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Equation-by-equation estimation of multivariate periodic electricity price volatility ☆

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ABSTRACT

Electricity prices are characterised by strong autoregressive persistence, periodicity (e.g. intraday, day-of-the week and month-of-the-year effects), large spikes or jumps, GARCH and – as evidenced by recent findings – periodic volatility. We propose a multivariate model of volatility that decomposes volatility multiplicatively into a non-stationary (e.g. periodic) part and a stationary part with log-GARCH dynamics. Since the model belongs to the log-GARCH class, the model is robust to spikes or jumps, allows for a rich variety of volatility dynamics without restrictive positivity constraints, can be estimated equation-by-equation by means of standard methods even in the presence of feedback, and allows for Dynamic Conditional Correlations (DCCs) that can – optionally – be estimated subsequent to the volatilities. We use the model to study the hourly day-ahead system prices at Nord Pool, and find extensive evidence of periodic volatility and volatility feedback. We also find that volatility is characterised by (positive) leverage in one third of the hours, and that a DCC model provides a better fit of the conditional correlations than a Constant Conditional Correlation (CCC) model.

1. Introduction

Modelling the uncertainty or volatility of electricity prices is of great importance for energy market participants. On the supply side, producers of electricity need estimates of the time-varying price volatility in order to determine the risks of future production levels. On the demand side, consumers of electricity need the same type of information in order to ascertain the risks associated with decisions about when and where to produce goods, and in order to hedge against adverse price changes.

It is well known that electricity prices are characterised by autoregressive persistence and periodicity effects (e.g. hour-of-the-day, day-of-the-week and month-of-the-year effects) in the conditional mean, see e.g. Bunn (2000), Knittel and Roberts (2005), Janczura et al. (2013), and Weron (2014). It is also well known that the volatility of electricity prices is characterised by Autoregressive Conditional Heteroscedasticity (ARCH) and large spikes or jumps, see e.g. Escribano et al. (2002, 2011), Koopman et al. (2007),

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and Hellström et al. (2012). Since the periodicity effects in the conditional mean usually account for a considerable proportion of the conditional mean dynamics, it is reasonable to conjecture that the same may also be the case for volatility. Recently, this line of research has received increasing attention. Bauwens et al. (2013, Section 4.2), for example, in a three-dimensional multivariate model of monthly, quarterly and yearly Phelix baseload futures at the European Energy Exchange, find that volatility depends on the number of days-to-delivery, i.e. that the volatility increases as the future in question approaches maturity. Sucarrat et al. (2016, Section 4), in a two-dimensional multivariate model of peak and off-peak day-ahead prices in the Oslo region (Nord Pool), find that day-of-the-week effects matter for volatility, and that peak volatility dynamics is less persistent than off-peak. Dupuis (2017), in a fifteen-dimensional multivariate model of electricity prices in the New York area, includes dummies in the volatility equations to accommodate hour-of-the-day and day-of-the-week effects.

There are two main challenges in the multivariate modelling of electricity price volatility. The first is the socalled "curse of dimensionality": As the multivariate dimension grows, joint estimation of the full model becomes infeasible in practice due to the number of parameters that has to be estimated. This problem is not specific to electricity prices, but it is more severe. The reason is that volatility is likely to depend on additional covariates, e.g. weather and market specific stochastic conditioning variables, in addition to periodicity effects similar to those that often characterise the conditional mean dynamics. Moreover, if standard or non-exponential GARCH models are used, then the curse of dimensionality problem is compounded, since the covariates and/or their parameters need to be restricted in estimation in order to ensure the positivity of fitted volatility. An example in which such a parameter restriction is needed in electricity price markets is the socalled "inverse leverage effect", as coined by Knittel and Roberts (2005), whereby negative shocks in one period leads to a reduction in volatility in the next period.[1] Knittel and Roberts (2005) avoid the need for a restriction by using Nelson's (1991) Exponential GARCH (EGARCH). However, as is well-known, the EGARCH is not robust to spikes.[2] This leads to the second main challenge in the modelling of electricity prices: The occurrence of price spikes. It is well-known that the ordinary GARCH model is not robust to such spikes. This is because the spikes affect estimation and inference inadvertently (Carnero et al., 2007; Gregory and Reeves, 2010), and because it makes the model propensive to volatility forecast failure subsequent to the spikes, see e.g. Harvey and Sucarrat (2014, Introduction). One multivariate model specification that has been put forward as being able to accommodate fat-tailed standardised errors, is the exponential version of the Generalised Autoregressive Score (GAS) model, see e.g. Creal et al. (2011). However, even univariate versions of this model can be very difficult to estimate due to its nature (see the section on "Computational challenges" in Sucarrat (2013, p. 142)), and the problem is compounded even further in the multivariate case.

We propose a multivariate model of electricity price volatility that is robust to spikes, that sidesteps the curse of dimensionality through equation-by-equation estimation, and which can include both deterministic and stochastic covariates to accommodate periodicity effects, leverage, the effect of weather-related variables, and so on. The model we propose is a multivariate multiplicative component log-GARCH-X model that decomposes volatility multiplicatively into a non-stationary deterministic part of arbitrary form, and a stationary stochastic part. In order to enable equation-by-equation estimation, we make use of recent ideas developed formally in Francq and Zakoïan (2016), and in Francq and Sucarrat (2017). In particular, our model allows for feedback volatility effects among the equations, and Dynamic Conditional Correlations (DCCs) that – optionally – can be estimated subsequent to the volatility equations. As long as the DCC specification is appropriately chosen, this will ensure positive definiteness of the conditional covariance matrix. The model we propose can be viewed as a generalisation of Sucarrat et al. (2016, Section 4) in two ways. First, the deterministic component is much more general, since it can be of arbitrary form (i.e. it needs not be a linear combination of non-stochastic covariates). Second, we set up the estimation problem in such a way that the deterministic and stationary parts can be estimated separately, each by common methods that are widely available. In particular, in many cases the deterministic part will be estimable by an Ordinary Least Squares (OLS) regression, and the stochastic part will be estimable via an ARMA-regression. The equation-by-equation estimation procedure that we propose is thus readily implemented in software that is widely available. We use the model to study the multivariate volatility of hourly day-ahead system prices at Nord Pool. We find extensive evidence of periodicity in the volatility in that it depends on the day-of-the-week, and in that volatility dynamics varies intradaily. We also find extensive evidence of volatility feedback from adjacent hours. Leverage (of positive type), however, is only present in about one third of the instances, and mostly between 1 am and 5 am. In only a single instance – at 7 pm – does a plain log-GARCH(1,1) without periodicity provide a better fit of the volatility. Finally, we also find that the corrected DCC (cDCC) of Aielli (2013) provides a better fit of the conditional correlations than a Constant Conditional Correlation (CCC) specification. Interestingly, the correlations are found to be at their strongest among adjacent hours, and that the strength is inversely related to the degree of adjacency: The further away, the weaker the correlation. This has implications for risk-management, since it implies that portfolio risk is reduced if the degree of adjacency among the portfolio components is reduced.

The rest of the paper is organised as follows. The next section, Section 2, outlines the model and the equation-by-equation estimation procedure. Section 3 contains our study of hourly day-ahead price volatility at Nord Pool. Section 4 contains the conclusions, whereas tables and figures are located at the end after the references.

2. Model and estimator

2.1. The model

Let $\boldsymbol{r}_t = (r_{1t}, \ldots, r_{Mt})'$ denote an M-dimensional vector of price returns at t. A generic model of $\boldsymbol{r}_t$ can be written as (see e.g. Engle (2002))

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \epsilon_t, \quad t \in \mathbb{Z}, \tag{1}$$

$$\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Mt})', \quad \boldsymbol{H}_t = E_{t-1}\left(\epsilon_t \epsilon_t'\right), \quad \boldsymbol{D}_t^2 = \mathrm{diag}(\boldsymbol{H}_t), \tag{2}$$

$$\boldsymbol{\eta}_t = \boldsymbol{D}_t^{-1} \epsilon_t, \quad \boldsymbol{R}_t = E_{t-1}\left(\boldsymbol{\eta}_t \boldsymbol{\eta}_t'\right), \tag{3}$$

where $\boldsymbol{\mu}_t$ is the conditional mean (say, a VAR-X as in the empirical section, see Section 3.2), $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Mt})'$ is the error term, $\boldsymbol{H}_t$ is an $M \times M$ covariance matrix conditional on the past information set $\mathcal{F}_{t-1}$, $E_{t-1}(\cdot)$ is shorthand notation for $E(\cdot|\mathcal{F}_{t-1})$, $\boldsymbol{D}_t^2$ is a diagonal $M \times M$ matrix with the conditional variance or volatility

[1] In stock markets, by contrast, a negative shock is usually followed by an increase. Arguably, the inverse leverage effect should instead be referred to as negative asymmetry, since the effect is not due to leverage in many markets (e.g. electricity and currency markets), and because a negative parameter value is not obtained as the mathematical inverse of a positive parameter.

[2] This is the reason why Nelson proposed his model in combination with the Generalised Error Distribution (GED) rather than with the standardised Student's t, since the unconditional variance will generally not exist if the standardised error is distributed as the latter, see Nelson (1991, p. 365).