

# Likelihood-based Estimation of Latent Generalised ARCH Structures

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## Abstract

GARCH models are commonly used as latent processes in econometrics, financial economics and macroeconomics. Yet no exact likelihood analysis of these models has been provided so far. In this paper we outline the issues and suggest a Markov chain Monte Carlo algorithm which allows the calculation of a classical estimator via the simulated EM algorithm or a Bayesian solution in  $O(T)$  computational operations, where  $T$  denotes the sample size. We assess the performance of our proposed algorithm in the context of both artificial examples and an empirical application to 26 UK sectorial stock returns, and compare it to existing approximate solutions.

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# 1 Introduction

A key feature of the class of parametric ARCH processes pioneered by Engle (1982) and Bollerslev (1986)

$$f_t = \varepsilon_t \lambda_t^{1/2}, \quad \varepsilon_t \stackrel{i.i.d.}{\sim} N(0, 1),$$

is that the volatility process  $\{\lambda_t\}$  is measurable by construction with respect to the sequence of natural filtrations generated by the past values of the  $\{f_t\}$  ARCH process,  $\mathcal{F}_{t-1}^f$  say, at least up to a finite dimensional vector of unknown parameters  $\varphi$ . An extensive review of the econometric literature on this topic is given in Bollerslev, Engle, and Nelson (1994). An immediate consequence of this setup is that the usual prediction error decomposition delivers the likelihood function of the sample conditional on initial values  $\mathcal{F}_0$  as

$$p(f|\varphi, \mathcal{F}_0) = \prod_{t=1}^T p(f_t|\mathcal{F}_{t-1}^f, \varphi) = \prod_{t=1}^T \frac{1}{\sqrt{\lambda_t(\varphi)}} \phi\left(\frac{f_t}{\sqrt{\lambda_t(\varphi)}}\right),$$

where  $T$  is the sample size,  $f = (f_1, \dots, f_T)'$ , and  $\phi(\cdot)$  denotes a standard normal density. This means that inference on unknown parameters can be carried out relatively easily.

This argument continues to hold when the normality assumption on  $\varepsilon_t$  is replaced by another parametric distribution, such as the Student  $t$  (e.g. Bollerslev (1987)) or the normal inverse Gaussian (e.g. Jensen and Lunde (2001)). Further, it does not really get any more complicated when we deal with the fractional ARCH models of Baillie, Bollerslev, and Mikkelsen (1996), although some care has to be taken with dealing with  $\mathcal{F}_0$  appropriately (see the contribution of Diebold and Schuermann (2000)). The same prediction error decomposition has been used in the multivariate ARCH context by Engle and Kroner (1995) among many others (see again Bollerslev, Engle, and Nelson (1994)).

The fact that the conditional likelihood function for ARCH models is easily computed is a major reason for the rapid adoption of this class of models in econometrics, financial economics and macroeconomics. However, the analysis becomes substantially more complicated if an ARCH model is used as a latent process, for the log-likelihood function of the observed variables can no longer be written in closed form.

The main modern way of carrying out likelihood inference on latent models is via a Markov chain Monte Carlo (MCMC) algorithm (see Chib (2001) for an extensive review of the use of such methods in the context of econometrics). The MCMC algorithm generates simulations from the distribution of the latent process  $\{f_t\}$  conditional upon the data  $\{x_t\}$  and parameters  $\varphi$ . This simulation procedure can be used either to carry out Bayesian inference on the unknown  $\varphi$ , or to classically estimate  $\varphi$  by means of a simulated EM algorithm. In either case, a crucial

feature of these methods is the continual conditional simulation of the latent vector  $f$  given  $x$  and  $\varphi$ , either one element at a time or in blocks. Unfortunately, the non-Markovian nature of the GARCH process implies that each time we simulate a single  $f_t$ , we implicitly change all future conditional variances. As pointed out by Shephard (1996), a regrettable consequence of this path-dependence in volatility is that standard MCMC algorithms will involve a  $O(T^2)$  computational load. Since this cost has to be borne for each value of  $\varphi$ , such procedures are generally infeasible for the types of large financial datasets that we see in practice, even with the massive computational power economists have available to them. To some degree this has prompted interest in models that replace the ARCH assumption with discrete-time versions of the multivariate log-normal stochastic volatility (SV) process (see the reviews of SV models by Taylor (1994), Ghysels, Harvey, and Renault (1996) and Shephard (1996)), because their first-order Markovian structure is particularly convenient for conducting inference via MCMC methods. Papers which fit these models in practice include Pitt and Shephard (1999b), Aguilar and West (2000) and Chib, Nardari, and Shephard (2001). A related line of research that also relies on MCMC methods concentrates on models in which the volatility dynamics of the latent variables is characterised by a discrete-state first-order Markov chain (see Albert and Chib (1993), Carter and Kohn (1994), Shephard (1994), Kim and Nelson (1999), and the references therein).

Nonetheless, economists have built, and continue to build, many models that involve latent GARCH processes in order to tackle a number of important empirical problems. Here we discuss two main categories of models that have been extensively used, together with some illustrative examples:

## 1. Asset pricing models

- (a) **Aggregate models.** Chou, Engle, and Kane (1992) proposed a time-varying parameter ARCH in mean model in which the slope coefficient in the linear relationship between the mean excess return on a stock market index and its variance changes over time according to a random walk. Specifically,

$$\begin{aligned}x_t &= b_t \lambda_t + f_t \\b_t &= b_{t-1} + v_t \\ \lambda_t &= \theta + \beta \lambda_{t-1} + \alpha f_{t-1}^2.\end{aligned}$$

The problem is that  $f_t$  is not measurable with respect to the econometrician's information set  $\mathcal{F}_{t-1}^x$  as long as the variance of  $v_t$  is positive, which means that the

conditional variance of the observable process  $\{x_t\}$  given its past  $\mathcal{F}_{t-1}^x$  cannot be written in closed form. Both Chou, Engle, and Kane (1992) and Harvey, Ruiz, and Sentana (1992) proposed approximate maximum likelihood estimators to this problem, but the quality of their approximations remains unknown.

- (b) **Multiasset models.** Starting with Diebold and Nerlove (1989) and King, Sentana, and Wadhvani (1994),  $N$ -dimensional multivariate dynamic heteroskedasticity models for asset returns have been developed on the basis of traditional factor structures. In this paper we will discuss in detail the case where we observe the return vector

$$x_t = Cr_{ft} + w_t, \quad (1)$$

where

$$r_{ft} = \Lambda_t \tau + f_t \quad (2)$$

are the risk awarded factors, and

$$\begin{pmatrix} f_t \\ w_t \end{pmatrix} | \mathcal{F}_{t-1}^{x,f} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \Lambda_t & 0 \\ 0 & \Gamma \end{pmatrix} \right]. \quad (3)$$

This model is called a *conditionally heteroskedastic factor* model. Here  $f_t$  is a  $k \times 1$  vector of unobserved common factors,  $C$  is a  $N \times k$  matrix of factor loadings, with  $N \geq k$  and  $\text{rank}(C) = k$ ,  $\Gamma$  is a  $N \times N$  diagonal matrix of constant idiosyncratic variances,  $\Lambda_t$  is a  $k \times k$  diagonal positive definite matrix of time-varying factor variances, and  $\tau$  is a  $k \times 1$  vector of factor risk prices. These assumptions imply that the distribution of  $x_t$  conditional on  $\mathcal{F}_{t-1}^{x,f}$  is  $N(C\Lambda_t\tau, \Sigma_t)$ , where the conditional covariance matrix  $\Sigma_t = C\Lambda_t C' + \Gamma$  has the usual factor structure. However, when  $f_t$  is a latent ARCH process cloaked in the noise  $w_t$ , we cannot directly write down the likelihood function of the observable process  $\{x_t\}$ . Papers which propose estimators of this model include Diebold and Nerlove (1989), Harvey, Ruiz, and Sentana (1992), Gouriéroux, Monfort, and Renault (1993), Calzolari, Fiorentini, and Sentana (2001) and Dungey, Martin, and Pagan (2000). Nevertheless, none of them works out how to perform exact likelihood-based inference, which remains an unsolved problem. Further, it is previously not known how to estimate the density of  $f|x, \varphi$  or its moments.

## 2. Hidden equilibrium prices

- (a) **Bid/ask prices.** Many economic models use the concept that there is an evolving equilibrium price which cannot be observed due to market imperfections. A classic

example of this is the market microstructure work of Hasbrouck (1999), who models the bid and ask price on the New York stock exchange (observed, say, every thirty minutes) as being the outcome of three continuous random variables: the equilibrium price (say  $F_t$ ) and the costs of quote exposure on the bid ( $B_t$ ) and ask sides ( $A_t$ ). The bid and ask prices in the market are then formed by rounding, with the observed bid and ask prices being

$$b_t = \text{Floor}(F_t - B_t) \quad \text{and} \quad a_t = \text{Ceiling}(F_t + A_t).$$

In a simple model, the logs of  $F_t$ ,  $B_t$  and  $A_t$  are assumed to be Gaussian autoregressions with i.i.d. innovations, although Hasbrouck mentioned his desire to allow the innovations of  $f_t$  ( $= \ln F_t$ ) to follow an ARCH process, which he was unable to handle econometrically.

- (b) **Target interest rates:** There are also examples in macroeconomics in which prices can only change in discrete amounts. For instance, ordered probit models have been used by Eichengreen, Watson, and Grossman (1985) and Dueker (1999) to describe the interest rate setting behaviour of monetary policy authorities. In their models, the desired change in a target interest rate is given by an equation of the form

$$\Delta x_t^* = \Delta z'_{t-1} \beta + f_t$$

where  $z_t$  is a set of observable conditioning variables, and  $f_t$  follows a possibly dynamic heteroskedastic process. Although Dueker (1999) motivates his work by reference to ARCH processes, he only derives MCMC estimation methods for the case in which the volatility of  $f_t$  follows a discrete-state Markov chain. An elegant approach to likelihood inference for these types of situations is put forward by Lee (1999), who employs importance sampling to estimate the likelihood function.

- (c) **Futures contracts.** Some cash markets and many futures markets often shut when the price of a futures contract moves in one day beyond a prespecified maximum. This is discussed in theory by Brennan (1986) and econometrically by McCurdy and Morgan (1987), Kodres (1988), Kodres (1993), Morgan and Trevor (1999) and Wei (2002). We might think about this problem as being one where  $\{x_t\}$  are the observed, potentially truncated, geometric returns while we think of  $\{f_t\}$  as the corresponding daily (unobserved) geometric return which we would have observed had there being no constraints. In effect,  $f_t$  measures the notional equilibrium return. Similar situations arise in target zone exchange rate agreements and commodity price support

mechanisms. Given the empirical behaviour of future prices, it makes sense to have  $f_t$  following an ARCH process. But since in regulated markets  $f_t$  is not always observed, especially in volatile periods, ignoring the censoring will deliver biased results typically underestimating the true level of volatility in the market.

In this context, our main contribution is to show that MCMC likelihood-based estimation of latent GARCH models can in fact be handled by means of feasible  $O(T)$  algorithms. The crucial idea will be a novel transformation of the latent GARCH processes that makes them first-order Markovian. For the sake of concreteness, this will be developed within the context of the conditionally heteroskedastic factor model in which the common factors follow the Quadratic GARCH in mean process introduced by Sentana (1995), but applies much more widely.

The structure of our paper is as follows. In Section 2 we outline both classical and Bayesian likelihood approaches to inference for the conditionally heteroskedastic factor model. We show in both cases that the key task is to be able to produce simulators for  $\{f_t\} | \{x_t\}, \varphi$ , that is the factors given the data and the parameters. Section 3 explains how we exploit our Markov inducing transformation to design fast, and yet simple, algorithms to carry this out. We also assess the properties of our solution by use of a Monte Carlo experiment. This section is written in a self-contained manner, so that readers who are not interested in factor models can read its contribution directly in order to be able to apply it to other problems. An illustrative empirical application of the factor model to UK sectorial stock market returns is presented in section 4. Finally, our conclusions can be found in section 5.

## 2 Likelihood inference: EM and Bayesian approaches

### 2.1 The model

In this section we discuss the basic likelihood framework for a conditionally heteroskedastic factor (CH factor) model with ARCH conditional variances. Therefore, the complete model is given by the equations (1), (2), and (3), plus the assumption that each diagonal element of  $\Lambda_t$ ,  $\lambda_{jt}$  say, follows some univariate GARCH process that depends on a set of unknown parameters  $\psi_j$ . In this respect, since (1) can be equivalently written as

$$x_t = \left(C\Lambda^{1/2}\right) \left(\Lambda^{-1/2}r_{ft}\right) + w_t,$$

where  $\Lambda$  is any  $k \times k$  diagonal positive definite (p.d.) matrix of constant factor scales, we shall initially impose restrictions on  $\psi_j$  which guarantee that

$$\lambda_j = E(\lambda_{jt}) = V(f_{jt}) = 1 \quad (j = 1, \dots, k)$$

in order to eliminate such a scale indeterminacy. We will return to this issue in section 2.4.2.<sup>1</sup>

Throughout the parameters of interest are

$$\varphi' = (c', \gamma', \delta')$$

where  $c = \text{vec}(C') = (c'_1, \dots, c'_N)'$ ,  $c'_i = (c_{i1}, \dots, c_{ik})$ ,  $\gamma = \text{vecd}(\Gamma) = (\gamma_1, \dots, \gamma_N)'$ ,  $\delta = (\delta'_1, \dots, \delta'_k)'$ , and  $\delta_j = (\tau_j, \psi_j)$ . We first discuss the basics of the simulated EM algorithm before going on to develop the corresponding Bayesian approach. As we shall see, in order to implement both these procedures the most important unsolved task is to design a method to rapidly simulate from  $\{f_t\} | \{x_t\}, \varphi$ . This will be addressed in section 3 of the paper.

## 2.2 Simulated EM algorithm

### 2.2.1 Complete likelihood $p(x, r^f | \varphi)$

Suppose for a moment that both the returns  $x$  and the risk awarded factors  $r_f$  were observed, where

$$x = (x'_1, \dots, x'_T)', \quad r_f = (r'_{f1}, \dots, r'_{fT})'$$

Then, we can write down the log-likelihood function of  $x, r_f | \varphi, \mathcal{F}_0$ , as

$$-\frac{TN}{2} \ln 2\pi - \frac{1}{2} \sum_{i=1}^N \sum_{t=1}^T \left\{ \ln |\gamma_i| + \frac{(x_{it} - c'_i r_{ft})^2}{\gamma_i} \right\} \quad (4)$$

$$-\frac{Tk}{2} \ln 2\pi - \frac{1}{2} \sum_{j=1}^k \left\{ \sum_{t=1}^T \left[ \ln |\lambda_{jt}(\delta_j)| + \frac{[r_{fjt} - \tau_j \lambda_{jt}(\delta_j)]^2}{\lambda_{jt}(\delta_j)} \right] \right\}. \quad (5)$$

Given our parametrisation of factors as univariate ARCH processes, such a factorisation performs a sequential cut on the joint log-likelihood function of  $x_t, r_{ft}$ , which would make  $r_{ft}$  strongly exogenous for  $c$  and  $\gamma$  (see Engle, Hendry, and Richard (1983)). As a result, since these parameters only enter through (4), their unrestricted MLE's would be multivariate regression estimates, which could be simply obtained from  $N$  univariate OLS regressions of each  $x_{it}$  ( $i = 1, \dots, N$ ) on  $r_{ft}$ . In addition, ML estimates of the conditional variance parameters  $\psi_j$  and price of risk coefficients  $\tau_j$  could be obtained from  $k$  univariate dynamic heteroskedasticity in mean models for  $r_{fjt}$  ( $j = 1, \dots, k$ ).

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<sup>1</sup>If the unconditional variance is unbounded, as in Integrated GARCH-type models, other symmetric scaling assumptions can be made. For instance, we could choose  $\inf_t \lambda_{jt} = 1$ , or simply fix to 1 the constant element of  $\lambda_{jt}$ . Alternatively, we can use the asymmetric scaling approach described in section 2.4.2 below, which fixes  $c_{ii}$  to 1 for  $i = 1, \dots, k$ . In any case, note that in principle there is no need to set to zero the strict upper triangle of the factor loading matrix  $C$  in view of the identification results in Sentana and Fiorentini (2001).



### 2.2.2 EM algorithm

Unfortunately, the  $r'_{ft}$ s are generally unobserved. Nevertheless, the previous discussion suggests using the EM algorithm of Dempster, Laird, and Rubin (1977) as a convenient way to obtain estimates of  $\varphi$  as close to the optimum as desired. An elegant review of this method is given by Ruud (1991). At each iteration, the EM algorithm obtains  $\varphi^{(n+1)}$  by maximising the expectation of the complete log-likelihood given by equations (4) and (5) conditional on the data and the current parameter values, i.e.

$$E \left\{ \ln p(r_f, x | \varphi, \mathcal{F}_0) | x, \varphi^{(n)}, \mathcal{F}_0 \right\},$$

with respect to  $\varphi$  keeping  $\varphi^{(n)}$  fixed. When we do this it is helpful to write

$$r_{ft|x}^{(n)} = E \left( r_{ft} | x, \varphi^{(n)} \right) \quad \text{and} \quad \Omega_{t|x}^{(n)} = V \left( r_{ft} | x, \varphi^{(n)} \right).$$

For the moment, we abstract from the fact that such quantities are not easy to calculate. Then, the expectation of the complete likelihood is

$$-\frac{TN}{2} \ln 2\pi - \frac{1}{2} \sum_{i=1}^N \sum_{t=1}^T \left\{ \ln |\gamma_i| + \frac{\left( x_{it} - c'_i r_{ft|x}^{(n)} \right)^2 + c'_i \Omega_{t|x}^{(n)} c_i}{\gamma_i} \right\} \quad (6)$$

$$-\frac{Tk}{2} \ln 2\pi - \frac{1}{2} \sum_{j=1}^k \sum_{t=1}^T E \left\{ \ln |\lambda_{jt}(\delta_j)| + \frac{[r_{fjt} - \tau_j \lambda_{jt}(\delta_j)]^2}{\lambda_{jt}(\delta_j)} \middle| x, \varphi^{(n)} \right\}, \quad (7)$$

where  $^{(n)}$  refers to expressions evaluated at  $\varphi^{(n)}$ . Such a factorisation is particularly useful for the Maximisation step of the EM algorithm, for  $C$  and  $\Gamma$ , which are typically high dimensional objects, only enter through (6). Specifically:

$$c_i^{(n+1)} = \left\{ \sum_{t=1}^T \left( r_{ft|x}^{(n)} r'_{ft|x}^{(n)} + \Omega_{t|x}^{(n)} \right) \right\}^{-1} \left\{ \sum_{t=1}^T r_{ft|x}^{(n)} x_{it} \right\}, \quad (8)$$

$$\gamma_i^{(n+1)} = \frac{1}{T} \sum_{t=1}^T \left\{ \left( x_{it} - c'_i{}^{(n+1)} r_{ft|x}^{(n)} \right)^2 + c'_i{}^{(n+1)} \Omega_{t|x}^{(n)} c_i^{(n+1)} \right\}. \quad (9)$$

This is very helpful for it means the M-step is extremely easy to compute for the vast majority of the parameter space.

Similarly,  $\delta_j^{(n+1)}$  can be obtained by maximizing (7) for  $j = 1, \dots, k$ . But since no closed expression exists in general, one has to resort to numerical optimization methods. This is the price to be paid for modelling the time variation in the conditional variance of the factors, but can be regarded as a sunk cost which is completely independent of the number of series under consideration. In fact, a very large number of series constitutes a computational blessing

in this framework, because for large  $N$  the unobservable factors can be consistently estimated (see Sentana (2002)), and the model effectively becomes a multivariate regression model, plus  $k$  univariate conditionally heteroskedastic ones. Furthermore, it is not really necessary to maximize (7) at each EM iteration if it is too costly relative to maximizing (6). In practice, we can do a few iterations over (8) and (9) alone, before maximizing (7).

### 2.2.3 Computation of the score

Nevertheless, it is well known (e.g. Tanner (1996, p. 84-85)) that the convergence of the EM algorithm slows down significantly in the neighbourhood of the optimum. As a result, after some initial EM iterations it is tempting to switch to a derivative based optimisation routine, which is more likely to quickly converge to the maximum. EM type arguments can be used to facilitate this switch by allowing the computation of the score. In particular, it is easy to see that

$$E \left\{ \frac{\partial \ln p(x, r_f | \varphi, \mathcal{F}_0)}{\partial \varphi} \Big| x, \varphi, \mathcal{F}_0 \right\} = 0,$$

so it is clear that the score can be obtained as the expected value (given  $x$ ,  $\varphi$  and  $\mathcal{F}_0$ ) of the sum of the unobservable scores corresponding to  $\ln p(x | r^f, \varphi, \mathcal{F}_0)$  and  $\ln p(r^f | \varphi, \mathcal{F}_0)$ . This result was first noted by Louis (1982); see also Ruud (1991) and Tanner (1996, p. 84).

Let  $q_t(x_t | \varphi) = \partial \ln p(x_t | \varphi, \mathcal{F}_{t-1}^x) / \partial \varphi$  denote the contribution to the score function from observation  $t$ , and partition it into three components corresponding to  $c, \gamma$  and  $\delta$ . Assuming that  $\gamma > 0$ , this yields

$$\begin{aligned} q_{ct}(x_t | \varphi) &= \text{vec} \left\{ E \left[ r_{ft}(x_t - Cr_{ft})' \Big| x, \varphi \right] \cdot \Gamma^{-1} \right\}, \\ q_{\gamma t}(x_t | \varphi) &= \frac{1}{2} \text{vecd} \left\{ \Gamma^{-1} \cdot E \left[ (x_t - Cr_{ft})(x_t - Cr_{ft})' - \Gamma \Big| x, \varphi \right] \cdot \Gamma^{-1} \right\}, \end{aligned}$$

and

$$\begin{aligned} q_{\delta_j t}(x_t | \varphi) &= E \left\{ \left[ \lambda_{jt}(\delta_j) \frac{\partial \tau_j}{\partial \delta_j} + \tau_j \frac{\partial \lambda_{jt}(\delta_j)}{\partial \delta_j} \right] \cdot \left[ \frac{r_{fjt} - \tau_j \lambda_{jt}(\delta_j)}{\lambda_{jt}(\delta_j)} \right] \right. \\ &\quad \left. + \frac{1}{2} \left[ \frac{1}{\lambda_{jt}(\delta_j)} \frac{\partial \lambda_{jt}(\delta_j)}{\partial \delta_j} \right] \cdot \left( \frac{[r_{fjt} - \tau_j \lambda_{jt}(\delta_j)]^2}{\lambda_{jt}(\delta_j)} - 1 \right) \Big| x, \varphi \right\}. \end{aligned}$$

The first two components can be conveniently re-written in terms of  $r_{ft|x}$  and  $\Omega_{t|x}$  as

$$\begin{aligned} q_{ct}(x_t | \varphi) &= \text{vec} \left\{ \left[ r_{ft|x} x_t' - (r_{ft|x} r_{ft|x}' + \Omega_{t|x}) C' \right] \Gamma^{-1} \right\}, \\ q_{\gamma t}(x_t | \varphi) &= \frac{1}{2} \text{vecd} \left\{ \Gamma^{-1} \left[ (x_t - Cr_{ft|x})(x_t - Cr_{ft|x})' + C \Omega_{t|x} C' - \Gamma \right] \Gamma^{-1} \right\}. \end{aligned}$$

### 2.2.4 Simulated versions

All the above algorithms are infeasible for we do not know how to analytically compute the required conditional expectations. The approach we follow here is to replace each of the expectations by averages of simulations drawn from  $r^f | x, \varphi^{(n)}, \mathcal{F}_0$ . In section 3 we will show how to

carry out this simulation, the major contribution of the paper. The replacement of expectations by averages of simulations means that the algorithms described in the previous two subsections will become a simulated EM algorithm and a simulated score one, respectively. These approaches to computing the maximum likelihood estimator are discussed in the statistics literature by Celeux and Diebolt (1985) and Tanner (1996). They have also appeared in econometrics on a number of occasions. Prominent references include Bresnahan (1981), Hajivassiliou and McFadden (1998), Nielsen (2000), Ruud (1991) and Shephard (1993).

### 2.3 Simulation-based Bayesian inference

The task of simulating from  $r_f|x, \varphi$  also appears in the Bayesian analysis of this model. Recall that in our problem the key issue is that the likelihood function of the sample

$$p(x|\varphi, \mathcal{F}_0) = \int p(x|r_f, \varphi, \mathcal{F}_0)p(r_f|\varphi, \mathcal{F}_0)dr_f$$

is intractable, which precludes the direct analysis of the posterior density  $p(\varphi|x, \mathcal{F}_0)$ . This problem can be overcome by focusing instead on the density

$$p(\varphi, r_f|x, \mathcal{F}_0) \propto p(x|r_f, \varphi, \mathcal{F}_0) \cdot p(r_f|\varphi, \mathcal{F}_0) \cdot p(\varphi|\mathcal{F}_0).$$

We will aim to sample from this joint density, for we can then discard the  $r_f$  draws yielding a sample from the posterior  $p(\varphi|x, \mathcal{F}_0)$ . Assuming independent priors between static and dynamic variance parameters, our suggestion is to carry this out in some natural blocks.

1. Initialise  $\varphi$ .
2. Update draw from  $p(r_f|\varphi, x, \mathcal{F}_0)$ .
3. Update draw from  $p(\varphi|r_f, x, \mathcal{F}_0)$  in the following blocks:
  - (a) Update  $p(c, \gamma|x, r_f)$ . This is updated in a block.
  - (b) Update  $p(\delta_j|\{r_{fjt}\}, \mathcal{F}_0)$  for  $j = 1, \dots, k$ .
4. Goto 2.

Step 3b is the task of simulating from the posterior of the parameters of  $k$  univariate ARCH-M processes. This has already been briefly addressed by Kim, Shephard, and Chib (1998), and at more length later by Bauwens and Lubrano (1998) and Nakatsuma (2000). Similarly, the tasks in 3a are those which appear in standard regression models. All that remains therefore is Step 2, sampling from  $r_f|\varphi, x, \mathcal{F}_0$ .

The algorithm above is a special case of a Markov chain Monte Carlo (MCMC) algorithm, which converges, as it iterates, to draws from the required density  $p(\varphi, r_f | x, \mathcal{F}_0)$ . It should be kept in mind that sample variates from a MCMC algorithm are a high-dimensional (correlated) sample from the target density of interest. These draws can be used as the basis for making inferences by appealing to suitable ergodic theorems for Markov chains. For example, posterior moments and marginal densities can be estimated (simulation consistently) by averaging the relevant function of interest over the sampled variates. The posterior mean of  $\varphi$  is simply estimated by the sample mean of the simulated  $\varphi$  values. These estimates can be made arbitrarily accurate by increasing the simulation sample size. The accuracy of the resulting estimates (the so called numerical standard error) can be assessed by standard time series methods that correct for the serial correlation in the draws. Unfortunately, the serial correlation can be quite high for badly behaved algorithms.

MCMC methods, namely the Metropolis-Hastings and Gibbs sampling algorithms, have had a widespread influence on the theory and practice of Bayesian inference. Early work on these methods appears in Metropolis, Rosenbluth, Rosenbluth, Teller, and Teller (1953), Hastings (1970), Ripley (1977) and Geman and Geman (1984), while some of the more recent developments, spurred by Tanner and Wong (1987) and Gelfand and Smith (1990), are included in Gilks, Richardson, and Spiegelhalter (1996), Tanner (1996, Ch. 6) and Chib (2001). The latter reference provides an excellent self-contained discussion of the use of these methods in the context of econometrics.

## 2.4 Implementation details

### 2.4.1 The sufficient statistics for $\{r_{ft}\} | \{x_t\}, \varphi, \mathcal{F}_0$

As we have already seen, whether we follow a classical or a Bayesian approach to estimation, our main task is to simulate from  $r_f | \varphi, x, \mathcal{F}_0$ . This is not straightforward. One of the challenges of working with the CH factor model is that the cross-sectional dimension of vector of returns  $x_t$  can be rather large. Nevertheless, enormous computational savings can be made by realizing that there are  $k$  stochastic processes which suffice to represent  $\{x_t\}$  in the simulation steps. The intuition for this result can be obtained from standard likelihood theory of Gaussian regressions. In particular, if we think of the CH model as a heteroskedastic regression of  $x_{it}$  on the “regressors”  $c'_i$  with regression parameters  $r_{ft}$  and residual variances  $\gamma_i$ , then the generalised least squares estimator of  $r_{ft}$  will provide a set of sufficient statistics.<sup>2</sup> Hence, defining the matrix

$$P = (C'\Gamma^{-1}C)^{-1} C'\Gamma^{-1},$$

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<sup>2</sup>These factor mimicking portfolios are usually known as Barlett scores in the multivariate statistical analysis literature (see e.g. Sentana (2002)).

then the “sufficient statistics” are  $\{Px_t\}$ , which we will write as  $\{y_t\}$ . Note that

$$y_t = \Lambda_t \tau + f_t + \eta_t \quad \text{where} \quad \eta_t = Pw_t, \quad \text{and}$$

$$\begin{pmatrix} f_t \\ \eta_t \end{pmatrix} | \mathcal{F}_{t-1}^{y,f} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \Lambda_t & 0 \\ 0 & \Upsilon \end{pmatrix} \right], \quad \Upsilon = (C' \Gamma^{-1} C)^{-1}.$$

Therefore, the key remaining issue in MCMC is to how deal with this “compressed” model structure. In particular, we focus on simulating from

$$\begin{aligned} p(r_f | x, \varphi, \mathcal{F}_0) &= p(r_f | y, \varphi, \mathcal{F}_0) \\ &\propto p(y | r_f, \varphi) p(r_f | \varphi, \mathcal{F}_0). \end{aligned}$$

For simplicity of exposition we will assume a single factor hereinafter, as the extension to the multifactor case is tedious but straightforward. Thus the model we study will be

$$y_t = r_{ft} + \eta_t \quad r_{ft} = \lambda_t \tau + f_t \quad f_t = \varepsilon_t \lambda_t^{1/2}.$$

For the same reason, we will assume a Generalised Quadratic ARCH structure of orders 1,1 - or GQARCH(1,1) for short - for the conditional variance

$$\lambda_t = \theta + \beta \lambda_{t-1} + \alpha (f_{t-1} - \mu)^2, \quad (10)$$

where the dynamic asymmetry parameter  $\mu$  is usually different from 0, allowing for the possibility of a leverage effect (see Sentana (1995)). The special case of  $\mu = 0$  gives the GARCH(1,1) model, while the additional assumption of  $\beta = 0$  gives ARCH(1). Given that this process is covariance stationary if  $\alpha + \beta < 1$ , we can define the innovations’ unconditional signal to noise ratio as  $\lambda/v$ , where

$$\begin{aligned} \lambda &= \frac{\theta + \alpha \mu^2}{1 - \beta - \alpha}, \\ v &= (c' \Gamma^{-1} c)^{-1}. \end{aligned}$$

In section 3 we study different ways of generating non-independent draws from the conditional distribution of  $r_f | y, \varphi$ . As we shall see, the value of  $\lambda/v$  will be one of the most important determinants of the performance of the different simulators.

#### 2.4.2 Scaling and related parametrisation issues

We have assumed so far that the scale indeterminacy of the common factors is resolved by restricting their unconditional variance to be 1. In particular, in the single factor GQARCH(1,1) model we can set

$$\theta = (1 - \beta - \alpha) - \alpha \mu^2,$$

which implies  $\lambda = 1$  and  $\theta \geq 0$  as long as  $\beta + \alpha < 1$  and  $\mu$  is not too large. More specifically, we use the re-parametrisation  $\alpha + \beta = \psi_1 = \sin^2(\psi_1^*)$  and  $\beta(\alpha + \beta)^{-1} = \psi_2 = \sin^2(\psi_2^*)$  to guarantee  $0 \leq \beta \leq 1 - \alpha \leq 1$ . In addition, we set  $\mu = [(1 - \alpha - \beta)/\alpha]^{1/2} \sin(\psi_3^*)$  to ensure  $\theta \geq 0$  and  $\lambda = 1$ . However, the performance of the Gibbs sampler can be very sensitive to the chosen normalisation (for further discussion, see Pitt and Shephard (1999a) and section 4 below). For that reason, we have also considered an alternative asymmetric scaling assumption that sets the value of a particular factor loading,  $c_1$  say, to 1, and unrestricts the unconditional variance parameter  $\lambda$  (as in Aguilar and West (2000), Chib, Nardari, and Shephard (2001), or Pitt and Shephard (1999b)).<sup>3</sup> Although such a scaling assumption does not constitute a proper, symmetric normalisation, it solves the sign indeterminacy that would otherwise exist (cf. Geweke and Zhou (1996)). Once the drawings from this alternative parametrisation have been obtained, though, we transform them back to make them comparable with the earlier one.

From a practical point of view, fixing one factor loading to 1 introduces two main differences. First, the log-likelihood function of the limiting factor representing portfolio  $r_{ft}$  will depend on an extra parameter,  $\lambda$ . And second, the posterior distributions of the factor loading parameter and idiosyncratic variance corresponding to the first element of the vector  $x_t$  have to be modified appropriately to reflect the fact that the prior distribution of  $c_1$  is now degenerate. It turns out, though, that in the single factor case all we have to do is to apply standard Bayesian inference procedures to the variance of  $(x_{1t} - r_{ft})$  under the assumption that its mean is zero. It is also straightforward to modify the EM algorithm so as to impose the restriction  $c_1^{(n+1)} = 1$  for all  $n$ . First, note that (9) is unaffected. Second, since  $\Gamma$  is diagonal, expression (8) remains valid for rows  $2, \dots, N$ . Finally, the unconditional variance parameter  $\lambda$  will enter in (7) multiplying  $\lambda_t(\delta)$ .

### 3 MCMC simulation of $\{f_t\} | \{y_t\}, \varphi$

It is clear from the discussion in the previous section that the key econometric issue in carrying out likelihood-based inference for CH factor models and other latent generalised ARCH structures is to be able to effectively simulate from  $\{f_t\} | \{y_t\}, \varphi$ , where the relationship between the latent stochastic process  $\{f_t\}$  and the observed process  $\{y_t\}$  is described by a dynamic model of the form:

$$y_t = r_{ft} + \eta_t, \quad r_{ft} = \lambda_t \tau + f_t, \quad f_t = \varepsilon_t \lambda_t^{1/2}, \\ \lambda_t = \theta + \beta \lambda_{t-1} + \alpha (f_{t-1} - \mu)^2,$$

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<sup>3</sup>In this respect, note that while  $\gamma_i$ ,  $\alpha$  and  $\beta$  are invariant to scale, the same is not true of  $c_i$ ,  $\mu$  or  $\tau$ , which must be multiplied, divided and multiplied by  $\sqrt{\lambda}$ , respectively.

where

$$\begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix} \stackrel{i.i.d.}{\sim} N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} v & 0 \\ 0 & 1 \end{pmatrix} \right\}.$$

This section deals with this issue in detail, and represents the main contribution of the paper. The first subsection discusses a simple but computationally expensive approach, which is in fact infeasible in many cases of practical interest, while the other subsections develop computationally feasible algorithms.<sup>4</sup>

### 3.1 A simple but extremely expensive $O(T^2)$ algorithm

The task is to simulate from  $p(f|y, \varphi)$ . Now sampling from

$$\begin{aligned} p(f|y, \varphi) &\propto p(y|f, \gamma)p(f|\varphi) \\ &= \prod_{t=1}^T \left\{ \frac{1}{\sqrt{v}} \phi \left( \frac{y_t - \tau \lambda_t - f_t}{\sqrt{v}} \right) \right\} \cdot \left\{ \frac{1}{\sqrt{\lambda_t}} \phi \left( \frac{f_t}{\sqrt{\lambda_t}} \right) \right\}, \end{aligned}$$

is entirely feasible by using a Metropolis-Hastings algorithm. In particular, let us write the  $r^{\text{th}}$  iteration of a Markov chain as  $f^r$ . Then we could generate a potential new value of the Markov chain  $f^{\text{new}}$  by proposing it from some candidate density  $g(f|f^r, y, \varphi)$ , which we accept with probability

$$\min \left[ 1, \frac{p(f^{\text{new}}|y, \varphi) g(f^r|f^{\text{new}}, y, \varphi)}{p(f^r|y, \varphi) g(f^{\text{new}}|f^r, y, \varphi)} \right].$$

If it is accepted then we set  $f^{r+1} = f^{\text{new}}$ , otherwise we keep  $f^{r+1} = f^r$ . This procedure is iterated and will generate an ergodic Markov chain with equilibrium distribution  $p(f|y, \varphi)$  so long as  $g(f|f^r, y, \varphi) > 0$  for all  $f$  (e.g. Tierney (1994) and Chib (2001)).

There are many potential candidate choices for  $g(f|f^r, y, \varphi)$ . For instance, we could use an independent wholmove sampler which proposes  $f$  from the Kalman filter approximation to  $p(f|y, \varphi)$  put forward by Harvey, Ruiz, and Sentana (1992) (HRS). Unfortunately, the dimension of the state vector  $f$  is so huge that it is likely that each choice will be rather poor, unless, of course, the correct distribution  $p(f|y, \varphi)$  were known, as in the conditionally homoskedastic Gaussian case discussed by Geweke and Zhou (1996). As a result, the MCMC algorithm will hardly ever accept a proposal, generating unacceptably large dependence in the chain. A conventional MCMC strategy for overcoming this problem is to update only a subset of the required elements. In particular, following a suggestion made by Shephard (1996), Wei (2002) updates

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<sup>4</sup>In this respect, it is important to note that for a given set of parameter values and initial conditions, it is generally simpler to simulate  $f_t$  for  $t = 1, \dots, T$  and then compute  $r_{ft} = \lambda_t \tau + f_t$ , than to simulate  $r_f$  directly. For that reason, we concentrate on simulators of  $f_t$  given  $y$  and  $\varphi$ . Importantly, we systematically set the mean and variance of the initial factor  $f_1$  to their unconditional values of 0 and  $\lambda$  respectively. Given that  $\lambda_t$  is a sufficient statistic for  $\mathcal{F}_{t-1}^f$ , and that  $\lambda$  is a deterministic function of  $\varphi$ ,  $\mathcal{F}_0$  can thus be eliminated from the conditioning set without information loss.

only one  $f_t$  at a time, leaving all the others unchanged. In this context, if we propose from  $g(f_t|f_{\setminus t}^r, y, \varphi)$ , where  $f_{\setminus t}^r = \{f_1^{r+1}, \dots, f_{t-1}^{r+1}, f_{t+1}^r, \dots, f_T^r\}$ , the acceptance rate will be

$$\min \left[ 1, \frac{p(f_t^{new}|f_{\setminus t}^r, y, \varphi)}{p(f_t^r|f_{\setminus t}^r, y, \varphi)} \frac{g(f_t^r|f_{\setminus t}^r, y, \varphi)}{g(f_t^{new}|f_{\setminus t}^r, y, \varphi)} \right],$$

since

$$p(f|y, \varphi) = p(f_{\setminus t}|y, \varphi) p(f_t|f_{\setminus t}, y, \varphi).$$

The proposal is now much better as it is only in a single dimension, but unfortunately, each time we consider modifying a single factor we have to compute

$$\frac{p(f_t^{new}|f_{\setminus t}^r, y, \varphi)}{p(f_t^r|f_{\setminus t}^r, y, \varphi)} = \frac{p(y_t|f_t^{new}, \lambda_t^{new,t}, \varphi) p(f_t^{new}|\lambda_t^{new,t}, \varphi)}{p(y_t|f_t^r, \lambda_t^{r,t}, \varphi) p(f_t^r|\lambda_t^{r,t}, \varphi)} \prod_{s=t+1}^T \frac{p(y_s|f_s^r, \lambda_s^{new,t}, \varphi) p(f_s^r|\lambda_s^{new,t}, \varphi)}{p(y_s|f_s^r, \lambda_s^{r,t}, \varphi) p(f_s^r|\lambda_s^{r,t}, \varphi)},$$

where for  $s = t + 1, \dots, T$

$$\begin{aligned} \lambda_s^{new,t} &= V(f_s|f_{s-1}^r, f_{s-2}^r, \dots, f_{t+1}^r, f_t^{new}, f_{t-1}^{r+1}, \dots, f_1^{r+1}), \\ \lambda_s^{r,t} &= V(f_s|f_{s-1}^r, f_{s-2}^r, \dots, f_{t+1}^r, f_t^r, f_{t-1}^{r+1}, \dots, f_1^{r+1}), \end{aligned}$$

while  $\lambda_t^{new,t} = \lambda_t^{r,t}$ . So even if we propose  $f_t^{new}$  from the conditional distribution of  $f_t$  given  $y_t$ ,  $\lambda_t^{r,t}$  and  $\varphi$  to simplify the acceptance rate slightly, unless  $\beta = 0$ , or indeed  $\alpha = 0$ , doing so requires  $O(T - t)$  univariate normal density evaluations in view of the recursive nature of the GQARCH process in (10), which makes  $\lambda_s^{new,t}$  to depend upon  $f_t^{new}$  for  $s = t + 1, \dots, T$ . As this cost would have to be borne  $T$  times in an MCMC sweep through all the elements of  $f_t$ , this algorithm is  $O(T^2)$  for each value of  $\varphi$ , and so is generally impractical for the sort of large values of  $T$  characteristic of most financial time series applications.

## 3.2 Sampling the factors in $O(T)$ operations

### 3.2.1 Markov transformations of GQARCH

An alternative approach is to work with a transformation of the latent GQARCH process that becomes first-order Markov. The simplest way to achieve this is to augment the factor with the conditional variance  $\lambda_{t+1}$ , and then sample the joint Markov process  $\{f_t, \lambda_{t+1}\}$  given  $y$  and  $\varphi$ . To see the validity of this argument, we recall that

$$\begin{aligned} \lambda_{t+1} &= \theta + \beta\lambda_t + \alpha(f_t - \mu)^2, \\ f_t &= \sqrt{\lambda_t}\varepsilon_t. \end{aligned}$$

Notice that the time-shift between both variables is only apparent, as  $f_t, \lambda_{t+1} \in \mathcal{F}_t^f$ . A technical difficulty with this approach is that the joint distribution of  $\{f_t, \lambda_{t+1}\}$  is singular, which



makes sampling slightly complicated as various Jacobian terms enter the acceptance rate of the Metropolis-Hastings algorithm (see Spivak (1965, chap. 5)). This type of algorithm is discussed in some detail in section 3.2.3. But an equivalent approach which avoids the singularities is to map from the factors  $\{f_t\}$  into a different set of Markov variables: the conditional variances  $\lambda_{t+1}$  and their “signs”  $s_t$ , where

$$s_t = \text{sign}(f_t - \mu),$$

so that  $s_t = \pm 1$  with probability 1, because  $s_t = 0$  is a zero-probability event. Although the resulting transformation involves working with a partly discrete distribution, the mapping is one-to-one with no singularities. Specifically, if we know  $\{\lambda_{t+1}\}$  and  $\varphi$  (and consequently  $\lambda$ ), then we know the value of

$$(f_t - \mu)^2 = \frac{\lambda_{t+1} - \theta - \beta\lambda_t}{\alpha}, \quad \forall t \geq 1.$$

Hence the additional knowledge of the signs of  $(f_t - \mu)$  would reveal the entire path of  $\{f_t\}$  so long as  $\lambda_1 (= \lambda$  in our case) is known. Given that this second transformation also shares the Markov nature of  $\{f_t, \lambda_{t+1}\}$ , we can easily design MCMC algorithms which sample  $\{s_t, \lambda_{t+1}\}$ , and hence the factors, in  $O(T)$  flops.

In this respect, it is worth mentioning that as we flip from  $s_t = -1$  to  $s_t = 1$ , we do not alter the volatility process (implying the signs do not cause the volatility process), but we do alter  $f_t$ . As a result, we can first simulate the Markovian process  $\{\lambda_{t+1}\}$  disregarding the values of  $\{s_t\}$ , and then we go on to simulate  $\{s_t\}$  from its distribution conditional on  $\{\lambda_{t+1}\}$ ,  $\{y_t\}$  and  $\varphi$ . Note that the second step is effectively a Gibbs sampling scheme whose acceptance rate is always 1. In addition, conditional on  $\{\lambda_{t+1}\}$ ,  $\{y_t\}$  and  $\varphi$ , the elements of  $\{s_t\}$  are independent, which further simplifies the calculations.

In the next subsections, we shall discuss in detail simulators of  $\{\lambda_{t+1}\}$ , but first, we shall briefly explain how to simulate  $s_t$ . To obtain the required conditionally Bernoulli distribution, it is helpful to establish some notation. Let us write

$$\begin{aligned} c_{t+1} &= \frac{1}{\sqrt{\omega_{t|y_t, \lambda_t}}} \left[ \phi \left( \frac{\mu + d_t - f_{t|y_t, \lambda_t}}{\sqrt{\omega_{t|y_t, \lambda_t}}} \right) + \phi \left( \frac{\mu - d_t - f_{t|y_t, \lambda_t}}{\sqrt{\omega_{t|y_t, \lambda_t}}} \right) \right], \\ d_t &= \sqrt{\frac{\lambda_{t+1} - \theta - \beta\lambda_t}{\alpha}}, \\ f_{t|y_t, \lambda_t} &= E(f_t | y_t, \lambda_t, \varphi) = \frac{\lambda_t}{\lambda_t + v} (y_t - \tau\lambda_t) = \frac{\omega_{t|y_t, \lambda_t}}{v} (y_t - \tau\lambda_t), \end{aligned}$$

and

$$\omega_{t|y_t, \lambda_t} = V(f_t | y_t, \lambda_t, \varphi) = (\lambda_t^{-1} + v^{-1})^{-1}$$

Since, conditional on  $\{\lambda_{t+1}\}$ , the probability that  $s_t$  is 1 is the same as the probability that  $f_t = d_t + \mu$ , then

$$p(s_t = 1 | \{\lambda_{t+1}\}, \{y_t\}, \varphi, \lambda_1) = p(f_t = d_t + \mu | \lambda_{t+1}, \lambda_t, y_t, \varphi) = \frac{1}{c_t \sqrt{\omega_t | y_t, \lambda_t}} \phi \left( \frac{\mu + d_t - f_t | y_t, \lambda_t}{\sqrt{\omega_t | y_t, \lambda_t}} \right).$$

This is extremely cheap to compute. Further, in the special case of  $\mu = 0$ , we can exploit the fact that

$$p(f_t | \lambda_t, y_t, \varphi) = \frac{p(y_t | f_t, \lambda_t, \varphi) p(f_t | \lambda_t, \varphi)}{p(y_t | \lambda_t, \varphi)} = \frac{1}{\sqrt{\omega_t | y_t, \lambda_t}} \phi \left( \frac{f_t - f_t | y_t, \lambda_t}{\sqrt{\omega_t | y_t, \lambda_t}} \right), \quad (11)$$

and the symmetry of the normal distribution to prove that we can alternatively draw  $s_t = +1$  with probability

$$\frac{\phi [v^{-1/2} (y_t - \tau \lambda_t - d_t)]}{\phi [v^{-1/2} (y_t - \tau \lambda_t - d_t)] + \phi [v^{-1/2} (y_t - \tau \lambda_t + d_t)]}$$

without affecting the results.

### 3.2.2 Single move samplers of $\{\lambda_{t+1}\}$

In this section, we concentrate on updating one single  $\lambda_{t+1}$  at a time, leaving all the others unchanged. In general, if we draw  $\lambda_{t+1}^{new}$  from an arbitrary proposal density  $g(\lambda_{t+1} | \lambda_{\setminus t+1}^r, y, \varphi)$ , where  $\lambda_{\setminus t+1}^r = \{\lambda_2^{r+1}, \dots, \lambda_t^{r+1}, \lambda_{t+2}^r, \dots, \lambda_{T+1}^r\}$ , then the MH acceptance rate would be

$$\min \left[ 1, \frac{p(\lambda_{t+1}^{new} | \lambda_{\setminus t+1}^r, y, \varphi) g(\lambda_{t+1}^r | \lambda_{\setminus t+1}^{new}, y, \varphi)}{p(\lambda_{t+1}^r | \lambda_{\setminus t+1}^{new}, y, \varphi) g(\lambda_{t+1}^{new} | \lambda_{\setminus t+1}^r, y, \varphi)} \right].$$

Such an acceptance rate turns out to be exactly the same as in the popular discrete time version of the log-normal stochastic volatility process (see e.g. Kim, Shephard, and Chib (1998)). In fact, the similarity is not merely coincidental, because latent GARCH models are effectively parameter driven processes, as opposed to standard GARCH models, which are observation driven ones (see Andersen (1994) and Shephard (1996)). Nevertheless, there are important differences in the distribution of  $\lambda_t$  between the two cases. In particular, since we are dealing with volatilities as opposed to their logs, the range of values of  $\lambda_{t+1}$  compatible with  $\lambda_{t+2}$  and  $\lambda_t$  in the GQARCH case is bounded from above and below to preserve positivity. Specifically, the lower limit corresponds to  $d_t = 0$ , and the upper limit to  $d_{t+1} = 0$ . Therefore, in practice it makes sense to make the proposal to obey the support of the density. The crucial thing, though, is that we can quickly evaluate

$$\begin{aligned} p(\lambda_{t+1} | \lambda_{\setminus t+1}, y, \varphi) &\propto p(\lambda_{t+2} | \lambda_{t+1}, \varphi) p(\lambda_{t+1} | \lambda_t, \varphi) p(y_{t+1} | \lambda_{t+2}, \lambda_{t+1}, \varphi) p(y_t | \lambda_{t+1}, \lambda_t, \varphi), \\ \lambda_{t+1} &\in [\theta + \beta \lambda_t, \beta^{-1} (\lambda_{t+2} - \theta)], \end{aligned}$$

where  $p(y_t|\lambda_{t+1}, \lambda_t, \varphi)$  is a mixture of two univariate normal densities, and  $p(\lambda_{t+1}|\lambda_t, \varphi)$  is a scaled non-central chi-squared distribution with a single degree of freedom.<sup>5</sup>

There are many ways in which we can carry out MCMC on  $p(\lambda_{t+1}|\lambda_{t+1}, y, \varphi)$ . At first sight, it is tempting to simplify the acceptance rate by proposing  $\lambda_{t+1}$  from  $p(\lambda_{t+1}|\lambda_t, \varphi)$ , appropriately truncated from above, since the lower truncation will be automatically satisfied. However, such a proposal would be ignoring the information in  $y_{t+1}$ . Our experience suggests that the conditional distribution of  $\lambda_{t+1}$  can be radically modified by incorporating the information in the observed series, especially when the signal to noise ratio  $\lambda/v$  is high. For that reason, we can achieve a substantially higher acceptance rate by proposing  $\lambda_{t+1}$  from  $p(\lambda_{t+1}|y_t, \lambda_t, \varphi)$ . A numerically efficient way to simulate  $\lambda_{t+1}$  from this distribution is to sample an underlying Gaussian random variable  $f_t^{new} \sim N(f_t|y_t, \lambda_t, \omega_t|y_t, \lambda_t)$  doubly truncated so that it remains within the interval  $\mu \pm l_t$ , where

$$l_t = \sqrt{\frac{\lambda_{t+2} - \theta(1 + \beta) - \beta^2\lambda_t}{\alpha\beta}},$$

and then compute

$$\lambda_{t+1}^{new} = \theta + \beta\lambda_t + \alpha(f_t^c - \mu)^2.$$

Note that the truncation implicitly guarantees a real value for

$$d_{t+1}^{new} = \sqrt{\frac{\lambda_{t+2} - \theta - \beta\lambda_{t+1}^{new}}{\alpha}},$$

which in turn implies that  $\lambda_{t+1}^{new}$  lies within the acceptable bounds. Simulating from the truncated normal distribution of  $f_t$  (given  $y_t$ ,  $\lambda_t$  and  $\varphi$ ) can be done by using a simple accept/reject algorithm, or by exploiting the probability integral transform.<sup>6</sup> In any case, since the conditional

<sup>5</sup>The density of a scaled non-central chi-squared variable  $z = \sigma(x + \mu)^2$ , where  $x \sim N(0, 1)$ , is

$$p_{NC}(z; \delta, \sigma) = \frac{1}{2\sigma} \exp\left\{-\frac{(\delta + z/\sigma)}{2}\right\} \left(\frac{z}{\sigma\delta}\right)^{-1/4} \sqrt{\frac{2\sigma}{\pi z}} \cosh(\sqrt{\delta z/\sigma}), \quad z \geq \delta,$$

where  $\delta = \mu^2$  and  $2 \cosh(u) = \exp(u) + \exp(-u)$ . This result is due to Fisher (1928) and is discussed by Johnson, Kotz, and Balakrishnan (1995, Ch. 29). In addition, if we wish to compute,  $\Pr(z < c^2)$  for  $c > 0$ , then we have

$$\Pr\left\{x \in (-c/\sigma^{1/2} - \mu, c/\sigma^{1/2} - \mu)\right\} = \Phi\left(c/\sigma^{1/2} - \mu\right) - \Phi\left(-c/\sigma^{1/2} - \mu\right).$$

<sup>6</sup>Specifically, we can compute the value of the conditionally Gaussian distribution function at both truncation limits, draw a uniform random number in the intermediate range, and use the inverse Gaussian distribution function to obtain the truncated normal variate. If the degree of truncation is small, the extra computations involved may make this method unnecessarily slow. On the other hand, a simple accept/reject method can be very inefficient if the double truncation of  $f_t^{new}$  is in the tails of its conditional distribution. Therefore, it may worth assessing the degree of truncation first, and depending on its tightness, choose one simulation method or the other.

density of  $f_t^{new}$  will be given by the following expression

$$p(f_t^{new} || |f_t^{new} - \mu| \leq l_t, y_t, \lambda_t, \varphi) = \frac{1}{\sqrt{\omega_t|y_t, \lambda_t}} \phi \left( \frac{f_t^{new} - f_t|y_t, \lambda_t}{\sqrt{\omega_t|y_t, \lambda_t}} \right) \\ \times \left[ \Phi \left( \frac{\mu + l_t - f_t|y_t, \lambda_t}{\sqrt{\omega_t|y_t, \lambda_t}} \right) - \Phi \left( \frac{\mu - l_t - f_t|y_t, \lambda_t}{\sqrt{\omega_t|y_t, \lambda_t}} \right) \right]^{-1},$$

where  $\Phi(\cdot)$  is the cumulative distribution function of a standard normal, the density of  $\lambda_{t+1}^{new}$  will be

$$p(\lambda_{t+1}^{new} | \lambda_{t+1}^{new} \in [\theta + \beta\lambda_t, \beta^{-1}(\lambda_{t+2} - \theta)], y_t, \lambda_t, \varphi) \\ = \frac{c_t^{new}}{|2\alpha d_t^{new}|} \times \left[ \Phi \left( \frac{\mu + l_t - f_t|y_t, \lambda_t}{\sqrt{\omega_t|y_t, \lambda_t}} \right) - \Phi \left( \frac{\mu - l_t - f_t|y_t, \lambda_t}{\sqrt{\omega_t|y_t, \lambda_t}} \right) \right]^{-1}$$

by virtue of the usual change of variable formula. But since the degree of truncation is the same for old and new, the acceptance probability will be the minimum of 1 and

$$\frac{p(y_{t+1} | \lambda_{t+1}^{new}) p(\lambda_{t+2} | y_{t+1}, \lambda_{t+1}^{new})}{p(y_{t+1} | \lambda_{t+1}^r) p(\lambda_{t+2} | y_{t+1}, \lambda_{t+1}^r)} = \frac{p(y_{t+1} | \lambda_{t+1}^{new})}{p(y_{t+1} | \lambda_{t+1}^r)} \cdot \frac{c_{t+1}^{new}}{c_{t+1}^r} \cdot \frac{d_{t+1}^r}{d_{t+1}^{new}},$$

where we have again used (11).

Although the sign of  $(f_t^{new} - \mu)$  does not affect the acceptance rate, note that if we retain  $f_t^{new}$ , then we will not need to simulate  $s_t$  at a later stage. Taken together this implies that we sweep through all  $T$  conditional variances, signs and factors in  $O(T)$  operations. In addition, if  $\beta = 0$ , the upper truncation disappears, and this sampler coincides with the single move sampler over  $\{f_t\}$  described in section 3.1.

### 3.2.3 Equivalent double-move samplers for $\{f_t, \lambda_{t+1}\}$

In fact, it is possible to arrive at the same sampling procedure by jointly sampling  $(f_t, \lambda_{t+1}, f_{t+1}, \lambda_{t+2})$  conditional on  $f_{\setminus t, t+1}^r, \lambda_{\setminus t+1, t+2}^r, y$  and  $\varphi$ , where  $f_{\setminus t, t+1}^r = \{f_1^{r+1}, \dots, f_{t-1}^{r+1}, f_{t+2}^r, \dots, f_T^r\}$  and  $\lambda_{\setminus t+1, t+2}^r = \{\lambda_2^{r+1}, \dots, \lambda_t^{r+1}, \lambda_{t+3}^r, \dots, \lambda_{T+1}^r\}$ . To see why, note that given that  $\lambda_{t+2}$  will be fully revealed by  $\lambda_{t+3}$  and  $f_{t+2}$  when  $\beta \neq 0$ , the candidate random vector must satisfy  $\lambda_{t+2}^{new} = \lambda_{t+2}^r$ . In addition, since

$$\lambda_{t+2} = \theta(1 + \beta) + \alpha(f_{t+1} - \mu)^2 + \alpha\beta(f_t - \mu)^2 + \beta^2\lambda_t,$$

any admissible proposal for  $f_t$  and  $f_{t+1}$  must actually lie on the two-dimensional ellipse

$$\beta(f_t - \mu)^2 + (f_{t+1} - \mu)^2 = [\lambda_{t+2} - \theta(1 + \beta) - \beta^2\lambda_t] / \alpha \quad (12)$$

The implication is twofold. First, any candidate  $f_t$  must be restricted to the interval  $[\mu - l_t, \mu + l_t]$ .

Second, for any given  $f_t$  then we can solve out  $f_{t+1} = \mu \pm d_{t+1}$ .

Let  $g(f_{t+1}, f_t)$  denote any proposed distribution whose drawings  $(f_{t+1}^{new}, f_t^{new})$  satisfy equation (12) - otherwise, we simply discard them. Then, the acceptance rate will be the minimum of 1 and<sup>7</sup>

$$\frac{p(y_t|f_t^{new}, \lambda_t)p(y_{t+1}|f_{t+1}^{new}, \lambda_{t+1}^{new})p(f_{t+1}^{new}, \lambda_{t+2}| \lambda_{t+1}^{new})p(f_t^{new}, \lambda_{t+1}^{new}|\lambda_t^r)}{p(y_t|f_t^r, \lambda_t)p(y_{t+1}|f_{t+1}^r, \lambda_{t+1}^r)p(f_{t+1}^r, \lambda_{t+2}|\lambda_{t+1}^r)p(f_t^r, \lambda_{t+1}^r|\lambda_t^r)} \cdot \frac{g(f_{t+1}^r, f_t^r)}{g(f_{t+1}^{new}, f_t^{new})}.$$

If we then simulate  $f_t^{new}$  from its distribution given  $y_t, \lambda_t^{r+1}$ , and  $\varphi$ , but taking into account the truncation bounds on  $f_t$ , it is clear that associated with this proposal, there is a single candidate  $\lambda_{t+1}^{new}$ , and two possible values for  $f_{t+1}$  on the ellipse. If we finally choose between those two values by means of the conditional distribution of  $f_{t+1}$  given  $y_{t+1}, \lambda_{t+1}^{new}$  and  $\varphi$ , we can prove that we obtain exactly the same acceptance rate as before. The only difference is that in this case we actually propose a value for  $f_{t+1}$ , while in the previous subsection we only implicitly proposed a value for  $|f_{t+1} - \mu|$ .

In terms of an algorithm then this works as follows:

0. Set  $t = 1$ .
1. Current values are  $f_t^r, f_{t+1}^r$ .
2. Sample  $f_t^{new} \sim N(f_t|y_t, \lambda_t, \omega_t|y_t, \lambda_t)$  doubly truncated so that it remains within the interval  $\mu \pm l_t$ , which implies the permissible values of  $f_{t+1}^{new}$  are  $\mu \pm d_{t+1}^{new}$ .
3. Draw

$$f_{t+1}^{new} = \begin{cases} \mu + d_{t+1}^{new}, & \text{with probability } P(f_{t+1} = \mu + d_{t+1}^{new} | \lambda_{t+2}, \lambda_{t+1}^{new}, y_{t+1}) \\ \mu - d_{t+1}^{new}, & \text{with probability } 1 - P(f_{t+1} = \mu + d_{t+1}^{new} | \lambda_{t+2}, \lambda_{t+1}^{new}, y_{t+1}) \end{cases}$$

and accept proposal  $\{f_t^{new}, f_{t+1}^{new}\}$  with probability

$$\min \left\{ 1, \frac{p(y_{t+1}|\lambda_{t+1}^{new}) p(\lambda_{t+2}|y_{t+1}, \lambda_{t+1}^{new})}{p(y_{t+1}|\lambda_{t+1}^r) p(\lambda_{t+2}|y_{t+1}, \lambda_{t+1}^r)} \right\}$$

4. Increase  $t$  by 1 and Goto 2.

### 3.2.4 Block-samplers

Unfortunately, the degree of truncation of the distribution of  $\lambda_{t+1}$  conditional with  $\lambda_{t+2}$  and  $\lambda_t$  can be severe. For that reason, it is convenient to consider double, triple, and in general  $h$ -tuple move samplers for  $\lambda_{t+1}$ . In addition, the mixing properties of the resulting chain are

<sup>7</sup>As we mentioned before, a technical complication with this approach is that since  $f_{t+1}, f_t$  satisfy (12), we have to be particularly careful in evaluating  $g(f_{t+1}, f_t)$  as a function of the marginal density of  $f_t$  and the conditional probability of  $f_{t+1}$  given  $f_t$ , because there are extra Jacobian terms involved, which reflect the differentials along the ellipse (12) at the points  $f_{t+1}^{new}, f_t^{new}$  and  $f_{t+1}^r, f_t^r$ . For analogous reasons, we also have to be careful in evaluating  $p(f_t, \lambda_{t+1}|\lambda_t)$ , since  $f_t, \lambda_{t+1}$  lie on a parabola.

usually much better as a result (see e.g. Kim, Shephard, and Chib (1998) and Liu, Wong, and Kong (1994)). For  $h = 2$  for instance, a numerically efficient procedure is to simulate  $f_t^{new} \sim N(f_t|y_t, \lambda_t, \omega_t|y_t, \lambda_t)$ , but taking into account that

$$|f_t - \mu| \leq \sqrt{\frac{\lambda_{t+3} - \theta(1 + \beta + \beta^2) - \beta^3 \lambda_t}{\alpha \beta^2}}.$$

Associated with this proposal, there is a candidate  $\lambda_{t+1}^{new}$ , which we can combine with  $y_{t+1}$  to simulate  $f_t^{new}$ , but taking into account again that

$$|f_{t+1} - \mu| \leq \sqrt{\frac{\lambda_{t+3} - \theta(1 + \beta) - \beta^2 \lambda_{t+1}^{new}}{\alpha \beta}},$$

which in turn implies a candidate  $\lambda_{t+2}^{new}$  that is fully compatible with  $\lambda_{t+3}$ . Tedious algebraic manipulations show that for a given set of parameter values  $\varphi$ , the acceptance probability will be the minimum of 1 and

$$\frac{p(\lambda_{t+3}|y_{t+2}, \lambda_{t+2}^{new}) \cdot p(\lambda_{t+2} \leq (\lambda_{t+3} - \theta)/\beta | y_{t+1}, \lambda_{t+1}^{new}) \cdot p(y_{t+2} | \lambda_{t+2}^{new}) \cdot p(y_{t+1} | \lambda_{t+1}^{new})}{p(\lambda_{t+3}|y_{t+2}, \lambda_{t+2}^r) \cdot p(\lambda_{t+2} \leq (\lambda_{t+3} - \theta) | y_{t+1}, \lambda_{t+1}^r) \cdot p(y_{t+2} | \lambda_{t+2}^r) \cdot p(y_{t+1} | \lambda_{t+1}^r)},$$

where the terms  $p(\lambda_{t+2} \leq (\lambda_{t+3} - \theta)/\beta | y_{t+1}, \lambda_{t+1})$  reflect the degree of truncation of the conditional distribution of  $\lambda_{t+2}$ . Again, since we can use  $f_{t+1}^{new}$  and  $f_t^{new}$  to sample  $s_{t+1}$  and  $s_t$ , we can reinterpret this double move sampler over  $\lambda_{t+2}, \lambda_{t+1}$  as a triple move sampler over  $f_t, f_{t+1}, f_{t+2}, \lambda_{t+1}, \lambda_{t+2}$  and  $\lambda_{t+3}$ , which effectively becomes a sampler of  $f_t, f_{t+1}, f_{t+2}$  on the tridimensional ellipsoid:

$$\beta^2(f_t - \mu)^2 + \beta(f_{t+1} - \mu)^2 + (f_{t+2} - \mu)^2 = [\lambda_{t+3} - \theta(1 + \beta + \beta^2) - \beta^3 \lambda_t]/\alpha.$$

As we increase  $h$ , this procedure converges to the following independent wholemover sampler: starting with  $\lambda_1 = \lambda$ , we recursively propose  $f_t^{new}$  from the unrestricted univariate normal density  $N(f_t|y_t, \lambda_t^{new}, \omega_t|y_t, \lambda_t^{new})$ , where  $\lambda_t^{new} = V(f_t | f_1^{new}, \dots, f_{t-1}^{new})$ . The acceptance probability in this case is the minimum of 1 and

$$\frac{\prod_{t=1}^T p(y_t | \lambda_t^{new}, \varphi)}{\prod_{t=1}^T p(y_t | \lambda_t^r, \varphi)}.$$

Since this  $T$ -tuple method suffers from the problem discussed at the beginning of section 3.1, it is clear that as far the choice of  $h$  is concerned, there is an implicit trade-off between alleviating the degree of truncation, and increasing the dimension of the proposal. For that reason, our preferred method is a mixed procedure, in which the value of  $h$  is randomly chosen from a uniform distribution in the range  $1 \leq h \leq H \leq T$ .

### 3.3 A comparison of the different simulators

In order to compare the performance of the different MCMC samplers introduced in the previous subsections, we have generated realizations of size  $T = 240$  of the GLS factor representing portfolios that would correspond to the trivariate single factor models analyzed by Monte Carlo methods in Sentana and Fiorentini (2001). These authors set  $\lambda = 1$ ,  $c=(1, 1, 1)'$ , and  $\Gamma=\gamma I_3$ , with  $\gamma = 2$  or  $1/2$ , corresponding to low and high signal to noise ratios.<sup>8</sup> They also set  $(\alpha, \beta) = (.2, .6)$  or  $(.4, .4)$ , to represent persistent but smooth GARCH behaviour, and persistent but volatile conditional variances respectively ( $\gamma = 1/2, \alpha = .2, \beta = .6$  matches roughly what we tend to see in the empirical literature for monthly data). In addition, for each of the four combinations, we have considered not only  $\mu = 0$ , but also  $\mu = 1/2$ , to allow for leverage effects in the conditional variance of the factors. Finally, we have interacted the resulting eight combinations with  $\tau = 0$  and  $\tau = 1/2$ , the second of which reflects the fact that conditioning information often plays a crucial role in deriving asset risk premia (see King, Sentana, and Wadhvani (1994)).

We first examine how much the variance of the sample mean of  $f_t$  across 500,000 MCMC simulations increases due to the autocorrelation in the drawings relative to an ideal but infeasible independent sampler. We do so by estimating the autocorrelation generating function at the origin for observations  $t = 80$  and  $t = 160$  using standard spectral density estimation techniques (see e.g. Priestley (1981)). In addition, we record the mean acceptance probabilities over all observations, as well as the average CPU time needed to simulate one complete drawing of  $f|y, \varphi$ . We analyze four different samplers: inefficient, single move ( $h = 1$ ), block move ( $h = 9$ ), and random length block move ( $h \sim U(1, 19)$ ). The behaviour of the different simulators, which is summarised in Table 1 and Figures 1a-1b, is very much as one would expect. The computationally inefficient sampler shows relatively little serial correlation, and a high acceptance rate for each individual  $t$ , but it is extremely time consuming to compute even though our sample size is fairly small. In fact, when we increase  $T$  from 240 to 2,400 and 24,000, the average CPU time increases by a factor of 100 and 10,000, respectively, as opposed to 10 and 100 for the other three simulators, which makes it impossible to implement in most cases of practical interest. On the other hand, the single and 9-tuple move samplers over  $\lambda_{t+1}$  produce results much faster, with a reasonably high acceptance rate but more autocorrelation in the drawings. As expected, the best overall performance seems to be achieved by the simulator with random block size. Importantly, the distributions of  $f_t$  generated by the four samplers are indistinguishable from

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<sup>8</sup>More specifically, when  $\tau = 0$  the coefficient of determination in the regression of  $y_t$  on  $f_t$  will be  $R^2 = 3/5$  or  $6/7$  for  $v = 2/3$  or  $1/6$  respectively. Note that  $R^2 = \lambda/(\lambda + v)$  is a monotonic transformation of the innovations' signal to noise ratio  $\lambda/v$ .

one another.<sup>9</sup>

We also assess the quality of the approximate Kalman filter procedure put forward by HRS by comparing the Gaussian distributions for  $f_t$  given data and parameters that their method implies with the ones we have obtained by our exact MCMC approach. As can be seen from Table 2 and Figures 2a-2h, the results crucially depend on the parameter values. In particular, the approximate Kalman filter provides more reliable results the closer the unconditional distribution of the latent factors is to the normal ( $\alpha = .2$ ,  $\beta = .6$ ), and the larger the signal to noise ratio ( $\gamma = 1/2$ ). In contrast, the degree of approximation is significantly worse when there is substantial variation in the conditional variance of the factors ( $\alpha = .4$ ,  $\beta = .4$ ), and the signal to noise ratio is smaller ( $\gamma = 2$ ). Nevertheless, while increasing the variability of the conditional variances keeping everything else constant directly leads to a deterioration of the HRS approximation, *ceteris paribus* increases in the idiosyncratic variance parameter  $\gamma$  mostly seem to magnify the existing differences in proportion to the reciprocal of the root mean square error  $\omega_{t|x}^{1/2}$ . Increases in the price of risk parameter  $\tau$  also affect negatively the quality of the approximation. In contrast, variations in the dynamic asymmetry parameter  $\mu$  (not reported here) have a rather small effect, with an ambiguous sign. Similar results are obtained when we compare the distributions of the risk rewarded factors,  $r_{ft}$ . Therefore, given that in many empirical applications it is likely that the signal to noise ratio will be high, and the conditional variance a fairly smooth process, we would expect the HRS simulators to be fairly accurate in practice for monthly data, but probably less so at higher frequencies.

## 4 Empirical Application to UK Sectorial Stock Returns

In this section, we investigate the practical performance of the procedures discussed above. To do so, we revisit the empirical application in Sentana (1995), who analyzed the relationship between first and second conditional moments for monthly excess stock returns on 26 U.K. sectors for the period 1971:2 to 1990:10 (237 observations). On the basis of the approximate Kalman filter-based Gaussian pseudo-likelihood function, he estimated a conditionally heteroskedastic *in mean* latent factor model, in which the common unobservable factor follows a GQARCH (1,1) process. Therefore, the total number of parameters is  $2 \times 26 + 4 = 56$ .

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<sup>9</sup>For the sake of brevity, we only present results for the parameter configuration  $\alpha = .2$ ,  $\beta = .6$ ,  $\pi = .5$ ,  $\tau = .5$  and  $\gamma = 2$ . However, the relative performance of the simulators is not affected much by changes in the parameter values. Their mean acceptance rates, though, are sensitive to the parameter values, being uniformly higher the higher the signal to noise ratio, and the lower the variability in  $\lambda_t$ . But while they are lower for  $\tau = .5$  than for  $\tau = 0$ , they are hardly sensitive to  $\mu$ .



## 4.1 Scaling choice

Before applying either the classical or Bayesian estimation procedures, though, we must decide between the alternative normalisations  $c_1 = 1$  and  $\lambda = 1$  discussed in section 2. In this respect, our results clearly favour the former over the latter, which is line with the theoretical and empirical findings obtained by Pitt and Shephard (1999a) for univariate stochastic volatility models. In particular, if we set  $c_1 = 1$  for estimation purposes, but then re-scale the results so that  $\lambda = 1$ , we obtain significantly less serial correlation in the MCMC drawings from the posterior distributions of the factor loadings than if we directly set  $\lambda = 1$  (see Table 3). For that reason, in what follows the reported results correspond to the first approach.

## 4.2 Simulated EM algorithm

Although in this example we knew the approximate ML estimates produced by the HRS method, in practice no such initial values are necessarily available. For that reason, we decided to set all parameters to plausible but arbitrary starting values. Specifically, we set all factor loadings to 1, all idiosyncratic variances to 0.1, the ARCH and GARCH parameters to 0.2 and 0.6 respectively, and both the price of risk,  $\tau$ , and the dynamic asymmetry parameter,  $\mu$ , to 0. Importantly, the numerical maximisation of (7) with respect to the underlying parameters  $\psi_1^*$ ,  $\psi_2^*$ ,  $\psi_3^*$ ,  $\tau$  and  $\lambda$  described in section 2.4.2 was performed every single iteration.<sup>10</sup>

After just a few iterations, the EM algorithm takes the parameters fairly close to their ML estimates. However, it slows down considerably in the neighbourhood of the optimum. For that reason, we decided to stop it after 1250 iterations, at which point the Euclidean norm of the changes in the parameter vector between iterations was around  $10^{-4}$ . As can be seen from Tables 4 and 5, the differences with respect to the approximate ML estimates are fairly small, which is not surprising in view of the results in section 3.3 because the signal to noise ratio is around 100. The most noticeable discrepancies appear in the conditional variance parameters  $\alpha$ ,  $\beta$  and  $\mu$ , the price of risk coefficient  $\tau$ , and the first factor loading  $c_1$ , which remember coincides with the unconditional standard deviation of the common factor in the normalisation used for estimation purposes. In this respect, it is important to note that the discrepancies in the remaining factor loadings are simply the result of the fact that the sample average of the estimated  $\lambda_t$ 's obtained by the HRS method is approximately 5% smaller than the average factor variance generated by our proposed MCMC procedure. If we look at the ratio of any two factor loading estimates (excluding the first), the differences are as small as in the idiosyncratic variances.

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<sup>10</sup>Note that in order to maximise (7) at each EM iteration, we must maintain the latest simulated values of  $r_f$  constant. We must also maintain the underlying random drawings constant across EM iterations in order to allow the algorithm to converge (cf. Nielsen (2000)).

### 4.3 Simulated Bayesian inference

Since the model for  $r_{ft}|\delta$  corresponds to a univariate GQARCH in mean process, whose log-likelihood function can be easily evaluated, we use Metropolis-Hastings MCMC methods to simulate from the posterior distribution of  $\delta$  given the “observed”  $r_{ft}$ .<sup>11</sup> In particular, we employed the Adaptive Rejection Metropolis Sampling (ARMS) algorithm of Gilks, Best, and Tan (1995), and Gilks, Neal, Best, and Tan (1997).<sup>12</sup> In this case, we use independent beta priors on  $\psi_1(= \alpha + \beta)$  and  $\psi_2(= \beta/(\alpha + \beta))$ , with mean  $3/4$  and standard deviation  $.1443$ , which are centred around the typical values estimated by previous studies with monthly return data. We also use a shifted and scaled independent beta prior on  $\psi_3^*$ , so that it fluctuates between  $\pm\pi/2$  with zero mean and standard deviation  $\pi/4$ . Please note that such a distribution implies that we do not take any ex-ante view on the sign of the dynamic asymmetry effect. Similarly, we assume a normal prior for the price of risk coefficient  $\tau$ , with zero mean and standard deviation  $.1$ , which is also neutral about its possible sign. Finally, we use a standard inverted gamma prior for the unconditional variance of the common factor,  $\lambda$ , with mean  $1$  and variance  $1/2$ .

As for the static variance parameters, given that we chose to normalise with  $c_1 = 1$  for estimation purposes, and that previous studies suggest that the dispersion of the factor loadings across different industrial sectors during our sample period is likely to be small, we chose informative normal priors for the remaining factor loadings, with unit mean and variance  $\gamma_i/5$ . In addition, we specified the usual marginal inverted gamma prior for  $\gamma_i$  ( $i = 1, \dots, 26$ ), with mean and standard deviation equal to  $1/4$ . If we recall the prior distribution for  $\lambda$ , such values imply that the theoretical  $R^2$  in the regression of each sectorial return on the common factor would be on average approximately equal to  $.8$ , which seems plausible for the sectorial return data that we are analyzing.

If we use the posterior means of the parameters reported in Tables 4 and 5 as point estimates, our results suggests that the Bayesian and classical procedures are largely in agreement. Again, the discrepancies in the second and successive factor loadings are almost entirely driven by the differences in the sample means of the estimated conditional variances of the factors across the three methods. The most noticeable difference, in fact, corresponds to the dynamic asymmetry parameter  $\mu$ , which is the least precisely estimated. Nevertheless, our findings confirm the main result in Sentana (1995), namely that there appears to be a significant leverage effect in

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<sup>11</sup>In this respect, it is important to note that we must recompute  $\lambda_t$  every time the conditional variance parameters are updated, before proceeding to the next round of simulation of the common factors given observed data and parameters (cf. Nakatsuma (2000)).

<sup>12</sup>We also considered the procedure suggested by Chib and Greenberg (1994), which makes proposals from a multivariate normal prior on  $\psi_1^*$ ,  $\psi_2^*$ ,  $\psi_3^*$ ,  $\tau$  and  $\lambda$ , with mean given by their ML estimators obtained on the current  $r_f$ , and variance given by the estimated inverse information matrix. But since both pcedures yield almost identical results, we only report the ARMS ones.

the sectorial returns through the common factor. They also confirm that the price of risk is estimated as being positive.

We have also performed an analysis of the sensitivities of the results in Tables 4 and 5 to our choice of priors. In particular, we have halved and doubled the dispersion of the prior distributions of the factor loadings, idiosyncratic variances, price of risk coefficient  $\tau$ , and unconditional variance of the common factor,  $\lambda$ , around their respective means. As for the three parameters with beta priors, we increased and reduced their prior variances as much as possible, but without changing the mean or the concavity of the distribution. Specifically, we could only increase the prior variances of  $\psi_1$  and  $\psi_2$  by approximately 50% each, and the prior variance of  $\psi_3^*$  by 30%. The results, which are reported in Figures 3a-d and 4a-4d, indicate that the choice of priors does not unduly influence our conclusions. In particular, the positivity of the dynamic asymmetry parameter  $\mu$  and the price of risk coefficient  $\tau$  seems to be robust.

## 5 Conclusions

We derive exact likelihood-based estimators of latent variable models in which the variances of the unobservable processes are functions of their past values. Since in general the expression for the likelihood function is unknown, we resort to simulation methods. In this context, we show that MCMC likelihood-based estimation of latent GARCH models can in fact be handled by means of feasible  $O(T)$  algorithms. Although we have developed our results within the context of a CH factor model in which the common factors follow the Quadratic GARCH in mean process introduced by Sentana (1995), it applies much more widely.

Our samplers of the latent variables given data and parameters involve three main steps. First, we perform a significant dimensionality reduction through the use of the so-called GLS factor scores. Second, we augment the state vector to achieve a first-order Markovian process. And third, we discuss alternative ways of dealing with the dynamic singularity implicit in the GARCH model that results from the fact that there is only one shock driving innovations to the level of the process and its variance. In this sense, the situation is radically different from the one existing in stochastic volatility models.

A numerical comparison of our proposed procedures suggests that a random size block sampler yields the best trade-off between serial dependence of the drawings, and speed. It also shows that the Kalman filter-based Gaussian approximation introduced by HRS produces reasonable results when the signal to noise ratio is high, and the unconditional distribution of the common factor is not too far away from the normal, but that it may lead to substantial differences in other cases likely to arise in situations where high frequency data is used.

On the basis of our samplers, we can then use several recent proposals from the simulation-based direct inference literature to estimate the model parameters. In particular, from a classical perspective, we consider both a simulated EM algorithm, and the related method of simulated scores. We also develop simulation-based Bayesian inference procedures by combining within a Gibbs sampler the MCMC simulators with the posterior distributions of the parameters given observed series and latent variables. In this respect, we find that the parametrisations induced by two alternative scaling assumptions can have a substantial effect on the efficiency of the Gibbs sampler.

In order to investigate the practical performance of our proposed procedures, we fully reassess the empirical application in Sentana (1995), who analyzed the relationship between first and second conditional moments for monthly excess stock returns on 26 U.K. sectors for the period 1971 to 1990. Given the extremely high signal to noise ratio, our exact-likelihood based results are not very different from his. In particular, we confirm his main findings that there is a dynamic leverage effect in sectorial returns through the common factor, and that the price of risk coefficient is positive. Nevertheless, we also show that there are some differences in the estimation of the conditional variance parameters.

Given the quantity and variety of empirically interesting situations in which models with latent GARCH variables arise, we hope that our study will encourage others to estimate them on a firmer theoretical basis.

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Table 1

Comparison between alternative MCMC simulators of  $f|y, \varphi$ 

	MAP	IR		Time		
		$f_{80}$	$f_{160}$	$T = 240$	$T = 2,400$	$T = 24,000$
Inefficient	.901	1.42	3.39	7.116	692.94	71,761.1
$h = 1$	.690	8.10	68.76	1	10.09	100.4
$h = 9$	.518	19.01	16.77	.942	9.56	95.7
random $h$	.602	3.42	7.91	.895	9.13	89.9

Notes: MAP denotes mean acceptance probability over the whole sample, while IR refers to the inefficiency ratio of the MCMC drawings of the latent factor at observations 80 and 160. Finally, Time refers to the total CPU time taken to simulate one complete drawing of  $f|y, \varphi$  relative to the  $h = 1, T = 240$  simulator.

Parameter values:  $\alpha = .2, \beta = .6, \mu = .5, \tau = .5, \gamma = 2$ .

Table 2

Comparison between the simulated distribution generated by our proposed MCMC method, and the Kalman-filter based Gaussian approximation. The focus of attention is on the latent factor at observations 80 and 160 for different parameter configurations.

	$f_{80}$		$f_{160}$	
	MCMC	HRS	MCMC	HRS
$\alpha = .4, \beta = .4, \mu = .5, \tau = .5, \gamma = 2$				
mean	.818	.896	-2.450	-2.009
variance	.412	.471	.465	.471
skewness	-.139	0	-.075	0
kurtosis	3.079	3	2.813	3
$\alpha = .2, \beta = .6, \mu = .5, \tau = .5, \gamma = 2$				
mean	.973	1.006	-2.066	-1.883
variance	.426	.444	.434	.432
skewness	-.048	0	-.117	0
kurtosis	3.031	3	3.118	3
$\alpha = .2, \beta = .6, \mu = .5, \tau = .5, \gamma = .5$				
mean	.884	.850	-2.349	-2.304
variance	.156	.149	.144	.143
skewness	-.041	0	-.062	0
kurtosis	2.989	3	2.976	3
$\alpha = .2, \beta = .6, \mu = .5, \tau = 0, \gamma = .5$				
mean	.911	.901	-2.206	-2.178
variance	.148	.148	.135	.143
skewness	-.011	0	-.018	0
kurtosis	3.006	3	3.009	3

Note: HRS denotes the Harvey, Ruiz, and Sentana (1992) approximation.

Table 3

Inefficiency ratios for posterior drawings of static variance parameters under alternative scaling assumptions

Parameter	$c_1$	$c_{26}$	$\gamma_1$	$\gamma_{26}$
IR ( $c_1 = 1$ )	27.11	5.52	1.42	1.79
IR ( $\lambda = 1$ )	210.20	280.43	1.32	1.31

Table 4  
Estimates of static variance parameters

Sector	Factor Loadings				Idiosyncratic Variances			
	HRS	SEM	Bayesian		HRS	SEM	Bayesian	
			PM	PSD			PM	PSD
1	.805	.836	.852	.092	.349	.349	.348	.033
2	.764	.784	.806	.090	.198	.198	.199	.019
3	.969	.994	1.016	.110	.123	.123	.127	.013
4	.740	.759	.782	.087	.182	.182	.183	.017
5	1.027	1.053	1.075	.117	.182	.182	.185	.018
6	.816	.837	.860	.096	.230	.230	.230	.022
7	.816	.837	.859	.093	.115	.115	.118	.012
8	.771	.791	.813	.088	.091	.091	.094	.009
9	.812	.833	.856	.095	.219	.219	.220	.021
10	.826	.847	.870	.101	.410	.410	.407	.038
11	.801	.822	.844	.095	.258	.258	.258	.024
12	.876	.899	.921	.102	.255	.255	.255	.024
13	.797	.818	.840	.092	.149	.149	.151	.015
14	.884	.907	.930	.100	.118	.118	.121	.012
15	.970	.996	1.018	.113	.329	.329	.329	.031
16	.810	.832	.854	.095	.220	.220	.221	.021
17	.835	.857	.879	.095	.096	.096	.099	.010
18	.767	.787	.810	.092	.285	.285	.284	.027
19	.783	.804	.827	.094	.280	.280	.280	.026
20	.834	.855	.878	.098	.269	.269	.268	.025
21	.644	.661	.683	.085	.526	.526	.523	.048
22	.829	.850	.873	.095	.131	.131	.134	.013
23	.862	.885	.907	.103	.365	.365	.363	.034
24	.656	.673	.696	.080	.254	.254	.255	.024
25	.872	.894	.917	.101	.197	.197	.198	.019
26	.808	.830	.852	.095	.211	.211	.211	.020

Notes: HRS denotes the Harvey, Ruiz, and Sentana (1992) approximation, SEM simulated EM, while PM and PSD represent the posterior mean and standard deviation respectively.

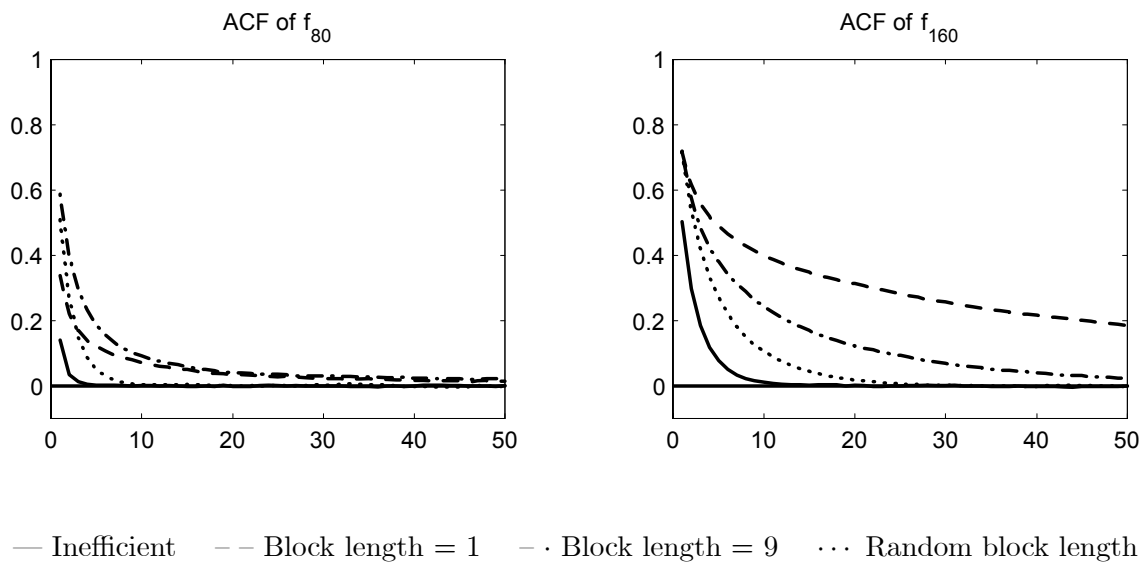
Table 5

Estimates of dynamic variance parameters

Parameter	HRS	SEM	Bayesian	
			PM	PSD
$\alpha$	.143	.159	.173	.064
$\beta$	.639	.591	.627	.080
$\mu$	.892	.944	.785	.400
$\tau$	.145	.142	.140	.061

Notes: HRS denotes the Harvey, Ruiz, and Sentana (1992) approximation, SEM simulated EM, while PM and PSD represent the posterior mean and standard deviation respectively.

Figure 1: Comparison of the alternative simulators of the latent factors given observables and parameters by means of the autocorrelation functions (ACF) of the drawings.



$$(\alpha = .2, \quad \beta = .6, \quad \mu = .5, \quad \tau = .5, \quad \gamma = 2).$$

Figure 2: Comparison of the p.d.f. of the simulated latent factors given observables and parameters with its Kalman filter-based Gaussian approximation for different parameter configurations.

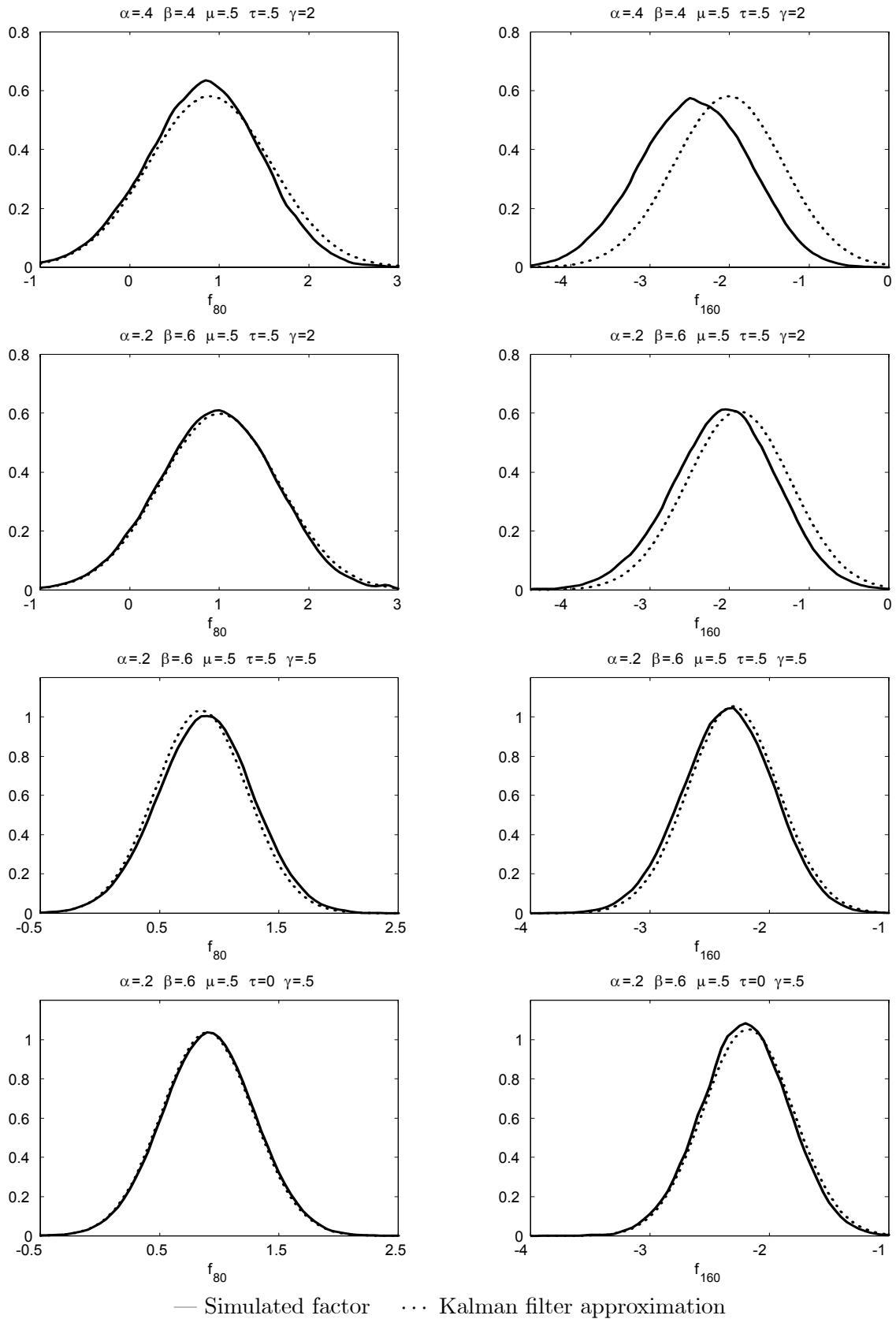
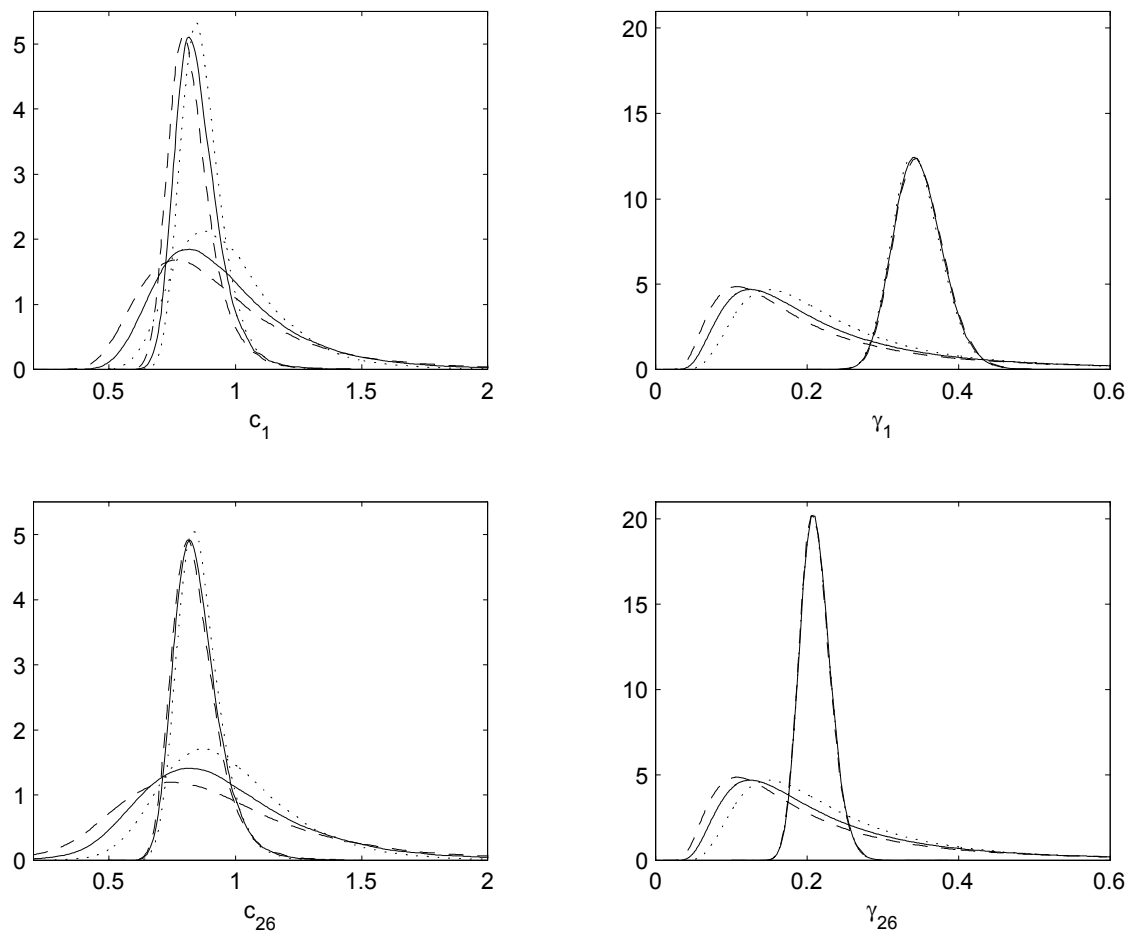




Figure 3: Sensitivity of the simulated posterior distributions of the static variance parameters  $c_1$ ,  $\gamma_1$ ,  $c_{26}$ , and  $\gamma_{26}$  to increases and decreases in the variance of the prior distributions.



- Baseline prior and posterior
- Large variance prior and posterior
- ... Small variance prior and posterior

Figure 4: Sensitivity of the simulated posterior distributions of the dynamic variance parameters  $\alpha$ ,  $\beta$ ,  $\mu$ , and  $\tau$  to increases and decreases in the variance of the prior distributions.

