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A new approach to bad news effects on volatility: the Multiple-Sign-Volume sensitive regime EGARCH model (MSV-EGARCH)

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Abstract

In this paper, using daily data for six major international stock market indexes and a modified EGARCH specification, the links between stock market returns, volatility and trading volume are investigated in a new nonlinear conditional variance framework with multiple regimes and volume effects.

Volatility forecast comparisons, using the Harvey-Newbold test for multiple forecasts encompassing, seem to demonstrate that the MSV-EGARCH complex threshold structure is able to correctly fit GARCH-type dynamics of the series under study and dominates competing standard asymmetric models in several of the considered stock indexes.

KEYWORDS: GJR, multiple regimes, trading volume, estimation, forecasting.

JEL: C52, C53

1 Introduction

A frequently documented feature of stock market data is that returns appear to be drawn from a time-dependent heteroskedastic distribution. As early noted in the pioneering studies of Mandelbort (1963) and Fama (1965), financial time series vary systematically with time and tend to display periods of unusually large volatility, followed by periods of low volatility.

Despite these early studies, efforts to model volatility dynamics have only been developed in the last decades. In fact, until recently, the variance of the disturbance term was assumed to be constant in conventional econometric models, i.e., financial time series modelling centered on the conditional first moment, with any temporal dependencies in the higher order moments treated as a nuisance.

However, the increased importance played by risk and uncertainty considerations has recently spurred a vast literature on modelling and forecasting return's volatility. The trade-off between risk and return, where risk is associated with the variability of the random (unforeseen) component of a time series (volatility), constitutes one of the cornerstones of modern finance. In effect, finance is nowadays a field where the explicit modelling of uncertainty takes on a particularly significant role, since valuation models for the majority of assets are essentially based on the first two moments of the return series: mean, variance and covariances. Moreover, due to the compelling theoretical and empirical results supporting the efficient market theory, academicians and practitioners have to some extent ignored the question of return's forecastibility in recent decades; concentrating, instead, on exploring the question of risk. Understanding the statistical properties of volatility is currently considered an important area of interest, given the impact of volatility changes, namely, in risk analysis, portfolio selection, market timing, and derivative pricing.

Recent studies on stock return's volatility have been dominated by ARCH models (Engle, 1982; Bollerslev, 1986), which stand for autoregressive conditional heteroskedasticity. The conditional heteroskedasticity framework is a stationary, parametric, conditional approach which postulates that the main time-varying feature of returns is the conditional volatility, while it assumes that the unconditional volatility remains unchanged through time.

The popular autoregressive conditional heteroskedasticity models have been extremely successful in accounting for the main characteristics of financial data time series. Nevertheless, in some applications it has been found that ARCH models with conditional normal distributions fail to fully capture the leptokurtosis present in high frequency data. The empirical evidence against the normality assumption, pointed firstly by Mandelbort (1963) and Fama (1965), has led to the use of non-normal distributions capable of modelling the excess of kurtosis, such as the Student's t distribution in Bollerslev (1987), the Generalised Error Distribution in Nelson (1991), the Laplace Distribution in Granger and Ding (1995) and the Stable Paretian Distribution in Liu and Brorsen (1995), Panorska et al. (1995), Mittnik et al. (1998), Curto et al. (1998) and Tavares et al. (2007).

The Student's t distribution, in particular, has a long tradition in the econometrics literature as a popular choice of a fat-tailed distribution, since it has finite second moment (in contrast to stable non-Gaussian distributions), its mathematical properties are well known, it is undemanding to estimate, and is often found capable of capturing the excess of kurtosis observed in financial time-series.

In some aspects ARCH relative success has made it less interesting to continue research on volatility models. Nonetheless, there are key aspects that warrant further investigation. Using daily data for six major international stock market indexes from January 1995, through April 2008, this paper analyses the links between stock market returns, volatility and unexpected trading volume in a new nonlinear conditional variance framework. First, a new multiple regime model is proposed, in opposition to the standard single zero threshold adopted by nonlinear GARCH models. This provides increased flexibility to the proposed MSV-EGARCH specification, allowing it to capture individual irregular bursts in the volatility time series that, otherwise, could be treated as mere outliers. Second, as part of the literature on volatility clustering suggests that ARCH effects in stock returns can be explained by temporal dependence in trading volume, unexpected volume, defined as above-average trading activity, is used as a variance regressor variable, helping to bridge the gap between theory and practice in volatility modelling.

This paper is organized as follows. Next section presents the MSV-EGARCH model specification and section 3 describes the data sets. Section 4 discusses estimation results, compares goodness-of-fit and presents out-of-sample evaluation results for the MSV-EGARCH, GJR and EGARCH models. Finally, section 5 presents some concluding remarks.

2 The Multiple Sign-Volume sensitive regime EGARCH model (MSV-EGARCH)

In GARCH models the autoregressive structure in the variance specification allows for the persistence of volatility shocks, enabling to capture the frequently observed clustering of similar-sized price changes, the so-called ARCH effects. In this paper, using an EGARCH specification, the relationship between volatility, bad news and trading volume is re-examined through the modelling of multiple sign-volume-sensitive regimes in the conditional variance behaviour. This yields a distinctive EGARCH model specification that extends previous research by combining multiple news and volume asymmetric dynamics in a new conditional variance formulation.

In the original EGARCH(p, q) model, introduced by Nelson (1991), the conditional variance σ_t^2 is an asymmetric function of past unpredictable returns ε_t's:

$$\log \sigma_t^2 = w + \sum_{i=1}^{p} \beta_i \log \sigma_{t-i}^2 + \sum_{i=1}^{p} \alpha_i \frac{|\,\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}. \tag{1}$$

Unlike the symmetric GARCH(p, q) model in the EGARCH(p, q) specification no parameters restrictions are needed to ensure the non-negativity of the conditional variance and "bad news" (unexpected decreases in returns) are allowed to have a greater impact on future volatility when compared to "good news" (unexpected increases in returns) if the asymmetry parameters γ_i are negative. As most of the empirical papers in the financial econometrics literature deal only with (1,1)–type and due to its noteworthy success in financial volatility modelling, in this paper the simplest asymmetric EGARCH(1, 1) specification is adopted.

The proposed multiple sign-volume sensitive EGARCH model, MSV-EGARCH(1,1), is described by the following equations:

$$r_t = E\left(r_t|\Phi_{t-1}\right) + \varepsilon_t, \quad \varepsilon_t = z_t\sigma_t, \quad z_t \sim \mathrm{iid}(0,1), \tag{2}$$

$$\log \sigma_t^2 = w + \beta_1 \log \sigma_{t-1}^2 + \alpha_1 \frac{|\,\varepsilon_{t-1}|}{\sigma_{t-1}} + \sum_{i=1}^{3} \gamma_i N_{it} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \lambda V_{t-1} \tag{3}$$

where r_t is the continuously compounded daily rate of return at period t, ε_t is the conditional error term and V_{t-1} is a high/low volume indicator variable:

$$N_{it} = \begin{cases} 1 \text{ if } \begin{cases} (-i-1.25)\sigma < \varepsilon_{t-1} < -i\sigma & i = 0, 1.25 \\ \\ \varepsilon_{t-1} < -i\sigma & i = 2.5 \end{cases} \\ \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

$$V_{t-1} = \begin{cases} 1 \text{ if } \mathrm{Volume}_{t-1} > \frac{\sum_{i=2}^{51} \mathrm{Volume}_{t-i}}{50} \\ \\ 0 \text{ otherwise} \end{cases}, \tag{5}$$

where σ is the unconditional standard deviation of ε_t. Thus, the indicator variable V_{t-1} is "one" if the lagged volume is above its fifty days[1] lagged moving average, and is "zero" otherwise.

Equation (3) mimics many of the well known time series properties of traditional GARCH models and takes into account additional dynamic asymmetries. The conditional variance is assumed to be predicted by the previous conditional variance, the lagged shock terms and the above-average trading volume. The previous negative shocks are differentiated using indicator variables, which depend on the sign and intensity of the shocks.

2.1 Multiple Regimes

A fundamental idea in the proposed model specification is the existence of multiple thresholds in the conditional variance equation. Threshold parameters determine abrupt changes in the dynamics of the process as it moves through regions of the state space.

Financial time series present a non-negligible probability of occurrence of violent market movements. These significant market movements, far from being discardable as mere outliers, focus the attention of market participants since their magnitude may be such that they may account for an important fraction of the return accumulated over a large period of time. However, ARCH type models often fail to fully capture the nonlinearity in stock returns. A natural approach to address such nonlinearity is to define different regimes and to allow the dynamic behaviour of volatility to depend on the regime that occurs at any given point in time.

A pioneering effort to allow the data to estimate the shape of the conditional volatility equation was proposed in Engle and Ng (1993) Partially Non-Parametric (PNP) model:

[1]We follow Wagner and Marsh (2005) to determine the length of the moving average.

$$\sigma_t^2 = w + \beta\sigma_{t-1}^2 + \sum_{i=0}^{m+} \theta_i P_i(\varepsilon_{t-1} - i\sigma) + \sum_{i=0}^{m-} \delta_i N_i(\varepsilon_{t-1} + i\sigma), \tag{6}$$

where the range of $\{\varepsilon_t\}$ was divided into m intervals with break points at $i\sigma$ (m^+ positive intervals and m^- negative intervals) and $P_i = 1$ if ($\varepsilon_{t-1} > i\sigma$) and $N_i = 1$ if ($\varepsilon_{t-1} < i\sigma$).

This model, which regarded the long memory component as being parametric while the relationship between news and volatility was considered nonparametric, used equally spaced bins with knots at ε_{t-1} equal to 0, $\pm\sigma$, $\pm 2\sigma$, $\pm 3\sigma$ and $\pm 4\sigma$ (where σ is the unconditional standard deviation) to estimate the news impact curve.

In the empirical analysis of the PNP model, conducted for the Topix Index for the period ranging from 1980 to 1988, Engle and Ng found that the non-parametric approach was able to capture both the leverage and size effects and to outperform all the other estimated models: GARCH(1,1), EGARCH(1,1), Asymmetric-GARCH(1,1), VGARCH(1,1), Nonlinear-Asymmetric-GARCH(1,1) and GJR-GARCH(1,1). Nevertheless, several of the estimated parameters presented unexpected signs and magnitudes, and were found statistically insignificant, regarding the robust standard errors.

Hence, in contrast to Engle and Ng, in this paper the indicator intervals are chosen as less extreme multiples of the unconditional standard deviation of the unpredictable index returns series ε_{t-1}.

The conditional variance specification now proposed, accommodates both the sign and magnitude of return innovations. Levels of lagged ε_{t-1} are employed to capture the perception that volatility is related in an asymmetric way to lagged return innovations, with sharp drops in stock prices causing more future volatility than upturns cause. Furthermore, by allowing the existence of more than two regimes, the model specification extends the asymmetry of the EGARCH specification where the threshold is predetermined and equal to zero.

A fundamental idea in the proposed model specification is also the principle of parsimony. The aim of the model is to approximate the true data-generating process without incorporating an excessive number of coefficients. It would be possible to present multiple regimes with infinite threshold values. However, it would prove to be statistically unfeasible. The sample space of ε_t is therefore partitioned into m^- "news" intervals below zero. The model is estimated for $m^- = 3$ with kinks equal to 0, -1.25σ and -2.5σ.

Despite the groundwork of Engle and Ng, time series models that incorporate multiple thresholds in the conditional variance equation are rare. In fact, GARCH models tend to assume a rather stable environment, failing to capture irregular phenomena. One of the few exceptions is Medeiros and Veiga (2008) that found strong evidence of the existence of more than two regimes for most of the worldwide stock indexes analysed.

2.2 Volume

Trading volume can be considered as an important source of information in the context of the future volatility process, providing information which is not available from historical prices. In fact, whereas returns reflect average changes in market expectations as a whole, trading occurs when market participants value an asset differently. Thus, trading volume reflects the sum of the distinct investors' reactions, preserving the differences among individual investors that are averaged out in return data.

The inclusion of unexpected trading volume in equation (3) allows low and high volatilities to be triggered by positive and negative shocks and by the associated trading activity that flows into the market – a behaviour which standard GARCH models fail to accommodate. In fact, although the literature on the GARCH models is quite extensive, asymmetric GARCH models rely primarily on news shocks but tend to be silent on the role trading volume plays in market volatility.

We propose the use of "surprise volume" (Wagner and Marsh, 2005) as a volume variable which is defined as unexpected above-average trading activity. In contrast to those authors, the conditional volatility structure we propose does not consider a contemporaneous relation between volume and volatility, focusing, instead, in a lagged relation that is more suitable for forecasting. The reasoning is that portfolio reallocations for the market as a whole tend to be somewhat sticky, i.e., due to market uncertainty, non-trivial trading costs, short-sale restrictions, liquidity and time constraints; investors tend to take time to update their beliefs about the private information flows, to reassess their daily investment performance and then to restructure their portfolios, often adopting trend-following trading strategies.

Since high trading volume is usually associated with an influx of informed traders, prices tend to become more informative in these periods. In the MSV-EGARCH model specification, if period $t-1$ unexpected trading volume is positive, period t variance equation will include lagged unexpected trading volume as a regressor (V_{t-1}=1). When this occurs, the market values the sign ($\varepsilon_{t-1} > 0$ or $\varepsilon_{t-1} < 0$) and the size of the information reflected in the market in the preceding period, leading to an upward revision of period t conditional volatility. The model specification adopted assumes that more information arrives to investors when return moves are large and therefore allows "bad news" followed by significant volume to have much more impact on volatility than the traditional EGARCH model, whose asymmetry is based only on the sign of the lagged return innovations.

The adopted volume-volatility relation provides a market information aggregate-based explanation for both the volatility clustering and volatility persistence phenomena. Given that differences in the price reactions of investors to both good and bad news are partially lost by the averaging of prices, but are preserved in trading volume, the proposed conditional volatility model takes into account the sign of the shock, the size of the shock and the associated trading volume.

In addition, since information arrives at an uneven rate, periods of high and low volatility will tend to cluster. Lastly, given that financial asset trades must, at some future date, be reversed, volatility persistence will arise.

3 Statistical properties of returns

The empirical analysis is based on daily closing prices and trading volume for six major international stock market indexes from January 1, 1995 through April 30, 2008. The investigated indexes are the CAC 40 (France), DAX 30 (Germany), FTSE 100 (UK), NASDAQ 100 (United States), NIKKEI 225 (Japan) and S&P 500 (United States). All data series are drawn from Bloomberg and represent a local currency perspective. Dividends are not included in the calculation of the indexes.

The dataset contains several episodes of regional as well as global "market stress", involving high volatility. Noteworthy examples are the October 1997 Asian mini-crash, the 1998 Russian financial crisis, the March 2000 dot-com bubble crash, the September 2001 post-9/11 crash and the still prevailing subprime crisis.

Following the conventional approach, daily stock returns (r_t) are obtained by taking the logarithmic difference of daily stock index price data:

$$r_t = 100 \times \log\left(\frac{P_t}{P_{t-1}}\right) \tag{7}$$

Table 1 provides a general overview of the data used and presents preliminary descriptive statistics and diagnostics for the return series of each of the six stock indexes.

The sample moments for all return series indicate empirical distributions with heavy tails relative to the normal. Not surprisingly, the Jarque-Bera statistic (Jarque and Bera, 1987) rejects the normality assumption for each of the series.

Table 1: Summary statistics of returns

	CAC	DAX	FTSE	NASDAQ	NIKKEI	S&P500
Observations	3376	3370	3368	3356	3281	3355
Mean	0.0289	0.0358	0.0204	0.0469	-0.0107	0.0329
Median	0.0563	0.1099	0.0526	0.1396	0.0026	0.0623
Maximum	7.0023	7.5527	5.9038	17.2030	7.6605	5.5732
Minimum	-7.6781	-8.8747	-5.8853	-10.3777	-7.2340	-7.1127
Std. Dev.	1.3620	1.4880	1.0956	2.0465	1.4357	1.0846
Skewness	-0.1291	-0.2747	-0.1974	0.1287	-0.0811	-0.1156
Kurtosis	5.8233	6.3484	5.9275	7.1768	4.8760	6.3014
JB[a]	1616.66*	1224.56*	1474.95*	2448.74*	484.71*	1531.13*
LB Q(10)[b]	24.44*	22.26**	46.56*	31.46*	18.28**	18.68**
LB $Q^2(10)$[c]	1595.2*	2028.8*	2078.2*	1411.0*	406.4*	788.9*
ARCH-LM[d]	555.9*	644.68*	668.35*	560.76*	209.24*	353.39*

*, ** Denote significant at the 1% and 5% level, respectively
[a]JB is the Jarque Bera test for normality
[b]LB Q(10) is the Ljung-Box test for returns
[c]LB $Q^2(10)$ is the Ljung-Box test for squared returns
[d]LM is the Engle's Lagrange Multiplier test for conditional heteroskedasticity

The first striking feature is that the mean of daily returns is higher in NASDAQ and DAX and higher returns go hand in hand with higher standard deviations. The unfavourable outcome of Japanese stock returns is attributable to the fact that the Japanese market has been a bear market since 1989.

The excess of kurtosis ranges from 1.876 for the NIKKEI to 4.1768 for the NASDAQ, suggesting that big shocks, of either sign, are likely to be present.

According to the Ljung-Box statistics on returns, computed at a tenth-order lag, there is relevant autocorrelation in all of the stock indexes. The Ljung-Box statistic on the squared returns and the LM test for a tenth-order linear ARCH effect strongly suggest the presence of time-varying volatility. Since variations in ε_t^2 are not purely random, the variance is predictable, by conditioning the volatility of the process on past information.

4 Estimation results

4.1 In-sample and out-of-sample analysis

The proposed model is estimated through maximum likelihood (MLE)[2] under the assumption that the standardized innovations are independently and identically distributed (i.i.d.) with Student's t distribution.

The structure of the MSV-EGARCH model is such that it can adapt flexibly to capture different features of the conditional distribution of returns. However, altering the EGARCH specification through the introduction of additional parameters involves the risk of in-sample over-fitting. Therefore, it is essential to determine whether or not the improved in-sample fit is useful for forecasting out-of-sample.

The sample is partitioned in two distinct periods: the first 3/4 of the sample is retained for the estimation of parameters while the remaining 1/4 is considered as the forecast period. Parameters for the variance equation are therefore estimated for the 1995-2004 period (corresponding roughly to 2500 observations). These parameters are used to estimate the daily conditional volatility and together with the diagnostics constitute the in-sample set of results. To estimate the ex-ante out-of sample predictive power of the model, the estimated parameters are used to compute the conditional volatility in the following period (01/2005-04/2008).

The statistically significant returns autocorrelations are removed by fitting AR model specifications to the series (the mean equation parameters are represented by ϕ_j). In all cases the residuals become white noise.

To compare the conditional in-sample fitted MSV-EGARCH with the standard GJR (Glosten et al., 1993) and EGARCH asymmetric models, three likelihood based goodness-of-fit criteria are used. The first is the maximum log-likelihood value obtained from ML estimation. The second is the AIC: Akaike information criteria (Akaike, 1978) and the third is the SBC: Schwarz Bayesian criteria (Schwarz, 1978).

Out-of-sample volatility forecast evaluation is conducted by applying the modified Diebold-Mariano (Diebold and Mariano, 1995) test proposed by Harvey and Newbold (2000) to gauge

[2]Estimates are obtained using EVIEWS 5.0-based custom software.

whether the MSV-EGARCH encompasses the standard GJR and EGARCH models. According to Hansen (2005), when the comparison involves nested models (the MSV-EGARCH model nests EGARCH) it is more appropriate to apply a test for equal predictive accuracy (EPA), such as that of Harvey and Newbold (2000). In the null we state that each particular model (MSV-EGARCH, EGARCH and GJR) encompasses its competitors, in the sense that they do not contain useful information not present in the forecasts resulting from the model considered in the null.

Since volatility itself is not directly observable, establishing the effectiveness of the volatility forecast involves the use of a "volatility proxy" that may constitute an imperfect estimate of the true volatility, as mentioned by Andersen and Bollerslev (1998), Hansen and Lunde (2003) and Hansen and Lunde (2005). Following the conventional approach, squared returns are used as a proxy for the latent volatility process. However, as those authors argue, this volatility proxy can constitute a noisy estimator of the actual variance dynamics that can compromise the inference regarding the forecast accuracy. Yet, more recently, Patton (2006) showed that the squared daily returns constitutes in fact a valid volatility proxy.

4.2 Results

Tables 2 to 7 report in-sample results for the six stock indexes. The in-sample estimation results confirm that markets become more volatile in response to "bad news" (negative return surprises) as the sign of the parameters estimates proxying for asymmetry in the three regimes is always negative (the exception is NIKKEI's second regime). According to the Wald test, the differences among the three regimes estimates are statistically significant in the case of CAC, FTSE and NIKKEI, pointing to multiple regimes in financial volatility.

The results also confirm that above-average trading volume is an important factor to consider in explaining volatility, with volume playing the role of a switching variable between states. The estimates for the unexpected volume indicator variable are always positive and statistically significant in the case of DAX, NASDAQ, NIKKEI and S&P500. Thus, financial volatility increases with lagged above-average trading volume.

The largest log-likelihood values indicate that the MSV-EGARCH is the model more prone to have generated the data.

Regarding the information criteria, the proposed MSV model presents lower AIC values in the case of CAC, FTSE and NIKKEI. When the SBC is used instead, the standard EGARCH dominates the other two models: GJR and MSV-EGARCH. This is due to the fact that although both the Akaike and Schwarz criterion are based on parsimony, the Schwarz criterion imposes a larger penalty for additional coefficients, which penalizes in particular the additional complexity of the MSV specification. Thus, AIC and SBC provide inconclusive results in the French, English and Japanese stock indexes whereas both information criteria favour the standard EGARCH model in the case of DAX, NASDAQ and S&P500. The MSV-EGARCH outperforms the standard GJR in most of the six stock indexes whatever the information criteria considered.

INCLUDE TABLES 2 TO 7 HERE

In the out-of-sample analysis, based on Harvey-Newbold (HN) test (table 8), we fail to reject the null that the MSV-EGARCH forecasts encompass, or cannot be improved by combination with, the corresponding EGARCH and GJR volatility predictions at the 10% significance level in the case of CAC, DAX, FTSE and NASDAQ. The null is rejected at this significance level in the case of the NIKKEI and S&P, implying that combination of the EGARCH and/or GJR predictions with those of MSV-EGARCH would lead to an improvement in the NIKKEI and S&P forecast performance. Excluding the case of the FTSE index, the HN test results point to the same conclusions when one tests if EGARCH forecasts encompass those of the competing MSV-EGARCH and GJR. In contrast, the hypothesis that the GJR forecasts encompass its rivals is rejected in four of the six stock indexes.

Thus, even if the failure to reject the null hypothesis of forecast encompassing among multiple forecasts does not necessarily imply that the forecast under the null is superior and dominant with respect to its competitors, this constitutes one legitimate possibility (Harvey and Newbold, 2000). Based on this, along with the fact that the number of non null hypothesis rejections in the HN test is higher when compared to the standard EGARCH and GJR models, we can admit the superior predictability of the MSV-EGARCH model.

INCLUDE TABLE 8 HERE

5 Conclusions

Using daily data for six major international stock market indexes from January 1995, through April 2008, in this paper, the links between stock market returns, volatility and trading volume are analysed in a new nonlinear conditional variance framework. An innovative multiple regime EGARCH model is proposed, in opposition to the single zero threshold adopted by the conventional model. In this modified model, the asymmetry of the EGARCH is decomposed into multiple regimes, with the transition across regimes being controlled by threshold variables, related to the level of the unconditional standard deviation of the return series. In addition, the model smoothes the gap between theory and practice in volatility modelling by incorporating an on-off volume effect, with above-average trading volume playing the role of a switching variable between states.

An empirical example shows that multiple regimes are statistically significant for three of the return series analysed and also that above-average trading volume is an important factor to consider when explaining volatility.

A comparison between the increased flexibility of the proposed model and the parsimony of the conventional GJR and EGARCH specifications leads to goodness-of-fit statistics that are not unanimous regarding the in-sample superiority of the MSV-EGARCH model. Yet, when the predictive performance is compared, based on Harvey-Newbold encompassing test, there is evidence that MSV-EGARCH dominates the competing standard asymmetric models in several of the considered stock indexes.

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Table 2: MLE estimation results - CAC 40

Statistics	GJR	EGARCH	MSV
c	0.0436	-0.3716	-0.2632
ϕ_1	0.0056	-0.5639*	-0.5277*
ϕ_2	-0.0058	-0.5223**	-0.4834*
ϕ_3	-0.0514*	0.1048	0.1249
ω	0.0204*	-0.0611*	-0.0684*
β	0.932*	0.9835*	0.9868*
α	0.0174***	0.0299**	0.0266***
γ_1	0.0771*	-0.1063*	-0.1357**
γ_2			-0.0628*
γ_3			-0.1170*
λ			0.0176
TDF[a]	16.5112*	18.8506*	19.3995*
Log-lik	-4115.93	-4104.7	-4098.89
AIC	3.3441	3.3350	3.3327
SBC	3.3653	3.3562	3.3609
Wald[b]			5.694***

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a]"TDF" denotes the degrees of freedom for the Student's t distribution

[b]Wald tests the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 3: MLE estimation results - DAX 30

Statistics	GJR	EGARCH	MSV
c	0.0688*	0.1495	0.239
ϕ_1	-0.0225	-0.2968*	-0.3342*
ω	0.0232*	-0.124*	-0.1145*
β	0.9040*	0.9863*	0.985*
α	0.0409*	0.1075*	0.0926**
γ_1	0.0881*	-0.1007*	-0.046
γ_2			-0.0904**
γ_3			-0.0904**
λ			0.0257***
TDF[a]	14.5299*	14.6808*	13.2338*
Log-lik	-4252.63	-4242.14	-4240.018
AIC	3.4561	3.4476	3.448
SBC	3.4726	3.4641	3.472
Wald[b]			1.5186

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a]"TDF" denotes the degrees of freedom for the Student's t distribution

[b]Wald testS the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 4: MLE estimation results - FTSE 100

Statistics	GJR	EGARCH	MSV
c	0.0222	-0.1021	0.3294
ϕ_1	0.0003	-0.7602*	-0.7082
ω	0.0092*	-0.064*	-0.0628*
β	0.9363*	0.9862*	0.9841*
α	0.0019	0.0110	0.0048
γ_1	0.1047*	-0.1203*	-0.0468
γ_2			-0.0904**
γ_3			-0.1287*
λ			0.0132
TDF[a]	17.1293*	18.5901*	18.5318*
Log-lik	-3423.2	-3409.5	-3405.4
AIC	2.7752	2.7642	2.7633
SBC	2.7917	2.7806	2.7868
Wald[b]			3.8844**

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a] "TDF" denotes the degrees of freedom for the Student's t distribution

[b] Wald tests the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 5: MLE estimation results - NASDAQ 100

Statistics	GJR	EGARCH	MSV
c	0.0875*	-0.5620**	-0.5488
ϕ_1	-0.0344	-0.7160*	-0.7046*
ω	0.0394*	-0.0699*	-0.059*
β	0.9308**	0.9814*	0.9814*
α	0.0214*	0.0496*	0.0362*
γ_1	0.0769*	-0.1327*	-0.1017**
γ_2			-0.1414*
γ_3			-0.1050*
λ			0.0163***
TDF[a]	25.6564	47.1643	35.9078**
Log-lik	-5156.5	-5143.4	-5141.8
AIC	4.1851	4.1839	4.1851
SBC	4.2087	4.2004	4.2087
Wald[b]			1.5169

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a]"TDF" denotes the degrees of freedom for the Student's t distribution

[b]Wald tests the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 6: MLE estimation results - NIKKEI 225

Statistics	GJR	EGARCH	MSV
c	-0.0166	-0.6152**	1.0633
ω	0.0488*	-0.0274	-0.0655
β	0.919*	0.965*	0.9899*
α	0.0157***	0.0067	-0.0595**
γ_1	0.0875*	-0.2118*	-0.0957**
γ_2			0.0595***
γ_3			-0.0754
λ			0.0492*
TDF[a]	10.0875*	9.7254*	10.2751*
Log-lik	-4223.0560	-4222.7	-4212.5
AIC	3.5140	3.5136	3.5077
SBC	3.5284	3.5281	3.5293
Wald[b]			16.6815*

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a]"TDF" denotes the degrees of freedom for the Student's t distribution

[b]Wald tests the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 7: MLE estimation results - S&P 500

Statistics	GJR	EGARCH	MSV
c	0.0504*	0.2373**	0.1212***
ϕ_1	0.0058	0.5181*	0.5353*
ω	0.013*	-0.1081*	-0.073*
β	-0.0167***	1.0093*	0.9897*
α	0.9359*	-0.1885*	-0.1922*
γ_1	0.1386*	-0.4629*	-0.3838*
γ_2			-0.4098*
γ_3			-0.4283
λ			0.0508*
TDF[a]	10.8539*	10.9328*	11.3527*
Log-lik	-3505.089	-3494.8	-3490.9
AIC	2.8542	2.8458	2.8458
SBC	2.8707	2.8623	2.8658
Wald[b]			1.5216

*, **, *** denote significant at the 1%, 5% and 10% level, respectively

[a]"TDF" denotes the degrees of freedom for the Student's t distribution

[b]Wald tests the restriction that $\gamma_1 = \gamma_2 = \gamma_3$

Table 8: Harvey-Newbold forecast encompassing test (probability values are given in brackets)

Index	MSV	EGARCH	GJR
CAC 40	0.377 [0.539]	2.464 [0.117]	1.967 [0.161]
DAX 30	1.500 [0.221]	1.717 [0.190]	4.425 [0.036]
FTSE 100	1.314 [0.252]	3.288 [0.070]	5.739 [0.017]
NASDAQ 100	1.235 [0.267]	0.109 [0.742]	3.913 [0.048]
NIKKEI 225	4.447 [0.035]	3.204 [0.074]	5.157 [0.023]
S&P 500	4.509 [0.034]	4.978 [0.034]	0.267 [0.606]