Volume and volatility in European electricity markets

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Joint work with:

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- **Angelica Gianfreda**, lecturing at University of York
- **Davide Pirino**, Ph.D. student, University of Pisa, Italy
Introduction and motivation

• We study the link between volatility and volume in European markets
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• We analyze hourly and daily electricity prices and volumes of Germany, The Netherlands, France, Spain
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- We analyze hourly and daily electricity prices and volumes of Germany, The Netherlands, France, Spain
- We study the drift and volatility of normal operational status with non-parametric techniques
Time series of prices

Germany

France

The Netherlands

Spain

Volume detrending

We do not directly use volume as our regressor, but the detrended volume, defined after estimating the regression:

\[ V_t = C + \alpha t + \epsilon_t, \]

where \( V_t \) is the observed volume at day \( t \) and \( \epsilon_t \) is IID noise.
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where \( V_t \) is the observed volume at day \( t \) and \( \varepsilon_t \) is IID noise.

\[ \tilde{V}_t = V_t - \hat{\alpha}t \]
Time series of detrended volumes

Germany

The Netherlands

France

Spain
First approach: GARCH modelling

We use daily data (intraday data averaged with volumes).

\[ r_t = \log P_t - \log P_{t-1} \]
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\[ r_t = \mu + \delta r_{t-1} + \sum_{i=1}^{6} c_i D_i + \varepsilon_t \sqrt{h_t} \]

\[ h_t = \omega + \sum_{i=1}^{6} d_i D_i + \alpha r_{t-1}^2 + \beta h_{t-1} + \gamma \hat{V}_t \]
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We exclude prices larger than a given threshold \( T = 50, 70, 90 \) (Euros/Megawatt).
Related literature


### GARCH estimates - mean equation

<table>
<thead>
<tr>
<th>Threshold</th>
<th>France</th>
<th>Germany</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
<td>70</td>
</tr>
<tr>
<td>$\delta$</td>
<td>-0.251*</td>
<td>-0.257*</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.349*</td>
<td>0.388*</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>$c_1$</td>
<td>-0.195*</td>
<td>-0.200*</td>
</tr>
<tr>
<td>$c_2$</td>
<td>-0.341*</td>
<td>-0.378*</td>
</tr>
<tr>
<td>$c_3$</td>
<td>-0.370*</td>
<td>-0.419*</td>
</tr>
<tr>
<td>$c_4$</td>
<td>-0.388*</td>
<td>-0.445*</td>
</tr>
<tr>
<td>$c_5$</td>
<td>-0.541*</td>
<td>-0.609*</td>
</tr>
<tr>
<td>$c_6$</td>
<td>-0.645*</td>
<td>-0.690*</td>
</tr>
</tbody>
</table>
## GARCH estimates - variance equation

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
<td>70</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.062*</td>
<td>0.058*</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.313*</td>
<td>0.304*</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\gamma \cdot 10^7$</td>
<td>-3.190*</td>
<td>-3.530*</td>
</tr>
<tr>
<td></td>
<td>(1.140)</td>
<td>(1.680)</td>
</tr>
<tr>
<td>$d_1$</td>
<td>-0.044*</td>
<td>-0.035*</td>
</tr>
<tr>
<td>$d_2$</td>
<td>-0.046*</td>
<td>-0.038*</td>
</tr>
<tr>
<td>$d_3$</td>
<td>-0.034*</td>
<td>-0.257*</td>
</tr>
<tr>
<td>$d_4$</td>
<td>-0.047*</td>
<td>-0.040*</td>
</tr>
<tr>
<td>$d_5$</td>
<td>-0.032*</td>
<td>-0.027*</td>
</tr>
<tr>
<td>$d_6$</td>
<td>-0.016</td>
<td>-0.011</td>
</tr>
</tbody>
</table>
Regression-based approach

\[
\log \hat{\sigma}_t^2 = \alpha + \lambda_1 \log \hat{\sigma}_{t-1}^2 + \lambda_2 \log \hat{\sigma}_{t-2}^2 + \lambda_3 \log \hat{\sigma}_{t-3}^2 + \sum_{i=1}^{6} e_i D_i + \gamma \hat{V}_t + \varepsilon_t
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+ \sum_{i=1}^{6} e_i D_i + \gamma \hat{Y}_t + \varepsilon_t
\]

To estimate \( \hat{\sigma}_t^2 \), we use realized volatility:

\[
\hat{\sigma}_t^2 = (\log p_t^1 - \log p_{t-1}^{24})^2 + \sum_{h=2}^{24} (\log p_h^t - \log p_{t-1}^{h-1})^2
\]
Regression-based approach

\[
\log \hat{\sigma}^2_t = \alpha + \lambda_1 \log \hat{\sigma}^2_{t-1} + \lambda_2 \log \hat{\sigma}^2_{t-2} + \lambda_3 \log \hat{\sigma}^2_{t-3} \\
+ \sum_{i=1}^{6} e_i D_i + \gamma \hat{V}_t + \epsilon_t
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To estimate \( \hat{\sigma}^2_t \), we use realized volatility:

\[
\hat{\sigma}^2_t = (\log p^1_t - \log p^{24}_{t-1})^2 + \sum_{h=2}^{24} (\log p^h_t - \log p^{h-1}_{t-1})^2
\]

We cut intraday prices larger than a given threshold \( T \).
Time series of realized volatilities

Germany

France

The Netherlands

Spain
**Estimates - using intraday prices**

<table>
<thead>
<tr>
<th>Threshold</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
<td>70</td>
<td>90</td>
<td>50</td>
</tr>
<tr>
<td>(\lambda_1)</td>
<td>0.302*</td>
<td>0.247*</td>
<td>0.232*</td>
<td>0.441*</td>
</tr>
<tr>
<td>(\lambda_2)</td>
<td>0.119*</td>
<td>0.123*</td>
<td>0.132*</td>
<td>0.119*</td>
</tr>
<tr>
<td>(\lambda_3)</td>
<td>0.145*</td>
<td>0.107*</td>
<td>0.080*</td>
<td>0.156*</td>
</tr>
<tr>
<td>(\gamma \cdot 10^5)</td>
<td>-1.500*</td>
<td>-1.140*</td>
<td>-0.870</td>
<td>0.072</td>
</tr>
<tr>
<td>(e_1)</td>
<td>-0.065</td>
<td>0.151</td>
<td>0.207*</td>
<td>-0.776*</td>
</tr>
<tr>
<td>(e_2)</td>
<td>-0.669*</td>
<td>-0.479*</td>
<td>-0.444*</td>
<td>-0.825*</td>
</tr>
<tr>
<td>(e_3)</td>
<td>-0.546*</td>
<td>-0.387*</td>
<td>-0.358*</td>
<td>-0.856*</td>
</tr>
<tr>
<td>(e_4)</td>
<td>-0.576*</td>
<td>-0.428*</td>
<td>-0.374*</td>
<td>-0.665*</td>
</tr>
<tr>
<td>(e_5)</td>
<td>-0.461*</td>
<td>-0.416*</td>
<td>-0.375*</td>
<td>-0.688*</td>
</tr>
<tr>
<td>(e_6)</td>
<td>-1.110*</td>
<td>-1.086*</td>
<td>-1.080*</td>
<td>-0.519*</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.280</td>
<td>0.246</td>
<td>0.232</td>
<td>0.434</td>
</tr>
</tbody>
</table>
Discussion of results

Why do we observe a null relation between volatility and volume?
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In financial market, it takes volume to move prices. That is, the relation is positive (Karpoff, 1987) and driven by less informed agents (Daigler and Wiley, 1999).
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Many theoretical models explain this positive relation.
Theoretical models

- Mixture of Distributions Hypothesis (Clark, 1973)
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- Does volatility display heteroskedasticity?
Nonparametric estimation

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However, a simple threshold in price, as above, is not enough.

We use the above model in combination with threshold estimators.
The modulus of continuity

Our idea to disentangle diffusion from jumps is based on the modulus of continuity of the Brownian motion:

\[ r(\delta) = \sqrt{2\delta \log \frac{1}{\delta}} \]

which has the following property, as established by Lévy:

\[ \mathbb{P} \left[ \limsup_{\delta \to 0} \frac{\max_{|t-s| \leq \delta} |W(t) - W(s)|}{r(\delta)} \right] = 1 \]

It measures the speed at which the BM shrinks to zero.
The intuition

When $\delta \to 0$, diffusive variations go to zero, while jumps do not.

Moreover, we know the rate at which the diffusive variations shrink to zero: the modulus of continuity.
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Thus, we can identify the jumps as those variations which are larger than a suitable threshold $\vartheta(\delta)$ which goes to zero, as $\delta \to 0$, slower than $r(\delta)$. 

**The intuition**
The theorem (Mancini, 2004)

Suppose $X = Y + J$, where $Y$ is a Brownian martingale plus drift and $J$ is a jump process with counting process $N$ with $E[N_T] < \infty$ and time horizon $T < \infty$.

If $\vartheta(\delta)$ is a real deterministic function such that

$$\lim_{\delta \to 0} \vartheta(\delta) = 0 \quad \text{and} \quad \lim_{\delta \to 0} \frac{\delta \log \frac{1}{\delta}}{\vartheta(\delta)} = 0,$$

then for $P$-almost all $\omega$, $\exists \bar{\delta}(\omega)$ such that $\forall \delta < \bar{\delta}(\omega)$ we have

$$\forall i = 1, \ldots, n, \quad I_{\{\Delta N = 0\}}(\omega) = I_{\{(\Delta X)^2 \leq \vartheta(\delta)\}}(\omega).$$
The non-parametric model

\[ r_{t+1} = \mu(r_t) + \sigma(r_t) \varepsilon_t + dJ_t \]
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First we separate \( dJ \) from continuous variations.

Then we estimate the functions \( \mu \) and \( \sigma \).
Threshold estimation

Jumps are detected using threshold estimation:

\[ r_t^2 \geq 9 \cdot \sigma_t. \]
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For the threshold, we use the above model as an auxiliary model:

\[
\begin{align*}
  r_t &= \mu + \delta r_{t-1} + \sum_{i=1}^{6} c_i D_i + \varepsilon_t \sqrt{h_t} \\
  h_t &= \omega + \sum_{i=1}^{6} d_i D_i + \alpha r_{t-1}^2 + \beta h_{t-1}
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\]

We set \( \vartheta_t \) equal to the filtered values of \( h_t \).
Jump fast mean reversion

We have to face the problem of fast jump mean-reversion. To accommodate for this problem, if we detect a jump at time $t^*$, do not modify the threshold for the next time instant, that is

$$r^2_{t^*} \geq 9 h_{t^*} \implies h_{t^*+1} = h_{t^*}.$$
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We iterate the filtering technique until no more jumps are detected.
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**It works!**
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We iterate the filtering technique until no more jumps are detected.

It works!
Few iterations are enough for convergence.
Nadaraya-Watson threshold estimators

\[ \hat{\mu}(x) = \frac{N \sum_{i=1}^{N-1} K \left( \frac{r_i-x}{h} \right) (r_{i+1} - r_i) I\{r_i^2 \leq \vartheta_i\}}{T \sum_{i=1}^{N} K \left( \frac{r_i-x}{h} \right)} \]

\[ \hat{\sigma}(x) = \frac{N \sum_{i=1}^{N-1} K \left( \frac{r_i-x}{h} \right) (r_{i+1} - r_i)^2 I\{r_i^2 \leq \vartheta_i\}}{T \sum_{i=1}^{N} K \left( \frac{r_i-x}{h} \right)} \]

where \( K(.) \) is the standard Gaussian kernel:

\[ K(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}. \]
The bandwidth parameter $h$ is set according to the typical thumb rule:

$$h = \frac{h_s \bar{\sigma}}{N^5}$$
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You have to choose $h_s$ (here we set $h_s = 3.2$).
Drift estimation

Volatility estimation

![Graph showing volatility estimation for different countries (Germany, Spain, France, The Netherlands). The graph plots the diffusion coefficient against logarithmic returns.](image)
What did we neglect?
What did we neglect?

Jumps!
What did we neglect?

Jumps!


Summary and conclusions

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• We discuss this result under the light of theories on *informed trading* borrowed by financial economics
• We propose a procedure to separate *spikes* from normal operation behaviour
• We estimate *non-parametrically* drift and volatility of electricity price returns
• European markets are pretty similar!