation and θ represents the impact of the innovation. In other words, θ can be interpreted as the amount in which market participants revise their price belief due to new information arising out of the trade direction of the last and the actual trade. Because it is thought that informed traders trigger this innovation and uninformed traders follow and revise their price belief, θ is therefore an indicator for the information asymmetry in the market. The innovation in order flow can be indicated by the difference between the realised and the expected trade indicator variable. Note that the market maker sets ex-post regret

[4] following formulas and derivations in this chapter are quoted from Madhavan et al. (1997)

free prices. Even if the market maker does not know the trade direction of the next trade, he can set the quoted prices for both possible options. In the equation this can be seen in the fact that x_t is used to predict u_t, even if x_t is unknown at transaction time $t-1$. Therefore u_t is called ex post asset value (or regret free value).
(Madhavan et al. 1997, P.7) showed that

$$\mathrm{E}[x_t|x_{t-1}] = \rho \cdot x_{t-1} \tag{6}$$

with ρ equal to the autocorrelation of the trade indicator variable.
Let $\phi \geq 0$ be the transaction costs for the market maker to supply liquidity and ξ an i.i.d. random variable, which covers the effect of stochastic rounding errors induced by price discreteness, we get

$$p_t^{Ask} = u_{t-1} + \theta(x_t - \mathrm{E}[x_t|x_{t-1}]) + \phi + \epsilon_t + \xi_t \tag{7}$$
$$p_t^{Bid} = u_{t-1} - \theta(x_t + \mathrm{E}[x_t|x_{t-1}]) - \phi + \epsilon_t + \xi_t \tag{8}$$
$$p_t = u_t + \phi \cdot x_t + \xi_t \tag{9}$$

In equation 9 the term transitory costs get clear. The transaction costs ϕ influence the quoted price of the underlying, but not the value.
Combining Formula 5, 6 and 8 we obtain

$$p_t = p_{t-1} - \phi x_{t-1} - \xi_{t-1} + \theta(x_t - \rho x_{t-1}) + \epsilon_t + \phi \cdot x_t + \xi_t \tag{10}$$
$$p_t - p_{t-1} = (\phi + \theta)x_t - (\phi + \rho \cdot \theta)x_{t-1} + \epsilon_t + \xi_t + \xi_{t-1} \tag{11}$$

Equation 11 forms the basis of the paper from Madhavan et al. (1997). In case of a perfect market, the model reduces to ϵ_t. In case of zero autocorrelation, every new trade contains information, which the market maker implies in his quotes. If the autocorrelation equals one, only complete changes in the trade direction influence the market maker quotes. This is intuitive since an autocorrelation of one implies that we expect a pattern of equal values. The only innovation is a value change (we have in our case just two conditions, x_t can be 1 or -1). With zero autocorrelation we have no expectations for futures values and every new x_t is an innovation with new information.
The bid-ask spread is defined as $p^{Ask} - p^{Bid}$ which leads in this framework to (eq. 7 - eq. 8)

$$s = p_t^{Ask} - p_t^{Bid} = 2(\phi + \theta)\hat{s} = p_t^{Ask} - p_t^{Bid} = 2(\hat{\phi} + \hat{\theta}) \tag{12}$$

where s denotes the true implied bid-ask spread of the model and $\hat{s}$ the estimated implied bid-ask spread. On that basis it is straightforward that

$$r = \theta/(\phi + \theta) \tag{13}$$

with r being the ratio of the asymmetric information component of the spread to the implied total spread.

Lets call s the quoted bid-ask spread and s^{eff} the effective bid-ask spread as proposed by Glosten & Harris (1988). The effective bid-ask spread just represents the costs for buying a round trip. The effective bid-ask spread is defined as

$$s^{eff} = 2\phi + \theta$$

and can be interpreted as the price difference between buying/selling in t and closing the position in $t + 1$. You can qualitatively explain the price difference between effective spread and quoted spread with the argumentation, that the trader who buys/sells the round trip is informed about the last trade (because he initiated it) and therefore the spread for him is smaller.

In addition Madhavan et al. (1997) calculated the implied price variance and bid-ask variance from their model, as well as the implied amount of quote revision, which is represented in the autocorrelation of transactions at the ask, respectively the bid. These calculations are not particularly relevant for this paper but could be addressed in further research.

3.2 Application on Intraday Power Market

First, the model assumption of a liquid market has to be considered. This assumption is not completely true for the German intraday power market. Therefore, only the last period before trade closing get used, since these hours provide the highest liquidity. Figure 6 compares a two and four hours long last period before time to maturity (two and four are arbitrary chosen). We compare the whole amount of trades in Q2 2015 and 2016. Logically we see that the mean number of trades in four hours is higher than in two hours. But in relation to the time span, the last two hours have a higher relative amount of number of trades per quarter hour. Furthermore, we see in this figure that more trades occur in the middle of the day than in the morning hours. Since we do not consider the time interval between trades but assume that we get better estimation results with a higher amount of observations we set the length of the last period to four hours to fit the model. Moreover, we see in figure 16 that in the last two hours are significantly more trades, but the rise starts generally four hours before time to maturity. To define this cluster more accurately further research is necessary.

Furthermore, only last periods get estimated in which more than 30 transactions are

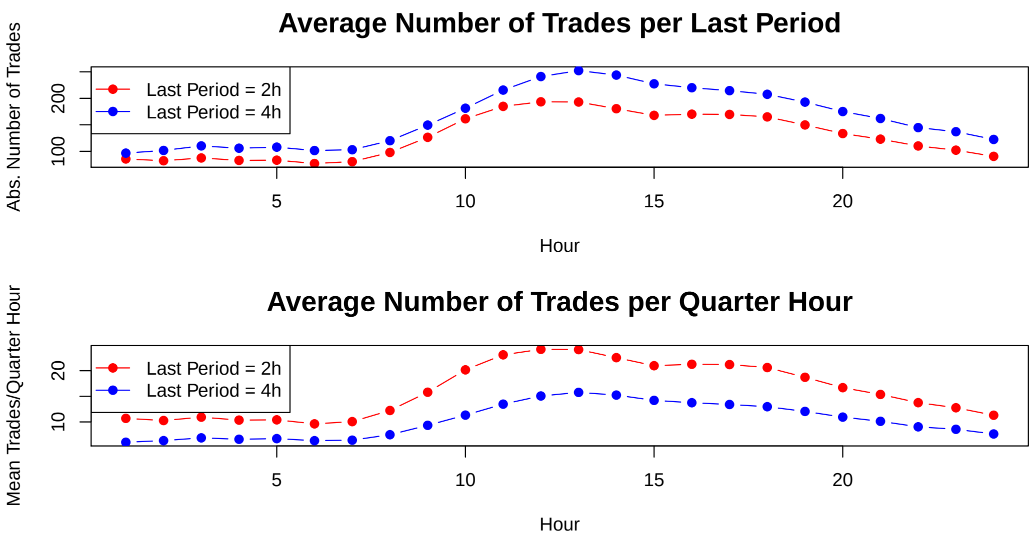

Figure 6: Comparison of Number of Trades for Last Period with length of 2 Hours and 4 Hours.

observed. The amount of 30 is here arbitrary chosen to estimate reliable coefficients.
A technical adjustment is that in our market are no transactions within the bid-ask spread. Hence the indicator variable reduces to

$$x_t = \begin{cases} 1 & \text{if } p_t \text{ is seller initiated} \\ -1 & \text{if } p_t \text{ is buyer initiated} \end{cases} \tag{14}$$

and λ will get neglected in the further study.

3.3 Model Estimation

Madhavan et al. (1997) estimated the model via the generalized method of moments (GMM, see Hansen (1982)). The GMM approach tries to fit observed sample moments to the population moments implied by the structural model. GMM allows to consistently estimate the coefficients without making strong assumptions about the distribution of the variables. Moreover, it allows adjustment for autocorrelation and heteroskedasticity in the data basis. In more technical terms, if we want to estimate in this framework the parameter vector β with $\beta = (\theta, \phi, \rho, \alpha)$ (α represents any constant) we specify the condition equations $g_T(\beta)$ of our model and solve the resulting system of equations. Considering ρ as the autocorrelation of x_t we get $\rho = \dfrac{x_t \cdot x_{t-1}}{x_t^2}$ and from equation 11 we can define $m_t = p_t - p_{t-1} - (\phi +$

$\theta)x_t + (\phi + \rho \cdot \theta)x_{t-1}$. Furthermore, with the condition $\mathrm{E}[e_t \cdot x_t] = 0$, where e_t represent the residuals i.e. $m_t - alpha$ and x_t represent the regressor variables[5] $(1, x_t, x_{t-1})$, following moment conditions are resulting:

$$g_T(\beta) = \mathrm{E}\begin{pmatrix} x_t \cdot x_{t-1} - x_t^2 \cdot \rho \\ m_t - \alpha \\ (m_t - \alpha)x_t \\ (m_t - \alpha)x_{t-1} \end{pmatrix} = 0 \tag{15}$$

In practice, we applied the `gmm`-Package from R which includes the `gmm()`-Function and used the classical two-step approach from Hansen (1982). For numerical solving of the equation system we use the in-built optimizer which allows positive as well as negative values. The starting point values are arbitrary chosen as $\theta = 0, \phi = 0, \alpha = 0, \rho = 0$. For further research with subject to the variance we could define the procedure to identify the variance-covariance matrix of β, from which the implied price variance in the model could be derived. Madhavan et al. (1997) used the Newey-West procedure. For this paper a specification is not directly necessary, since the variance-covariance matrix in the GMM-procedure is only needed, if we specify more moment conditions than variables. In this case we have to weight the conditions to determine β but in our framework we have the same number of conditions and coefficients and therefore determine an explicit solution for the equation system.
We estimated the model in the time period 2015-04-01 till 2015-06-30 and 2016-04-01 till 2016-06-30 each day for every product (hour) for the last four hours before time to maturity.

[5] Note that this is equivalent to the OLS normal equations

4 Model Evaluation

In this chapter the model results get first presented and described and in the next subsection classified. Originating from these results the model will be reviewed for modelling the German intraday power market.

4.1 Model Results

Table 2 presents all average model coefficients per hour estimated for the year 2015, Table 5 is provided in the appendix and shows all model parameters for the year 2016. Note that these are the absolute model parameters. Figure 7 visualizes these results. The mean values over all hours are given in Table 1. As expected the constant drift term α has values around

Table 1: Mean Parameter Values for 2015 and 2016

	2015	2016
Theta	0.4186	0.2279
Phi	0.4348	0.2308
Rho	0.4429	0.4382
Alpha	-0.0043	0.0038
Implied Bid-Ask	1.7068	0.9174
Asy. Inf. [%]	0.4892	0.5025

zero. In Table 2 the parameter θ reaches values from 0.34 to 0.5 with slightly higher values in the last hours of the day. The standard deviation from θ increases in the night hours. ϕ has a higher mean than θ but as well higher values in the last hours and a higher standard deviation in the night hours. ρ takes values from 0.41 to 0.46 and seems relatively stable over the hours. The decrease of θ and ϕ in the midday could be fundamentally driven by the infeed from RES in the middle of the day, which leads to higher liquidity in the market and therefore a shrinking spread (structure of the spread is shown in Figure 8). In Figure 7 we see that both for θ and ϕ negative values occur. This is contra intuitive, since the parameter representing adverse selection and transaction costs are defined as positive variables. Negative parameters imply a negative spread, because if a trade is buyer-initiated (indicator variable = 1) the market maker would subtract his costs and for a seller initiated trade (indicator variable = -1) he would add them. Thus the resulting ask price would be lower than the resulting bid price. The problem will be addressed in the critique section.
Comparing 2015 and 2016 slightly lower values can be seen for θ and ϕ in 2016 with lower variance. Yet ρ stays at the same level.

To investigate the reliability of the estimators the number of accepted t-tests for every parameter is stated in Table 3. It can be seen, that θ has a high acceptance rate, whereas ϕ

Table 2: Results of Model Parameter Estimates - Q2 2015

	θ		ϕ		ρ		α	
Hour	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
1	0.3857	0.4345	0.5651	0.4012	0.4125	0.1210	-0.0261	0.1416
2	0.3904	0.2976	0.5551	0.4096	0.4113	0.1347	-0.0141	0.1126
3	0.4264	0.3783	0.5729	0.3443	0.4280	0.1236	-0.0234	0.0710
4	0.4724	0.3206	0.5391	0.4295	0.4366	0.1426	-0.0479	0.1347
5	0.4943	0.5209	0.5557	0.3759	0.4634	0.1233	-0.0184	0.1563
6	0.4848	0.2837	0.5778	0.5113	0.4583	0.1169	-0.0156	0.0990
7	0.5208	0.3296	0.5680	0.4307	0.4543	0.1150	0.0056	0.1362
8	0.5378	0.3375	0.5351	0.3655	0.4530	0.1083	-0.0213	0.1165
9	0.4943	0.2992	0.3674	0.2692	0.4491	0.1194	-0.0144	0.0929
10	0.3782	0.1812	0.3750	0.2420	0.4461	0.0913	-0.0015	0.0685
11	0.3417	0.1983	0.3322	0.2078	0.4495	0.0733	-0.0031	0.0580
12	0.3248	0.1764	0.3002	0.1638	0.4567	0.1016	0.0007	0.0421
13	0.3308	0.2003	0.3013	0.2093	0.4433	0.0891	0.0184	0.0908
14	0.3440	0.2389	0.3087	0.1566	0.4388	0.0958	0.0005	0.0507
15	0.3900	0.3656	0.3507	0.2380	0.4450	0.0980	-0.0123	0.0813
16	0.4022	0.4584	0.3622	0.2475	0.4378	0.0915	-0.0150	0.1543
17	0.3555	0.3172	0.3923	0.1610	0.4264	0.0942	-0.0048	0.0781
18	0.3316	0.1734	0.3495	0.1794	0.4373	0.0870	0.0050	0.0524
19	0.3550	0.2017	0.3522	0.2751	0.4400	0.0775	0.0182	0.0755
20	0.4186	0.2682	0.3439	0.2136	0.4457	0.1025	0.0000	0.0842
21	0.4283	0.2910	0.3713	0.2910	0.4635	0.0907	-0.0065	0.0857
22	0.4583	0.3258	0.4141	0.2889	0.4558	0.1231	0.0144	0.0980
23	0.4855	0.4763	0.4856	0.2694	0.4260	0.1137	0.0470	0.1365
24	0.4939	0.4049	0.5610	0.4086	0.4500	0.1304	0.0108	0.1019

and ρ gets rejected every fourth time at a significance level of 90%. α get rejected most of the time, but this is close to our expectation, as we assume that the price differences in the intraday market have no drift. The uncertainty in ϕ and ρ could be traced back to some extend to the estimation technique, since GMM provides just an asymptotically normal estimator and our sample size for estimation is on many days very limited. And with the weak assumptions on the underlying data we loose information and therefore estimation accuracy. Figure 14 (in the appendix) indicates that more parameters get accepted in the hours between 8 and 20. That corresponds to the number of trades and therefore the limited number of observations could lead to the lower acceptance rate.

More information about the spread is shown in Table 4, where the implied bid-ask spread and the share of asymmetric information are listed. The model implies a slightly higher spread in the night hours than through the day. The asymmetric information share (as noted in equation 13) has lower values in the first three hours of the day but varies around 0.5% the rest of the day. By comparison of 2015 and 2016 it can be seen, that the implied

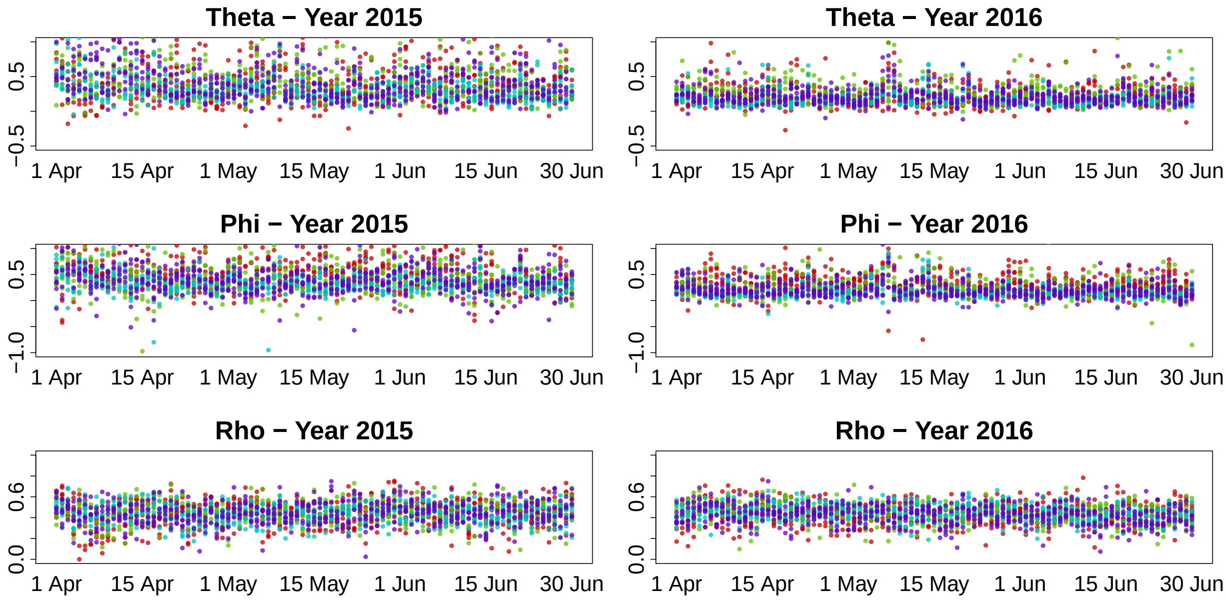

Figure 7: Model Parameter estimations for all Hours in Q2 2015 and 2016

Table 3: Number of accepted t-Tests for Significance of Model Parameter

Parameter	θ	ϕ	ρ	α
p-value $\leq 0.1\%$	4296	3027	3492	296
p-value $\leq 0.05\%$	4254	2632	3033	115
p-value $\leq 0.01\%$	4088	1844	1926	20
Total Number of Estimations: 4368				

bid-ask spread shrinks but the asymmetric information component slightly increases. It can be stated as a result, that the asymmetric information component explains approximately 50% of the implied bid-ask-spread in this model framework, which can be seen as an indicator for the German intraday power market.

Figure 8 compares the implied bid-ask spread with the realised bid-ask spread in the market. It can be seen that the implied bid-ask spread is lower than the real spread in every hour. Both, realised and implied spread are decreasing from 2015 to 2016. The structural model does not capture the high values in the morning hours, but decreases at midday as well as the real bid-ask spread and increases slightly in the last hours. Hence, the overall structure, besides the first four hours, is similar to the real bid-ask spread. But the spread level is clearly underestimated. This indicates that our model lacks some important information to describe the bid-ask spread in an appropriate manner.

Figure 9 demonstrates the relation between the implied bid-ask spread and the number of trades in the last period. Since trading activity is one dimension of liquidity, we would expect a strong relation between higher number of trades and lower bid-ask spreads. This

Table 4: Implied Spread and Share of Asymmetric Information from Model Estimation

	Implied Spread [EUR/MWh]				As. Information [%]	
	2015		2016		2015	2016
hour	Mean	St. Dev.	Mean	St. Dev.	Mean	
1	1.9015	0.9467	1.0217	0.4809	0.3825	0.4332
2	1.8909	0.9469	1.0641	0.4610	0.4226	0.3768
3	1.9986	1.1119	0.9619	1.0616	0.4112	0.4396
4	2.0229	1.0086	1.1196	0.4480	0.4864	0.4314
5	2.0999	1.4060	1.1028	0.5207	0.4504	0.3993
6	2.1252	1.2111	1.1488	0.5258	0.4821	0.4748
7	2.1775	1.0150	1.3326	0.5272	0.4545	0.4839
8	2.1458	0.7247	1.1847	0.4340	0.5158	0.5688
9	1.7235	0.5881	1.0061	0.3870	0.5795	0.5595
10	1.5064	0.5925	0.8082	0.3645	0.5144	0.5280
11	1.3477	0.4712	0.7790	0.5229	0.5097	0.5081
12	1.2500	0.4670	0.6981	0.3797	0.5175	0.5221
13	1.2642	0.5605	0.7112	0.6780	0.4936	0.5111
14	1.3055	0.5545	0.7652	0.8473	0.5142	0.5233
15	1.4814	0.9832	0.7988	1.1233	0.4985	0.5706
16	1.5288	1.1435	0.8088	0.8868	0.4906	0.4999
17	1.4958	0.7803	0.7662	0.7916	0.4535	0.5296
18	1.3623	0.5212	0.7430	0.6388	0.4861	0.5321
19	1.4145	0.5517	0.6935	0.2525	0.5286	0.5607
20	1.5250	0.6604	0.7719	0.3283	0.5441	0.5568
21	1.5992	0.7285	0.8750	0.3729	0.5387	0.5132
22	1.7447	0.7978	0.9034	0.4051	0.5224	0.4976
23	1.9423	1.0744	0.9399	0.3950	0.4772	0.5587
24	2.1097	0.9850	1.0134	0.3921	0.4676	0.4812

relation can be seen, but is not highly distinct. Though we can identify that the hours with the highest number of trades (hours 13-18) have on average lower prices and a smaller variance, whereas hours 1-6 have slightly higher prices with higher variance of prices.

4.2 Critique

One of the main differences between the results of this paper and the results by Madhavan et al. (1997) are that we observe negative values for θ and ϕ. An explanation from our data set would be situations, in which the trade direction is opposed to the price difference. To put this in other words, the ask price is lower than the bid price of two consecutive trades. If for example $p_t = 40$ and in $t+1$ follows a buyer-initiated trade we would expect $p_{t+1} \geq 40$, because of the bid-ask bounce if the previous trade was seller initiated, or on the same level if the previous trade was buyer initiated. Because of relatively long time intervals

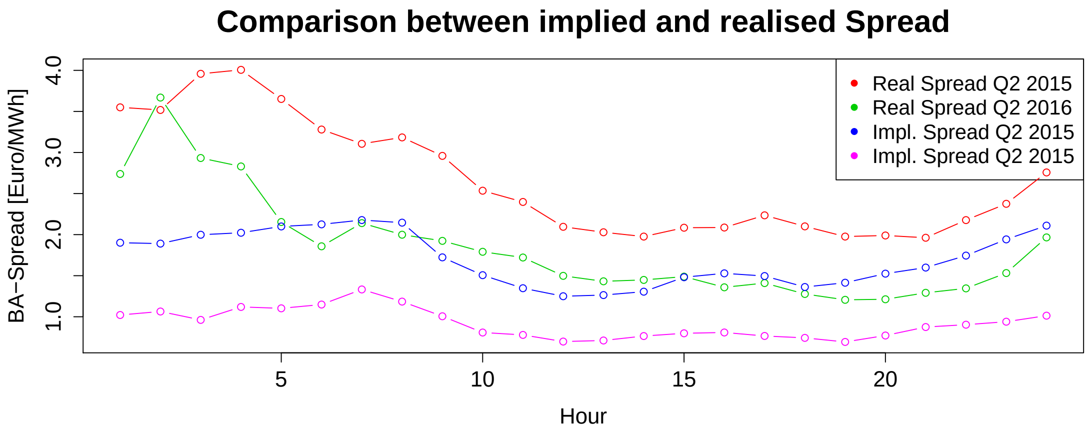

Figure 8: Comparing the Implied and Realised Bid-Ask-Spread for all Hours in Q2 2015/2016

between the trades situations occur in which $p_{t-1} < 40$ even if the trade was buyer initiated in our example. This can happen due to price revision, when the quoted price level changes. Traders can revise their orders anytime and in situations where new public information arise (updated weather forecast) many traders revise their orders simultanesly and the quoted price level changes without any transaction taking place. This problem is shown in Figure 10 and Figure 11. Figure 10 pictures the transaction prices at the 2015-05-09 for hour 1. The trades around 21:30 till 22:00 are clearly unintuitive since the trades are seller initiated but the price rises. A similar structure can be seen in the trades before 23:00. Although the trades are buyer initiated the price drops. Figure 11 displays the quoted prices in situations where this pattern can occure. We assume that the price jumps in Figure 11 are only due to revision in belief. These price behaviours could occure due to the fact, that our market is way more fundamental driven than for example stock prices. As a result buyer and seller do not act like rational agents, but have fundamental restrictions. Thus this is additional evidence for the preposition, that fundamental variables have high impact on the bid-ask spread, as shown by Pape et al. (2016). The consideration of these fundamental variables should improve the structural model.
Another solution could be considering the time differences between trades, which can be used as an indicator if the price level has changed.

Some further research should be done to explain the rate of rejected model coefficients. θ got accepted most times but ϕ got rejected by the t-test nearly every fourth time. One possible argumentation is that the transaction costs are just not important for explaining the bid-ask spread. Therefore, they are nearly zero and everything got explained by asymmetric information. This is at least questionable since in reality there are order processing costs and we see a very wide spread. In fact we are clearly underestimating the bid-ask spread,

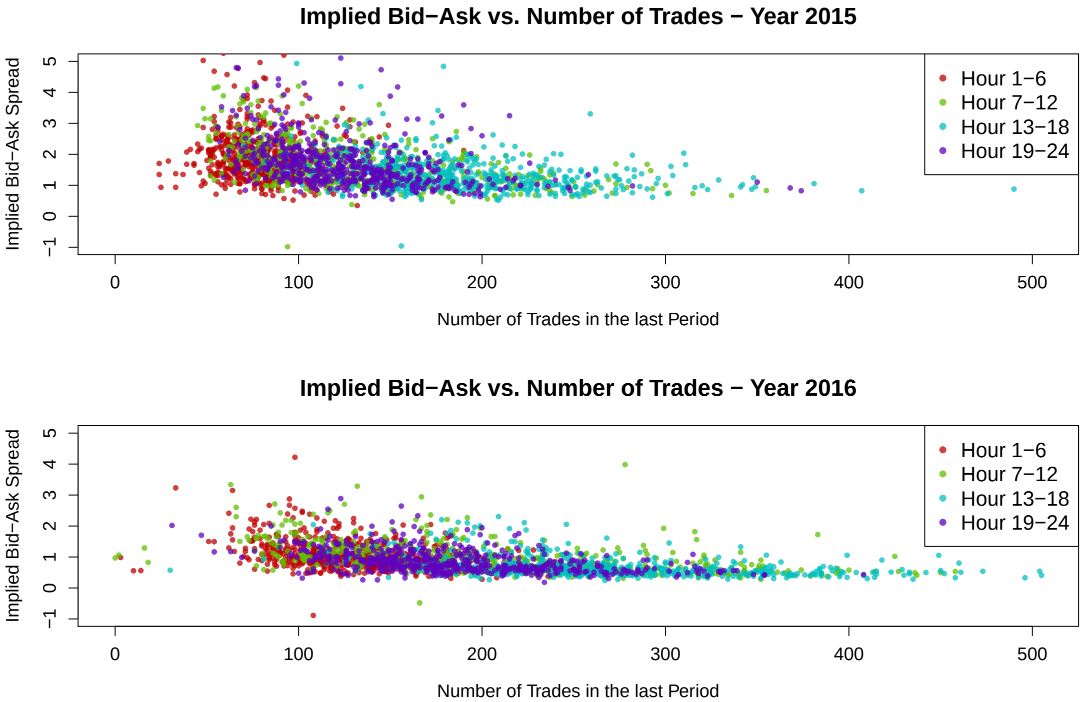

Figure 9: Comparing the Implied Bid-Ask Spread and Number of Trades in Q2 2015/2016

so we possibly do not capture correctly all components. But Theissen & Zehnder (2014) show in their paper, that to some extend the underestimation of the real bid ask spread is a general drawback from structural indicator variable models.

Another extension for the model could be to differentiate the transaction costs into order processing costs and inventory costs, as in Huang & Stoll (1997). But the influence of inventory costs tends to decrease at least in stock markets, because of the decreasing average volume size of products. Kim & Murphy (2013) showed therefore, that the benefit from consideration of traded volume in structural indicator variable models dropped in the last years. Ryu (2016) introduced an extensive structural model which includes additional factors as trade duration, order sizes and market depth, which takes liquidity into account and could therefore be better suited for the power market.

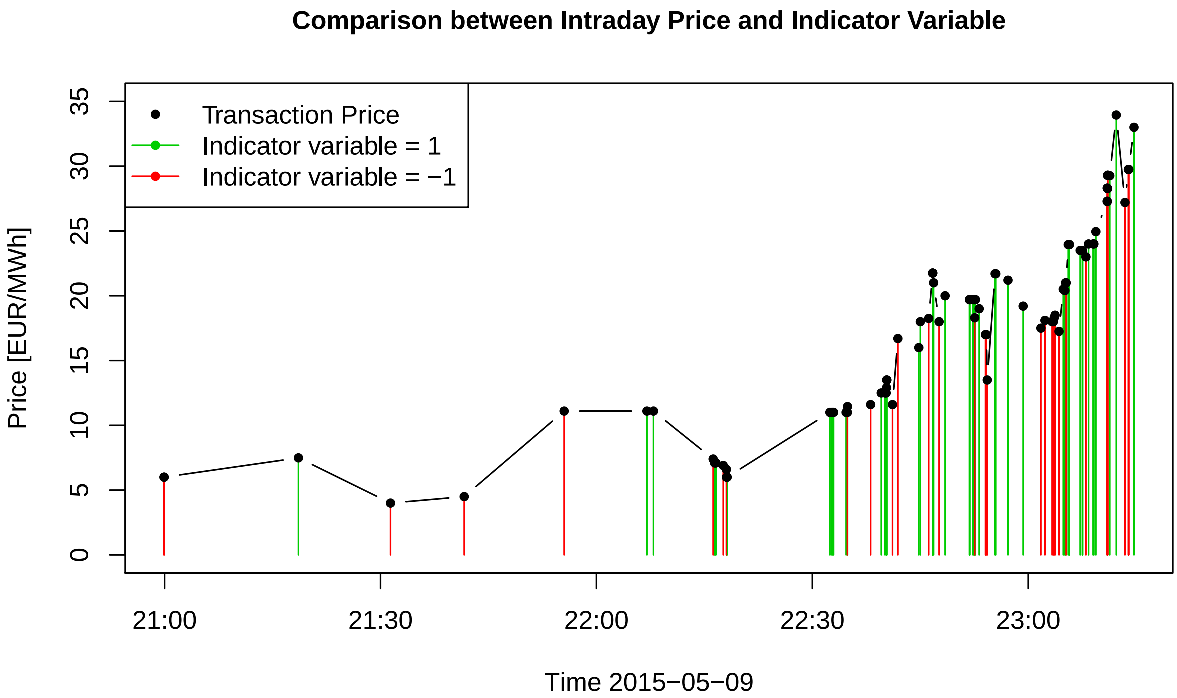

Figure 10: Transaction Price and Indicator Variable - Hour 1 2015-05-09

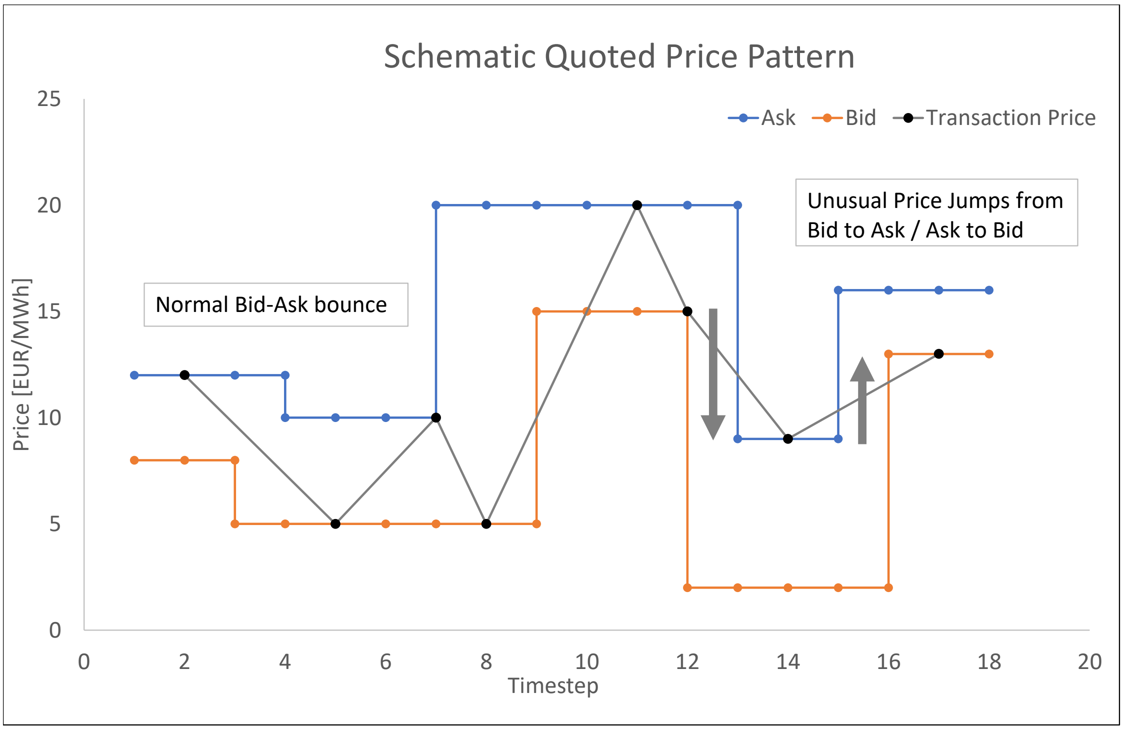

Figure 11: Change of Quoted Price Level and Transaction Price

5 Summary and Outlook

In this paper the bid-ask spread of the German intraday power market got modelled with a structural approach utilizing an indicator variable which represents the trade direction. Within the model framework the spread got decomposed into adverse selection costs and transaction costs. The asymmetric information are represented in the order flow innovation whereas the transaction costs are the distance between asset value (midprice) and asset price (quoted price). The coefficients got estimated from data of 2015 and 2016 for the last four hours before time to maturity and the implied bid ask spread got calculated. It was found, that shares around 0.4892 in 2015 and 0.5025 in 2016 from the implied bid-ask spread are due to asymmetric information.

In comparison to the realised bid-ask spread it can be stated, that the model captures the overall structure of the single hours but underestimates the realised bid-ask spread by around 2 EUR/MWh in the morning hours and $0.5 - 1$ EUR/MWh over the day. Moreover, negative model parameters got observed which can lead in the framework of the model to negative spreads. This occurs due to unintuitive transaction price jumps within the quoted prices in the German power market. Because of these jumps situations arise in which the ask price is lower than the bid price of two consecutive trades and vice versa. These transaction price movements are the outcome of price revision, which lead to a change of the quoted price level without any executed trade.

Further research can be done on extending the model to achieve a more detailed decomposition of the bid-ask spread. Possible indicators are the trade duration and market depth and the decomposition of transaction costs in order processing and inventory costs. Also external fundamental variables like weather forecasts and power plant outages could help explaining the spread.

With this paper a foundation is laid for further research on the indicator variable model approach with application in the intraday power market and to investigate the bid-ask spread driver in the German intraday power market.

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Appendix

Table 5: Results of Model Parameter Estimates - Q2 2016

	2016							
	θ		ϕ		ρ		α	
Hour	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
1	0.2133	0.1602	0.2975	0.2044	0.4205	0.1142	0.0082	0.0611
2	0.1946	0.1591	0.3375	0.2041	0.4198	0.1075	-0.0045	0.0651
3	0.2292	0.1589	0.2518	0.5047	0.4276	0.0993	-0.0036	0.0541
4	0.2588	0.3523	0.3010	0.2799	0.4462	0.1033	-0.0038	0.0676
5	0.2229	0.2861	0.3286	0.2154	0.4313	0.1089	-0.0036	0.0550
6	0.2895	0.2001	0.2849	0.2135	0.4631	0.0923	0.0135	0.0572
7	0.3063	0.1762	0.3600	0.2478	0.4306	0.0983	0.0028	0.0692
8	0.3183	0.1361	0.2740	0.2070	0.4468	0.1002	0.0188	0.0595
9	0.2824	0.1729	0.2207	0.1488	0.4461	0.0939	0.0192	0.0619
10	0.2245	0.1788	0.1796	0.1761	0.4453	0.0877	0.0161	0.0804
11	0.1850	0.1021	0.2045	0.1932	0.4412	0.0785	-0.0005	0.0269
12	0.1767	0.1115	0.1724	0.1185	0.4573	0.0731	0.0068	0.0337
13	0.1737	0.1297	0.1819	0.2337	0.4582	0.0766	0.0019	0.0528
14	0.2081	0.3450	0.1746	0.1381	0.4342	0.0793	-0.0159	0.1608
15	0.2612	0.7236	0.1382	0.2176	0.4524	0.0661	-0.0280	0.3165
16	0.2066	0.3400	0.1978	0.1547	0.4427	0.0770	-0.0043	0.0352
17	0.1932	0.1690	0.1899	0.2567	0.4446	0.0788	-0.0017	0.0345
18	0.2009	0.2265	0.1706	0.1311	0.4505	0.0883	0.0065	0.0434
19	0.1924	0.1055	0.1544	0.1040	0.4304	0.0853	0.0040	0.0398
20	0.2126	0.1236	0.1733	0.1187	0.4286	0.0877	0.0086	0.0497
21	0.2195	0.1142	0.2180	0.1342	0.4284	0.0969	0.0147	0.0461
22	0.2127	0.1179	0.2390	0.1642	0.4199	0.0933	0.0153	0.0539
23	0.2503	0.1383	0.2197	0.1806	0.4290	0.1031	0.0201	0.0610
24	0.2371	0.1348	0.2696	0.1698	0.4218	0.1064	0.0000	0.0571

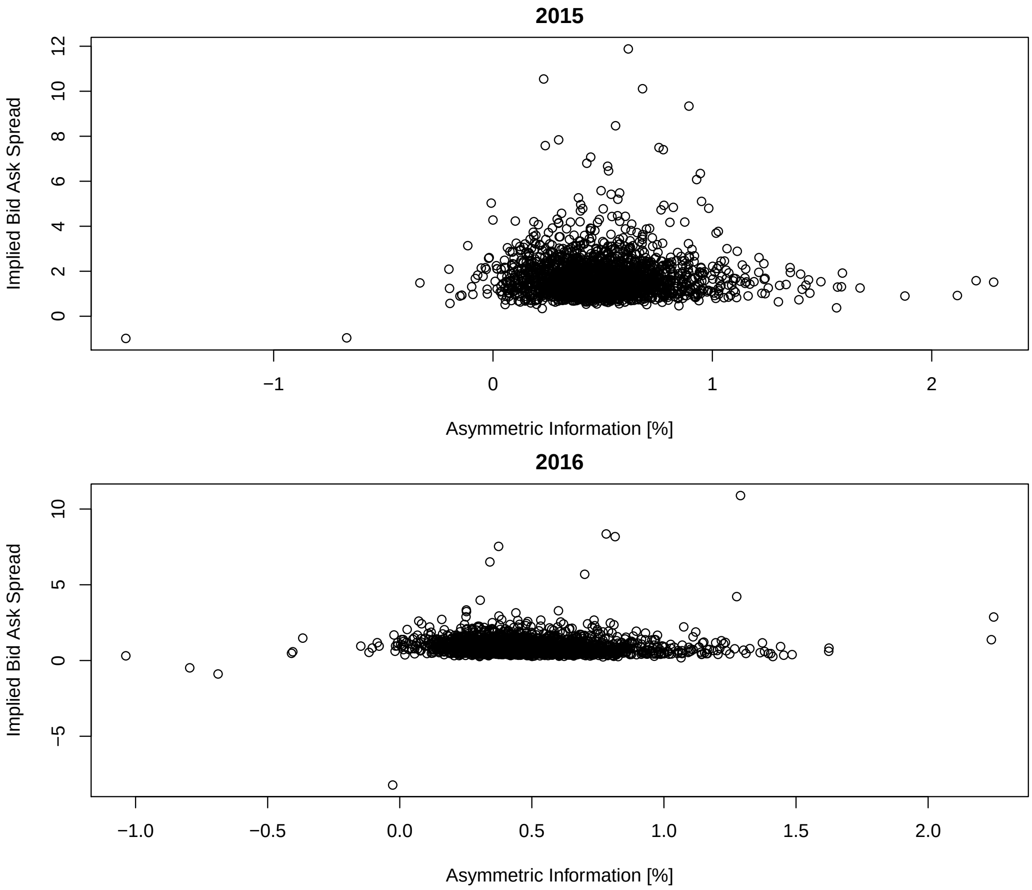

Figure 12: Scatterplot of Implied Bid-Ask-Spread and Share of Asymmetric Information

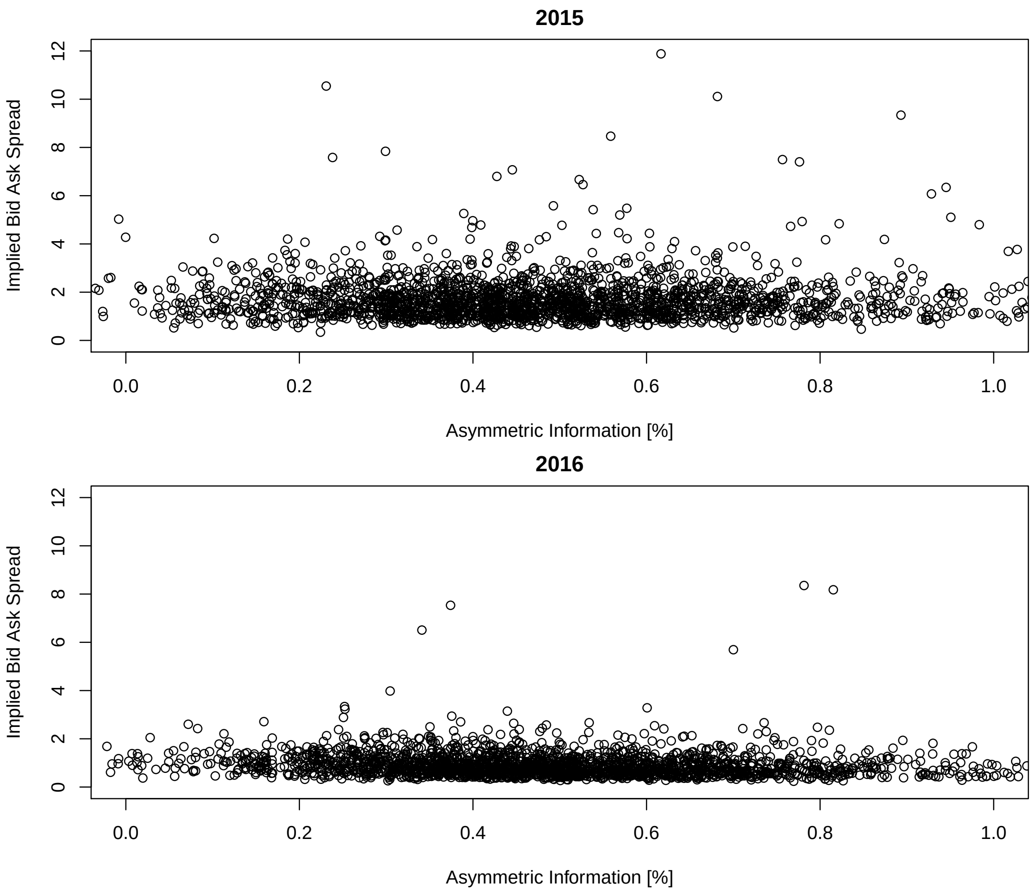

Figure 13: Scatterplot of Implied Bid-Ask-Spread and Share of Asymmetric Information (Bounded Window)

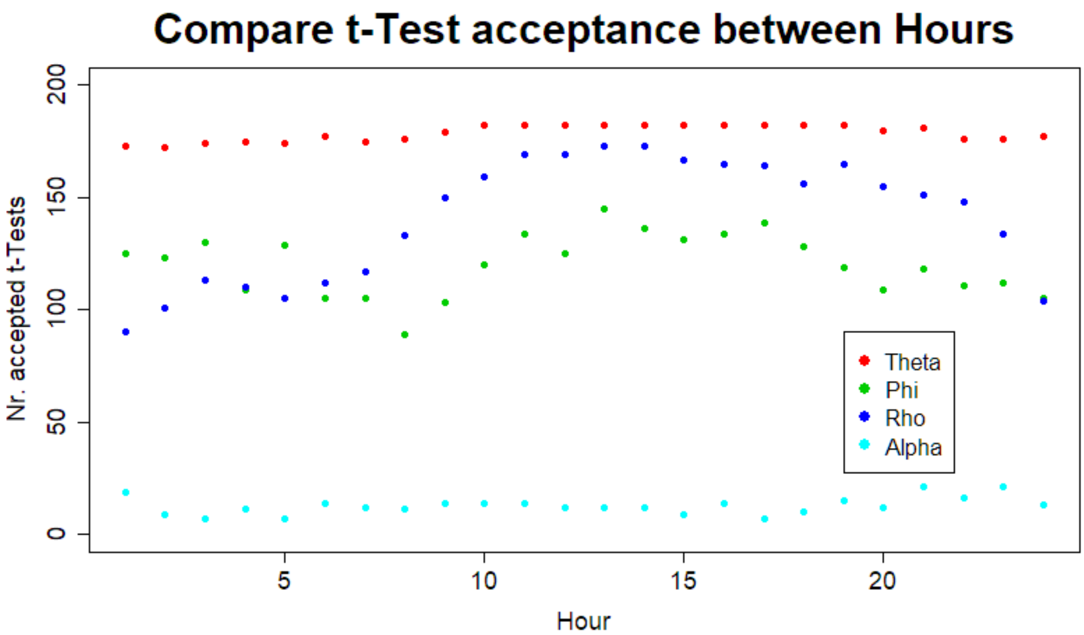

Figure 14: Number of accepted t-Tests over all Hours (Data from Q2 2015 and 2016)

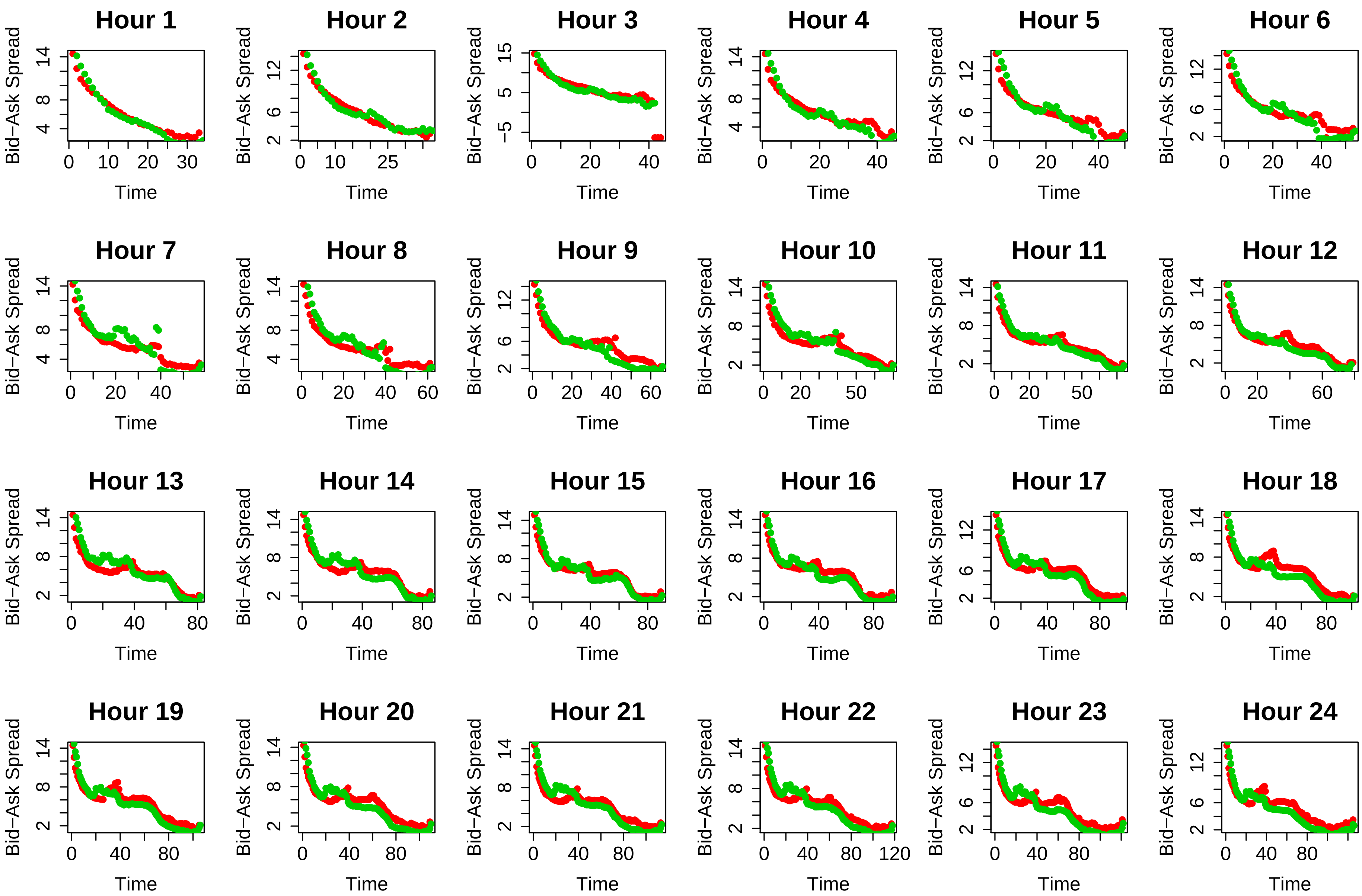

Figure 15: Realised Bid-Ask-Spread for all Hours in Q2 2015/2016 (Red = 2015, Green = 2016)

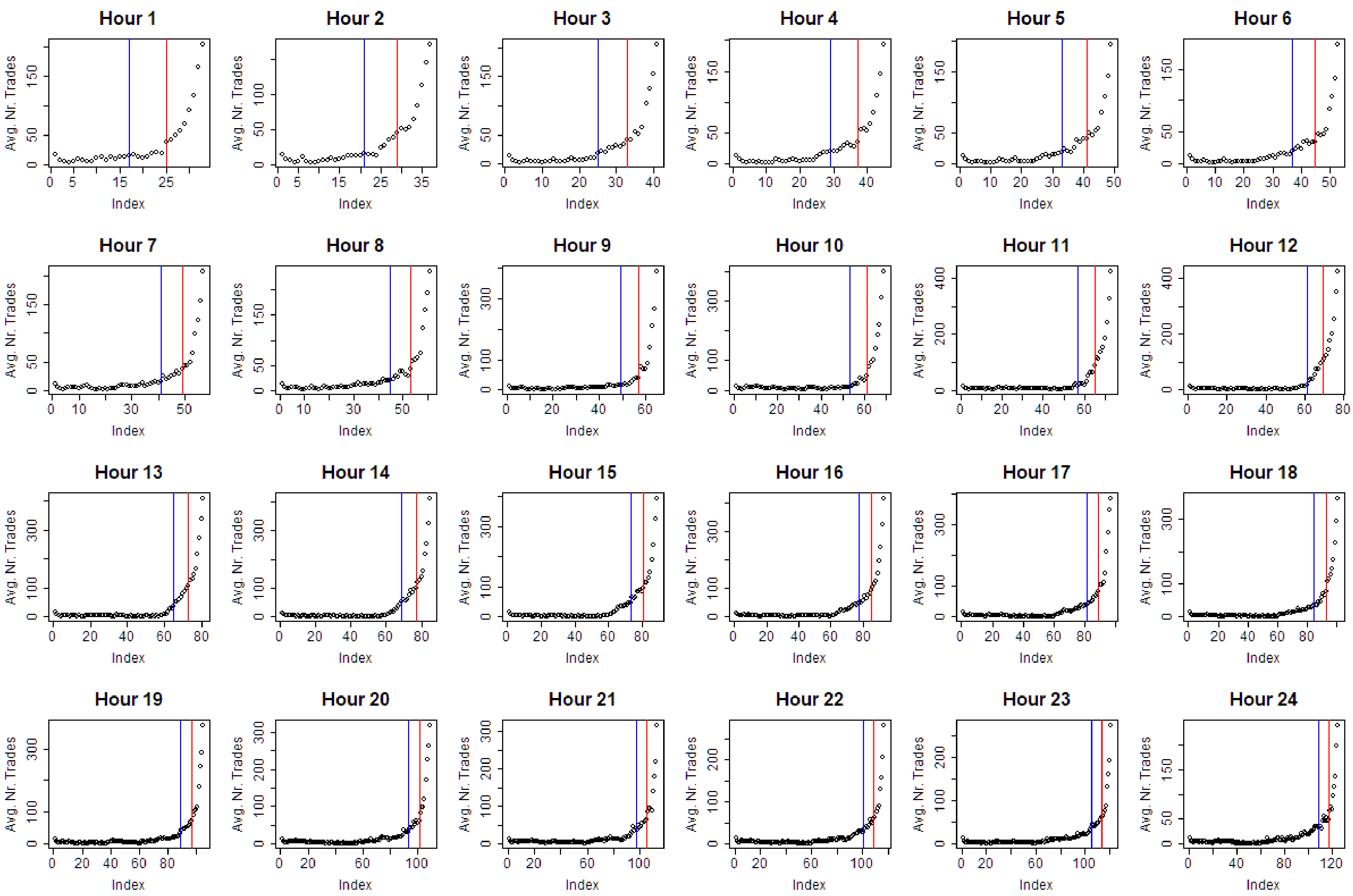

Figure 16: Number of Trades over the Trading Period for all Hours in Q2 2015/2016. The vertical lines indicate the 4th and 2nd Hour before time to Maturity

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