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Bayesian option pricing using asymmetric GARCH models

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Abstract

This paper shows how one can compute option prices from a Bayesian inference viewpoint, using a GARCH model for the dynamics of the volatility of the underlying asset. The proposed evaluation of an option is the predictive expectation of its payoff function. The predictive distribution of this function provides a natural metric, provided it is neutralised with respect to risk, for gauging the predictive option price or other option evaluations. The proposed method is compared to the Black and Scholes evaluation, in which a marginal mean volatility is plugged, but which does not provide a natural metric. The methods are illustrated using symmetric, asymmetric and smooth transition GARCH models with data on a stock index in Brussels. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

The Black and Scholes (hereafter BS) formula for option pricing is a function of the parameters of the diffusion process describing the dynamics of the underlying asset price. The BS formula is derived for a geometric Brownian motion with a constant volatility parameter σ (corresponding to a hypothesis of homoskedasticity in an econometric model).

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In order to apply the BS formula, the econometrician has to estimate the parameter σ of the diffusion process. Hull and White (1987) studied option pricing in the case of stochastic volatility, where σ^2 follows an independent geometric Brownian motion. Provided the increments of the volatility process are independent of the increments of the process governing the asset price, they showed that options can be priced by averaging the BS formula over the stochastic volatility, i.e. that there is no need to price the risk attached to the stochastic volatility. Noh et al. (1994) predict the future mean volatility using a generalised autoregressive conditional heteroskedasticity (GARCH) model on the past returns and plug it in the BS formula.[1] They conclude that the GARCH estimated volatility has more economic content than the volatility estimates obtained by inverting the BS formula using observed past option prices.

When relaxing the hypothesis of constant volatility, it is very difficult, if not impossible, to solve the partial differential equation that leads to the BS formula (see, however, the restrictive case of Hull and White (1987) cited above and also the paper of Heston and Nandi (2000)). One has to apply the risk-neutral pricing methodology of Cox and Ross (1976), that is to say, for evaluating the price of a call option at time t with maturity at time $T>t$, compute

$$C_t^T = e^{-r(T-t)} E\left[\max(S_T - K, 0)\right], \tag{1}$$

where K is the exercise price, r the riskless interest rate and S_T the predicted price of the underlying asset at time T. This procedure requires to find an equivalent martingale measure for the returns, which leaves the volatility unchanged (in a way to be precised later) and for which the returns behave like a martingale. Duan (1995) derived the equivalent martingale measure for the case where the returns follow a discrete GARCH process with normal errors. Duan (1999) provides extensions to the case of leptokurtik errors. Kallsen and Taqqu (1998) make the bridge to continuous time GARCH, while Garcia and Renault (1997) compare option pricing and hedging when heteroskedasticity is of the GARCH type or of the stochastic volatility type.

The object of this paper is to investigate the interesting features that the Bayesian approach may bring in the risk-neutral methodology for option pricing. We have first to select an econometric model that captures as best as possible the well-known stylised facts of financial return series: volatility clustering[2], strong kurtosis, and often in the case of stocks, the leverage effect. We have basically the choice between two families of models. The stochastic volatility model in discrete time is certainly the model that is the closest to the continuous time diffusion processes considered in Hull and White (1987). Mahieu and Schotman (1998) estimated various specifications of the stochastic volatility model and applied directly the solution of Hull and White (1987) for option pricing. However, when we introduce a leverage effect in this model, we allow for possible correlation between volatility increments and the increments of the process and thus violate Hull and White's

[1] Note, however, that using the BS formula with an estimated σ computed as the average volatility results in mispricing because of Jensen's inequality.

[2] Volatility clustering of the returns induces a slowly decaying autocorrelation function of the squared returns, starting at a rather small value (about 0.2, 0.3). See, e.g. Terasvirta (1996) and Pagan (1996).

assumption. Moreover, Mahieu and Schotman concluded that the obtained estimates for the volatility were very imprecise. The GARCH model, which is much simpler to estimate, recovers thus all of its interest and we make it our baseline model.

Once risk neutralisation is taken into account, we have to simulate the chosen model in a way that takes into account all the available information contained in the data. The Bayesian viewpoint is particularly well suited for this requirement. The predictive density is a natural by-product of inference that can be used for prediction as it represents the density of future observations. The risk-neutral valuation requires the use of the predictive expectation of the payoff function of the option given in Eq. (1), which we call the predictive option price. We can even compute the predictive density of the payoff function. In the classical framework, a point estimate of the option price can also be computed, but the Bayesian approach delivers naturally a probability distribution. This distribution integrates the uncertainty both over the parameter values of the underlying econometric model (contained in the posterior distribution of the parameters) and over the future stock price. Therefore, an interval estimate of any confidence level can be formed for an option price. If an agent wants to buy (or sell) an option on the market, he can gauge the market price of the option with the predictive distribution of the option price, e.g. he could decide not to buy (sell) if the market price is too far in the right (left) tail of his predictive distribution.

Let us define returns in discrete time[3] as

$$y_t = (S_t - S_{t-1})/S_{t-1}. \tag{2}$$

The baseline GARCH(1,1) model with Gaussian errors[4]

$$\begin{cases} y_t = \mu_t + u_t \\ u_t \mid I_{t-1} \sim N(0, h_t) \\ h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} \end{cases}, \tag{3}$$

where μ_t represents the conditional expectation of the returns, was used for instance by Noh et al. (1994). This simple model does not succeed completely in reproducing the stylised facts present in the data and consequently may give a wrong account of the volatility persistence. The degree of persistence in the volatility process is important for option pricing since a higher persistence results in a longer delay for the predictive conditional variance to converge to its unconditional value. As shown in detail by Terasvirta (1996), the introduction of Student errors improves greatly the possibility that the GARCH(1,1) model reproduces the behaviour of data with a high empirical kurtosis. A second possible improvement of GARCH models for stock returns consists in taking into

[3] Duan (1995) considers in fact $y_t = \Delta\log(S_t)$, which is the continuous time equivalent of $y_t = (S_t - S_{t-1})/S_{t-1}$. The discrete time formulation leads to simpler results for risk neutralisation as one does not have to manipulate lognormal distributions.

[4] The parameters α, β and ω are restricted to be positive. The starting value h_0 is treated as a known constant. The $\{\varepsilon_t\}$ sequence is conditionally independent. I_{t-1} is the past information set.

account the leverage effect, which is the negative correlation between current stock returns and future volatility. In the model of Glosten et al. (1993), the conditional variance can react asymmetrically to past squared shocks in the mean process, a stronger effect for negative shocks than for positive ones corresponding to the leverage effect. Finally, besides asymmetry, the news impact curve of the GARCH model may saturate for large returns. Lubrano (2001) introduces a smooth transition GARCH model that combines both asymmetry and saturation.

The paper is organised as follows. Section 2 presents in general terms the predictive option pricing method and the option pricing rules. Section 3 introduces and discusses two variants of the GARCH model that are used for an empirical application on an index of the Brussels stock exchange. Section 4 provides the computational details on Bayesian option pricing and illustrates the method on the empirical GARCH models developed in the previous section. Section 5 concludes.

2. Predictive option pricing: principles

2.1. Introduction

The terminal payoff at time T of a European call option is given by

$$P_T = \max(S_T - K, 0). \tag{4}$$

If we manage to find a risk-neutral equivalent martingale measure Q to the measure P of the empirical process of the underlying security return, then an option can be priced as the discounted expected value of its future terminal payoff. When the empirical process follows a geometric Brownian motion, an analytical solution to this problem is provided by the celebrated BS formula

$$C_t^T = S_t \Phi(d_1) - K e^{-r(T-t)} \Phi(d_2)$$

$$d_1 = \frac{\ln\left(S_t / K e^{-r(T-t)}\right)}{\sigma\sqrt{T-t}} + 0.5\sigma\sqrt{T-t}$$

$$d_2 = \frac{\ln\left(S_t / K e^{-r(T-t)}\right)}{\sigma\sqrt{T-t}} - 0.5\sigma\sqrt{T-t}, \tag{5}$$

where $\Phi(\cdot)$ is the cumulative Gaussian distribution function, S_t the observed price at time t of the underlying security, and K the exercise price or strike. The arguments depend on the volatility σ, which is the standard deviation (per time unit) of the process of the return of the underlying asset. Methods to estimate this parameter can be found for instance in Campbell et al. (1997) as well as an extension for the case where the underlying price follows a trending Ornstein–Uhlenbeck process.

2.2. Stochastic volatility

In the case of stochastic volatility (σ indexed by t), provided volatility is uncorrelated with the security price (which excludes GARCH processes), one can follow Hull and White (1987) and average the BS formula over future volatility in a Monte Carlo simulation of N draws so as to obtain

$$C_t^T = \frac{1}{N}\sum_{j=1}^{N} BS_j(S_t, K, \sigma_j), \tag{6}$$

where

$$\sigma_j^2 = \frac{1}{T-t}\sum_{i=t+1}^{T} \sigma_{j,i}^2. \tag{7}$$

The main advantage of this approach is that we do not have to predict the future price S_T of the underlying asset. We have only to predict future volatility under measure P. Consequently, there is no need to find an equivalent risk-neutral process to the data generating process. However, this approach is limited in its application as, first, it precludes any correlation between the price of the underlying asset and the volatility (leverage effect) and, second, it cannot price the risk attached to stochastic volatility.

2.3. GARCH option pricing and risk neutralisation

Duan (1995) provides a general method for option pricing in the case of GARCH processes. Risk neutralisation should leave the variance unchanged and should transform the conditional expectation so that the discounted expected price of the underlying asset follows a martingale. In GARCH processes, it is not possible to find a risk-neutralisation procedure that leaves unchanged the marginal variance of the process or the conditional variance beyond one period. Duan (1995) introduces the *local risk-neutral valuation relationship*, which leaves unchanged the one period ahead conditional variance and implies that the expected future return is equal to the risk-free interest rate r. Adapted to discrete time, this means that

$$E\left[(S_T - S_{T-1})/S_{T-1}\right] = r. \tag{8}$$

The econometric model (3) specifies the empirical distribution of y_t defined in Eq. (2), conditionally on the past. The pricing measure Q shifts the error term u_t so that the conditional expectation of y_t becomes equal to r. The new error term is $v_t = u_t + \mu_t - r$ and we have

$$\begin{cases} y_t = r + v_t \\ v_t \mid I_{t-1} \sim N(0, h_t) \\ h_t = \omega + \alpha(v_{t-1} - \mu_{t-1} + r)^2 + \beta h_{t-1}. \end{cases} \tag{9}$$

The functional form of the conditional variance remains unchanged. However, h_t is no longer governed by a χ^2 variable as under measure P but by a noncentral χ^2. This type of shifting can be applied to many other GARCH processes, in particular those reviewed in the introduction, which take into account asymmetry, leverage effect and saturation.

Duan (1995) used the GARCH-M model of Engle et al. (1987), which implies that $\mu_t = \mu + \lambda\sqrt{h_t}$ (one must note that the GARCH-M model combines nicely with the properties of the lognormal distribution). This model, which may find some justification in the financial literature, generally has not a very good fit and provides poor estimates for λ. As noted for instance by Campbell et al. (1997, Chap. 2), financial series such as stock indexes often present positive autocorrelation of the returns. Positive autocorrelation may be due to various phenomena such as infrequent and nonsynchronous trading of individual stocks entering the index, but it also may be due to the risk premium attached to nonconstant volatility. Consequently, the baseline GARCH model with normal errors we selected is

$$\begin{cases} y_t = \mu + \rho y_{t-1} + u_t \\ u_t \mid I_{t-1} \sim N(0, h_t) \\ h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}. \end{cases} \tag{10}$$

We follow the same approach as Hafner and Herwartz (2001) who found on German securities that incorporating ρy_{t-1} in the conditional expectation gave a higher likelihood value than incorporating λh_t. The variance of y_t is as usual equal to $\omega/(1-\alpha-\beta)$ and the stationarity condition is given by $\alpha+\beta<1$. For the risk-neutralised process, we show in Appendix A that the variance is

$$\mathrm{Var}(y_t) = \frac{\omega + \alpha[(1-\rho)r - \mu]^2}{1 - \alpha(1+\rho^2) - \beta}. \tag{11}$$

The process is stationary if $\alpha(1+\rho^2)+\beta<1$. Consequently, risk neutralisation increases the marginal variance of y, fragilises the stationarity condition and increases volatility persistence as the predictive variance will take a longer time to converge to its limiting value given in Eq. (11).

2.4. Predictive option pricing

The predictive density of the terminal payoff P_T under measure Q is defined by

$$f_Q(P_T \mid y) = \int f_Q(P_T \mid \theta, y)\varphi(\theta \mid y)\mathrm{d}\theta, \tag{12}$$

where $\varphi(\theta|y)$ is the posterior density of the parameters of the econometric model (10), $f_Q(P_T|\theta, y)$ is the density of a future payoff after translation of the error term, and y is the sample of returns used for estimation. The predictive density (12) gives us all the information we need to compute the predictive option price, which is just the predictive expectation of P_T multiplied by $(1+r)^{-(T-t)}$ as we are in discrete time for discounting.

The Bayesian approach provides a complete density so that a measure of uncertainty can be attached to the option price by computing a confidence interval.

The predictive density of either P_T, S_T or y_T is not straightforward to compute in a GARCH model. Details can be found in Bauwens et al. (1999, Chap. 7) for the usual GARCH model. When $T=t+1$, which means that *ns* (the number of predictions ahead) is equal to one, the conditional density of a future return y_T under measure Q is a normal density given by

$$f_Q(y_T \mid \theta, y_t) = f_N\left(r, \omega + \alpha[y_t - \mu - \rho y_{t-1} + r]^2 + \beta h_t\right). \tag{13}$$

Conditionally on θ, all the parameters of this distribution are known as y_t and h_t are observed or already computed. When $ns>1$, the complete predictive is obtained by the multiple integral

$$\begin{aligned} f_Q(y_T \mid y_t) = \int_\theta \int_{R^{ns-1}} & f_Q(y_T \mid \theta, y_{T-1}) f_Q(y_{T-1} \mid \theta, y_{T-2}) \cdots \\ & \times f_Q(y_{t+1} \mid \theta, y_t) \varphi(\theta \mid y) \mathrm{d}y_{T-1} \cdots \mathrm{d}y_{t+1} \mathrm{d}\theta. \end{aligned} \tag{14}$$

We have to integrate θ as in Eq. (12), but also $y_{t+1},\ldots, y_{T-1}$, which are unobserved, but can be simulated sequentially. The dimension of the integration over future y_{t+j} is thus $ns-1$. Each element in Eq. (14) is a normal density with mean r and variance h_{t+j}, but the resulting density in the inner integral is not of a known form. We propose in Section 4 a simulation algorithm that draws random numbers in the predictive density (14) and is inspired from Geweke (1989). Once a simulated sequence y_i ($i=t+1,\ldots, T$) is obtained, it is transformed into a draw from the predictive density of P_T through the following transformation

$$\begin{aligned} S_T &= S_t \prod_{i=t+1}^{T} (1 + y_i) \\ P_T &= \max(S_T - K, 0). \end{aligned} \tag{15}$$

The predictive option price is defined as the discounted expectation of P_T. When we have obtained N draws P_T^j ($j=1,\ldots, N$) of P_T, the predictive option price can be approximated by the empirical mean

$$C_t^T \simeq (1+r)^{-(T-t)} \frac{1}{N} \sum_{j=1}^{N} P_T^j. \tag{16}$$

With the same draws, we can estimate the complete predictive density of P_T using a nonparametric approach.

The empirical mean (16) converges to its population value if the empirical process is stationary. As we are in a Bayesian framework, the stationarity condition may be verified at the posterior mean of θ, but not necessarily for every point drawn from the posterior density. The points for which the stationarity condition is not met have to be rejected for the predictive evaluation[5]

As Eq. (16) is a Monte Carlo estimator, we would like to qualify its precision. Let us define the empirical standard deviation of C_t^T as

$$\hat{\sigma}_C = (1+r)^{-(T-t)}\sqrt{\frac{1}{N}\sum (P_T^j)^2 - \left(\frac{1}{N}\sum P_T^j\right)^2}.$$

Provided the N draws are independent and N is large, the Monte Carlo error is asymptotically normal (see Bauwens et al., 1999, p. 75). A confidence interval for C_T^t is given by

$$C_T^t \pm z_\alpha \frac{\hat{\sigma}_C}{\sqrt{N}},$$

where z_α is the $1-\alpha$ quantile of the standard normal distribution.

If the model is estimated with an MCMC method (as this will be the case later on with the Griddy Gibbs sampler), the empirical standard deviation cannot be computed directly because the obtained draws of θ are not independent. A modified estimator is difficult to implement, but an easy solution is to compute the Monte Carlo error using only a part of the draws, say $\theta_{(j)}, j=1, 11, 21, \ldots$ so that the resulting sequence of θ can fairly reasonably be taken as independent.

2.5. Comparison with the classical approach

Whether in the Bayesian or in the classical framework, a simulation method has to be used to compute option prices when volatility follows a GARCH process. In both cases, we have to simulate the risk-neutralised GARCH process. The classical approach fixes θ at its maximum likelihood estimate, whereas the Bayesian approach integrates θ with respect to its posterior density. As a consequence, the Bayesian approach takes completely into account the uncertainty, that coming from the prediction and that coming from the parameters. Nevertheless, a common element to the two approaches is the simulation of the GARCH process given the parameter values.

2.6. Comparison with the BS formula

The BS formula ignores the stochastic nature of volatility as it is modeled for instance by the GARCH model. It assumes incorrectly homoskedasticity when the real governing process is heteroskedastic. If we want to compare the pricing obtained by an incorrect use of the BS formula to the predictive option pricing in case of GARCH volatility, we have to plug in the BS formula the marginal variance of the empirical GARCH process. The stationary marginal variance of the neutralised GARCH process is greater than that of the

[5] This problem is common to all dynamic models. Bauwens et al. (1999, p. 139) give details for the homoskedastic AR(1) model.

empirical process. However, Duan (1995) explains that this difference between the two variances cannot exhaust all the differences of results between GARCH and BS option pricing. It is well known (see for instance the references in Duan, 1995) that the BS formula underprices out-of-the-money options, options on low-volatility securities, and short maturity options. If we observe option prices, we can invert the BS formula to find the implied BS volatility. When plotting the result against the exercise price for a fixed maturity, the theory predicts a straight horizontal line when this empirical curve is typically convex and known as the "smile" (see Duan, 1996 for an illustration).

3. GARCH models for Brussels stock index

We have estimated three different GARCH models on a return series of the Brussels stock exchange. We used daily data on the spot market index of shares of Belgian firms, for the period 23/11/93 to 30/01/96. The data consist of closing quotes, providing 550 observations. The dependent variable (y_t) is the index return defined in Eq. (2) and multplied by 100 to get percentages. A time series plot of the percentage returns is provided in Fig. 1. The mean return is equal to 0.043% and the standard deviation to 0.48%. The greatest positive and negative returns are 1.30% and -1.82%, the last observation is 1.30% and the last but one observation is -1.07%. The index (not reproduced here) exhibits a downward trend over the first half of the sample period and an upward trend after.

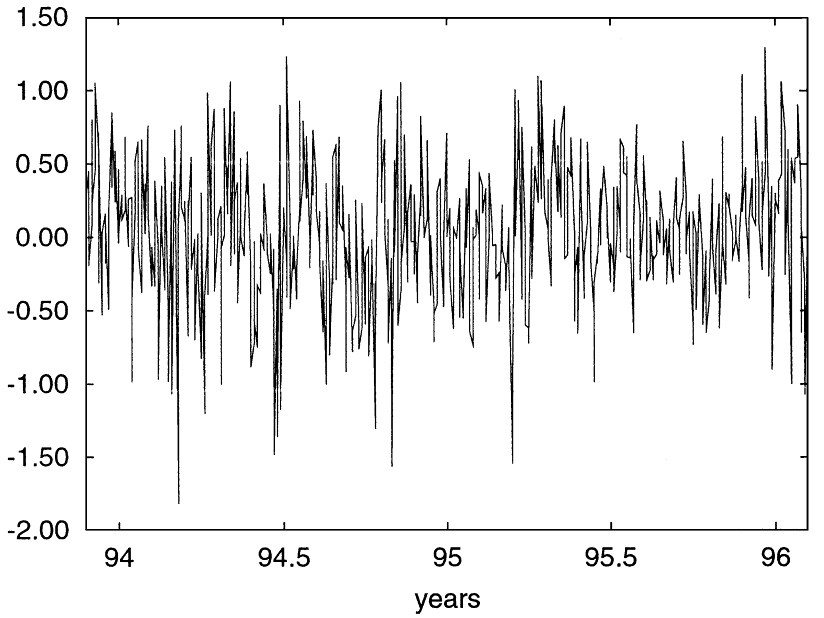

Fig. 1. Brussels spot market index return (23/11/93 to 30/01/96).

3.1. Models and likelihood function

The general form of the three models that we estimate and their likelihood functions are given by:

$$y_t = \rho y_{t-1} + \sqrt{h_t}\epsilon_t \qquad \epsilon_t \sim N(0,1)$$

$$h_t = g(y_{t-1}, h_{t-1}, \theta)$$

$$l(\theta; y) \propto \prod_{t=2}^{T} h_t^{-1/2} \exp\left(-\frac{1}{2}\sum_{t=2}^{T} y_t^2/h_t\right). \tag{17}$$

For the symmetric model, h_t is given in Eq. (10). We use a uniform prior on finite intervals for all the parameters. The posterior moments exist provided h_t is strictly positive and finite. This implies that the range of integration for ω starts at a strictly positive value.

The two variants of the symmetric GARCH model (10) we shall consider adopt the common formulation

$$h_t = \omega + \alpha_1 u_{t-1}^2(1-f_t) + \alpha_2 u_{t-1}^2 f_t + \beta h_{t-1}. \tag{18}$$

The model of Glosten et al. (1993) assumes an asymmetry between positive and negative shocks and is obtained by defining f_t as a Heavyside function with

$$f_t = \begin{cases} 1 & \text{if } u_{t-1} < 0 \\ 0 & \text{otherwise.} \end{cases} \tag{19}$$

The leverage effect is present in Eq. (18) if α_2 is larger than α_1, so that the news impact curve is steeper for negative shocks than for positive ones. In this asymmetric model (hereafter GJR), the impact of shocks on the variance depends on the sign of the shock. This model was already used in a Bayesian framework by Bauwens and Lubrano (1998) on weekly data for the Brussels stock index. We use the same type of prior as above. Posterior moments exist under the same condition provided there are enough observations in each regime.

The second variant considers the possibility of saturation in an asymmetric model. Volatility is increased by bigger shocks, but till a certain extent beyond which it stays constant. This effect is obtained by a smooth transition model introduced in Lubrano (2001) who replaces the above f_t Heavyside function by a smooth exponential transition function with a threshold:

$$f_t(u, \gamma, c) = 1 - \exp(-\gamma(u-c)^2). \tag{20}$$

In this transition function, the threshold c monitors the degree of asymmetry and γ the saturation. In order to get a scale-free γ, the quantity $u - c$ has to be normalised by the standard deviation of y_t. This model (hereafter STR) is known to present identification and estimability problems at both ends of the support of γ. For $\gamma = 0$, the transition function is zero. Consequently, α_2 becomes not identified. When $\gamma \to \infty$, the transition function becomes a Heavyside function equal to zero for $u = c$ and equal to one otherwise. The parameter c will tend to pick up an outlier so that the model tends to be equivalent to a linear GARCH model with a dummy variable for that point. As this is another well defined model having a positive probability, the posterior density of γ is not integrable because its right tail does not tend to zero quickly enough (see Lubrano, 2001 for a formal proof). We introduce a gamma prior to solve both problems:

$$\varphi(\gamma) \propto \gamma^{\nu-1}\exp(-\gamma/\gamma_0). \tag{21}$$

The prior is zero at $\gamma = 0$ if $\nu > 1$ and has an exponentially decaying tail that insures the existence of posterior moments.[6] Generally speaking, the problem of existence of posterior moments arises every time the likelihood function does not go to zero quickly enough or presents a nonintegrable singularity. This is the case for some simultaneous equation models and for cointegration models (see Bauwens et al., 1999). For GARCH models, the likelihood function based on Gaussian errors does not present this kind of pathology. The problem could have arisen with the STR model only. However, the prior solves the matter and as anyway we integrate on a finite interval and the function is finite, the resulting integrals converge.

3.2. Inference results

Classical and Bayesian inference results for the three models are given in Table 1. The following general comments apply to these results:

(1) Negative shocks have a stronger impact than positive shocks on the next conditional variance. In the GJR model, the difference $\lambda = \alpha_2 - \alpha_1$ has a posterior mean equal to 0.090 with a standard deviation equal to 0.066. The posterior probability that λ is negative is small (less than 6%). The posterior probability that α_2 is negative in the STR model is zero.

(2) For the smooth transition model, we chose $\nu = 3$ and $\gamma_0 = 0.5$ for the gamma prior, which implies $E(\gamma) = 1.5$ and $\mathrm{Var}(\gamma) = 0.75$. The posterior density is dominated by the prior. The coefficient corresponding to positive shocks, α_1 was set equal to zero, as the maximum likelihood algorithm could not depart from this starting value. The news impact curve (not reported here) is not flat for positive shocks as the transition between the two regimes is smooth. Note that the news impact curves of the GJR and the smooth transition model are fairly similar, but with a difference in the right tail that implies a further dampening influence of large positive shocks for the smooth transition model compared to the GJR model.

(3) Classical estimates and Bayesian posterior moments are very close for the regression parameters μ and ρ. Note the differences for ω and β because the posterior densities of these two parameters are rather skewed. The gamma prior on γ entails a much smaller posterior mean and standard deviation than their classical counterparts for γ and c. However, Bayesian posterior standard deviations are substantially larger for the GARCH

[6] Note that with $\nu = 1$, we get as a particular case the exponential prior used for instance by Geweke (1993) in a regression model with Student errors.

Table 1
Inference in the GARCH models

Model	μ	ρ	ω	β	α_1	α_2	γ	c
Classical results								
Basic	0.031 [0.019]	0.24 [0.044]	0.0075 [0.0053]	0.91 [0.036]	0.056 [0.019]			
GJR	0.027 [0.020]	0.25 [0.045]	0.0098 [0.0069]	0.90 [0.042]	0.021 [0.021]	0.083 [0.031]		
STR	0.028 [0.019]	0.24 [0.045]	0.0081 [0.0058]	0.90 [0.038]	0.0 [–]	0.088 [0.031]	2.17 [4.36]	1.16 [0.46]
Bayesian results								
Basic	0.032 [0.020]	0.24 [0.046]	0.028 [0.020]	0.80 [0.11]	0.082 [0.037]			
GJR	0.026 [0.020]	0.25 [0.047]	0.027 [0.020]	0.80 [0.11]	0.039 [0.033]	0.13 [0.064]		
STR	0.028 [0.020]	0.25 [0.047]	0.028 [0.016]	0.79 [0.088]	0.0 [–]	0.13 [0.063]	1.15 [0.81]	0.91 [0.44]

'Basic' is the model defined by Eq. (17) and h_t in Eq. (10), 'GJR' corresponds to Eqs. (17)–(19), and 'STR' to (Eqs. (17), (18) and (20). Classical results are maximum likelihood estimates and standard errors (in brackets). Bayesian results are posterior means and standard deviations (in brackets). Five thousand draws (plus 750 for warming) were used for the Griddy–Gibbs algorithm (see Bauwens and Lubrano, 1998). The average computing time is 10 min on a Pentium 1Gh. All computations were done with GAUSS.

Table 2
Marginal volatilities for the empirical models

	Basic		GJR		STR	
	P	Q	P	Q	P	Q
Classical σ^2	0.232	0.260	0.220	0.237	0.892	2.110
Bayesian σ^2	0.249	0.299	0.249	0.319	0.375	0.470
Prob. stat.	0.986	0.976	0.984	0.979	0.874	0.837

Moments and posterior probabilities for P and Q are computed on the same set of draws, supposing that $r=0$ for the Q case. Prob. stat. is the posterior probability of stationarity.

parameters ω, α and β, giving certainly a better account of parameter uncertainty than that provided by classical standard errors.

3.3. Comparing estimated volatilities

We can compute the implied marginal variance for each empirical model. For the Q-measure, the formulae are given by Eqs. (11), (25), and (27), depending on the model. For the P-measure, the usual formulae for GARCH models apply (set $\rho=0$ in the denominators, and set the numerators to ω). These variances can be used in the BS formula if one decides to ignore heteroskedasticity. They should be compared to the empirical variance (0.231).

Table 2 presents the classical and the Bayesian results for the three models. They are obtained as transformations of the original parameters. Classical results are evaluated at the MLE and are thus very unreliable if the estimates are close to the nonstationarity boundary, which corresponds to a denominator close to 0 in the formula. This produces the relatively large values for the STR model (as its estimates are close to the nonstationarity boundary). Bayesian marginal moments are obtained as a transformation of every draw of the posterior density, the expectation being taken at the end (instead of computing the marginal moments at the posterior expectation of the parameter). They are truncated moments since the draws that do not verify the stationarity condition are rejected. The reported posterior probabilities indicate that a small amount of draws had to be rejected and that the processes can be taken as stationary. Due to the way they are computed, the Bayesian results are more reliable than the classical ones, especially for the STR model.

The results indicate a significant increase in the marginal volatility when risk neutralisation is taken into account. The adoption of the asymmetric model in its GJR version hardly makes a difference. On the contrary, the smooth transition model yields about 50% higher marginal variances because this model implies a higher probability of nonstationarity.

4. Predictive option prices: computations and results

Predictive option pricing requires the evaluation of a high-dimensional integral as we have to take the expectation both over the parameter space of θ and over future returns. As indicated before, Geweke (1989) has proposed a simulation algorithm to compute the integrals in Eq. (14). In order to adapt this algorithm, we must take into account the fact that the original GARCH model has an autoregressive mean and that the prediction has to be done with the risk-neutralised GARCH process. We first detail the predictive skedastic function for each model and then give the simulation algorithm. The rest of the section is devoted to empirical results.

4.1. Predictive skedastic functions

Let us write down the risk-neutralised predictive skedastic function for each of the three proposed empirical models. The general formula is given in Eq. (9) and we have justified previously the choice $\mu_t = \mu + \rho y_{t-1}$. For the symmetric GARCH, we get

$$h_T = \omega + \alpha v_{T-1}^2 + \beta h_{T-1}, \tag{22}$$

where

$$v_{T-1} = (1-\rho)r - \mu + \epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}, \tag{23}$$

and $\varepsilon \sim N(0,1)$. For the asymmetric models, we have

$$h_T = \omega + \alpha_1 v_{T-1}^2 + (\alpha_2 - \alpha_1)v_{T-1}^2 f_T + \beta h_{T-1}. \tag{24}$$

Let us first consider the case where f_T is the Heavyside function ($=1$ if v_{T-1} is negative and 0 otherwise). We show in Appendix A that the predictive variance of y_T is

$$\mathrm{Var}(y_T) = \frac{\omega + [(1-\rho)r - \mu]^2(\alpha_1 + \alpha_2)/2}{1 - (1+\rho^2)(\alpha_1 + \alpha_2)/2 - \beta}, \tag{25}$$

provided

$$(1+\rho^2)(\alpha_1 + \alpha_2)/2 + \beta < 1. \tag{26}$$

When f_T is the exponential smooth transition function defined in Eq. (20), the predictive variance is

$$\mathrm{Var}(y_T) = \frac{\omega + \alpha_2[(1-\rho)r - \mu]^2}{1 - (1+\rho^2)\alpha_2 - \beta}, \tag{27}$$

provided

$$(1+\rho^2)\alpha_2 + \beta < 1. \tag{28}$$

These two stationarity conditions, together with $\alpha + \beta < 1$ for the symmetric case, serve to reject draws of θ for which stationarity is not verified.

4.2. Computational aspects

The algorithm given in Table 3 produces $N \times M$ draws of the predictive density of P_T. It uses draws from the posterior density of θ that are easily obtained provided a Monte Carlo method has been used to make inference and that the draws have been stored. The draws

Table 3
Simulation algorithm for option prices with maturity ns periods ahead of t

$i=1, N$
  $\theta_i \sim \varphi(\theta \mid y)$
  $k=1, M$
    $\epsilon \sim N_{ns}(0, I_{ns})$
    $hs_1=\omega_i+\alpha_i(y_t-\mu_i-\rho_i y_{t-1})^2+\beta_i h_t$
    $ys_1 = r+\epsilon_1\sqrt{hs_1}$
    $hs_2=\omega_i+\alpha_i(ys_1-\mu_i-\rho_i yt)^2+\beta_i hs_1$
    $ys_2 = r+\epsilon_2\sqrt{hs_2}$
    $j=3, ns$
      $hs_j=\omega_i+\alpha_i(ys_{j-1}-\mu_i-\rho_i ys_{j-2})^2+\beta_i hs_{j-1}$
      $ys_j = r+\epsilon_j\sqrt{hs_j}$
    $j=j+1$
    $S_T = S_t \Pi_{j=1}^{ns}(1+ys_j/100)$
    $P_T=(1+r)^{-ns}\max(S_T-K, 0)$
  $k=k+1$
$i=i+1$

that do not satisfy the stationarity conditions stated in the previous subsection have to be rejected. The inner loop on k approximates the inner integral in y while the outer loop on i approximates the outer integral in θ.

This algorithm can be improved (variance reduction) by implementing the technique of "antithetic variates" (see, e.g. Davidson and MacKinnon, 1993, Chap. 21 and also Hull and White, 1987). The draws of ϵ are used twice in the inner loop, but with an opposite sign the second time. Let us call P_T^1 and P_T^2 the two option prices obtained corresponding to one draw of θ. The price that is finally delivered is $P_T=(P_T^1+P_T^2)/2$. Geweke (1989) shows that when $N\rightarrow\infty$, the value of M no longer matters to obtain consistent results. However, as θ is typically costly to obtain, there is an incentive to take M greater than 1. In the example treated below, we took $N=5000$ (minus the number of rejections) and $M=50$. As detailed in Section 2.4, we retained only every tenth draw of θ to limit the autocorrelation in θ generated by the MCMC algorithm. Consequently, the final number of draws used for prediction is $5000/10\times 50=25\,000$. In a classical approach, N would be equal to 1 as θ is fixed at the maximum likelihood estimate and M would be chosen large. Duan (1996), for instance, uses $M=5000$.

The predictive density of the payoff function of the option can be approximated by a kernel estimate of the $N\times M$ simulated values of that function. Option prices are computed as the discounted sample mean of P_T as given in Eq. (16) with $r=0$.

4.3. Option pricing for the Brussels spot index

We report in Table 4 the predictive option prices for the Brussels spot index for three different maturities: 15, 30 and 60 days, starting at the end of the observed sample minus two observations (because this $n-2$ observation is largely negative and thus constitutes a good example for the asymmetric models). A 15-day maturity is certainly very short for an option, but one should remember that its price is also the price of any option 15 days before its maturity. When we observe a real option market for say 3-month options, the

Table 4
Predictive call option prices for Brussels stock index

Maturity (days)	Moneyness					
	0.959 (out)		1.000 (at)		1.045 (in)	
	C_t^T	BS_t^T	C_t^T	BS_t^T	C_t^T	BS_t^T
Basic						
15	0.00021 (0.02)	0.00013	0.0081 (0.50)	0.0076	0.0430 (0.98)	0.0430
30	0.00099 (0.07)	0.00079	0.0113 (0.50)	0.0108	0.0437 (0.94)	0.0435
60	0.00315 (0.14)	0.00278	0.0159 (0.49)	0.0153	0.0457 (0.86)	0.0453
GJR						
15	0.00018 (0.02)	0.00015	0.0084 (0.51)	0.0077	0.0431 (0.91)	0.0430
30	0.00088 (0.07)	0.00081	0.0116 (0.51)	0.0109	0.0440 (0.93)	0.0435
60	0.00306 (0.14)	0.00283	0.0162 (0.50)	0.0153	0.0461 (0.86)	0.0453
STR						
15	0.00020 (0.02)	0.00038	0.0082 (0.50)	0.0090	0.0430 (0.98)	0.0432
30	0.00089 (0.06)	0.00158	0.0113 (0.50)	0.0128	0.0438 (0.94)	0.0442
60	0.00283 (0.14)	0.00455	0.0159 (0.50)	0.0180	0.0457 (0.86)	0.0469

C_t^T is the predictive option price defined in Eq. (16). Numbers in parentheses are the probabilities of exercise of the option. BS_t^T is the mean of Eq. (5) evaluated at the marginal variance under measure P, the mean being taken with respect to θ. Moneyness is S_T/K. It is equal to 1 for options at the money, smaller than 1 for out-of-the-money options, and larger than 1 for in-the-money options (at time t). The computing time (with GAUSS on a Pentium 350Mh) using 500 (N) times 50 (M) repetitions is 77 s with the basic model for a maturity of 60 days, shorter maturities being obtained as a by-product. This time goes up to 102 s for the GJR model and 109 s for the STR model.

market is very quiet at the beginning of the option life, but gets very active a few weeks before the maturity. We have supposed that the riskless interest rate r was equal to zero. We took the normalisation rule $S_t = 1$ and considered a range of moneyness (S_T/K) between 0.959 and 1.045.

We have computed the Monte Carlo standard errors. We do not give them in full detail, but the following indications are useful. For out-of-the-money options, t statistics are slightly above the maturity (20 for a 15-day maturity, etc). For at-the-money options, they are all of the order of 200. For in-the-money options, they are between 1000 and 15000. Translated in term of precision for the estimates, a 1% precision needs a t of 200, and 10% precision a t of 20 (if the mean is 0.010, then 0.011 is at the border of the 95% confidence interval in the case of a 10% precision). Every time we shall say that two option prices are different, we mean that the second is not contained within a 95% confidence interval of the first.

We computed but do not report classical results. Broadly speaking, classical estimates of the option prices are close the Bayesian predictive means. They are slightly different for out-of-the-money options. The differences are weaker for at-the-money options. We can say that there are no noticeable differences for in-the-money options, except when using the STR model. This is a sign of the robustness of the risk-neutral pricing methodology.

Table 5
Mean predictive volatilities

	15 days	30 days	60 days
Basic	0.282	0.275	0.270
GJR	0.304	0.290	0.282
STR	0.291	0.278	0.269

The mean predictive volatility is defined in Eqs. (29) and (30) together with Table 3.

Let us now compare the prices obtained using the predictive method and those obtained with the expectation of the BS formula[7], both reported in Table 4. For in-the-money options, there are no economically significant differences. For at-the-money options, significant differences are appearing (more than a 5% difference in price when the numerical precision is of the order of 1%), but these differences are decreasing with maturity. The BS formula underprices options for the basic and GJR models, but overprices it for the STR model. For out-of-the-money options, the BS formula underprices strongly short maturities (38% for 15 days) for the basic model. This underpricing attenuates with maturity and when the GJR model is used. This means that the GJR model gives a better account of the marginal volatility of the underlying security. With the STR model, the BS formula strongly overprices, showing that the marginal volatility is not estimated with a satisfactory accuracy in this model. All these results amplify when we plug in the BS formula the classical estimate of the marginal volatility.

We report in Table 5 the implied mean predictive volatilities. This is defined as the mean, over the number of periods to maturity, of the predictive volatilities $\overline{hs}_j$:

$$\frac{1}{ns}\sum_{j=1}^{ns}\overline{hs}_j. \tag{29}$$

The predictive volatility in period j (between t and $t+ns$) is the mean of the volatilities hs_j generated according to the simulation algorithm described in Table 3:

$$\overline{hs}_j = \frac{1}{N\times M}\sum_{i=1}^{N}\sum_{j=1}^{M} hs_j. \tag{30}$$

For the three models, the mean predictive volatilities decrease with maturity. The decrease is due to the configuration of the sample and convergence results from stationarity. These mean conditional volatilities converge also to smaller values than the computed marginal volatilities reported in Table 2. The latter were computed as truncated moments (as explained in Section 3.3). Table 5 reveals no serious differences (not more than 5%) between the models, but Table 2 reveals a similar picture for the Bayesian estimates of the basic and the GJR models. Therefore, the differences we have found between the BS and the predictive pricing methods for out-of-the-money options come just from the fact that the BS formula is too sensitive to variations of the volatility.

[7] We computed $E_{\theta|y}(BS[\sigma(\theta)])$. This is the posterior expectation of the BS formula of Section 2.1. It is different from the Hull and White (1987) approach of Section 2.2.

Looking at the results given in Table 4, we note that the expected option prices are not much different between the basic and the two asymmetric models (within the Monte Carlo precision). On one side, this gives confidence about the robustness of the predictive pricing method compared to a misuse of the BS formula as reported above. On the other side, this is disrupting as one may think that asymmetric models would have produced a different pricing in the presence of negative shocks and short maturities. However, we must not forget that the Bayesian approach gives not only an expected option price, but also a complete density. Considering the complete density may shed some more light on the question.

The interest of our approach is to provide a probability distribution with respect to which (observed) option prices can be assessed, namely the predictive distribution of the option payoff function (the expected value of this distribution being the predictive option price). We provide in Fig. 2 (left panel) the computed predictive densities for the three maturities and a strike of 1. Actually, this type of density has a discrete component and a continuous one: the discrete component is at zero and corresponds to the fact that the payoff function is the maximum of zero and the difference $S_T - K$, and the continuous part corresponds to the positive values of this difference. Only the continuous part is drawn on the figures so that the densities integrate to the probability of being positive (e.g. about equal to 0.5 for at-the-money options). The probability at zero is the predictive probability that the option will not be exercised. It is evaluated by the proportion of null values of the payoff function in the total number of simulations ($N \times M$). The complementary probabilities are reported in Table 4 (see the numbers in parentheses). The message that is apparent from the left panel of Fig. 2 is that, at least for the observed sample, uncertainty increases with maturity while the predictive mode does not increase significantly. On the contrary, as shown in the right panel of Fig. 2, the option price is very sensitive to the moneyness (given there for a maturity of 60 days and a smaller range of moneyness than that displayed in Table 4).

It is difficult to detect an influence of modelling asymmetry on option prices. For out-of-the-money options and at-the-money options, there is no significant differences in the

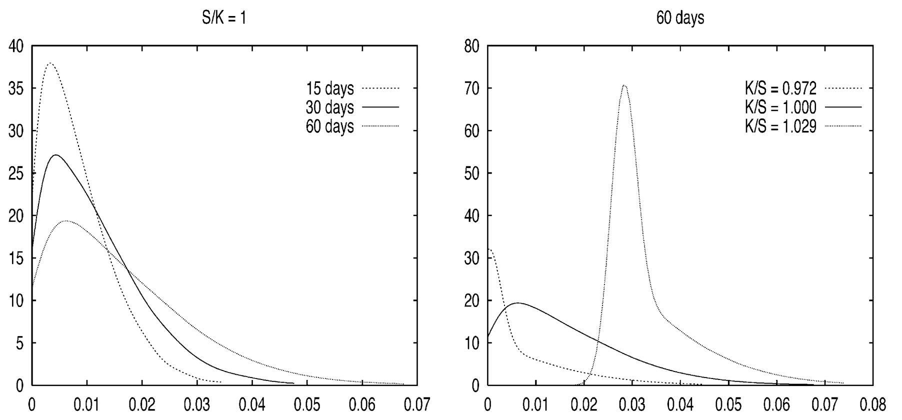

Fig. 2. Predictive density for the payoff function for the basic model.

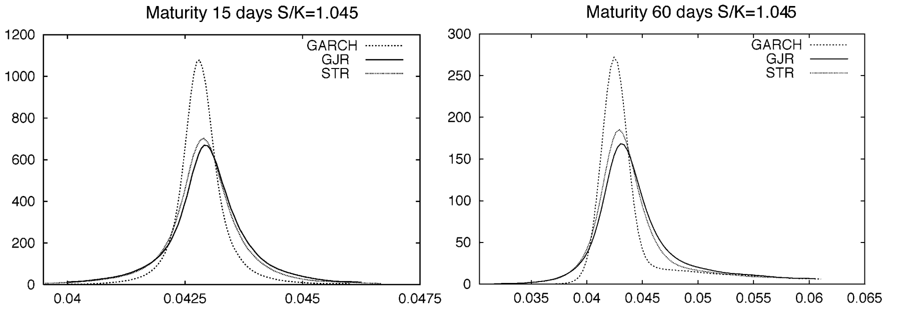

Fig. 3. Impact of the model choice on the predictive density for the payoff function.

graphs of the predictive payoffs. However, surprisingly for options largely out-of-the-money as those reported here, a difference appears as shown in Fig. 3. The two asymmetric models perform similarly (which is not so surprising) but ignoring asymmetry apparently gives a too-high precision about the mean option price for our particular sample. This effect seems to be valid independently of the maturity.

5. Conclusion

This paper shows how option prices can be evaluated from a Bayesian viewpoint using an econometric model to predict the future stock price and volatility. The option price provided by our method is the predictive expectation of the payoff function of the option. Other characteristics of options (delta, gamma,...) could be predicted. Our method delivers the predictive distribution of the payoff function for a given econometric model. This probability distribution could be useful to market participants who wish to compare the model prediction to potential prices on the market or to other predictions.

This paper also shows that in a Bayesian approach, an additional source of uncertainty is taken into account, which has consequences on the measure of volatility and as a result on option pricing. It shows how the predictive method finally produces a better evaluation of the actual volatility contained in the data when there is a large uncertainty on marginal measures due to nearly nonstationarity. Because of this nearly nonstationarity, using a marginal measure to be plugged in the BS formula can be very dangerous.

Finally, this paper shows that modelling asymmetry does not seem essential for pricing options nearly at the money, but may have a significant impact on the dispersion of the predicted prices for in-the-money options.

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Appendix A. Variance and stationarity condition for risk-neutralised GARCH processes

The marginal variance of y in GARCH processes is computed using the law of iterated expectations and the fact that the process is supposed to be stationary. See Bauwens et al. (1999, Chap. 7) for details.

Let us write down the risk-neutralised predictive process for each of the three proposed empirical models. We have first

$$y_T = r + \epsilon_T\sqrt{h_T} \quad \epsilon_T \sim N(0,1). \tag{31}$$

For the skedastic function, the general formula is given in Eq. (9) and we have justified previously the choice $\mu_t = \mu + \rho y_{t-1}$. For the symmetric GARCH, the predictive skedastic function is

$$h_T = \omega + \alpha v_{T-1}^2 + \beta h_{T-1}, \tag{32}$$

where

$$v_{T-1} = (1-\rho)r - \mu + \epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}. \tag{33}$$

The predictive expectation of h_T is given by

$$E(h_T) = \omega + \alpha E(v_{T-1}^2) + \beta E(h_{T-1}). \tag{34}$$

We have essentially to compute

$$\begin{aligned} E(v_{T-1}^2) &= [(1-\rho)r-\mu]^2 + E\left[\left(\epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}\right)^2\right] \\ &= [(1-\rho)r-\mu]^2 + E[\epsilon_{T-1}^2 h_{T-1} + \rho^2\epsilon_{T-2}^2 h_{T-2}] \\ &= [(1-\rho)r-\mu]^2 + (1+\rho^2)E[h]. \end{aligned} \tag{35}$$

Solving for $E(h)$, we get Eq. (11)

For the GJR asymmetric model, the skedastic function is

$$h_T = \omega + \alpha_1 v_{T-1}^2 + (\alpha_2 - \alpha_1)v_{T-1}^2 f_T + \beta h_{T-1}, \tag{36}$$

where f_T is the Heavyside function that is one if $v_{T-1} < 0$ and zero otherwise. We have to compute

$$E(h_T) = \omega + \alpha_1 E(v_{T-1}^2) + (\alpha_2 - \alpha_1)E(v_{T-1}^2 \mid v_{t-1} < 0) + \beta E(h_{T-1}). \tag{37}$$

We have already got $E(v_{T-1}^2)$ from the symmetric case. It thus remains to compute the truncated conditional expectation $E(v_{T-1}^2 | v_{t-1} < 0)$

$$E(v_{T-1}^2 \mid v_{t-1} < 0) = ((1-\rho)r - \mu)^2 + E\left[\left(\epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}\right)^2 \middle| v_{t-1} < 0\right]$$

Supposing that the distribution of v_{t-1} is symmetric and that the function $\epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}$ is also symmetric, we have

$$E\left[\left(\epsilon_{T-1}\sqrt{h_{T-1}} - \rho\epsilon_{T-2}\sqrt{h_{T-2}}\right)^2 \middle| v_{t-1} < 0\right] = (1+\rho^2)E(h)/2,$$

which is just half the quantity obtained in the symmetric case. Regrouping partial results, we get Eqs. (25) and (26).

When f_T is a smooth transition function, it seems natural to study the stationarity condition for the limiting case when $\gamma \to \infty$. With an even smooth transition function, the limiting case is the GJR model. When the smooth transition function is the asymmetric exponential function defined in Eq. (20), it must be noted that the model becomes linear when $\gamma \to \infty$. Consequently, $E(h)$ and the stationarity condition in this case are identical to the results derived for the standard GARCH(1,1) model, just replacing α by α_2 (see Eqs. (27) and (28)).

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