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

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May 2020

Abstract

Liquidity is decisive for a well-functioning market. As most of the literature on the subject is based on financial markets, the extrapolation of its insights to the power market is fragile. This paper shows the specificities of the liquidity of the German power market. Using the bid-ask spread as a proxy, thanks to the detailed order book for the hourly contracts, I first describe the evolution of the liquidity over the trading session. The bid-ask spread has a "L-shaped" pattern over it. Second, I identify the four main drivers of the liquidity using the bid-ask spread as a proxy: the risk, the adjustments' need, the activity and the concentration of the market. I find that an increase of the volatility or the market concentration increases the bid-ask spread while an increase of the adjustments' need or the market activity decreases it.

Keywords: bid-ask spread, market depths, continuous market, power market.

Acknowledgments: This paper has benefited from the support of the Chaire European Electricity Markets (CEEM) of the Université Paris-Dauphine under the aegis of the Foundation Paris-Dauphine, supported by RTE, EDF, EPEX Spot and CELEST.

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

Liquidity is the major component of a well-functioning market. The more liquid is a market, the easiest it is for a market participant to find a trading counterpart to match its requirements. A typical proxy for liquidity is the bid-ask spread, that is the difference 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. It measures the difference between the first non-executed orders.

Market participants gain opportunities by exploiting the bid-ask spread which can be interpreted as a premium for immediate execution (Demsetz, 1968). For example, in a setup where the best sell order is at 35€ per MWh and the best buy order is at 32€ per MWh, if the best buyer (resp. seller) wants to be immediately executed, she has to increase (resp. decrease) her unit price by 3€. It can also be interpreted as an implicit transaction cost; the smaller the bid-ask spread is, the smaller is the implicit transaction cost for the traders and so the end-consumers. Further, the bid-ask spread is a showcase for the quality of the market.

Figure 1: Example of an order book

Asl	k		Bid
Quantity	Price	Price	Quantity
20	35	32	4
5	36	31	15
12	39	29	7
3	42	28	9
		25	30

The German market is the most liquid continuous power market in Europe where about 53% of the German consumption was traded on in 2015. The same year, almost 20 millions¹ of euros were traded each week on the market. The German continuous power market faces a growing attention in the public debate. First, the continuous market has been playing a growing role in the integration of the renewable energy sources (RES); thus, the traded volume increased by about 170% from 2012 to 2018. It is then a benchmark for the other European countries with a growing renewable capacity. Second, it is also important to understand the liquidity of the market in the context of the European single intraday coupling (SIDC) project where new countries are adopting continuous trading such as Spain or Italy.

Despite similarities between the continuous spot power market and the traditional financial markets in their mechanisms, there are some major differences due to the physical aspect of power. For example, it is not storable and the market participants are balance responsible². In comparison to the financial markets, the power market has

¹This result corresponds to the weekly volume time the weekly weighted average price.

²"Balance responsible party' means a market participant or its chosen representative responsible for

a lower liquidity, a higher volatility, a higher concentration and a highly inelastic demand (Dupuis et al., 2016). Thus, the one-size-fits-all approach is not straightforward and the observations of the so-called microstructure literature may not hold in the context of electricity markets. For example, in the financial literature, the pattern of the bid-ask spread ("L-shaped" versus "U-shaped") is explained by the difference in the market making process (Lhabitant and Gregoriou, 2008); this result cannot be transposed to the power market because it does not have market makers. The reason behind the "L-shaped" pattern of the bid-ask spread in the power market can be explained by the urge to trade close to the delivery: there is a peak of activity during the last hours of the trading session.

The market participants want to know when it is the most timely to participate in the trading session in order to reduce their implicit transaction costs. The bid-ask spread is also an important factor for market design. The value of the introduction of official market markers³ in order to increase the liquidity of the market can be evaluated. Market making is currently implemented in the power future market in Germany but not in the spot market. This article is the first one to review the stable facts and to determine the immediate causes of the bid-ask spread of the German spot power market. It can be useful for regulators in order to propose adequate monitoring tools. For example, in assessing the impact of the concentration of the market on the liquidity.

To the best of my knowledge, it is the first paper that studies the actual bid-ask spread of a power market. The complete order book allows me to reconstitute the best order streams (best bid, best ask, and market depths) 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 easily extended to other continuous markets. From an academic perspective, the contribution of the paper is twofold. First, the paper assesses the impact of the renewable and the load forecast errors on the liquidity of the market. Beyond the negative and significant impact of the forecast errors on the bid-ask spread, it shows that the market handles the uncertainty of the supply and the demand: it is more liquid after a forecast error which reveals that the actors have to rebalance their positions. Second, a unique dataset is used which allows me to compute the concentration of the market as well as assessing the impact of it on the liquidity of the market. While the generation part of electricity is highly concentrated in Germany (Amanatidis, 2009), I find that the concentration on the continuous market is moderate. This article quantifies the negative impact of the concentration on the bid-ask spread and highlights that the supply concentration have a larger impact on the liquidity in comparison to the demand concentration.

My dataset enables me to do a dynamic analysis of the bid-ask spread and the market depths over an average trading session at a granular level (microsecond). The market depth is the volume available in the order book. It can be divided into the buy depth and the sell depth. They represent respectively the total volume available on the buy side and on the sell side at one moment of the trading session. For example, in the setup

its imbalances in the electricity market" (EU regulation 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity, Article 2(14))

³Official market makers are participants that are active on both sides of the market and that should maintain a determined bid-ask spread in exchange of trading rebates.

proposed in figure 1, the sell depth is equal to 40 MW and the buy depth is equal to 65 MW. Thanks to these precise data, I identify the main drivers of the bid-ask spread: the risk, the adjustments' need, the activity and the concentration of the market.

Three stylized facts can be retained. First, the bid-ask spread has a "L-shaped" pattern during a trading session of a power market. Second, the average bid-ask spread is 3.5€ per MWh over the trading session of the German power continuous market. Third, the bid-ask spread can be explained by four components: the risk, the adjustments' need, the activity, and the competition in the market. Using a fixed effect model, 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 adjustments' need, 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: electricity markets and market microstructure.

While the literature on the power markets is dense, the literature on the continuous ones is limited and mainly focuses on two issues: wind generation integration (how to handle forecast errors) and market design. The closest literature to this paper is the one on price formation in the intraday continuous market. Hagemann (2015), Hagemann et al. (2016), Karanfil and Li (2017) and Ziel (2017) model the price of this market. Weber (2010) is the first to address the question of the liquidity of the German continuous power market. He finds 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 a dataset from 2007 when the yearly 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; it increased the need to adjust the renewable generation's position close to the delivery time in order to be balanced at delivery. Chaves-Avila et al. (2013) explain 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. Hagemann and Weber (2013) develop two models to explain the liquidity of the German continuous power market. To the best of my knowledge, the work of Hagemann and Weber (2013) is the first paper that investigates the bid-ask spread in the German continuous power market. However, their work neither uses the order book sent by the market participants or a reconstitution of it as input data for their models: they estimate the bid-ask spread using the transactions data. 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 the market depths as well as a positive relation between the liquidity and the market depths of the 15-minute intraday auction in Germany.

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

Demsetz (1968) initiated the literature on the bid-ask spread. He defines market makers⁴ as immediacy providers in which the bid-ask spread is a premium paid by a market participant for immediate execution. The work of Demsetz highlights the negative relation between the volume and the bid-ask spread. It is also raised in the paper of Copeland and Galai (1983) who model the bid-ask spread using the volatility and the level of trading as explanatory variables.

In the theoretical part of the literature, the bid-ask spread reflects three components: the transaction or the order processing costs⁵ (Roll, 1984), the adverse selection costs⁶ (Glosten and Milgrom, 1985), and the inventory costs⁷ (Stoll, 1978). Glosten and Harris (1988) and Kim and Ogden (1996) model the spread with both the inventory and the 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. Hasbrouck (2004) proposes a Roll estimator⁸ using a Markov chain and a Monte-Carlo simulation. Chen et al. (2019) extend the Roll model where only the transaction prices are needed as input for the model.

The empirical literature in microstructure also uses these three components of the spread. Schultz (2000) applies the Roll estimator to a dataset 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 called MRR that decomposes the spread in two components: the adverse selection and the order processing. This model has led to a multitude of papers on different markets such as future exchanges (Huang, 2004, Ryu, 2011), stock exchanges (Angelidis, and Benos, 2009), Exchange Trading Funds or ETS (Ivanov, 2016) or the European climate exchange (Mizrach and Otsubo, 2013). Many studies find empirical evidence of the inventory cost such as Hasbrouck and Sofianos (1993), Manaster and Mann (1996), or Madhavan and Sofianos (1998). Huang and Stoll (1996) estimate and compare the spreads of the NASDAQ and the NYSE from the three elements. Huang and Stoll (1997) quantitatively estimate the impact of the three components. They find that the bid-ask spread can be explained by the order processing for 61.8%, the aver-

⁴A market maker is a market participant who have orders at the best price limits on both side of the order book: the buy order with the highest price and the sell order with the lowest price.

⁵The transaction or order processing costs are measured in Roll (1984) as the first-order serial covariance of a price change.

⁶The adverse selection costs are due to the asymmetry of information between traders.

⁷The inventory costs are incurred by the imbalance between the volume bought and the volume sold by a market participant.

⁸The Roll estimator is an estimation of the bid-ask spread using the time series of the trades.

age inventory cost for 28.7%, and the average adverse-information for 9.6%. McInish and Wood (1992) empirically estimate the bid-ask spread of the NYSE with four components: activity, risk, information, and competition based on the previous work of Schwartz (1988). The econometric model of this paper is inspired by the work of McInish and Wood (1992). The present paper adapts the definitions to the power market that has specific characteristics.

III. THE INTRADAY POWER MARKET

In power markets, the financial flow goes along with the physical one: the market participants do not buy "papers" but electricity that will then be injected into the grid.

Power trading can be divided into two categories: the one occurring bilaterally (Overthe-Counter - OTC) and the one taking place on an exchange. An exchange differs from the OTC because it is an organized marketplace with uniform rules and with standardized contracts (Geman, 2005). The trades that occur on an exchange are anonymous and transparent. The power spot market takes place 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). On the electricity spot market, the contract unit is the megawatt for a certain amount of time (15, 30 or 60 minutes). Contract are also called "products".

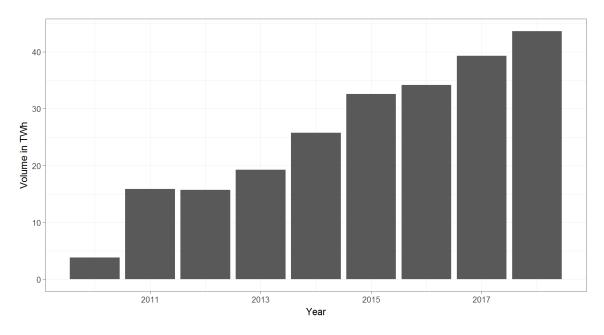


Figure 2: Transaction volume of the German continuous market

In Germany, the Energy Industry Act (1998) unbundled the generation and the supply of electricity from the network segment - transmission and distribution. The German spot power market was created in 2000 by the LPX - Leipzig Power Exchange, and is now operated by EPEX SPOT. It is the most liquid spot market in Europe: traders moved 302 TWh (terawatt-hour) 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 as illustrated in the figure 2.

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 noon. The 24 contracts exchanged on the DAM are hourly contracts for the next day. The period called "intraday" starts right after the day-ahead auction and lasts until delivery. The 15-minute call auction is a uniform price auction that occurs every day at 15:00 in Germany. The 96 traded contracts are 15-minute products for delivery on the next day. The continuous market for hourly contracts starts at 15:00 the day before delivery and closes 5 minutes before delivery. For example, the product 2 of tomorrow (D+1) (ie. an hour of electricity between 1:00 and 2:00) is available for trading from 15:00 today until 00:55 tomorrow. The duration of the trading session for a contract is between 9 and 32 hours.

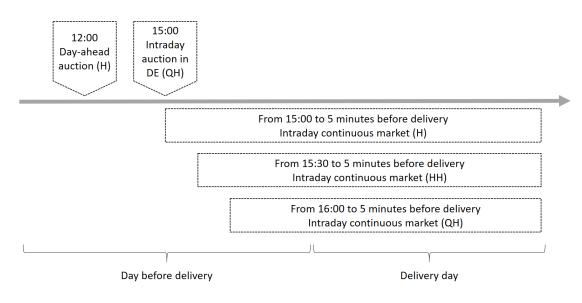


Figure 3: The German spot power market

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 adjust their position and to optimize their portfolio close to delivery. Scharff and Amelin (2016) justify the need for an intraday market in three points: it reduces the imbalance settlement costs, it helps optimizing market participants' production and consumption schedules, and it promotes flexibility.

Market participants can submit limit price orders for a given contract to the exchange at any time during the trading session¹⁰. A limit order is composed of a price and a

⁹Trading was first possible up to 45 minutes before delivery, then 30 minutes before delivery, and since June 2017 up to 5 minutes before delivery. This paper uses data from 2015 when the gate closure was 30 minutes before delivery.

¹⁰Orders 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. The price is the minimum (maximum) price at which they are willing to sell (buy) the associated quantity. The orders are listed by price: increasing order on the sell side and decreasing order on the buy side as illustrated on figure 1. The IDM is continuous in its matching procedure¹¹: orders are matched when they arrive in the order book if there is a counterpart in the market with whom the price and the volume requirements match¹². Orders can either be fully or partially executed if only part of the match is possible. An order is executed at or above (under) the specified price for a seller (buyer): the transaction price is the price of the order that was first posted in the order book. 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 matching possibility, then the order remains in the order book. Members can also withdraw or modify their orders during the trading session.

The process presented above represents the local (within a country) order book; however, countries in Europe are interconnected. Under the capacity constraint on a border, the capacity available will allow the best orders from a source country with a maximum volume of the capacity constraint to be visible in the order book of a sink country and vice versa. For example, if 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 of 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. The capacity is implicitly¹³ given and not priced in the market. The order book does not display if the orders are local or cross-border.

The table 1 displays some descriptive statistics on the trades of the German continuous market from January 1, 2015, to December 31, 2015. The mean daily price is 31.85€/MWh. The mean daily number of trades per contract is 267.5 while the mean

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 expires with a minimum of two contiguous expires 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 their own order book, different from the order book of the hourly products.

¹¹Orders sent to the market are processed one at the time - serial processing, in general within milliseconds.

¹²A market participant is called "initiator" of the trade if he or she submits a new order in the order book and is called "aggressor" when he or she hits the price of an existing order in the order book.

¹³The energy is sold along with the interconnection capacity.

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

	Min	Quartile 1	Median	Mean	Quartile 3	Max
Weighted price (€/MWh)	-84.60	25.12	31.53	31.85	39.52	120.16
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

daily number of orders per contract is 1072: on average, a member sends 4 orders for 1 execution (trade). There is on average 51 active members¹⁴ in the market which represent around a quarter of the members registered on the market.

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

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

4.1. Data

The complete order book contains only the German local orders and does not account for cross-border or block orders. It covers a period of one year from January 1, 2015 to December 31, 2015. Each line of the dataset displays an order that a market participant sent to the power exchange during a continuous trading session. It includes a range of variables: 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, as well as the day and the time when the order was executed/cancelled/deactivated/expired/modified, the price, and the quantity asked/offered by the market participant. This dataset serves as input for the reconstitution tool that was first developed by the Product and Market Development team of EPEX SPOT by using the software R. The tool computes the best order stream (best bid and ask prices) and the market depths 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 depths. 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 at the best prices - it can be the sum of two orders or more. The last information the output shows is the buy and the sell depths. In other terms, it displays the first line of the order book and the market depths for both the buy and sell sides - information that can be seen by the participants at the time they trade. I then compute the bid-ask spread at each moment of the trading

¹⁴A market participant is considered as active if he sends at least one order during the trading session.

session as the difference between the best ask and the best bid:

$$BAS_{it'} = \text{best ask}_{it'} - \text{best bid}_{it'}$$
 (1)

where t' is a vector of three dimensions composed of the delivery date, the trading date, and the trading time; i is the contract concerned and $i \in \{1, 24\}$.

4.2. Descriptive statistics

The table 2 presents the descriptive statistics for the bid-ask spread and the market depths aggregated at the contract level (per delivery date and delivery hour) for the year 2015. The mean bid-ask spread is 3.52€/MWh which is slightly more than the mean bid-ask spread of 2.97€/MWh found by Hagemann and Weber (2013). The mean bid-ask spread is about 350 times the tick size (0.01€/MWh). It 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 book¹⁵. The value of the bid-ask spread is overestimated due to the absence of cross-border orders in the dataset. With cross-border data, the spread would not be impacted or would be lower: an order from a neighboring country can only impact the bid-ask spread by either proposing a sell price lower than the best ask or a buy price above the best bid.

For comparison, Ryu (2011) estimates the bid-ask spread at 4-5% of the price on the KOSPI 2000 (index performance of the Korea Stock Exchange) for a period of about 2 years from 2002 to 2004. A survey on the equity market by Angel, Harris and Spatt (2013) finds that the effective spread on the NASDAQ (resp. NYSE) between 2010 and 2013 is about 2.5 cents (resp. 1.5 cents). The limited liquidity of the power market is due to the physical aspect of electricity, and particularly that it is not storable and that the traders are selected - they have to be balance responsible.

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

	Min	Quartile 1	Median	Mean	Quartile 3	Max
Bid-ask spread (€/MWh)	0.96	2.51	3.14	3.52	3.99	31.09
Buy depth (MW)	299,64	2230,32	3090,52	3419,84	4627,68	18556,8
Sell depth (MW)	447,6	2163,6	3034	3314,4	4517,6	8196

The average bid-ask spread is higher during the weekends (+ 13%) because of the decrease of the demand as well as the decrease of the number of participants. The distribution of the bid-ask spread is displayed in the appendices (figure .1). I observe peaks of frequency of the bid-ask spread every 5 cents per MWh. This observation highlights the use of price steps of 5 cents by the members ¹⁶.

¹⁵The value of the French local bid-ask spread is calculated by the author, using the EPEX SPOT data. ¹⁶In the period studied, the tick size of the continuous market was 0.01€/MWh. It has been 0.10€/MWh since June 2016.

In order to get some insights on the case where the bid-ask spread is high (top 25%), I use a subset of the data where the spread is above 4€/MWh. In this subset, lower depths exist (respectively -17% and -21% in comparison to the mean buy and sell depths) which is consistent with the negative correlation between the bid-ask spread and the depths explained later in this section. Off-peak products (before 8:00 or after 20:00) and weekends are over-represented in the subset. This result is reasonable because the liquidity and the number of active participants are lower during off-peak hours, which is also valid for weekends. From the observed subset, I also find a higher sell price (+8,5% on average) and a lower buy price (-2% on average).

The buy and sell depths are respectively 3420 MW and 3314 MW on average per contract and 25% of the time they are respectively above 4628 MW and 4518 MW. The same argument on the absence of the cross-border data applies to the market depths: they are underestimated; the market depths could only be above the result as a cross-border order can only increase the volume in the order book. The mean depths are higher for the base-load contracts (from 8:00 to 20:00) in comparison to the off-peak contracts. The distributions of the depths¹¹² aggregated at the contract level are bi-modal. On the one hand, when I study the subset that only includes the high mode (depth above 3600 MW), the spread is on average lower (2.58€/MWh), the forecasted wind generation higher (+ 12% in comparison to the overall mean) and there is an overepresentation of business days and peak contracts - the most liquid ones. On the other hand, in the subset that includes only the low mode (depth below 3600 MW), the reverse is true: I find high bid-ask spread, low wind generation's forecast as well as an overepresentation of weekends and off-peak contracts.

Using observations at the millisecond level, 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, when aggregating the values at the minute level, the correlation increases particularly for the morning hours where the mean correlation for the contracts 1 to 11 is -0.66. I observe that at a higher frequency scale, the correlation breaks down: each order added or removed from the order book does not have an impact on the bid-ask spread; a new order is not always at the limit price. However, when I aggregate the values, I observe a negative correlation: when the volume in the order book increases, the bid-ask spread tends to decrease. These correlations are negative which is reasonable and consistent with the literature. This negative relation is also observable by looking at the evolution of the depths and the bid-ask spread over an average trading session¹⁸. When aggregating at the hourly level, the correlation between the bid-ask spread and the depths are high: the correlation between the bid-ask spread and the buy (resp. sell) depth is -0.83 (resp. -0.86).

4.3. Dynamic analysis

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

 $^{^{17}}$ The distribution of the buy and the sell depths are displayed in the figures .2 and .3 of the appendices. 18 The figure 4 and the figure 5 illustrate the behavior of the bid-ask spread and the sell depth over an average trading session.

The figure 4 represents the evolution of the bid-ask spread over an average trading session aggregated at the minute level for the product 8 (60 minutes of power from 7:00 to 8:00)¹⁹. The bid-ask spread decreases over the trading session. This result is valid for all the 24 contracts studied. This decrease is due to the strong uncertainty away from the delivery time. During the last hours in which a contract can be traded, I observe the lowest values of the bid-ask spread. As the contract gets closer to the delivery, 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 $session^{20}$. The continuous market is mainly used to adjust positions, previously taken, in continuous manner and close to the delivery of the contract. The adjustments' need are due to the arrival of new information such as a new weather forecast, a new load forecast, or an unplanned outage. The longer the trading session is (from 8,5 hours for the contracts 1 to 31,5 hours for the contract 24), the smoother is the curve of the bid-ask spread over time. At the end of the trading session, the bid-ask spread slightly increases due to the decrease of the volume of the order book.

To sum up, the bid-ask spread has a "L-shape" pattern over the trading session and is on average of 3.5€/MWh.

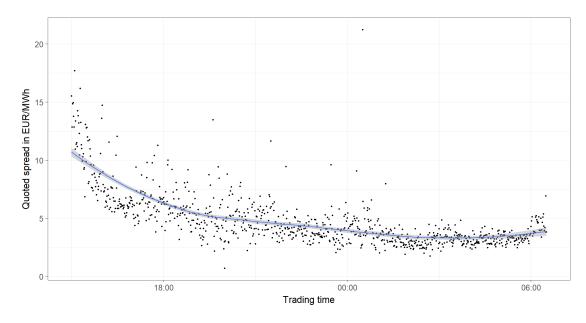


Figure 4: The bid-ask spread over an average trading session for the product 8

The figure 5 shows the evolution of the sell depth over an average trading session for

¹⁹The figure .5 in the appendices illustrates the evolution of the bid-ask spread over an average trading session for the products 5, 9, 13 and 17. 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. The product 9 represents a peak hour where the demand is the highest. However, the "L-shaped" pattern is observable across the contracts.

²⁰The figure .4 in the appendices shows the cumulative share of the volume traded during an average trading session.

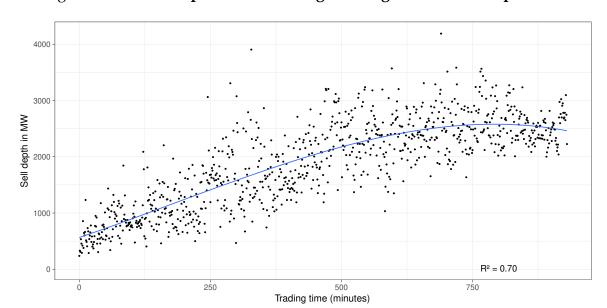


Figure 5: The sell depth over an average trading session for the product 8

the product 8²¹. The buy and the sell depths increase over the trading session. They have a reverse shape in comparison to the bid-ask spread. The correlation between the buy and the sell depths, using the data set at its lowest granularity (millisecond), is 0.95. As the time gets closer to delivery, more quantities are added to the order book. The highest liquidity during the trading session occurs at the end of it. The reason behind this result is the growing need for trading because of the arrival of new information as well as the increasing pressure to be balanced. An important liquidity can be translated by more important matching opportunities, which is consistent with the fact that 80% of the market volume is traded during the last three hours before delivery. At the opening of the trading session, market depths are around 500 MW no matter which product is traded. For off-peak products (before 8:00 or after 20:00), the average buy and sell depths are respectively 3144 MW and 3076 MW while for peak products (between 8:00 and 20:00), the average depths are respectively 3744 MW and 3596 MW. The market depths for off-peak products tend to increase to a lower level in comparison with the depths of peak products because the economic activity is lower at those hours. At the end of most trading sessions, I observe a decrease of the market depths particularly 30 minutes before the gate closure due to the decrease in market opportunities: the crossborder trading closes an hour before delivery. This decrease could also be explained by the activity of the traditional producers who want to fix their production few hours before delivery for operational purposes but also due to the large inflexibility of some power plants. It can also be explained by the absence of cross-border trading during the hour before delivery that can be translated into a decrease of market opportunities for a market participant.

First, I find a mean (local) bid-ask spread of 3.5€/MWh in the German intraday power market. The spread is large at the beginning of the session and decreases as the end of the session approaches. Second, I find the average (local) buy and sell market depths at respectively 3420 MW and 3316 MW. Both depths increase along the trading session.

²¹The figure .6 in the appendices illustrates the sell depth of the contracts 2, 9, 13 and 17.

V. DATA AND METHODOLOGY

The present section is divided in two parts. The first subsection introduces the four hypothesis to be tested as well as the datasets that are used to check them. The second section is dedicated to the econometric specification.

5.1. Hypothesis and data

This study uses various datasets: the firm-level energy bids on the continuous market or order book (source: EPEX SPOT), the day-ahead auction's aggregated curves (source: EPEX SPOT), the solar and the wind forecasts (source: Eurowind), the actual wind and solar generation (source: EEX transparency platform) as well as the forecast and the actual load (source: ENTSO-E transparency platform). From the order book, I construct²² a novel dataset with the bid-ask spread and the market depths at each moment of each trading session of the year 2015. The order book data that I use is highly confidential and includes market participants' identifiers which permits me to compute the concentration ratio (HHI index). Due to the frequency of the data (from the milliseconds for the bid-ask spread to once an hour for the actual wind generation), I choose to aggregate all the variables at the daily level for each contract. In the rest of the paper, I will refer to t as the delivery date and t the contract.

The aim of the econometric specification is to find the main drivers of the bid-ask spread of the German continuous power market. The bid-ask spread was chosen as a proxy for liquidity as it represents an implicit transaction cost for the market participants. Using the outcome from the reconstitution tool, I compute the mean bid-ask per day and per contract (BAS_{it}).

In order to find the main drivers of the bid-ask spread, I use the methodology from McInish and Wood (1992) who use the four following explanatory components: the risk, the information, the activity and the competition on the market.

Hypothesis 1: There is a positive relationship between the bid-ask spread and the risk or the volatility of the market. When the volatility is high, there is more risk and uncertainty on the market; in this situation, the buyers are willing to buy at a lower price and the sellers are willing to sell at a higher price in order to hedge the risk linked to the volatility; they wants a risk premium. Therefore, the bid-ask spread should increase. The volatility is measured in this paper by the elasticity of the supply curve of the day-ahead market, the elasticity of the demand curve of the day-ahead market and the weighted price standard deviation of the transaction.

The slopes of the demand and the supply curves around the equilibrium point can be interpreted as the elasticities. When the elasticity increases (slope tends to infinity), a small change in quantity has an important impact on the price; thus, it increases the volatility of the market and the bid-ask spread should increase. When the inelasticity on one side of the market increases (slope goes to zero), the bid-ask spread should

²²The reconstitution tool is explained in section 4.1.

decrease.



Figure 6: An example of aggregated curves of the DAM (25/10/2015 - product 9)

The elasticities, ES_{it} (supply elasticity) and ED_{it} (demand elasticity), are calculated using the aggregate curves of the German day-ahead market. Those variables represent an approximation of the elasticities around the equilibrium. The supply elasticity (respectively demand elasticity) is the slope of the linear interpolation of the supply (respectively demand) curve between the two points. Those points correspond to the equilibrium volume (Q^*) of the auction plus or minus 500 MWh. The figure 6 illustrates the concept of the calculation. The slopes are computed as follow:

$$ES_{it} = \left| \frac{[Q^* - 500] - [Q^* + 500]}{p^s(Q^* - 500) - p^s(Q^* + 500)} \right| \tag{2}$$

$$ED_{it} = \left| \frac{[Q^* - 500] - [Q^* + 500]}{p^d(Q^* - 500) - p^d(Q^* + 500)} \right|$$
(3)

where p^s is the supply price, and p^d is the demand price at the points (Q*-500) and (Q*+500). The elasticity represents the average price variation around the equilibrium; it measure the impact of a quantity variation of 1 MWh on the price.

The second proxy variable for the volatility is the weighted (by the volume) price standard deviation. It measures the variability of the price around its average. When the weighted price standard deviation increases, the volatility increases and the bid-ask spread should get wider as the price's expectations of the sellers and buyers fluctuate

more. It is computed as followed:

$$\sigma_p = \sqrt{\frac{\sum_{i=1}^N v_i (p_i - \bar{p}*)^2}{\frac{M-1}{M} \sum_{i=1}^N v_i}}$$
 (4)

where

$$\bar{p}* = \frac{\sum_{i=1}^{N} v_i p_i}{\sum_{i=1}^{N} v_i} \tag{5}$$

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

Hypothesis 2: There is a negative relationship between the bid-ask spread and the need for adjustments. When the demand or the supply diverge from their initial forecasts, the positions of the market participants may change, and they need to adjust them; therefore, it increases the volume in the market. The renewable production (wind and solar generation) and the load forecast errors are used to measure the need for adjustments from both the supply and the demand side.

Kiesel and Paraschiv (2017) find a significant effect of the wind and the solar forecast errors on the prices of the continuous market. When the supply changes consecutive to a change in the forecast of the renewable, the bid-ask spread is expected to decrease. When an intermittent power supplier faces a positive shock in his production, he will produce more than he planned and so he will need to sell the extra production. The reverse is also true: when an intermittent supplier faces a negative shock of her production; if she already committed her production, she will need to buy the difference on the market.

In order to assess the impact of the wind and the solar forecast errors, I subtract the wind (solar) forecast (WF_{it} and SF_{it}) to the wind (solar) generation (WG_{it} and SG_{it}). I use the wind (solar) generation - at delivery, as a proxy for the forecast at the gate closure - 30 minutes before the delivery. The intuition behind it is that the forecast 30 minutes before delivery is the same as the actual value thanks to its closeness in time. The chosen forecast is issued at 14:00 ("PREV4") the day before delivery: it is after the DAM and before the beginning of the intraday market. The relative forecast errors are expressed in percentage of variation and are defined as:

$$\Delta_{it}^W = \frac{WG_{it} - WF_{it}}{WF_{it}} * 100 \tag{6}$$

$$\Delta_{it}^S = \frac{SG_{it} - SF_{it}}{SF_{it}} * 100 \tag{7}$$

Inspired by Ziel (2017), I split the above equations depending on the algebraic sign of

the shock. A positive shock is defined as:

$$W_{it}^{FE+} = max\{\Delta_{it}^W, 0\} \tag{8}$$

$$S_{it}^{FE+} = max\{\Delta_{it}^S, 0\} \tag{9}$$

and a negative shock is defined as:

$$W_{it}^{FE-} = max\{-\Delta_{it}^{W}, 0\}$$
 (10)

$$S_{it}^{FE-} = max\{-\Delta_{it}^S, 0\} \tag{11}$$

When the demand (load) changes, I expect the bid-ask spread to decrease: retailers sell their extra quantity on the market if the load decreases and they buy quantities from the market if the load increases in order to meet their commitment. The load forecast error is computed with the same methodology as the wind and the solar forecast errors:

$$\Delta_{it}^L = \frac{LG_{it} - LF_{it}}{LF_{it}} * 100 \tag{12}$$

where LG_{it} is the actual load and LF_{it} the forecasted one at 14:00 the day before delivery. I then split the forecast error depending of the algebraic sign of the shock:

$$L_{it}^{FE+} = max\{\Delta_{it}^L, 0\} \tag{13}$$

$$L_{it}^{FE-} = max\{-\Delta_{it}^{L}, 0\}$$
(14)

Hypothesis 3: There is a negative relationship 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 should be narrowed. Indeed, when the load (demand) is high, the volume available on the market should increase (higher liquidity) and therefore the bid-ask spread should be narrowed.

I use the forecasted load as a proxy for the activity on the market.

Hypothesis 4: There is a negative relationship between the bid-ask spread and the competition in the market. When the concentration of the market decreases, the competition increases and there is less asymmetry of information due to the smaller market shares; the spread should then decrease.

In order to measure the concentration of the market, the Herfindahl-Hirschman Index (HHI) is computed on both sides of the market. This index captures the concentration and measures the market competitiveness.

$$HHI = \sum_{i=1}^{m} s_i^2 \tag{15}$$

where

$$s_i = \frac{v_i}{\sum_{i=1}^m v_i} \tag{16}$$

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

Variable	Min	Quartile1	Mean	Median	Quartile3	Max	Skewness	Kurtosis
Bid-ask spread (EUR/MWh)	0,965	2,510	3,518	3,137	3,995	31,093	3,815	30,546
Weighted price std. dev. (EUR/MWh)	0,571	2,382	4,154	3,340	4,714	355,743	40,050	1 920,235
Demand elasticity	0,001	0,004	0,026	900'0	0,016	0,994	8,858	96,284
Supply elasticity	0,001	0,005	0,010	0,007	0,011	0,237	6,095	74,449
Positive solar forecast err. (%)	0,000	000′0	3 261,488	0,000	12,936	934 900,000	16,077	391,863
Negative solar forecast err. (%)	0,000	00000	6,735	0,000	000'0	98,013	2,863	11,100
Positive wind forecast err. (%)	0,000	00000	15,035	4,489	19,824	379,402	4,378	34,747
Positive wind forecast err. (%)	0,000	0,000	5,632	0,000	7,270	78,514	2,459	9,651
Positive load forecast err. (%)	0,000	000′0	1,560	0,277	2,405	19,713	2,739	13,820
Positive load forecast err. (%)	0,000	000′0	1,365	0,000	1,902	21,103	2,870	14,640
Load forecast (MWh)	135 802,000	211 292,000	246 932,926	246 841,000	285 548,000	325 957,000	-0,106	1,862
HHI - demand	401,008	753,707	1 087,434	996,065	1 279,941	5 747,157	1,978	888'6
HHI - supply	396,627	709,833	1 034,253	902,124	1 190,507	5 159,769	2,444	12,608

where s_i is the market share of the firm i (the volume traded by the firm over the total volume of the market) and m is the number of firms.

The table 3 gives the descriptive statistics of the variables described above for the year 2015. The variables are at the contract level (a specific delivery date and delivery hour). The average bid-ask spread per contract is 3.5€/MWh which is about 10% of the weighted average price (WAP) for the same period. The mean weighted standard deviation of the price is 4.15€/MWh or 11.5% of the mean WAP. The mean slopes of the buy and sell curves of the DAM are respectively equal to 0.026 and 0.010. The average hourly load is 247 GWh. The average concentration ratio is 1087 for the demand and 1034 for the supply. While the European Commission (Amanatidis, 2009) finds a HHI between 1800 and 5000 (highly concentrated market) for the power generation in Germany, I find that the German continuous market is less concentrated than the production. The mean HHIs of the continuous market correspond to a moderate concentration.

5.2. Methodology

This subsection describes the econometric specification used to explain the average bidask spread per contract.

Due to the configuration of the dataset, the panel data methods are the most appropriate because the dataset combines information on individuals' behaviors (contracts) and over time (delivery date). The contracts are independent as each of them are traded individually by the market participants. They also have their own specificities. The figure 6 shows the heterogeneity across contracts.

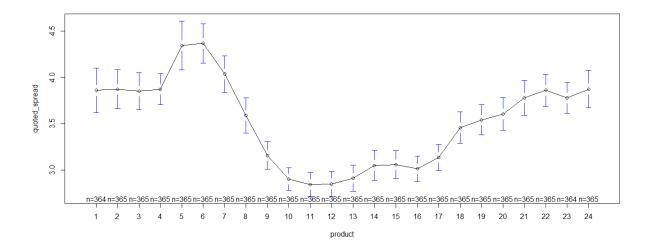


Figure 7: The heterogeneity across contracts

I compare the fixed effects model with the pooled OLS model using the F-test, and conclude that the fixed effects model is a better choice. I then compare the fixed effects model with a random one using the Hausman test. The fixed effects model is more appropriated.

Using the Levin-Li-Chu test for panel data, I find that none of the variables has a unit root; however, when I perform a stationarity test (Kwiatkowski-Phillips-Schmidt-Shin or KPSS test) for each group, I find that most of the variables are not stationary. In this sense, a first difference model is used to stationarize each variable. An additional KPSS test on each of the first difference variable confirms the stationarity of them.

The Breusch-Pagan test detects heteroskedasticity in the model. It can cause bias in the results of the standard deviations in the variables' estimations that use an OLS estimator; I then produce HAC (Heteroskedasticity and Autocorrelation Consistent) standard errors for the OLS models. The Breusch-Godfrey/ Wooldridge test identifies serial correlation in the panel model. For this reason, a feasible generalized least square (FGLS) estimator is used 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).

I explain the daily average bid-ask spread per contract as a function of the volatility (weighted price standard deviation and elasticities), the need for adjustments (relative wind, solar and load forecast errors), the activity (load) and the competition (HHI) on the market and estimate the equation below:

$$\triangle BAS_{it} = \alpha_{i}$$

$$+ \beta_{1} \triangle \sigma_{it} + \beta_{2} \triangle ES_{it} + \beta_{3} \triangle ED_{it}$$

$$+ \beta_{4} \triangle W_{it}^{FE+} + \beta_{5} \triangle S_{it}^{FE+} + \beta_{6} \triangle W_{it}^{FE-} + \beta_{7} \triangle S_{it}^{FE-}$$

$$+ \beta_{8} \triangle L_{it}^{FE+} + \beta_{9} \triangle L_{it}^{FE-}$$

$$+ \beta_{10} \triangle L_{it}$$

$$+ \beta_{11} \triangle HHI_{it}^{D} + \beta_{12} \triangle HHI_{it}^{S}$$

$$+ 1_{summer} + 1_{winter} + u_{it}$$

$$(17)$$

Table 4: **Definition of the notations**

Notation	Definition
σ_{it}	Weighted price standard deviation of the trades (EUR/MWh)
ES_{it}	Elasticity of the supply
ED_{it}	Elasticity of the demand
W_{it}^{FE+}	Positive wind forecast error (%)
S_{it}^{FE+}	Positive solar forecast error (%)
$W^{FE-}_{\cdot \cdot \cdot}$	Negative wind forecast error (%)
S_{it}^{FE-}	Negative solar forecast error (%)
L_{it}^{FE+}	Positive load forecast error (%)
$L_{it}^{\widetilde{F}E-}$	Negative load forecast error (%)
L_{it}	Forecasted load (MWh)
HHI_{it}^D	Herfindahl index for the demand side
HHI_{it}^S	Herfindahl index for the supply side
1_{summer}	Dummy variable for summer
1_{winter}	Dummy variable for winter

A summer and a winter binary variables are included in order to capture the

seasonal effects. The mid-season (spring and fall) binary variable is not included in order to avoid collinearity issues.

One may be concerned about the endogeneity problem that may arise with the weighted standard deviation variable, particularly due to its aggregation at the daily level. Instrumental variables are commonly used to address this issue; however, I cannot find any robust instrumental variable for the volatility. I compute the correlation and the covariance between the weighted price standard deviation and the error term of the regression. Both are null. On top of that, I perform the Granger causality test using data at the milliseconds level and find that "the volatility causes the bid-ask spread". The reverse does not hold. For the reason mentioned above, I discard the endogeneity hypothesis in the model.

VI. RESULTS

This section describes and discusses the results of the panel data model. The model is first run on the whole dataset. Then, I split the data in peak (between 8:00 and 20:00) and off-peak (before 8:00 or after 20:00) contracts. The results are displayed in the table 5.

Volatility - The weighted price standard deviation has a positive impact on the bid-ask spread, particularly during off-peak hours. When the volatility increases by $1 \in /MWh$, the bid-ask spread tends to increase by $0.03 \in /MWh$. An increase of the volatility by $1 \in /MWh$ during the trading session of an off-peak contract, increases the bid-ask spread by $0.115 \in /MWh$; while, the impact is only of $0.02 \in /MWh$ for peak contracts. The volatility has a stronger impact on the bid-ask spread during off-peak contracts.

An increase of the elasticities of the demand and the supply also has a positive impact on the bid-ask spread. As the aggregated curves get more elastic, a small change in the quantity leads to an important change of the price. The higher the elasticity (slope tends to infinity) is, higher is the volatility and so the spread. The slope of the supply curve has a stronger effect on the bid-ask spread than the slope of the demand curve. Overall, when the slope of the supply curve increases by 0.1, the bid-ask spread increases by 97 cents per MWh while an increase of the slope of the demand curve by 0.1 increases the spread by only 7 cents per MWh. This difference can be explained by the inelasticity of the demand. The elasticities do not have a significant impact on peak contracts. Interestingly, the demand elasticity has a negative impact on the bid-ask spread during off-peak hours; thus, when the elasticity increases by 0.1, the bid-ask spread decreases by 5 cents. The supply elasticity does not have a significant impact on the bid-ask spread during off-peak hours.

Need for adjustments - The variation of the fundamentals (load, wind and solar) have a significant impact on the bid-ask spread. 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 of the volume/market depths. This second explanation seems to gain over the first one. Looking at the results, most of the

load, wind or solar forecast errors (positive or negative) have a negative impact on the bid-ask spread.

A negative load forecast error has a positive impact on the bid-ask spread while a positive load forecast error has a negative impact on the bid-ask spread. The positive impact may be due to the behaviors of the suppliers who remove their orders from the order book they need to buy less from the market and so they increase the bid-ask spread. However, this positive effect is not observed when the analysis is splitted between peak and off-peak contracts: a negative load forecast error does not have a significant impact during the peak hours and has a negative impact during the off-peak hours. When there is a negative load forecast error of 1% for an off-peak hour, the bid-ask spread of the contract increases by 1 cent per MWh.

When the wind positive (resp. negative) forecast error increases by 1%, the bidask spread tends to decreases by 0.5 cent/MWh (resp. 0.2 cent/MWh). A 1% negative solar forecast error have an impact of -0.2 cent per MWh on the bid-ask spread. A positive solar forecast error has a negative but negligeable impact on the bid-ask spread. The difference between a positive wind forecast error and a positive solar forecast error can be explained by the difference of behavior of the TSOs who market the solar production while the aggregators market the wind production. The aggregators may adjust their position on the market after a positive forecast error while the TSOs may net their volume; for example, by using it to buy their grid losses. The difference between the positive and the negative wind forecast error may be due to the activity of the agreggators: they are liquidity providers or trade's originators in the case of a positive forecast error (ie. they send an order at a limit price to the order book) while they are more trade's agressors or liquidity demanders (they will hit an order already in the order book) in the case of a negative forecast error in order to buy some volume. While a wind forecast error is not significant during peak contracts, they are significant for off-peak contracts which contain most of the night hours. Ziel (2017) find a stronger impact of the forecast errors on prices during the night.

Activity - When the load increases by 1 GWh, the bid-ask spread decreases by 1 cent per MWh. When the load is high, during business days for example, there is an increase of the trading's need and so more volume/orders are sent to the market. This result holds independently of the type of contract (peak versus off-peak).

Competition - When the concentration on the sell side increases by 100, the bidask spread increases by about 3 cents/MWh while it only increases by 1 cent/MWh when the concentration on the buy side increases by 100. This result is intuitive as an increase of the concentration goes along with a decrease of the number of market participants as well as an increase of the market power of some firms. The bigger influence of the concentration on the sell side may be due to the inelasticity of the demand for power.

Table 5: Results using the panel FGLS estimator.

Estimate Si std. dev. (EUR/MWh) 0,03180 0,66791 0,66791 0,66791 0,66791 0,74710 0,002317 0,002317 0,00000 0,000016 0,000216 0,000219 0,00001 0,00009 0,000034 0,000034	Dependen	Dependent variable: Bid-ask spread	-ask spread			
Estimate Std. Error td. dev. (EUR/MWh) 0,03180 0,00343 y 0,66791 0,16232 9,74710 0,82758 -0,01387 0,00359 . (%) 0,02317 0,00339 . (%) 0,00000 0,00000 e. (%) 0,00016 0,00029 e. (%) -0,00515 0,00053 (Wh) 0,00001 0,00001		Peak			Off-peak	
itd. dev. (EUR/MWh) 0,03180 0,00343 y 0,66791 0,16232 9,74710 0,82758 (%) 0,02317 0,00359 e. (%) 0,00000 0,00000 e. (%) 0,00216 0,00045 e. (%) 0,00216 0,00029 e. (%) 0,00019 0,00003 (Wh) 0,00001 0,00001 0,00001 0,00001) Estimate	Std. Error	$\Pr(> z)$	Estimate	Std. Error	$\Pr(> \mid z \mid)$
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9,74710 0,82758 (%) -0,01387 0,00359 (%) 0,02317 0,00339 (%) 0,00000 0,00000 e. (%) -0,00216 0,00045 e. (%) -0,00515 0,00029 e. (%) -0,00219 0,00053 (Wh) 0,00009 0,00001 0,00034 0,00001	0,40977	0,58798		-0,51581	0,30044	٠
(%) -0,01387 0,00359 (%) 0,02317 0,00339 (%) 0,00000 0,00000 e. (%) -0,00216 0,00045 e. (%) -0,00515 0,00029 e. (%) -0,00219 0,00053 (Wh) 0,00009 0,00001 0,00003 0,00001	2,17080	4,31690		-2,81070	2,39150	
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e. (%) -0,00216 0,00045 e. (%) -0,00515 0,00029 f.e. (%) -0,00219 0,00053 4Wh) -0,00001 0,00000 0,00009 0,00001	0,00000	0,00000				
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f.e. (%) -0,00219 0,00053 4Wh) -0,00001 0,00000 0,00009 0,00001 0,00034 0,00001	-0,00196	0,00151		-0,01105	0,00148	***
-0,00001 0,00000 0,00009 0,00001 0,00034 0,00001	0,00544	0,00535		-0,00038	0,00219	
0,00009 0,00001 0,00034 0,00001	-0,00001	0,00000	* * *	-0,00001	0,00000	**
0,00034 0,00001	0,00008	0,00003	* *	-0,00001	0,00002	
	0,00030	90000′0	* * *	0,00026	0,00004	**
Winter dummy -0,01540 0,22450	0,22748	0,53703		-0,90928	0,43453	*
Summer dummy 0,07826 0,66582	0,78838	1,58200		-2,65730	1,28270	*
Number of observations 8625	4684			3941		
Note: ***p<0.1; **p<0.05; ***p<0.01	71					

VII. REMARKS AND CONCLUSION

The continuous market is getting more and more attention in the literature as well as in the public debate thanks to (i) the growing renewable capacity that increases the willingness to trade very close to delivery and (ii) the single intraday coupling or XBID project which aims to harmonize the cross-border intraday trading across Europe. The market quality and so the liquidity is of major importance for institutions but also market participants. This paper brings to light the behavior of the liquidity along a trading session and find the main drivers of this liquidity.

While the literature on the bid-ask spread is dense, it remains applied to the financial markets. The power market has its own specificities that fully justifies a proper study. The present paper investigates the bid-ask spread of the German continuous market taking into account those specificities.

First, I observe a «L-shaped» behavior of the bid-ask spread over an average trading session of the German intraday market. There is a strong dispersion of the bid-ask spread at the beginning of the trading session which then diminishes as the delivery time approaches. The dispersion reflects the uncertainty away from the delivery time mainly due to the intermittent renewable generation. On average, the local bid-ask spread is 3.5€ per MWh. The reverse shape applies for the market depths that increase over the trading session.

Second, I explain the bid-ask spread by four components: the risk, the information, the activity and the competition on the market. I find that the risk and volatility of the market increase the bid-ask spread. A fundamental (wind, solar or load) forecast error leads to a decrease of the bid-ask spread by bringing more liquidity to the market except for the case of a negative load forecast error which has a positive effect on the bid-ask spread. Interestingly, I observe that a demand (load) and a supply (wind or solar) shock do not have the same impact on the bid-ask spread: a load forecast error has a stronger impact on the bid-ask spread in comparison to a wind or a solar forecast error. When the activity on the market increases, the spread tends to decrease, in line with the positive relationship between the concentration on the market and the bid-ask spread.

Some typical results of the financial literature hold such as the positive relation between the volatility and the bid-ask spread or the negative relation between the market activity and the bid-ask spread. However, there are important specificities of the power market such as the impact of a forecast error that have a positive effect on the liquidity of the market. I find a lower concentration in the wholesale market in comparison to the generation segment. There is a positive relationship between the bid-ask spread and the concentration. The effort of promoting competition via regulation or market design should continue.

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.

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APPENDICES

Figure .1: Distribution of the bid-ask spread

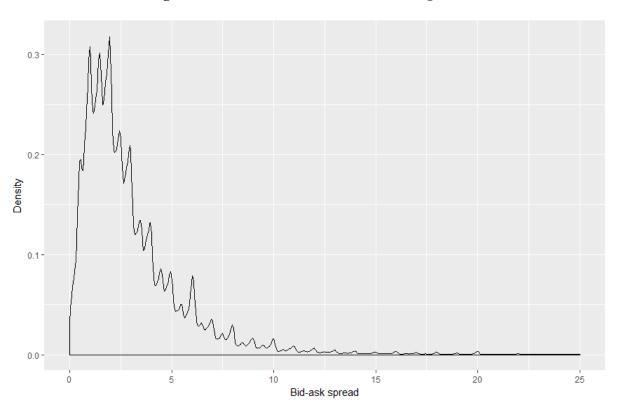


Figure .2: Distribution of the buy depth at the contract level

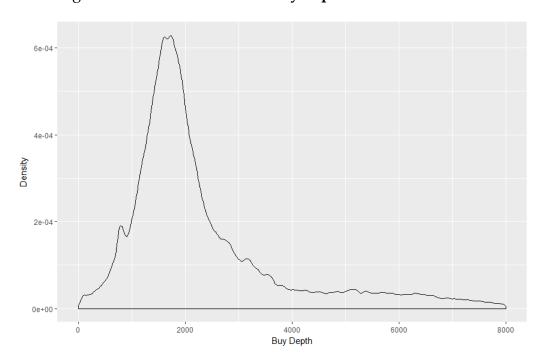


Figure .3: Distribution of the sell depth at the contract level

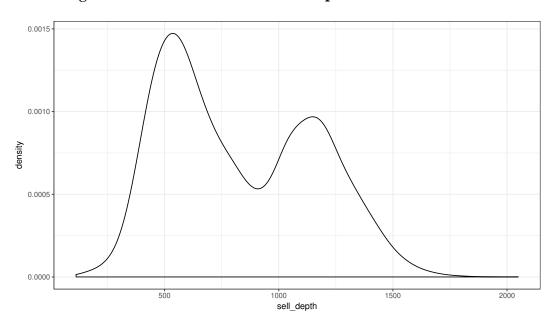


Figure .4: Cumulative share of the volume traded along an average trading session

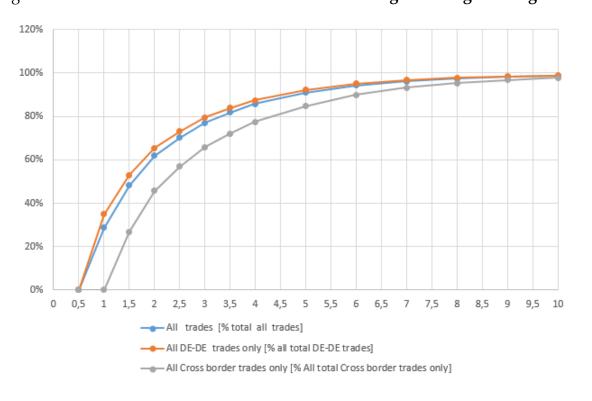


Figure .5: Bid-ask spread over an average trading session for various products

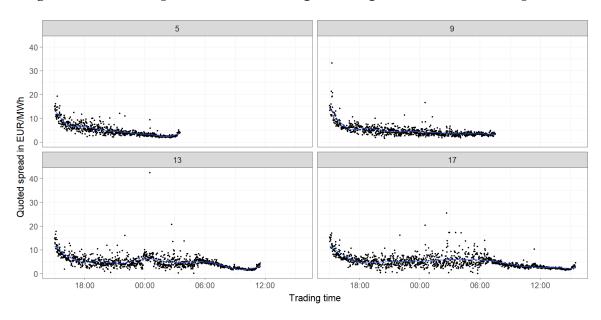
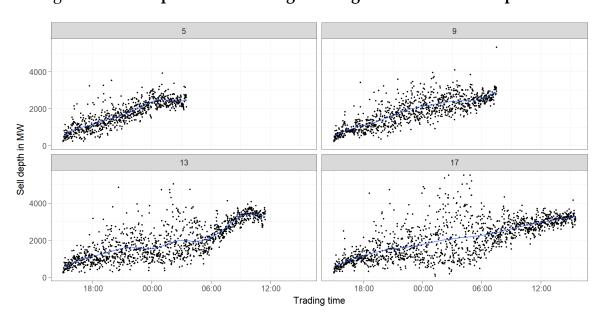


Figure .6: Sell depth over an average trading session for various products



AHHI^S
-0,017
-0,033
0,057
0,041
0,002
0,030
-0,001
0,099
0,099
0,099
1,000 $^{D}_{it}$ 0,000 0,000 0,014 0,023 0,012 0,008 -0,008 0,078 -0,078 -0,078 -0,078 -0,078 0,078 -0,078 $\triangle L_{it}$ 0,007
0,007
0,051
-0,132
-0,132
0,012
0,012
0,010
0,010
-0,0112
-0,0112 ΔL_{it}^{FE-} 0,022
0,013
0,019
0,045
0,045
0,025
0,025
0,025
0,026
0,027
0,099 $^{\perp}L_{it}^{FE+}$ $^{\perp}L_{it}^{FE+}$ $^{\perp}$ $^{\perp}$ Table .1: Correlation matrix $\sum_{it} S_{it}^{FE} - S_{it}^{FE}$ 0,005
0,030
0,015
-0,034
0,040
1,000
-0,028
0,025
-0,033 N_{it}^{FE} 0,004
-0,016
0,006
-0,010
0,012
1,000
-0,001
0,004
0,012
0,008
0,008 $\sum_{t} \sum_{t} \sum_{t} E_{t} + \sum_{t} \sum_{t} C_{t} C_$ NM_{it}^{FE+} 0,006
-0,036
0,059
1,000
-0,219
-0,010
-0,034
0,023
-0,055
-0,055 \(\textit{LED}_{it}\)
0,024
-0,003
1,000
0,059
-0,015
0,006
0,015
-0,036
0,019
-0,121
0,023
0,023 $\triangle ES_{it}$ 0,056
1,000
0,036
0,036
0,005
0,016
0,030
0,018
0,013 $\triangle \sigma_{it}$ 1,000
0,056
0,024
0,047
0,004
0,005
0,005
0,005
0,007
0,007
0,007 $\triangle \sigma_{it}$ $\triangle ES_{it}$ $\triangle ED_{it}$ $\triangle ED_{it}$ $\triangle W_{it}^{E+}$ $\triangle W_{it}^{E}$ $\triangle S_{it}^{EE+}$ $\triangle W_{it}^{EE-}$ $\triangle L_{it}^{EE-}$ $\triangle L_{it}^{EE-}$ $\triangle L_{it}^{EE-}$ $\triangle L_{it}^{EE-}$ $\triangle L_{it}^{EE-}$ $\triangle HHI_{it}^{EE-}$