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SEMINAR OF ECONOMIC AND SOCIAL STATISTICS
UNIVERSITY OF COLOGNE

No. 8/10

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by

Frowin C. Schulz

2nd version
March 25, 2011

DISKUSSIONSBEITRÄGE ZUR STATISTIK UND ÖKONOMETRIE

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Explaining Time-Varying Risk of Electricity Forwards: Trading Activity and News Announcements[1]

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Abstract

We elaborate economic explanations for the time-varying risk of month, quarter and year base load electricity forward contracts traded on the Nord Pool Energy Exchange from January 2006 to March 2010. Daily risk quantities are generated by decomposing realized volatility in its continuous and discontinuous jump component. First, we analyze the relation between volatility and trading activity. Coherent with existing studies we find that the driving factor of the relation between continuous variation and trading activity is the number of trades. New insights are obtained by considering the relation between jump factor and trading activity. Our results indicate that the number of trades and absolute order imbalance, which can be explicitly measured in our dataset, are positively related to the jump factor, a result in line with theoretical models. Second, we study unscheduled news announcements causing high volatilities. For this, a unique dataset of urgent market messages (UMMs), published by the Nord Pool Energy Exchange, is created. We extract relevant unscheduled UMMs, here failures, from both transmission system operators (TSOs) and market participants (MPs), and measure their impact over varying event windows. We find that certain unscheduled TSO/MP-UMMs have a significant impact on continuous variation, especially when they are published close to maturity, their content refers to a rare and extreme event or the contract is a month forward. The analysis also provides economic evidence for the occurrence of price jumps.

Keywords: Electricity Forward Contract, High Frequency Data, Realized Volatility, Price Jump, Trading Activity, Urgent Market Message.

JEL: G10, G12, G13, G14.

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1 Introduction

What drives the time-varying risk of month, quarter and year base load electricity forward contracts traded on the Nord Pool Energy Exchange? A necessary condition to deal with this general and concurrently complex question is to quantify risk at first. Aiming for an accurate and well established daily risk measure, we use the concept of realized volatility. The basis of this concept is price data collected at the highest possible frequency, to reflect more precisely the risk exposure over a trading day. Recent developments suggest to separate realized volatility in its continuous and discontinuous jump component (also referred to as jump factor). The motivation in doing so is to obtain an improved picture of risk, valuable in a variety of typical financial applications, e.g., risk explanation, modeling and forecasting, portfolio rebalancing, and asset pricing. To distinguish between contributions of the diffusion and jump part of a price process to realized volatility, we implement a method proposed by Schulz (2011). This method is designed such that it is robust against flat prices and no trading, a finite sample issue present in any high frequency time series. Having specified beforehand how to measure daily risk of the forwards, we turn to discuss two linked approaches selected to support the explanation of risk within January 2006 to March 2010.[1]

The first approach focuses on the relation between volatility and *trading activity*. The reason for investigating the relation is to find empirical evidence on theoretical models, which give insights into the direct market environment on the exchange, i.e. the way market participants are processing and reacting to new information (Chan and Fong, 2006). There are mainly two theoretical model categories.[2] The first category is introduced by Clark (1973), stating that the number of new information arrivals is influencing asset price changes (volatility) and trading activity. In this context, the amount of new information arrivals is not observable but behaves under certain assumptions proportionally to the number of traded financial assets, one measure of trading activity. As such we should observe a positive correlation between volatility and number of trades. This class of models is referred to mixture of distributions models. The second category are microstructure models going back to, e.g., Kyle (1985). Under the assumption of asymmetric information, microstructure models assign distinguishable market participants (here: market makers, liquidity or noise traders, and informed traders) a trading motive. Depending on a model specific set of assumptions, e.g., the measure of trading activity, each theory provides that an increase in a certain measure of trading activity is due to actions of informed traders. Suggested measures of trading activity are number of trades, trading volume, average trade size and absolute order imbalance.[3] The briefly described theoretical background of analyzing the relation between volatility and trading activity has been empirically studied

[1]'Risk' and 'volatility' are henceforth used interchangeably.

[2]For an overview of several theoretical models, the reader is referred to Chang and Fong (2006), Huang and Masulis (2003), and Giot et al. (2010).

[3]A common definition of number of trades is the number of transactions per day. Trading volume corresponds to the number of traded contracts per day, average trade size is the daily ratio of the number of traded contracts over the number of transactions, and absolute order imbalance reflects the daily absolute value of the difference between number of transactions initiated by the long and short position of a contract. Further details on this can be found in Section 3.

in several papers, e.g., Chan and Fong (2000), Chan and Fong (2006), Herbert (1995), Huang and Masulis (2003), and Jones et al. (1994). These studies mainly differ in the definition of volatility and set of analyzed financial assets.[4] The only empirical study known to us, which decomposes realized volatility in its continuous and discontinuous jump component to separately examine the relation is by Giot et al. (2010).[5] They decompose realized volatility with a method introduced by Barndorff-Nielsen and Shephard (2004, 2006). One of the main contributions of their study is that they estimate a negative correlation between the jump factor and number of trades/absolute order imbalance, a controversial result to the theoretical models. Their result might be driven by the fact that the method to decompose realized volatility is highly exposed to flat prices and no trading, generating biased conclusions.[6] Also, in each study known to us, absolute order imbalance has to be estimated because of the limited information content of the datasets. As such, several reasons speak in favor of revisiting the discussion on the relation between volatility and trading activity.

The advantage of our study is that we decompose realized volatility with the more accurate method by Schulz (2011). Beyond that, we can explicitly measure absolute order imbalance and we give specific insights to the market environment of electricity forwards traded on the Nord Pool Energy Exchange (henceforth Nord Pool). Our empirical analysis yields that the relation between continuous variation and trading activity is mainly explained by number of trades. Of minor importance in explaining the relation is trading volume, absolute order imbalance and average trade size. These results are in line with Chan and Fong (2006) and Giot et al. (2010). However, the estimation of the relation between the jump factor and trading activity with a Tobit-GARCH model provides new insights. Coherent with the theory by, e.g., Kyle (1985), we obtain that the correlation between the jump factor and number of trades/absolute order imbalance is actually positive.

In the first discussed approach we learn how the market is processing and reacting to new relevant information and find valuable results. However, we do not specify what kind of information can be relevant for the market causing periods of high volatility. Therefore, our second approach tries to identify *news announcements* causing an increase in the size of continuous variation and the occurrence of jump factors. There exist several recent empirical studies, examining the impact of most important (US) macroeconomic public announcements on the jump factor of currencies, stocks, index futures or bonds (futures). Examples are Asgharian et al. (2010), Dungey et al. (2009), Huang (2007), Jiang et al. (2009), and Lahaye et al. (2009). Besides impacts on the jump factor, Huang (2007) analyzes the impact of announcements on continuous variation. In the fields of energy markets, there is only one study known to us by Wang et al. (2008), who analyze the impact of OPEC announcements on realized volatility of oil and gas futures. Other studies like, e.g., Demirer and Kutan (2010), are focusing on the impact of OPEC announcements on returns of crude oil spot and futures markets.

[4] Amongst the referenced authors, only Herbert (1995) conducts an energy specific study on gas futures.

[5] Giot et al. (2010) investigate the 100 largest stocks traded on the New York Stock Exchange.

[6] For a detailed discussion on this finite sample issue, the reader is referred to Schulz and Mosler (2011) and Schulz (2011).

As there is no established study analyzing the impact of any news announcements on decomposed realized volatility of electricity forwards, we perform such an analysis with the following news announcements, published by the Nord Pool: urgent market messages (UMMs). According to the Nord Pool, UMMs are meant to be price sensitive information. Consequently, we create a unique dataset of UMMs announced either by a transmission system operator (TSO) or by a market participant (MP).[7] For the event study we select unscheduled UMMs as they are most likely price sensitive information. Generally, unscheduled UMMs announced by TSOs (MPs) are failures on the grid affecting capacities (production and consumption failures). Their impact is estimated over varying event windows. Our analysis shows that unscheduled TSO-UMMs have a significant impact on continuous variation, mostly on month forwards. The impact on the size of continuous variation and conditional probability of a jump factor intensifies for unscheduled TSO-UMMs published closer to maturity of a contract and/or within the trading hours of a contract. Also, we find that it matters whether there are multiple events within a trading day or whether the capacity loss on the grid is large. Proceeding with unscheduled MP-UMMs shows that they have a significant impact on continuous variation as well, but less often. A stronger impact on continuous variation can be likewise measured for unscheduled MP-UMMs announced closer to maturity and for forwards with a shorter delivery period. A differentiated effect is obtained for unscheduled MP-UMMs referring to a consumption failure, larger affected capacities or when multiple unscheduled MP-UMMs have to be processed by the market within the trading period of a contract.

The structure of the paper is the following. In the next section, we provide further details on decomposing realized volatility, discuss the empirical high frequency dataset, and report on descriptive statistics of continuous variation and jump factor. The analysis of the relation between volatility and trading activity follows in Section 3. Section 4 elaborates on UMMs and their impact on volatility. Finally, Section 5 concludes and suggests further research.

2 Measuring Risk with Realized Volatility

2.1 Methodology

We assume that the process for the log-price $X(t)$ is described by a continuous-time stochastic jump diffusion process:

$$dX(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \,, \qquad t \in [0,1] \,, \tag{1}$$

where $\mu(t)$ is a drift term, $\sigma(t)$ is a strictly positive stochastic càdlàg process and $W(t)$ is a standard Brownian motion. $\kappa(t)$ is the size of a discrete jump in time t and $q(t)$ is a counting process with finite activity and (possibly time-varying) intensity. The notional variance for the

[7]TSOs are mainly responsible for the security of supply and the high-voltage grid. MPs are typically electricity production companies buying and/or selling physical electricity on the Nord Pool Spot Exchange.

process of $X(t)$ over the interval $[t-1,t]$ is (Andersen et al., 2002)

$$NV_t \equiv \underbrace{\int_{t-1}^{t} \sigma^2(s)ds}_{\text{continuous variation}} + \underbrace{\sum_{q_{t-1}<s\le q_t} \kappa^2(s)}_{\text{jump factor}} . \tag{2}$$

NV_t consist of two components, **continuous variation** and **jump factor**, explicated in Equation (2). Using discretely sampled prices, the total amount of NV_t can be approximated with realized variance (Andersen and Bollerslev, 1998):

$$RV_t \equiv \sum_{j=1}^{M} r_j^2 , \qquad \text{with} \quad r_j := r_{j,t,M} := X\left(\frac{j\,t}{M}\right) - X\left(\frac{(j-1)t}{M}\right) \quad \text{and} \quad M \in \mathbb{N}^+ , \tag{3}$$

where M is the number of equidistant intraday sampling intervals, and r_j is the return for interval j. A well-known asymptotic result is that under the maintained assumptions, realized variance is converging in probability to the notional variance for $M \to \infty$, i.e., $RV_t \xrightarrow{p} NV_t$.

To separately measure the contribution of price jumps and diffusion to realized variance, several elaborated methods can be applied. In the present study, we implement one of the methods proposed by Schulz (2011), which is based on Corsi et al. (2010). The main reason for executing this method is that it is robust against flat price and no trading bias, a finite sample issue present in the high frequency dataset of electricity forwards.[8] The essence of the method is the following. The initial step requires to compute a consistent estimator for the continuous variation, which is robust against a finite number of jumps over $[t-1,t]$. This estimator is called sustained threshold bipower variation:

$$STBP_t = \frac{\pi}{2}\frac{M}{M-2}\sum_{j=3}^{M}\left(\mathbb{1}_{a1}\,\tilde{r}_{j-2}\,\tilde{r}_j + \tfrac{1}{2}\,\mathbb{1}_{a2}\,\tilde{r}_{j-2}\,\hat{\wp}_j + \tfrac{1}{2}\,\mathbb{1}_{a3}\,\hat{\wp}_{j-2}\,\tilde{r}_j\right) , \tag{4}$$

where $\tilde{r}_j$ denotes a trimmed absolute interval return, and $\hat{\wp}_j$ is a sustainer determined with a local Kernel smoothed and jump controlled spot variance estimator. The indicator functions $\mathbb{1}_{a1}, \mathbb{1}_{a2}$, $\mathbb{1}_{a3}$ and the sustainer $\hat{\wp}_j$ provide the bias corrections mechanisms.

Now, to conclude with RV_t and $STBP_t$ on an estimate of the jump factor, the following test statistic is implemented on a daily basis:

$$Z_t = \sqrt{M}\frac{(RV_t - STBP_t)/RV_t}{\sqrt{\left(\frac{\pi^2}{4}+\pi-5\right)\max\left\{1, STTriP_t/(STBP_t)^2\right\}}} \quad \xrightarrow{\text{d}} \quad N(0,1) , \tag{5}$$

where $STTriP_t$ is part of the asymptotic variance of the relative jump factor measure in the numerator. It is called sustained threshold tripower quarticity and it is likewise robust against flat price and no trading bias. An estimator of the jump factor and continuous variation to the

[8] An alternative approach can be found in the empirical study by Asgharian et al. (2010). They try to circumvent the mentioned finite sample issues by performing a pure ad-hoc plausibility mechanism.

square root now can be defined:

$$J_t \equiv \left([RV_t - STBP_t]\mathbb{1}_{\{Z_t > \Phi^{-1}_{1-\alpha}\}}\right)^{1/2}, \qquad \text{and} \qquad CV_t \equiv \left(RV_t - J_t^2\right)^{1/2}. \tag{6}$$

That means, the difference between RV_t and $STBP_t$ solely amounts to a jump factor estimate greater than zero, if the test statistic in Equation (5) is greater than a predefined quantile function ($\Phi^{-1}_{1-\alpha}$). In the empirical application we set $\alpha = 5\%$. We set it to this value as simulations by Schulz (2011) show that the test statistic in Equation (5) is slightly negative biased in the upper quantiles for high frequency datasets with an increased flat price and no trading bias.

A final note on the notation, used henceforth in this paper. If we talk about realized volatility, we mean the square root of RV_t. With the jump factor we mean J_t, whereas jump factor, jump(s) or price jump(s) are used synonymously. Continuous variation is from now on referred to as CV_t.

2.2 Data and Descriptives: Electricity Forward Contracts

Our high frequency dataset of transaction prices consists of three exchange traded base load forward contracts (year, quarter and month) of the Nord Pool. It covers the time period from January 2006 to March 2010. The delivery period of each forward amounts to the contractual identification, i.e., one year, quarter or month. Each contract has a finite life cycle, cash settlement and the system price of the Nordic Elspot bidding area as the underlying.[9] The contracts are traded just before their individual delivery date, which is specified in the product calendar of the Nord Pool. The main conceptual difference of these forwards to well-known future contracts on classic commodity exchanges is that there is no daily 'marked-to-market'. At the maturity date of a contract, the clearing service of the Nord Pool amounts the debit/credit of the seller and buyer for the first time. Registered market participants, like (international/local) energy companies, energy trading companies, and financial institutions, can trade the contracts via the Nord Pool within weekdays from 8:00 am to 3:30 pm.

As we intend to draw conclusions for year, quarter and month electricity forwards, we create one time series for each contract class. Following Schulz (2011), we merge periods of the corresponding class of contracts shortest to maturity up to seven days before settlement. Therewith, we capture the heaviest trading period of a contract, speaking in terms of daily number of trades. Excluded from the time series are inactive trading periods, like overnights, weekends and holidays. Also not included are several inactive trading days fulfilling the condition: daily percentage amount of zero-returns is greater than or equal to 95%.

This brings us to the computation of intraday continuously compounded interval returns over equidistant time grids, required to check for the mentioned condition, and to conclude on

[9] The Nordic Elspot bidding area comprises geographical areas within the Nordic electricity market. On the Nord Pool Spot Exchange, each MP has to bid according to where its production or consumption is physically connected to the Nordic transmission grid.

what the jump factor and the continuous variation amounts to. For this, we assign a price to each time grid using the previous tick method by Hansen and Lunde (2003, 2006). According to Schulz (2011), we solely apply the previous tick method, if there is actually a price observation within two time grids. The computation of interval returns requires two adjacent time grids with an assigned price, otherwise we set it to zero. The distance between time grids is chosen for each contract individually. In line with Schulz and Mosler (2011) we choose 15 minute sampling intervals for the quarter contract. For the year and month forward, we choose a 30 and 50 minute sampling frequency, respectively, as the declining number of trades from the quarter to the year and month forward suggests the choice of a longer sampling length.

The first empirical results of CV_t and J_t for each contract can be found in Figure 1 in combination with further descriptive statistics in Table 1. Across contracts, we can observe that CV_t is time-varying with typical clustering effects. Furthermore, the variability of CV_t increases from the year, quarter to month forward. That means, the shorter the predefined delivery period of a contract, the more intense is the reaction of the contract on information arrivals as short-term effects might not average out in the delivery period. The unconditional mean of CV_t is highest for the quarter and lowest for the year forward. This might be due to the fact that the quarter forward is the most actively traded contract on the Nord Pool. Speaking in terms of annualized continuous variation, we receive 18% for the year, 26% for the quarter and 22% for the month forward.[10] Turning now to J_t, we can notice that the probability of a jump factor greater than zero is highest for the quarter and lowest for the year forward. The increased number of jumps might be again due to the market relevance of the quarter contract. The mean of the size of $J_t > 0$ is largest for the month forward, whereas quite similar for the quarter and year forward. This phenomenon might be due to the same reason as for CV_t. Not very distinctive across contracts seems to be the standard deviation of J_t. Finally, we want to mention that the number of jumps occurring across contracts at the same time is very low.[11] This result maintains our explanation that information is differently processed, i.e., individually valued, by each forward because of a differing delivery period.

Comparing our results to several relevant studies,[12] we can state that the level in mean and standard deviation of CV_t is comparable to other financial markets. However, the probability of a jump factor often seems less intense in our empirical case. This is likely due to the fact that we applied the robust method by Schulz (2011) and therefore did not obtain so-called illiquidity jumps, which do not exist by theory and are a result of a distorted test statistic if the method is not robust against flat price and no trading bias (Schulz and Mosler, 2011).

The presented initial empirical results stimulate further economic discussion, i.e., we want to investigate economic reasons for different levels in CV_t and J_t across contracts.

[10] For the annualized figures, we assumed 250 trading days per year: $\sqrt{250} \times \text{mean}(CV_t)$.

[11] The number of concurrent jumps is 7 for 'month-quarter', 3 for 'quarter-year', 3 for 'month-year', and 0 for 'month-quarter-year'.

[12] Examples are Wang et al. (2008), Jiang et al. (2009), Dungey et al. (2009), Giot et al. (2010), and Asgharian et al. (2010).

3 Relation between Volatility and Trading Activity

3.1 Data and Descriptives: Trading Activity

To analyze the relation between continuous variation/jump factor and trading activity, a more precise definition on how to measure trading activity is required. Before introducing the distinct measures for trading activity, we specify the information content of a single trade:

A transaction between n buyers and m sellers at a certain point in time includes the transaction price and the number of contracts of each long and short position. Furthermore, it is reported whether n buyers or m sellers are the 'initiator' of the transaction, i.e., whether the long or short position initiated the placing of a price at which the trade shall be executed. The price taking position is referred to as 'aggressor'. The number of purchased and sold contracts is always balanced for each trade. The standardized specifications of a single contract (delivery hours, first and last trading day, start of the delivery period, currency, etc.) are specified in the product calendar of the Nord Pool.

Example:
For illustration purposes, we can think of the following recorded information for one trade in time. The number of buyers and sellers is 1 and 5, the number of traded month contracts is 5 at a transaction price of 50€. Each seller is short with one month contract and the buyer is long with 5 month contracts. The trade was initiated by the buyer. Therefore, the buyer (each seller) is referred to as initiator (aggressor).

In our case, trading activity is defined in four varying kinds: number of trades (NT; number of transactions per day), trading volume (V; number of traded contracts per day) average trade size (ATS; daily ratio of number of traded contracts over number of transactions) and absolute order imbalance (AOI; daily absolute value of the difference between number of transactions initiated by the long and short position of a contract). Unique in our dataset is that we can explicitly measure absolute order imbalance, i.e., we know whether the transaction is initiated by n buyers or m sellers. There is no study known to us which has accessed such data. In other empirical studies absolute order imbalance has to be estimated from the quotes using the standard algorithm by Lee and Ready (1991). The listed kinds of trading activity can be measured on the basis of the previously introduced high frequency dataset for each contract. However, the dataset only allows us to compute absolute order imbalance until April 17, 2009. This means that the sample is adjusted when absolute order imbalance is considered. In the following investigation we expect to receive promising results for the relation between jump factor and absolute order imbalance as it is an indicator for market imbalance. If absolute order imbalance increases we would expect an increase in probability and size of jump occurrences.

Basic descriptive results of trading activity are reported in Table 2. In terms of number of trades, the most actively traded contract is the quarter forward, followed by the year and month forward. The importance of the quarter contract to market participants of the Nord Pool is supported by the results for trading volume. Average trade size increases from the year to month, i.e., traders buying or selling a contract with a long delivery period tend to buy or sell a reduced number of contracts. Finally, absolute order imbalance is quite different across contracts as it is driven by the trade frequency. To compare absolute order imbalance across contracts, we report the ratio of absolute order imbalance over number of trades as well. The month forward seems to be the most imbalanced market, followed by the year. The smallest imbalance is obtained for the quarter forward.

3.2 Relation between Continuous Variation and Trading Activity

A first indicator of the relation between continuous variation and trading activity yields the correlation matrix in Table 3. In line with the empirical studies by Chan and Fong (2006) and Giot et al. (2010), we obtain a strong correlation coefficient for number of trades, and a lower one for trading volume and absolute order imbalance. Beyond that, the correlation coefficient is very small for average trade size and month forward. Only the negative correlation coefficient of average trade size for the year and quarter forward steps out of the line. So far, our results indicate that number of trades is the driving factor of the relation between continuous variation and trading activity.

We perform further analyses on the relation by separately estimating the following general linear equation model for each forward contract i (Huang and Masulis, 2003):

$$CV_{t,i} = \alpha_{1,i} + \alpha_{2,i}\mathcal{M}_{t,i} + \sum_{s=1}^{S} \beta_{i,s} A_{t,i,s} + \omega_{t,i} \,, \qquad i = 1, 2, 3 \,. \tag{7}$$

$A_{t,i,s}$ represents one form of trading activity. To account for a trading gap, we follow Jones et al. (1994) and include a Monday dummy ($\mathcal{M}_{t,i}$) in our model. The parameters $\alpha_{1,i}$, $\alpha_{2,i}$ and $\beta_{i,s}$ are estimated with the generalized method of moments. For the optimal weighting matrix, we choose the one of Newey-West to account for both heteroscedastic and autocorrelated residuals. At first, we estimate the model with a single regressor for trading activity, and increase it to two in a second stage. This proceeding is in line with, e.g., Huang and Masulis (2003). For brevity, we solely report and discuss $\beta_{i,s}$.[13]

I. Model in (7) with single s:

Table 4 (left part) reports the main estimation output using a single measure of trading activity in (7). Starting with the year forward, we can observe that each estimate for β_s yields an extremely small p-value, i.e., we can reject the null hypothesis ($\beta_s = 0$) on a 1% level of significance. As motivated by several theoretical models, the sign of the β_s estimate is positive for number of trades, trading volume and absolute order imbalance. For average trade size, we receive a negative and significant parameter estimate. This result is in contrast to the competitive microstructure model by Gloston and Milgrom (1985), but fits in the realm of strategic microstructure models by e.g., Kyle (1985). It suggests that informed traders break up their intended total transaction amount and trade it piecewise in smaller transactions.

[13]The estimation output for the remaining parameters can be obtained upon request.

Now, which of the regressions yields the best fit, i.e., which form of trading activity is the dominant one? R^2_{adj} yields an initial indication for this matter. We obtain the largest R^2_{adj} for number of trades, followed by trading volume, absolute order imbalance and average trade size. Interestingly, despite the fact that we can explicitly measure absolute order imbalance does not change but rather confirms existing conclusions, i.e., number of trades remains to be the dominant continuous-trading activity relation factor.

Proceeding with our analysis to the quarter forward, we can summarize that the conclusions of the year forward remain approximately the same for the quarter forward. Though, we would like to note that the estimated fit of the relation is overall weaker. Almost the same conclusions hold for the month forward. The fit seems less intense as for the year but stronger as for the quarter forward. Beyond that, we cannot find empirical evidence for a significant correlation to average trade size. We obtain a positive parameter estimate for β_s with a large p-value, i.e., we cannot reject the null hypothesis on a 10% level of significance.

II. Model in (7) with $S = 2$:
The intension for estimating our model in (7) with two different regressors for trading activity is to figure out whether this consideration increases the explanatory power of the relation. Beyond that, we can gather more evidence about the driving factor of the relation. In detail, we estimate our model including number of trades and absolute order imbalance, and number of trades and average trade size. We decided on this, since number of trades and trading volume can be used interchangeably (see correlation matrix in Table 3), and number of trades showed strongest results in the previous analysis. The model extension and variable selection is conform with the related literature by Chan and Fong (2006) and Giot et al. (2010).

The results can be found in Table 4 (right part). Starting with the estimation output for number of trades and absolute order imbalance shows that the parameter estimate for absolute order imbalance is insignificant across contracts, whereas the parameter estimate for number of trades is significant. The explanatory power (R^2_{adj}) shows a slight increase for the year contract, and even a decrease for the month and quarter forward. Interesting is the result for number of trades and average trade size. Each parameter estimate for β_s is significantly different from zero. Besides, including average trade size in addition to number of trades for explaining the relation of the quarter forward does increase the explanatory power. Finally, the negative parameter estimate of average trade size for the month forward is consistent with the results for the year and quarter forward.

In response to the discussion initiated by Andersen (1996) of correcting number of trades and trading volume for their trend feature, we have detrended number of trades and trading volume with a nonparametric kernel regression procedure (see Andersen, 1996) before estimating the model in (7). Evidence for the existence of a stochastic trend in the detrended time series can be excluded, based on the Phillips-Perron test. Qualitatively, our conclusions concerning the relation between continuous variation and number of trades/trading volume do not change by employing the detrended time series.[14]

[14]Detailed results are available upon request.

3.3 Relation between Jump Factor and Trading Activity

The analysis of the relation between the jump factor and trading activity begins with the correlation matrix in Table 3. Each form of trading activity shows to be positively correlated with the jump factor, except average trade size of the year forward. Likewise, we can observe a positive correlation between continuous variation and jump factor. Up to here, our findings are quite contrary to the empirical results presented by Giot et al. (2010). For this very reason, they seem promising as they explain that increasing new information arrivals or actions of informed traders do not only lead to a rise in continuous variation, as shown in the previous section, but also in the occurrence and size of price jumps.

We extend this analysis of the relation between jump factor and trading activity by estimating a Tobit-GARCH model as proposed by Calzolari and Fiorentini (1998). We decided on choosing this model as the time series of jump factors is censored with a huge piling up at zero. Beyond that, we allow for a GARCH structure in the conditional variance process of the error term, a stylized fact in financial data. The model is defined in the following:

$$J_{t,i} = \max\{a_{1,i} + a_{2,i}\mathcal{M}_{t,i} + \sum_{s=1}^{S} b_{i,s}A_{t,i,s} + \epsilon_{t,i},\ 0\}, \quad \epsilon_{t,i}|\mathscr{F}_{t-1,i} \sim N(0, \sigma^2_{t|t-1,i}) \ , \quad i = 1, 2, 3, \quad (8)$$

where $A_{t,i,s}$ and $\mathcal{M}_{t,i}$ are defined as in the previous section. $\mathscr{F}_{t-1,i}$ contains all relevant information as of time $t-1$ to specify the conditional mean and variance. The conditional variance ($\sigma^2_{t|t-1,i}$) is assumed to follow an ARCH or GARCH process. The parameters $a_{1,i}$, $a_{2,i}$ and $b_{i,s}$ are estimated with maximum likelihood. Before estimating the actual model, we individually determine with the well-known likelihood ratio test the ARCH(1), ARCH(2), GARCH(1,1) or homoscedastic specification of the conditional variance (Lahaye et al., 2009).[15] The goodness of fit in (8) is measured with a pseudo R-squared (R^2_{psd}), proposed by Aldrich and Nelson (1984) and further discussed by Veall and Zimmermann (1994).[16]

I. Model in (8) with single s:

The estimation results for each forward and form of trading activity can be found in the left part of Table 5. Not surprising by theory but empirically is that the probability and size of price jumps of the year forward are positively related to number of trades and trading volume. The positive relation indicates that increasing information arrivals or actions of informed traders increase the size and probability of price jumps. Furthermore, we can observe a significantly positive correlation between jump factor and absolute order imbalance. That means, if the market is increasingly imbalanced, the probability of price jumps is enhanced. Utilizing average trade size as a regressor yields a negative but insignificant parameter estimate. According to R^2_{psd}, we may say that the best model fit of all forms of trading activity is obtained for number of trades.

[15] Hence, the quarter contract is estimated with an ARCH(1), and the year/month with homoscedastic conditional variance.

[16] $R^2_{psd} = LRT/(LRT{+}T)$, where $LRT = 2(logl_m{-}logl_0)$ and T is the sample length. $logl_m$ is the log-likelihood of the model in (8) with the desired amount of regressor, and $logl_0$ is the log-likelihood of our model in (8) by considering solely the constant on the right hand side.

Generally, our empirical conclusions do not change by examining the output for the quarter as well as for the month forward. Most interestingly is that number of trades, trading volume and absolute order imbalance remain candidates in explaining the probability and size of price jumps. Additionally, there is evidence that number of trades is primarily driving the relation to the jump factor.

II. Model in (8) with $S = 2$*:*
The motivation for estimating the model in (8) with two $A_{t,i,s}$ is congruent to the one of continuous variation. Considering absolute order imbalance or average trade size as an additional regressor to number of trades in our model points out that number of trades is likely the driving factor of the relation (see right part of Table 5). For each contract, the estimation of the parameters of absolute order imbalance and average trade size yields highly insignificant estimates. In contrast, significant parameter estimates are obtained for number of trades.

A final note, our empirical conclusions remain valid even after detrending number of trades and trading volume.[17]

4 Impact of Urgent Market Messages on Volatility

4.1 General Facts to Urgent Market Messages

In this section, we will generally describe the nature of UMMs published by the Nord Pool. A UMM contains inside information of an MP or TSO, who is registered at the Nord Pool. Each MP and TSO is obliged to publish a UMM via the Nord Pool if an inside information occurs. The term 'inside information' is explicitly regulated by the Nord Pool in disclosure guidelines (see Nord Pool, 2009a, b). An overview concerning the definition of inside information, event types, which are classified as inside information, general content of a UMM and some reporting rules can be found in Table 6.

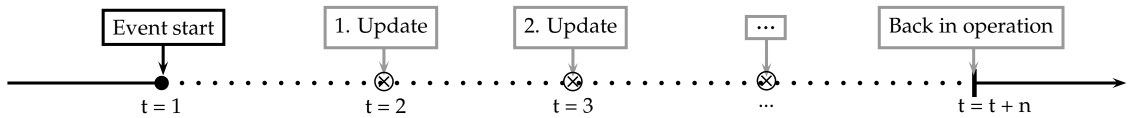
To get a better understanding for the column with event types, we will provide several examples for the connotation of some event terms. Concrete possible examples for a production (consumption) failure is a restricted river due to ice (strike in paper mill). UMMs by MPs, named special information, can contain information about a special request from a TSO to hold back production or consumption, besides other. If a TSO classifies its UMM as special information, it intends to inform the market about, e.g., sealed in production/consumption, acquisitions of reserves, or counter trades. Failures on grid affecting capacities might occur due to, e.g., a blocked or damaged transmission cable.

4.2 Data and Descriptives: Urgent Market Messages

To analyze the impact of UMMs on volatility more closely, we collect each UMM published via the Nord Pool within January 2006 to March 2010 in a database. The number of UMMs

[17]Detailed results are available upon request.

amounts to 18957 (5083) from 68 (17) different MPs (TSOs). A more detailed overview of the frequency of events within the analyzed period of time can be found in Figure 2. The left (right) panel graphs the frequency of events announced by MPs (TSOs). In the middle panel, we further present how often each fuel of an MP is affected. Not surprising is that hydro generation is affected the most. Worth noting, the briefly described UMM database not only includes messages about a new event but also follow-up messages, related to a specific event. The general structure of an initiating UMM with n subsequent event-related UMMs is the following:



The initiating UMMs in our database either have $n \geq 1$ subsequent follow-up messages with(out) a message noting ‘back in operation’, or no subsequent ones at all.

Now, to perform an event study, we need to decide on which UMMs (or events) are potentially of high economic relevance for the contracts, contain a surprise component, are not predictable and thus most likely cause an immediate adjustment of the contract’s price after the announcement. In this context, we want to focus on certain types of UMMs, including *initiating unscheduled UMMs*, here production and consumption failures by MPs, and failures on the grid affecting capacities by TSOs. These events randomly occur and thus cannot be predicted by the market. Therefore, such kind of UMM is a surprise for the market, regarding occurrence time and content. After the announcement, we expect that the contracts possibly require a revaluation causing a measurable market reaction because the market conditions suddenly change and potential inefficiencies arise. Henceforth, an initiating unscheduled UMM is simply referred to as ϒMM.

4.3 Event Study Setup

As previously discussed, we want to analyze the impact of ϒMMs on the size of continuous variation and the conditional probability of price jumps. To investigate the former case, we estimate an event regression (similar to Huang, 2007) for each contract i:

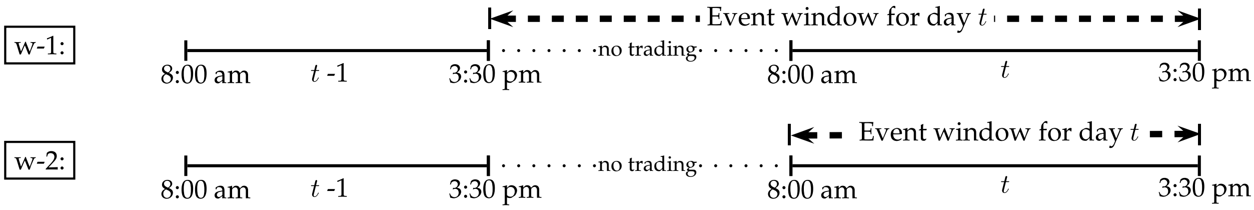
$$CV_{t,i} = c_i + \gamma_i D_{t,i} + \xi_{t,i} \,, \qquad i = 1, 2, 3, \tag{9}$$

where $D_{t,i}$ is a dummy variable for a predefined event day. The constant c_i and the parameter γ_i of the dummy variable are estimated with the generalized method of moments. As in the previous estimation procedures, we choose a Newey-West optimal weighting matrix to account for both heteroscedastic and autocorrelated residuals. For interpretation purposes, we compute the ratio of γ_i over c_i, which we call mean-effect, based on the estimation output. This ratio describes how much larger or smaller the average continuous variation amounts to on event days compared to non-event days.

In order to provide insights how ϒMMs impact the occurrence of price jumps, we compute conditional probabilities, i.e., $\mathrm{P}_1 = \mathrm{P}(J_{t,i} > 0 | D_{t,i} = 1)$. It shows the conditional probability of a jump factor greater than zero given the occurrence of a predefined event. To solely understand the coincidence of an event on days with price jumps we additionally compute $\mathrm{P}_2 = \mathrm{P}(D_{t,i} = 1 | J_{t,i} > 0)$. Here, we are aware of the fact that a price jump does not generate a ϒMM.

Before proceeding with the empirical analysis, we need to define when the dummy variable $D_{t,i}$ is actually set to one. Generally, we want to differentiate between the occurrence time of an event, and the content and frequency of a ϒMM, to identify those events causing the heaviest measurable market reactions.

We start with explicating the differentiation in the **occurrence time** of an event. Each forward is only traded on working days between 8:00 am and 3:30 pm and an unscheduled event can occur in non-trading periods as well (e.g., in the night, on the weekend or on a holiday). Therefore, we generally define two various event windows, 'w-1' and 'w-2':



That means, if at least one ϒMM is published within the respective event window, $D_{t,i}$ is set to one and zero otherwise. We differentiate between 'w-1' and 'w-2' as we want to understand whether the ϒMMs published within the trading period cause a more intense market reaction than events occurring in the 'no trading' period. As we analyze forward contracts, which have a finite life cycle, we additionally want to question whether events occurring closer to maturity of a contract cause a more intense market reaction. This is motivated by the consideration that the duration of such events more likely lasts into the delivery period of a contract. Therefore, we define the event windows 'w-1-clm' and 'w-2-clm' as well. These event-windows have in addition to 'w-1' and 'w-2' the condition that the event has to occur close to maturity. Here, month/quarter/year forwards close to maturity are defined as 14/30/60 days until maturity. The days until maturity are adjusted according to the trading period of the contract.

The second main classification is performed with respect to the **content and frequency** of an event. First of all, we distinguish between MP-ϒMMs and TSO-ϒMMs to measure the potential difference between production/consumption failures and failures on the grid affecting capacities. Among the respective set of TSO/MP-ϒMMs, we further categorize the events, which is motivated by economic reflections of the content of a ϒMM. For the TSO-ϒMMs, we define relevant features and provide a brief explanation:

- *Duration unknown:* A ϒMM either contains information about an estimate of the event stop-time or not. By focusing only on events providing no estimate of the event stop-time we expect that the market reacts more heavily to greater uncertainty.

- *Affected area belongs to Nordic Elspot area:* As the underlying of each contract is the Nordic system price, the market is expected to react more to events where the Nordic Elspot bidding area is directly affected.
- *Larger affected capacities:* The larger the affected capacities, the smaller the amount of electricity which can be transported from one area to the next. Such an inefficiency is expected to cause heavy market reactions. For the analysis, we decided to analyze events where the affected capacity is very large in both transmission directions, i.e., ≥ 650 Megawatt (MW) in both directions. This is roughly 80% more than the mean of the affected capacities of all TSO-ϒMMs.
- *Number of TSO-ϒMMs is ≥ 2 per event day:* Resulting from the discussion in Section 3, increasing information arrivals cause higher volatilities. Therefore, we also analyze event days with above average number of TSO-ϒMMs compared to all event days with TSO-ϒMMs. In our dataset, the number of TSO-ϒMMs ranges between 1 to 5 on an event day and has a mean of 1.28 considering all TSO-ϒMMs.

For the MP-ϒMMs, most of the differentiations are similar to the TSO-ϒMMs and are analogically motivated:

- *Duration unknown.*
- *Production or consumption failure:* Consumption failures are compared to production failures rare events (e.g., a strike, fire or insolvency). As such, the implications are more difficult to be valuated, and are expected to cause more intense market reactions.
- *Larger affected capacities:* ≥ 450 MW, which is roughly 80% more than the mean of the affected capacities for all MP-ϒMMs.
- *Number of MP-ϒMMs is ≥ 3 per event day:* The number of MP-ϒMMs ranges between 1 to 8 on an event day and has a mean of 2.15 considering all MP-ϒMMs.

Having specified the differentiation in time, and content and frequency of a ϒMM, we further discuss the implementation. In our case, we perform a top-down approach. That means, the first analysis includes all relevant TSO(MP)-ϒMMs and varies the event window and also 'duration unknown'. Events in an event-window with the heaviest market reactions are further differentiated according to the content of a ϒMM to isolate those events affecting the size of continuous variation or the occurrence of a jump factor the most.

4.4 Event Study: Continuous Variation, Jump Factor and UMMs

In this section, we present the empirical results for estimating the impact of ϒMMs on continuous variation and jump factor, starting the analysis with TSO-ϒMMs before proceeding with MP-ϒMMs. The analysis starts with including all TSO(MP)-ϒMMs and continues with isolating the effects according to the specifications as motivated in the previous section.

I. Impact of TSO-ϒMMs:

In Table 7, we report the impact of TSO-ϒMMs on continuous variation and jump factor. This analysis investigates all TSO-ϒMMs, varies with respect to the event window length and further restricts the TSO-ΥMMs to 'duration unknown'. Starting with all TSO-ΥMMs ('all') and the long event window 'w-1', we can observe that the mean-effect (γ/c) is quite low across contracts, and γ is only significant for the year contract.[18] By considering only events closer to maturity in the larger event window, i.e., 'w-1-clm', the mean-effect increases overall, whereas most for the month contract. Yet, a significant γ can be only reported for the month contract. To understand whether events published within the active trading period of a contract cause more intense market reactions, we perform the analysis with the shortened event window 'w-2' and 'w-2-clm'. The results show that the mean-effect is increasing from 'w-1' to 'w-2' and also from 'w-1-clm' to 'w-2-clm'. Likewise interesting is that the conditional probability of a jump factor given the specified events (P_1) greatly increases for the year and month forward from 'w-1' to 'w-2-clm'.

When we restrict all TSO-ΥMMs to 'duration unknown', there is evidence that the market reacts more heavily to TSO-ΥMMs providing no information about an estimate for the event stop-time. This effect can be observed both in the size of continuous variation and the conditional probability of the jump factor given the days with events.

As we have seen in our analysis in Table 7, the heaviest market reactions are within 'w-2-clm', i.e., the event happens within the trading period of a contract and closer to maturity. Therefore, we further differentiate the events within this window with respect to the three characteristics: 'affected area belongs to Nordic Elspot area', 'capacity loss ≥ 650 MW in both directions' and '# of events per day ≥ 2'. For interpretation, it seems most natural to compare these new results, reported in Table 8, with 'w-2-clm & all'. Focusing only on events where the affected area belongs to the Nordic Elspot area, we have a measurable increase in the mean effect and P_1 for the month forward. There is no change at all for the year and quarter contract as '$\#D_t = 1$' remains the same. Proceeding to the next characteristic, i.e., capacity loss ≥ 650 MW in both directions, the month contract seems to exhibit a heavy mean-effect.[19] Interesting is also that P_1 strongly increases for all contracts. Finally, we examine the results for '# of events per day ≥ 2'. It seems that the market reactions are even stronger as soon as an increased number of events arrive on the market, both observable in the mean-effect and P_1.

Overall, we can summarize that a significant impact of TSO-ΥMMs on continuous variation is predominately estimated for the month forward. We find that events occurring closer to maturity and within the trading period of a contract are most positively influencing the size of continuous variation and the conditional probability of a price jump. Besides, it can be relevant whether there are multiple events within a trading day and whether the capacity loss on a grid is large.

II. Impact of MP-ΥMMs:

We analyze the impact of MP-ΥMMs on continuous variation and jump factor in a similar fashion as for the TSO case. Table 9 provides details concerning the investigation of all MP-

[18] If we generally say that γ is significant, we reject the null hypothesis either on a 1, 5 or 10% level of significance, depending on the p-value.

[19] We want to point out that the number of event days is very small. As such, the estimated coefficients have to be interpreted with caution from a statistical point of view.

ϒMMs. In the analysis, we also vary with the event window length and further restrict all MP-ϒMMs to 'duration unknown'. The first overall assessment shows that the number of event days is at least three times larger than in the TSO case. For 'w-1', the longer event window, we obtain a moderate mean-effect. The event parameter γ is significant for each contract. The mean-effect slightly increases, when we put our focus on events occurring closer to maturity. However, γ is then only significant for the quarter and month forward. Different to the TSO case are the results for the shortened event window 'w-2' and 'w-2-clm'. Here, we cannot observe an intensification of the mean-effect. Besides, each γ estimate is insignificant. Yet, an interesting result is that P_1 of the quarter contract increases from 'w-1' to 'w-2', and even further for 'w-1-clm' to 'w-2-clm'.

Now, restricting all MP-ϒMMs with 'duration unknown' only yields for 'w-2-clm' and month forward a significant γ paired with the largest estimated mean-effect. For all other cases, the results suggest that there is no evidence that the market reacts more heavily to MP-ϒMMs providing no estimate for the event stop-time.

Since we could measure overall larger impacts of all MP-ϒMMs on continuous variation in the event window 'w-1-clm', we want to further distinguish the impact. Those events are classified into the following characteristics: 'production failure', 'consumption failure', 'capacity loss ≥ 450 MW' and '# of events per event day ≥ 3'. The results can be found in Table 10. For production failures, there is not much of a difference in comparison to the impact estimated for 'w-1-clm & all' in Table 9. However, consumption failures, which occur less often in our dataset, cause a more intense market reaction. We obtain a significant γ for the quarter contract (the p-value of the event parameter of the year contract is very close to 10%) and a larger P_1 for each contract. As soon as we focus on events with larger affected capacities, the mean-effect only increases for the month forward, with a significant γ. In our last classification of events, we can find evidence for a slight increase of the mean-effect for the quarter contract, maintained by a significant event parameter.

In summary, we can state that there is less evidence for the impact of MP-ϒMMs on the size of continuous variation and the occurrence of a price jump than for the TSO-ϒMMs. Nonetheless, our analysis shows that events happening closer to maturity have a larger impact on our risk measures for forwards with a shorter delivery period. Beyond that, it seems relevant whether the MP-ϒMM is referring to a consumption failure, the affected capacity is large or multiple relevant events have to be processed by the market within the trading period.

5 Conclusion

In this paper, we study the time-varying risk of month, quarter and year base load electricity forward contracts traded on the Nord Pool in the time period from January 2006 to March 2010. To provide the framework for an extensive risk analysis we generate daily risk measures, based on the concept of realized volatility. Furthermore, we decompose realized volatility into its continuous and discontinuous jump component with the robust method proposed by Schulz

(2011). The generated daily risk measures are investigated by means of two approaches.

First, we analyze the relation between continuous/discontinuous variation and trading activity, measured by number of trades, trading volume, average trade size or absolute order imbalance. Motivated by existing theoretical models that comprise various notions of trading activity we investigate whether greater trading activity, which can reflect an increased new information arrival or actions of informed traders, cause price changes and therefore a rise in volatility. We find that not only the continuous variation but also the discontinuous variation is positively related to number of trades and absolute order imbalance. These results fit in the existing theories by, e.g., Kyle (1985). Increasing trading activity does not only lead to an increase of continuous variation but also of the probability and size of price jumps, a result contrary to Giot et al. (2010).

The second investigation is to identify unscheduled news announcements which actually cause a market reaction and hence a rise in volatility. For this analysis, we create a unique dataset of urgent market messages (UMMs) published by the Nord Pool. We extract certain unscheduled news announcements from both transmission system operators (TSOs) and market participants (MPs), and measure their impact over varying event windows. Relevant news announcements from TSOs (MPs) are failures on the grid affecting capacities (production and consumption failures). Our results indicate that the information content of these TSO-UMMs and MP-UMMs is economically important for the contracts. Heavy market reaction, captured with volatility, can be especially observed when these UMMs are published closer to maturity of a contract, when their content is referring to a rare and extreme event or when the contract has a shorter delivery period.

This study rises several relevant future research questions. Of interest is to widen investigations on UMMs. It would be worthwhile to analyze whether scheduled or unscheduled UMMs cause market reactions on the physical day-ahead electricity spot market of the Nord Pool. A closely linked extension is to compare the generated results with those of other electricity markets, which likewise have a well-established information system for UMMs. Additionally, there are several uncovered topics related to the time-varying risk of electricity forwards, e.g., to understand the economic importance of deviations in weather forecasts.

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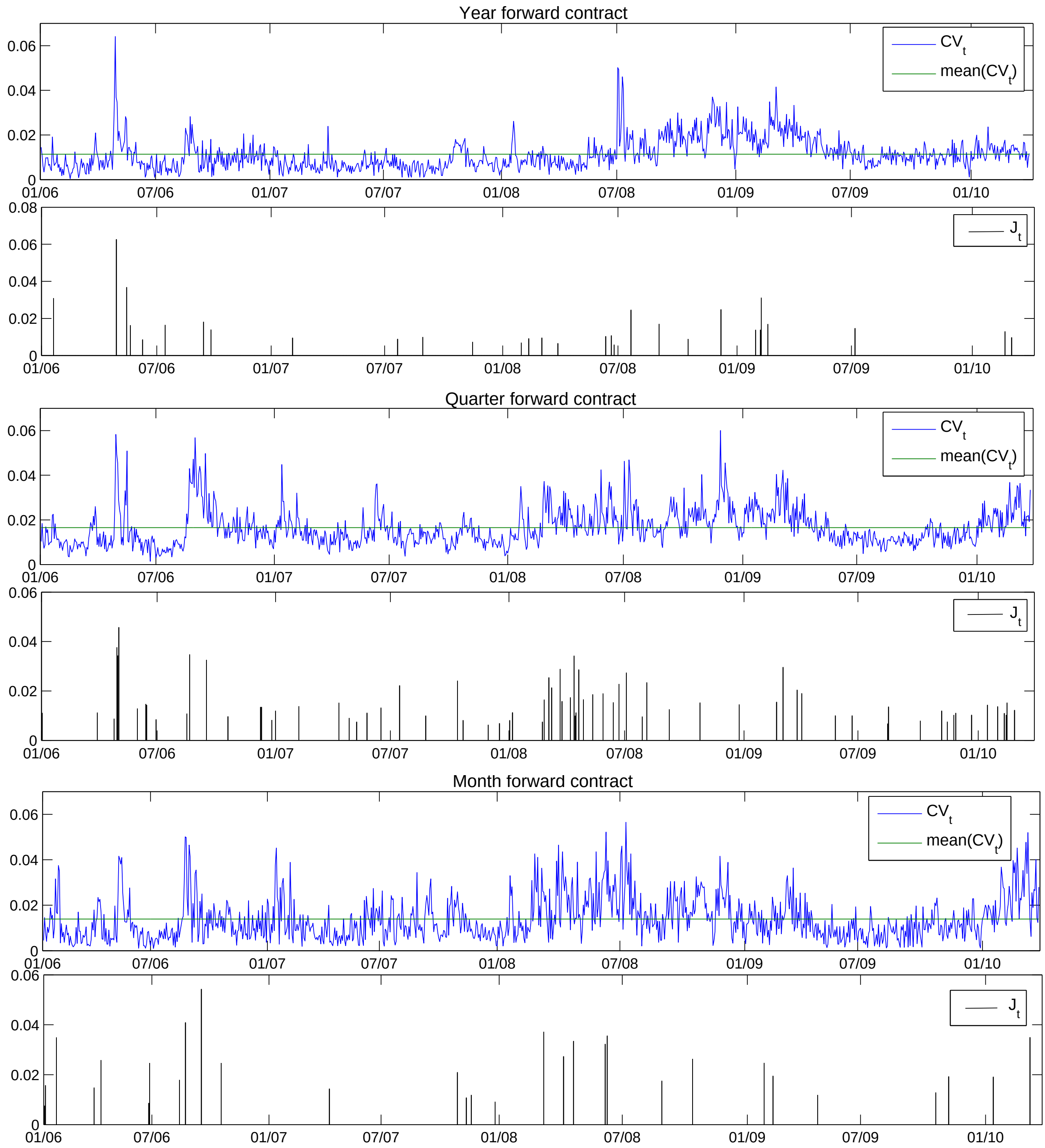
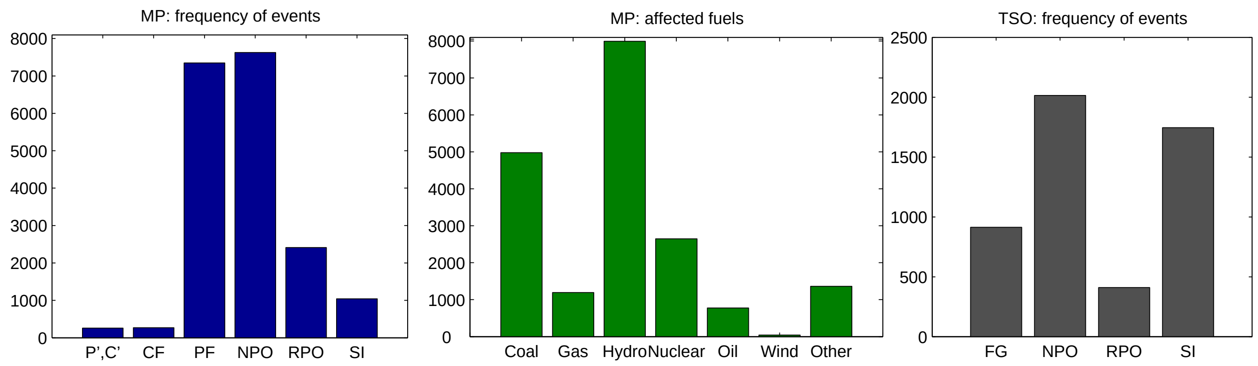
Figures

Figure 1: Continuous variation and jump factor: year, quarter and month forward



Remarks: Sample from January 2006 to March 2010. The top panel graphs the continuous variation of the year forward contract over time with its unconditional mean for the sampling period. The panel directly below graphs correspondingly the size of the jump factor for each trading day. Accordingly, the middle (bottom) two panels refer to the quarter (month) forward contract.

Figure 2: Descriptives: all urgent market messages



Remarks: Sample from January 2006 to March 2010. The left (right) panel graphs the frequency of UMMs by MPs (TSOs) separated in event types: changes in production or consumption (P', C'), consumption failure (CF), production failure (PF), failure on grid affecting capacities (FG), new planned outage (NPO), revised planned outage (RPO) and special information (SI). The middle panel gives an overview of the affected fuels, reported in UMMs by MPs.

Tables

Table 1: Descriptive statistic: continuous variation and jump factor of year, quarter and month forward

			CV		$J > 0$			
Contract	M	sample	mean	std	mean	std	# $(J > 0)$	$\mathrm{P}(J > 0)$
Year	15	1055	0.0114	0.0071	0.0161	0.0118	30	2.8%
Quarter	30	1061	0.0165	0.0083	0.0158	0.0084	74	7.0%
Month	9	1006	0.0139	0.0096	0.0229	0.0112	30	3.0%

Remarks: Sample from January 2006 to March 2010. The table reports descriptive statistics for the year, quarter and month electricity forward contract, including number of intraday intervals (M), sample length in # of trading days (sample), mean and standard deviation (std) for continuous variation (CV) and jump factor (J) as of Equation (6), number of days with a jump factor greater than zero (# $(J > 0)$), and the probability of a jump factor greater than zero ($\mathrm{P}(J > 0)$).

Table 2: Descriptive statistic: trading activity of year, quarter and month forward

	NT		V		ATS		AOI*		(AOI/NT)*	
Contract	mean	std	mean	std	mean	std	mean	std	mean	std
Year	81.1	57.8	150.6	105.2	1.93	0.39	12.07	15.86	0.25	0.19
Quarter	213.3	121.4	823.0	545.9	3.76	0.86	23.25	28.37	0.16	0.12
Month	30.5	21.3	198.2	162.3	6.20	1.87	6.41	7.87	0.32	0.23

Remarks: Sample from January 2006 to March 2010 (*: sample from January 2006 to April 17, 2009). The table reports basic descriptive statistics (mean and standard deviation) for the year, quarter and month electricity forward contract, including number of trades (NT), trading volume (V), average trade size (ATS), and absolute order imbalance (AOI).

Table 3: Correlation matrix: volatility and trading activity of year, quarter and month forward

Year	CV	J	NT	V	ATS	AOI*
CV	1					
J	0.211	1				
NT	0.685	0.099	1			
V	0.622	0.108	0.959	1		
ATS	-0.295	-0.017	-0.245	-0.015	1	
AOI*	0.443	0.109	0.607	0.620	-0.068	1
Quarter	CV	J	NT	V	ATS	AOI*
CV	1					
J	0.193	1				
NT	0.414	0.096	1			
V	0.268	0.102	0.932	1		
ATS	-0.245	0.021	0.206	0.503	1	
AOI*	0.269	0.106	0.530	0.502	0.140	1
Month	CV	J	NT	V	ATS	AOI*
CV	1					
J	0.133	1				
NT	0.486	0.142	1			
V	0.413	0.131	0.933	1		
ATS	0.030	0.027	0.228	0.493	1	
AOI*	0.283	0.155	0.609	0.575	0.188	1

Remarks: Sample from January 2006 to March 2010 (*: sample from January 2006 to April 17, 2009). The table reports correlation matrices for the year, quarter and month forward contract, including continuous variation (CV), jump factor (J), number of trades (NT), trading volume (V), average trade size (ATS), and absolute order imbalance (AOI).

Table 4: Relation between continuous variation and trading activity

		I. Model in (7) with single s				II. Model in (7) with $S = 2$			
		NT	V	ATS	AOI*	NT* & AOI*		NT & ATS	
Year	β_s	0.84	0.42	-0.54	0.21	0.95	0.003	0.80	-0.25
	std.err.	0.066	0.044	0.091	0.026	0.087	0.024	0.068	0.068
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.903*	*0.000*	*0.000*
	R^2_{adj}	0.47	0.39	0.09	0.19	0.52		0.49	
Quarter	β_s	0.28	0.04	-0.24	0.08	0.28	0.02	0.33	-0.33
	std.err.	0.033	0.008	0.053	0.015	0.049	0.014	0.032	0.052
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.115*	*0.000*	*0.000*
	R^2_{adj}	0.17	0.07	0.06	0.07	0.16		0.28	
Month	β_s	0.22	0.24	0.02	0.34	0.24	-0.002	0.23	-0.04
	std.err.	0.020	0.025	0.021	0.045	0.027	0.048	0.020	0.016
	p-value	*0.000*	*0.000*	*0.472*	*0.000*	*0.000*	*0.965*	*0.000*	*0.005*
	R^2_{adj}	0.24	0.17	0.00	0.08	0.21		0.24	

Remarks: Sample from January 2006 to March 2010 (*: sample from January 2006 to April 17, 2009). The table reports a shortened estimation output for the continuous variation (CV) of a forward contract i (here: year, quarter and month) using the following models:

· *I. Model:* $CV_{t,i} = \alpha_{1,i} + \alpha_{2,i}\mathcal{M}_{t,i} + \beta_{i,1}A_{t,i,1} + \omega_{t,i}$,

· *II. Model:* $CV_{t,i} = \alpha_{1,i} + \alpha_{2,i}\mathcal{M}_{t,i} + \beta_{i,1}A_{t,i,1} + \beta_{i,2}A_{t,i,2} + \omega_{t,i}$.

$\mathcal{M}$ is a Monday dummy. Varying regressors are number of trades (NT), trading volume (V), average trade size (ATS), and absolute order imbalance (AOI). Each model is estimated with the generalized method of moments and a Newey-West optimal weighting matrix. We explicitly report estimates, robust standard errors and two-sided p-values for $\beta_{i,s}$, and the adjusted R-squared (R^2_{adj}). For convenience, we scaled each estimate and standard error of $\beta_{i,s}$ by 10000, 1000 or 100.

Table 5: Relation between jump factor and trading activity

		I. Model in (8) with single s				II. Model in (8) with $S = 2$			
		NT	*V*	*ATS*	*AOI**	*NT** & *AOI**		*NT* & *ATS*	
Year [Tobit]	b_s	0.119	0.062	-0.090	0.341	0.139	0.038	0.114	-0.046
	std.err.	0.052	0.029	0.066	0.192	0.060	0.215	0.055	0.070
	p-value	*0.021*	*0.032*	*0.172*	*0.075*	*0.021*	*0.860*	*0.038*	*0.514*
	R^2_{psd}	0.0089	0.0086	0.0043	0.0087	0.0147		0.0091	
Quarter [Tobit-ARCH(1)]	b_s	0.047	0.011	0.031	0.142	0.041	0.054	0.044	0.016
	std.err.	0.014	0.003	0.020	0.063	0.022	0.079	0.014	0.020
	p-value	*0.001*	*0.000*	*0.115*	*0.023*	*0.062*	*0.490*	*0.001*	*0.415*
	R^2_{psd}	0.0121	0.0142	0.0038	0.0073	0.0119		0.0127	
Month [Tobit]	b_s	0.057	0.070	0.024	0.124	0.059	0.030	0.056	0.008
	std.err.	0.015	0.018	0.017	0.046	0.023	0.051	0.016	0.019
	p-value	*0.000*	*0.000*	*0.145*	*0.007*	*0.010*	*0.549*	*0.000*	*0.672*
	R^2_{psd}	0.0128	0.0116	0.0015	0.0099	0.0151		0.0129	

Remarks: Sample from January 2006 to March 2010 (*: sample from January 2006 to April 17, 2009). The table reports a shortened estimation output for the jump factor (J) of a forward contract i (here: year, quarter and month) using the following models:

· *I. Model:* $J_{t,i} = \max\{a_{1,i} + a_{2,i}\mathcal{M}_{t,i} + b_{i,1}A_{t,i,1} + \epsilon_{t,i},\ 0\}$,

· *II. Model:* $J_{t,i} = \max\{a_{1,i} + a_{2,i}\mathcal{M}_{t,i} + b_{i,1}A_{t,i,1} + b_{i,2}A_{t,i,2} + \epsilon_{t,i},\ 0\}$.

For the quarter, we assume that the conditional volatility of $\epsilon_{t,i}$ follows an ARCH(1) process, and is homoscedastic for the year/month forward. $\mathcal{M}$ is a Monday dummy. Varying regressors are number of trades (NT), trading volume (V), average trade size (ATS), and absolute order imbalance (AOI). Each model is estimated with the quasi maximum likelihood procedure. We explicitly report estimates, standard errors and two-sided p-values for $b_{i,s}$, and the pseudo R-squared (R^2_{psd}) by Aldrich and Nelson (1984). For convenience, we scaled each estimate and standard error of $b_{i,s}$ by 1000, 100 or 10.

Table 6: General facts to urgent market messages

<table>
<tr><th rowspan="2">Entity</th><th rowspan="2">Inside information*</th><th rowspan="2">Event type</th><th colspan="2">Content of UMM</th><th colspan="2">Some reporting rules</th></tr>
<tr><th>General</th><th>Specific</th><th>Time</th><th>Threshold</th></tr>
<tr><td>Market participant (MP)</td><td rowspan="2">- “... any information of a precise nature which has not been made public relating to one or more listed products, and which MPs would expect to receive...”
- “...any other information that would be likely to have a significant impact on the prices in one or more listed products if made public...”</td><td>- unplanned production or consumption failure
- planned production or consumption outage (maintenance: new/ revised)
- changes in production or consumption
- special information</td><td rowspan="2">- message/ decision/failure/ publishing time
- company
- affected area(s)
- event start/ stop/status
- remarks/ additional information</td><td>- station
- production/ consumption
- affected unit(s)
- available production/ consumption during event</td><td rowspan="2">≤ 60 min after failure or decision time</td><td>- capacity change > 100 MW of one generator, consumption unit or transmission facility
- capacity change > 200 MW per production station</td></tr>
<tr><td>Transmission system operator (TSO)</td><td>- unplanned failure on grid affecting capacities
- planned outage in the grid affecting capacities (maintenance: new/ revised)
- special information</td><td>- line
- endpoints
- installed outgoing capacity
- available outgoing capacity during event</td><td>transmission capacity change > 100 MW</td></tr>
</table>

Remarks: *: see §1.1. in Nord Pool (2009a,b). The table is a summary of the main TSO/MP disclosure guidelines for UMMs (see Nord Pool, 2009a,b). MW is the unit for Megawatt.

Table 7: Impact of initiating unscheduled TSO-UMMs on continuous variation and jump factor

		all			*duration unknown*		
window	parameter	year	quarter	month	year	quarter	month
	$\#\ D_t = 1$	237	236	230	146	145	140
	γ	0.00098	0.00089	0.00104	0.00145	0.00107	0.00174
	std.err.	0.00053	0.00067	0.00082	0.00070	0.00074	0.00098
w-1	p-value	*0.066*	*0.183*	*0.203*	*0.038*	*0.148*	*0.076*
	γ/c	8.8%	5.5%	7.6%	13.0%	6.5%	12.7%
	P_1	4.6%	7.6%	2.6%	4.8%	5.5%	2.1%
	P_2	37%	24%	20%	23%	11%	10%
	$\#\ D_t = 1$	36	72	61	21	38	40
	γ	0.00185	0.00202	0.00298	0.00285	0.00125	0.00263
	std.err.	0.00237	0.00149	0.00148	0.00275	0.00179	0.00187
w-1-clm	p-value	*0.435*	*0.173*	*0.045*	*0.300*	*0.485*	*0.159*
	γ/c	16.4%	12.3%	21.7%	25.2%	7.6%	19.1%
	P_1	2.8%	5.6%	1.6%	4.8%	2.6%	2.5%
	P_2	50%	19%	13%	50%	5%	13%
	$\#\ D_t = 1$	97	96	92	53	52	48
	γ	0.00172	0.00145	0.00219	0.00217	0.00192	0.00352
	std.err.	0.00078	0.00095	0.00105	0.00120	0.00124	0.00150
w-2	p-value	*0.027*	*0.129*	*0.037*	*0.071*	*0.123*	*0.019*
	γ/c	15.3%	8.8%	16.0%	19.2%	11.7%	25.6%
	P_1	4.1%	6.3%	3.3%	5.7%	5.8%	6.3%
	P_2	13%	8%	10%	10%	4%	10%
	$\#\ D_t = 1$	14	29	24	10	15	17
	γ	0.00409	0.00409	0.00434	0.00472	0.00337	0.00336
	std.err.	0.00363	0.00232	0.00176	0.00418	0.00314	0.00237
w-2-clm	p-value	*0.259*	*0.077*	*0.014*	*0.259*	*0.282*	*0.156*
	γ/c	36.2%	24.9%	31.4%	41.7%	20.5%	24.3%
	P_1	7.1%	6.9%	4.2%	10.0%	6.7%	5.9%
	P_2	50%	10%	13%	50%	5%	13%

Remarks: Sample from January 2006 to March 2010. The table reports a shortened estimation output of Equation (9), and $P(J_t > 0|D_t = 1)$ ($\hat{=}P_1$) and $P(D_t = 1|J_t > 0)$ ($\hat{=}P_2$), for each forward contract i (here: year, quarter and month) and TSO-ϒMMs (ϒMM $\hat{=}$ initiating unscheduled UMM). For Equation (9), estimates of γ_i, along with robust Newey-West standard errors and two-sided p-values are provided. Furthermore, the ratio of γ_i over the constant c_i is given, whereas c_i has a p-value < 0.0001 in each listed case. We differentiate between the length of the event-window ('w-1' or 'w-2') and events occurred close to maturity ('-clm') on the basis of all TSO-ϒMMs ('all') or those additionally providing no estimate of the event stop-time ('duration unknown'). The number of resulting event days is '$\#D_t = 1$'.

Table 8: Further analysis to impact of initiating unscheduled TSO-UMMs on continuous variation and jump factor: window 'w-2-clm'

	$\# \, D_t = 1$	γ	std.err.	p-value	γ/c	P_1	P_2
Affected area belongs to Nordic Elspot area							
year	14	0.00409	0.00363	*0.259*	36.2%	7.1%	50%
quarter	29	0.00409	0.00232	*0.077*	24.9%	6.9%	10%
month	22	0.00455	0.00189	*0.016*	33.0%	4.5%	13%
Capacity loss ≥ 650 MW in both directions							
year	2	-0.00041	0.00162	*0.799*	-3.6%	50.0%	50%
quarter	4	-0.00342	0.00204	*0.094*	-20.7%	25.0%	5%
month	4	0.00680	0.00373	*0.068*	49.0%	25.0%	13%
# of ϒMMs per event day ≥ 2							
year	3	0.00490	0.00364	*0.179*	43.2%	33.3%	50%
quarter	3	0.01216	0.00387	*0.002*	73.6%	33.3%	5%
month	4	0.00012	0.00299	*0.968*	0.9%	25.0%	13%

Remarks: Sample from January 2006 to March 2010. The table reports a shortened estimation output of Equation (9), and $P(J_t > 0|D_t = 1)$ ($\hat{=}P_1$) and $P(D_t = 1|J_t > 0)$ ($\hat{=}P_2$), for each forward contract i (here: year, quarter and month) and TSO-ϒMMs (ϒMM $\hat{=}$ initiating unscheduled UMM). For Equation (9), estimates of γ_i, along with robust Newey-West standard errors and two-sided p-values are provided. Furthermore, the ratio of γ_i over the constant c_i is given, whereas c_i has a p-value < 0.0001 in each listed case. Each analysis is performed with 'w-2-clm' and the specified additional distinction. The number of resulting event days is '$\# D_t = 1$' and MW is the unit for Megawatt.

Table 9: Impact of initiating unscheduled MP-UMMs on continuous variation and jump factor

		all			*duration unknown*		
window	parameter	year	quarter	month	year	quarter	month
	# $D_t = 1$	843	847	814	646	649	628
	γ	0.00173	0.00139	0.00150	0.00086	0.00045	0.00016
	std.err.	0.00059	0.00080	0.00085	0.00055	0.00067	0.00068
w-1	p-value	*0.003*	*0.081*	*0.077*	*0.116*	*0.504*	*0.808*
	γ/c	17.4%	9.0%	11.8%	7.9%	2.8%	1.2%
	P_1	2.8%	7.3%	2.9%	2.8%	6.9%	2.1%
	P_2	80%	84%	80%	60%	61%	43%
	# $D_t = 1$	127	226	221	107	166	163
	γ	0.00195	0.00218	0.00204	0.00135	0.00126	0.00157
	std.err.	0.00179	0.00131	0.00095	0.00161	0.00123	0.00097
w-1-clm	p-value	*0.276*	*0.096*	*0.032*	*0.402*	*0.304*	*0.103*
	γ/c	17.5%	13.5%	15.1%	12.0%	7.7%	11.5%
	P_1	1.6%	8.4%	2.7%	0.9%	8.4%	1.2%
	P_2	100%	90%	75%	50%	67%	25%
	# $D_t = 1$	544	547	517	334	336	322
	γ	0.00062	0.00007	0.00038	0.00055	-0.00004	0.00058
	std.err.	0.00043	0.00056	0.00059	0.00044	0.00055	0.00062
w-2	p-value	*0.149*	*0.904*	*0.523*	*0.213*	*0.939*	*0.351*
	γ/c	5.6%	0.4%	2.8%	4.9%	-0.3%	4.2%
	P_1	1.7%	7.7%	2.3%	2.1%	7.4%	1.9%
	P_2	30%	57%	40%	23%	34%	20%
	# $D_t = 1$	86	141	143	51	82	82
	γ	0.00134	0.00172	0.00133	0.00105	0.00119	0.00241
	std.err.	0.00145	0.00123	0.00097	0.00140	0.00134	0.00114
w-2-clm	p-value	*0.358*	*0.162*	*0.170*	*0.454*	*0.375*	*0.034*
	γ/c	11.9%	10.5%	9.7%	9.3%	7.2%	17.6%
	P_1	2.3%	9.2%	2.8%	2.0%	8.5%	2.4%
	P_2	100%	62%	50%	50%	33%	25%

Remarks: Sample from January 2006 to March 2010. The table reports a shortened estimation output of Equation (9), and $P(J_t > 0 | D_t = 1)$ ($\hat{=} P_1$) and $P(D_t = 1 | J_t > 0)$ ($\hat{=} P_2$), for each forward contract i (here: year, quarter and month) and MP-ϒMMs (ϒMM ≙ initiating unscheduled UMM). For Equation (9), estimates of γ_i, along with robust Newey-West standard errors and two-sided p-values are provided. Furthermore, the ratio of γ_i over the constant c_i is given, whereas c_i has a p-value < 0.0001 in each listed case. We differentiate between the length of the event-window ('w-1' or 'w-2') and events occurred close to maturity ('-clm') on the basis of all MP-ϒMMs ('all') or those additionally providing no estimate of the event stop-time ('duration unknown'). The number of resulting event days is '$\#D_t = 1$'.

Table 10: Further analysis to impact of initiating unscheduled MP-UMMs on continuous variation and jump factor: window 'w-1-clm'

	$\# D_t = 1$	γ	std.err.	p-value	γ/c	P_1	P_2
Production failure							
year	127	0.00195	0.00179	*0.276*	17.5%	1.6%	100%
quarter	223	0.00208	0.00130	*0.109*	12.9%	8.5%	90%
month	220	0.00210	0.00096	*0.028*	15.6%	2.7%	75%
Consumption failure							
year	9	0.00506	0.00313	*0.106*	44.7%	11.1%	50%
quarter	18	0.00508	0.00217	*0.019*	30.9%	11.1%	10%
month	15	-0.00134	0.00200	*0.501*	-9.7%	6.7%	13%
Capacity loss ≥ 450 MW							
year	33	0.00095	0.00125	*0.450*	8.3%	3.0%	50%
quarter	47	0.00118	0.00147	*0.422*	7.1%	6.4%	14%
month	50	0.00302	0.00180	*0.092*	22.0%	2.0%	13%
# of ϒMMs per event day ≥ 3							
year	68	0.00047	0.00122	*0.698*	4.2%	1.5%	50%
quarter	96	0.00240	0.00127	*0.058*	14.7%	1.0%	5%
month	101	0.00104	0.00099	*0.293*	7.5%	1.0%	13%

Remarks: Sample from January 2006 to March 2010. The table reports a shortened estimation output of Equation (9), and $P(J_t > 0|D_t = 1)$ ($\hat{=}P_1$) and $P(D_t = 1|J_t > 0)$ ($\hat{=}P_2$), for each forward contract i (here: year, quarter and month) and MP-ϒMMs (ϒMM $\hat{=}$ initiating unscheduled UMM). For Equation (9), estimates of γ_i, along with robust Newey-West standard errors and two-sided p-values are provided. Furthermore, the ratio of γ_i over the constant c_i is given, whereas c_i has a p-value < 0.0001 in each listed case. Each analysis is performed with 'w-2-clm' and the specified additional distinction. The number of resulting event days is '$\#D_t = 1$' and MW is the unit for Megawatt.