

Les Cahiers de la Chaire / N°48

**Risk-parameter estimation in volatility models**

Christian Franck & Jean-Michel Zakoian



**CHAIRE**

Finance & Développement Durable

# Risk-parameter estimation in volatility models

**Christian Francq**

*University Lille 3, BP 60149  
59653 Villeneuve d'Ascq cedex, France*

*and  
CREST*

*e-mail: [christian.francq@univ-lille3.fr](mailto:christian.francq@univ-lille3.fr)*

**and**

**Jean-Michel Zakoïan**

*CREST, 15 Boulevard Gabriel Peri  
92245 Malakoff Cedex, France*

*and*

*FIME, Laboratoire de finance des marchés d'énergie*

*e-mail: [zakoian@ensae.fr](mailto:zakoian@ensae.fr)*

\*

**Abstract:** This paper introduces the concept of risk parameter in conditional volatility models of the form  $\epsilon_t = \sigma_t(\theta_0)\eta_t$  and develops statistical procedures to estimate this parameter. For a given risk measure  $r$ , the risk parameter is expressed as a function of the volatility coefficients  $\theta_0$  and the risk,  $r(\eta_t)$ , of the innovation process. A two-step method is proposed to successively estimate these quantities. An alternative one-step approach, relying on a reparameterization of the model and the use of a non Gaussian QML, is proposed. Asymptotic results are established for smooth risk measures as well as for the Value-at-Risk (VaR). Asymptotic comparisons of the two approaches for VaR estimation suggest a superiority of the one-step method when the innovations are heavy-tailed. For standard GARCH models, the comparison only depends on characteristics of the innovations distribution, not on the volatility parameters. Monte-Carlo experiments and an empirical study illustrate these findings.

**Keywords and phrases:** GARCH, Quantile Regression, Quasi-Maximum Likelihood, Risk measures, Value-at-Risk.

---

\*This work has been partly supported by the "Finance and Sustainable Development Chair".

## 1. Introduction

Modern financial risk management generally focuses on risks measures based on distributional information. Compared to traditional approaches relying on the marginal distribution of returns, more sophisticated approaches view risk as a stochastic process. For instance, conditional Value-at-Risk (VaR) - arguably the most widely used measure since the 1996 amendment of the Basel Capital Accord - is defined as a quantile of the returns (or profit & losses, P&L, variables) conditional distribution. Many econometric approaches have been proposed in the finance and statistical literatures for measuring conditional risk.

A crucial issue that arises in this context is how to evaluate the performance of conditional risk estimators. Comparison of the performances of estimators of parameters based on the asymptotic theory is standard. But comparing the performances of VaR estimators, for instance, is more intricate because the conditional VaR is a random process, not a parameter.

The first objective of this paper is to introduce a concept of risk parameter in conditional volatility models. The risk parameter can be interpreted as a summary of conditional risk. Summaries of unconditional risk (such as the VaR based on historical simulation) are commonly used but they do not account for the dynamics of risk. On the other hand, conditional risk measures estimators (such as the conditional VaR) are stochastic processes for which no asymptotic theory exists. By contrast, risk parameters are vector coefficients which take into account the returns dynamics and for which an asymptotic theory of estimation can be derived.

To be more specific, consider a conditional volatility model of the form

$$\epsilon_t = \sigma_t(\theta_0)\eta_t, \quad (1.1)$$

where  $\epsilon_t$  denotes the log-return,  $\sigma_t$  is a volatility process, that is a positive measurable function of the past log-returns,  $\theta_0$  is a finite-dimensional parameter and  $(\eta_t)$  is a sequence of independent and identically distributed (iid) random variables,  $\eta_t$  being also independent of the past returns. Consider a risk measure,  $r$ , satisfying the assumption of positive homogeneity, such as the VaR or the Expected Shortfall. Then the conditional risk of  $\epsilon_t$  is given by

$$r_{t-1}(\epsilon_t) = \sigma_t(\theta_0)r(\eta_t),$$

where  $r(\eta_t)$  is a constant. In most parametric volatility models, multiplying the volatility by a constant amounts to modifying the parameter value. Under

this assumption, we have

$$r_{t-1}(\epsilon_t) = \sigma_t(\theta_0^*), \quad \text{where} \quad \theta_0^* = H\{\theta_0, r(\eta_t)\} \quad (1.2)$$

for some function  $H$  which is specific to the model under consideration. In this setting, we call  $\theta_0^*$  the risk parameter associated to the risk function  $r$ . It incorporates not only the volatility parameters but also the (unconditional) risk of the innovation process  $(\eta_t)$ .

Deriving an asymptotic theory for estimators of risk parameters is the second objective of this article. Two estimation procedures will be studied and compared. A two-step approach relies on the expression of  $\theta_0^*$  in (1.2). Under the identifiability assumption

$$E\eta_t^2 = 1, \quad (1.3)$$

a consistent and asymptotically normal (CAN) estimator  $\hat{\theta}$  of the parameter  $\theta_0$  can be obtained by standard methods for conditional volatility models, the most widely used being the Gaussian Quasi-Maximum Likelihood (QML). In a second step, an estimator  $\hat{r}$  of the innovation risk  $r(\eta_t)$  can be constructed, under conditions to be discussed, from the residuals  $\hat{\eta}_t = \epsilon_t/\sigma_t(\hat{\theta})$  of the first step. A consistent estimator  $H\{\hat{\theta}, \hat{r}\}$  of the risk parameter,  $\theta_0^*$ , will be deduced (under smoothness assumptions on the function  $H$ ). The asymptotic distribution of this estimator will follow from the joint asymptotic distribution of  $\{\hat{\theta}, \hat{r}\}$ .

An alternative strategy of estimation introduced in this article relies on a reparameterization of the conditional volatility model. The multiplicative form of model (1.1) generally allows us to rewrite it as

$$\epsilon_t = \sigma_t(\theta_0^*)\eta_t^*, \quad \text{with} \quad r(\eta_t^*) = 1.$$

The latter equality replaces the standard assumption (1.3). The interest of such a representation is that, if a consistent estimator  $\hat{\theta}_0^*$  of  $\theta_0^*$  can be obtained, the conditional risk  $r_{t-1}(\epsilon_t)$  of  $\epsilon_t$  can be estimated in one step by  $\sigma_t(\hat{\theta}_0^*)$ .

Estimation of conditional volatility models under moment conditions different from (1.3) has been studied by Francq and Zakoïan (2010a), Francq, Lepage and Zakoïan (2011), Zhu and Ling (2011). In the framework of this paper, the condition  $r(\eta_t^*) = 1$  is not necessarily a moment condition. We propose a QML approach based on non-Gaussian densities depending on the risk function  $r$ . A case of particular importance is the VaR at a given level  $\alpha$ : the identifiability condition consists in setting an appropriate quantile of the

distribution of  $\eta_t^*$  to unity. It turns out that the only asymptotically valid QML criterion, that is, ensuring the consistency of the QML estimator of  $\theta_0^*$  whatever the distribution of  $\eta_t^*$ , takes the form of a non linear quantile regression criterion.

The third objective of this article is to compare the one-step and two-step estimators of the risk parameter  $\theta_0^*$ . As we will see, the assumptions required for the CAN of the two estimators are quite different. When such assumptions are met, the asymptotic variances can be compared and an important issue is whether the true parameter value matters for the superiority of one estimator over the other. Surprisingly, the answer turns out to be negative for important subclasses of conditional volatility models. Another question, which seems particularly interesting for financial applications, concerns the asymptotic accuracy of the two estimators when the innovation distribution is heavy-tailed.

Most of previous work on statistical inference for GARCH-type models dealt exclusively with the estimation of volatility parameters. While our aim in this paper is to estimate risk parameters, the techniques used have similarity with those developed for the volatility parameter, at least when the risk function is sufficiently smooth. The asymptotic theory of the QML estimation for volatility parameters has been extensively studied, in particular for the GARCH(1,1) by Lee and Hansen (1994), Lumsdaine (1996), for the GARCH( $p, q$ ) by Berkes, Horváth and Kokoszka (2003) and Francq and Zakoïan (2004), for general models by Mikosch and Straumann (2006), Straumann and Mikosch (2006), Bardet and Wintenberger (2009). For the VaR, it turns out that the QML criterion can be written under the form of a M-estimation criterion which is similar to those introduced in the quantile regression literature (see Koenker (2005) for a comprehensive book on quantile regression, and see Xiao and Koenker (2009), Xiao and Wan (2010) for recent applications to linear GARCH models) and in the least-absolute deviations (LAD) time series literature (see Davis, Knight and Liu (1992), Davis and Dunsmuir (1997), Breidt, Davis and Trindade (2001)).

The paper is organized as follows. In Section 2 we introduce the concept of risk parameter and discuss identifiability issues in conditional volatility models. Section 3 is devoted to the asymptotic properties of non-Gaussian QML estimators for general smooth risk measures  $r$ . Section 4 considers the important case of the VaR, assuming that the innovations are symmetrically distributed. The smoothness assumptions used in Section 3 do not hold for the VaR and the asymptotic properties of the one-step estimator have to be established in a completely different manner. In Section 5, the asymptotic properties of the two-step method are established for VaR estimation and

compared with those of the one-step estimator. In Section 6, we relax the assumption of symmetrically distributed innovations. Proofs are displayed in Section 7. A Monte-Carlo study and applications on real financial data are provided in Section 8. Section 9 concludes.

## 2. Risk parameter in volatility models

Most conditional volatility models are of the form

$$\begin{cases} \epsilon_t = \sigma_t \eta_t \\ \sigma_t = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_0) \end{cases} \quad (2.1)$$

where  $(\eta_t)$  is a sequence of iid random variables,  $\eta_t$  being independent of  $\{\epsilon_u, u < t\}$ ,  $\theta_0 \in \mathbb{R}^m$  is a parameter belonging to a parameter space  $\Theta$ , and  $\sigma : \mathbb{R}^\infty \times \Theta \rightarrow (0, \infty)$ . When  $E\eta_t = 0$  and  $E\eta_t^2 = 1$ , the variable  $\sigma_t^2$  is generally referred to as the volatility of  $\epsilon_t$ . However, we will not make such moment assumptions in this section and the following ones. A leading model, the most widely used among practitioners, is the GARCH(1,1) model of Engle (1982) and Bollerslev (1986), defined by

$$\sigma_t^2 = \omega_0 + \alpha_0 \epsilon_{t-1}^2 + \beta_0 \sigma_{t-1}^2, \quad (2.2)$$

where  $\theta_0 = (\omega_0, \alpha_0, \beta_0)' \in (0, \infty) \times [0, \infty) \times [0, 1)$ . For this model we have  $\sigma_t^2 = \sum_{i=1}^{\infty} \beta_0^{i-1} (\omega_0 + \alpha_0 \epsilon_{t-i}^2)$ , which is of the form (2.1).

It is assumed throughout that

**A0:** There exists a function  $H$  such that for any  $\theta \in \Theta$ , for any  $K > 0$ , and any sequence  $(x_i)_i$

$$K\sigma(x_1, x_2, \dots; \theta) = \sigma(x_1, x_2, \dots; \theta^*), \quad \text{where } \theta^* = H(\theta, K).$$

Most conditional volatility models are such that for  $K \geq 1$ ,  $\theta^* \geq \theta$  componentwise. For instance, in the GARCH(1,1) case we have  $\theta^* = (K^2\omega, K^2\alpha, \beta)'$  with standard notation. The parameter  $\theta_0$  can thus be interpreted as a *volatility parameter* in the sense that the larger  $\theta_0$  the larger the volatility.

Now we define the notion of *risk parameter*. Let  $r$  denote a risk measure, that is, a function from the set of the real random variables to  $\mathbb{R}^+$ . Assume that  $r$  is positively homogenous, that is,  $r(\lambda X) = \lambda r(X)$  for any risk variable  $X$  and any  $\lambda > 0$ . Then the risk of  $\epsilon_t$  conditional on  $\{\epsilon_u, u < t\}$  is given by

$$r_{t-1}(\epsilon_t) = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_0) r(\eta_t). \quad (2.3)$$

Now let  $\eta_t^* = \eta_t/r(\eta_t)$  and let  $\theta_0^* = H(\theta_0, r(\eta_t))$ . Under **A0**, the model can be reparameterized as

$$\begin{cases} \epsilon_t = \sigma_t^* \eta_t^*, & r(\eta_t^*) = 1, \\ \sigma_t^* = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_0^*). \end{cases} \quad (2.4)$$

Because the conditional risk of  $\epsilon_t$  is now simply

$$r_{t-1}(\epsilon_t) = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_0^*),$$

$\theta_0^*$  will be called the risk parameter.

**Example 2.1 (VaR parameter).** An important example is the VaR, which is the most standard risk measure used in the current regulations introduced in Finance (Basel 2), or Insurance (Solvency 2) to fix the required capital (Pillar 1), or to monitor the risk by means of internal risk models (Pillar 2). For a risk variable  $X$  with quantile function  $F_X^{-1}$ , the VaR at level  $\alpha$ , with  $\alpha \in (0, 1)$ , is given by  $r(X) = -F_X^{-1}(\alpha)$ . The *conditional* VaR of the process  $(\epsilon_t)$  at risk level  $\alpha \in (0, 1)$ , denoted by  $\text{VaR}_t(\alpha)$ , is defined by

$$P_{t-1}[\epsilon_t < -\text{VaR}_t(\alpha)] = \alpha,$$

where  $P_{t-1}$  denotes the historical distribution conditional on  $\{\epsilon_u, u < t\}$ . When  $(\epsilon_t)$  satisfies (2.1), the theoretical VaR is then given by

$$\text{VaR}_t(\alpha) = -\sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_0) F_\eta^{-1}(\alpha)$$

where  $F_\eta$  is the probability distribution function of  $\eta_t$ . Let  $\alpha$  be small enough so that  $F_\eta^{-1}(\alpha) < 0$ . Thus (2.3) holds with  $r_{t-1}(\epsilon_t) = \text{VaR}_t(\alpha)$  and  $r(\eta_t) = -F_\eta^{-1}(\alpha)$ . Now suppose that the volatility model is the GARCH(1,1) model (2.2). Then the risk parameter at level  $\alpha$  is given by  $\theta_0^* = (K^2\omega_0, K^2\alpha_0, \beta_0)'$  with  $K = -F_\eta^{-1}(\alpha)$ . This coefficient takes into account the dynamics of the GARCH process through the volatility parameters, but also the lower tail of the innovations distribution.

For the sake of illustration, consider the two following GARCH(1,1) models

$$\begin{cases} \epsilon_t = \sigma_t \eta_t, & \eta_t \sim \mathcal{N}(0, 1) \\ \sigma_t^2 = 1 + 0.05\epsilon_{t-1}^2 + 0.9\sigma_{t-1}^2 \end{cases} \quad \text{and} \quad \begin{cases} \epsilon_t = \sigma_t \eta_t, & \eta_t \sim \frac{1}{\sqrt{2}} St_4 \\ \sigma_t^2 = 1 + 0.04\epsilon_{t-1}^2 + 0.9\sigma_{t-1}^2. \end{cases}$$

Then the volatility parameter  $\theta_0 = (1, 0.05, 0.9)$  of the Gaussian-innovation model is larger than the volatility parameter  $\theta_0 = (1, 0.04, 0.9)$  of the Student-innovation model. Now consider the VaR at level 1% for the two

models. Simple computation shows that the risk parameter of the first model is  $\theta_0^* = (5.41, 0.27, 0.9)$ , whereas that of the second model is  $\theta_0^* = (7.01, 0.28, 0.9)$ . In other words, the first model is more volatile but less risky than the second one for the VaR at 1%.

We consider estimating  $\theta_0^*$  by an appropriate QML method in the next section.

### 3. QML estimators of general risk parameters

In this section, we consider QML estimation of Model (2.4). The usual identifiability condition  $E\eta_t^{*2} = 1$  being replaced by  $r(\eta_t^*) = 1$ , we will define a non Gaussian QML estimator.

Given observations  $\epsilon_1, \dots, \epsilon_n$ , and arbitrary initial values  $\tilde{\epsilon}_i$  for  $i \leq 0$ , we define, under assumptions given below

$$\tilde{\sigma}_t(\theta) = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_1, \tilde{\epsilon}_0, \tilde{\epsilon}_{-1}, \dots; \theta).$$

This random variable will be used to approximate

$$\sigma_t(\theta) = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_1, \epsilon_0, \epsilon_{-1}, \dots; \theta).$$

We choose an arbitrary density  $h$  which can be called *instrumental* density, and define the QML criterion

$$\tilde{Q}_n(\theta) = \frac{1}{n} \sum_{t=1}^n g(\epsilon_t, \tilde{\sigma}_t(\theta)), \quad g(x, \sigma) = \log \frac{1}{\sigma} h\left(\frac{x}{\sigma}\right). \quad (3.1)$$

Let the QMLE

$$\hat{\theta}_n^* = \arg \max_{\theta \in \Theta} \tilde{Q}_n(\theta) \quad (3.2)$$

for some compact subspace  $\Theta$  of  $\mathbb{R}^m$ . This estimator is the standard Gaussian QMLE when  $h$  is the standard Gaussian density  $\phi$ . However, the Gaussian QMLE is in general an inconsistent estimator of  $\theta_0^*$ , unless if, for instance, the risk measure is  $r(X) = \sqrt{E(X^2)}$ .

To derive the asymptotic properties of  $\hat{\theta}_n^*$  we introduce the following assumptions. Such assumptions are similar to those introduced by Berkes and Horváth (2004) and Francq and Zakoïan (2010a) for the estimation of the volatility parameters.

**A1:**  $(\epsilon_t)$  is a strictly stationary and ergodic solution of Model (2.4).



**A2:** Let  $\underline{\omega} > 0$ . Almost surely,  $\sigma_t(\theta) \in (\underline{\omega}, \infty]$  for any  $\theta \in \Theta$ . Moreover,  $\sigma_t(\theta_0^*)/\sigma_t(\theta) = 1$  a.s. iff  $\theta = \theta_0^*$ .

In addition, we assume that the function  $\sigma \rightarrow Eg(\eta_0^*, \sigma)$  is valued in  $[-\infty, +\infty)$  and has a unique maximum at 1:

**A3:**  $Eg(\eta_0^*, \sigma) < Eg(\eta_0^*, 1)$ ,  $\forall \sigma > 0, \sigma \neq 1$ .

**A4:**  $h$  is differentiable except on a finite set  $A$ , and there exist constants  $\delta \geq 0$  and  $C_0 > 0$  such that for all  $u \in A^c$ ,  $|uh'(u)/h(u)| \leq C_0(1 + |u|^\delta)$  with  $E|\epsilon_0|^\delta < \infty$ .

**A5:** There exist a random variable  $C_1$  measurable with respect to  $\{\epsilon_u, u < 0\}$  and a constant  $\rho \in (0, 1)$  such that  $\sup_{\theta \in \Theta} |\sigma_t(\theta) - \tilde{\sigma}_t(\theta)| \leq C_1 \rho^t$ .

**Theorem 3.1 (Consistency of the risk parameter estimator).** *If A0-A5 hold then the QMLE defined by (3.1) and (3.2) satisfies*

$$\hat{\theta}_n^* \rightarrow \theta_0^*, \quad a.s.$$

Many risks measures involve a moment of a function of the risk variable  $X$ , in the sense that

$$r(X) = 1 \quad \text{iff} \quad E\{\psi(X)\} = 0 \quad (3.3)$$

for some measurable function  $\psi : \mathbb{R} \rightarrow \mathbb{R}$ . The following result shows that, for such risk measures, **A3** can be omitted provided the QML instrumental density is appropriately chosen.

**Proposition 3.1 (Choice of the instrumental density).** *Let  $r(\cdot)$  satisfying (3.3). Assume **A4** holds with  $A = \emptyset$ . Then **A3** holds for any distribution of  $\eta_0^*$  satisfying  $r(\eta_0^*) = 1$  iff the density  $h$  is such that*

$$\{\log h(x)\}' = \frac{1}{x} [\lambda \psi(x) - 1], \quad \text{for all } x \quad (3.4)$$

and for some constant  $\lambda \neq 0$ .

This result provides a practical way to choose the QML density  $h$ , as illustrated in the next examples.

**Example 3.1.** Let  $r(X) = \sqrt{E(X^2)}$ . Then we have  $\psi(X) = X^2 - 1$  and, for any constant  $\lambda > 0$ , by solving (3.4) we find

$$h(x) \propto x^{-(1-\lambda)} \exp(-\lambda x^2/2). \quad (3.5)$$

In particular for  $\lambda = 1$   $h$  is the density of the standard Gaussian distribution. Thus, we retrieve the gaussian likelihood for the standard identifiability condition  $E(\eta_t^{*2}) = 1$ . It can be seen that any density  $h$  of the form (3.5) provides the same QMLE, it is thus not restrictive to take  $\lambda = 1$ .

**Example 3.2.** More generally, let  $r(X) = \|X\|_s = (E|X|^s)^{1/s}$  where  $s$  is a positive number. This risk measure has interest, for  $s < 2$ , when the variable  $X$  has an infinite second-order moment. In this case  $\psi(X) = |X|^s - 1$  and we find , for any constant  $\lambda > 0$  and for some constant  $c$ ,

$$h(x) \propto x^{-(1-\lambda)} \exp(-\lambda|x|^s/s). \quad (3.6)$$

QML estimators based on such functions  $h$  were studied in detail in Francq and Zakoïan (2010a).

**Example 3.3 (Example 2.1 continued).** When the measure of risk is the VaR at level  $\alpha$ , we have  $r(X) = -F_X^{-1}(\alpha)$ . Suppose that the distribution of the risk variable  $X$  is symmetric and  $\alpha \in (0, 0.5)$ . Thus (3.3) is satisfied with  $\psi(X) = \mathbf{1}_{\{|X|>1\}} - 2\alpha$ . Solving (3.4) yields

$$h(x) = h_\alpha(x) = \lambda\alpha(1 - 2\alpha)|x|^{2\lambda\alpha-1} \{ |x|^{-\lambda} \mathbf{1}_{\{|x|>1\}} + \mathbf{1}_{\{|x|\leq 1\}} \} \quad (3.7)$$

for some positive constant  $\lambda$ . The choice of  $\lambda$  does not matter, any value leading to the same  $\hat{\theta}_n^*$ . Since  $h$  is not differentiable everywhere, the assumptions of Proposition 3.1 are not satisfied. However, it will be shown in the next section that, under mild additional assumptions on the distribution of  $\eta_0$ , Assumptions **A3** and **A4** of Theorem 3.1 hold true.

To show the asymptotic normality of  $\hat{\theta}_n^*$  we need the following additional assumptions.

**A6:**  $\theta_0^*$  belongs to the interior of  $\Theta$ .

**A7:** There exist no non-zero  $x \in \mathbb{R}^m$  such that  $x' \frac{\partial \sigma_t(\theta_0^*)}{\partial \theta} = 0$ , *a.s.*

**A8:** The function  $\theta \mapsto \sigma(x_1, x_2, \dots; \theta)$  has continuous second-order derivatives, and

$$\sup_{\theta \in \Theta} \left\| \frac{\partial \sigma_t(\theta)}{\partial \theta} - \frac{\partial \tilde{\sigma}_t(\theta)}{\partial \theta} \right\| + \left\| \frac{\partial^2 \sigma_t(\theta)}{\partial \theta \partial \theta'} - \frac{\partial^2 \tilde{\sigma}_t(\theta)}{\partial \theta \partial \theta'} \right\| \leq C_1 \rho^t,$$

where  $C_1$  and  $\rho$  are as in **A5**.

**A9:**  $h$  is twice differentiable with  $|u^2 (h'(u)/h(u))'| \leq C_0(1 + |u|^\delta)$  for all  $u \in \mathbb{R}$  and  $E|\epsilon_0|^{2\delta} < \infty$ .

**A10:** There exists a neighborhood  $V(\theta_0^*)$  of  $\theta_0^*$  such that

$$E \sup_{\theta \in V(\theta_0^*)} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial^2 \sigma_t(\theta)}{\partial \theta \partial \theta'} \right\|^2 < \infty.$$

**Theorem 3.2 (Asymptotic normality).** Under **A0-A10** and if  $Eg_2(\eta_0^*, 1) \neq 0$  then

$$\sqrt{n} \left( \hat{\theta}_n^* - \theta_0^* \right) \xrightarrow{\mathcal{L}} \mathcal{N}(0, 4\tau_{h,f}^2 I^{-1})$$

where

$$I = I(\theta_0^*) = E \left( \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \theta} \frac{\partial \sigma_t^2}{\partial \theta'} (\theta_0^*) \right) \quad \text{and} \quad \tau_{h,f}^2 = \frac{Eg_1^2(\eta_0^*, 1)}{\{Eg_2(\eta_0^*, 1)\}^2},$$

with  $g_1(x, \sigma) = \partial g(x, \sigma) / \partial \sigma$  and  $g_2(x, \sigma) = \partial g_1(x, \sigma) / \partial \sigma$ .

Theorem 3.2 does not apply to the VaR because **A9** is not satisfied for densities  $h$  of the form (3.7).

#### 4. One step VaR estimation

To estimate in one step the conditional VaR at level  $\alpha$ , as defined in Example 2.1, we first need to reparameterize Model (2.1). If  $\alpha$  is not too large (more precisely  $\alpha < P(\eta_0 > 0)$ ), from  $P[\eta_t < F^{-1}(\alpha)] = \alpha$  we deduce  $P[\eta_t^* < -1] = \alpha$  where  $\eta_t^* = -\eta_t / F^{-1}(\alpha)$ . Letting  $\theta_{0,\alpha} = \theta_0^* = H(\theta_0, -F^{-1}(\alpha))$ , under **A0**, the model can be reparameterized as

$$\begin{cases} \epsilon_t = \sigma_t^* \eta_t^*, & P[\eta_t^* < -1] = \alpha, \\ \sigma_t^* = \sigma(\epsilon_{t-1}, \epsilon_{t-2}, \dots; \theta_{0,\alpha}). \end{cases} \quad (4.1)$$

The theoretical VaR is now given by

$$\text{VaR}_t(\alpha) = \sigma_t(\theta_{0,\alpha}). \quad (4.2)$$

We will thus call  $\theta_{0,\alpha}$  the *VaR parameter* at level  $\alpha$ .

Define a QMLE of  $\theta_{0,\alpha}$  by

$$\hat{\theta}_{n,\alpha} = \arg \max_{\theta \in \Theta} \sum_{t=1}^n \log \frac{1}{\tilde{\sigma}_t(\theta)} h_\alpha \left( \frac{\epsilon_t}{\tilde{\sigma}_t(\theta)} \right) \quad (4.3)$$

where  $h_\alpha$  is defined by (3.7). The following corollary of Theorem 3.1 shows that a one-step consistent estimator of the VaR parameter, not requiring any estimation of the quantile function of the innovations  $\eta_t$ , is given by

$$\widehat{\text{VaR}}_t(\alpha) = \tilde{\sigma}_t(\hat{\theta}_{n,\alpha}). \quad (4.4)$$

**Corollary 4.1 (Consistency of the VaR parameter estimator).** *Let  $(\epsilon_t)$  be a strictly stationary and ergodic solution of (4.1), where the distribution of  $\eta_0^*$  is symmetric, satisfies the moment condition  $E|\log |\eta_0^*|| < \infty$ , and admits a density in a neighborhood of 1. If **A0**, **A2** and **A5** hold, then, for all  $\alpha \in (0, 1/2)$ , the QMLE defined by (4.3) satisfies*

$$\hat{\theta}_{n,\alpha} \rightarrow \theta_{0,\alpha}, \quad a.s.$$

The non-Gaussian QML estimator of the VaR parameter is also related to estimators introduced in the quantile regression literature (see references in the introduction). Let  $\rho_\alpha(u) = u(\alpha - \mathbf{1}_{\{u \leq 0\}})$ . Then, from the proof of Corollary 4.1 it can be seen that

$$\begin{aligned} \hat{\theta}_{n,\alpha} &= \arg \min_{\theta \in \Theta} \frac{1}{n} \sum_{t=1}^n \log \left( \frac{|\epsilon_t|}{\tilde{\sigma}_t(\theta)} \right) \mathbf{1}_{\{|\epsilon_t| > \tilde{\sigma}_t(\theta)\}} - 2\alpha \log \left( \frac{|\epsilon_t|}{\tilde{\sigma}_t(\theta)} \right) \\ &= \arg \min_{\theta \in \Theta} \frac{1}{n} \sum_{t=1}^n \rho_{1-2\alpha} \left\{ \log \left( \frac{|\epsilon_t|}{\tilde{\sigma}_t(\theta)} \right) \right\}. \end{aligned} \quad (4.5)$$

To interpret this expression, note that the first equation in Model (4.1) can be equivalently written as

$$\log |\epsilon_t| = \log \sigma_t^* + \log |\eta_t^*|, \quad P[\log |\eta_0^*| < 0] = 1 - 2\alpha \quad (4.6)$$

under the assumption of a symmetric distribution for  $\eta_0^*$ . Model (4.6) resembling a quantile regression model, it is not surprising to get an estimator of the form (4.5). An important difference with the quantile regression or autoregression, however, is that  $\tilde{\sigma}_t(\theta)$  is not assumed to be a linear combination of explanatory variables, or past observables.

To study the asymptotic distribution of  $\hat{\theta}_{n,\alpha}$  we need the following additional assumptions.

**A11:** There exists a neighborhood  $V(\theta_{0,\alpha})$  of  $\theta_{0,\alpha}$  such that the variables

$$\sup_{\theta \in \Theta} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\|^4, \quad \sup_{\theta \in \Theta} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial^2 \sigma_t(\theta)}{\partial \theta \partial \theta'} \right\|^2, \quad \sup_{\theta \in V(\theta_{0,\alpha})} \left| \frac{\sigma_t(\theta_{0,\alpha})}{\sigma_t(\theta)} \right|^{2\delta}$$

have finite expectations.

**A12:** The random variable  $\eta_0^*$  has a density  $f^*$  which is continuous at 1 and satisfies  $f^*(1) > 0$  and  $M = \sup_{x \in \mathbb{R}} |x| f^*(x) < \infty$ .

**Theorem 4.1 (Asymptotic normality).** *Under the assumptions of Corollary 4.1, A6-A8 and A11-A12, there exists a sequence of local minimizers  $\hat{\theta}_{n,\alpha}$  of the criterion defined in (4.5) satisfying*

$$\sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha}) \xrightarrow{d} \mathcal{N}\left(0, \Xi_\alpha := \frac{2\alpha(1-2\alpha)}{4f^{*2}(1)} J_\alpha^{-1}\right)$$

where  $J_\alpha = ED_t(\theta_{0,\alpha})D_t'(\theta_{0,\alpha})$  and  $D_t(\theta) = \sigma_t^{-1}(\theta)\partial\sigma_t(\theta)/\partial\theta$ .

Let  $\hat{\Xi}_\alpha$  denote a consistent estimator of the asymptotic variance  $\Xi_\alpha$ . The delta method thus suggests a  $(1-\alpha_0)\%$  confidence interval for  $\text{VaR}_t(\alpha)$  whose bounds are

$$\tilde{\sigma}_t(\hat{\theta}_{n,\alpha}) \pm \frac{\Phi_{1-\alpha_0}^{-1}}{\sqrt{n}} \left\{ \frac{\partial\tilde{\sigma}_t(\hat{\theta}_{n,\alpha})}{\partial\theta'} \hat{\Xi}_\alpha \frac{\partial\tilde{\sigma}_t(\hat{\theta}_{n,\alpha})}{\partial\theta} \right\}^{1/2}, \quad (4.7)$$

where  $\Phi_{\alpha_0}^{-1}$  denotes the  $\alpha_0$ -quantile of the standard gaussian distribution. Drawing such confidence intervals allows to underline that the VaR evaluation is subject to estimation risk. Even when the model is correctly specified, the market risk, as measured by the theoretical VaR defined by (4.2), is not known with exactness, but is likely to belong to the confidence interval (4.7).

## 5. Comparing accuracies of VaR estimators

In this section, we consider the usual approach for estimating the VaR in Model (2.1) under the identifiability condition

$$E\eta_t^2 = 1. \quad (5.1)$$

This approach involves two steps. In a first step, the model is estimated by the standard QMLE and, in a second step, the theoretical quantile  $\xi_\alpha := F_\eta^{-1}(\alpha)$  is estimated using the estimated rescaled innovations. More precisely, let  $\hat{\theta}_n$  denote the QMLE of  $\theta_0$  in Model (2.1) under the constraint (5.1), let

$$\hat{\eta}_t = \frac{\epsilon_t}{\tilde{\sigma}_t(\hat{\theta}_n)},$$

and let  $\xi_{n,\alpha}$  denote the empirical  $\alpha$ -quantile of  $\hat{\eta}_1, \dots, \hat{\eta}_n$ .

### 5.1. Two-step estimators

An estimator of the VaR at level  $\alpha$  is then given by

$$\widetilde{\text{VaR}}_t(\alpha) = -\tilde{\sigma}_t(\hat{\theta}_n)\xi_{n,\alpha} = \tilde{\sigma}_t\{H(\hat{\theta}_n, -\xi_{n,\alpha})\}$$

under **A0** and provided  $-\xi_{n,\alpha} > 0$ . A comparison of the VaR estimators  $\widetilde{\text{VaR}}_t(\alpha)$  and  $\widehat{\text{VaR}}_t(\alpha)$  defined in (4.4) can then be based on the asymptotic accuracies of the estimators  $\hat{\theta}_{n,\alpha}$  and  $H(\hat{\theta}_n, -\xi_{n,\alpha})$  of  $\theta_{0,\alpha}$ .

Contrary to the one-step estimator, the resulting two step estimator of the VaR does not take advantage of the (hypothesized) symmetry of the errors distribution. An estimator exploiting this additional information is

$$\widetilde{\widetilde{\text{VaR}}}_t(\alpha) = \tilde{\sigma}_t(\hat{\theta}_n)\tilde{\xi}_{n,1-2\alpha} = \tilde{\sigma}_t\{H(\hat{\theta}_n, \tilde{\xi}_{n,1-2\alpha})\}$$

where  $\tilde{\xi}_{n,1-2\alpha}$  is the empirical  $(1-2\alpha)$ -quantile of  $|\hat{\eta}_1|, \dots, |\hat{\eta}_n|$ .

The next result gives the joint asymptotic distributions of  $(\hat{\theta}'_n, -\xi_{n,\alpha})$  and  $(\hat{\theta}'_n, \tilde{\xi}_{n,1-2\alpha})$ .

**Theorem 5.1.** *Assume  $\xi_\alpha < 0$ ,  $E\eta_t^2 = 1$  and  $\kappa_4 := E\eta_t^4 < \infty$ . Suppose that  $\eta_1$  admits a density  $f$  in a neighborhood of  $\xi_\alpha$ . Let **A1**, **A5**, **A8** hold. Let **A2**, **A6**, **A7** and **A10** hold with  $\theta_0^*$  replaced by  $\theta_0$ . Then*

$$\begin{pmatrix} \sqrt{n}(\hat{\theta}_n - \theta_0) \\ \sqrt{n}(\xi_\alpha - \xi_{n,\alpha}) \end{pmatrix} \xrightarrow{\mathcal{L}} \mathcal{N}(0, \Sigma_\alpha), \quad \Sigma_\alpha = \begin{pmatrix} \frac{\kappa_4-1}{4}J^{-1} & \lambda_\alpha J^{-1}\Omega \\ \lambda_\alpha \Omega' J^{-1} & \zeta_\alpha \end{pmatrix},$$

where  $\Omega = E(D_t)$ ,  $J = E(D_t D_t')$  with  $D_t = D_t(\theta_0)$ , and

$$\lambda_\alpha = \xi_\alpha \frac{\kappa_4 - 1}{4} + \frac{p_\alpha}{2f(\xi_\alpha)}, \quad \zeta_\alpha = \xi_\alpha^2 \frac{\kappa_4 - 1}{4} + \frac{\xi_\alpha p_\alpha}{f(\xi_\alpha)} + \frac{\alpha(1-\alpha)}{f^2(\xi_\alpha)}.$$

with  $p_\alpha = E(\eta_1^2 \mathbf{1}_{\{\eta_1 < \xi_\alpha\}}) - \alpha$ .

Under the additional assumption that  $\eta_1$  is symmetrically distributed, we have

$$\sqrt{n} \begin{pmatrix} \hat{\theta}_n - \theta_0 \\ \tilde{\xi}_{n,1-2\alpha} + \xi_\alpha \end{pmatrix} \xrightarrow{\mathcal{L}} \mathcal{N}(0, \tilde{\Sigma}_\alpha), \quad \tilde{\Sigma}_\alpha = \begin{pmatrix} \frac{\kappa_4-1}{4}J^{-1} & -\lambda_\alpha J^{-1}\Omega \\ -\lambda_\alpha \Omega' J^{-1} & \tilde{\zeta}_\alpha \end{pmatrix}$$

where

$$\tilde{\zeta}_\alpha = \xi_\alpha^2 \frac{\kappa_4 - 1}{4} + \frac{\xi_\alpha p_\alpha}{f(\xi_\alpha)} + \frac{2\alpha(1-2\alpha)}{4f^2(\xi_\alpha)} = \zeta_\alpha - \frac{\alpha}{2f^2(\xi_\alpha)}.$$

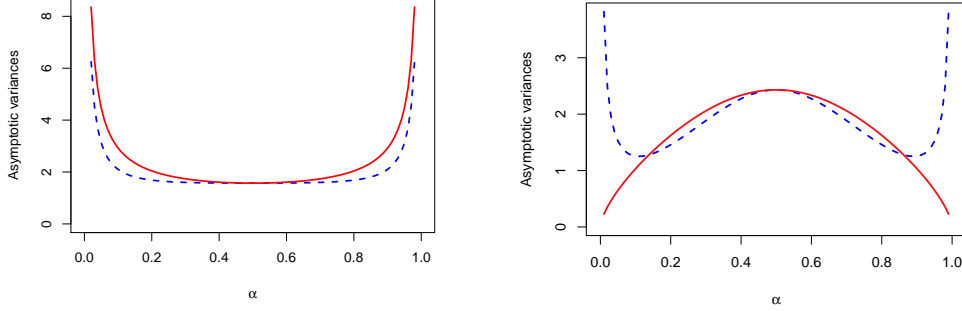


FIG 1. Asymptotic variances  $\zeta_\alpha$  in dotted lines, and  $\alpha(1-\alpha)/f^2(\xi_\alpha)$  in full line, for a standard Gaussian distribution (left panel) and the standardized GED( $\nu$ ) with  $\nu = 0.25$  (right panel).

**Remark:** The asymptotic variance  $\zeta_\alpha$  of the empirical quantile of the standardized residuals  $\hat{\eta}_t$  is the sum of  $\alpha(1-\alpha)/f^2(\xi_\alpha)$ , which can be interpreted as the asymptotic variance of the empirical  $\alpha$ -quantile of the  $\eta_t$ 's, and a term due to the estimation of  $\theta_{0,\alpha}$ . The same remark applies to  $\tilde{\zeta}_\alpha$ . Unexpectedly, this additional term can be negative. For instance, for a standard Gaussian distribution we have

$$\xi_\alpha^2 \frac{\kappa_4 - 1}{4} + \frac{\xi_\alpha p_\alpha}{f(\xi_\alpha)} = \frac{-1}{2} \xi_\alpha^2 \leq 0.$$

This is illustrated in the left panel of Figure 1. For fat tailed distribution, on the contrary, this term can be positive and arbitrarily large. For thin tailed distributions, the comparison can depend on the value of  $\alpha$ . This is illustrated in the right panel of Figure 1 for a standardized GED ( $\nu$ ) (Generalized Error Distribution of parameter  $\nu$ ) of density  $f(x) \propto \exp\{-0.5|x|^{1/\nu}\}$ .

We now deduce the asymptotic distributions of the *two-step* and the *symmetric two-step* estimators  $\hat{\theta}_{n,\alpha}^{2S} := H(\hat{\theta}_n, -\xi_{n,\alpha})$  and  $\hat{\theta}_{n,\alpha}^{S2S} := H(\hat{\theta}_n, \tilde{\xi}_{n,1-2\alpha})$  of  $\theta_{0,\alpha} = H(\theta_0, -\xi_\alpha)$ .

**Corollary 5.1.** *Under the assumptions of Theorem 5.1, the two-step estimators of the VaR-parameter at level  $\alpha$  satisfy*

$$\sqrt{n} \left( \hat{\theta}_{n,\alpha}^{2S} - \theta_{0,\alpha} \right) \xrightarrow{\mathcal{L}} \mathcal{N}(0, \Upsilon_\alpha), \quad \sqrt{n} \left( \hat{\theta}_{n,\alpha}^{S2S} - \theta_{0,\alpha} \right) \xrightarrow{\mathcal{L}} \mathcal{N}(0, \tilde{\Upsilon}_\alpha)$$

where

$$\Upsilon_\alpha = \left[ \frac{\partial H(\theta, \xi)}{\partial(\theta', \xi)} \right]_{(\theta_0, -\xi_\alpha)} \Sigma_\alpha \left[ \frac{\partial H(\theta, \xi)}{\partial(\theta', \xi)'} \right]_{(\theta_0, -\xi_\alpha)},$$

and  $\tilde{\Upsilon}_\alpha$  is obtained by replacing  $\Sigma_\alpha$  by  $\tilde{\Sigma}_\alpha$  in  $\Upsilon_\alpha$ .

It can be noted that, because the matrices  $\tilde{\Sigma}_\alpha$  and  $\Sigma_\alpha$  only differ by their lower-right term, with  $\xi_\alpha > \tilde{\xi}_\alpha$ , we have, in the sense of positive definite matrices,

$$\tilde{\Upsilon}_\alpha \preceq \Upsilon_\alpha.$$

Thus the symmetric two-step estimator is asymptotically more accurate than the two-step estimator. But the former estimator is inconsistent if the errors distribution is not symmetric.

### 5.2. The standard GARCH case

The results of Theorem 3.1 are now applied to the standard GARCH( $p, q$ ) model

$$\begin{cases} \epsilon_t = \sigma_t \eta_t \\ \sigma_t^2 = \omega_0 + \sum_{i=1}^q \alpha_{0i} \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_{0j} \sigma_{t-j}^2 \end{cases} \quad (5.2)$$

where  $\theta_0 = (\omega_0, \alpha_{01}, \dots, \beta_{0p})'$  satisfies  $\omega_0 > 0, \alpha_{0i} \geq 0, \beta_{0j} \geq 0$ . Let

$$\bar{\theta}_0 = \begin{pmatrix} \theta_0^{[1:q+1]} \\ 0_p \end{pmatrix}, \quad \theta_0^{[1:q+1]} = (\omega_0, \alpha_{01}, \dots, \alpha_{0q})', \quad A = \begin{pmatrix} \xi_\alpha^2 I_{q+1} & 0 \\ 0 & I_p \end{pmatrix}.$$

**Corollary 5.2.** *Under the assumptions of Corollary 5.1, for the standard GARCH model (5.2) the asymptotic variances of the two-step estimators of the VaR parameter take the form*

$$\begin{aligned} \Upsilon_\alpha &= \frac{\kappa_4 - 1}{4} A \{J^{-1} - 4\bar{\theta}_0 \bar{\theta}_0'\} A + 4\xi_\alpha^2 \frac{\alpha(1-\alpha)}{f^2(\xi_\alpha)} \bar{\theta}_0 \bar{\theta}_0' \\ \tilde{\Upsilon}_\alpha &= \frac{\kappa_4 - 1}{4} A \{J^{-1} - 4\bar{\theta}_0 \bar{\theta}_0'\} A + \xi_\alpha^2 \frac{2\alpha(1-2\alpha)}{f^2(\xi_\alpha)} \bar{\theta}_0 \bar{\theta}_0'. \end{aligned}$$

To compare the asymptotic variances of the two estimators of  $\theta_{0,\alpha}$  note that

$$J_\alpha^{-1} = A J^{-1} A, \quad f_{\eta^*}(1) = -\xi_\alpha f(\xi_\alpha).$$

Hence

$$\text{Var}_{as}\{\sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha})\} = \frac{2\alpha(1-2\alpha)}{4\xi_\alpha^2 f^2(\xi_\alpha)} A J^{-1} A.$$

It follows that

$$\text{Var}_{as}\{\sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha})\} - \Upsilon_\alpha = \Delta_\alpha A \left\{ \frac{J^{-1}}{4} - \bar{\theta}_0 \bar{\theta}_0' \right\} A - \frac{2\alpha}{\xi_\alpha^2 f^2(\xi_\alpha)} A \bar{\theta}_0 \bar{\theta}_0' A',$$



$$\text{Var}_{as}\{\sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha})\} - \tilde{\Upsilon}_\alpha = \Delta_\alpha A \left\{ \frac{J^{-1}}{4} - \bar{\theta}_0 \bar{\theta}'_0 \right\} A$$

where

$$\Delta_\alpha = \frac{2\alpha(1-2\alpha)}{\xi_\alpha^2 f^2(\xi_\alpha)} - (\kappa_4 - 1). \quad (5.3)$$

The following result is a consequence of the fact that  $4\bar{\theta}_0 \bar{\theta}'_0 \preceq J^{-1}$  (see Francq and Zakoian, 2010a). It allows to compare the asymptotic variances of the one-step estimator  $\hat{\theta}_{n,\alpha}$  and two-step estimator  $\hat{\theta}_{n,\alpha}^{S2S}$ .

**Corollary 5.3.** *Under the assumptions of Corollary 5.1, for the standard GARCH model (5.2) with symmetric innovations, we have*

$$\text{Var}_{as}\{\sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha})\} \preceq \text{Var}_{as}\left\{\sqrt{n}\left(\hat{\theta}_{n,\alpha}^{S2S} - \theta_{0,\alpha}\right)\right\} \quad \text{iff} \quad \Delta_\alpha \leq 0.$$

Interestingly, comparing the asymptotic variance matrices of the estimators amounts to determining the sign of a real coefficient, which solely depends on the distribution of  $\eta_t$ . None of the methods is superior in every situation. If the fourth-order moment is large, *a fortiori* if it does not exist, the one-step estimator will be better. Conversely, for distributions admitting moments at any order (such as the Gaussian) the two-step estimator may be superior. Figure 2 shows the surface  $\Delta_\alpha \leq 0$ , as a function of  $\alpha$  and  $\nu$ , for Student distributions with  $\nu$  degrees of freedom. It can be seen that for small and moderate values of  $\nu$ , the one-step estimator is asymptotically more efficient than the two-step estimator for the values of  $\alpha$  which are used in practice. In Figure 3,  $\Delta_\alpha$  is drawn as a function of  $\nu$ , for GED( $\nu$ ) and  $\alpha \in \{0.01, 0.05\}$ . The comparison is in favor of the one-step estimator for  $\nu < 0.15$ , and also for sufficiently large values of  $\nu$ .

## 6. Consistent one-step estimation without the symmetry assumption

We have seen that, under the assumption that the distribution of  $\eta_0^*$  is symmetric and under some regularity assumptions, the VaR parameter  $\theta_{0,\alpha}$  defined by (4.2) is consistently estimated by a QMLE, if and only if the instrumental density  $h$  is that defined by (3.6). This estimator has the form of the

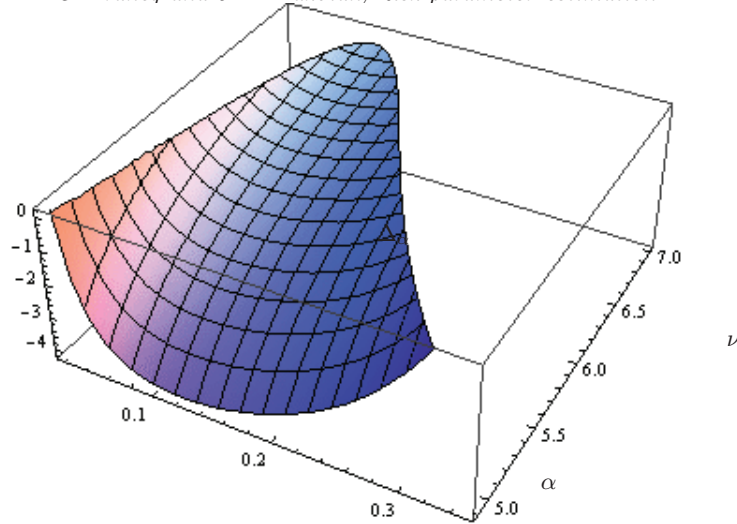


FIG 2. Surface  $\Delta_\alpha \leq 0$ , with  $\Delta_\alpha$  defined in (5.3), for which the one-step estimator is asymptotically more efficient than the symmetric two-step estimator of  $\theta_{0,\alpha}$  when the distribution of  $\eta_t$  is a standardized Student with  $\nu$  degrees of freedom,  $\nu \in [4.9, 7]$  and  $\alpha \in [0.01, 0.35]$ .

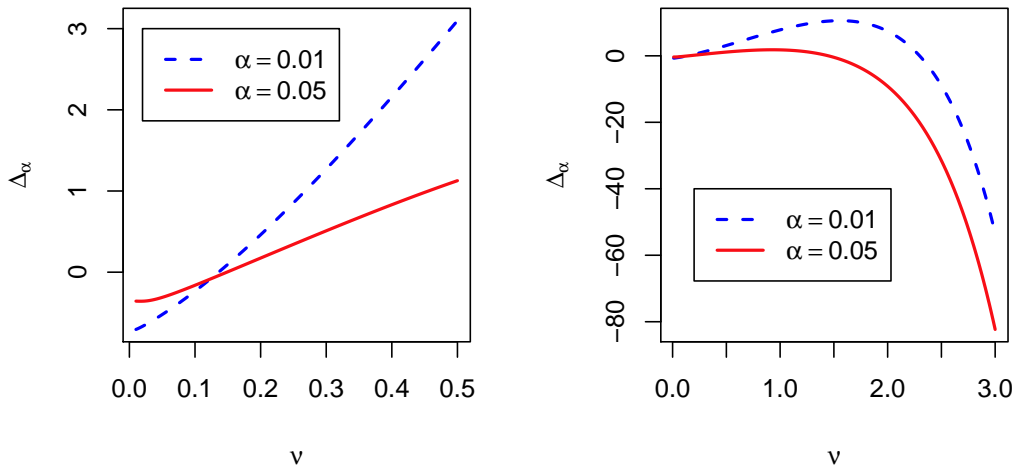


FIG 3.  $\Delta_\alpha$ , defined in (5.3), for  $\alpha \in \{0.01, 0.05\}$ , when the distribution of  $\eta_t$  follows a GED with  $\nu$  degrees of freedom.

quantile estimator  $\hat{\theta}_{n,\alpha}$  defined by (4.5) in the nonlinear regression model (4.6), but may be inconsistent when the distribution of  $\eta_0^*$  is asymmetric.

It is however possible to define a one-step quantile estimator of the VaR parameter without assuming that  $\eta_0^*$  is symmetric. To this aim, note that similarly to (4.6) we have for  $\epsilon_t < 0$

$$\log \epsilon_t^- = \log \sigma_t^* + \log \eta_t^{*-}, \quad P[\log \eta_t^{*-} < 0 \mid \epsilon_t < 0] = \tau_0$$

where  $x^- = \max\{0, -x\}$  and  $\tau_0 = 1 - \{\alpha/P(\eta_t^* < 0)\}$ . This leads us to consider the quantile estimator

$$\check{\theta}_{n,\alpha} = \arg \min_{\theta \in \Theta} \sum_{t:\epsilon_t < 0} \rho_{\hat{\tau}} \left\{ \log \left( \frac{\epsilon_t^-}{\tilde{\sigma}_t(\theta)} \right) \right\}, \quad \hat{\tau} = 1 - \left( \frac{1}{n} \sum_{t=1}^n \mathbf{1}_{\{\epsilon_t < 0\}} \right)^{-1} \alpha.$$

It is known (see Lemma 2.3 in Berkes, Horváth and Kokoszka, 2003) that any strictly stationary GARCH model possesses a fractional moment of order  $s \in (0, 1)$ . It is then easy to check that for these models the following assumption holds true.

**A13:**  $E \sup_{\theta \in \Theta} |\log \sigma_1(\theta)| < \infty$ .

**Theorem 6.1.** *Let  $(\epsilon_t)$  be a strictly stationary and ergodic solution of (4.1), where the distribution of  $\eta_0^*$  satisfies  $E \log^+ \eta_0^{*-} < \infty$ , and admits a density in a neighborhood of -1. If **A0**, **A2**, **A5** and **A13** hold, then, for all  $\alpha \in (0, P(\eta_0^* < 0))$ , we have*

$$\check{\theta}_{n,\alpha} \rightarrow \theta_{0,\alpha}, \quad a.s.$$

where  $\theta_{0,\alpha}$  is the VaR parameter satisfying (4.2).

The asymptotic distribution of this estimator is left for future research.

## 7. Proofs

### 7.1. For the results of Section 3

We start by a lemma. For  $x/\sigma \in A^c$ , let

$$g_1(x, \sigma) = \frac{\partial g(x, \sigma)}{\partial \sigma} = -\frac{1}{\sigma} - \frac{h'(x/\sigma)}{h(x/\sigma)} \frac{x}{\sigma^2}.$$

**Lemma 7.1.** *Under Assumption **A4**, for  $\sigma, \tilde{\sigma} > \underline{\omega}$  we have, for  $\sigma^*$  between  $\sigma$  and  $\tilde{\sigma}$ ,*

$$|g(x, \sigma) - g(x, \tilde{\sigma})| \leq \begin{cases} |g_1(x, \sigma^*)| |\sigma - \tilde{\sigma}| & \text{if } x \neq 0, \\ \frac{1}{\underline{\omega}} |\sigma - \tilde{\sigma}| & \text{if } x = 0. \end{cases}$$

**Proof.** It is not restrictive to assume  $\sigma > \tilde{\sigma}$ . For  $x \neq 0$ , write  $A \cap (x/\sigma, x/\tilde{\sigma}) = \{x/\sigma_1, \dots, x/\sigma_j\}$  when this set is non empty. By convention,  $j = 0$  when this set is empty. Assume

$$\sigma = \sigma_0 > \sigma_1 > \dots > \sigma_{j+1} = \tilde{\sigma}.$$

By applying Rolle's theorem on the sets  $(x/\sigma_i, x/\sigma_{i+1})$  we get, for  $\sigma_i^* \in (\sigma_i, \sigma_{i+1})$ ,

$$|g(x, \sigma) - g(x, \tilde{\sigma})| = \left| \sum_{i=0}^j g_1(x, \sigma_i^*)(\sigma_{i+1} - \sigma_i) \right| \leq \sup_i |g_1(x, \sigma_i^*)|(\sigma - \tilde{\sigma}).$$

We also have  $|g(0, \sigma) - g(0, \tilde{\sigma})| = \log \sigma - \log \tilde{\sigma}$  and the conclusion follows.  $\square$

**Proof of Theorem 3.1.** The consistency is a consequence of the following intermediate results (see *e.g.* the proofs of Theorem 7.1 in Francq and Zakoian, 2010b):

- i)  $\lim_{n \rightarrow \infty} \sup_{\theta \in \Theta} |Q_n(\theta) - \tilde{Q}_n(\theta)| = 0$ , *a.s.*
- ii)  $\mathbb{E}|g(\epsilon_t, \sigma_t(\theta_0^*))| < \infty$  and if  $\theta \neq \theta_0^*$ ,  $\mathbb{E}g(\epsilon_t, \sigma_t(\theta)) < \mathbb{E}g(\epsilon_t, \sigma_t(\theta_0^*))$ ,
- iii) any  $\theta \neq \theta_0^*$  has a neighborhood  $V(\theta)$  such that

$$\limsup_{n \rightarrow \infty} \sup_{\theta^* \in V(\theta)} \tilde{Q}_n(\theta^*) < \lim_{n \rightarrow \infty} \tilde{Q}_n(\theta_0^*), \quad \textit{a.s.}$$

where

$$Q_n(\theta) = \frac{1}{n} \sum_{t=1}^n g(\epsilon_t, \sigma_t(\theta)).$$

We begin to show *i*). Using a Taylor expansion, almost surely

$$\begin{aligned} & \sup_{\theta \in \Theta} |Q_n(\theta) - \tilde{Q}_n(\theta)| \\ & \leq n^{-1} \sum_{t=1}^n \sup_{\theta \in \Theta} |g_1(\epsilon_t, \sigma_t^*(\theta))| |\tilde{\sigma}_t(\theta) - \sigma_t(\theta)| \mathbf{1}_{\{\epsilon_t \neq 0\}} \\ & \quad + n^{-1} \sum_{t=1}^n \sup_{\theta \in \Theta} \frac{1}{\underline{\omega}} |\tilde{\sigma}_t(\theta) - \sigma_t(\theta)| \mathbf{1}_{\{\epsilon_t = 0\}} \\ & \leq n^{-1} C_1 \sum_{t=1}^n \rho^t \sup_{\theta \in \Theta} \left| \frac{1}{\sigma_t^*} \frac{\epsilon_t}{\sigma_t^*} \frac{h'}{h} \left( \frac{\epsilon_t}{\sigma_t^*} \right) \right| \mathbf{1}_{\{\epsilon_t \neq 0\}} + \frac{C_1}{\underline{\omega}} n^{-1} \sum_{t=1}^n \rho^t \\ & \leq K n^{-1} \sum_{t=1}^n \rho^t (1 + |\epsilon_t|^\delta), \end{aligned}$$

where  $\sigma_t^*(\theta)$  is between  $\tilde{\sigma}_t(\theta)$  and  $\sigma_t(\theta)$ . The first inequality is a consequence of Lemma 7.1. The last two inequalities rest on Assumptions **A2**, **A4** and **A5**. Thus, *i*) follows by the Borel-Cantelli lemma and the Markov inequality.

Condition *ii*) is a consequence of **A2-A3**. Indeed,

$$\mathbb{E}\{g(\epsilon_t, \sigma_t(\theta)) - g(\epsilon_t, \sigma_t(\theta_0^*))\} = \mathbb{E}\left\{g\left(\eta_t^*, \frac{\sigma_t(\theta)}{\sigma_t(\theta_0^*)}\right) - g(\eta_t^*, 1)\right\} \leq 0,$$

with equality iff  $\theta = \theta_0^*$ .

The proof of *iii*) is omitted because it uses standard arguments (see *e.g.* the proof of (d) Page 157 in Francq and Zakoïan, 2010b).

□

**Proof of Proposition 3.1.** First assume that  $h$  satisfies (3.4). By Assumptions **A4** and **A2**, the function  $\sigma \mapsto \partial \log h(\eta_0^*/\sigma) \partial \sigma$  is bounded by an integrable random variable, uniformly in a neighborhood of any  $\sigma > 0$ . By the dominated convergence theorem, we thus have

$$\frac{\partial}{\partial \sigma} E g(\eta_0^*, \sigma) = \frac{-1}{\sigma} - \frac{1}{\sigma} E \left\{ \lambda \psi \left( \frac{\eta_0^*}{\sigma} \right) - 1 \right\},$$

which is equal to zero if and only if  $r(\eta_0^*/\sigma) = 1$ . By  $r(\eta_0^*) = 1$  and by the positive homogeneity assumption **A0**,  $r(\eta_0^*/\sigma) = 1$  is equivalent to  $\sigma = 1$ . Thus, for  $h$  satisfying (3.4), **A3** is a consequence of **A1** and (3.3).

Now, to prove the "only if" part, note that **A3** entails the moment condition

$$E \left( \frac{h'(\eta_0^*)}{h(\eta_0^*)} \eta_0^* \right) = -1. \quad (7.1)$$

The problem is to find  $h$  satisfying (7.1) for any distribution satisfying  $r(\eta_0^*) = 1$ . The set of all possible densities  $h$  is thus,

$$\mathcal{H} = \left\{ h \text{ density} \mid r(\eta) = 1 \Rightarrow E \left( \frac{h'(\eta)}{h(\eta)} \eta \right) = -1 \right\}.$$

Under (3.3) we have

$$\mathcal{H} = \left\{ h \text{ density} \mid E\{\psi(\eta)\} = 0 \Rightarrow E \left( \frac{h'(\eta)}{h(\eta)} \eta \right) = -1 \right\}.$$

We note that this set contains the set

$$\mathcal{H}' = \left\{ h \text{ density} \mid \exists \lambda, \frac{h'(x)}{h(x)} x + 1 = \lambda \psi(x) \right\}.$$

It remains to show that  $\mathcal{H} \subset \mathcal{H}'$ . If  $h \notin \mathcal{H}'$  then for some  $x_1, x_2$  with  $|x_1| \neq 1$ , and  $\lambda_1 \neq \lambda_2$

$$\frac{h'(x_i)}{h(x_i)}x_i + 1 = \lambda_i\psi(x_i), \quad i = 1, 2.$$

Let  $\eta$  such that  $P(\eta = x_i) = p_i > 0$  with  $p_1 + p_2 = 1$ , and  $\psi(x_1)p_1 + \psi(x_2)p_2 = 0$ . Then  $E\psi(\eta) = 0$  and

$$E\left(\frac{h'(\eta)}{h(\eta)}\eta\right) + 1 = \lambda_1\psi(x_1)p_1 + \lambda_2\psi(x_2)p_2 = (\lambda_1 - \lambda_2)\psi(x_1)p_1 \neq 0.$$

Then  $h \notin \mathcal{H}$ . We have proven that  $\mathcal{H} = \mathcal{H}'$  and the proposition follows.  $\square$

**Proof of Theorem 3.2.** The proof is based on a Taylor expansion of the criterion  $\tilde{Q}_n$  at  $\theta_0^*$ . Since  $\hat{\theta}_n^*$  converges to  $\theta_0^*$ , which stands in the interior of the parameter space by **A6**, for  $n$  large enough the derivative of the criterion is equal to zero at  $\hat{\theta}_n^*$ . We thus have

$$0 = \sqrt{n} \sum_{t=1}^n \frac{\partial}{\partial \theta} g(\epsilon_t, \tilde{\sigma}_t(\theta_0^*)) + \left( \frac{1}{n} \sum_{t=1}^n \frac{\partial^2}{\partial \theta_i \partial \theta_j} g(\epsilon_t, \tilde{\sigma}_t(\theta_{ij}^*)) \right) \sqrt{n} (\hat{\theta}_n^* - \theta_0^*)$$

where the  $\theta_{ij}^*$ 's are between  $\hat{\theta}_n^*$  and  $\theta_0^*$ . The asymptotic normality is proven by means of the following intermediate results: for some neighborhood  $V(\theta_0^*)$  of  $\theta_0^*$ ,

$$iv) \lim_{n \rightarrow \infty} \sqrt{n} \sup_{\theta \in V(\theta_0^*)} \left\| \frac{\partial}{\partial \theta} Q_n(\theta) - \frac{\partial}{\partial \theta} \tilde{Q}_n(\theta) \right\| = 0, \quad \text{in probability,}$$

$$v) \frac{\partial^2}{\partial \theta \partial \theta'} \tilde{Q}_n(\theta_0^*) \rightarrow \frac{Eg_2(\eta_0^*, 1)}{4} I, \quad \text{in probability,}$$

$$vi) \sqrt{n} \frac{\partial}{\partial \theta} Q_n(\theta_0^*) \xrightarrow{\mathcal{L}} \mathcal{N}\left(0, \frac{Eg_1^2(\eta_0^*, 1)}{4} I\right),$$

vii)  $I$  is nonsingular,

for any  $\theta^*$  between  $\hat{\theta}_n^*$  and  $\theta_0^*$ . For brevity, we will skip the proof of *v)-vii*), which follows from the lines of the proof of Theorem 2.1 in Francq and Zakoïan (2010a). Note that *vii*) follows from **A7** which, for most classical GARCH formulations, reduces to standard assumptions on lag polynomials.

To prove *iv)* we note that

$$\begin{aligned}
& \sup_{\theta \in V(\theta_0^*)} \sqrt{n} \left\| \frac{\partial}{\partial \theta} Q_n(\theta) - \frac{\partial}{\partial \theta} \tilde{Q}_n(\theta) \right\| \\
& \leq \sup_{\theta \in V(\theta_0^*)} \frac{1}{\sqrt{n}} \sum_{t=1}^n |g_1(\epsilon_t, \sigma_t(\theta)) - g_1(\epsilon_t, \tilde{\sigma}_t(\theta))| \left\| \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\| \\
& \quad + \sup_{\theta \in V(\theta_0^*)} \frac{1}{\sqrt{n}} \sum_{t=1}^n |g_1(\epsilon_t, \tilde{\sigma}_t(\theta))| \left\| \frac{\partial \sigma_t(\theta)}{\partial \theta} - \frac{\partial \tilde{\sigma}_t(\theta)}{\partial \theta} \right\|. \tag{7.2}
\end{aligned}$$

Note that  $|g_1(\epsilon_t, \tilde{\sigma}_t(\theta))| \leq K(1 + |\epsilon_t|^\delta)$  by **A4** and the first part of **A2**. Thus, using **A8**, the last term in (7.2) is bounded by

$$\frac{KC_1}{\sqrt{n}} \sum_{t=1}^n \rho^t (1 + |\epsilon_t|^\delta),$$

Now, since  $E|\epsilon_t|^\delta < \infty$  by **A4**, we have

$$E \left( \sum_{t=1}^{\infty} \rho^t (1 + |\epsilon_t|^\delta) \right) < \infty.$$

It follows that

$$\frac{KC_1}{\sqrt{n}} \sum_{t=1}^n \rho^t (1 + |\epsilon_t|^\delta) \leq \frac{KC_1}{\sqrt{n}} \sum_{t=1}^{\infty} \rho^t (1 + |\epsilon_t|^\delta) \rightarrow 0, \quad a.s.$$

Thus the second term in the right-hand side of (7.2) goes to 0 *a.s.* The first term in (7.2) is bounded by

$$\sup_{\theta \in V(\theta_0^*)} \frac{1}{\sqrt{n}} \sum_{t=1}^n |g_2(\epsilon_t, \sigma_t^*)| K \rho^t \left\| \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\| \tag{7.3}$$

where  $\sigma_t^* = \sigma_t^*(\theta)$  is between  $\tilde{\sigma}_t(\theta)$  and  $\sigma_t(\theta)$ . Noting that

$$g_2(x, \sigma) = \frac{1}{\sigma^2} \left[ 1 + \frac{x}{\sigma} \left\{ 2 \frac{h'}{h} + \frac{x}{\sigma} \left( \frac{h'}{h} \right)' \right\} \left( \frac{x}{\sigma} \right) \right],$$

we have

$$|g_2(\epsilon_t, \sigma_t^*)| \leq \frac{KC_1}{\sigma_t(\theta)} (1 + |\epsilon_t|^\delta)$$

by **A4**, **A9** and the first part of **A2**. The term in (7.3) is thus bounded by

$$\frac{KC_1}{\sqrt{n}} \sum_{t=1}^n \rho^t (1 + |\epsilon_t|^\delta) \sup_{\theta \in V(\theta_0^*)} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\|.$$

By the Cauchy-Schwarz inequality and **A10** we have

$$\begin{aligned} & E \left( \sum_{t=1}^{\infty} \rho^t (1 + |\epsilon_t|^\delta) \sup_{\theta \in V(\theta_0^*)} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\| \right) \\ & \leq \left( \sum_{t=1}^{\infty} \rho^t \{E(1 + 2|\epsilon_t|^\delta + |\epsilon_t|^{2\delta})\}^{1/2} \left\{ E \sup_{\theta \in V(\theta_0^*)} \left\| \frac{1}{\sigma_t(\theta)} \frac{\partial \sigma_t(\theta)}{\partial \theta} \right\|^2 \right\}^{1/2} \right) < \infty. \end{aligned}$$

We can conclude that the first term in the right-hand side of (7.2) goes to 0 *a.s.*, which completes the proof of *iv*).  $\square$

## 7.2. For the results of Section 4

**Proof of Corollary 4.1.** The distribution of  $\eta_t^*$  being symmetric, first note that Model (4.1) is in the form (2.4) with  $r(\eta_t^*) = F_{\eta^*}^{-1}(1 - \alpha)$ . Thus **A1** is satisfied. Now note that  $\hat{\theta}_{n,\alpha} = \hat{\theta}_n^*$ , where  $\hat{\theta}_n^*$  is defined by (3.1)-(3.2) with, up to an additive constant,  $g(\epsilon_t, \tilde{\sigma}_t(\theta))$  equal to

$$(2\lambda\alpha - 1) \log |\epsilon_t| - \lambda \mathbf{1}_{\{|\epsilon_t| > \tilde{\sigma}_t(\theta)\}} \log |\epsilon_t| - \lambda(2\alpha - \mathbf{1}_{\{|\epsilon_t| > \tilde{\sigma}_t(\theta)\}}) \log \tilde{\sigma}_t(\theta).$$

Assumption **A4** being satisfied with  $A = \{-1, 0, 1\}$  and  $\delta = 0$ , it remains to show that **A3** holds true and the conclusion will follow from Theorem 3.1.

Note that  $E|g(\eta_0^*, 1)| < \infty$  under the moment condition on  $\log |\eta_0^*|$ . Moreover, for any  $\sigma > 0, \sigma \neq 1$ , the distribution of  $\eta_0^*$  being symmetric,

$$Eg(\eta_0^*, \sigma) - Eg(\eta_0^*, 1) = -\lambda E(\log |\eta_0^*| - \log \sigma)(\mathbf{1}_{\{|\eta_0^*| > \sigma\}} - \mathbf{1}_{\{|\eta_0^*| > 1\}}) \leq 0.$$

Note that the inequality is strict because  $\eta_0^*$  admits a density in a neighborhood of 1, which completes the proof.  $\square$

**Proof of Theorem 4.1.** First note that  $\hat{\nu}_n := \sqrt{n}(\hat{\theta}_{n,\alpha} - \theta_{0,\alpha})$  is such that

$$\hat{\nu}_n = \arg \min_{\nu \in \Lambda_n} \tilde{S}_n(\nu),$$

where  $\Lambda_n := \sqrt{n}(\Theta - \theta_{0,\alpha})$  and

$$\tilde{S}_n(\nu) = \sum_{t=1}^n \rho_{1-2\alpha} \left\{ \log \left( \frac{|\epsilon_t|}{\tilde{\sigma}_t(\theta_{0,\alpha} + n^{-1/2}\nu)} \right) \right\} - \rho_{1-2\alpha} \left\{ \log \left( \frac{|\epsilon_t|}{\tilde{\sigma}_t(\theta_{0,\alpha})} \right) \right\}.$$



Showing that the initial values are asymptotically negligible, and linearizing  $\log \sigma_t(\theta_{0,\alpha} + n^{-1/2}\nu)$  around  $\nu = 0$ , Lemma 7.2 below demonstrates that  $\tilde{S}_n(\nu)$  can be approximated by

$$S_n(\nu) = \sum_{t=1}^n \rho_{1-2\alpha} \left\{ \log |\eta_t^*| - \frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) \right\} - \rho_{1-2\alpha} (\log |\eta_t^*|).$$

Let  $f_{\log |\eta^*|}$  denote the density of the variable  $\log |\eta_t^*|$ . Using a convexity argument, Lemma 7.3 then shows that  $S_n(\nu)$  weakly converges to the process

$$S(\nu) = \sqrt{2\alpha(1-2\alpha)}\nu'N + f_{\log |\eta^*|}(0)\nu'J_\alpha\nu/2, \quad N \sim \mathcal{N}(0, J_\alpha).$$

The process is minimized at

$$\hat{\nu} = -\frac{\sqrt{2\alpha(1-2\alpha)}}{f_{\log |\eta^*|}(0)}J_\alpha^{-1}N \sim \mathcal{N}\left(0, \frac{2\alpha(1-2\alpha)}{f_{\log |\eta^*|}^2(0)}J_\alpha^{-1}\right)$$

The conclusion follows from Remark 1 and Lemma 2.2 in Davis, Knight and Liu (1992).  $\square$

**Lemma 7.2.** *Let  $\mathcal{C}_K = \{\nu \in \mathbb{R}^m : \|\nu\| \leq K\}$ . Under the assumptions of Theorem 4.1, for all  $K > 0$ , we have*

$$\sup_{\nu \in \mathcal{C}_K} |S_n(\nu) - \tilde{S}_n(\nu)| = o_P(1).$$

**Proof:** Let  $\dot{D}_t(\theta) = \frac{\partial}{\partial \theta} D_t'(\theta)$ , and let  $\tilde{D}_t(\theta)$  (resp.  $\dot{\tilde{D}}_t(\theta)$ ) be obtained by replacing  $\sigma_t(\theta)$  by  $\tilde{\sigma}_t(\theta)$  in  $D_t(\theta)$  (resp.  $\dot{D}_t(\theta)$ ). A Taylor expansion yields

$$\log \tilde{\sigma}_t\left(\theta_{0,\alpha} + \frac{\nu}{\sqrt{n}}\right) = \log \tilde{\sigma}_t(\theta_{0,\alpha}) + \sum_{i=0}^1 \tilde{v}_{t,n}^{(i)}(\nu),$$

with

$$\tilde{v}_{t,n}^{(0)}(\nu) = \frac{1}{\sqrt{n}}\nu' \tilde{D}_t(\theta_{0,\alpha}), \quad \tilde{v}_{t,n}^{(1)}(\nu) = \frac{1}{2n}\nu' \dot{\tilde{D}}_t(\tilde{\theta}_t^*)\nu,$$

where  $\tilde{\theta}_t^*$  is between  $\theta_{0,\alpha}$  and  $\theta_{0,\alpha} + n^{-1/2}\nu$ . Let  $\tilde{\eta}_t = \epsilon_t/\tilde{\sigma}_t(\theta_{0,\alpha})$ . Using the identity

$$\begin{aligned} & \rho_{1-2\alpha}(u-v) - \rho_{1-2\alpha}(u) \\ &= -v(1-2\alpha - \mathbf{1}_{\{u < 0\}}) + (u-v) \{ \mathbf{1}_{\{0 > u > v\}} - \mathbf{1}_{\{0 < u < v\}} \} \\ &= -v(1-2\alpha - \mathbf{1}_{\{u < 0\}}) + \int_0^v \{ \mathbf{1}_{\{u \leq s\}} - \mathbf{1}_{\{u < 0\}} \} ds \end{aligned} \quad (7.4)$$

for  $u \neq 0$  (see Equation (A.3) in Koenker and Xiao, 2006), we obtain

$$\tilde{S}_n(\nu) = \sum_{i=0}^1 \tilde{T}_n^{(i)}(\nu) + \tilde{U}_n^{(i)}(\nu),$$

with

$$\tilde{T}_n^{(i)}(\nu) = - \sum_{t=1}^n \tilde{v}_{t,n}^{(i)}(\nu) (1 - 2\alpha - \mathbf{1}_{\{|\tilde{\eta}_t| < 1\}}),$$

and

$$\begin{aligned} \tilde{U}_n^{(0)}(\nu) &= \sum_{t=1}^n \tilde{\xi}_{t,n}^{(0)}(\nu), & \tilde{\xi}_{t,n}^{(0)}(\nu) &= \int_0^{\tilde{v}_{t,n}^{(0)}(\nu)} \{ \mathbf{1}_{\{\log |\tilde{\eta}_t| \leq s\}} - \mathbf{1}_{\{\log |\tilde{\eta}_t| < 0\}} \} ds, \\ \tilde{U}_n^{(1)}(\nu) &= \sum_{t=1}^n \tilde{\xi}_{t,n}^{(1)}(\nu), & \tilde{\xi}_{t,n}^{(1)}(\nu) &= \int_{\tilde{v}_{t,n}^{(0)}(\nu)}^{\sum_{i=0}^1 \tilde{v}_{t,n}^{(i)}(\nu)} \{ \mathbf{1}_{\{\log |\tilde{\eta}_t| \leq s\}} - \mathbf{1}_{\{\log |\tilde{\eta}_t| < 0\}} \} ds. \end{aligned}$$

Define  $T_n^{(i)}(\nu)$  by replacing  $\tilde{\sigma}_t(\cdot)$  by  $\sigma_t(\cdot)$  in  $\tilde{T}_n^{(i)}(\nu)$ . Define  $U_n^{(i)}(\nu)$ ,  $\xi_{t,n}^{(i)}(\nu)$  and  $v_{t,n}^{(i)}(\nu)$  similarly. Noting that  $T_n^{(1)}(\nu)$  is centered and has a variance of order  $O(1/n)$  uniformly in  $\nu$ , in view of **A11**, we obtain  $\sup_{\nu \in \mathcal{C}_K} |T_n^{(1)}(\nu)| = o_P(1)$ . Now we have

$$\begin{aligned} \left| \tilde{T}_n^{(1)}(\nu) - T_n^{(1)}(\nu) \right| &\leq \frac{1}{2n} \sum_{t=1}^n \left| \nu' \dot{D}_t(\tilde{\theta}_t^*) \nu \right| \left| \mathbf{1}_{\{|\epsilon_t| \in (\sigma_t(\theta_{0,\alpha}), \tilde{\sigma}_t(\theta_{0,\alpha}))\}} \right| \\ &\quad + \frac{1}{2n} \sum_{t=1}^n \left| \nu' \left\{ \dot{D}_t(\tilde{\theta}_t^*) - \dot{D}_t(\theta_t^*) \right\} \nu \right| \end{aligned}$$

with  $\mathbf{1}_{\{X \in (a,b)\}}^* = \mathbf{1}_{\{X < b\}} - \mathbf{1}_{\{X < a\}}$  for any real numbers  $a, b$  and any real random variable  $X$ . The second term of the right-hand side of the previous inequality is bounded by  $K \sum_{t=1}^n \rho^t / n = o(1)$  by **A2**, **A5** and **A8**. Using the Hölder inequality, **A11**, and

$$E \left| \mathbf{1}_{\{|\epsilon_t| \in (\sigma_t(\theta_{0,\alpha}), \tilde{\sigma}_t(\theta_{0,\alpha}))\}}^* \right| \leq P \left\{ |\eta_t^*| \in \left( 1, \frac{\sigma_t(\theta_{0,\alpha})}{\tilde{\sigma}_t(\theta_{0,\alpha})} \right) \right\} \leq K \rho^t \quad (7.5)$$

the first term also tends to zero. Thus  $\sup_{\nu \in \mathcal{C}_K} |\tilde{T}_n^{(1)}(\nu)| = o_P(1)$ . Furthermore

$$\begin{aligned} \left| \tilde{T}_n^{(0)}(\nu) - T_n^{(0)}(\nu) \right| &\leq \frac{1}{\sqrt{n}} \sum_{t=1}^n \left| \nu' \tilde{D}_t(\theta_{0,\alpha}) \right| \left| \mathbf{1}_{\{|\epsilon_t| \in (\sigma_t(\theta_{0,\alpha}), \tilde{\sigma}_t(\theta_{0,\alpha}))\}}^* \right| \\ &\quad + \frac{1}{\sqrt{n}} \sum_{t=1}^n \left| \nu' \left\{ \tilde{D}_t(\theta_{0,\alpha}) - D_t(\theta_{0,\alpha}) \right\} \right| \end{aligned}$$

is also of order  $o_P(1)$  uniformly in  $\nu$ , by the Markov inequality and already used arguments.

Now, using the elementary relation

$$\int_0^{\tilde{a}} \tilde{f}(x) dx - \int_0^a f(x) dx = \int_a^{\tilde{a}} \tilde{f}(x) dx + \int_0^a \left\{ \tilde{f}(x) - f(x) \right\} dx$$

with standard notations, we have

$$\begin{aligned} |\tilde{\xi}_{t,n}^{(0)}(\nu) - \xi_{t,n}^{(0)}(\nu)| &= \left| \int_{v_{t,n}^{(0)}(\nu)}^{\tilde{v}_{t,n}^{(0)}(\nu)} \left\{ \mathbf{1}_{\{\log |\tilde{\eta}_t| \leq s\}} - \mathbf{1}_{\{\log |\tilde{\eta}_t| < 0\}} \right\} ds \right. \\ &\quad \left. + \int_0^{v_{t,n}^{(0)}(\nu)} \left\{ \mathbf{1}_{\{|\eta_t^*| \in \left( e^s, e^s \frac{\tilde{\sigma}_t(\theta_{0,\alpha})}{\sigma_t(\theta_{0,\alpha})} \right)\}} - \mathbf{1}_{\{|\eta_t^*| \in \left( 1, \frac{\tilde{\sigma}_t(\theta_{0,\alpha})}{\sigma_t(\theta_{0,\alpha})} \right)\}} \right\} ds \right|. \end{aligned}$$

Using the inequalities  $\sqrt{n}|v_{t,n}^{(0)}(\nu) - \tilde{v}_{t,n}^{(0)}(\nu)| \leq K\rho^t$  and (7.5), splitting the latter integral into two parts, and taking conditional expectation, we then obtain

$$E_{t-1} |\tilde{\xi}_{t,n}^{(0)}(\nu) - \xi_{t,n}^{(0)}(\nu)| \leq \frac{K\rho^t}{\sqrt{n}} + \int_0^{\frac{1}{n^{1/4}}} K\rho^t ds + 2|v_{t,n}^{(0)}(\nu)| \mathbf{1}_{\{|v_{t,n}^{(0)}(\nu)| \geq n^{-1/4}\}}$$

where  $E_{t-1}$  denotes the expectation conditional on  $\{\eta_u : u < t\}$ . Using in particular

$$\begin{aligned} E|v_{t,n}^{(0)}(\nu)| \mathbf{1}_{\{|v_{t,n}^{(0)}(\nu)| \geq n^{-1/4}\}} &\leq \|\nu' D_t(\theta_{0,\alpha}) / \sqrt{n}\|_4 \left\{ P(|\nu' D_t(\theta_{0,\alpha})| \geq n^{1/4}) \right\}^{3/4} \\ &\leq K/n^{11/16}, \end{aligned}$$

the Markov inequality shows that  $\sup_{\nu \in \mathcal{C}_K} |\tilde{U}_n^{(0)}(\nu) - U_n^{(0)}(\nu)| = o_P(1)$ . Similarly, one can show that  $\sup_{\nu \in \mathcal{C}_K} |\tilde{U}_n^{(1)}(\nu) - U_n^{(1)}(\nu)| = o_P(1)$ .

Now note that

$$\begin{aligned} \left| E_{t-1} \xi_{t,n}^{(1)}(\nu) \right| &\leq \left| \int_{v_{t,n}^{(0)}(\nu)}^{\sum_{i=0}^1 v_{t,n}^{(i)}(\nu)} \int_0^s f_{\log |\eta^*|}(s) ds \right| \\ &\leq \left| \int_{v_{t,n}^{(0)}(\nu)}^{\sum_{i=0}^1 v_{t,n}^{(i)}(\nu)} s \max_{[0,s]} |f_{\log |\eta^*|}(x)| ds \right|. \end{aligned}$$

By **A12** and arguments already given, the expectation of the previous variable is of order  $O_P(n^{-3/2})$ . It follows that  $\sup_{\nu \in \mathcal{C}_K} |U_n^{(1)}(\nu)| = o_P(1)$ .

We have thus shown that

$$\sup_{\nu \in \mathcal{C}_K} |\tilde{S}_n(\nu) - T_n^{(0)}(\nu) - U_n^{(0)}(\nu)| = o_P(1).$$

The conclusion follows by noting that, in view of (7.4),  $S_n(\nu) = T_n^{(0)}(\nu) + U_n^{(0)}(\nu)$ .  $\square$

**Lemma 7.3.** *Under the assumptions of Theorem 4.1 we have*

$$S_n(\cdot) \xrightarrow{d} S(\cdot)$$

on the space  $C(\mathbb{R}^m)$  of the continuous functions on  $\mathbb{R}^m$  where convergence means uniform convergence on every compact set.

**Proof:** We have shown in Lemma 7.2 that (7.4) entails

$$S_n(\nu) = T_n(\nu) + U_n(\nu),$$

with

$$T_n(\nu) = -\frac{\nu'}{\sqrt{n}} \sum_{t=1}^n D_t(\theta_{0,\alpha})(1 - 2\alpha - \mathbf{1}_{\{|\eta_t^*| < 1\}})$$

and

$$\begin{aligned} U_n(\nu) &= \sum_{t=1}^n \xi_{t,n}(\nu), \\ \xi_{t,n}(\nu) &= \left( \log |\eta_t^*| - \frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) \right) \\ &\quad \times \left( \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) < \log |\eta_t^*| < 0\}} - \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) > \log |\eta_t^*| > 0\}} \right). \end{aligned}$$

We have

$$\begin{aligned} &E_{t-1} \left( \log |\eta_t^*| - \frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) \right) \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) > \log |\eta_t^*| > 0\}} \\ &= \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) > 0\}} \int_0^{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha})} \left( x - \frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) \right) f_{\log |\eta_t^*|}(x) dx \\ &= f_{\log |\eta_t^*|}(0) \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) > 0\}} \int_0^{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha})} \left( x - \frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) \right) dx + R_{n,t} \\ &= \frac{-1}{2n} f_{\log |\eta_t^*|}(0) \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}} D_t(\theta_{0,\alpha}) > 0\}} \nu' D_t(\theta_{0,\alpha}) D_t'(\theta_{0,\alpha}) \nu + R_{n,t} \end{aligned}$$

where  $R_{n,t}$  is equal to

$$\mathbf{1}_{\{\frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})>0\}} \int_0^{\frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})} \left(x - \frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})\right) (f_{\log|\eta^*|}(x) - f_{\log|\eta^*|}(0))dx.$$

By **A12**, for any  $\epsilon > 0$  there exists  $\tau > 0$  such that  $|x| < \tau$  entails  $|f_{\log|\eta^*|}(x) - f_{\log|\eta^*|}(0)| < \epsilon$ . It follows that

$$|R_{n,t}| \leq \frac{1}{2n} \{\nu' D_t(\theta_{0,\alpha})\}^2 (\epsilon + 2M \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})>\tau\}}).$$

By the Hölder and Markov inequalities and **A11**, we then show that  $\sum_{t=1}^n |R_{n,t}| = o(1)$  *a.s.* Similarly,

$$\begin{aligned} & E_{t-1} \left( \log|\eta_t^*| - \frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha}) \right) \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})<\log|\eta_t^*|<0\}} \\ &= \frac{1}{2n} f_{\log|\eta^*|}(0) \mathbf{1}_{\{\frac{\nu'}{\sqrt{n}}D_t(\theta_{0,\alpha})<0\}} \nu' D_t(\theta_{0,\alpha}) D_t'(\theta_{0,\alpha}) \nu + R_{n,t}^* \end{aligned}$$

where  $R_{n,t}^*$  is analogous to  $R_{n,t}$ . We thus have

$$\begin{aligned} \sum_{t=1}^n E_{t-1} \xi_{t,n}(\nu) &= f_{\log|\eta^*|}(0) \frac{1}{2n} \sum_{t=1}^n \nu' D_t(\theta_{0,\alpha}) D_t'(\theta_{0,\alpha}) \nu + o(1) \\ &= f_{\log|\eta^*|}(0) \nu' J \nu / 2 + o(1) \text{ a.s.} \end{aligned}$$

Now, note that if  $X$  is an integrable random variable and  $c$  is a real constant, then the random variable

$$Y = (X - c)(\mathbf{1}_{\{c < X < 0\}} - \mathbf{1}_{\{0 < X < c\}})$$

satisfies  $\text{Var}Y \leq -cEY$ . Using this elementary inequality and the previous results, the martingale difference  $\bar{\xi}_{t,n}(\nu) := \xi_{t,n}(\nu) - E_{t-1}\xi_{t,n}(\nu)$  satisfies  $\sum_{t=1}^n E_{t-1} \bar{\xi}_{t,n}^2(\nu) = o_P(1)$ .

It follows that  $U_n(\nu) \rightarrow f_{\log|\eta^*|}(0) \nu' J \nu / 2$  in probability as  $n \rightarrow \infty$ . The martingale CLT entails that  $T_n(\nu)$  converges in distribution to the gaussian vector  $\sqrt{2\alpha(1-2\alpha)} \nu' N$  where  $N \sim \mathcal{N}(0, J_\alpha)$ . We thus have shown that the finite dimensional distributions of  $S_n(\cdot)$  converge to that of the process  $S(\cdot)$ . Since the process  $S_n(\cdot)$  has convex sample paths, the convexity lemmas of Knight (1989) and Pollard (1991) show that  $S_n$  converges weakly to the process  $S$ .  $\square$

### 7.3. For the results of Section 5

**Proof of Theorem 5.1.** It will be sufficient to prove the first asymptotic normality result. The symmetric case can be handled similarly and the proof is available from the authors. We have

$$\xi_{n,\alpha} = \arg \min_{z \in \mathbb{R}} \frac{1}{n} \sum_{t=1}^n \rho_\alpha(\hat{\eta}_t - z).$$

Thus

$$\sqrt{n}(\xi_{n,\alpha} - \xi_\alpha) = \arg \min_{z \in \mathbb{R}} Q_n(z)$$

where

$$Q_n(z) = \sum_{t=1}^n \rho_\alpha \left( \hat{\eta}_t - \xi_\alpha - \frac{z}{\sqrt{n}} \right) - \sum_{t=1}^n \rho_\alpha(\eta_t - \xi_\alpha).$$

A Taylor expansion around  $\theta_0$  yields

$$\hat{\eta}_t = \eta_t - \eta_t D'_t(\hat{\theta}_n - \theta_0) + \frac{1}{2}(\hat{\theta}_n - \theta_0)' \frac{\partial^2 \eta_t(\theta^*)}{\partial \theta \partial \theta'} (\hat{\theta}_n - \theta_0)$$

where  $\theta^*$  is between  $\hat{\theta}_n$  and  $\theta_0$ . We thus have

$$\begin{aligned} Q_n(z) &= \sum_{t=1}^n \rho_\alpha \left( \eta_t - \xi_\alpha - \eta_t D'_t(\hat{\theta}_n - \theta_0) - \frac{z}{\sqrt{n}} + o(n^{-1/2}) \right) \\ &\quad - \rho_\alpha(\eta_t - \xi_\alpha) \\ &= zX_n + Y_n + I_n(z) + J_n(z) \end{aligned}$$

where

$$\begin{aligned} X_n &= \frac{1}{\sqrt{n}} \sum_{t=1}^n (\mathbf{1}_{\{\eta_t < \xi_\alpha\}} - \alpha), \quad Y_n = \frac{1}{\sqrt{n}} \sum_{t=1}^n R_{t,n} (\mathbf{1}_{\{\eta_t < \xi_\alpha\}} - \alpha), \\ I_n(z) &= \sum_{t=1}^n \int_0^{z/\sqrt{n}} (\mathbf{1}_{\{\eta_t \leq \xi_\alpha + s\}} - \mathbf{1}_{\{\eta_t < \xi_\alpha\}}) ds, \\ J_n(z) &= \sum_{t=1}^n \int_{z/\sqrt{n}}^{(z+R_{t,n})/\sqrt{n}} (\mathbf{1}_{\{\eta_t \leq \xi_\alpha + s\}} - \mathbf{1}_{\{\eta_t < \xi_\alpha\}}) ds \end{aligned}$$

with  $R_{t,n} = \eta_t D'_t \sqrt{n}(\hat{\theta}_n - \theta_0) + o(1)$  a.s.

By the change of variable  $u = s - z/\sqrt{n}$ , we have  $J_n(z) = \sum_{i=1}^2 J_n^{(i)}(z)$  with  $J_n^{(i)}(z) = \sum_{t=1}^n X_{n,t}^{(i)}$  where

$$\begin{aligned} X_{n,t}^{(1)} &= \int_0^{R_{t,n}/\sqrt{n}} (\mathbf{1}_{\{\eta_t - \xi_\alpha - z/\sqrt{n} \leq u\}} - \mathbf{1}_{\{\eta_t - \xi_\alpha - z/\sqrt{n} < 0\}}) du, \\ X_{n,t}^{(2)} &= \int_0^{R_{t,n}/\sqrt{n}} (\mathbf{1}_{\{\eta_t - \xi_\alpha - z/\sqrt{n} < 0\}} - \mathbf{1}_{\{\eta_t - \xi_\alpha\} < 0}) du \\ &= \left\{ D'_t(\hat{\theta}_n - \theta_0) + o(n^{-1/2}) \right\} \eta_t \mathbf{1}_{\{\eta_t - \xi_\alpha \in (0, z/\sqrt{n})\}}^*. \end{aligned}$$

It follows that

$$\sum_{t=1}^n X_{n,t}^{(2)} = \left( \frac{1}{\sqrt{n}} \sum_{t=1}^n \eta_t \mathbf{1}_{\{\eta_t - \xi_\alpha \in (0, z/\sqrt{n})\}}^* D'_t \right) \sqrt{n}(\hat{\theta}_n - \theta_0) + o(1) \quad a.s.$$

Note that, for  $z > 0$ ,

$$E(\eta_t \mathbf{1}_{\{\eta_t - \xi_\alpha \in (0, z/\sqrt{n})\}}^*) = \int_0^{z/\sqrt{n}} (x + \xi_\alpha) f(x + \xi_\alpha) dx = \xi_\alpha f(\xi_\alpha) \frac{z}{\sqrt{n}} + o(1/\sqrt{n}).$$

The same equality holds for  $z \leq 0$ . Thus, in view of the independence of  $\eta_t$  and  $D_t$ , we have

$$E \left( \frac{1}{\sqrt{n}} \sum_{t=1}^n \eta_t \mathbf{1}_{\{\eta_t - \xi_\alpha \in (0, z/\sqrt{n})\}}^* D'_t \right) = z \xi_\alpha f(\xi_\alpha) \Omega' + o(1).$$

By similar computations we find

$$\text{Var} \left( \frac{1}{\sqrt{n}} \sum_{t=1}^n \eta_t \mathbf{1}_{\{\eta_t - \xi_\alpha \in (0, z/\sqrt{n})\}}^* D'_t \right) = o(1).$$

It follows that

$$\sum_{t=1}^n X_{n,t}^{(2)} = z \xi_\alpha f(\xi_\alpha) \Omega' \sqrt{n}(\hat{\theta}_n - \theta_0) + o(1) \quad a.s.$$

We now denote by  $E_{t-1}X$  the expectation of some variable  $X$  conditional on  $\{\hat{\theta}_n - \theta_0, (\eta_u : u < t)\}$ . We have, by the change of variable  $u = \eta_t v$ ,

$$\begin{aligned} E_{t-1}X_{n,t}^{(1)} &= \int_0^{D'_t(\hat{\theta}_n - \theta_0) + o(n^{-1/2})} E_{t-1}(\eta_t \mathbf{1}_{\{\eta_t \in (\xi_\alpha + z/\sqrt{n}, (\xi_\alpha + z/\sqrt{n})(1-v)^{-1})\}}^*) dv \\ &= \frac{\xi_\alpha^2}{2} f_{n,t}(\xi_\alpha) (\hat{\theta}_n - \theta_0)' D_t D'_t (\hat{\theta}_n - \theta_0) + o(n^{-1}) \quad a.s. \end{aligned}$$

where  $f_{n,t}$  denotes the density of  $\eta_t$  conditional on  $\{\hat{\theta}_n - \theta_0, (\eta_u : u < t)\}$  and  $o(n^{-1})$  is a function of  $(\hat{\theta}_n - \theta_0)$  and the past values of  $\eta_t$ . By the arguments used for  $X_{n,t}^{(2)}$  it can therefore be shown that  $J_n^{(1)}(z)$  converges in distribution to a random variable which does not depend on  $z$ . Note also that  $Y_n$  can be subtracted to the objective function  $Q_n(z)$  because it does not depend on  $z$ . Moreover  $I_n(z) \rightarrow \frac{z^2}{2}f(\xi_\alpha)$  in probability as  $n \rightarrow \infty$ . Finally,

$$\tilde{Q}_n(z) := Q_n(z) - Y_n = \frac{z^2}{2}f(\xi_\alpha) + z\{X_n + \xi_\alpha f(\xi_\alpha)\Omega' \sqrt{n}(\hat{\theta}_n - \theta_0)\} + O_P(1).$$

Since the process  $\tilde{Q}_n(\cdot)$  has convex sample paths, the convexity Lemmas of Knight (1989) and Pollard (1991) show that  $\tilde{Q}_n$  converges weakly to some convex process. By Lemma 2.2 in Davis et al. (1992), we can conclude that

$$\begin{aligned} \sqrt{n}(\xi_\alpha - \xi_{n,\alpha}) &= \xi_\alpha \Omega' \sqrt{n}(\hat{\theta}_n - \theta_0) + \frac{1}{f(\xi_\alpha)} \frac{1}{\sqrt{n}} \sum_{t=1}^n (\mathbf{1}_{\{\eta_t < \xi_\alpha\}} - \alpha) \\ &\quad + o_P(1). \end{aligned}$$

We now derive the joint asymptotic distribution of  $(\sqrt{n}(\hat{\theta}_n - \theta_0)', \sqrt{n}(\xi_\alpha - \xi_{n,\alpha}))$ . The following Taylor expansion holds

$$\sqrt{n}(\hat{\theta}_n - \theta_0) = \frac{-J^{-1}}{2\sqrt{n}} \sum_{t=1}^n (1 - \eta_t^2) D_t + o_P(1).$$

Hence

$$\text{Cov}_{as} \left( \sqrt{n}(\hat{\theta}_n - \theta_0), \frac{1}{\sqrt{n}} \sum_{t=1}^n (\mathbf{1}_{\{\eta_t < \xi_\alpha\}} - \alpha) \right) = \frac{1}{2} p_\alpha J^{-1} \Omega$$

and thus

$$\begin{aligned} \text{Var}_{as}\{\sqrt{n}(\xi_{n,\alpha} - \xi_\alpha)\} &= \left\{ \xi_\alpha^2 \frac{\kappa_4 - 1}{4} + \frac{\xi_\alpha p_\alpha}{f(\xi_\alpha)} \right\} \Omega' J^{-1} \Omega + \frac{\alpha(1-\alpha)}{f^2(\xi_\alpha)}, \\ \text{Cov}_{as} \left( \sqrt{n}(\hat{\theta}_n - \theta_0), \sqrt{n}(\xi_\alpha - \xi_{n,\alpha}) \right) &= \lambda_\alpha J^{-1} \Omega. \end{aligned}$$

We have  $\Omega' J^{-1} \Omega = 1$  (see Remark 3.1 in Francq and Zakoïan, 2011) and thus we obtain

$$\text{Var}_{as}\{\sqrt{n}(\xi_\alpha - \xi_{n,\alpha})\} = \zeta_\alpha.$$



By the CLT for martingale differences, we get the announced result.  $\square$

**Proof of Corollary 5.1.** The asymptotic normality of the two-step estimator follows from Theorem 5.1 and the following Taylor expansion of  $H$  around  $(\theta_0, -\xi_\alpha)$

$$\sqrt{n} \left( \hat{\theta}_{n,\alpha}^{2S} - \theta_{0,\alpha} \right) = \left[ \frac{\partial H(\theta, \xi)}{\partial(\theta', \xi)} \right]_{(\theta_0, -\xi_\alpha)} \begin{pmatrix} \sqrt{n} (\hat{\theta}_n - \theta_0) \\ \sqrt{n} (\xi_\alpha - \xi_{n,\alpha}) \end{pmatrix} + o_P(1).$$

A similar expansion holds for  $\sqrt{n} \left( \hat{\theta}_{n,\alpha}^{S2S} - \theta_{0,\alpha} \right)$ .  $\square$

**Proof of Corollary 5.2.** For the standard GARCH model, we have

$$J^{-1}\Omega = 2\bar{\theta}_0,$$

see Francq and Zakoian (2011), and the asymptotic variance in Theorem 5.1 takes the form

$$\Sigma_\alpha = \begin{pmatrix} \frac{\kappa_4 - 1}{4} J^{-1} & 2\lambda_\alpha \bar{\theta}_0 \\ 2\lambda_\alpha \bar{\theta}_0' & \zeta_\alpha \end{pmatrix}.$$

Moreover,

$$H(\theta, \xi) = (\xi^2 \bar{\theta}', \beta_1, \dots, \beta_p)', \quad \frac{\partial H(\theta, \xi)}{\partial(\theta', \xi)} = [A \quad 2\xi \bar{\theta}].$$

Therefore

$$\begin{aligned} \Upsilon_\alpha &= \frac{\kappa_4 - 1}{4} A J^{-1} A + 4\xi_\alpha^2 (2\lambda_\alpha \xi_\alpha + \zeta_\alpha) \bar{\theta}_0 \bar{\theta}_0' \\ &= \frac{\kappa_4 - 1}{4} A J^{-1} A + 4\xi_\alpha^2 \left( \frac{\alpha(1 - \alpha)}{f^2(\xi_\alpha)} - \xi_\alpha^2 \frac{\kappa_4 - 1}{4} \right) \bar{\theta}_0 \bar{\theta}_0' \\ &= \frac{\kappa_4 - 1}{4} A \{ J^{-1} - 4\bar{\theta}_0 \bar{\theta}_0' \} A + 4\xi_\alpha^2 \frac{\alpha(1 - \alpha)}{f^2(\xi_\alpha)} \bar{\theta}_0 \bar{\theta}_0'. \end{aligned}$$

Similarly

$$\begin{aligned} \tilde{\Upsilon}_\alpha &= \frac{\kappa_4 - 1}{4} A J^{-1} A + 4\xi_\alpha^2 \left( -\xi_\alpha^2 \frac{\kappa_4 - 1}{4} + \frac{2\alpha(1 - 2\alpha)}{4f^2(\xi_\alpha)} \right) \bar{\theta}_0 \bar{\theta}_0' \\ &= \frac{\kappa_4 - 1}{4} A \{ J^{-1} - 4\bar{\theta}_0 \bar{\theta}_0' \} A + \frac{2\alpha(1 - 2\alpha)}{\xi_\alpha^2 f^2(\xi_\alpha)} A \bar{\theta}_0 \bar{\theta}_0' A. \end{aligned}$$

$\square$

#### 7.4. For the results of Section 6

**Proof of Theorem 6.1.** We have  $\check{\theta}_{n,\alpha} = \arg \min_{\theta \in \Theta} \mathcal{Q}_{n,\tau}(\theta)$  where

$$\mathcal{Q}_{n,\tau}(\theta) = \frac{1}{n} \sum_{t=1}^n q_{t,\tau}(\theta), \quad q_{t,\tau}(\theta) = \rho_\tau \left\{ \log \left( \frac{\epsilon_t^-}{\sigma_t(\theta)} \right) \right\} \mathbf{1}_{\{\epsilon_t < 0\}}.$$

We follow the line of proof of Theorem 3.1, replacing the point *ii*) by

$$\begin{aligned} ii') \quad & \lim_{\tau \rightarrow \tau_0} \mathbb{E} \sup_{\theta \in \Theta} |q_{1,\tau}(\theta) - q_{1,\tau_0}(\theta)| = 0; \\ ii'') \quad & \mathbb{E} q_{1,\tau_0}(\theta) > \mathbb{E} q_{1,\tau_0}(\theta_0), \quad \forall \theta \neq \theta_0. \end{aligned}$$

The point *ii'*) follows from **A13**, since

$$q_{1,\tau}(\theta) - q_{1,\tau_0}(\theta) = (\tau - \tau_0) \log \left( \frac{\epsilon_1^-}{\sigma_1(\theta)} \right) \mathbf{1}_{\{\epsilon_1 < 0\}}.$$

Note that when  $\eta_1 < 0$  we have

$$\rho_\tau \left\{ \log \left( \frac{\epsilon_1^-}{\sigma_1(\theta)} \right) \right\} - \rho_\tau (\log \eta_1^-) = d \left( \eta_1^-, \frac{\sigma_1(\theta)}{\sigma_1(\theta_0)} \right),$$

where  $d(\eta_1^-, \sigma) = (\log \eta_1^-)(\mathbf{1}_{\{\eta_1^- \leq 1\}} - \mathbf{1}_{\{\eta_1^- \leq \sigma\}}) - (\log \sigma)(\tau - \mathbf{1}_{\{\eta_1^- \leq \sigma\}})$ . Since  $\tau = E \left( \mathbf{1}_{\{\eta_1^- \leq 1\}} \mid \eta_1 < 0 \right)$ , we have

$$E \left( d(\eta_1^-, \sigma) \mid \eta_1 < 0 \right) = E \left\{ (\log \eta_1^- - \log \sigma) \left( \mathbf{1}_{\{\eta_1^- \leq 1\}} - \mathbf{1}_{\{\eta_1^- \leq \sigma\}} \right) \mid \eta_1 < 0 \right\}$$

which is strictly positive when  $\sigma \neq 1$ . Point *ii''*) follows. The rest of the proof is similar to that of Theorem 3.1.  $\square$

## 8. Numerical experiments

A Monte Carlo study was conducted in order to throw light on the performance of the VaR-parameter estimators in finite sample. We also report an empirical application to stock indices.

### 8.1. On simulated data

We begin by considering one of the simplest volatility model, the ARCH(1) where  $\eta_t$  follows the Student distribution with  $\nu$  degrees of freedom:

$$\epsilon_t = \sigma_t \eta_t, \quad \sigma_t^2 = \omega_0 + \alpha_0 \epsilon_{t-1}^2, \quad \eta_t \sim St_\nu. \quad (8.1)$$

In this model, the VaR parameter is equal to  $\theta_{0,\alpha} = (\omega_{0,\alpha}, \alpha_{0,\alpha})$  where  $\omega_{0,\alpha} = \omega_0 K_\nu^2$ ,  $\alpha_{0,\alpha} = \alpha_0 K_\nu^2$ , and  $K_\nu$  denoted the  $\alpha$ -quantile of the  $St_\nu$ . Simulating  $N = 1,000$  independent trajectories of size  $n = 500$  and  $n = 5,000$  of this model, we compared the estimations of  $\theta_{0,\alpha}$  obtained by the one-step estimator  $\hat{\theta}_{n,\alpha}$  and the two-step estimator  $\hat{\theta}_{n,\alpha}^{S2S}$ . We considered the VaR levels  $\alpha = 0.01$  and  $\alpha = 0.05$ . The intercept was fixed to  $\omega_0 = 1$  and we took  $\alpha_0 = \exp(-E \log \eta_1^2)/5$ , which guarantees strict stationarity model for any value of  $\nu$  (the necessary and sufficient strict stationarity condition being  $E \log \alpha_0 \eta_1^2 < 0$ ). Over the  $N$  simulations, and for both components of  $\theta_{0,\alpha}$ , the root mean squared error of estimation of the two methods are respectively denoted by  $RMSE_1$  and  $RMSE_2$ . We then defined the empirical relative efficiency (ERE) of the one-step method with respect to the two-step method by the ratio  $RMSE_2/RMSE_1$ . For instance, with an ERE of two the one-step method can be considered as twice more efficient than the two-step method. Table 8.1 shows that, as expected from the asymptotic theory, the estimator  $\hat{\theta}_{n,\alpha}$  is much more accurate than  $\hat{\theta}_{n,\alpha}^{S2S}$  when the distribution of  $\eta_t$  is heavy-tailed (*i.e.*  $\nu$  is small) whereas  $\hat{\theta}_{n,\alpha}^{S2S}$  is slightly more accurate than  $\hat{\theta}_{n,\alpha}$  when the distribution of  $\eta_t$  is close to the normal (*i.e.*  $\nu$  is large). Similar conclusions were obtained for other distributions of the noise and for more elaborate volatility models. In particular, we considered the Threshold GARCH model introduced by Zakoïan (1994)

$$\epsilon_t = \sigma_t \eta_t, \quad \sigma_t = \omega_0 + \alpha_{0+} \epsilon_{t-1}^+ + \alpha_{0-} \epsilon_{t-1}^- + \beta_0 \sigma_{t-1}, \quad \eta_t \sim \text{GED}(\nu). \quad (8.2)$$

The VaR parameter is now  $\theta_{0,\alpha} = (\omega_{0,\alpha}, \alpha_{0+,\alpha}, \alpha_{0-,\alpha}, \beta_0)$  where  $\omega_{0,\alpha} = -\omega_0 K_\nu$ ,  $\alpha_{0+,\alpha} = -\alpha_{0+} K_\nu$ ,  $\alpha_{0-,\alpha} = -\alpha_{0-} K_\nu$ , and  $K_\nu$  denotes the  $\alpha$ -quantile of the  $\text{GED}(\nu)$ . In our simulation experiments, we chose  $\omega_0 = 0.001$ ,  $\beta_0 = 0.87$ ,  $\alpha_{0+} = \bar{\alpha}/4$  and  $\alpha_{0-} = \bar{\alpha}$  where  $\bar{\alpha}$  is such that  $E \log(\bar{\alpha} |\eta_t| + \beta_0) = 0$ , which ensures a strict stationary solution to (8.2). The results presented in Table 2 are in accordance with Figure 3. The one-step estimator of the VaR parameter is more accurate than the two-step estimator when  $\nu \leq 0.1$  or when  $\nu$  is large (depending on the value of  $\alpha$ ). In the gaussian case ( $\nu = 0.5$ ), the two-step method should be preferred.

TABLE 1

ERE of the one-step method with respect to the two-step method for estimating the VaR parameter for the ARCH(1) model with Student innovations (8.1). The number of replication is  $N = 1,000$ , the level of the VaR is  $\alpha = 5\%$  or  $\alpha = 1\%$  and the length of each simulation is  $n = 500$  or  $n = 5,000$ .

	$n = 500$							$n = 5,000$						
	$\nu$							$\nu$						
	1	2	3	4	5	6	$\infty$	1	2	3	4	5	6	$\infty$
$\alpha = 5\%$														
$\omega_{0,\alpha}$	7.5	2.8	1.7	1.3	1	0.9	0.9	13.9	6.6	2.7	1.3	1.1	1	0.8
$\alpha_{0,\alpha}$	7.3	3.6	1.7	1.3	1	1.0	0.8	22.2	8.7	3.2	1.3	1.1	1	0.9
$\alpha = 1\%$														
$\omega_{0,\alpha}$	6.1	1.6	1.0	0.8	0.7	0.7	0.7	41.1	3.6	1.6	0.9	0.8	0.8	0.7
$\alpha_{0,\alpha}$	3.8	1.8	2.6	0.8	0.7	0.7	0.7	13.7	6.0	2.1	0.9	0.8	0.7	0.7

TABLE 2

ERE of the one-step method with respect to the two-step method for estimating the VaR parameter for the TGARCH(1,1) with GED( $\nu$ ) innovations (8.2). The number of replication is  $N = 1,000$ , the level of the VaR is  $\alpha = 5\%$  or  $\alpha = 1\%$  and the length of each simulation is  $n = 500$  or  $n = 1,000$ .

	$n = 500$						$n = 1,000$					
	$\nu$						$\nu$					
	0.01	0.1	0.5	1	2	3	0.01	0.1	0.5	1	2	3
$\alpha = 5\%$												
$\omega_{0,\alpha}$	1.5	1.2	0.8	2.0	4.7	2.3	1.3	1.2	0.8	2.0	6.3	2.4
$\alpha_{0+,\alpha}$	1.3	1.1	0.9	0.9	2.5	2.2	1.5	1.2	0.8	0.9	2.0	2.7
$\alpha_{0-,\alpha}$	1.4	1.1	0.8	1.0	2.2	2.1	1.4	1.2	0.9	0.9	1.5	2.7
$\beta_0$	1.5	1.1	0.9	1.6	4.0	1.9	1.4	1.2	0.8	1.6	4.6	2.4
$\alpha = 1\%$												
$\omega_{0,\alpha}$	2.1	1.2	0.6	0.7	3.0	4.7	2.2	1.3	0.6	0.6	4.2	4.2
$\alpha_{0+,\alpha}$	2.6	1.3	0.8	0.7	1.5	1.7	3.2	1.3	0.6	0.7	1.2	1.8
$\alpha_{0-,\alpha}$	2.6	1.3	0.8	0.8	1.3	1.6	2.7	1.2	0.7	0.7	1.0	2.2
$\beta_0$	2.2	1.2	0.7	0.7	2.4	2.3	2.7	1.3	0.7	0.7	3.0	2.8

## 8.2. On real data

We considered nine major world stock indices covering the period from January, 2 1991 to August, 26 2011 : CAC (Paris), DAX (Frankfurt), FTSE (London), Nikkei (Tokyo), NSE (Bombay), SMI (Switzerland), SP500 (New York), SPTSX (Toronto), and SSE (Shanghai). For each series of log-returns,  $\epsilon_t = \log(p_t/p_{t-1})$  where  $p_t$  denotes the value of the index, we estimated the VaR parameter  $\theta_{0,\alpha}$  of GARCH(1,1) models, for  $\alpha = 5\%$  and  $1\%$ . We report in Table 3 our estimates of  $\theta_{0,\alpha}$  obtained by the one-step and the symmetric two-step methods, along with standard deviations. We also report two estimates of  $\Delta_\alpha$  based on residuals  $\hat{\eta}_t$  or  $\hat{\eta}_t^*$  of the two-step or the one-step method. Such estimates are negative for 7 out of 9 indices indicating, by Corollary 5.3, a superiority in accuracy of the one-step method for the risk level 5%. The conclusions are quite different when more extreme risks are considered. Table 4 shows that, for  $\alpha = 1\%$ , the two-step method is probably more efficient than the one-step method for large  $n$  (except perhaps for the SMI).

Figure 4 displays the returns, estimated -VaR (at the 5% and 1% levels) and VaR accuracy intervals for the SP index from April, 6, 2011 to August, 26, 2011. The  $(1 - \alpha_0)\%$  confidence intervals (for  $\alpha_0 = 5\%$ ) are obtained from formula (4.7). We preferred to report the opposite of the VaR, because the aim of such risk measures is to determine the capital reserve which acts as a protection against big losses (*i.e.* large negative values of  $\epsilon_t$ ). Obviously the estimated VaR's increase in module during the recent hectic period, while the confidence intervals are generally larger in such periods.

## 9. Conclusion

This paper presented two methods for estimating the risk parameter in conditionally heteroskedastic models. Asymptotic results were established for general risk measure, and a particular attention was devoted to the VaR.

The introduction of a VaR parameter facilitates the asymptotic comparison of the risk evaluation procedures. In particular, for the standard GARCH models the ranking of the two methods, in terms of asymptotic relative efficiency, only depends on the sign of the scalar  $\Delta_\alpha$  defined by (5.3), involving the risk level  $\alpha$  and simple characteristics of the innovations distribution. Moreover, the estimation risk, namely the effect of the inaccuracy of the parameter estimation on the VaR determination, can be explicitly taken into account, leading to confidence bounds for the VaR.

TABLE 3

One-step estimator  $\hat{\theta}_{n,\alpha}$  and two-step estimator  $\hat{\theta}_{n,\alpha}^{S2S}$  for the VaR parameter  $\theta_{0,\alpha}$  at level  $\alpha = 5\%$  of GARCH(1,1) models for 9 stock market indices. The estimated standard deviations are given into brackets. The last two columns displays estimations of  $\Delta_\alpha$  ( $\hat{\theta}_{n,\alpha}$  should be asymptotically more efficient than  $\hat{\theta}_{n,\alpha}^{S2S}$  if and only if  $\Delta_\alpha < 0$ ) based on residuals of the two-step and one-step methods.

Index	Estimator	$\omega_{0,5\%}$	$\alpha_{0,5\%}$	$\beta_{0,5\%}$	$\hat{\Delta}_{5\%}^{S2S}$	$\hat{\Delta}_{5\%}$
CAC	$\hat{\theta}_{n,5\%}^{S2S}$	0.08 (0.02)	0.23 (0.03)	0.90 (0.01)	-0.43	-0.70
	$\hat{\theta}_{n,5\%}$	0.05 (0.01)	0.23 (0.03)	0.90 (0.01)		
DAX	$\hat{\theta}_{n,5\%}^{S2S}$	0.09 (0.03)	0.22 (0.04)	0.90 (0.02)	-4.68	-6.84
	$\hat{\theta}_{n,5\%}$	0.04 (0.01)	0.22 (0.02)	0.91 (0.01)		
FTSE	$\hat{\theta}_{n,5\%}^{S2S}$	0.04 (0.01)	0.25 (0.02)	0.89 (0.01)	0.29	0.15
	$\hat{\theta}_{n,5\%}$	0.03 (0.01)	0.25 (0.02)	0.90 (0.01)		
Nikkei	$\hat{\theta}_{n,5\%}^{S2S}$	0.08 (0.02)	0.33 (0.05)	0.87 (0.02)	-3.86	-4.54
	$\hat{\theta}_{n,5\%}$	0.04 (0.01)	0.30 (0.03)	0.88 (0.01)		
NSE	$\hat{\theta}_{n,5\%}^{S2S}$	0.16 (0.06)	0.26 (0.06)	0.87 (0.03)	-3.11	-3.30
	$\hat{\theta}_{n,5\%}$	0.18 (0.05)	0.31 (0.05)	0.85 (0.02)		
SMI	$\hat{\theta}_{n,5\%}^{S2S}$	0.12 (0.03)	0.31 (0.05)	0.84 (0.03)	-3.05	-5.00
	$\hat{\theta}_{n,5\%}$	0.07 (0.02)	0.30 (0.04)	0.87 (0.02)		
SP500	$\hat{\theta}_{n,5\%}^{S2S}$	0.02 (0.00)	0.20 (0.02)	0.92 (0.01)	-2.10	-2.31
	$\hat{\theta}_{n,5\%}$	0.02 (0.00)	0.19 (0.01)	0.92 (0.01)		
SPTSX	$\hat{\theta}_{n,5\%}^{S2S}$	0.02 (0.01)	0.17 (0.03)	0.93 (0.01)	-0.06	-0.52
	$\hat{\theta}_{n,5\%}$	0.04 (0.01)	0.23 (0.03)	0.90 (0.01)		
SSE	$\hat{\theta}_{n,5\%}^{S2S}$	0.07 (0.03)	0.17 (0.03)	0.93 (0.01)	0.58	0.07
	$\hat{\theta}_{n,5\%}$	0.12 (0.04)	0.19 (0.04)	0.91 (0.02)		

TABLE 4  
As Table 3 but for the risk level  $\alpha = 0.01$

Index	Estimator	$\omega_{0,1\%}$	$\alpha_{0,1\%}$	$\beta_{0,1\%}$	$\hat{\Delta}_{1\%}^{S2S}$	$\hat{\Delta}_{1\%}$
CAC	$\hat{\theta}_{n,1\%}^{S2S}$	0.18 (0.04)	0.52 (0.07)	0.90 (0.01)	3.29	3.31
	$\hat{\theta}_{n,1\%}$	0.17 (0.06)	0.54 (0.09)	0.89 (0.02)		
DAX	$\hat{\theta}_{n,1\%}^{S2S}$	0.19 (0.06)	0.48 (0.09)	0.90 (0.02)	2.38	0.61
	$\hat{\theta}_{n,1\%}$	0.23 (0.07)	0.68 (0.13)	0.87 (0.02)		
FTSE	$\hat{\theta}_{n,1\%}^{S2S}$	0.09 (0.02)	0.53 (0.05)	0.89 (0.01)	5.22	4.63
	$\hat{\theta}_{n,1\%}$	0.08 (0.03)	0.58 (0.08)	0.89 (0.02)		
Nikkei	$\hat{\theta}_{n,1\%}^{S2S}$	0.17 (0.05)	0.76 (0.11)	0.87 (0.02)	2.07	1.20
	$\hat{\theta}_{n,1\%}$	0.24 (0.06)	0.88 (0.12)	0.84 (0.02)		
NSE	$\hat{\theta}_{n,1\%}^{S2S}$	0.42 (0.15)	0.69 (0.16)	0.87 (0.03)	11.84	11.0
	$\hat{\theta}_{n,1\%}$	0.36 (0.23)	0.70 (0.26)	0.87 (0.04)		
SMI	$\hat{\theta}_{n,1\%}^{S2S}$	0.27 (0.07)	0.72 (0.12)	0.84 (0.03)	0.31	-0.93
	$\hat{\theta}_{n,1\%}$	0.24 (0.06)	0.80 (0.13)	0.83 (0.02)		
SP500	$\hat{\theta}_{n,1\%}^{S2S}$	0.04 (0.01)	0.47 (0.04)	0.92 (0.01)	1.17	0.51
	$\hat{\theta}_{n,1\%}$	0.04 (0.01)	0.44 (0.04)	0.92 (0.01)		
SPTSX	$\hat{\theta}_{n,1\%}^{S2S}$	0.05 (0.02)	0.42 (0.07)	0.93 (0.01)	2.92	3.18
	$\hat{\theta}_{n,1\%}$	0.03 (0.02)	0.42 (0.09)	0.93 (0.01)		
SSE	$\hat{\theta}_{n,1\%}^{S2S}$	0.18 (0.07)	0.43 (0.08)	0.93 (0.01)	9.33	6.47
	$\hat{\theta}_{n,1\%}$	0.30 (0.15)	0.60 (0.16)	0.90 (0.02)		

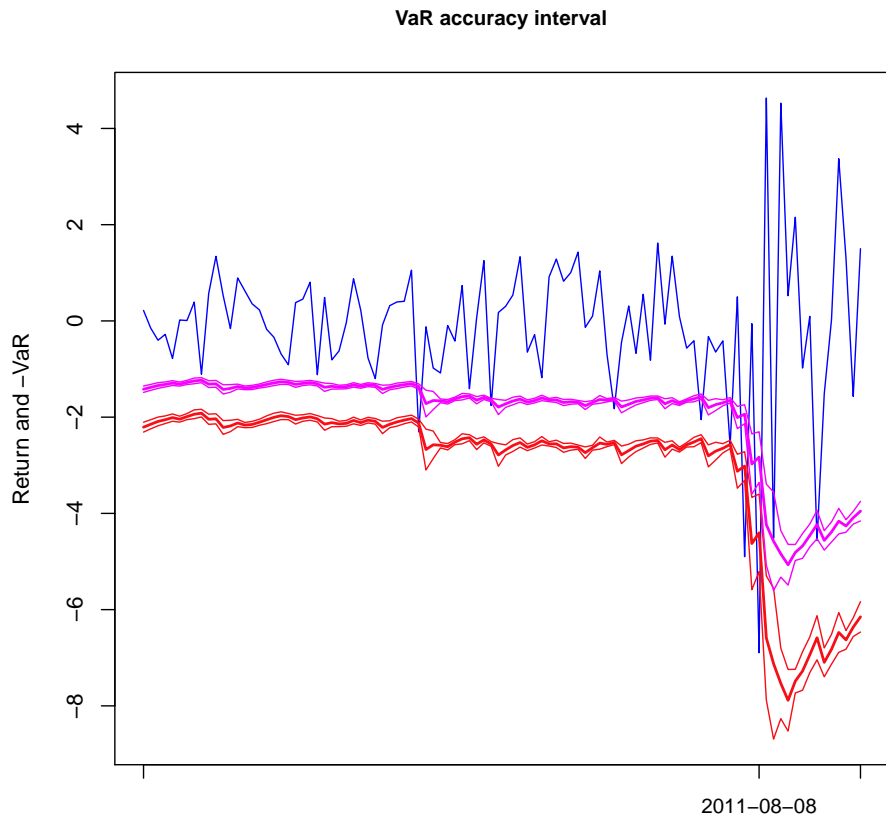


FIG 4. Returns, estimated  $-VaR$  (at the 5% and 1% levels) and VaR accuracy intervals for the SP index from April, 6, 2011 to August, 26, 2011. Estimation of the VaR parameter is based on the 500 previous values.



## References

- Bardet, J-M. and O. Wintenberger** (2009) Asymptotic normality of the Quasi-maximum likelihood estimator for multidimensional causal processes. *The Annals of Statistics* 37, 2730–2759.
- Berkes, I. and L. Horváth** (2004) The efficiency of the estimators of the parameters in GARCH processes. *The Annals of Statistics* 32, 633–655.
- Berkes, I., Horváth, L. and P. Kokoszka** (2003) GARCH processes: structure and estimation. *Bernoulli* 9, 201–227.
- Bollerslev, T.** (1986) Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307–327.
- Breidt, F.J., Davis, R.A. and A. A. Trindade** (2001) Least absolute deviation estimation for all-pass time series models. *The Annals of Statistics* 29, 919–946.
- Davis, R.A., Knight, K. and J. Liu** (1992) M-estimation for autoregressions with infinite variance. *Stochastic Processes and their Applications* 40, 145–180.
- Davis, R.A. and W.T.M. Dunsmuir** (1997) Least absolute deviation estimation for regression with ARMA errors. *Journal of Theoretical Probability* 10, 481–497.
- Francq, C., Lepage, G. and J-M. Zakoïan** (2011) Two-stage non Gaussian QML estimation of GARCH Models and testing the efficiency of the Gaussian QMLE. *Journal of Econometrics* 165, 246–257.
- Francq, C. and J-M. Zakoïan** (2004) Maximum likelihood estimation of pure GARCH and ARMA-GARCH processes. *Bernoulli* 10, 605–637.
- Francq, C. and J-M. Zakoïan** (2010a) Optimal predictions of powers of conditionally heteroskedastic processes. MPRA Preprint No. 22155.
- Francq, C. and J-M. Zakoïan** (2010b) *GARCH Models: Structure, Statistical Inference and Financial Applications*. John Wiley.
- Knight, K.** (1998) Limiting distributions for  $L_1$  regression estimators under general conditions. *The Annals of Statistics* 26, 755–770.
- Koenker, R.** (2005) *Quantile Regression*. Cambridge: Cambridge University Press.
- Koenker, R. and Z. Xiao** (2006) Quantile autoregression. *Journal of the American Statistical Association* 101, 980–990.
- Lee, S.W. and B.E. Hansen** (1994) Asymptotic theory for the GARCH(1,1) quasi-maximum likelihood estimator, *Econometric Theory* 10, 29–52.

- Lumsdaine, R.L.** (1996) Consistency and asymptotic normality of the quasi-maximum likelihood estimator in IGARCH(1,1) and covariance stationary GARCH(1,1) models. *Econometrica* 64, 575–596.
- Mikosch, T. and D. Straumann** (2006) Stable limits of martingale transforms with application to the estimation of GARCH parameters. *The Annals of Statistics* 34, 493–522.
- Pollard, D.** (1991) Asymptotics for Least Absolute Deviation Regression Estimators *Econometric Theory* 7, 186–199.
- Straumann, D. and T. Mikosch** (2006) Quasi-maximum likelihood estimation in conditionally heteroscedastic Time Series: a stochastic recurrence equations approach. *The Annals of Statistics* 5, 2449–2495.
- Xiao, Z. and R. Koenker** (2009) Conditional quantile estimation for generalized autoregressive conditional heteroscedasticity models. *Journal of the American Statistical Association* 104, 1696–1712.
- Xiao, Z. and C. Wan** (2010) A robust estimator of conditional volatility. Unpublished document.
- Zakoïan J.M.** (1994) Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*, 18, 931–955.
- Zhu, K. and S. Ling** (2011) Global self-weighted and local quasi-maximum exponential likelihood estimators for ARMA-GARCH/IGARCH models. *The Annals of Statistics* 32, 2131–2163.