Estimation and Inference in Univariate and Multivariate Log-GARCH-X Models When the Conditional Density is Unknown

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11 August 2013

Estimation and Inference in Univariate and Multivariate Log-GARCH-X Models When the Conditional Density is Unknown *

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10th July 2014
(Updated version)

Abstract

Exponential models of Autoregressive Conditional Heteroscedasticity (ARCH) are of special interest, since they enable richer dynamics (e.g. contrarian or cyclical), provide greater robustness to jumps and outliers, and guarantee the positivity of volatility. The latter is not guaranteed in ordinary ARCH models, in particular when additional exogenous and/or predetermined variables ("X") are included in the volatility specification. Here, we propose estimation and inference methods for univariate and multivariate Generalised log-ARCH-X (i.e. log-GARCH-X) models when the conditional density is not known. The methods employ (V)ARMA-X representations and relies on a bias-adjustment in the log-volatility intercept. The bias is induced by (V)ARMA estimators, but the remaining parameters are consistently estimated by (V)ARMA methods. We derive a simple formula for the bias-adjustment, and a closed-form expression for its asymptotic variance. Next, we show that adding exogenous or predetermined variables and/or increasing the dimension of the model does not change the structure of the problem. Accordingly, the univariate bias-adjustment result is likely to hold not only for univariate log-GARCH-X models, but also for multivariate log-GARCH-X models equation-by-equation. Extensive simulation evidence verify our results, and an empirical application show that they are particularly useful when the X-vector is high-dimensional.

JEL Classification: C22, C32, C51, C52
Keywords: Log-GARCH-X, ARMA-X, multivariate log-GARCH-X, VARMA-X

*An earlier version of this paper was entitled "The Power Log-GARCH Model", see Sucarrat and Escribano (2010). We are grateful to Jonas Andersson, Luc Bauwens, Christian Francq, Andrew Harvey, Emma Iglesias, Sebastien Laurent, Enrique Sentana and seminar and conference participants at Université de Lille, Universidad Carlos III de Madrid, BI Norwegian Business School (Oslo), IHS (Vienna), 2nd. Rimini Time Series Workshop (2013), 21st. SNDE Symposium (Milan, 2013), ESEM 2011 (Oslo), Interdisciplinary Workshop in Louvain-la-Neuve 2011, CFE conference 2010 (London), FIBE 2010 (Bergen), IWAP 2010 (Madrid) and Foro de Finanzas 2010 (Elche) for useful comments, suggestions and questions. Funding from the 6th. European Community Framework Programme, MICIN ECO2009-08308 and from The Bank of Spain Excellence Program is gratefully acknowledged.

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1 Introduction

The Autoregressive Conditional Heteroscedasticity (ARCH) class of models due to Engle (1982) is useful in a wide range of applications. In finance in particular, it has been extensively used to model the clustering of large (in absolute value) financial returns. Engle (1982) himself, however, originally motivated the class as useful in modelling the time-varying conditional uncertainty (i.e. conditional variance) of economic variables in general, and of UK inflation in particular. Other areas of application include, amongst other, the uncertainty of electricity prices (e.g. Koopman et al. (2007)), the evolution of temperature data (e.g. Franses et al. (2001)) and – more generally – positively valued variables, i.e. socalled Multiplicative Error Models (MEMs), see Brownlees et al. (2012).

Within the ARCH class of models exponential versions are of special interest. This is because they enable richer autoregressive volatility dynamics (e.g. contrarian or cyclical) compared with non-exponential ARCH models, and because their fitted values of volatility are guaranteed to be positive. The latter is not necessarily the case for ordinary (i.e. non-exponential) ARCH models, in particular when additional exogenous or predetermined variables ("X") are included in the volatility equation. In fact, the greater the dimension of X, the more restrictions are needed in order to ensure positivity. Another desirable property is that volatility forecasts are more robust to jumps and outliers. Robustness can be important in order to avoid volatility forecast failure subsequent to jumps and outliers.

The log-GARCH class of models can be viewed as a dynamic version of Harvey's (1976) multiplicative heteroscedasticity model,[1] and was first proposed independently by Pantula (1986), Geweke (1986) and Milhøj (1987). Engle and Bollerslev (1986) argued against log-ARCH models because of the possibility of applying the log-operator

[1] In some statistical softwares, e.g. JMP (2013), the multiplicative heteroscedasticity model is referred to as the log-variance model.

(in the log-ARCH terms) on zero-values, which occurs whenever the error term in a regression equals zero. A solution to this problem, however, is provided in Sucarrat and Escribano (2013) for the case where the zero-probability is zero (e.g. because zeros are due to discreteness or missing values).[2] The solution is only available when estimation is via the (V)ARMA representation. Another issue that has been cited in the literature (e.g. Teräsvirta (2009)), is that the first unconditional autocorrelations of the squared errors – a measure of volatility persistence – can be unreasonably high. But this only occurs in very specific cases: The log-GARCH class allows for a much larger range of autocorrelation patterns than ordinary GARCH models, since the autocorrelation pattern depends on the shape of the conditional density (the more fat-tailed, the lower correlations) in addition to the persistence parameters. Finally, two competing classes of exponential ARCH models are Nelson's (1991) EGARCH and Harvey's (2013) Beta-t-EGARCH model. The former has proved to be much more difficult theoretically (more on this below), and the latter is not – by its very nature – amenable to the assumption of an unknown conditional density (i.e. the conditional density must be known). Moreover, the model is much more difficult to estimate for sufficiently general densities due to the complicated nature of the score expression (see e.g. equation (5) in Sucarrat (2013, p. 139) and the discussion on computational challenges on p. 142).

The assumption that the conditional density is unknown is particularly convenient from a practitioner's point of view, since the user then does not need to worry about changing the conditional density from application to application, or alternatively to work with a sufficiently general density that will often make estimation and inference numerically more challenging. This explains the attraction of Quasi Maximum Likelihood Estimators (QMLEs). In the univariate case consistency and asymptotic normality of QMLE for GARCH models under mild conditions were first established by Berkes et al. (2003) and Francq and Zakoïan (2004). In the exponential case most of the attention has been directed at Nelson's (1991) EGARCH, whose asymptotic properties have turned out to be very difficult to establish, see e.g. Straumann and Mikosch (2006). Only recently was consistency and asymptotic normality proved under the somewhat complicated condition of continuous invertibility, see Wintenberger (2013), but for the univariate EGARCH(1,1) only. The log-GARCH model is much more tractable. Francq et al. (2013) prove consistency and asymptotic normality of the Gaussian QMLE for an asymmetric log-GARCH(P,Q) model under mild conditions. Their method does not employ ARMA representations, which means it is more efficient when the conditional error is normal or close to normal, but not when the conditional density is fat-tailed, see the asymptotic efficiency comparison in Francq and Sucarrat (2013, section 4.1)). Moreover, the estimator of Francq et al. (2013) cannot handle zero-errors or missing values as suggested in Sucarrat and Escribano (2013). Finally, Francq and Sucarrat (2013) propose an estimator that achieves efficiency for conditional densities that are normal or close to the normal, by combining the ARMA-approach with the Centred Exponential Chi-Squared as instrumental QML-density. In the multivariate case, QML results have been established for the BEKK model of Engle and Kroner (1995) by Comte and Lieberman (2003), for an ARMA-GARCH

[2]The same idea can be extended to the case where the zero-probability is non-zero and time-varying.

with constant conditional correlations (CCCs) by Ling and McAleer (2003), for a factor GARCH model by Hafner and Preminger (2009), for a multivariate GARCH with CCCs by Francq and Zakoïan (2010) and for a multivariate GARCH with stochastic correlations by Francq and Zakoïan (2014) under the assumption that the system is estimable equation-by-equation.[3] For exponential ARCH models there are no multivariate results. Kawakatsu (2006) has proposed a multivariate exponential ARCH model, the matrix exponential GARCH, which contains a multivariate version of Nelson's 1991 model. But there are no proofs for the estimation and inference methods that he proposes.

This paper makes four contributions. It is well-known that all the coefficients apart from the log-volatility intercept in a univariate log-GARCH specification can be estimated consistently (under suitable assumptions) via an ARMA representation, see for example Psaradakis and Tzavalis (1999), and Francq and Zakoïan (2006). However, the estimate of the log-volatility intercept will be asymptotically biased, and the bias is made up of a log-moment expression that depends on the unknown density of the conditional error. We propose a simple estimator of the log-moment expression made up of the empirical residuals of the ARMA regression, and derive an expression for its asymptotic variance (Theorem 1). The practical consequence of this is that *all* the log-GARCH parameters can be estimated consistently, including the log-volatility intercept.

In the second contribution of our paper (Subsection 2.2), we show that the addition of exogenous, determinstic and/or predetermined conditioning variables, i.e. the log-GARCH-X model, does not alter the relation between the ARMA coefficients and the log-GARCH coefficients. So consistent estimation of the ARMA-X representation will produce exactly the same bias as earlier, and the bias correction procedure described above is likely to hold for ARMA-X models as well. We provide simulation-based evidence in support of this hypothesis.

In the third contribution (Section 3) we propose a multivariate log-GARCH-X model that admits time-varying conditional correlations. Since the positivity of the volatilites is guaranteed due to the exponential specification, restrictive assumptions are not needed in order to ensure the positive definiteness of the (possibly) time-varying covariance matrix of the errors. The multivariate log-GARCH-X model has a VARMA-X representation with a vector of error-terms. The vector is either IID, which corresponds to the Constant Conditional Correlation (CCC) case, or independent but non-identical (ID), which corresponds to the time-varying correlations case. In both cases, however, each entry in the vector of errors is marginally IID. So the bias-correction from the univariate case can be used equation-by-equation – under suitable assumptions – subsequent to the estimation of the VARMA-X representation. Also here do we provide simulation-based evidence in support of our hypothesis, both in the CCC and time-varying correlation cases.

In the fourth contribution (Section 4) we illustrate the usefulness of our results by an application to the modelling of the uncertainty of electricity prices. Electricity prices are characterised by autoregressive persistence, day-of-the week effects, large

[3] Jeantheau (1998) established general conditions for strong consistency for QML estimation of multivariate GARCH models. However, as pointed out by Ling and McAleer (2003, p. 281), his results are based on the unrealistic assumption that the initial values are known.

spikes or jumps, ARCH and non-normal conditional errors that are possibly skewed. For robust (to jumps) forecasts of uncertainty (i.e. volatility) that accommodates all these characteristics, the log-GARCH-X model is particularly suited. The investigation shows that electricity price volatility is much more variable than for, say, stock prices and exchange rates, and that volatility can be substantially underestimated if sufficient ARCH-lags and day-of-the-week effects are not accommodated.

The rest of the paper is organised as follows. The next section, section 2, presents the univariate log-GARCH model, and the relation between the univariate log-GARCH model and its ARMA representation. Also, it is shown that the addition of exogenous and predetermined variables does not alter the relationship between the log-GARCH and ARMA parameters. Section 3 shows how the ideas extend to the multivariate case. Section 4 contains our empirical application, whereas Section 5 concludes. Tables and Figures are placed at the end.

2 Univariate log-GARCH

The univariate log-GARCH(p, q) model is given by

$$\epsilon_t = \sigma_t z_t, \quad z_t \sim IID(0,1), \quad P(z_t = 0) = 0, \quad \sigma_t > 0, \tag{1}$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2, \quad t \in \mathbb{Z}, \tag{2}$$

where p is the ARCH order and q is the GARCH order. In finance, ϵ_t is often interpreted as return or mean-corrected return, but more generally it is simply the error in a regression model. Throughout we will assume ϵ_t is observable and known. Of course, this is not a realistic nor a desirable assumption, but simply reflects the current state of the literature.[4] Denoting $p^* = \max\{p, q\}$, if the roots of the lag polynomial $1 - (\alpha_1 + \beta_1)L - \cdots - (\alpha_{p^*} + \beta_{p^*})L^{p^*}$ are all greater than 1 in modulus and if $|E(\ln z_t^2)| < \infty$, then $\ln \sigma_t^2$ is stable. For common densities like the Student's t with degrees of freedom greater than 2, and the Generalised Error Distribution (GED) with shape parameter greater than 1, then ϵ_t will generally be stable as well if $\ln \sigma_t^2$ is stable. Practitioners are often interested in the dynamics of other powers than the 2nd., e.g. the 1st. power (i.e. the conditional standard deviation). For that purpose it should be noted that the dth. power log-GARCH(p, q) can be written as

$$\ln \sigma_t^d = \alpha_{0,d} + \sum_{i=1}^{p} \alpha_i \ln |\epsilon_{t-i}|^d + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^d, \quad d > 0, \tag{3}$$

where $\alpha_{0,d} = \alpha_0 d/2$. This means that a complete analysis of the dth. power log-GARCH model can be undertaken in terms of the $d = 2$ representation.

The log-GARCH model accommodates a broader range of persistency structures than the ordinary GARCH model. In particular, in contrast to the ordinary GARCH

[4]To the best of our knowledge there are only two results in the literature that do not need to assume that ϵ_t is known, namely Ling and McAleer (2003) and Francq and Zakoïan (2004). Both accommodate the joint estimation of the mean and variance equations simultaneously.

model, the unconditional autocorrelations of log-GARCH models depend on the distribution of z_t: The more fat-tailed, the weaker correlations. Also, the log-GARCH is capable of generating both weaker and stronger autocorrelations than the GARCH, and autocorrelation functions that decline either more rapidly or more slowly.

2.1 The ARMA representation

If $|E(\ln z_t^2)| < \infty$, then the log-GARCH(p,q) model (1)-(2) admits the ARMA(p,q) representation

$$\ln \epsilon_t^2 = \phi_0 + \sum_{i=1}^{p} \phi_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t, \tag{4}$$

where

$$\phi_0 = \alpha_0 + (1 - \sum_{j=1}^{q} \beta_j) \cdot E(\ln z_t^2), \tag{5}$$

$$\phi_i = \alpha_i + \beta_i, \quad 1 \leq i \leq p, \qquad \theta_j = -\beta_j, \quad 0 \leq j \leq q, \tag{6}$$

$$u_t = \ln z_t^2 - E(\ln z_t^2). \tag{7}$$

Consistent and asymptotically normal estimates of all the ARMA parameters – and hence all the log-GARCH parameters except the log-volatility intercept α_0 – is thus readily obtained via usual ARMA estimation methods subject to appropriate assumptions, see e.g. Brockwell and Davis (2006). In order to obtain an estimate of α_0 the most common solutions have been to either impose restrictive assumptions regarding the distribution of z_t (say, normality, see e.g. Psaradakis and Tzavalis (1999)), or to use an *ex post* scale-adjustment (see e.g. Bauwens and Sucarrat (2010), and Sucarrat and Escribano (2012)). What Theorem 1 below states is that a slightly modified version of an *ex post* scale-adjustment provides a consistent and asymptotically normal estimate of $E(\ln z_t^2)$ for a range of ARMA estimators. Consequentially, the final log-GARCH parameter, α_0, can also be estimated consistently via a range of ARMA estimators.

To obtain an understanding of the motivation behind the scale-adjustment, consider writing (1) as

$$\epsilon_t = \sigma_t^* z_t^*, \quad z_t^* \sim IID(0, \sigma_{z^*}^2),$$

where σ_t^* is a time-varying scale not necessarily equal to the standard deviation, and where z_t^* does not necessarily have unit variance. Of course, by construction $\sigma_t = \sigma_t^* \sigma_{z^*}$ and $z_t = z_t^* / \sigma_{z^*}$. Next, suppose a log-scale specification (e.g. an ARMA specification contained in (4)) is fitted to $\ln \epsilon_t^2$, with $\ln \hat{\sigma}_t^{*2}$ denoting the fitted value of the ARMA specification such that $\hat{\sigma}_t^* = \exp(\ln \hat{\sigma}_t^*)$, and with the ARMA residual defined as $\hat{u}_t = \ln \epsilon_t^2 - \ln \hat{\sigma}_t^{*2}$. In order to obtain an estimate of the time-varying conditional standard deviation, which is needed for comparison with other volatility models, then it is natural to consider adjusting $\hat{\sigma}_t^*$ by multiplying it with an estimate of σ_{z^*}, say, the sample standard deviation of the standardised residuals $\hat{z}_t^*$. Although this argument is fine heuristically, it may not be apparent what underlying magnitude the adjustment in fact estimates, nor may it be straightforward to obtain the limiting properties of the adjustment under suitable conditions. In the log-GARCH model, however, the log of the scale-adjustment provides an estimate of $-E(\ln z_t^2)$. To see this consider the scale adjustment and its approximation:

$$\hat{\sigma}_{z^*}^2 = \frac{1}{T-1}\sum_{t=1}^{T}(\hat{z}_t^* - \overline{\hat{z}}_t^*)^2 \quad \approx \quad \frac{1}{T}\sum_{t=1}^{T}(\hat{z}_t^*)^2 = \frac{1}{T}\sum_{t=1}^{T}\exp(\hat{u}_t).$$

The population analogue of the final expression on the right is $E[\exp(u_t)]$. Taking the natural log of $E[\exp(u_t)]$ gives $\ln E[\exp(u_t)] = -E(\ln z_t^2)$ under the assumption that $E(z_t^2) = 1$, i.e. the identifiability assumption from (1). This suggests

$$-\ln\left[\frac{1}{T}\sum_{t=1}^{T}\exp(\hat{u}_t)\right] \longrightarrow E(\ln z_t^2) \tag{8}$$

when $T \to \infty$, due to the continuity of the logarithm. The expression involves the ARMA residuals $\hat{u}_t$, which means that the standard law of large numbers does not apply. However, we conjecture that the result by Bai (1993) in combination with an argument similar to that of Yu (2007) can be used to prove that a slightly modified version of (8) provides a consistent and asymptotically normal (CAN) estimate of $E(\ln z_t^2)$ (work in progress) for a range of ARMA estimators. Meanwhile, we formulate a set of assumptions and conditions (**A1** – **A3** and Theorem 1 below) that will be sufficient for the consistent and asymptotically normal estimation of $E(\ln z_t^2)$.

Formally, we rely on the following assumptions:

A1: $E(z_t^2) = 1$ and $|E(\ln z_t^2)| < \infty$.

A2: Let $\{\hat{u}_t\}_{t=1}^T$ denote the ARMA-residuals resulting from estimating the ARMA representation (4). Denoting $\overline{\hat{u}}_T$ and $\overline{u}_T$ as the averages of $\hat{u}_t$ and u_t, respectively:

$$a) \qquad \frac{1}{T}\sum_{t=1}^{T}\exp(\hat{u}_t - \overline{\hat{u}}_T) - \frac{1}{T}\sum_{t=1}^{T}\exp(u_t - \overline{u}_T) = o_P(1)$$

$$b) \qquad \sqrt{T}\left[\frac{1}{T}\sum_{t=1}^{T}\exp(\hat{u}_t - \overline{\hat{u}}_T) - \frac{1}{T}\sum_{t=1}^{T}\exp(u_t - \overline{u}_T)\right] = o_P(1)$$

A3: $E(z_t^4) < \infty$ and $|E[(\ln z_t^2)^2]| < \infty$.

In **A1** the first condition is simply the identifiability condition from (1), whereas the second condition is required for the ARMA representation (4) to exist. For the two most commonly used densities of z_t in finance, i.e. $N(0,1)$ and t, $E(\ln z_t^2)$ is finite. The intuition behind the expressions in **A2** is that they provide conditions under which sums of exponentials like $T^{-1}\sum_t \exp(\hat{u}_t - \overline{\hat{u}}_T)$ can be treated *as if* we observe the actual errors $\{u_t\}$. The mean-correction term $\overline{\hat{u}}_T$ is required, since the conditions may not be valid if the residuals are not mean corrected. However, in some cases, e.g. when OLS is used to estimate the AR(p) representation of a log-ARCH(p) specification, then $\overline{\hat{u}}_T$ will by construction be zero. The conditions in **A2** are relatively mild, but not easily proved in the general case. Moreover, different proof-strategies may be required according to ARMA estimator and Data Generating Process (DGP). Nevertheless, an extensive amount of simulation-based evidence (Tables 1 to 6) suggest the formulas below – which rely on the conditions – hold for several ARMA estimators and DGPs.[5] Finally, the conditions in **A3** are needed for the asymptotic normality of our estimator of $E(\ln z_t^2)$.

Theorem 1. Suppose (1)-(2) and **A1** hold:

a) If **A2**a) also holds, then

$$\hat{\tau}_T = -\ln\left[\frac{1}{T}\sum_{t=1}^{T}\exp(\widehat{u}_t - \overline{\widehat{u}}_T)\right] \xrightarrow{P} E(\ln z_t^2). \tag{9}$$

b) If **A2**b) and **A3** also hold, then

$$\sqrt{T}\left[\hat{\tau}_T - E(\ln z_t^2)\right] \xrightarrow{D} N(0,\zeta^2), \tag{10}$$

where

$$\zeta^2 = Var(z_t^2 - \ln z^2). \tag{11}$$

Proof. The consistency result in a) follows straightforwardly from the continuity of the log-transformation. So let us turn to the proof of b). **A2**b) and the smoothness of the logarithm function imply that $\hat{\tau}_T$ and

$$\tilde{\tau}_T = -\ln\left[\frac{1}{T}\sum_{t=1}^{T}\exp(u_t - \overline{u}_T)\right]$$

have the same behaviour up to $o_P(T^{-1/2})$. Denoting $\tau = E\ln(z_1^2) = -\ln Ee^{u_t}$, this means $\sqrt{T}(\hat{\tau}_T - \tau) = \sqrt{T}(\tilde{\tau}_T - \tau) + o_P(1)$. Slutsky's Theorem hence implies that we only need show that $\tilde{\Delta}_T = \sqrt{T}(\tilde{\tau}_T - \tau)$ is asymptotically normal. We have that

$$\tilde{\tau}_T = -\ln\frac{1}{T}\sum_{t=1}^{T}e^{u_t-\bar{u}_T} = \bar{u}_T - \ln\frac{1}{T}\sum_{t=1}^{T}e^{u_t},$$

so

$$\tilde{\Delta}_T = \sqrt{T}\bar{u}_T + \sqrt{T}\left[f\left(\frac{1}{T}\sum_{t=1}^{T}e^{u_t}\right) - f(Ee^{u_1})\right],$$

where $f(x) = -\ln x$, with $f'(x) = -1/|x|$. By the smoothness of f, the delta method

[5] We also checked **A2** directly by simulation (not reported but available on request).

implies that

$$\begin{aligned}\tilde{\Delta}_T &= \sqrt{T}\bar{u}_T + f'(Ee^{u_1})\sqrt{T}\left[\frac{1}{T}\sum_{t=1}^{T} e^{u_t} - Ee^{u_1}\right] + o_P(1)\\ &= (f'(Ee^{u_1}), 1)\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\begin{pmatrix} e^{u_t} - Ee^{u_1} \\ u_t \end{pmatrix} + o_P(1).\end{aligned}$$

By the Multivariate Central Limit Theorem, we have that

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\begin{pmatrix} e^{u_t} - Ee^{u_1} \\ u_t \end{pmatrix} \xrightarrow{d} \begin{pmatrix} X \\ Y \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Vare^{u_1} & Eu_1e^{u_1} \\ Eu_1e^{u_1} & Varu_1 \end{pmatrix}\right)$$

where we used that $Eu_1 = 0$ and $Cov(u_1, e^{u_1}) = Eu_1e^{u_1}$. Hence, $\tilde{\Delta}_T \xrightarrow{d} f'(Ee^{u_1})X + Y$, which is mean zero normal with variance equal to

$$\begin{aligned}\zeta^2 &= (f'(Ee^{u_1}))^2\, VarX + VarY + 2f'(Ee^{u_1})Cov(X,Y)\\ &= \frac{Var[\exp(u_1)]}{[E\exp(u_1)]^2} + Var(u_1) - 2\frac{E[u_1\exp(u_1)]}{E\exp(u_1)}.\end{aligned}$$

Using the equalities

$$\begin{aligned}Var(u_1) &= E[(\ln z_1^2)^2] - [E\ln(z_1^2)]^2\\ Var[\exp(u_1)] &= \frac{1}{\{\exp[E\ln(z_1^2)]\}^2}\cdot(Ez_1^4 - 1)\\ E\exp(u_1) &= \frac{1}{\exp[E\ln(z_1^2)]}\\ E[u_1\exp(u_1)] &= \frac{1}{\exp[E\ln(z_1^2)]}\cdot\left\{E[(\ln z_1^2)z_1^2] - E\ln(z_1^2)\right\}\end{aligned}$$

we see that

$$\begin{aligned}\zeta^2 &= E[(\ln z_1^2)^2] - [E(\ln z_1^2)]^2 + (E(z_1^4) - 1) - 2E[(\ln z_1^2)z_1^2] + 2E(\ln z_1^2)\\ &= Var(z_1^2 - \ln z_1^2).\end{aligned}$$

From **A3** we have that $E(z_1^4) < \infty$, and the Cauchy-Schwarz inequality implies that $|E[(\ln z_1^2)z_1^2]|^2 \leq (E[(\ln z_1^2)^2])(Ez_1^4)$, whose right-hand side terms are assumed to be finite. Hence, ζ^2 is finite. □

The practical implication of Theorem 1 is that the residuals resulting from estimating the ARMA representation (4) can be plugged into the formula in order to obtain a consistent and asymptotically normal estimate of $E(\ln z_t^2)$. Next, the estimate of $E(\ln z_t^2)$ can be combined with the ARMA-estimates via the formulas in (5) and (6) to obtain a consistent estimate of the log-volatility intercept α_0. For an estimate of the standard error of $\hat{\tau}_T$ based on the asymptotic expression ζ^2, it should be noted that $\ln\hat{z}_t^2 = \hat{u}_t - \hat{\tau}_T$ and $\hat{z}_t^2 = \exp(\ln\hat{z}_t^2)$. Hence, if $s(x)$ denotes the sample standard deviation of x, then $s\left(\exp(\hat{u}_t - \hat{\tau}_T) - (\hat{u}_t - \hat{\tau}_T)\right)/\sqrt{T}$ can be used to compute the standard error of $\hat{\tau}_T$. A practitioner's interest in testing values of $E(\ln z_t^2)$ is mainly to test z_t for normality, i.e. whether $E(\ln z_t^2) = -1.27$, since normality is a common assumption in finance.

An extensive set of Monte Carlo simulations have been performed, of which Table 1 only contains a small subset (more simulations are contained in Tables 2 to 6, and additional simulations are available on request). The last three columns of the table confirm that the Gaussian QMLE via the ARMA representation (w/mean-correction) provides consistent estimates and empirical sample standard errors that coincide with their asymptotic counterparts. Although, as expected, a larger number of observations is needed as the persistence parameter $\phi_1 = \alpha_1 + \beta_1$ approaches 1, and when α_1 goes towards zero (i.e. a common root). Additional simulations, which are available on request, show similar properties for the Gaussian QMLE without mean-correction, and for the Least Squares Estimator (LSE). All simulations and computations are in *R* (R Core Team (2014)) with the `lgarch` package (Sucarrat (2014)).

2.2 Log-GARCH-X

Additional exogenous or predetermined variables ("X") can be added linearly or non-linearly to the log-volatility specification $\ln \sigma_t^2$ without affecting the relationship between the log-GARCH coefficients and the ARMA coefficients. Specifically, let the log-GARCH-X model be given by

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 + g(\lambda, x_t), \tag{12}$$

where g is a linear or nonlinear function of the exogenous and/or predetermined variables x_t, and a parameter vector λ. The index t in x_t does not necessarily mean that all (or any) of its elements are contemporaneous. If $|E(\ln z_t^2)| < \infty$, then (12) admits the ARMA-X representation

$$\ln \epsilon_t^2 = \phi_0 + \sum_{i=1}^{p} \phi_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \theta_j u_{t-j} + g(\lambda, x_t) + u_t, \tag{13}$$

where the ARMA coefficients are defined as before, i.e. by (5)-(6), and where u_t is the same as earlier, i.e. $u_t = \ln z_t^2 - E(\ln z_t^2)$. Rigorous proofs of consistency and asymptotic normality, which we do not provide here, would of course require precise assumptions on the behaviour of x_t, see for example Hannan and Deistler (2012, chapter 4). However, if all the ARMA-X parameters are estimated consistently, then a reasonable conjecture is that (9) provides a consistent estimate of $E(\ln z_t^2)$, and hence that all the log-GARCH parameters can be estimated consistently.

One type of conditioning variable that is of special interest in financial applications is leverage or volatility asymmetry. Table 2 provides simulation results that suggests Theorem 1 holds for a simple version of leverage, namely

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 \ln \epsilon_{t-1}^2 + \beta_1 \ln \sigma_{t-1}^2 + \lambda_1 I_{\{z_{t-1}<0\}}, \tag{14}$$

where $I_{\{z_{t-1}<0\}}$ is an indicator function equal to 1 if $z_{t-1} < 0$ and 0 otherwise. Note that $I_{\{z_{t-1}<0\}}$ is observable, since $I_{\{z_{t-1}<0\}} = I_{\{\epsilon_{t-1}<0\}}$. The simulations suggest that all the parameters are estimated consistently, and the last three columns suggest the finite sample empirical standard errors of the estimate of $E(\ln z_t^2)$ correspond to their asymptotic counterparts for both the normal and the t distributions. Additional simulations are contained in Table 5, where the univariate log-GARCH-X form is used equation-by-equation to estimate a multivariate log-GARCH(1,1) model with diagonal GARCH matrix and time-varying correlations.

3 Multivariate log-GARCH

The M-dimensional log-GARCH model is given by

$$\begin{aligned}
\epsilon_t &\sim ID(0, H_t), \quad t \in \mathbb{Z}, && (15)\\
D_t^2 &= \text{diag}\left\{\sigma_{m,t}^2\right\}, \quad m = 1, \ldots, M, && (16)\\
z_t &= D_t^{-1}\epsilon_t, \quad \forall m : z_{m,t} \sim IID(0,1), \quad P(z_t = 0) = 0, && (17)\\
\ln \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2, \qquad p \geq q, && (18)
\end{aligned}$$

where ϵ_t, σ_t^2 and z_t are $M \times 1$ vectors, and where H_t and D_t are $M \times M$ matrices. In (18) we have that $\alpha_0 = (\alpha_{1.0}, \ldots, \alpha_{M.0})'$,

$$\alpha_i = \begin{pmatrix} \alpha_{11.i} & \cdots & \alpha_{1M.i} \\ \vdots & \ddots & \vdots \\ \alpha_{M1.i} & \cdots & \alpha_{MM.i} \end{pmatrix} \quad \text{and} \quad \beta_j = \begin{pmatrix} \beta_{11.j} & \cdots & \beta_{1M.j} \\ \vdots & \ddots & \vdots \\ \beta_{M1.j} & \cdots & \beta_{MM.j} \end{pmatrix}, \qquad (19)$$

where $'$ is the transpose operator. Equation (15) means ϵ_t is independent with mean zero and a time-varying conditional covariance matrix H_t. The IID assumption in equation (17) states that each marginal series $\{z_{m,t}\}$ is $IID(0,1)$. Marginal identicality is a key characteristic of the ARCH class of models, and is needed for the formula in Theorem 1 to be applicable after estimation via the VARMA representation. An implication of (17) is that $z_t \sim ID(0, R_t)$, where R_t is both the conditional covariance and correlation matrix – possibly time-varying – of z_t. In other words, the vector z_t is ID but not necessarily IID, even though each marginal series $\{z_{mt}\}$ is IID. In the special case where the vector z_t is IID, then R_t is a Constant Conditional Correlation (CCC) model. Estimation of the volatilities D_t^2 does not require that the off-diagonals of H_t (i.e. the covariances) are specified explicitly. Nor need we assume that ϵ_t is distributed according to a certain density, say, the normal.

3.1 The VARMA representation

If $|E(\ln z_t^2)| < \infty$, then the M-dimensional log-GARCH(p,q) model (18) admits the VARMA(p,q) representation

$$\ln \epsilon_t^2 = \phi_0 + \sum_{i=1}^{p} \phi_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t, \tag{20}$$

where

$$\phi_0 = \alpha_0 + (I_M - \sum_{j=1}^{q} \beta_j) \cdot E(\ln z_t^2), \quad \phi_i = \alpha_i + \beta_i, \quad \theta_j = -\beta_j \quad \text{and} \tag{21}$$

$$u_t = \ln z_t^2 - E(\ln z_t^2). \tag{22}$$

In the special case where the vector z_t is IID, which implies a CCC model for the correlations (assuming they exist), then the vector u_t is IID as well. In this case it is well known that the multivariate Gaussian QMLE provides consistent and asymptotically normal estimates of the VARMA coefficients under suitable assumptions, see e.g. Lütkepohl (2005). Accordingly, consistent estimation and asymptotically normal inference regarding all the log-GARCH coefficients – apart from the log-volatility intercept α_0 – is available as well. In order to obtain a consistent estimate of α_0, an estimate of the vector $E(\ln z_t^2)$ is needed. Since the process $\{u_{m,t}\}$ is marginally IID for each m, an equation-by-equation application of the formula in Theorem 1 after estimation of the VARMA representation is likely to provide consistent estimates of each element in $E(\ln z_t^2)$. Tables 3 and 4 contain simulation results that support this hypothesis. The estimates of α_0 and $E(\ln z_t^2)$ are consistent, and the last two columns suggest the empirical sample standard errors coincide with their asymptotic counterparts as implied by (11).

In the case where the vector z_t is only ID, which is implied by time-varying correlations, then the vector u_t is only ID as well. This corresponds to a VARMA model with heteroscedastic error u_t. Fewer QML results are available in this case, e.g. Bardet and Wintenberger (2009). However, in the special case where the β_j matrices are diagonal, then the M-dimensional VARMA model can be estimated equation-by-equation by univariate ARMA-X methods, since – equation-by-equation – each error term $u_{m,t}$ is IID (along the lines of Francq and Zakoïan (2014)). Next, equation-by-equation application of (9) in Theorem 1 is likely to provide consistent estimates of each element in $E(\ln z_t^2)$, and hence of the log-volatility intercept α_0. Table 5 contains simulation results that supports this hypothesis when the time-varying correlations are governed by Engle's (2002) Dynamic Conditional Correlations (DCC) model. The estimates of α_0 and $E(\ln z_t^2)$ are consistent, and the last two columns suggest the empirical sample standard errors coincide with their asymptotic counterparts as implied by (11).

3.2 Multivariate log-GARCH-X

Just as in the univariate case, the multivariate log-GARCH model permits exogenous and/or predetermined conditioning variables in each of the M equations. Specifically, write the multivariate log-GARCH-X specification as

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 + \lambda x_t, \tag{23}$$

where x_t is an $L \times 1$ vector of predetermined or exogenous variables, and where λ is an $M \times L$ matrix. Here, for notational economy, we let the predetermined or exogenous variables x_t enter linearly, but in principle they can enter non-linearly as in the univariate case, see (13). Similarly, the index t in x_t does not necessarily mean that all (or any) of its elements are contemporaneous. The VARMA-X representation of (23) is then given by

$$\ln \epsilon_t^2 \;\; = \;\; \phi_0 + \sum_{i=1}^{p} \phi_i \ln \epsilon_{t-i}^2 + \sum_{j=1}^{q} \theta_j u_{t-j} + \lambda x_t + u_t,$$

with the VARMA coefficients and u_t defined as before, i.e. by (21). In other words, the relation between the VARMA coefficients and the log-GARCH coefficients are not affected by adding λx_t to (23). So VARMA-X methods can be used to estimate all the log-GARCH parameters (under suitable assumptions on x_t) except the log-volatility intercept α_0 in a first step, and then in a second step equation-by-equation application of (9) in Theorem 1 can be used to estimate each element in $E(\ln z_t^2)$ and hence the log-volatility intercept α_0. Also here it is useful to distinguish between between the CCC and time-varying correlations cases. If u_t is IID, i.e. the CCC case, then – under suitable assumptions – the multivariate Gaussian QMLE provides consistent estimates of the VARMA-X representation, see e.g. Hannan and Deistler (2012). If correlations are time-varying, and if the matrices β_j are diagonal, then each equation can be estimated separately in terms of its ARMA-X representation. The empirical application illustrates this.

4 Application: Modelling the uncertainty of electricity prices

Short-term electricity price modelling and forecasting is of great importance for energy market participants. On the supply side, producers need forecasts of prices and the time-varying uncertainty associated with those forecasts in order to appropriately determine price and production levels. On the demand side, consumers and speculators need the same type of information in order to decide when and where to produce, whether to speculate and/or hedge against adverse price changes, and for risk management purposes. Daily electricity prices are characterised by autoregressive persistence, day-of-the week effects, large spikes or jumps, ARCH and non-normal conditional errors that are possibly skewed. Koopman et al. (2007), Escribano et al. (2011), and Bauwens et al. (2013) have proposed univariate and multivariate models that contain some or several of these features. However, in none of these models is the volatility specification – a non-exponential GARCH – robust to the large spikes that is a common characteristic of electricity prices (robustness is important to avoid large and persistent volatility forecast failure following spikes or "jumps"). Nor are they flexible enough to accommodate a complex and rich heteroscedasticity dynamics similar to that of the mean specification without imposing very strong parameter restrictions (e.g. non-negativity). Finally, automated model selection with a large number of variables is infeasible in practice due to computational complexity and positivity constraints. The log-GARCH-X class of models, by contrast, remedies these deficiencies.

The data consist of the daily peak and off-peak spot electricity prices (in Euros per kw/h) from 1 January 2010 to 20 May 2014 (i.e. 1601 observations before lag-adjustments) for the Oslo region in Norway.[6] Electricity forwards for this region is traded at the Nord Pool Spot energy exchange, which is the leading European market for electrical energy. Factories, companies and other institutions with electricity consumption may want to shift part of their activity to and from peak hours for efficient cost management, since the difference between peak and off-peak prices can be very large at times, see Figure 1. As an aid in the decision-making process, forecasts of future prices and of price uncertainty (volatility) can therefore be of great usefulness. The daily peak spot price $S_{1,t}$ is computed as the average of the spot prices during peak hours, that is, $S_{1,t} = (S_{t(8am)} + \cdots + S_{t(9pm)})/14$, whereas the daily off-peak spot price $S_{2,t}$ is computed as the average of the spot prices during off-peak hours, that is, $S_{2,t} = (S_{t(0am)} + \cdots + S_{t(7am)} + S_{t(10pm)} + S_{t(11pm)})/10$. Note that $S_{t(8am)}$ should be interpreted as the electricity price from 8am to 9am, $S_{t(9am)}$ should be interpreted as the electricity price from 9am to 10am, and so on. Graphs of $S_{1,t}, S_{2,t}$ and their log-returns ($r_t = \Delta \ln S_t$) are contained in Figure 1. The price and returns figures exhibit the usual characteristics of electricity prices, namely that the price variability is substantially larger than those of financial prices (say, stocks, stock indices and exchange rates), and that big jumps occur relatively frequently.

The conditional mean is specified as a two-dimensional Vector Error Correction Model (VECM) augmented with day-of-the-week dummies in both equations.[7] The residuals or mean-corrected returns from the estimated model are then used for the estimation of the log-volatility specifications. The univariate models that we fit to

[6]The source of the data is http://www.nordpoolspot.com/, and the sample was determined by availability: Observations prior to the sample period are not available, and the data were downloaded just after 20 May 2014.

[7]The R-squared of the two equations are 0.26 and 0.17, respectively. More details are available on request.

each of the two mean-corrected returns are

$$\text{log-GARCH(1,1)}: \quad \ln \sigma_t^2 = \alpha_0 + \alpha_1 \ln \epsilon_{t-1}^2 + \beta_1 \ln \sigma_{t-1}^2, \tag{24}$$

$$\text{log-GARCH(7,1)}: \quad \ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{7} \alpha_i \ln \epsilon_{t-i}^2 + \beta_1 \ln \sigma_{t-1}^2, \tag{25}$$

$$\text{log-GARCH(7,1)--X}: \quad \ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{7} \alpha_i \ln \epsilon_{t-i}^2 + \beta_1 \ln \sigma_{t-1}^2 + \sum_{l=1}^{6} \lambda_l x_{lt}, \tag{26}$$

$$\begin{aligned} \text{log-GARCH(7,1)--X}^*: \quad \ln \sigma_{1t}^2 =& \alpha_0 + \sum_{i=1}^{7} \alpha_{1.i} \ln \epsilon_{1,t-i}^2 + \beta_1 \ln \sigma_{1,t-1}^2 + \sum_{l=1}^{6} \lambda_l x_{lt} \\ &+ \sum_{i=1}^{7} \alpha_{2.i} \ln \epsilon_{2,t-i}^2, \end{aligned} \tag{27}$$

$$\begin{aligned} \text{log-GARCH(7,0)--X}^*: \quad \ln \sigma_{1t}^2 =& \alpha_0 + \sum_{i=1}^{7} \alpha_{1.i} \ln \epsilon_{1,t-i}^2 + \sum_{l=1}^{6} \lambda_l x_{lt} \\ &+ \sum_{i=1}^{7} \alpha_{2.i} \ln \epsilon_{2,t-i}^2, \end{aligned} \tag{28}$$

where ϵ_t is the mean-corrected return in question, and where $x_{1t}, \ldots, x_{6t}$ are six day-of-the-week dummies for Tuesday to Sunday. In the last two specifications, where we add an asterisk * to the X, $\epsilon_{2,t}$ is the mean-corrected off-peak return when $\epsilon_{1,t}$ is the mean-corrected on-peak return, and vice-versa $\epsilon_{2,t}$ is the mean-corrected on-peak return when $\epsilon_{2,t}$ is the mean-corrected off-peak return. Of course, this means the last two equations could be considered as an Equation-by-Equation-Estimation (EbEE) scheme similar to that of Francq and Zakoïan (2014) (except that we do not estimate the time-varying correlations). The last specification, i.e. log-GARCH(7,0)–X* (no GARCH term), actually refers to a more parsimonious version than the one displayed. The parsimonious specification is obtained by automated General-to-Specific (GETS) model selection starting from (28), see Sucarrat and Escribano (2012).

Table 7 contains the estimation results of the univariate models (only a selection of the estimated parameters are reported for parsimony). The first striking characteristic of the results is the large ARCH(1) estimate of about 0.2 or just below for almost all the models. By contrast, daily financial returns typically exhibit an ARCH(1) estimate of about 0.05 (or lower). This means the uncertainty (i.e. volatility) of electricity returns is much more volatile in comparison. Moreover, the estimate of about 0.2 does not change much if additional variables (e.g. lags of $\ln \epsilon_t^2$ and day-of-the-week dummies) are added. By contrast, the GARCH(1) term *is* affected when additional terms are added. In the plain log-GARCH(1,1) models, for example, it is estimated to 0.64 (peak) and 0.80 (off-peak), respectively. By contrast, when additional terms are added it falls – most of the time – to about 0 or close to 0. An interesting exception to this is the log-GARCH(7,1)-X* specification of the mean-corrected peak returns, and the log-GARCH(7,1)-X specification of the mean-corrected off-peak returns. Finally, Figure 2 shows that the different specifications can produce fundamentally different volatility forecasts. In particular, the bottom graphs show that the log-GARCH(1,1) underestimates volatility on average, and that the log-GARCH(7,1)-X* models can produce fitted standard deviations that are more than twice as big. In other words, one may seriously underestimate volatility if one does not properly take the day-of-the-week periodicity of volatility into account.

The multivariate models that we fit to the vector of mean-corrected return ϵ_t are

$$\text{m-log-GARCH(1,1)}: \quad \ln\sigma_t^2 = \alpha_0 + \alpha_1 \ln\epsilon_{t-1}^2 + \beta_1 \ln\sigma_{t-1}^2, \tag{29}$$

$$\text{m-log-GARCH(7,1)}: \quad \ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{7}\alpha_i \ln\epsilon_{t-i}^2 + \beta_1 \ln\sigma_{t-1}^2, \tag{30}$$

$$\text{m-log-GARCH(7,1)}-\text{X}^*: \quad \ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{7}\alpha_i \ln\epsilon_{t-i}^2 + \beta_1 \ln\sigma_{t-1}^2 + \lambda x_t, \tag{31}$$

where both α_i and β_1 are 2×2 matrices, x_t is a 6×1 vector containing the six day-of-the-week dummies and λ is a 2×6 matrix. Table 8 contains the estimation results of the three multivariate models (again only a selection of the estimated parameters are reported for parsimony). Just as in the univariate case the ARCH(1) estimates are considerably higher than for daily financial returns – often close to 0.2, and they do not fall when additional terms are added. The m-log-GARCH(1,1)-X* estimates might suggest that the model is not stable, since $\hat{\alpha}_{22.1} + \hat{\beta}_{22.1}$ is very close to 1. However, the roots of the lag-polynomial are in fact both outside the unit circle. Finally, also in the multivariate case is there sometimes a large difference between the fitted standard deviations. Specifically, just as in the univariate case, the plain multivariate log-GARCH(1,1) model may seriously underestimate the uncertainty (i.e. volatility) when compared with the multivariate model that also include lags and day-of-the-week periodicity in the volatility specification (i.e. m-log-GARCH(7,1)-X*). This is clearly apparent from Figure 3.

5 Conclusions

We have proposed estimation and inference methods for univariate and multivariate log-GARCH-X models via (V)ARMA-X representations. Estimation of log-GARCH-X models via the (V)ARMA-X representation induces a bias in the log-volatility intercept made up of a log-moment expression that depends on the conditional density. We proposed an estimator of the log-moment expression, and derived its asymptotic variance under mild assumptions. Due to the structure of the problem the bias-correction procedure is likely to also hold for univariate log-GARCH-X models and – equation-by-equation – for multivariate log-GARCH-X models. An extensive number of simulations support our conjecture. Finally, our empirical application to electricity prices shows that the methods are particularly useful when the volatility dynamics are complex and affected by many factors.

The results in this paper suggests a vast range of new possible research questions, both empirical and theoretical. Empirically, since the methods enable a much richer and flexible approach to volatility modelling in general – both univariate and multivariate, many problems that earlier could not be handled in practice due to computational complexity are now readily implemented. Theoretically, since estimation is via the (V)ARMA representation, the vast literature on ARMA models and variants thereof serves as an almost unlimited source of ideas for possible extensions.

This paper is part of a larger research agenda. Sucarrat and Escribano (2012) rely explicitly on the results of this paper, whereas Bauwens and Sucarrat (2010) is a precursor to that paper. These papers led to the development of `AutoSEARCH`, an *R* (R Core Team (2014)) package for automated General-to-Specific (Gets) model selection of log-ARCH-X models (see Sucarrat (2012)). An early critique of the log-ARCH class of models was that the log-ARCH terms in the log-volatility specification may not exist, since the errors of a regression in empirical practice can be zero. A solution to this problem, however, is proposed in Sucarrat and Escribano (2013). Finally, Francq and Sucarrat (2013) propose another ARMA-based QMLE for log-GARCH models (with the centred exponential chi-squared as instrumental density) that is asymptotically more efficient when the conditional error is normal or close to normal.

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Table 1: Finite sample properties of the Gaussian QMLE via the ARMA representation (w/mean-correction)

DGP $(\alpha_0,\alpha_1,\beta_1,\tau)$	T	$m(\hat{\alpha}_0)$	$se(\hat{\alpha}_0)$	$m(\hat{\alpha}_1)$	$se(\hat{\alpha}_1)$	$ase(\hat{\alpha}_1)$	$m(\hat{\beta}_1)$	$se(\hat{\beta}_1)$	$ase(\hat{\beta}_1)$	$m(\hat{\tau})$	$se(\hat{\tau})$	$ase(\hat{\tau})$
$z_t \sim N(0,1)$:												
$0, 0.1, 0.8, -1.27$	1000	-0.020	0.056	0.101	0.023	0.022	0.783	0.065	0.053	-1.269	0.055	0.054
	2000	-0.009	0.034	0.100	0.015	0.016	0.794	0.040	0.038	-1.270	0.038	0.038
	5000	-0.003	0.020	0.100	0.010	0.010	0.797	0.024	0.024	-1.270	0.025	0.024
	10000	-0.003	0.015	0.100	0.007	0.007	0.797	0.017	0.017	-1.268	0.016	0.017
$0, 0.05, 0.9, -1.27$	1000	-0.041	0.149	0.052	0.018	0.016	0.865	0.116	0.040	-1.272	0.054	0.054
	2000	-0.011	0.032	0.050	0.012	0.012	0.891	0.036	0.028	-1.271	0.039	0.038
	5000	-0.004	0.015	0.050	0.008	0.007	0.896	0.020	0.018	-1.270	0.024	0.024
	10000	-0.004	0.011	0.050	0.005	0.005	0.897	0.012	0.013	-1.270	0.019	0.017
$z_t \sim t(10)$:												
$0, 0.1, 0.8, -1.39$	1000	-0.022	0.070	0.100	0.022	0.022	0.785	0.067	0.053	-1.390	0.059	0.061
	2000	-0.008	0.038	0.101	0.015	0.016	0.792	0.041	0.038	-1.392	0.044	0.043
	5000	-0.004	0.024	0.100	0.010	0.010	0.797	0.025	0.024	-1.388	0.028	0.027
	10000	0.001	0.015	0.099	0.007	0.007	0.802	0.017	0.017	-1.389	0.018	0.019
$0, 0.05, 0.9, -1.39$	1000	-0.025	0.076	0.051	0.018	0.016	0.879	0.068	0.040	-1.384	0.061	0.061
	2000	-0.011	0.032	0.050	0.012	0.012	0.891	0.033	0.028	-1.389	0.043	0.043
	5000	-0.004	0.017	0.050	0.007	0.007	0.896	0.019	0.018	-1.389	0.027	0.027
	10000	-0.002	0.012	0.050	0.005	0.005	0.899	0.012	0.013	-1.391	0.021	0.019

The estimated model is $\ln\sigma_t^2 = \alpha_0 + \alpha_1 \ln\epsilon_{t-1}^2 + \beta_1 \ln\sigma_{t-1}^2$, and estimation proceeds in three steps. First, $\mu = E(\ln\epsilon_t^2)$ is estimated with the sample mean $\hat{\mu} = T^{-1}\sum_{t=1}^{T}\ln\epsilon_t^2$. Second, an ARMA-model with ϕ_0 set to zero is fitted to the mean-corrected series $\{\ln\epsilon_t^2 - \hat{\mu}\}$. Third, formula (9) is used to estimate $\tau = E(\ln z_t^2)$. The ARMA estimates are then used via the relationships (5) and (6) to obtain the log-GARCH estimates. $m(x)$, sample mean of the estimate x. $se(x)$, sample standard deviation (division by R instead of $R-1$, where $R = 1000$ is the number of replications). $ase(x)$, asymptotic standard error of x (computed as $\sqrt{av(x)}/\sqrt{n}$, where $av(x)$ is the asymptotic variance of x). The expressions of $av(\hat{\alpha}_1)$ and $av(\hat{\beta}_1)$ are based on the ARMA(1,1) formulas in Brockwell and Davis (2006, pp. 259-260), whereas $av(\hat{\tau}) = \zeta^2$ (see (11)). Computations in R (R Core Team (2014)) with a developer-version of the `lgarch` package, see Sucarrat (2014).

Table 2: Finite sample properties of the Least Squares Estimator (LSE) via the ARMA representation (without mean-correction) for a log-GARCH(1,1) with leverage

DGP $_{(\alpha_0,\alpha_1,\beta_1,\lambda_1,\tau)}$:	T	$m(\hat{\alpha}_0)$	$se(\hat{\alpha}_0)$	$m(\hat{\alpha}_1)$	$se(\hat{\alpha}_1)$	$m(\hat{\beta}_1)$	$se(\hat{\beta}_1)$	$m(\hat{\lambda}_1)$	$se(\hat{\lambda}_1)$	$m(\hat{\tau})$	$se(\hat{\tau})$	$ase(\hat{\tau})$
$z_t \sim N(0,1)$:												
$0, 0.1, 0.8, -0.01, -1.27$	1000	-0.021	0.079	0.099	0.023	0.785	0.065	-0.011	0.088	-1.271	0.054	0.054
	2000	-0.011	0.048	0.099	0.016	0.795	0.041	-0.008	0.063	-1.270	0.039	0.038
	5000	-0.004	0.028	0.100	0.010	0.797	0.024	-0.009	0.038	-1.269	0.024	0.024
	10000	-0.002	0.019	0.100	0.007	0.799	0.017	-0.010	0.026	-1.270	0.017	0.017
$0, 0.05, 0.9, -0.02, -1.27$	1000	-0.035	0.101	0.050	0.019	0.877	0.073	-0.016	0.079	-1.273	0.054	0.054
	2000	-0.013	0.045	0.050	0.012	0.891	0.039	-0.021	0.044	-1.270	0.038	0.038
	5000	-0.005	0.022	0.050	0.007	0.897	0.019	-0.020	0.028	-1.270	0.025	0.024
	10000	-0.002	0.015	0.050	0.005	0.899	0.013	-0.020	0.020	-1.270	0.017	0.017
$z_t \sim t(10)$:												
$0, 0.1, 0.8, -0.01, -1.39$	1000	-0.023	0.079	0.100	0.023	0.784	0.064	-0.010	0.094	-1.392	0.060	0.061
	2000	-0.009	0.050	0.100	0.016	0.793	0.039	-0.010	0.065	-1.391	0.043	0.043
	5000	-0.001	0.029	0.100	0.010	0.799	0.024	-0.012	0.038	-1.390	0.027	0.027
	10000	-0.003	0.022	0.100	0.007	0.798	0.017	-0.010	0.027	-1.391	0.019	0.019
$0, 0.05, 0.9, -0.02, -1.39$	1000	-0.038	0.119	0.050	0.018	0.874	0.090	-0.027	0.078	-1.392	0.061	0.061
	2000	-0.016	0.051	0.050	0.013	0.889	0.040	-0.022	0.049	-1.390	0.045	0.043
	5000	-0.004	0.024	0.050	0.008	0.897	0.019	-0.021	0.030	-1.390	0.027	0.027
	10000	-0.002	0.016	0.050	0.005	0.899	0.013	-0.021	0.021	-1.391	0.019	0.019

The estimated model is $\ln \sigma_t^2 = \alpha_0 + \alpha_1 \ln \epsilon_{t-1}^2 + \beta_1 \ln \sigma_{t-1}^2 + \lambda_1 I_{\{z_{t-1}<0\}}$, and estimation proceeds in two steps. First, the ARMA-representation $\ln \epsilon_t^2 = \phi_0 + \phi_1 \ln \epsilon_{t-1}^2 + \theta_1 u_{t-1} + \lambda I_{\{z_{t-1}<0\}} + u_t$ is fitted by the LSE. Second, formula (9) is used to estimate $\tau = E(\ln z_t^2)$. Next, the ARMA estimates are used via the relationships (5) and (6) to obtain the log-GARCH estimates. $m(x)$, sample mean of the estimate x. $se(x)$, sample standard deviation (division by R instead of $R-1$, where $R = 1000$ is the number of replications). $ase(\hat{\tau})$, asymptotic standard error of $\hat{\tau}$, see Table 1. Computations in R (R Core Team (2014)) with the `lgarch` package version 0.2, see Sucarrat (2014).

Table 3: Finite sample properties of multivariate Gaussian QML via the VARMA representation of a 2-dimensional CCC-log-GARCH(1,1): DGP no. 1

DGP1	T	$m(\hat{\alpha}_{1.0})$	$se(\hat{\alpha}_{1.0})$	$m(\hat{\alpha}_{11.1})$	$se(\hat{\alpha}_{11.1})$	$m(\hat{\alpha}_{12.1})$	$se(\hat{\alpha}_{12.1})$	$m(\hat{\beta}_{11.1})$	$se(\hat{\beta}_{11.1})$	$m(\hat{\beta}_{12.1})$	$se(\hat{\beta}_{12.1})$	$m(\hat{\tau}_1)$	$se(\hat{\tau}_1)$	$ase(\hat{\tau}_1)$
Eq. 1:	1000	-0.018	0.088	0.098	0.024	0.001	0.024	0.784	0.076	0.003	0.074	-1.272	0.057	0.054
	2000	-0.011	0.052	0.098	0.016	0.000	0.017	0.794	0.045	0.000	0.044	-1.272	0.038	0.038
	5000	-0.003	0.028	0.100	0.010	0.000	0.010	0.797	0.025	0.001	0.025	-1.271	0.025	0.024
	10000	-0.003	0.020	0.100	0.007	0.000	0.007	0.799	0.017	0.000	0.018	-1.271	0.017	0.017
	T	$m(\hat{\alpha}_{2.0})$	$se(\hat{\alpha}_{2.0})$	$m(\hat{\alpha}_{21.1})$	$se(\hat{\alpha}_{21.1})$	$m(\hat{\alpha}_{22.1})$	$se(\hat{\alpha}_{22.1})$	$m(\hat{\beta}_{21.1})$	$se(\hat{\beta}_{21.1})$	$m(\hat{\beta}_{22.1})$	$se(\hat{\beta}_{22.1})$	$m(\hat{\tau}_2)$	$se(\hat{\tau}_2)$	$ase(\hat{\tau}_2)$
Eq. 2:	1000	-0.020	0.085	0.001	0.024	0.097	0.025	-0.003	0.073	0.791	0.068	-1.268	0.055	0.054
	2000	-0.010	0.049	0.000	0.016	0.099	0.016	-0.001	0.042	0.793	0.043	-1.270	0.036	0.038
	5000	-0.006	0.028	0.000	0.010	0.100	0.010	-0.001	0.025	0.797	0.025	-1.272	0.024	0.024
	10000	-0.002	0.020	0.000	0.007	0.100	0.007	0.000	0.017	0.799	0.017	-1.270	0.017	0.017

The estimated model is $\ln\sigma_t^2 = \alpha_0 + \alpha_1 \ln\epsilon_{t-1}^2 + \beta_1 \ln\sigma_{t-1}^2$, where $\alpha_0 = (0,0)'$, $\alpha_1 = \begin{pmatrix} 0.1 & 0 \\ 0 & 0.1 \end{pmatrix}$, $\beta_1 = \begin{pmatrix} 0.8 & 0 \\ 0 & 0.8 \end{pmatrix}$ and $Corr(z_{1t}, z_{2t}) = 0.3$. Estimation proceeds in three steps. (Note: The correlation $Corr(z_{1t}, z_{2t})$ is not estimated.) First, the VARMA representation is estimated with the multivariate Gaussian QMLE. Second, the VARMA residuals are used equation-by-equation to estimate $\tau_1 = E(\ln z_{1t}^2)$ and $\tau_2 = E(\ln z_{2t}^2)$, respectively, with formula (9). Finally, the VARMA estimates and $\widehat{\tau}_1$ and $\widehat{\tau}_2$ are combined using the relationships in (21) to obtain the log-GARCH estimates. $m(x)$, sample mean of the estimate x. $se(x)$, sample standard deviation (division by R instead of $R-1$, where $R = 1000$ is the number of replications). $ase(x)$, asymptotic standard error of x (computed as $\sqrt{av(x)}/\sqrt{T}$, where $av(\hat{\tau}_1) = av(\hat{\tau}_2) = \zeta^2$, see (11)). Computations in R (R Core Team (2014)) with the `lgarch` package version 0.3, see Sucarrat (2014).

Table 4: Finite sample properties of multivariate Gaussian QML via the VARMA representation of a 2-dimensional CCC-log-GARCH(1,1): DGP no. 2 and 3

DGP2	T	$m(\hat{\alpha}_{1.0})$	$se(\hat{\alpha}_{1.0})$	$m(\hat{\alpha}_{11.1})$	$se(\hat{\alpha}_{11.1})$	$m(\hat{\alpha}_{12.1})$	$se(\hat{\alpha}_{12.1})$	$m(\hat{\beta}_{11.1})$	$se(\hat{\beta}_{11.1})$	$m(\hat{\beta}_{12.1})$	$se(\hat{\beta}_{12.1})$	$m(\hat{\tau}_1)$	$se(\hat{\tau}_1)$	$ase(\hat{\tau}_1)$
Eq. 1:	1000	-0.020	0.135	0.095	0.029	0.049	0.029	0.683	0.170	0.125	0.269	-1.277	0.056	0.054
	2000	-0.006	0.071	0.100	0.019	0.050	0.021	0.678	0.107	0.131	0.168	-1.270	0.038	0.038
	5000	-0.005	0.043	0.100	0.012	0.050	0.012	0.695	0.058	0.106	0.083	-1.270	0.024	0.024
	10000	-0.002	0.027	0.100	0.008	0.050	0.009	0.698	0.038	0.102	0.056	-1.271	0.016	0.017
	T	$m(\hat{\alpha}_{2.0})$	$se(\hat{\alpha}_{2.0})$	$m(\hat{\alpha}_{21.1})$	$se(\hat{\alpha}_{21.1})$	$m(\hat{\alpha}_{22.1})$	$se(\hat{\alpha}_{22.1})$	$m(\hat{\beta}_{21.1})$	$se(\hat{\beta}_{21.1})$	$m(\hat{\beta}_{22.1})$	$se(\hat{\beta}_{22.1})$	$m(\hat{\tau}_2)$	$se(\hat{\tau}_2)$	$ase(\hat{\tau}_2)$
Eq. 2:	1000	-0.021	0.164	-0.001	0.030	0.097	0.031	0.127	0.190	0.539	0.270	-1.269	0.056	0.054
	2000	-0.007	0.092	0.000	0.020	0.099	0.021	0.112	0.119	0.576	0.170	-1.269	0.038	0.038
	5000	-0.001	0.053	-0.001	0.013	0.099	0.013	0.106	0.067	0.592	0.096	-1.270	0.024	0.024
	10000	0.000	0.035	0.000	0.009	0.100	0.009	0.104	0.044	0.594	0.063	-1.270	0.017	0.017

DGP3	T	$m(\hat{\alpha}_{1.0})$	$se(\hat{\alpha}_{1.0})$	$m(\hat{\alpha}_{11.1})$	$se(\hat{\alpha}_{11.1})$	$m(\hat{\alpha}_{12.1})$	$se(\hat{\alpha}_{12.1})$	$m(\hat{\beta}_{11.1})$	$se(\hat{\beta}_{11.1})$	$m(\hat{\beta}_{12.1})$	$se(\hat{\beta}_{12.1})$	$m(\hat{\tau}_1)$	$se(\hat{\tau}_1)$	$ase(\hat{\tau}_1)$
Eq. 1:	1000	-0.010	0.220	0.096	0.029	0.049	0.030	0.653	0.253	0.151	0.263	-1.274	0.054	0.054
	2000	-0.012	0.136	0.099	0.020	0.050	0.020	0.648	0.213	0.151	0.216	-1.271	0.041	0.038
	5000	-0.004	0.066	0.100	0.012	0.050	0.012	0.683	0.118	0.117	0.119	-1.271	0.025	0.024
	10000	-0.002	0.041	0.100	0.008	0.050	0.008	0.696	0.072	0.104	0.073	-1.271	0.018	0.017
	T	$m(\hat{\alpha}_{2.0})$	$se(\hat{\alpha}_{2.0})$	$m(\hat{\alpha}_{21.1})$	$se(\hat{\alpha}_{21.1})$	$m(\hat{\alpha}_{22.1})$	$se(\hat{\alpha}_{22.1})$	$m(\hat{\beta}_{21.1})$	$se(\hat{\beta}_{21.1})$	$m(\hat{\beta}_{22.1})$	$se(\hat{\beta}_{22.1})$	$m(\hat{\tau}_2)$	$se(\hat{\tau}_2)$	$ase(\hat{\tau}_2)$
Eq. 2:	1000	-0.031	0.246	0.049	0.027	0.097	0.030	0.168	0.264	0.629	0.269	-1.269	0.054	0.054
	2000	-0.011	0.133	0.050	0.020	0.099	0.020	0.145	0.214	0.653	0.209	-1.273	0.037	0.038
	5000	-0.007	0.068	0.050	0.012	0.100	0.012	0.113	0.122	0.685	0.123	-1.269	0.025	0.024
	10000	-0.003	0.039	0.050	0.008	0.100	0.008	0.106	0.069	0.694	0.070	-1.271	0.017	0.017

Notes: See Table 3. DPG2: $\alpha_1 = c(0,0)'$, $\alpha_1 = \begin{pmatrix} 0.10 & 0 \\ 0.05 & 0.10 \end{pmatrix}$, $\beta_1 = \begin{pmatrix} 0.7 & 0.1 \\ 0.1 & 0.6 \end{pmatrix}$ and $Corr(z_{1t}, z_{2t}) = 0.2$. DPG3: $\alpha_1 = c(0,0)'$, $\alpha_1 = \begin{pmatrix} 0.10 & 0.05 \\ 0.05 & 0.10 \end{pmatrix}$, $\beta_1 = \begin{pmatrix} 0.7 & 0.1 \\ 0.1 & 0.7 \end{pmatrix}$ and $Corr(z_{1t}, z_{2t}) = 0.1$. Computations in R (R Core Team (2014)) with the `lgarch` package version 0.3, see Sucarrat (2014).

Table 5: Finite sample properties of equation-by-equation Gaussian QML (without mean-correction) of a 2-dimensional log-GARCH(1,1) w/diagonal matrix β_1 when the correlations follow the DCC of Engle (2002)

	T	$m(\widehat{\alpha}_{10})$	$m(\widehat{\alpha}_{20})$	$m(\widehat{\alpha}_{11})$	$m(\widehat{\alpha}_{21})$	$m(\widehat{\alpha}_{12})$	$m(\widehat{\alpha}_{22})$	$m(\widehat{\beta}_{11})$	$m(\widehat{\beta}_{22})$	$m(\widehat{\tau}_1)$	$se(\widehat{\tau}_1)$	$m(\widehat{\tau}_2)$	$se(\widehat{\tau}_2)$	$ase(\widehat{\tau})$
DGP1:	1000	-0.065	-0.229	0.046	0.101	0.101	0.048	0.902	0.680	-1.270	0.056	-1.270	0.054	0.054
	2000	-0.032	-0.109	0.048	0.101	0.101	0.049	0.901	0.690	-1.271	0.038	-1.270	0.039	0.038
	5000	-0.013	-0.042	0.049	0.100	0.100	0.049	0.900	0.697	-1.271	0.024	-1.270	0.023	0.024
	10000	-0.005	-0.023	0.049	0.100	0.100	0.050	0.900	0.698	-1.271	0.017	-1.270	0.017	0.017
DGP2:	1000	-0.029	-0.026	0.098	0.053	0.053	0.097	0.791	0.792	-1.270	0.055	-1.268	0.053	0.054
	2000	-0.019	-0.013	0.099	0.051	0.051	0.099	0.794	0.797	-1.271	0.038	-1.272	0.039	0.038
	5000	-0.005	-0.004	0.100	0.051	0.050	0.099	0.799	0.799	-1.270	0.024	-1.270	0.024	0.024
	10000	-0.003	-0.002	0.100	0.050	0.050	0.100	0.799	0.799	-1.269	0.017	-1.271	0.017	0.017

The estimated model is $\ln\sigma_t^2 = \alpha_0 + \alpha_1 \ln\epsilon_{t-1}^2 + \beta_1 \ln\sigma_{t-1}^2$, where $\alpha_0 = (\alpha_{10}, \alpha_{20})'$, $\alpha_1 = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$ and $\beta_1 = \text{diag}(\beta_{11}, \beta_{22})$. The standardised errors $(z_{1t}, z_{2t})'$ are governed by an Engle (2002) DCC given by $(z_{1t}, z_{2t})' \sim N(0, \Sigma_t)$, $\Sigma_t = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}$, $\rho_t = q_{12,t}/\sqrt{q_{1,t}q_{2,t}}$, $q_{12,t} = \overline{\rho} + a(z_{1,t-1}z_{2,t-1} - \overline{\rho}) + b(q_{12,t} - \overline{\rho})$, $q_{1,t} = 1 + a(z_{1,t-1}^2 - 1) + b(q_{1,t} - 1)$, $q_{2,t} = 1 + a(z_{2,t-1}^2 - 1) + b(q_{2,t} - 1)$ with $a = 0.05$ and $b = 0.9$. Estimation proceeds in three steps. (Note: The Engle (2002) DCC is not estimated.) First, a univariate ARMA-X specification is fitted to each of the two equations with the Gaussian QMLE. Second, the ARMA-X residuals $\widehat{u}_{1t}$ and $\widehat{u}_{2t}$, respectively, are used equation-by-equation to estimate τ_1 and τ_2, respectively, with formula (9). Finally, the ARMA-X estimates and $\widehat{\tau}_1$ and $\widehat{\tau}_2$ are combined using the relationships in (21) to obtain the log-GARCH estimates. $m(x)$, sample mean of the estimate x. $se(x)$, sample standard deviation (division by R instead of $R-1$, where $R = 1000$ is the number of replications). $ase(x)$, asymptotic standard error of x (computed as $\sqrt{av(x)}/\sqrt{T}$, where $av(\hat{\tau}_1) = av(\hat{\tau}_2) = \zeta^2$, see (11)). In DGP no. 1: $\alpha_1 = c(0,0)'$, $\alpha_1 = \begin{pmatrix} 0.05 & 0.10 \\ 0.10 & 0.05 \end{pmatrix}$, $\beta_1 = \text{diag}(0.90, 0.70)$ and $\overline{\rho} = -0.2$. In DGP no. 2: $\alpha_1 = c(0,0)'$, $\alpha_1 = \begin{pmatrix} 0.10 & 0.05 \\ 0.05 & 0.10 \end{pmatrix}$, $\beta_1 = \text{diag}(0.80, 0.80)$ and $\overline{\rho} = 0.4$. Computations in R (R Core Team (2014)) with the `lgarch` package version 0.2, see Sucarrat (2014).

Table 6: Finite sample properties of multivariate Gaussian QML via the VARMA-X representation of a multivariate CCC-log-GARCH-X

DGP1	T	$m(\hat{\alpha}_{1.0})$	$se(\hat{\alpha}_{1.0})$	$m(\hat{\alpha}_{11.1})$	$m(\hat{\alpha}_{12.1})$	$m(\hat{\beta}_{11.1})$	$m(\hat{\beta}_{12.1})$	$m(\hat{\lambda}_{11})$	$se(\hat{\lambda}_{11})$	$m(\hat{\tau}_1)$	$se(\hat{\tau}_1)$	$ase(\hat{\tau}_1)$
Eq. 1:	1000	-0.033	0.140	0.093	0.048	0.647	0.157	0.094	0.046	-1.272	0.054	0.054
	2000	-0.020	0.097	0.098	0.050	0.668	0.130	0.097	0.033	-1.272	0.040	0.038
	5000	-0.008	0.044	0.099	0.050	0.688	0.112	0.099	0.018	-1.270	0.023	0.024
	10000	-0.003	0.029	0.099	0.050	0.695	0.105	0.099	0.013	-1.271	0.017	0.017
	T	$m(\hat{\alpha}_{2.0})$	$se(\hat{\alpha}_{2.0})$	$m(\hat{\alpha}_{21.1})$	$m(\hat{\alpha}_{22.1})$	$m(\hat{\beta}_{21.1})$	$m(\hat{\beta}_{22.1})$	$m(\hat{\lambda}_{21})$	$se(\hat{\lambda}_{21})$	$m(\hat{\tau}_2)$	$se(\hat{\tau}_2)$	$ase(\hat{\tau}_2)$
Eq. 2:	1000	-0.006	0.128	0.049	0.095	0.138	0.668	0.204	0.045	-1.274	0.056	0.054
	2000	-0.003	0.086	0.050	0.097	0.125	0.679	0.203	0.032	-1.271	0.039	0.038
	5000	0.001	0.044	0.050	0.099	0.110	0.692	0.201	0.018	-1.269	0.024	0.024
	10000	0.000	0.028	0.050	0.099	0.105	0.695	0.201	0.012	-1.271	0.018	0.017

The estimated model is $\ln\sigma_t^2 = \alpha_0 + \alpha_1 \ln\epsilon_{t-1}^2 + \beta_1 \ln\sigma_{t-1}^2 + \lambda_1 x_t$, where $\alpha_0 = (0,0)'$, $\alpha_1 = \begin{pmatrix} 0.1 & 0.05 \\ 0.05 & 0.1 \end{pmatrix}$, $\beta_1 = \begin{pmatrix} 0.7 & 0.1 \\ 0.1 & 0.7 \end{pmatrix}$, $\lambda_1 = (0.1, 0.2)'$ and $Corr(z_{1t}, z_{2t}) = 0.4$. The variable x_t is governed by an the exogenous AR(1) process $x_t = 0.5x_{t-1} + u_{xt}$ with $u_{xt} \overset{IID}{\sim} N(0,1)$. Estimation proceeds in three steps. (Note: The correlation $Corr(z_{1t}, z_{2t})$ is not estimated.) First, the VARMA-X representation is estimated with the multivariate Gaussian QMLE. Second, the VARMA residuals are used equation-by-equation to estimate τ_1 and τ_2, respectively, with formula (9) in Theorem 1. Finally, the VARMA estimates and $\widehat{\tau}_1$ and $\widehat{\tau}_2$ are combined using (21) to obtain the log-GARCH estimates. $m(x)$, sample mean of the estimate x. $se(x)$, sample standard deviation (division by R instead of $R-1$, where $R = 1000$ is the number of replications). $ase(x)$, asymptotic standard error of x (computed as $\sqrt{av(x)}/\sqrt{T}$, where $av(\hat{\tau}_1) = av(\hat{\tau}_2) = \zeta^2$, see (11)). Computations in R (R Core Team (2014)) with the `lgarch` package, see Sucarrat (2014).

Table 7: Estimation results of the univariate models (24)-(28) (only selected parameters are reported)

	Model	$\hat{\alpha}_0$	$\hat{\alpha}_1$ $(s.e.)$	$\hat{\beta}_1$ $(s.e.)$	$\hat{\tau}$ $(s.e.)$	$LogL$	k	AIC	BIC
Peak:	log-GARCH(1,1)	-0.434	0.202 (0.03)	0.639 (0.06)	-1.95 (0.14)	1890.3	3	-2.380	-2.370
	log-GARCH(7,1)	-0.976	0.232 (0.03)	-0.039 (0.20)	-2.01 (0.18)	1841.9	9	-2.311	-2.281
	log-GARCH(7,1)-X	-0.127	0.228 (0.03)	0.014 (0.29)	-1.94 (0.15)	1896.4	15	-2.372	-2.322
	log-GARCH(7,1)-X*	0.850	0.200 (0.03)	0.798 (0.03)	-1.83 (0.12)	1989.0	22	-2.480	-2.406
	log-GARCH(7,0)-X*	-0.071	0.209 (0.03)	–	-1.87 (0.12)	1955.5	13	-2.450	-2.406
Off-peak:	log-GARCH(1,1)	-0.070	0.137 (0.02)	0.792 (0.03)	-2.03 (0.10)	1676.0	3	-2.110	-2.100
	log-GARCH(7,1)	-0.548	0.202 (0.03)	-0.103 (0.14)	-2.05 (0.10)	1665.9	9	-2.089	-2.059
	log-GARCH(7,1)-X	-0.656	0.199 (0.03)	0.801 (0.03)	-1.87 (0.08)	1807.4	15	-2.260	-2.209
	log-GARCH(7,1)-X*	0.129	0.163 (0.03)	-0.041 (0.33)	-1.81 (0.07)	1850.0	22	-2.305	-2.231
	log-GARCH(7,0)-X*	-0.047	0.179 (0.03)	–	-1.86 (0.08)	1812.6	13	-2.269	-2.225

$\hat{\tau}$, estimate of $E(\ln z_t^2)$. *s.e.*, standard error of estimate. $LogL$, Gaussian log-likelihood computed as $\sum_{t=1}^{T} \ln f_\epsilon(\epsilon_t; \hat{\sigma}_t)$, where $f_\epsilon(\epsilon_t; \hat{\sigma}_t)$ is the univariate normal density, ϵ_t is the mean-corrected return and $\hat{\sigma}_t$ is the fitted standard deviation ($T = 1586$ is the number of observations). k, the total number of log-GARCH parameters (τ not included). AIC and BIC, the Akaike (1974) and Schwarz (1978) information criterion, respectively, computed in terms of $LogL$, T and k. Estimation of the ARMA representation is with the LSE without mean-correction. Computations in R (R Core Team (2014)) with the `lgarch` and `AutoSEARCH` packages, see Sucarrat (2014, 2012).

Table 8: Estimation results of the multivariate models (29)-(31) (only selected parameters are reported)

	Equation	$\hat{\alpha}_{m0}$ $(s.e.)$	$\hat{\alpha}_{mm.1}$ $(s.e.)$	$\hat{\beta}_{mm.1}$ $(s.e.)$	$\hat{\tau}_m$ $(s.e.)$	$LogL$	k	AIC	BIC
m-log-GARCH(1,1):	Peak:	-0.344	0.165 (0.03)	0.642 (0.07)	-1.85 (0.10)	4095.7	10	-5.152	-5.118
	Off-peak:	-0.220	0.113 (0.02)	0.887 (0.02)	-1.96 (0.10)				
m-log-GARCH(7,1):	Peak:	-0.053	0.193 (0.03)	0.807 (0.03)	-1.874 (0.13)	4017.1	34	-5.023	-4.908
	Off-peak:	0.128	0.170 (0.03)	0.010 (0.165)	-2.02 (0.11)				
m-log-GARCH(7,1)-X*	Peak:	0.143	0.206 (0.02)	0.163 (0.02)	-1.85 (0.12)	4316.4	46	-5.385	-5.229
	Off-peak:	-0.296	0.160 (0.02)	0.840 (0.02)	-1.76 (0.07)				

$\hat{\tau}_m$, estimate of $E(\ln z_{m,t}^2)$. $s.e.$, standard error of estimate. $LogL$, Gaussian log-likelihood computed as $\sum_{t=1}^{T} \ln f_\epsilon(\epsilon_t; \hat{\sigma}_t, \hat{R})$, where $f_\epsilon(\epsilon_t; \hat{\sigma}_t, \hat{R})$ is the multivariate normal density, ϵ_t is the vector of mean-corrected returns, $\hat{\sigma}_t$ is the vector of fitted standard deviations and $\hat{R}$ is the sample correlation matrix of $\hat{z}_t$ ($T = 1586$ is the number of observations). k, the total number of log-GARCH parameters from the multivariate model (τ_1 and τ_2 are not included). AIC and BIC, the Akaike (1974) and Schwarz (1978) information criterion, respectively, computed in terms of $LogL$, T and k. Estimation of the VARMA representation is with the multivariate Gaussian QMLE without mean-correction. Computations in R (R Core Team (2014)) with the `lgarch` package, see Sucarrat (2014).

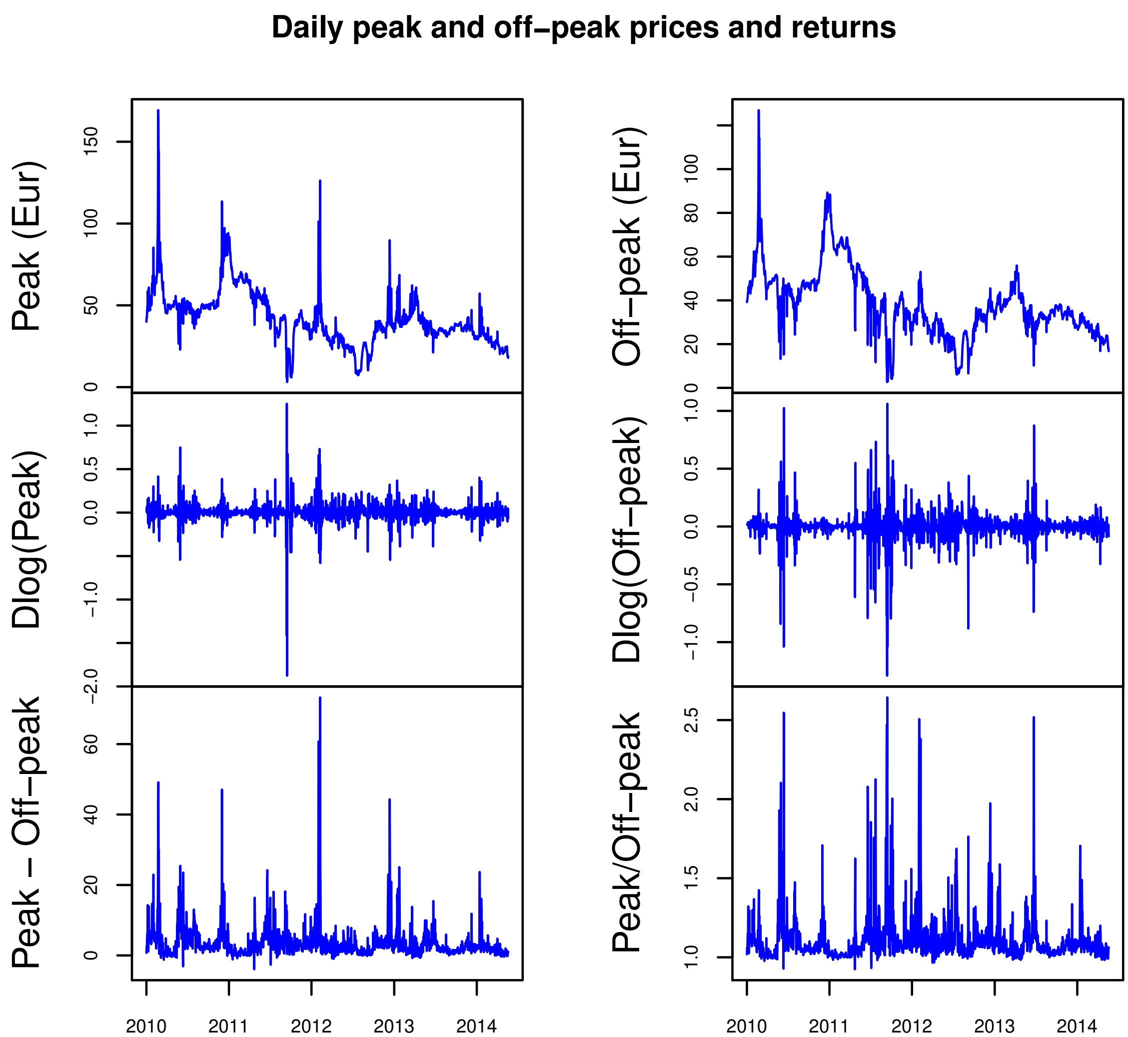

Figure 1: Daily peak and off-peak spot electricity prices (and their nominal and relative differences) in Euros per Mw/h, and log-returns for the Oslo area in Norway, 1 January 2010 - 20 May 2014 (1601 observations before lag-adjustments)

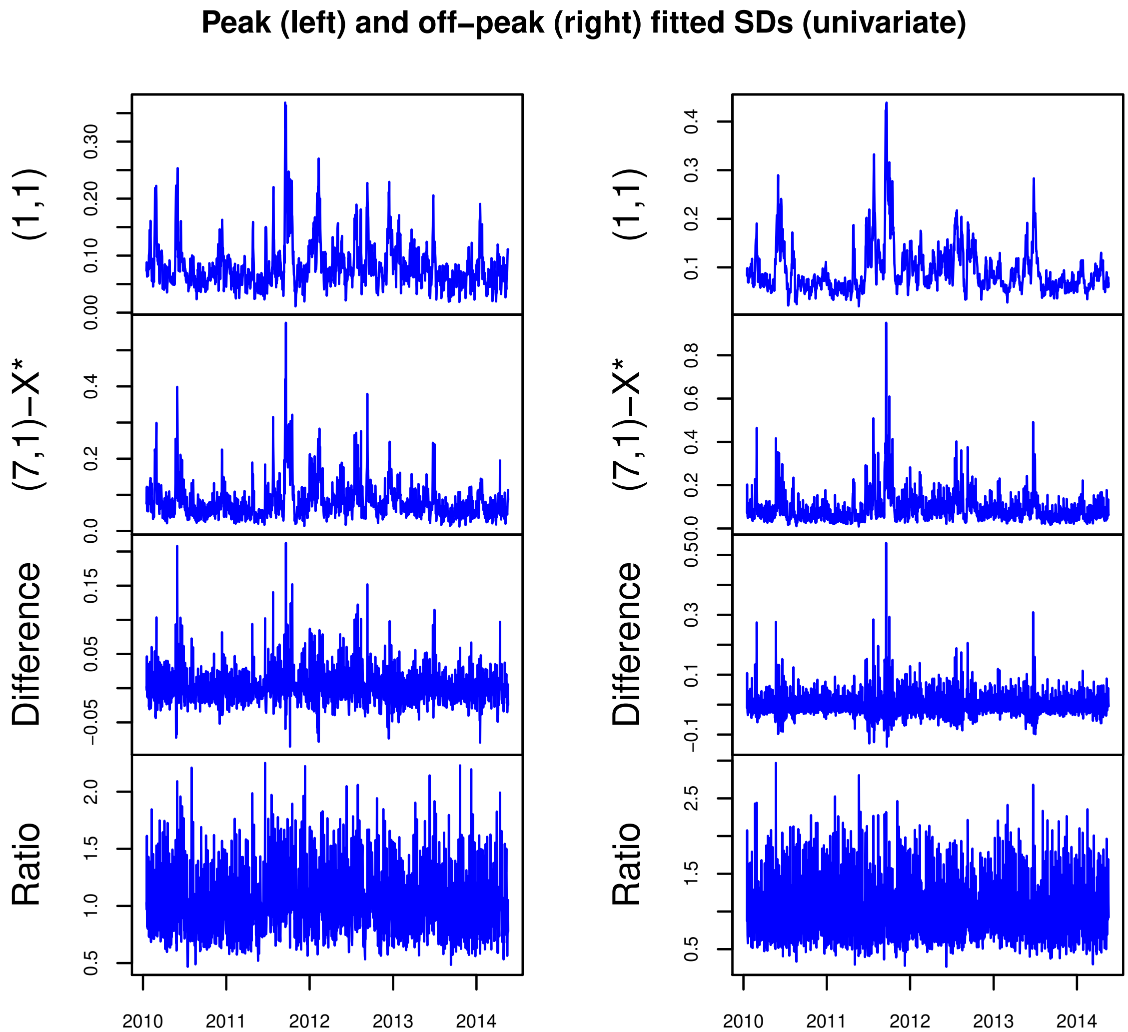

Figure 2: Fitted standard deviations (SDs) of the univariate log-GARCH(1,1) and log-GARCH(7,1)-X* models, and the nominal and relative differences between the SDs (computed as log-GARCH(1,1) minus log-GARCH(7,1)-X* and log-GARCH(1,1) over log-GARCH(7,1)-X*, respectively)

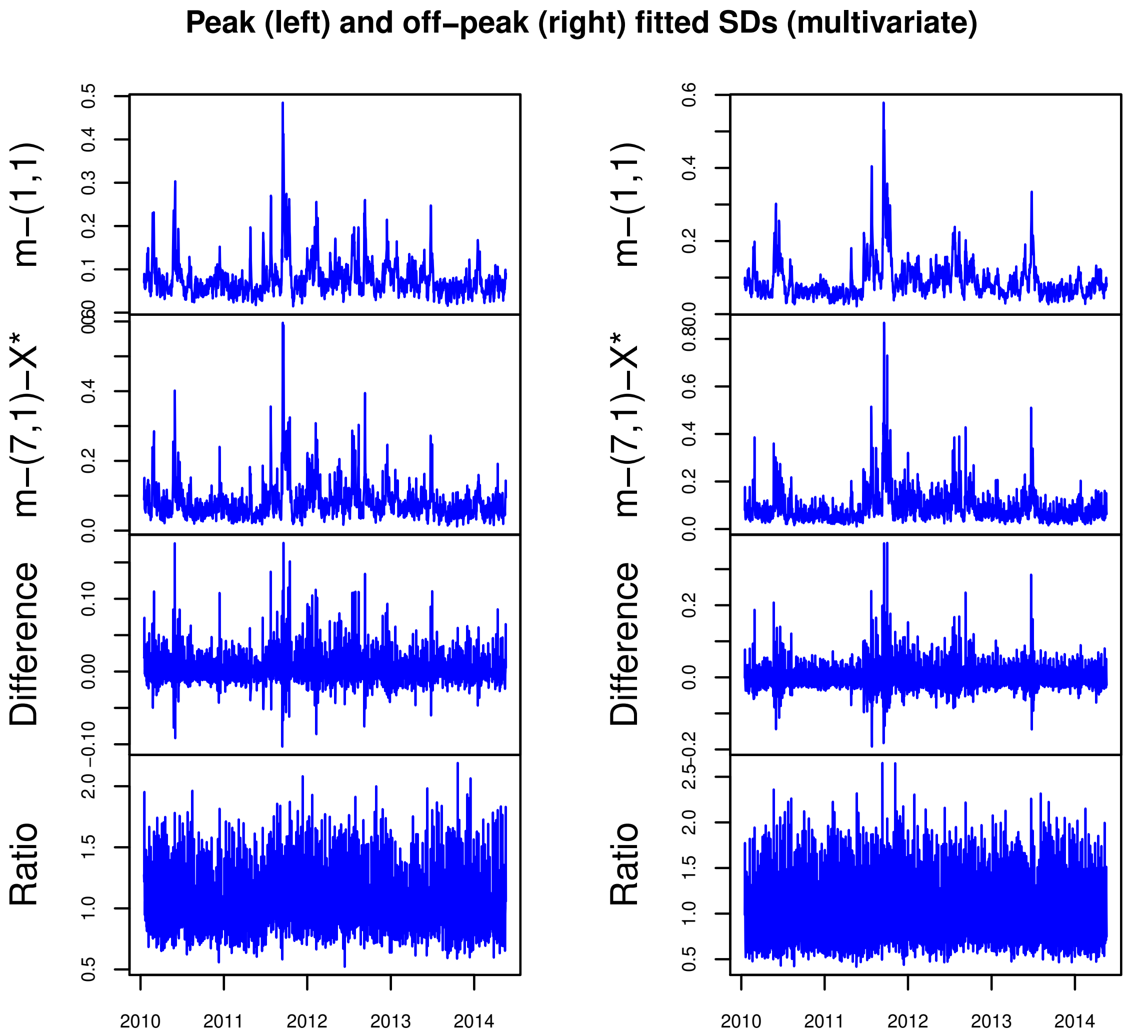

Figure 3: Fitted standard deviations (SDs) of the multivariate log-GARCH(1,1) and log-GARCH(7,1)-X* models, and the nominal and relative differences between the SDs (computed as log-GARCH(1,1) minus log-GARCH(7,1)-X* and log-GARCH(1,1) over log-GARCH(7,1)-X*, respectively)