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AN EMPIRICAL ANALYSIS OF THE BID-ASK SPREAD IN THE GERMAN POWER CONTINUOUS MARKET

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Abstract

A large amount of liquidity is decisive for a well-functioning market. In this paper, I determine the main drivers of the bid-ask spread, a measure of liquidity, in the German power market. Based on the order books for hourly contracts, I describe the evolution of the bid-ask spread and the market depths over the trading session. Further, I show the «L-shaped» behavior of the bid-ask spread during the trading session. Using panel econometrics, I find a positive relation between risk and the bid-ask spread as well as a negative relation between the bid-ask spread and the adjustment needs, the activity, and the competition in the market. To my knowledge, this paper is the first to use complete information from the order books for the power market to quantify the liquidity in a market and its evolution.

Keywords: Bid-Ask Spread, Market Depths, Continuous Market, Power Spot Market.

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Disclaimer: The views and opinions expressed in this paper are those of the authors and do not necessarily reflect those of the partners of the CEEM.

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I. INTRODUCTION

Over the past decades, the European power landscape has evolved. The three main components of the power system (generation, transport, and supply) started as a vertically integrated natural monopoly but became organized liberal markets - except for the transport section. In Germany, the Energy Industry Act (1998) unbundled the generation and supply of electricity from the network segment. The German spot power market was created in 2000 by LPX - Leipzig Power Exchange, and is now operated by EPEX SPOT across Europe. The German power market is the most liquid spot market in Europe: traders moved 302 TWh on the market in 2015 which represented 53% of the country's electricity consumption. The continuous intraday market (IDM) accounted for 36.3 TWh the same year and has increased since its creation. The intraday market highlights the growing need for flexibility close to delivery because of the high penetration of renewable power in Germany.

Power trading differs from financial trading because of the duration of the trading session and the properties of the contracts. The power market makes participants maintain a balance that adds complexity to the trading[1]. These aspects make power one of the most volatile markets, even more than the commodities which have the reputation of being highly volatile, like gas and oil. For example, during the second half of 2015, the mean standard deviation in the trading price on the German power market was 3.64 €while the standard deviation in the trading price for the 24-hour gas contract on PowerNext was 3 €/ MWh.

Liquidity is the major component of a well-functioning market. It is important in order to find a counterpart in a minimum amount of time that matches certain requirements (i.e., price, volume). In this paper, I study the liquidity of the German power market through the market depth and the bid-ask spread. The market depth is the volume available at a certain time in the order books. It can be divided into the buy depth and the sell depth. They respectively are the total volume available on the buy and sell sides at one moment in the trading session. The bid-ask spread is the absolute difference between the best ask price (sell side) and the best bid price (buy side). This is the difference in price between the lowest price for which a seller is willing to sell a megawatt hour of electricity and the highest price that a buyer is willing to pay for it. Market participants gain opportunities by exploiting the spread which can be interpreted as a premium for immediate execution. The bid-ask spread is also a transaction cost (Demsetz, 1968); the smaller the bid-ask spread is, the smaller the transaction cost is for traders. Further, the bid-ask spread is the showcase for the liquidity in a market; the level of liquidity is a measure of the quality of a market. Therefore, for the exchanges as well as for the market participants it is of major importance to their decision to participate or not in the market. It can also be considered as an indicator of volatility as there is a positive link between the price fluctuations in a market and the spread.

[1]Electricity can be considered as a commodity because the financial flux is accompanied by a physical one. However, power has some features which make it unique: it is not storable at a large scale and needs to be transported through the grid which should continuously be balanced (i.e., injections = ejections). Traders need to consider the following equation: generation + importation + purchase = sale + consumption + exportation.

The goal of this study is to determine the main drivers of the liquidity from the continuous intraday trading in the German power market. The aim of this paper is to apply the questions on the market microstructure to the power market literature to gain a better understanding of that market from a different perspective. In this paper, I address the question of the market's quality by using the bid-ask spread as a measure. Despite the various similarities between the power market and traditional financial markets, there are some major differences due to the physical aspect of the power market and its characteristics which makes it very interesting to financial researchers. Both the market microstructure and power literatures are dense, but the microstructure one mainly focuses on traditional financial markets such as securities or stocks while the power market literature does not deal much with financial issues. The present paper straddles on those two streams of literature. The study's contribution is twofold. First, I do a dynamic analysis that studies the evolution of the bid-ask spread and the market depth over an average trading session at a granular level (microseconds). Second, I identify the main drivers of the bid-ask spread. To my knowledge, this paper is the first to use not only the trade books but also the complete order books on the continuous intraday trading in the power market at a granular level. Further, I am able to reconstitute the best order streams (best bid, best ask, and market depth) each time a new event occurs in the power market (i.e., new/ modification/ cancellation of an order in the order book). The model could be extended to other power markets with different characteristics.

The study yields three main findings. First, I show the «L-shaped» behavior of the bid-ask spread during a trading session. Second, I find a negative link between the bid-ask spread and liquidity as well as a positive relation between the spread and volatility. Third, I identify four components in the spread: the risk, the adjustment needs, the activity, and the competition in the market. Using panel econometrics, I find a positive relation between the risk and the bid-ask spread as well as a negative relation between the bid-ask spread and the adjustment needs, the activity, and the competition in the market.

The paper is organized as follows: the second section is dedicated to the relevant literature, the third one is an overview of the current spot power market in Germany, the fourth section gives some statistical insights on the bid-ask spread and the market depth in the German intraday power market. The fifth part presents the data and the methodology used. Then, the sixth section displays the empirical results. The last section is the conclusion.

II. RELEVANT LITERATURE

The present paper straddles two streams of literature: the one on the continuously traded electricity market and the one on market microstructure.

While the literature on power markets is dense, the literature on intraday power markets is limited and mainly focuses on two issues: wind generation integration (how to handle forecast errors) and market design. The wind generation literature mainly deals with questions on bidding strategies in the continuous market (Chaves-Avila et al. (2013), Henriot (2014), Kiesel and Paraschiv (2017)) and price formation (Hangemann (2015), Hangemann et al. (2016), Karanfil and Li (2017), Ziel (2017)). Regarding the market design, Borggrefe and Neuhoff (2011) find that the German system does not fully meet the requirements and is not totally efficient, especially in comparison to the nodal pricing system (USA). Hiroux and Saguan (2010) study the impact of different support schemes for wind generation in Europe and the different signals and risks associated with them.

Weber (2010) was the first to address the question on the liquidity in the continuous power market. Weber claimed that the low liquidity might be the cause of a poor market design and/or the absence of a real need for a continuous market. However, those comments have to be balanced as the paper uses data from 2007 when the volume traded on the continuous market was 1.4 TWh - almost 26 times less than the volume traded in 2015. Also, the level of installed wind capacity more than doubled from 2007 to 2015 which increased the need to re-balance close to the delivery time and the importance of the market. Chaves-Avila et al. (2013) explains the low liquidity in the continuous power market as the preference of producers to commit their generation long ahead of time because of ramping-up costs and generation planning. Hangemann and Weber (2013) develop two models to explain the liquidity in the German continuous power market. To the best of my knowledge, the work of Hangemann and Weber (2013) is the first paper to deal with the bid-ask spread in the German continuous power market. However, their work neither uses the order books sent by the market participants or a reconstitution of the order books as input data for their model. Neuhoff et al. (2016) study the impact of an intraday auction before the opening of the continuous market. They find a negative relation between volatility and market depth as well as a positive relation between liquidity and market depth in the 15-minute intraday auction at the EPEX SPOT.

The microstructure can be defined as a branch of finance that deals with the trader's behavior and the market's design. The study of the bid-ask spread is part of the microstructure literature, particularly in the sub-literature on price formation and price discovery.

Demsetz (1968) initiated the literature on the bid-ask spread. Demsetz defined market makers as immediacy providers in which the bid-ask spread is a premium paid by a market participant for immediate execution. The work of Demsetz highlighted the negative relation between the volume and the bid-ask spread also raised in the paper of Copeland and Galai (1983) who developed a model of spread estimation by using the volatility and the level of trading as explanatory variables.

In the theoretical part of the literature, the spread reflects three components: transaction or order processing costs (Roll, 1984), adverse selection costs (Glosten and Milgrom, 1985), and inventory costs (Stoll, 1978). Glosten and Harris (1988) and Kim and Ogden (1996) have used models with both inventory and order processing costs. Glosten (1987) models the role of information asymmetries by separating the effect of order processing from the effect of adverse selection. The models of Stoll (1989) and Huang and Stoll (1997) present an estimation of the bid-ask spread with all three components.

The research has empirically tested these three components of the spread. Schultz (2000) applies the Roll estimator to a data set from the NASDAQ. The adverse selection paradigm was first empirically applied by Glosten and Harris (1988) to the NYSE based on an indicator variable for trade initiation. Madhavan et al. (1997) develop a model (MRR) that decomposes the spread into two components: adverse selection and order process. This model has led to a multitude of papers on different markets such as future exchanges (Chuan Huang, 2004, Ryu, 2011), stock exchanges (Angelidis, and Benos, 2009), and the European climate exchange (Mizrach and Otsubo, 2013). Many studies have found empirical evidence of the inventory cost such as Hasbrouck and Sofianos (1993), Manaster and Mann (1996), and Madhavan and Sofianos (1998). Huang and Stoll (1996) estimate and compare the spreads of the NASDAQ and NYSE from the three elements. Huang and Stoll (1997) quantitatively estimate the impact of the three components and find that order processing represents 61.8%, the average inventory cost 28.7%, and the average adverse-information represents 9.6%. McInish and Wood (1992) empirically estimate the bid-ask spread of the NYSE Stocks with four components: activity, risk, information, and competition based on the previous work of Schwartz (1988).

III. THE INTRADAY POWER MARKET

In power markets, the financial flow should go along with the physical one. On the electricity spot market, the contract unit is the megawatt for a certain amount of time (15 minutes, 30 minutes, 1 hour). Power trading can be divided into two categories: the one occurring bilaterally (Over-the-Counter - OTC) and the one taking place in an exchange. An exchange differs from the OTC because it is an organized marketplace with uniform rules and proposes standardized contracts (Geman, 2005). The trades that occur on an exchange are anonymous and transparent. The German spot power market exists between the long-term market (forwards, futures) and the balancing market operated by the Transmission System Operators (TSOs). The commodity spot trading differs from long-term trading because of the immediate delivery of the product (i.e., electricity, gas, gold, cotton, currencies, etc.) or with a minimum lag (due to technical constraints) between the trade and the delivery (Geman, 2005).

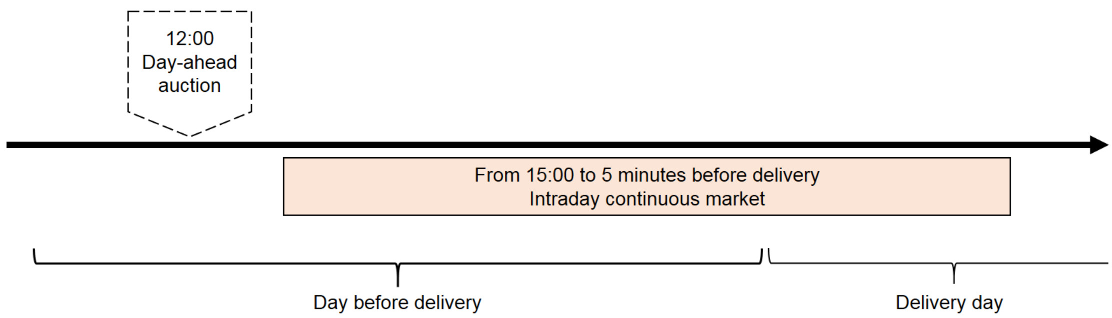

Figure 1: The German spot power market for hourly contracts

The German spot power market is divided into three sub-markets: the day-ahead market (DAM), the 15-minute intraday auction, and the continuous intraday market (IDM). The DAM is a uniform price auction that occurs every day at 12 am. The contracts exchanged on the DAM are hourly contracts (24) for the next day. The intraday period starts right after the DAM. The 15-minute auction is a uniform price auction that occurs every day at 3 pm in Germany. The traded contracts (96) are 15-minute products for the next day. My focus is on the continuous trading of the hourly contract in the intraday market. This market starts at 3pm for the 24 products of the next day and closes 5 minutes before delivery[2]. The duration of the trading session for a contract is between 9 and 32 hours.

The continuous market runs continuously 24 hours a day, 7 days a week, all year long. Thus, a market participant can trade up to 32 hourly contracts at the same time. This market allows participants to re-balance and optimize their portfolios close to delivery[3]. Scharff and Amelin (2016) use three points to justify the need for a intraday market: it reduces unbalanced costs, helps to optimize market participants' production and consumption schedules, and promotes flexibility.

Market participants can submit limit price orders for a given contract to the exchange with a price-quantity at any time during the trading session [4]. The price is the minimum (maximum) price at which they are willing to sell (buy) the associated quantity. The IDM is continuous in its matching procedure[5] where orders are matched when they arrive in the order book if there is a counterpart in the market with whom price and volume requirements match[6]. Orders can either be fully or partially executed if only

[2]For example, the product 2 of the next day (D+1) (ie. hour of electricity between 1am and 2am) will be available for trading from 4pm D until 00:30am D+1; D being a day, D+1 the following day

[3]Trading was progressively possible up to 45 minutes before delivery, then 30 minutes before delivery, and since June 2017 up to 5 minutes before delivery.

[4]Orders can be sent as single orders or within a group of orders. Limit orders can have execution and validity restrictions. Execution restrictions include fill-or-kill (FOK - "either the order is immediately and entirely executed or cancelled in its entirety"), immediate-or-cancel (IOC - "the order is either immediately executed or automatically cancelled; the order can be partially executed and any unexecuted quantity is cancelled"), linked fill-or-kill (LFOK - "linked orders are either all immediately and entirely executed or all cancelled in their entirety"), and all-or-none (AON - "the order is executed completely or not at all"). Validity restrictions include "good for session" ("the order is deleted on the trading end date and time of the contract unless it is matched, deleted, or deactivated beforehand"), "good-till-date" ("the order is deleted on the date and time specified by the exchange member when placing the order unless it is matched, deleted, or deactivated beforehand"), or iceberg ("large order is divided into several smaller orders which are entered in the order book sequentially"). Groups of orders can be of two types: block orders or basket orders. Blocks orders "combine several expiries with a minimum of two contiguous expiries on the same delivery day which depend on each other for their execution». A block order can be predefined or user-defined. In Germany, there are two predefined blocks: base-load that covers hours 1 to 24 and peak load that covers hours 9 to 20 during business days. User-defined block orders are designed by market participants. They can only use the same type of contract to compose their block. The execution restriction AON is applied by default for blocks. Basket orders are a group of orders which allows users to submit a set of orders all at once (max. 100 orders). One basket can contain quarter-hourly as well as hourly and half hourly products. There are three possible constraints: linked ("either all orders are fully executed or none at all"), valid ("all orders must be valid, or all will be rejected"), and none ("treat all orders in basket as separate orders"). The tool that I use does not take into account block orders as they have a different order book than the hourly products.

[5]Orders sent to the market are processed one at the time - serial processing, in general within milliseconds.

[6]A market participant is called the initiator of the trade if he or she submits a new order in the order

part of the match is possible. An order is executed at or above (under) the specified price for a seller (buyer), and there is no market price as each transaction that occurs on the IDM has a different price (pay-as-bid principle). If there is no possibility of a match, then the order remains in the order book. The orders are listed by price in the order book: increasing orders price on the sell side and decreasing orders price on the buy side. Members can also withdraw or modify their orders during the trading session.

The process that I have presented represents local (within a country) order books only; however, countries in Central Western Europe (CWE) are interconnected. Under the capacity constraint on a border, the capacity available will allow the best orders from the source country with a maximum volume of the capacity constraint to be visible in the order book of the sink country and vice versa[7]. The capacity is implicitly given and not priced in this market. The order book does not display if the orders are local or cross-border.

	Min	Quantile 1	Median	Mean	Quantile 3	Max
Price (€/ MWh)	-75,71	26,15	32,95	33,1	41,41	132,23
Number of trades	14	169	247	267,5	345	907
Number of orders	109	599	945	1072	1373	6724
Active members on both side	29	43	51	50,95	59	77

Table 1: Descriptive statistics of the continuous market, per contract

Table 1 shows some descriptive statistics for trades on the German contiunous market from the 1st of June, 2015, to the 15th of November, 2015. The mean daily price was 33.1 €/ MWh. The mean daily number of trades per contract was 267.5 trades while the mean daily number of orders per contract was 1,072 which means that on average, a member needed to send four orders to be executed as one trade. There was on average 51 active members in the market which represents around a quarter of the members of the market.

IV. BID-ASK SPREAD AND MARKET DEPTH OVER THE TRADING SESSION

This section first provides the data for the bid-ask spread and the market depth in the German power market. Then, I examine the behavior of these two variables over an average trading session. The data used for this dynamic analysis is fine-grained (milliseconds of the trading session).

book and is called an aggressor when he or she hits the price of an existing order in the order book.

[7]For example, the interconnection capacity available at time t for a specific product p is 20 MWh from Germany to France; so at that time, a volume of 20 MWh of the best sell orders from the German order book will be displayed on the French order book for product p. Simultaneously, a volume of 20 MWh of the best buy orders from the French order book will be visible on the German order book for the concerned contract.

4.1. Data

The gross orders book contains only the German local orders and does not account for cross-border or block orders. It covers a period of five and a half months from the 1st of June 2015 to mid-November 2015. Each line of the data set displays an order that a market participant sent to the power exchange during the continuous trading session (complete order books). It includes a range of variables such as the delivery date; the delivery instrument (specific hour, half hour, or quarter hour); the name of the member who sent the order, the side of the order (buy or sell); the day and time when the order was sent; and the day and time when the order was executed, cancelled, deactivated, expired, or modified the couple price-quantity of the member set. The gross order book serves as input for the reconstitution tool that was developed by the Product and Market Development team of EPEX SPOT by using the software R. I compute the best order stream (best bid and ask prices) and the market depth each time there is a change in the order book during the trading session. The R code sorts market orders and creates a row each time there is a change in the order book that affects the bid-ask spread and/ or the market depth. Each line of the output displays the particular contract and the associated delivery date, the date and time of trading, the best buy (highest) and sell (lowest) prices at that time, the respective quantities - it can be the sum of two orders or more at the best price. The last information the output shows is the buy and the sell depths. The tool displays the first line of the order book and the market depths for both the buy and sell sides, which can be seen by the market participants at the time they trade. Using the output of the reconstitution tool, I compute the bid-ask spread at each moment of the trading session:

$$BidAskSpread_{it'} = BestAskPrice_{it'} - BestBidPrice_{it'} \tag{1}$$

where t′ is a vector of three dimensions composed of a delivery day, a trading day, and a trading time; and i is the product that equals to 1 to 24.

4.2. Descriptive statistics

Table 2 presents the descriptive statistics for the bid-ask spread and the market depths at the millisecond level. Over the period, the mean bid-ask spread is 3.08 €/ MWh which is similar to the mean bid-ask spread of 2.97 €/ MWh 75% found by Hagemann and Weber (2013) . The mean is 300 times the tick size (0.01€/MWh) which is much bigger than the spread in the securities market which is only a few times the tick size; nonetheless it is smaller than the spread in the French intraday power market where the average bid-ask spread is about 1,100 times the tick size in 2015 for local order books. Both of those values are overestimated due to the absence of cross-border orders in my data set. If I add cross-border data, then the spread would be lower as an order from a neighboring country would only be displayed in the output data (i.e., first line of the order book that displays the best bid and ask at every moment of time) of the country. The average bid-ask spread is higher during the weekend (+ 13%) because of the decrease in the load as well as the decrease in the number of participants. There is no significant pattern regarding the average bid-ask spread per contract. The distribution of the bid-ask spread is uni-modal and asymmetric[8]. At the millisecond granularity, the multiple of bid-ask spread is over-represented by 0.05 €/ MWh. This observation highlights the use of the 5 cent price steps by the members[9].

	Quantile 1	Median	Mean	Quantile 3
Bid-ask spread (€/ MWh)	1.35	2.29	3.08	3.86
Buy depth (MWh)	1151	1 649	2 106	2 344
Sell depth (MWh)	996	1 390	1 712	1 935

Table 2: Descriptive statistics of the bid-ask spread and the market depths

In the subset where the bid-ask spread is above 4 €/ MWh, lower depths exist (respectively -17% and -21% of the mean buy and sell depths) which is consistent with the negative correlation between the bid-ask spread and the depths found in the descriptive statistics section. Off-peak products (before 8 am or after 8 pm) and weekends are over-represented in the subset. This result is reasonable because during off-peak hours, the liquidity and the number of active participants are lower, which is also valid for weekends. Regarding renewable production, I find lower solar production, which is consistent with a strong representation of off-peak hours without solar production, and no specific change in wind production. From the observed subset, I also find a higher sell price (+8,5% on average) and a lower buy price (-2% on average).

Over the period, the buy and sell depths are respectively 2 106 and 1 712 MWh on average per contract and 25% of the time they are respectively above 2 344 and 1 935 MWh. The same argument on a lack of the cross-border data applies to the market depths which are underestimated - market depths can only be higher than the result as cross-border orders would only increase the volume in the orders book. The mean depths are higher for baseload contracts (8 to 20): above 2 500 MWh on average for the sell depth and 3 000 MWh for the buy depth. The distributions of the depths are uni-modal[10] with a peak between 700 and 800 MWh. During those peaks, I observe a higher bid-ask spread compared to the whole data set (higher by 57% for the buy depth and by 58% for the sell depth).

At milliseconds, the correlations between the bid-ask spread and the market depths are weak (-0.16 with the buy depth and -0.11 with the sell depth). However, at the minute level (average spread and depths per minute), the correlation is higher from contract 1 to contract 11, particularly for the morning hours, with an average correlation of -0.66 for those contracts. These correlations are negative which is reasonable and consistent with the literature. I can also observe this negativity by looking at the evolution of the depths and the bid-ask spread over an average trading session[11]. At the hourly level (average bid-ask spread and depths per hour), the correlation between the bid-ask spread and the depths are high: -0.83 with the buy depth and -0.86 with the sell depth.

[8]See Figure 7 in the appendices

[9]In the period studied, the tick size of the IDM was 0.01 €/ MWh and has been 0.10 €/ MWh since June 2016.

[10]See Figures 8 and 9 in the appendices

[11]See Figures 2 and 3 in subsection 4.3

4.3. Dynamic analysis

This subsection describes the evolution of the bid-ask spread and the market depths over an average trading session.

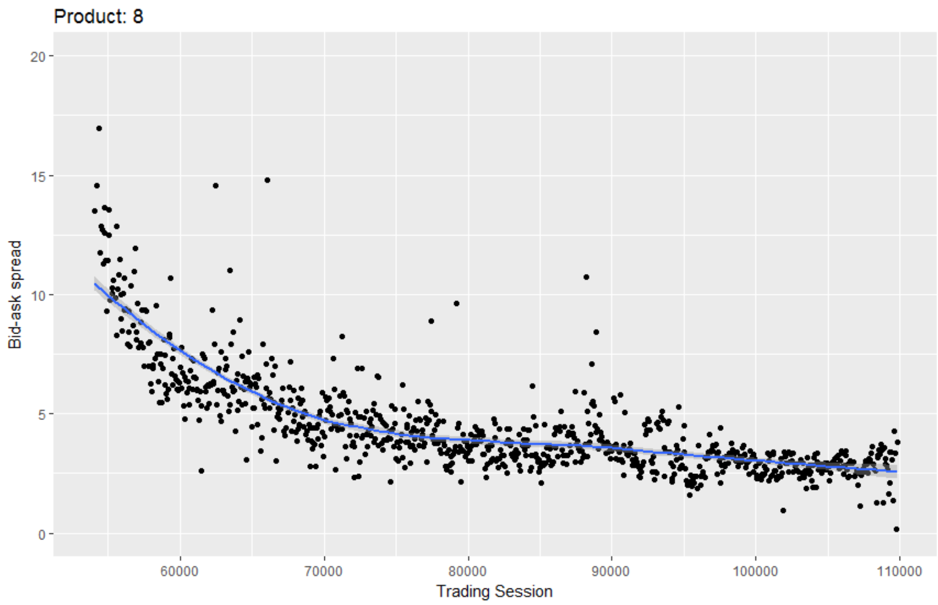

Figure 2: L-shape of the bid-ask spread over an average trading session (seconds) for product 8

Figure 2 represents the evolution of the bid-ask spread (unit: euro/ MWh) over an average trading session (unit: second) for product 8 (an hour of power from 7 am to 8 am)[12]. The bid-ask spread decreases over the trading session no matter what contract is traded. This decrease might be because of the strong uncertainty away from the delivery time. During the last three hours in which the contract can be traded, I observe the lowest values of the bid-ask spread. As the contract gets closer to the delivery time, the uncertainty linked to the production decreases and so does the spread. The volume traded on the continuous market increases over time and 80% of the volume is traded during the last three hours of the trading session[13]. The continuous market is mainly used to adjust positions previously taken close to the real time due to the arrival of new information such as the weather forecast, renewable production, or outages. The longer the trading session is (from seven and a half hours for contracts 1 to 32 to a half hour for contract 24), the smoother the curve of the bid-ask spread is over time. At the end of the trading session, the spread increases a bit due to the decrease in the volume of the orders book. The "L-shape" is consistent with the financial literature on microstructure but it is not straightforward due to the difference between financial and power markets, especially with the existence of a maturity in electricity contracts.

[12]See Figure 10 in the appendices to see the evolution of the spread over an average trading session for products 5 (from 4 am to 5 am), 9 (from 8 am to 9 am), 13 (from 12 am to 1 pm), 17 (from 4 pm to 5 pm) ,and 21 (from 8 pm to 9 pm). These contracts are different as the hours concerned have different profiles. For example, during contract 5, the demand for power is low and there is no solar generation. In contrast, product 13 represents the hour where solar production is the highest and the demand is high. Product 9 represents a peak hour where the demand is the highest.

[13]See Figure 14 in the appendices

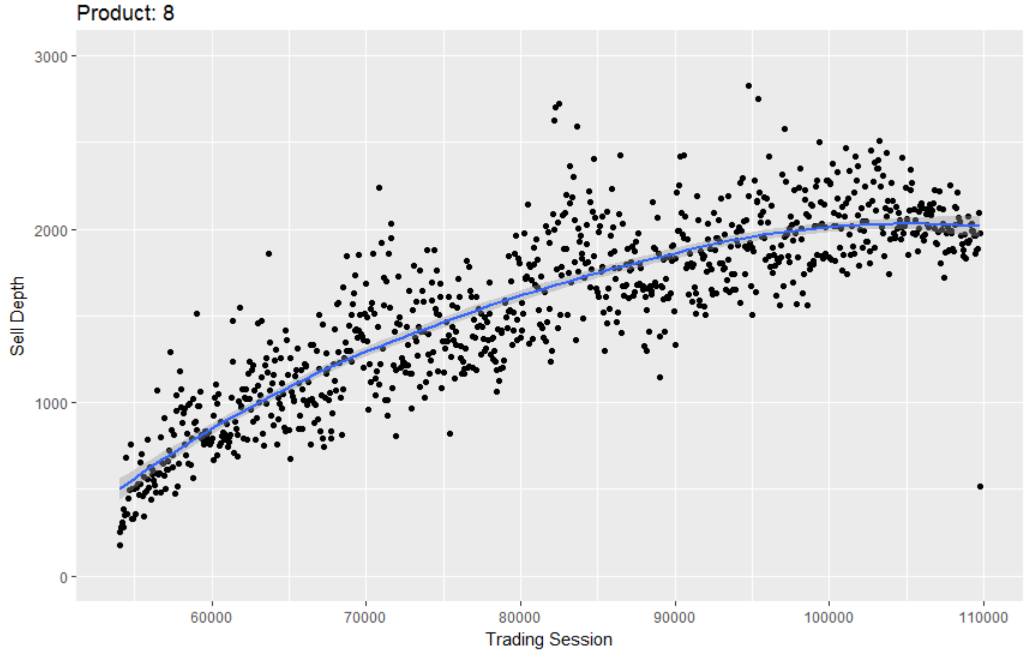

Figure 3: Mean buy depth over an average trading session (seconds) for product 8

Figure 3 shows the evolution of the buy depth over an average trading session for product 8[14]. The buy and the sell depths are similar over the trading session but with a reverse shape compared to the bid-ask spread. The correlation between the two depths is high: 0.95 milliseconds. As the contract gets closer to the delivery time, more and more quantities are added to the order books. The highest liquidity during the trading session occurs at the end. The reasoning behind this result is the increase in the need for trading because of new information as well as the need to balance the increases. More liquidity means there are more opportunities for matching, which is consistent with the fact that 80% of the trading volume is traded in the last three hours before delivery. At the opening of the trading session, market depths are around 500 MWh no matter what product is traded. For off-peak products, the average buy and sell depths are respectively 2 687 MWh and 2 241 MWh while for peak products, the average depths are respectively 3 345 MWh and 2 788 MWh. The market depths tend to increase to a lower level for off-peak products (before 8 am and after 8 pm) due to the lower economic activity in those hours. At the end of most trading sessions, I observe a decrease in the market depths 30 minutes before the gate closes due to the decrease in market opportunities as cross-border trading closes an hour before delivery. This decrease could be because the traditional producers want to fix their production at least an hour before delivery for operational purposes but also due to the large inflexibility of some power plants.

V. METHODOLOGY AND RESULTS

In this section, I present the data sets that I use as input for the econometrics model as well as the method behind the model.

[14]See Figure 12 in the appendices to see the buy depth of the contracts 2, 9, 13, 17, and 21

5.1. Datasets

From the outcome of the reconstitution tool, I compute the mean bid-ask per day (BAS_{it}) with t as a delivery day and i as the product concerned.

I use the realized wind and solar generation[15] (WG_{it} and SG_{it}) as well as the solar and wind generation forecasts (WF_{it} and SF_{it})[16]. In order to assess the impact of the forecast errors, I subtract the wind (solar) forecast from the wind (solar) generation by considering the difference between the forecast 30 minutes before delivery (gate closure) and the generation negligible. The relative forecast errors are expressed in percentage of variation. The forecast errors represent an exogenous shock on the market and therefore a need for market participants to adjust their position in order to be balanced before the gate closes. The relative forecast errors are defined as:

$$\Delta_{it}^{W} = \frac{WG_{it} - WF_{it}}{WF_{it}} \tag{2}$$

$$\Delta_{it}^{S} = \frac{SG_{it} - SF_{it}}{SF_{it}} \tag{3}$$

Inspired by Ziel (2017), I split the above equations depending on the algebraic sign of the shock. A positive shock is defined as:

$$\Delta_{it}^{W+} = max\{\Delta_{it}^{W}, 0\} \tag{4}$$

$$\Delta_{it}^{S+} = max\{\Delta_{it}^{S}, 0\} \tag{5}$$

and a negative shock is defined as:

$$\Delta_{it}^{W-} = max\{-\Delta_{it}^{W}, 0\} \tag{6}$$

$$\Delta_{it}^{S-} = max\{-\Delta_{it}^{S}, 0\} \tag{7}$$

I create a binary variable for the weekend (1_t^{wkd}) that equals zero if the delivery day is a business day (Monday to Friday) and one if the delivery day is a weekend day (Saturday, Sunday). The load (L_{it}) is expressed in gigawatt hours[17]. The load captures the difference in activity between peak and off-peak periods. The number of active members (AM_{it}) is calculated as the number of active participants on the market on both sides using the order book. A market participant is active if it puts at least one order on the product for a specific delivery day, regardless of whether that order is a buy or a sell. If a market participant sends an order to each side, it is counted as just one. This variable is new to the power literature as this information can only be extracted from the order book.

[15]Source: EEX

[16]Source: EuroWind. The chosen forecast is issued at 2 pm (”PREV4”) the day before delivery as it is after the DAM and before the beginning of the intraday market.

[17]Source: EEX transparency platform

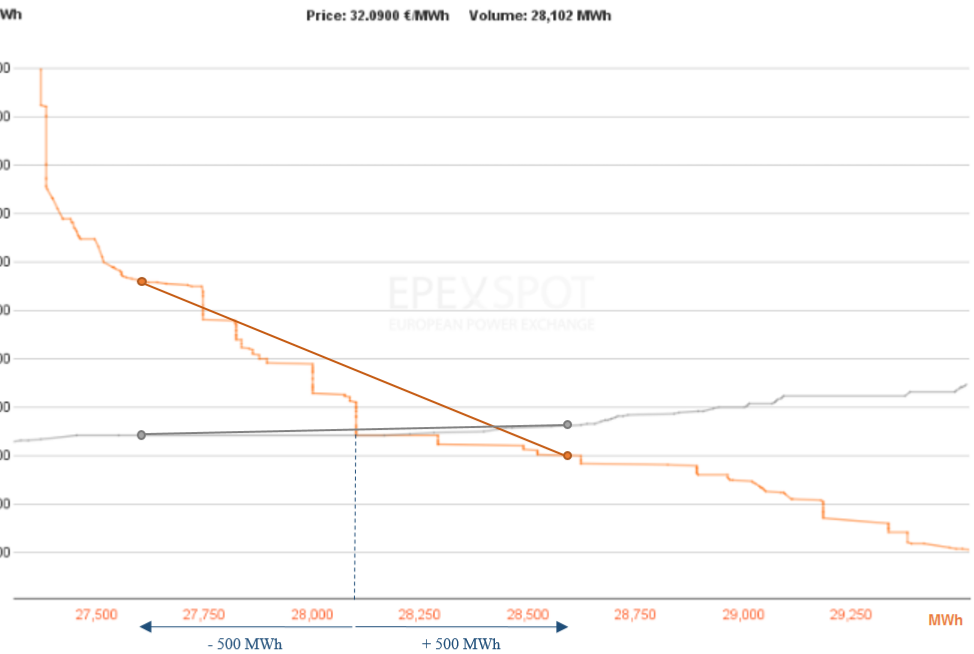

Figure 4: Example of aggregated curves of the DAM (25/10/2015 - product 9)

The elasticity variables ES_{it} and EB_{it} are calculated by using the aggregate curves of the German DAM[18]. They both represent an approximation of the elasticities around the equilibrium. The ES_{it} (respectively EB_{it}) is computed as the slope of a linear interpolation of the supply (respectively demand) curve between the two points corresponding to the equilibrium volume (Q*) of the auction plus or minus 500 MWh. Figure 4 illustrates the concept of the calculation with the example of the 25th of October 2015 for product 9. To the best of my knowledge, this is the first time that the elasticities of the demand and the supply curves for power have been calculated. I compute the slope as follows:

$$ES_{it} = \left|\frac{[Q^* - 500] - [Q^* + 500]}{p^s(Q^* - 500) - p^s(Q^* + 500)}\right| \tag{8}$$

$$EB_{it} = \left|\frac{[Q^* - 500] - [Q^* + 500]}{p^d(Q^* - 500) - p^d(Q^* + 500)}\right| \tag{9}$$

where p^s is the supply price, and p^d is the demand price at the points (Q*-500) and (Q*+500). The unit for these variables is the euro per megawatt hour. It represents the average price variation around the equilibrium that corresponds to a quantity variation of 1 MWh.

The price's standard deviation that is weighted by the volume measures its volatility in the trades on the intraday market. The volatility captures the price variation in a

[18] Source: EPEX SPOT.

contract during a trading session.

$$\sigma_p = \sqrt{\frac{\sum_{i=1}^{N} v_i (p_i - \bar{p}*)^2}{\frac{M-1}{M} \sum_{i=1}^{N} v_i}} \tag{10}$$

where

$$\bar{p}* = \frac{\sum_{i=1}^{N} v_i p_i}{\sum_{i=1}^{N} v_i} \tag{11}$$

The N is the number of observations, M the number of nonzero weights, v_i the volume (weight), p_i the price of the transaction, and $\bar{p}$* is the weighted mean of the price.

Table 3 gives the descriptive statistics of the variables in the model. The data are at the contract level (one value per day and contract) as in the regression. The average bid-ask spread per contract is 3.11€/MWh which is about 10% of the weighted average price (WAP) for the same period. The mean buy (resp. sell) depth is 2.55 GWh (resp. 2.19 GWh) per contract which represents 4.75% (resp. 4.08%) of the average load for a contract. This load means that at some point in the trading session, there is the possibility to buy or sell a maximum of 4-5% of the average hourly German energy consumption (load). The mean weighted standard deviation of the price is 3.8€/ MWh which means that the price variation within a trading session is 11.5% of the mean WAP. The mean slopes of the buy and sell curves of the DAM are equal to 0.01, which highlights the important elasticity of the curves around the equilibrium. The descriptive statistics of the forecast errors should be viewed skeptically as the positive and the negative forecast errors are complements: when one is positive, the other one equals zero. After removing the value of zero, I find a median positive (resp. negative) forecast error for solar of 20.5% (17.8%). The mean positive (resp. negative) forecast error for wind is equal to 31.06% (resp. 14.61%). On average, there are 51 active members in a contract which is about a quarter of the total number of members in Germany.

	Mean	Standard deviation	Min	Q1	Median	Q3	Max	Skewness	Kurtosis	N
Bid-ask spread (€/MWh)	3.11	1.25	1.039	2.32	2.851	3.62	21.24	3.16	25.72	3 712
Buy depth (MWh)	2 551.43	1 758.51	299.283	1 489.5	1 885.680	2 860.8	15 905.43	2.01	4.99	3 712
Sell depth (MWh)	2 187.60	1 421.29	420.983	1 331.0	1 688.282	2 379.0	13 226.10	1.93	4.48	3 712
Price std. deviation (€/MWh)	3.80	3.22	0.60	2.26	3.14	4.42	104.45	11.82	299.24	3 712
Dummy for week-end	0.27	0.45	0.000	0.000	0.000	1.00	1.00	1.02	-0.96	3 712
Slope of the buy curve of the DAM	0.01	0.01	0.003	0.000	0.005	0.01	0.46	16.52	435.52	3 712
Slope of the sell curve of the DAM	0.01	0.01	0.004	0.000	0.006	0.01	0.16	9.23	151.63	3 712
Load (GWh)	53.69	9.68	32.977	45.240	53.509	62.74	72.68	-0.07	-1.29	3 712
Positive forecast error for solar (%)	12.53	22 794.83	0.000	0.000	0.000	4.66	492.6	6.16	44.51	3 556
Negative forecast error for solar (%)	5.91	13.86	0.000	0.000	0.000	0.68	85.32	2.78	7.57	3 712
Positive forecast error for wind (%)	20.70	33.86	0.000	0.000	9.173	28.12	379.40	3.90	23.99	3 712
Negative forecast error for wind (%)	4.87	9.91	0.000	0.000	0.000	4.91	78.51	2.54	6.98	3 712
Number of active members	51.45	9.66	24.000	43.00	51.000	59.00	77.00	0.06	-0.93	3 712

Table 3: Descriptive statistics of the variables (contract level)

5.2. Methodology

This subsection describes the econometrics specification I use to explain the average bid-ask spread per contract[19] (one value per trading session so 24 values per delivery day).

Due to the configuration of the data set, the panel data econometrics are the most appropriate method as our data combine information on individuals' behaviors (contracts) and over time (delivery date). Contracts are independent as each of them are traded individually by the market participants. They also have their own specificities. For example, some contracts face a larger load or solar generation while some others do not. I also test for fixed effects with a F-test, and the fixed model is appropriated. The bid-ask spread can be interpreted as an additional transaction cost. It reflects price uncertainty as well as the liquidity in the order books and therefore the market's quality. I verify the hypothesis below with the panel data econometrics.

Hypothesis 1: There is a positive relation between the bid-ask spread and the risk and volatility in the market.

- The slopes of the demand and the supply curves around the equilibrium point can be interpreted as their elasticities: when the elasticity on one side of the market increases (slope tends to zero), the bid-ask spread decreases. When the inelasticity increases (slope tends to infinity), market participants are more sensitive to price variation: a small change in quantity means a strong change in prices which increases the volatility in the market and therefore the bid-ask spread.
- When the price's standard deviation that is weighted by the volume increases, the volatility on the market increases. The standard deviation is the most straightforward measure of volatility.

Hypothesis 2: There is a negative relation between the bid-ask spread and the need for adjustment. When the forecast error of the wind and the solar generation (absolute difference between the forecast and the production) increases, I expect the bid-ask spread to decrease. Thus, the positions of some market participants will change, and they will need to balance those positions that therefore increases the volume in the market.

Hypothesis 3: There is a negative relation between the bid-ask spread and the activity on the market. I expect that when the activity on the market increases, the bid-ask spread decreases. Indeed, when the delivery date is a business day or when the value of the load is high, the volume available on the market increases (higher liquidity) and therefore the bid-ask spread is narrower.

Hypothesis 4: There is a negative relation between the bid-ask spread and the competition in the market. When the number of market participants in the market increases, the bid-ask spread should decrease. This decrease occurs because an increasing number of counterparts could reduce the range between the best ask price and the best sell price.

As a result of a F-test, a Hausman test, and a Lagrange multiplier test, I compare the

[19]This aggregation is mainly due to the difficulty in getting some data at a lower granularity

different models and estimators possible for panel data. The fixed effect model is the most appropriate[20]. I choose a general feasible generalized least squares models (FGLS) estimation as it «allows the error co-variance structure inside every group of observations to be fully unrestricted and is therefore robust against any type of intragroup heteroskedasticity and serial correlation» (Croissant and Millo, 2008).

To explain the daily average bid-ask spread per contract as a function of the liquidity and the volatility, the estimated equation is:

$$\begin{aligned} BidAskSpread_{it} = \alpha_i + \beta_1 1_t^{wkd} + \beta_2 L_{it} + \beta_3 AM_{it} + \beta_4 \Delta_{it}^{W+} + \beta_5 \Delta_{it}^{S+} \\ + \beta_6 \Delta_{it}^{W-} + \beta_7 \Delta_{it}^{S-} + \beta_8 PriceSD_{it} + \beta_9 ES_{it} + \beta_{10} EP_{it} + u_{it} \end{aligned} \tag{12}$$

Notation	Definition
1_t^{wkd}	Dummy for week-ends
L_{it}	Load
AM_{it}	Number of active members
Δ_{it}^{W+}	Positive wind forecast error
Δ_{it}^{W-}	Negative wind forecast error
Δ_{it}^{S+}	Positive solar forecast error
Δ_{it}^{S-}	Negative solar forecast error
$PriceSD_{it}$	Weighted price standard deviation of the trades
EB_{it}	Elasticity (buy side)
ES_{it}	Elasticity (sell side)

The seasonality variable is not included in the model as the power load is correlated to the seasonality. The same argument also applies to the temperature.

5.3. Results

This section describes and discusses the results of the panel data model.

Table 4 displays the results of the regression of the bid-ask spread, first, with the whole data set then split into off-peak and on-peak contracts[21]. All the variables are significant at the 1% level when using the FGLS estimator for the overall data set. When the delivery day is on a weekend, the spread is higher by about 15.5 cents per MWh as compared to when the delivery day is a business day. This is linked to the lower economic activity on the weekends. The impact is stronger for off-peak than for on-peak contracts. When the load increases, the bid-ask spread tends to diminish which can be

[20]With fixed effects models, «within» or the first difference estimator can be used. In my test, the «within» estimator is the most appropriate for the data. I estimate the equation with an ordinary least squares (OLS) and general feasible generalized least squares models (FGLS). The Breusch-Pagan test detects the heteroskedasticity in the model. It can cause bias in the results of the standard deviations in the variables estimations that use an OLS estimator. The Breusch-Godfrey/ Wooldridge test identifies serial correlation in the panel model. I test the stationarity of the variables using the Dickey-Fuller test and find that all the variables are stationary.

[21]On-peak contracts are from 8 to 20 (included) and off-peak contracts are between midnight and 7 and from 21 to 24.

	All		On-peak		Off-peak	
Week-end dummy	0,1549	***	0,1464	*	0,1262	**
	(0,0036)		(0,0613)		(0,0447)	
Load	-0,0172	***	-0,0210	***	-0,0246	***
	(0,0004)		(0,0043)		(0,0067)	
Number of active members	-0,0179	***	-0,0112	***	-0,0273	***
	(0,0001)		(0,0017)		(0,0052)	
Elasticity of the sell curve	12,1723	***	7,2667	***	27,8145	***
	(0,2226)		(1,6166)		(5,3565)	
Elasticity of the buy curve	2,0652	***	-0,7383		8,1726	***
	(0,0418)		(2,1828)		(1,3952)	
Negative wind forecast error	-0,0062	***	-0,0062	***	-0,0001	
	(0,0001)		(0,0012)		(0,0078)	
Positive wind forecast error	-0,0019	***	-0,0033	***	-0,0008	
	(0,0000)		(0,0005)		(0,0005)	
Negative solar forecast error	-0,0016	***	-0,0045	***	0,0042	**
	(0,0000)		(0,0009)		(0,0013)	
Positive solar forecast error	0,0000		0,0000		0,0000	***
	(0,0000)		(0,0000)		(0,0000)	
Weighted price std. deviation	0,2659	***	0,2655	***	0,2638	***
	(0,0003)		(0,0062)		(0,0130)	
R2	0,4627		0,6102		0,3451	

Table 4: Results of the regressions of the bid-ask spread

explained by the increasing demand and therefore a greater need to trade. Each additional active member on the market contributes to a decrease in the spread of about 2 cents per MWh. The number of active members is linked to the activity on the market, and it is reasonable that a higher participation in the market, increases competition and thus liquidity.

An increase in the slopes (inelasticity) of the supply and the demand curves of the DAM increases the bid-spread. The higher the inelasticity (slope tends to infinity) is, the greater the volatility in the market is. As the buy or the sell aggregated curves get more inelastic, the price is more sensitive to a change in quantities; a small change in the quantity leads to an important change in prices. The slope of the supply curve has a stronger effect on the bid-ask spread than the slope of the demand curve by more than six times. When the slope of the supply curve increases by 0.1, the bid-ask spread increases by 1.22 €/MWh while an increase in the slope of the demand curve by 0.1 increases the spread by only 21 cents per MWh. The slope of the curves and so the risk has a stronger impact during the off-peak period (by more than ten times for the slope of the demand curve and by four times for the slope of the supply curve). The slope of the demand curve is not significant for on-peak contracts. Not surprisingly, when the volatility (weighted price standard deviation) increases, the bid-ask spread get wider. This variable alone explains a large part of the variance in the model, and an increase in the volatility by 1€/ MWh tends to increase the spread by 27 cents per MWh. The risk and volatility in the market increases the bid-ask spread.

The relative variation (positive or negative) in the wind or solar forecast error during the trading session has a negative impact on the bid-ask spread. First, seen as a volatility variable, the forecast error has more impact on liquidity than volatility (positive sign of the coefficients). The uncertainty linked to the forecast errors brings additional volatility to the market but at the same time, a forecast error creates a need to trade and therefore an increase in the volume. The negative wind forecast errors have more impact on the bid-ask spread than a positive forecast error by about four times. An increase of 1% of positive (negative) wind forecast error decreases the spread by 2 cents per MWh (6 cents per MWh). An increase of 1% for a negative solar forecast error decreases the spread by 2 cents per MWh in general or 4 cents per MWh during on-peak contracts. This is reasonable as the sun rises during on-peak hours. The positive solar forecast error that impacts the bid-ask spread is not significant. This lack of significance might be due to some outliers in the forecasted solar production (some values in the dataset are strongly underestimated). The wind forecast errors have more influence on the spread than the solar forecast errors. The re-balancing needs decrease the bid-ask spread by bringing more liquidity to the market.

This paper finds a positive relation between the volatility and the bid-ask spread and a negative relation between the bid-ask spread and the adjustment needs, the activity, and the competition in the market in line with the hypothesis formulated in the methodology.

VI. CONCLUSION

I might have thought that the differences between the financial and the power market would lead to different results. However, I find a negative link between the bid-ask spread and the liquidity as well as a positive relation between the spread and the volatility, which is in line with the financial literature. Further, I observe a similar shape in the bid-ask spread over an average trading session in the power and the financial (McInnish and Wood, 1992) markets. Thus, I show the "L-shaped" behavior of the bid-ask spread over the trading session. I observe a strong dispersion of the bid-ask spread on the German intraday market at the beginning of the trading session which then diminishes as the delivery time approaches. The dispersion highlights the uncertainty away from the delivery time mainly due to the intermittent renewable generation. The reverse shape applies for the market depths, and increases over the trading session.

The characteristics of the power market in comparison with the financial markets create different variables, such as the forecast errors or the load, to explain the bid-ask spread. To the best of my knowledge, this study is the first one to use the elasticities of the demand and the supply curves from an auction as an explanatory variable of the spread. I also explain the spread with four components: the risk (elasticity of the aggregate curves of the DAM, weighted price standard deviation), the adjustment needs (wind and solar forecast errors), the activity (load, dummy on weekends) and the competition in the market (number of active members). I find a positive relation between the risk and the bid-ask spread and a negative relation between the bid-ask spread and the adjustment needs, the activity, and the competition in the market.

Further work might include an extension of the model to other intraday power markets. The model can also be enriched by including cross-border data. Last but not least, further work could characterize the determinants of the bid-ask spread in a less aggregated form over the trading session.

References

[1] T. Angelidis and A. Benos (2008). ”The components of the bid-ask spread: the case of the Athens stock exchange”. European Financial Management 15, pp. 112-144.

[2] B. Biais, L. Glosten, and C. Spatt (2005). ”Market microstructure: a survey of microfoundations, empirical results and policy implications”. Journal of Financial Markets 8, pp. 217-264.

[3] F. Borggrefe and K. Neuhoff (2011). ”Balancing and intraday market design: options for wind integration”. DIW Berlin Discussion paper 1162.

[4] J. P. Chaves-Avila, R. A. Hakvoort A. Ramos (2013). ”Short-term strategies for Dutch wind power producers to reduce imbalance costs”. Energy Policy 52, pp. 573-582.

[5] Y. Chuan Huang (2004). ”The components of bid-ask spread and their determinants: TAIFEX versus SGX-DT”. Futures Markets 24, pp. 835-860.

[6] T. E. Copeland and D. Galai (1983). ”Information effects on the bid-ask spread”. Journal of Finance 38, pp. 1457-1469.

[7] Y. Croissant and G. Millo (2008). ”Panel Data Econometrics in R: The plm Package”. Journal of Statistical Software.

[8] H. Demsetz (1968). ”The cost of transacting”. Quarterly Journal of Economics 82, pp. 33-53.

[9] Energy Industry Act, Energiewirtschaftsgesetz (1998).

[10] EPEX Spot (2016). ”Annual Press Release 2016”.

[11] EPEX Spot (2016). ”Market Rules”.

[12] M. Garman (1976). ”Market microstructure”. Journal of Financial Economics 3, pp. 257-275.

[13] E. Jaeck and D. Lautier (2016). ”Volatility in electricity derivative markets: The Samuelson effect revisited”. Energy Economics 59, pp. 300-313.

[14] F. Karanfil and Y. Li (2017). ”The Role of Continuous Intraday Electricity Markets: The Integration of Large-Share Wind Power Generation in Denmark”. Energy Journal 38.

[15] R. Kiesel and F. Paraschiv (2017). ”Econometric analysis of 15-minute intraday electricity prices”. Energy Economics 65, pp. 77-90.

[16] S-H. Kim, J. P. Ogden (1996). ”Determinants of the components of bid-ask spreads in stocks”. European Financial Management 2, pp. 127-145.

[17] H. Geman (2005). ”Commodities and Commodity Derivatives: Pricing and Modeling Agricultural, Metals and Energy”. Wiley Finance.

[18] L. Glosten and P. Milgrom (1985). ”Bid ask and transaction prices in a specialist market with heterogeneously informed traders”. Journal of Financial Economics 14, pp. 71-100.

[19] L. Glosten and L. Harris (1988). ”Estimating the components of the bid ask spread”. Journal of Financial Economics 21, pp. 123-142.

[20] L. Glosten (1987) ”Components of the bid-ask spread and the statistical properties of transaction prices”. Journal of Finance 42, pp. 1293-1307.

[21] L. Glosten (1994). ”Is the electronic open limit order book inevitable?”. Journal of Finance 49, pp. 1127-1161.

[22] S. Hagemann (2013). ”Price Determinants in the German Intraday Market for Electricity: An Empirical Analysis”. EWL Working Paper No 18/13.

[23] S. Hagemann, C. Pape and C. Weber (2016). ”Are fundamentals enough? Explaining price variations in the German day-ahead and intraday power market”. Energy Economics 54, pp. 376-387.

[24] S. Hagemann and C. Weber (2013). ”An empirical analysis of liquidity and its determinants in the German intraday market for electricity”. EWL Working Paper.

[25] J. Hasbrouck (2000). ”Trading costs and returns for US equities: The evidence from daily data”. Working paper, New York University.

[26] J. Hasbrouck (2002). ”Stalking the «efficient price» in market microstructure specifications: an overview”. Journal of Financial Markets 5, pp. 329-339.

[27] J. Hasbrouck (2004). ”Liquidity in the futures pits Inferring market dynamics from incomplete data”. Journal of Financial and Quantitative Analysis 39, pp. 305-326.

[28] J. Hasbrouck and G. Sofianos (1993). ”The trades of market makers An empirical analysis of NYSE specialists”. Journal of Finance 48, pp. 1565-1593.

[29] A. Henriot (2014). ”Market design with centralized wind power management: handling low-predictability in traday markets”. Energy Journal 35, pp. 99-117.

[30] C. Hiroux and M. Saguan (2010). ”Large-scale wind power in European electricity markets: time for revisiting support schemes and market designs?”. Energy Policy 38, , pp. 3135-3145.

[31] R. D. Huang and H. R. Stoll (1996). ”Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE”. Journal of Financial Economics 41, pp. 313-357.

[32] R. D. Huang and H. R. Stoll (1997). ”The components of the bid-ask spread: a general approach”. Review of Financial Studies 10, No.4, pp. 995-1034.

[33] A. Madhavan, M. Richardson and M. Roomans (1997). ”Why do security prices change? A transaction-level analysis of NYSE stocks”. Review of Financial Studies 10, pp. 1035-1064.

[34] A. Madhavan and G. Sofianos (1998) ”An empirical analysis of NYSE specialist trading”. Journal of Financial Economics 48, pp. 189-210.

[35] S. Manaster and S. Mann (1996). ”Life in the pits Competitive market making and inventory control”. Review of Financial Studies 9, pp. 953-975.

[36] T. McInish and R. Wood (1992). ”An analysis of intraday patterns in bid/ ask spread for NYSE stocks”. Journal of Finance 47, pp. 753-764.

[37] B. Mizrach and Y. Otsubo (2014). ”The market microstructure of the European climate exchange”. Journal of Banking and Finance 39, pp. 107-116.

[38] K. Neuhoff, N. Ritter, A. Salah-Abou-El-Enien and P. Vassilopoulos (2016). ”Intraday Markets for Power: Discretizing the Continuous Trading?”. DIW Berlin Discussion Paper 1544.

[39] R. Roll (1984). ”A simple implicit measure of the effective bid-ask spread in an efficient market”. Journal of Finance 39, pp. 1127-1139.

[40] D. Ryu (2011) ”Intraday price formation and bid-ask spread components: A new approach using a cross-market model”. Journal of Futures Markets 31, pp. 1142-1169.

[41] R. Scharff, M. Amelin (2016). ”Trading behavior on the continuous intraday market ELBAS”. Energy Policy 88, pp. 544-557.

[42] P. Schultz (2000). ”Regulatory and legal pressure and the costs of Nasdaq trading”. Review of Financial Studies 13, pp. 917-958.

[43] R. Schwartz (1988). ”Equity Markets: Structure, Trading, and Performance”. Harper and Row, New York.

[44] F. Schweppe, M. Caramanis, R. Tabors, R. Bohn (1988). ”Spot Pricing of Electricity”. Springer.

[45] H. R. Stoll (1978). ”The supply of dealer services in securities markets”. Journal of Finance 33, pp. 1133-1151.

[46] H. R. Stoll (1989). ”Inferring the components of the bid-ask spread: theory and empirical tests”. Journal of Finance XLIV, pp. 115-134.

[47] W. Vickrey (1971). ”Responsive Pricing of Public Utility Services”. Bell Journal of Economics and Management Science 2, pp. 337-346.

[48] C. Weber (2010). ”Adequate intraday market design to enable the integration of wind energy into the European power systems”. Energy Policy 38, pp. 3155-3163.

[49] F. Ziel (2016). ”Modeling the impact of wind and solar power forecasting errors on intraday electricity prices”. Work in progress.

APPENDICES

A. ADDITIONAL FIGURES AND TABLES

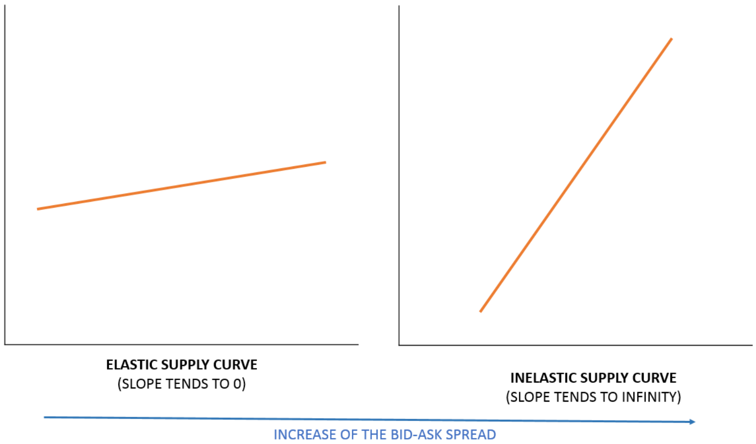

Figure A.1: Slopes and elasticity

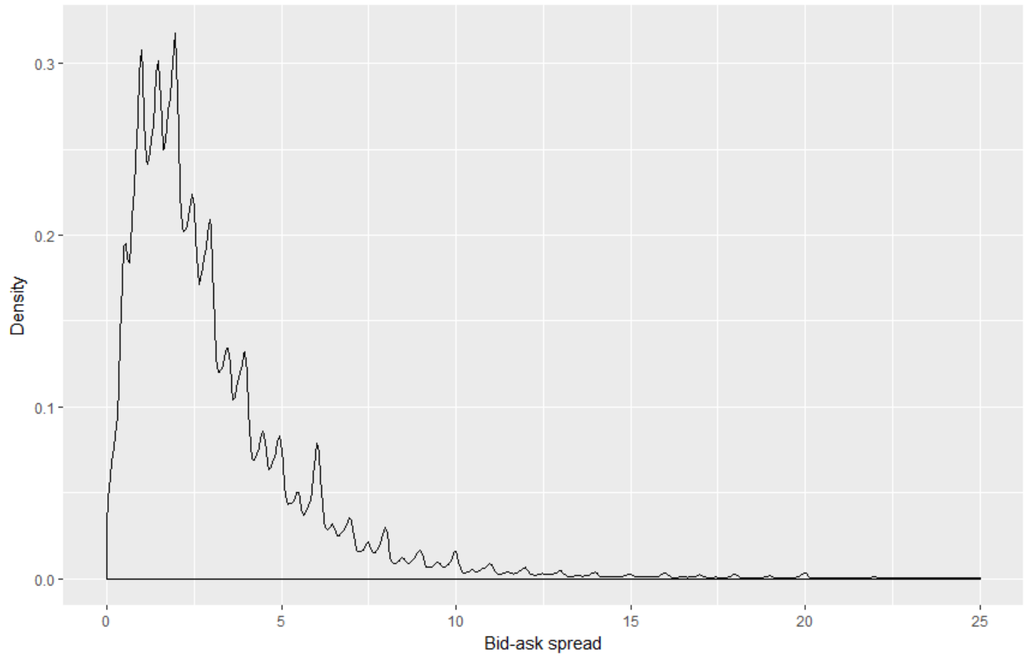

Figure A.2: Distribution of the bid-ask spread

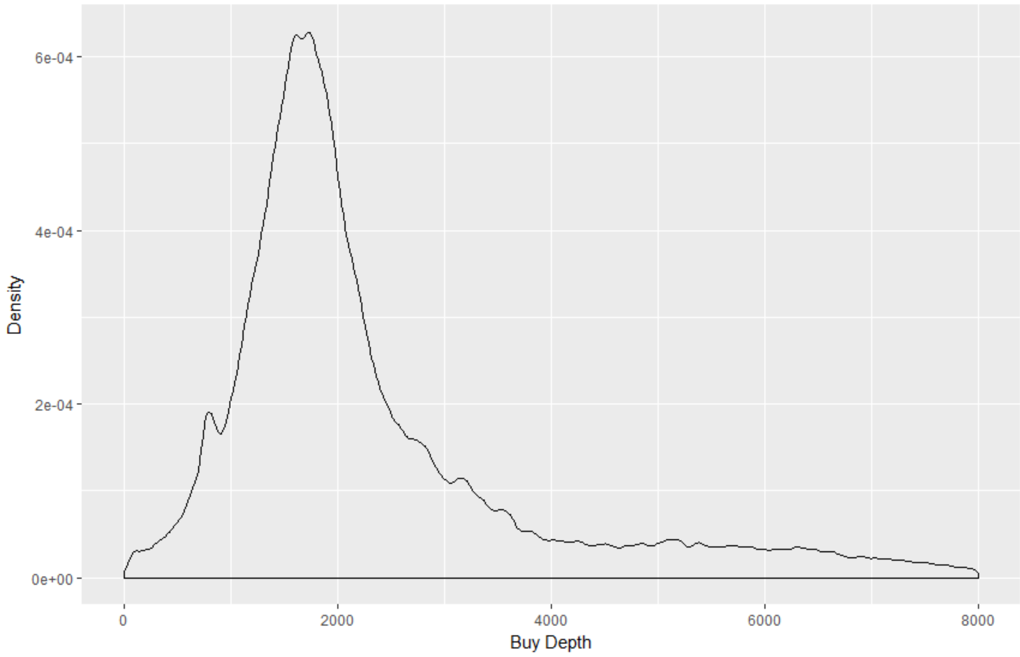

Figure A.3: Distribution of the buy depth

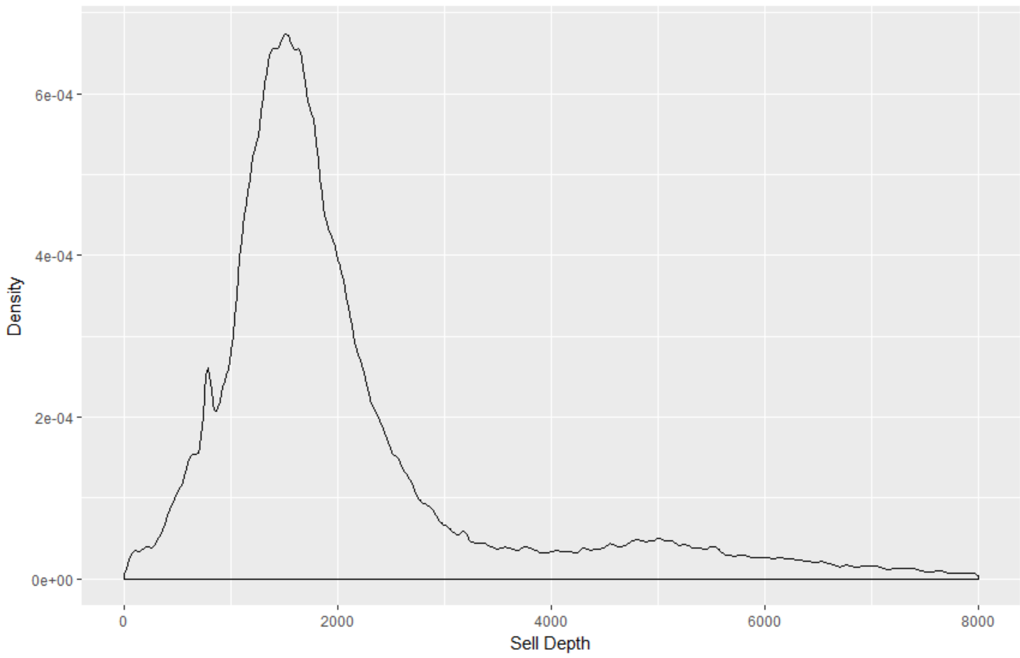

Figure A.4: Distribution of the sell depth

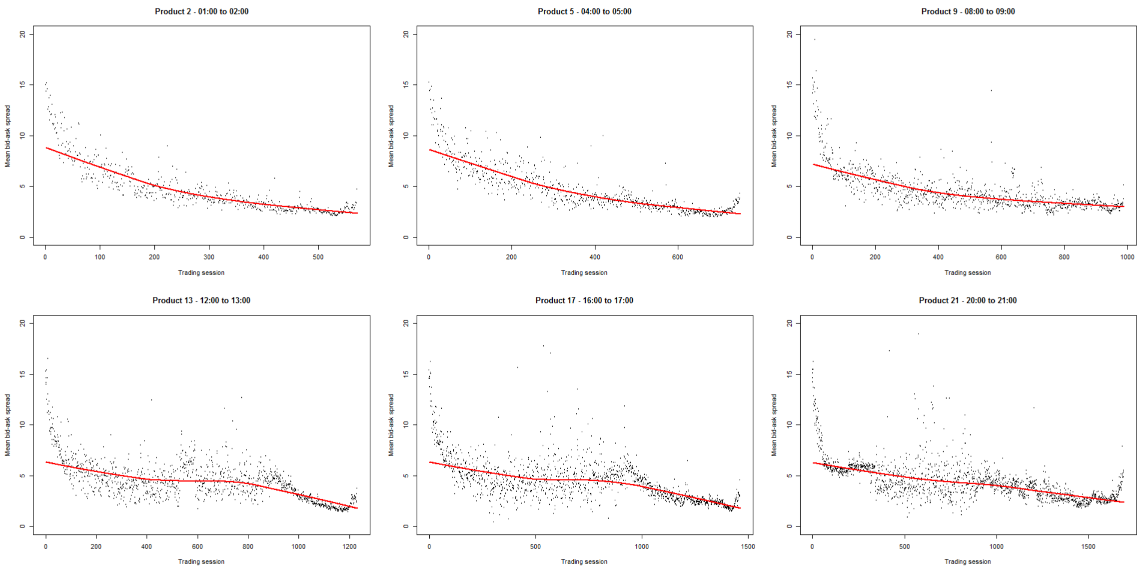

Figure A.5: Mean bid-ask spread over an average trading session

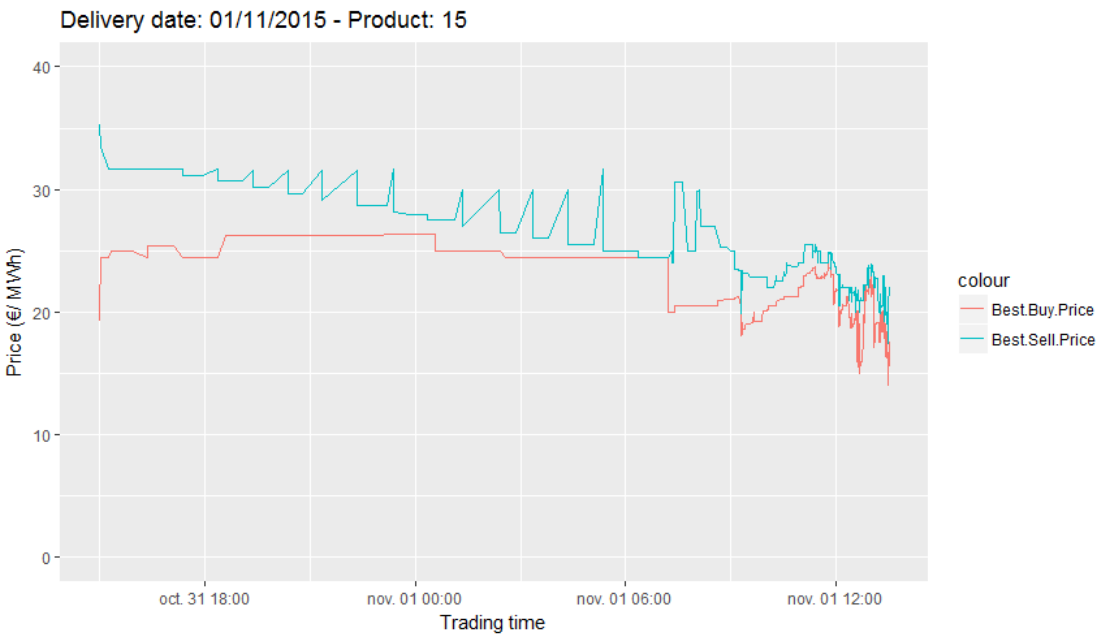

Figure A.6: Bid-ask spread's evolution over a specific trading session

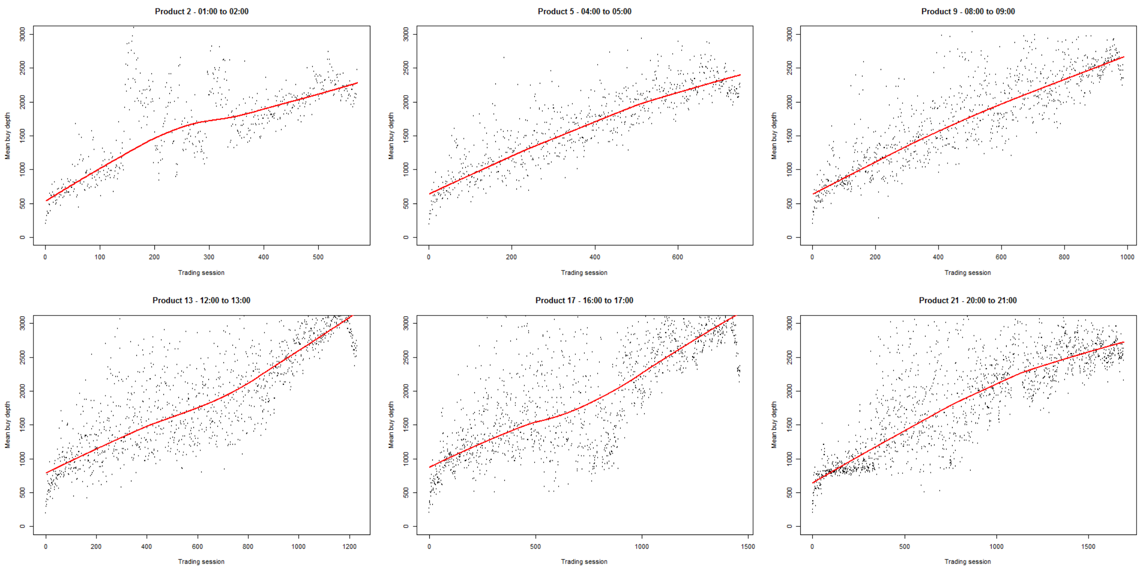

Figure A.7: Mean buy depth over an average trading session

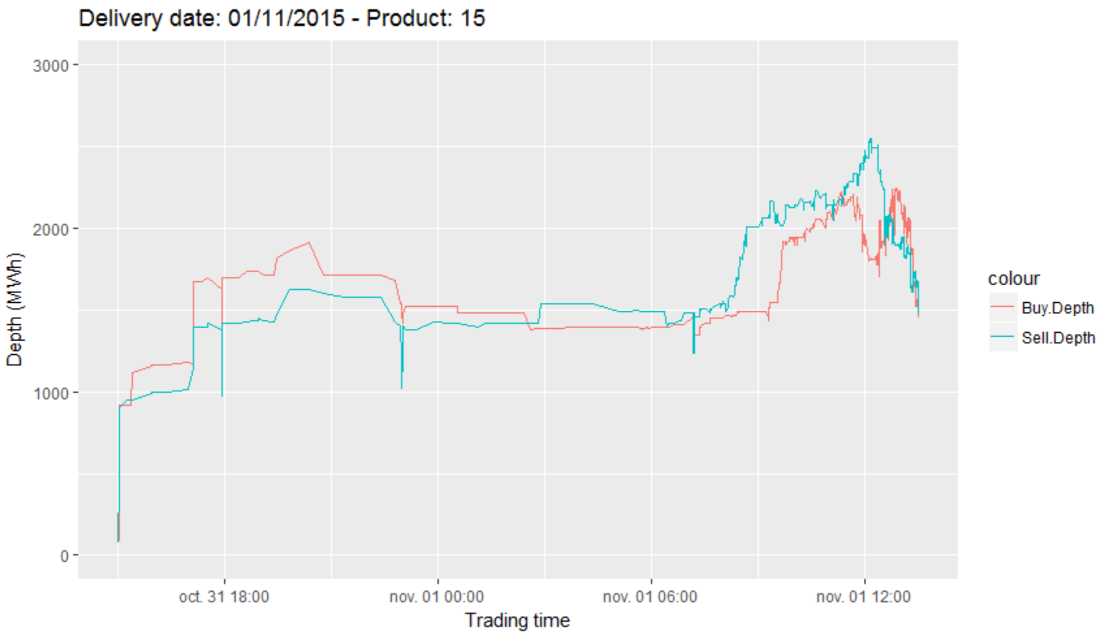

Figure A.8: Buy and sell depths' evolution over a specific trading session

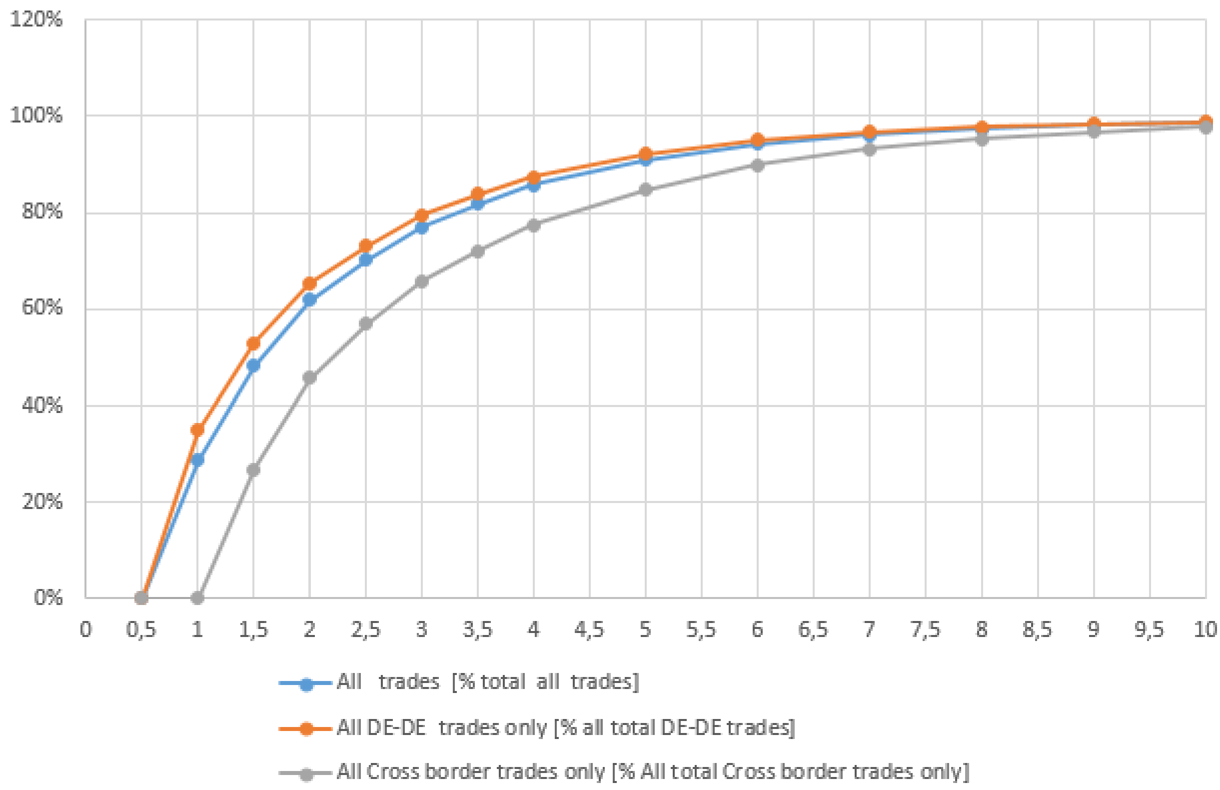

Figure A.9: Volume traded hours from the delivery time

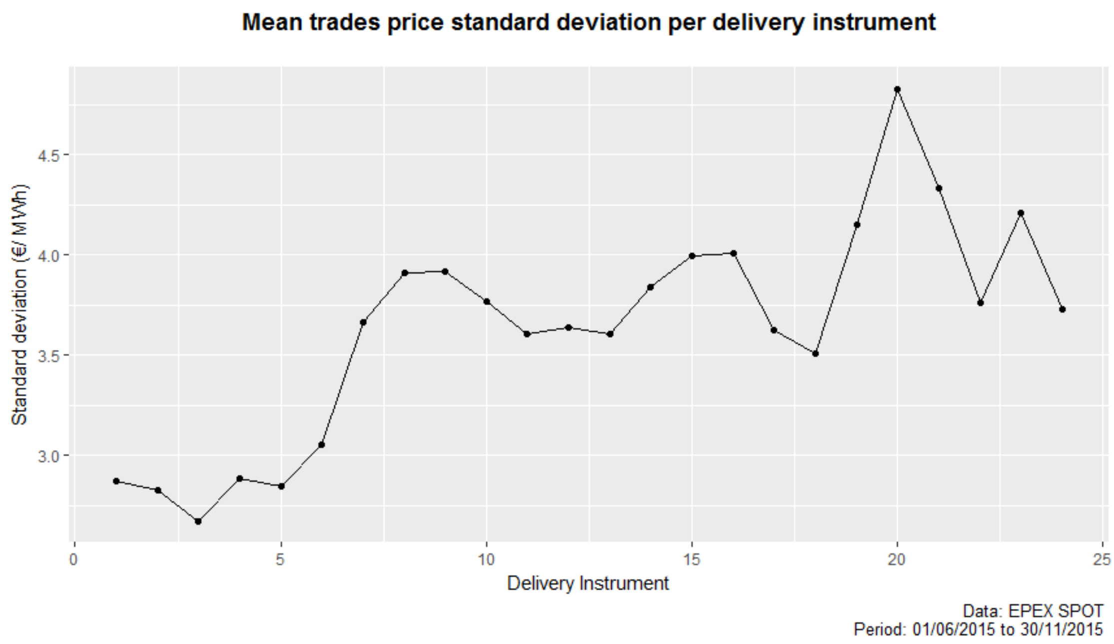

Figure A.10: Mean trades price standard deviation per contract

	Bid-ask spread	Week-end dummy	Elasticity (buy)	Elasticity (sell)	Load	Positive solar FE
Bid-ask spread	1,950	0,082	0,001	0,001	-2,670	989,699
Week-end dummy	0,082	0,198	0,000	0,000	-2,206	-169,091
Elasticity (buy)	0,001	0,000	0,000	0,000	0,012	-1,095
Elasticity (sell)	0,001	0,000	0,000	0,000	0,004	-4,088
Load	-2,670	-2,206	0,012	0,004	93,645	-3465,410
Positive solar forecast error	989,699	-169,091	-1,095	-4,088	-3465,410	519465510,732
Negative solar forecast error	-1,463	0,100	0,024	-0,006	21,850	-11310,807
Positive wind forecast error	-0,854	1,435	-0,001	-0,010	-19,056	-12739,246
Negative wind forecast error	-0,771	-0,404	0,006	0,003	19,046	-8139,174
Number of active members	-2,806	-1,425	0,012	0,004	74,123	-17259,287
Price standard deviation	2,601	-0,067	0,005	0,002	4,875	957,763

	Negative solar FE	Positive wind FE	Negative wind FE	Number of active members	Price standard deviation
Bid-ask spread	-1,463	-0,854	-0,771	-2,806	2,601
Week-end dummy	0,100	1,435	-0,404	-1,425	-0,067
Elasticity (buy)	0,024	-0,001	0,006	0,012	0,005
Elasticity (sell)	-0,006	-0,010	0,003	0,004	0,002
Load	21,850	-19,056	19,046	74,123	4,875
Positive solar forecast error	-11310,807	-12739,246	-8139,174	-17259,287	957,763
Negative solar forecast error	192,164	12,868	1,521	42,483	1,724
Positive wind forecast error	12,868	1146,688	-100,914	-2,519	-1,424
Negative wind forecast error	1,521	-100,914	98,184	22,749	2,324
Number of active members	42,483	-2,519	22,749	93,389	5,045
Price standard deviation	1,724	-1,424	2,324	5,045	10,370

Table A.1: Variance-covariance matrix

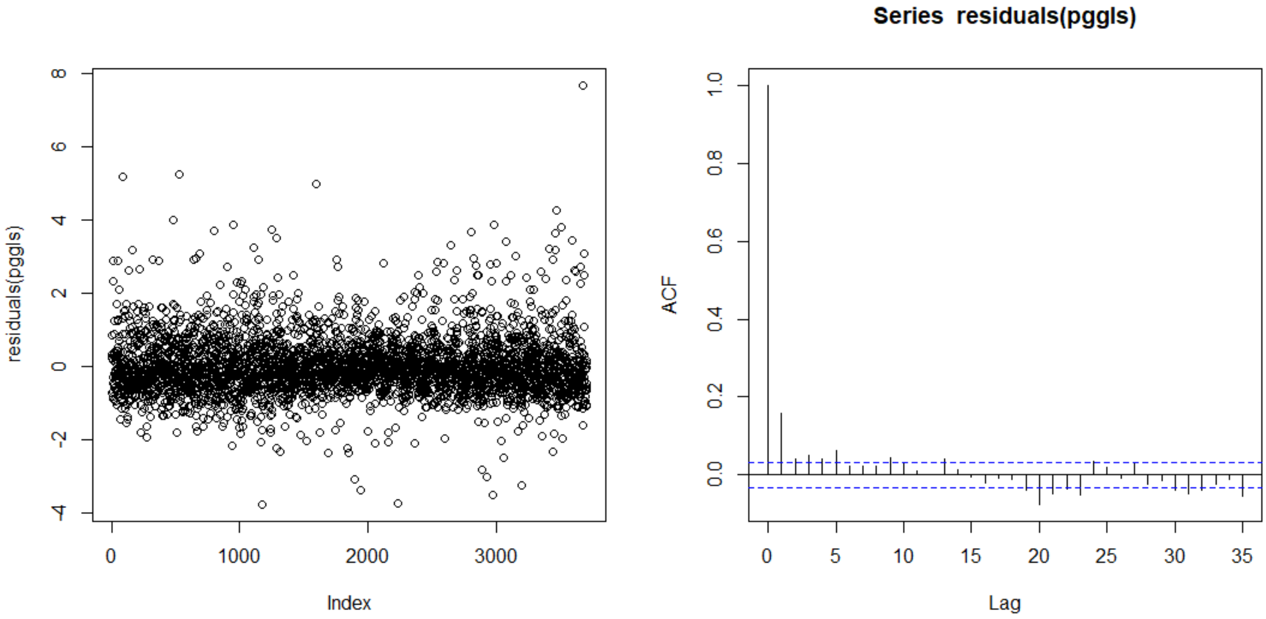

Figure A.11: Residuals of the regression with all products

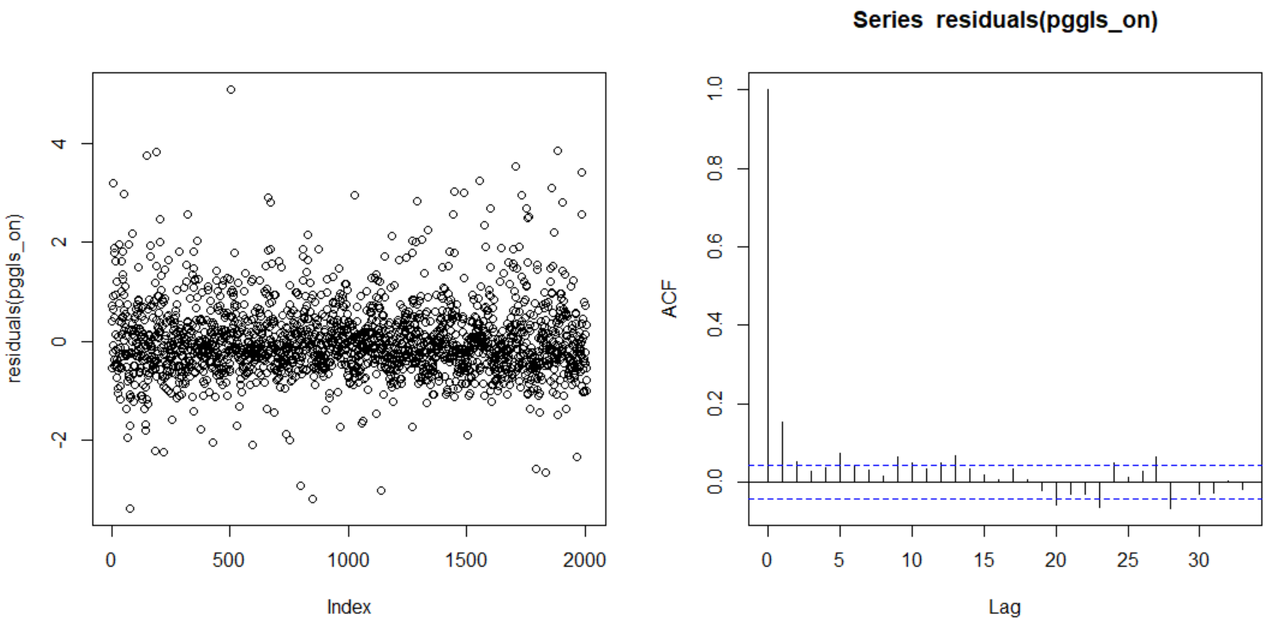

Figure A.12: Residuals of the regression with on-peak products only

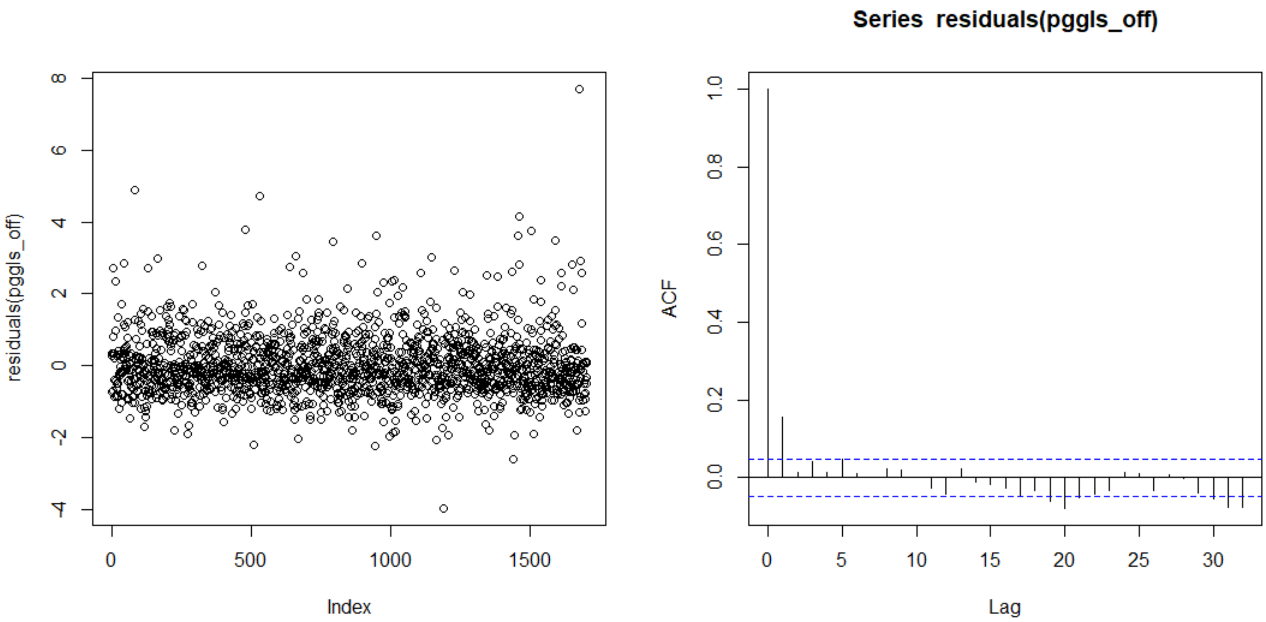

Figure A.13: Residuals of the regression with off-peak products only