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Private and Public Information on the Nordic Intra-Day Electricity Market

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Abstract: This paper is an empirical investigation of how traders react to public news in a market where there are lots of non-scheduled announcements, often arriving simultaneously. Using detailed trade information from the Nordic intra-day electricity market and GARCH models, this paper examines market participants' reaction to news about sudden production and transmission failures on the electricity grid. I divide the time of news announcement into three phases: the preannouncement period – the interval up to one hour before the hour of the public announcement of a message, the contemporaneous period – the same hour as the announcement of a message, and the post-announcement period – one hour after the hour of the announcement of a message. I find effect of news on prices in the preannouncement period, indicating that private information exists and is being used for trading on the intra-day market.

Key words: private information, public information, non-scheduled announcements, intra-day electricity market, Nord Pool, UMMs
JEL codes: G14, L94

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1. Introduction

The role of information and its impact on prices and trading is especially important in financial economics. The microstructure literature (O'Hara, 1995; Madhavan, 2000) distinguishes two types of information: private and public. The latter type is the publicly announced news that can be either random (unscheduled) or published at fixed times (scheduled announcements). Private information includes access to not yet released public information (i.e. payoff related private information (Lyons 2000)) or the so called unrelated payoff information that stems from trader's knowledge of the market and its interim states (for e.g. whether there is another trader willing to submit a large trade). There are several types of informed trader; someone who is illegally profiting from fundamental information i.e. an insider trader, or it can be "a trader that is more skilled than other and has superior knowledge based on analysis" (Baker and Kiymaz 2013 p.254). Informed traders can also have superior knowledge about order flow in a security e.g. knowing that a large asset manager will trade a sizable quantity of shares which would result in a price change.

This paper is an empirical investigation of how traders react to public news. I investigate a continuous commodities market with few trades and many unscheduled publicly announced pieces of news. These special characteristics are in contrast to high frequency financial markets where public announcements are rare and usually anticipated.[1] I use price data from the Nordic intra-day electricity market and the dataset of publicly announced Urgent Market Messages that inform about changes to generation, consumption or distribution of electricity that are larger than 100 MW and last for more than 60 minutes.

Market rules are designed to provide full and fair disclosure of all events that have a major impact on the power sector. However, before the information becomes publicly known, there is a period of time when

[1] Examples of studies with few scheduled announcements include Ederington and Lee (1993) who examine the impact of nineteen monthly macroeconomic announcements on the Treasury bond, Eurodollar and deutsche mark futures markets, or Goodhart et al. (1993) where they look at the effect of two news events on the foreign market.

especially generators affected by the event in question have private knowledge about it. Acting on the private information before it becomes public is considered market manipulation and is forbidden according to the Market Conduct Rules[2], which state that participants may not "place, change or remove bids or actively enter into transactions in the market when holding inside information". However, in 2012 alone the Nord Pool Market Surveillance investigated 10 instances of insider trading.[3]

According to the rules governing the disclosure of market news, issuers of messages can act on this information only after it has been made public. However, publishing the information publicly eliminates the private value of information. If public disclosure of information impacts negatively the profitability of the issuer, there exists an incentive to distort or delay the information (von der Fehr, 2013). Using the information for trading just before the news becomes public would allow the issuer to profit from the information prior to it becoming public.

In most analysis of insider trading it is not obvious whether traders have private information. There are studies that look at the proved instances of insider trading and try to verify how these instances affected asset price. Elliot (1984) uses a sample of insider trading instances as so does Meulbroek (1992). In the case that I investigate it can be assumed that generators who bid into the market have perfect information about their condition; they have private information, the question is whether they use it.

I empirically analyze the impact of market news and test for the presence of trades based on private information when there are lots of non-scheduled announcements, often arriving simultaneously. I use a detailed dataset with information about concluded trades and market messages issued by electricity producers and transmission system operators informing about sudden failures. I evaluate conditional variance models with exogenous variables describing announcement of news.

I find an effect of current and lagged news on mean price levels, traded volumes and number of trades. Additionally, the results for prices show

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[2] http://www.nordpoolspot.com/PageFiles/rulebook/MCR.pdf

[3] http://energitilsynet.dk/fileadmin/Filer/Internationalt/Nord_Pool_Spot_REMIT_Seminar.pdf

positive effects of news in the preannouncement period, indicating that some trading is being executed with the use of private information.

Public and private information and its impact on trading activity has been an important topic in the financial literature. Initially authors concentrated on analyzing the impact of news on trading in the post-announcement period. Ederington and Lee (1993) study the effect of nineteen regularly repeated macroeconomic announcements on the volatility of interest-rates and foreign exchange futures contracts in the US market. Goodhart et al. (1993) investigate the impact of two events on the dollar-sterling exchange rate. Berry and Howe (1994) investigated the impact of many public announcements and their impact on trading volume. Mitchel and Mulherin (1994) looked at large set of public news and their impact on daily trading volume and market returns. This strand of literature focused on the impact of news on trading after the news became public knowledge. However, public information announcement, following the microstructure approach, can help to identify the pre-announcement periods when some individuals might have insider knowledge about the public news prior to its announcement. The separation of traders into those possessing private information and those without it introduces different incentives for timing the trades and therefore can have effects on market activity. Degennero and Shrieves (1997) compare the importance of news and private information as conditioning factors of financial market volatility. They find that high market activity has a positive impact on volatility and spread and they contribute it to traders' private information. Bauwens et al. (2005) study the impact of nine categories of scheduled and unscheduled news on the euro-dollar return volatility and analyze the three time intervals around the announcement of each piece of news. They show that volatility increases in the pre-announcement periods in particular in case of scheduled events and they interpret this as trades done by players who want to make anticipatory trades based on their personal beliefs. The only effect of unscheduled news is observed for the rumors of central bank intervention.

This paper consists of six sections. Section 2 describes the functioning of the Nordic intra-day market and the data. Section 3 discusses the theoretical approaches to thinking about public and private information and their impact on trading. Section 4 presents empirical strategy and results follow in section 5. The final section concludes.

2. Market and data description

The Nordic electricity market is composed of physical and financial markets and covers electricity generation in Sweden, Finland, Denmark, Norway, Latvia, Lithuania and Estonia. Two physical markets form the Nord Pool Spot; the larger one, Elspot, enables trading of electricity contracts one day ahead of their physical delivery. The market is supplemented by the intra-day market, Elbas, which operates as a continuous market and enables trading up to one hour before the delivery of electricity. Elbas is a complementary market to the main day-ahead market and handles around 1% of electricity as compared with Elspot, but it is constantly growing. In 2010[4] Elbas turnover was slightly above 2TWh, rising to 2.5TWh in 2011 and reaching 3.2TWh in 2012. Elbas increases in importance as more wind generation enters the grid. The intra-day market functions as a continuous, discriminatory auction and the bids and offers are settled as soon as the offer meets demand. Trades happen irregularly, in some hours there is a lot of trading activity, in others, especially off-peak trades are rare. In order to put structure into the analysis and be able to use methods describing series uniformly spaced in time, I transform the available data series into hourly averages.[5]

[4] http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/annual-report_Nord-Pool-Spot_2012.pdf

[5] One class of models that investigate informational content of the time elapsed in between trades (and can be used for modeling data irregularly spaced through time) is referred to as ACD (Autocorrelated Conditional Duration) models; however, the analysis of these models is not in the scope of this paper.

2.1 Trade data

I analyze prices, volumes and the number of settled trades that took place between the 1st of January 2010 and the 20th of October 2012.[6] The studied sample contains 404,744 trades. There were on average 17 trades recorded every hour during the period of analysis (Table 1).

Table 1. Summary statistics describing the number of trades per hour

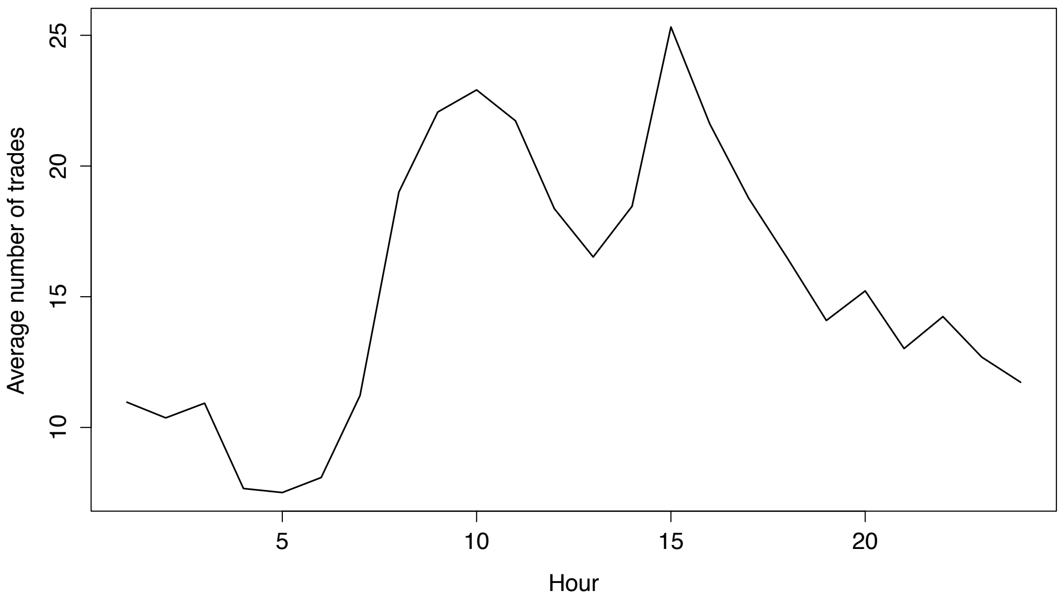
Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*
Trade count	24,574	16.5	14.8	0	260

Note: This table presents summary statistics for the hourly number of trades on the Nordic intra-day electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012.

Most trades take place at hours 10 in the morning and 15 in the afternoon with accordingly 22 and 25 trades on average (Figure 1). During the night there are on average fewer trades, the market is less active as demand is relatively low and can be easily met by suppliers. There is a drop in the number of trades between hours 11 and 13 resulting in a two-hump shape of the hourly distribution of trades.

[6] The identity of traders is not known either.

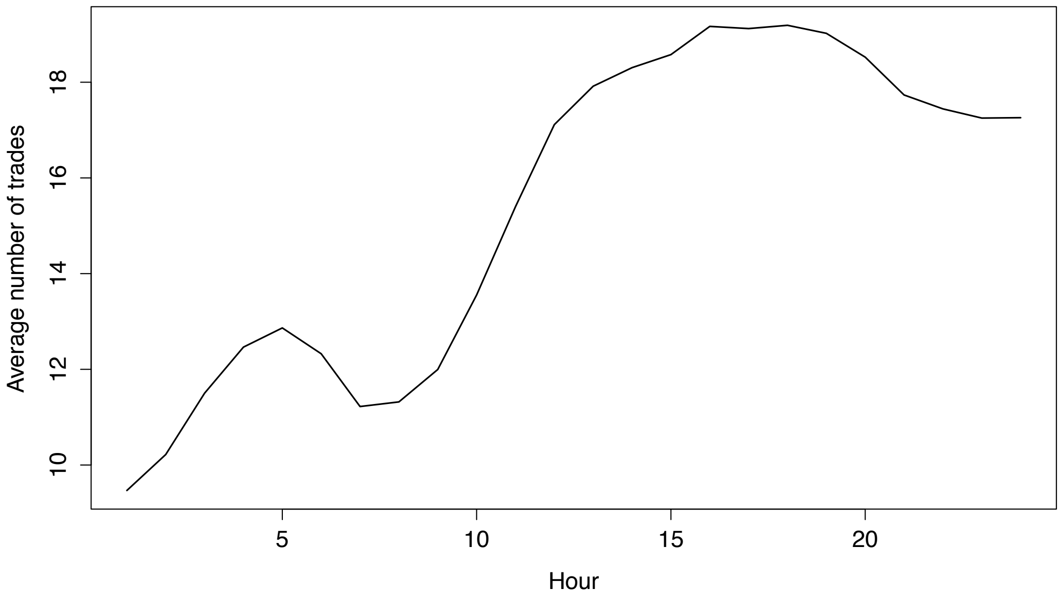
Figure 1. Average number of trades per hour



Note: This figure shows the average number of trades per hour.

While discussing the timing of particular trades it is important to note that the market in question is a continuous market and particular products (electricity that is to be delivered at a particular hour of the day) can be traded in different moments of the day. Therefore, a decrease in trading that is observed around noon does not necessarily correspond to the decrease in trades of the products to be delivered around noon. Figure 2 reports the average number of trades per product (there are 24 products every day). It shows that the number of contracts to be delivered later during the day increases. Contracts for delivery in the early morning hours (between hour 00:01 and 8:00) are not traded that often. Contracts for delivery later during the day are traded more frequently.

Figure 2. Average number of trades conditioned on the delivery time



Note: This figure shows the average number of trades according to the hour of contract's delivery.

2.2 Price

The average hourly price of electricity traded in the intra-day market was around 47€/MWh with the cheapest hour trading for approximately -45€/MWh and the most expensive hour with average electricity price above 805€/MWh (Table 2).

Table 2. Summary statistics describing the intra-day price

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*
Price	*24,574*	47.18	24.08	-45	805.7

Note: This table presents summary statistics for the hourly intra-day electricity price from the Nordic electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Price is reported in Euros per megawatt hour.

However, as the intra-day market operates as a discriminatory continuous auction, there is not one price for a product but a range of prices that can vary substantially. In the studied sample the range of prices obtained for the same product varied up to 951.5€/MWh (Table 3).

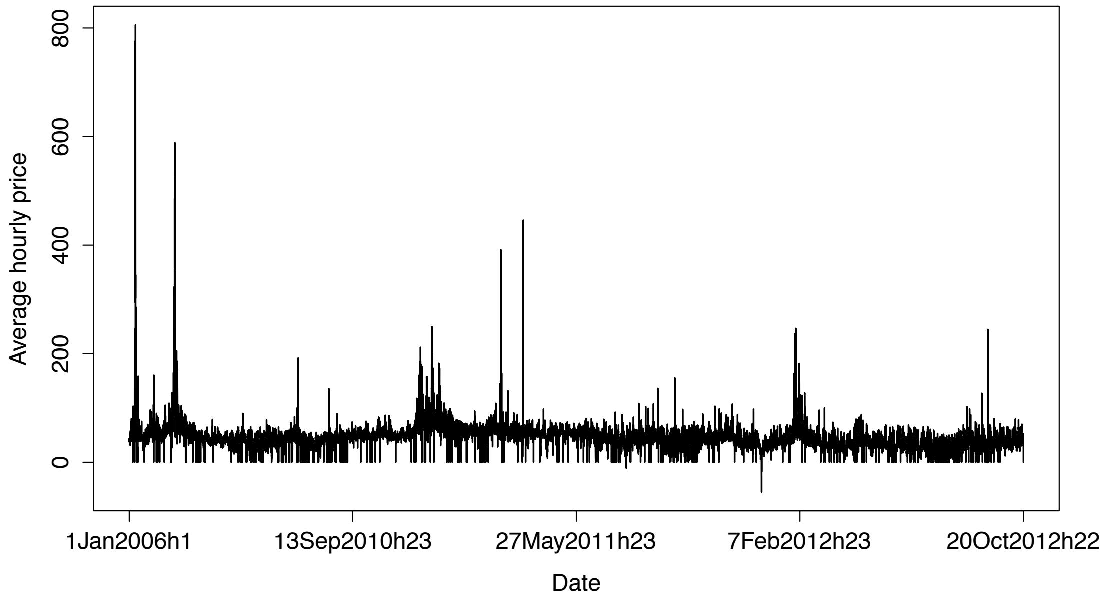
Table 3. Summary statistics describing the intra-day price

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*
Price	404,744	47	27.09	-150	1,500
Diff	404,744	24.4	31.22	0	951.5

Note: This table presents summary statistics for the intra-day electricity price from the Nordic electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Diff stands for the difference between the lowest and the highest price for the same product. Price is reported in Euros per megawatt hour.

During the analysed period there were instances with spikes (Figure 3). At the beginning of 2010 prices reached 1,500€/MWh (800€/MWh for hourly data) and several spikes were registered throughout the studied period when prices reached around 500€/MWh. Interestingly there were moments when utilities were paying to sell electricity – the minimum hourly price of -45€/MWh was reached in December 2011.

Figure 3. Evolution of electricity prices on the intra-day market



Note: This figure shows evolution of the hourly intra-day electricity prices on Nord Pool from the 1st of January 2010 until the 20th of October 2012.

2.3 Volume

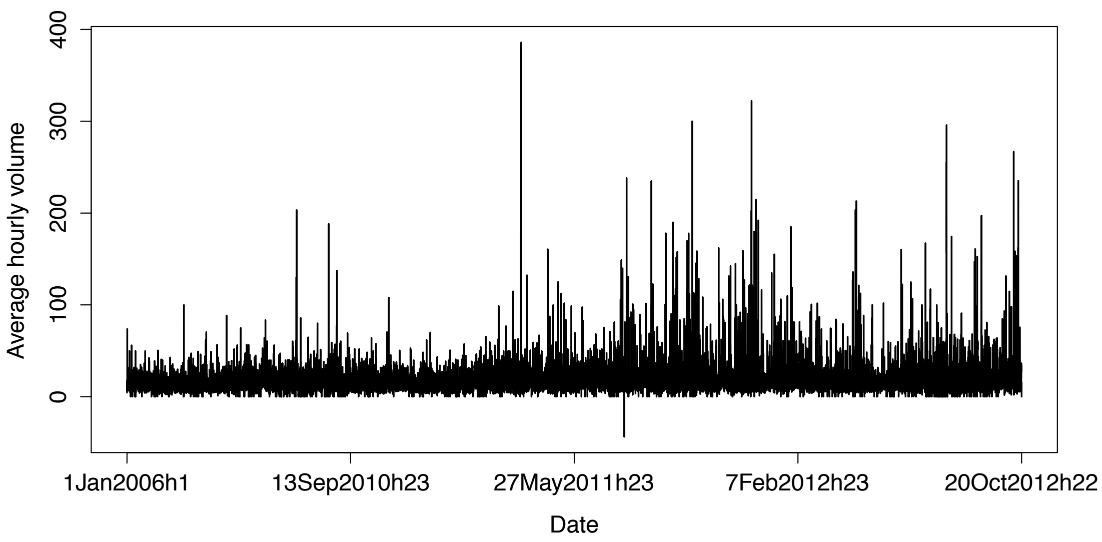
The size of traded contracts varies substantially from 1 kWh to 935 MWh. Summary statistics show that the mean size of volume traded in one trade was low and amounted to only 17.7 MWh (Table 4).

Table 4. Summary statistics describing volumes series

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*	*Median*
Hourly volume	*24,574*	17.69	13.39	0	300.00	15.31

Note: This table presents summary statistics for the hourly volumes of traded electricity on the Scandinavian electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Volume is in MWh

Figure 4. Evolution of volume traded on the Nordic intra-day electricity market



Note: This figure shows evolution of the hourly volumes transacted on the intra-day electricity market Nord Pool between the 1st of January 2010 and the 20th of October 2012.

2.4 News data

The news dataset is composed of time-stamped announcements of changes to capacity reported by market participants. In Nord Pool market participants are obliged to publicly inform about any changes to generation, transmission and consumption of electricity that are larger than 100 MW and last for longer than 60 min. The news is released through Urgent Market Messages (UMMs) that are publicly available and bring information about the announced event. UMMs inform about the identity of the issuer, size of the outage and area affected by the event as well as other data. News messages are unscheduled and can be roughly divided into failure messages and news informing about future maintenance. Nord Pool rules dictate that a member experiencing a failure has to report it through UMMs within 60 min of the discovery of the problem. There are no clear rules regarding when maintenance announcements need to be made, except that is has to be sufficiently in advance. In the analysed sample there were 2,702 novel failure messages, out of these 323 were due to transmission line failures (TSO) and 2,194 notifying about production failures.

For the purpose of this study I create a dataset describing the number of trades that took place every hour between the 31/12/2009 17:00 and 20/10/2012 22:59. For each hour I report average price, average volume[7] and three exogenous variables informing about the number of issued UMMs. I specify three UMMs variables informing about the number of novel announcement about the failures on the power grid:

Current_failure reporting a number of UMMs issued on hour t;
Past_failure reporting a number of UMMs issued on hour t-1;
Future_failure reporting a number of UMMs issued on hour t+1;

Electricity producers may hold private information about their own generating units, however they will not have any private knowledge about potential problems on the transmission lines. I expect that if the private information is used, it is done so only with relation to the UMMs issued by electricity producers not with the messages announced by system operators. Therefore, in order to check for these effects, I create six new variables where time intervals around the news announcement are as specified above (one hour before the trades, the same hour as the trades and one hour before the trades) but distinguishing the identity of the issuer: electricity producer and system operator (TSO) *Current_tso_failure*, *Past_tso_failure*, *Future_tso_failure*, *Current_producer_failure*, *Past_producer_failure*, *Future_producer_failure*.

2.5 Stationarity of series

Visual inspection of Figure 3 indicates that the series is stationary. To verify this statement I use Dickey-Fuller test. The results allow for rejecting the

[7] In high-frequency financial dataset there is often more detailed information available like: bid-ask spreads; in the dataset that I use this information does not exist.

null hypothesis of a unit root (Table A1 in the Appendix). The test for the stationarity of the series is run also for the series describing the number of trades per hour and for volumes (Table A1). Results allow for rejection of the hypothesis of a unit root.

3. Information and public information releases

The classic reference for the discussions of market microstructure issues such as insider trading or market manipulation is Kyle (1985). The static version of the model analyses a stock market with three types of risk neutral traders: liquidity traders, a market maker who sets the price after observing the order flow and a single informed investor who trades with the aim of exploiting his private information. Both liquidity traders and the informed investor trade at the same time. The informed trader acts strategically, knowing that his demand will influence the price of the traded asset and his aim is to maximize his profit. The informed trader and liquidity traders submit their orders simultaneously; the market maker cannot distinguish among different orders and traders and observes only net order flow. He sets the execution price equal to his best estimate of the value of the stock given the observed order flow.

A similar model but in a dynamic version is analyzed by Admati and Pfleiderer (1988) who concentrate on the evaluation of the intra-day price and volume patterns. In their model the informational advantage of informed traders is only short-lived. Informed traders have a noisy version of the public information one period in advance. This assumption leads to the observation that they have no incentive to postpone their trading to future periods as their private information becomes public in the next period. Asymmetries in information distribution influence the adjustment of prices in the preannouncement periods, which continues upon news arrival. In case there is no additional news in the following periods, the volatility decreases.

A related model, which introduces long-lived information with decreasing value over time, had been developed by Foster and Viswanathan (1990). The informed trader receives information every day but some portion of this information becomes public each day making the information less valuable over time. The informed trader trades more aggressively as he is aware of the forthcoming public signal; hence more information is released through trading.

In these models asymmetric information explains price fluctuations in the periods around the announcement of public news. Traders with private information want to benefit from their superior knowledge about future events. As a result prices adjust to private information before the news is publicly announced. In case there is no informed trading in the preannouncement period, prices adjust to the new information after news arrival.

4. Modeling trading activity

In financial studies returns are usually calculated over a fixed time-window often 5 minutes (Bauwens et al. 2005) or 10 minutes (DeGennaro and Shrieves 1997). This approach is used when studying high-frequency markets. Trades on the Nordic electricity intra-day market are not that frequent, with on average 16 trades in the analyzed period. Moreover, the trades are irregularly spaced over time and this is why I transform the trade-by-trade data into hourly.

In order to distinguish between pre-announcement and post-announcement intervals, I divide the period around news announcements into three non-overlaping time intervals: a pre-response interval of one hour before the hour of the announcement, a response interval which I define as the same hour as the hour of a UMM announcement, and a post-response interval – one hour after the hour of the news announcement.

4.1. Estimation

Modeling of price time series is often done with the use of generalized autoregressive conditional heteroskedasticity (GARCH) models. [8] The standard GARCH model has been described by Bollerslev (1986).

Using detailed trade information I estimate GARCH models with exogenous variables in the mean equation. Private information is defined as public information in the periods before the announcement and is captured by the variable *Future_failure*. I specify the following model:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (1)$$

$$y_t = \mu + \sum_{i=1}^{j} \vartheta_i r_{it} + \theta_1(y_{t-1} - \mu) + \theta_2\epsilon_{t-1} + \epsilon_t \quad (2)$$

$$\epsilon_t = \sigma_t z_t \quad \text{where} \quad z_t \sim N(0,1) \quad (3)$$

In the mean equation (2) I included j external variables r_{it}. I estimate the model (eq. 1-3) for GARCH (1,1)[9] first using number of trades as the dependent variable, then price and lastly, I repeat the estimation for the traded volumes. Initially I use three external variables *Lagged_failure*, *Current_failure* and *Future_failure*. Then, as the incentives can vary I divide the news announcements not only according to the announcement time but I also take into account the identity of the UMM issuer. I distinguish events reported by electricity producers from those announced by Transmission System Operators.

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[8] Some examples of garch modeling of the impact of news/exogenous factors on the volatility of exchange rates can be found in: Degennaro and Shrieves (1997), Melvin and Yin (2000), Bauwens et al. (2005) or Goodhart et al. (1993)

[9] Different models have been compared with the use of AIC criteria.

5. Results

Estimation is done with R, using the rugarch package Ghalanos, A., (2014). Results of the estimation are reported in Table 4. Standard errors, which are reported in the table, are computed with White (1992) methodology, which provides asymptotically valid confidence intervals in samples with not normally distributed errors.

Table 5. Estimation results with all failures

Variable	*Number of trades*	*Price*	*Volume*
Mu	16.15	42.16	16.79
	0.62***	0.81***	0.21***
Ar1	0.28	0.48	0.21
	0.009***	0.01***	0.01***
Ar2	0.11	0.22	0.11
	0.008***	0.013***	0.01***
Ar3	0.05	0.09	0.06
	0.008***	0.013***	0.007***
Ar4	0.018	0.04	0.04
	0.008**	0.01***	0.008***
Ar5	0.03	-0.01	0.04
	0.007***	0.001	0.008***
Ar6	0.023	0.02	0.04
	0.008***	0.01*	0.008***
Ar7	0.02	-0.02	0.03
	0.007***	0.016	0.008***
Ar8	-0.005	0.036	-
	0.007	0.019*	-
Ar9	-0.007	0.003	-
	0.008	0.02	-
Ar10	-0.01	0.049	-

	0.007	0.012***	-
Current_failure	1.31	0.81	0.688
	0.27***	0.25**	0.234***
Future_failure	-0.046	0.373	0.127
	0.233	0.205*	0.22
Past_failure	1.273	0.5	0.916
	0.282***	0.27*	0.21***
Omega	1.774	2.65	0.45
	0.286***	1.23**	0.149***
Alpha1	0.031	0.09	0.017
	0.002***	0.02***	0.002***
Beta1	0.96	0.9	0.982
	0.000***	0.03***	0.00***
AIC	7.8325	7.4853	7.8681

Note: This table shows results from the estimation of hourly data. The dependent variables are: number of trades, price and volume time series. Number of trades series (column 2) is estimated using ARMA (48,0) – GARCH (1,1) model. Price series (column 3) is estimated using ARMA (10,0) – GARCH (1,1). Volume series (column 4) is estimated using ARMA(7,0) – GARCH (1,1). Robust standard errors are in brackets. *Past_failure*$_t$ counts the number of failures registered in the hour t-1. *Current_failure* counts the number of failures registered in the hour t. *Future_failure* counts the number of failures registered in hour t+1. *Number_of_trades* counts the number of trades per hour. *Price*$_t$ is the hourly weighted average of prices registered during hour t; *Volume*$_t$ is the hourly weighted average of volumes registered during hour t. The terms: AR(p) with p = <11, 48> for number of trades are reported in Table A2 in the Appendix. Star levels: *p<0.1; **p<0.05; ***p<0.01

An ARMA (10,0) – GARCH(1,1) model for price among specifications of price series works the best, though it is not completely successful. However, more complex models do not provide better results (as compared with Akaike Information Criterion, autocorrelation and partial autocorrelation plots) and the conclusions derived from news variables from those different models are similar.

Results show that news about failures have a significant effect on price changes in all three periods: one hour before the news is realised *Future_failure*, in the hour of news release *Current_failure* and one hour after the news has been released *Past_failure*.

Table 6. Estimation results with producers' and tsos' failures

Variable	*Number of trades*	*Price*	*Volume*
Mu	16.168384	42.14	16.792158
	0.592919***	0.811***	0.207060***
Ar1	0.28	0.48	0.205186
	0.009***	0.01**	0.010156***
Ar2	0.11	0.22	0.113263
	0.008***	0.01***	0.009480***
Ar3	0.05	0.09	0.062765
	0.008***	0.01***	0.008697***
Ar4	0.02	0.04	0.040102
	0.008**	0.01***	0.008458***
Ar5	0.03	-0.01	0.035857
	0.007***	0.01	0.008402***
Ar6	0.02	0.02	0.038332
	0.008***	0.01*	0.007927***
Ar7	0.02	-0.02	0.033155
	0.007***	0.02	0.008302***
Ar8	-0.005	0.04	-
	0.007	0.02*	-
Ar9	-0.008	0.003	-
	0.008	0.02	-
Ar10	-0.01	0.05	-
	0.007	0.01***	-
Current tso's failure	1.227	0.88	0.709577
	0.871(*)	0.38**	0.514167
Past tso 'sfailure	1.639	0.18	1.626887
	0.744**	0.424	0.536170***
Future tso's failure	0.39	0.33	0.382902
	0.71	0.36	0.526987
Current producer's failure	1.275	0.85	0.734197
	0.279***	0.3**	0.262616***
Past producer's	1.413	0.66	0.262616

failure			
	0.318***	0.34**	0.245399***
Future producer's failure	-0.09	0.39	0.124916
	0.239	0.23*	0.251219
Omega	1.77	2.64	0.447659
	0.29***	1.23**	0.148876***
Alpha1	0.03	0.09	0.017351
	0.002***	0.02***	0.001692***
Beta1	0.96	0.9	0.981649
	0.00***	0.03***	0.000015
AIC	7.8327	7.4854	7.8682

Note: This table shows results from the estimation of hourly data. The dependent variables are: number of trades, price and volume time series. Number of trades series (column 2) is estimated using ARMA (48,0) – GARCH (1,1) model. Price series (column 3) is estimated using ARMA (10,0) – GARCH (1,1). Volume series (column 4) is estimated using ARMA(7,0) – GARCH (1,1). Robust standard errors are in brackets. *Number_of_trades* counts the number of trades per hour. $Price_t$ is the hourly weighted average of prices registered during hour t; $Volume_t$ is the hourly weighted average of volumes registered during hour t. The terms: AR(p) with p = <11, 48> for number of trades are reported in Table A2 in the Appendix.

Star levels: *p<0.1; **p<0.05; ***p<0.01; (*)p<0.15

The division according to the type of issuer brings some additional information (Table A6, Appendix). Results indicate that a failure reported by a TSO has an effect on the current trading (effects for price) and future trading (effects for number of trades and the volumes). Results for producers are similar when it comes to the effects of current and past news about failures (positive effects for all series). However, in contrast to the TSO results, I do find that the knowledge about a failure encountered by a producer that has not yet been publicly reported, *Future_failure* has an effect on electricity prices. This simple test indicates that there is some systematic evidence that producers use private information for trading while private information about the failures on the transmission network (failures reported by TSOs) is not affecting trading.

The volumes series have been estimated with the use of ARMA(7,0) – GARCH(1,1) specification, however, they were not completely successful either. Nevertheless, results for the news variables from different specifications, which were compared with the Akaike Information Criterion, autocorrelation and partial autocorrelation techniques, do not change much. The intra-day market is a continuous market and market players can trade electricity that will be delivered between 1 and 36 hours after the trading took place. The significant effect of the current news on the contemporaneous volumes (Table 5, column 4) indicates that, as soon as news is made public, trading of electricity to be delivered in one hour or later begins. Market players adjust their positions as soon as they learn about the new market condition reported through a UMM.

I model the hourly number of trades with the use of ARMA (48,0) – GARCH (1,1) specification. The results show that news has a significant effect on both the current and the future trading (Table 5, column 2). Moreover, the results in Table 6 indicate that the number of trades increases within one hour after the announcement of a problem reported by the TSOs. The effect of the current TSO failure announcement has a also a significant effect (result significant at on 15 present level).

6. Conclusions

The European Commission is introducing a set of new regulations on submission and publication of data in electricity markets (SPDEM)[10] accompanied by the rules on wholesale energy market integrity and transparency (REMIT).[11] These rules require public disclosure of detailed information concerning for example changes to transmission, generation or consumption that are larger than 100 MW and last for longer than "one market time unit" i.e. one hour for the Scandinavian electricity market (Nord Pool). In Scandinavia a similar system of information announcements has existed under the name of Urgent Market Messages (UMM) since 2004.

It is forbidden to use the information from UMMs before they are publicly disclosed. This paper has examined whether there are any patterns between news announcements and price, number of trades and traded

[10] EU, 2013

[11] EU, 2011b

volumes. In this market there are market players who posses private information and this paper analysed whether they are using their information before it is made public.

With the use of a time series approach I have investigated the behaviour of prices, number of trades and traded volumes in the period of one hour prior to the hour of the UMM announcement, during the hour of a UMM announcement and 60 minutes after a UMM was issued. I find an effect of current and lagged news on mean price levels, traded volumes and number of trades. Additionally, the results for prices show positive effects of news in the preannouncement period, indicating that some trading is being executed with the use of private information.

Although channels informing about real-time changes to the situation on the power grid raise questions whether this increased transparency of markets is beneficial (von der Fehr 2013), they give the authorities and researchers a tool to check in a systematic way for the presence of trades based on private information.

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Appendix

Table A1. Dickey-Fuller test for unit root

Series	*Test statistics*	*1% critical value*	*5% critical value*	*10% critical value*
Price	-13.9919	-3.430	-2.860	-2.570
Volume	-21.395	-3.430	-2.860	-2.570
Number of trades	-17.4789	-3.430	-2.860	-2.570

Note: Number of obs. = 24,574

Table A2. Remaining AR terms

Variable	*Number of trades (all failures specification)*	*Number of trades (producer & tso specification)*
Ar11	-0.004	-0.004
	0.007	0.007
Ar12	0.027	0.03
	0.007***	0.007***
Ar13	-0.009	-0.009
	0.008	0.008
Ar14	-0.01	-0.01
	0.008	0.008
Ar15	0.006	0.006
	0.008	0.008
Ar16	0.008	0.008
	0.007	0.007
Ar17	0.034	0.03
	0.009***	0.009***
Ar18	0.019	0.018
	0.007**	0.007**
Ar19	0.004	0.004
	0.008	0.008
Ar20	0.002	0.002

	0.008	0.008
Ar21	0.007	0.007
	0.008	0.008
Ar22	0.027	0.027
	0.009***	0.009**
Ar23	0.065	0.06
	0.008***	0.008***
Ar24	0.109	0.109
	0.009***	0.009***
Ar25	0.019	0.02
	0.008**	0.008**
Ar26	-0.002	-0.001
	0.008	0.008
Ar27	-0.013	-0.01
	0.009	0.008
Ar28	-0.028	-0.028
	0.009***	0.009**
Ar29	0.009	0.009
	0.008	0.008
Ar30	-0.012	-0.01
	0.008	0.008
Ar31	0.017	0.017
	0.008**	0.008**
Ar32	-0.005	-0.005
	0.009	0.009
Ar33	-0.012	-0.01
	0.007*	0.007*
Ar34	-0.017	-0.017
	0.007**	0.007**
Ar35	-0.02	-0.02
	0.007***	0.007***
Ar36	0.004	0.004
	0.007	0.007
Ar37	-0.009	-0.009
	0.007	0.007
Ar38	-0.003	-0.003
	0.007	0.007
Ar39	-0.015	-0.01

	0.007**	0.007*
Ar40	0.002	0.001
	0.007	0.007
Ar41	0.02	0.02
	0.009**	0.008**
Ar42	0.003	0.003
	0.008	0.008
Ar43	-0.001	-0.002
	0.008	0.007
Ar44	-0.006	-0.006
	0.008	0.008
Ar45	-0.002	-0.002
	0.007	0.007
Ar46	0.018	0.018
	0.007**	0.007**
Ar47	0.051	0.05
	0.008***	0.008***
Ar48	0.072	0.07
	0.009***	0.009***

Note: This table shows the estimates of AR terms from the estimation of the number of trades with all failures (column 1) and from the estimation of the number of trades with producers' and tsos' failures (column 2). Robust standard errors are in brackets. Star levels: *p<0.1; **p<0.05; ***p<0.01