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Master Thesis:

ESTIMATING VOLATILITY OF STOCK RETURNS: EVIDENCE FROM EMERGING MARKETS

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Contents

1. Introduction

Uncertainty and risk are crucial issues in economic theory and finance. The measure of an asset's risk is its volatility, which is defined as the conditional variance of its return. Empirical studies as early as in Mandelbrot (1963) had demonstrated that the variance of stock returns is time varying and persistent. However, until two decades ago econometric models focused mainly on the modeling of the conditional first moments. The increasing importance of risk management and the need for accurate volatility forecasts led to the development of models for the time-varying second-order moments of financial time series in recent years.

Volatility modeling and forecasting is a particularly important issue mainly in asset pricing and hedging, market making and portfolio selection. For example, volatility plays a key role in option pricing, as it is the only not directly observable variable in the Black and Scholes formula that determines the fair value of an option. Volatility is also input for the calculation of the Value at Risk of a financial position. Furthermore, volatility modeling can improve parameter estimation efficiency and interval forecast accuracy.

The first econometric tool for heteroskedastic variance modeling was the Autoregressive Conditional Heteroskedasticity (ARCH) model of R.F. Engle (1982) that inaugurated a voluminous literature concerning the theoretical properties, empirical applications as well as possible extensions and improvements of a new class of models. More than two decades after this seminal work, ARCH-type models remain of major importance in the field of volatility estimating and forecasting. Other methods have also been proposed in the literature such as continuous time models, nonparametric methods and implied volatility methods, while several papers encompass these methods into the traditional ARCH-type models. However, as Andersen and Bollerslev (1998b) and Engle (2002) indicate, ARCH models can still be of great practical importance in volatility forecasting and there are many new fields of research in which they can be extended

This study focuses on volatility estimation in emerging stock markets with the implementation of ARCH-type models. Theoretical and empirical properties of several ARCH-type models will be presented and their estimation and performance with daily stock data from different markets and under alternative evaluating criteria will be examined and compared. Data from fourteen emerging markets and four developed ones are utilized and the characteristics of conditional variance models are presented and confronted. The second dimension of the study is the examination of the conditional variance dynamics across stock markets and in particular the volatility transmission mechanism from developed stock markets to emerging ones. To this direction, the causality-in-variance test developed by Cheung and Ng (1996) is utilized. This test provides insight into the dynamics of stock prices and can be used to construct better econometric models. The forecasting performance of these augmented models is also a matter of research.

The results of the application indicate that each stock market requires a different ARCH-type model that better captures the characteristics of its conditional variance, however, some empirical findings, such as clustering and asymmetry are common across many markets. The selected ARCH-type models can fully account for heteroskedasticity, while the data period used for estimation appears to be an important factor. The explanatory variables suggested by the causality test improve the performance of models in-sample as well as out-of-sample (for the 1-step ahead forecasting horizon that is examined). United States and German stock markets are the major exporters of volatility towards emerging markets, while mean and variance spillover effects do not always stem from the same direction.

The rest of the study is organized as follows:

Section 2 presents some empirical findings of financial asset returns and volatility that have been documented in the literature, Section 3 presents briefly the existing volatility modeling methods, while Section 4 presents ARCH-type models and their theoretical properties. Section 5 makes a review of the volatility forecasting literature, while Section 6 summarizes the major findings of studies about emerging stock markets. Section 7 presents some existing models proposed for volatility spillover detecting and focuses in particular on Cheung and Ng (1996) methodology that is implemented in this study. Section 8 introduces the data employed in this study and describes their main characteristics, while Section 9 involves the estimation of mean and variance equations for each market. In section 10 variance causality patterns are detected and augmented models are estimated, while Section 11 involves the out-of-sample performance comparison. Finally, Section 12 concludes.

2. Empirical characteristics of asset returns and volatilities

In order to develop and select a conditional heteroskedasticity model, one must have a clear idea of what characteristics and regularities the model should capture. Some of these where observed many decades ago and are still common among many markets The most important ones are the following (Bollerslev et al.,1994; Engle & Patton, 2001):

- Asset returns tend to be leptokurtic, i.e. have fatter tails compared to the normal distribution. Mandelbrot (1963) and Fama (1965) were among the first to recognize this property.
- Volatility is time varying and not constant
- Volatility is clustering, which is evident when asset returns are plotted through time.

This means that large changes in the price of an asset (of either sign) tend to be followed by other large changes (of either sign) and small changes tend to be followed by small changes. This is an empirical finding that has been reported in numerous studies (Mandelbrot, 1963; Fama 1965; Chou, 1988 and Schwert, 1989). The result of clustering is that volatility shocks today will influence the expectation of volatility many periods in the future.

- Volatility seems to react differently to a big price increase or a big price drop as well as to negative returns and to positive returns (asymmetry).

Negative returns tend to increase conditional volatility, while positive returns tend to increase less or even decrease conditional volatility. Some researchers have suggested that this could be due to changes in leverage in response to changes in the value of equity (Black, 1976; Christie, 1982; Schwert, 1989). A drop in the value of the stock (negative return) increases financial leverage which makes the stock riskier and increases its volatility.

Others have argued that the asymmetry could rise from the feedback of volatility to stock price when changes in volatility induce changes in risk premium. If volatility is priced, an anticipated increase in volatility raises the required return on equity leading to an immediate stock price decline. French, Schwert and Stambaugh (1987) examine the intertemporal relation between risk (volatility) and expected stock returns. They use daily S&P data and find evidence of positive relation between the expected risk premium and the predictable level of volatility and of negative relation between excess holding period returns and the unpredictable component of volatility. The latter is of such a large magnitude that it cannot be fully explained by leverage hypothesis, giving rise to evidence of positive relation between expected risk premium and ex ante volatility.

Bekaert and Wu (2000) use the market portfolio and portfolios with different leverage, constructed from Nikkei 225, to examine these two explanations. They find that volatility feedback is enhanced by a strong conditional "covariance asymmetry" effect. When conditional covariance between market and stock returns responds more to negative than to positive market shocks, the volatility feedback is stronger. The covariance asymmetry is stronger for the high and low leverage portfolio than for the medium leverage portfolio.

Wu (2001) in order to provide a formal explanation for the observed asymmetry in volatility, models dividend volatility as a separate factor. He develops a volatility feedback model where the growth of a firm's dividend follows a stochastic volatility process, i.e. dividend shocks and dividend volatility shocks are two separate sources of uncertainty. Innovations of dividend growth and dividend volatility are allowed to be correlated. He finds that leverage effect and volatility feedback effect are both statistically significant in generating asymmetric volatility. The leverage effect contributes twice as much to the negative correlation between return and return variance as the volatility feedback effect does. Furthermore the total return consists of three parts: i. the conditional mean, which is the sum of the risk free rate plus a risk premium ii. the impact of dividend news and iii. the volatility feedback effect. News about dividends appears to have the biggest impact on returns. The volatility feedback effect is economically significant yet its magnitude is usually less than half of that of dividend news.

Glosten et al. (1993) find strict asymmetry in monthly US stocks returns in the sense that negative (positive) innovations increase (decrease) volatility.

- Non trading periods effect

when markets are closed information is accumulated and is reflected on prices when markets reopen. Fama (1965) has found that information accumulates more slowly when the markets are closed than when they are open. Variances are higher following weekend and holidays, but not as much as would be expected if the news arrival were constant.

- Comovements in volatility.

Black (1976) observed that when stock volatilities change, at market level and at individual stock level, they both change in the same direction. This comovement indicates that there are some common factors that may account for the temporal variation in the conditional variances and covariances of asset returns.

3. Volatility modeling methods

3.1 Basic classification

There exist several methods for volatility modeling, most of which aim at capturing the above mentioned characteristics. Andersen et al. (2002) provide a classification of the existing volatility measurement methods. The main distinction made is between parametric and nonparametric methods. The former explicitly parameterize expected volatility as a function of the past information set $\Im_{t-h}$, while the latter are data driven and offer direct ex-post empirical appraisals of volatility without any functional form assumptions.

PARAMETRIC METHODS:

The key distinguishing features are the functional form for the conditional moments (mean and variance) and the variables of the information set ($\Im_{t-h}$) , along with any additional distributional assumptions. The models included in this class are:

1. Discrete time models: i. ARCH models
   ii. Stochastic volatility models

2. Continuous time models: i. Continuous sample path diffusions
   ii. Jump diffusions & Levy driven processes

NONPARAMETRIC METHODS

Initial developments in the field of volatility measurement and forecasting were strictly parametric. However, recent literature has moved to less parametric or even nonparametric methods. While the estimates of parametric volatility measures depend explicitly on specific distributional assumptions, an alternative approach are model-free estimates based on squared returns over the relevant return horizon. The main methods are:

1. ARCH filters and smoothers: the basic idea is that, assuming that the sample path of price and the corresponding instantaneous volatility processes are continuous, an appropriately parameterized sequence of ARCH models will consistently estimate the instantaneous volatility at each point in time.
2. Realized volatility: it is the second sample moment of the return process over a fixed time interval scaled by the number of observations.

The parametric methods use the persistent, smoother aspects of conditional volatility, while non-parametric methods use the highly nonlinear response to large return shocks.

3.2. The use of implied volatility

As mentioned in the introduction, volatility is the only unobservable parameter in the Black-Scholes pricing formula. However, if an option is traded in the market and one assumes that a model such as the Black-Scholes governs options prices, then one can use the price observed in the market to obtain the "implied" volatility. Holding all the other parameters constant, the Black-Scholes formula yields a one-to-one relation between the option's price and the volatility of the underlying asset. Because implied volatilities are linked to current market prices, they are often regarded as better estimators of volatility than those based on historical data. If financial markets are informationally efficient, then implied volatility will be the market's expectation of future volatility and it should be an unbiased and well-informed estimator.

However, this approach is criticized because it uses a specific model based on assumptions that might not hold (e.g. lognormal return series). Furthermore, market irregularities also affect option-implied volatilities. Bid/ask spread, non-continuous trading, serial correlation induced by large blocktrades or non-synchronous trading will cause the observed transaction price to differ from the equilibrium market price. Figlewski (1997) indicates how bid-ask spread and tick size can make implied standard deviations different from the true volatility. Furthermore, if the pricing model is correct and the market is efficient, all options written on the same underlying should give the same implied volatility. However, empirical evidence shows implied volatilities differ across strike prices and moneyness giving rise to the observed volatility smiles, smirks and sneers.

Research on option implied volatility was initiated by Latane and Rendleman (1976). Further evidence on the use of implied volatility does gives contradictory results. Canina and Figlewski (1993) regress the volatility over the remaining contract life against the implied volatility of S&P 100 index options over 1983-1986. They report that Implied Standard Deviations have little predictive power for future volatility and are significantly biased forecasts. Furthermore implied volatilities appear to be worse than simple historical measures. Lamoureux and Lastrapes (1993) focus on individual stock options and find that historical time-series contain predictive information superior to that of implied volatilities. They view their results as a rejection of the joint hypothesis of market efficiency and of Black-Scholes class of option pricing models.

Jorion (1995) examines the informative content, as measured in terms of the ability of the explanatory variable to forecast 1-day volatility, and the predictive power, which focuses on the volatility over the remaining days of the contract, of implied standard deviations derived from CME options on foreign currencies futures (DM,SF, JY). He finds that statistical time series models are outperformed by option-implied forecasts. Even when accounting for measurement errors and statistical problems (due to infrequent trading, bid-ask spreads, stale prices etc), however, implied standard deviations remain biased volatility forecasts. The direction of the bias is such that ISDs appear to be too variable relative to future volatility. A linear transformation of the ISDs provides a superior forecast of exchange rate volatility.

Christensen and Prabhala (1998) reexamine the relation between implied volatility and the subsequent realized volatility using longer time series and sampling volatilities at monthly frequency, thus constructing volatility series with nonoverlapping data. Contrary to previous studies (e.g. Canina & Figlewski, 1993), they find that implied volatility provides less biased forecasts of future volatility than previously reported and that before the October 1987 Crash implied volatility appears more biased than afterwards. The Crash is associated with a structural change in the pricing of index options. They also find that past volatility has no incremental explanatory power over implied volatility.

3.3. Nonparametric Methods

In the recent literature an extensive use of realized volatility techniques has been observed. Andersen et al. (2001) use direct model-free measures of daily return volatility and correlation obtained from high-frequency intraday transaction prices on stocks of Dow Jones. They find that the unconditional distribution of the variances and covariances for all stocks are leptokurtic and highly skewed to the right, while the logarithmic standard deviations and correlations all appear approximately Normal. Moreover, returns scaled by standard deviations also appear Gaussian. There is strong evidence that equity volatilities and correlations move together possibly reducing the benefits to portfolio diversification. They confirm the existence of asymmetric relation between returns and volatility, however the effect is much weaker at the individual stock level than at the market level, lending support to a volatility risk premium feedback effect rather than a financial leverage effect.

In order to bridge the gap between ARCH modeling and realized volatility methods, Forsberg and Bollerslev (2002) build on the explicit modeling of realized volatilities and the Mixture of Distributions Hypothesis framework and apply the GARCH-NIG model. MD hypothesis postulates that the distribution of returns is normal, but with a stochastic (latent) variance. Using a 10-year sample of 5-minute returns of ECU versus USD, the authors find that realized volatilities constructed from the summation of the high frequency intraday squared returns conditional on past squared returns are approximately Inverse Gaussian distributed. Furthermore the daily GARCH model with NIG errors results in very accurate out-of-sample predictions.

Figlewski (1997) uses historical data in order to make volatility forecasts. The methodology involves computing historical volatility around an assumed mean of zero i.e. by averaging the squared returns and taking the squared root. This will be the forecast as of date t+1 for volatility over all future horizons. Realized volatility is then computed over the next T periods for all T values under examination and the forecast errors are recorded. The starting period is then advanced one data point and the process is repeated with one data point dropped off the beginning of the sample. This procedure, however, results in autocorrelation in forecast errors. Figlewski uses different sample sizes in order to make predictions for different forecasting horizons and some of the results are the following: i)Historical volatilities computed over many past periods provide the most accurate forecasts for both long and short horizons, ii)it typically increases forecast accuracy to compute volatility around an assumed mean of zero rather than around the realized mean in the data sample, except for very long time periods in relative low volatility markets.

In this non-parametric class other historical price models should also be included. The simplest historical model is *Random Walk* that assumes that variance is IID and uses volatility value at time t-1 to forecast volatility at time t. *Historical Average*, *Moving Average*, *Exponential smoothing* and *Exponentially Weighted Moving Average* are all based on past volatility prices but differ in the weights that are given to each observation.

3.4. Stochastic Volatility models

An alternative way to describe volatility is to introduce an innovation to the conditional variance equation of η_t. A Stochastic volatility model is defined as:

$$\varepsilon_t = \sigma_t \eta_t , \quad (1 - \alpha_1 B - \ldots - \alpha_m B^m) \ln (\sigma_t^2) = \alpha_0 + u_t$$

where η_t are iid N(0,1), u_t are iid N(0, σ_t^2), { ε_t} and { u_t} are independent, α_0 is a constant and all zeros of the polynomial 1 - $\sum_{i=1}^{m} \alpha_i B^i$ are greater than 1 in modulus. For each shock η_t the model uses two innovations η_t and u_t which makes the model more flexible. To estimate a SV model, we need a quasi-likelihood method via Kalman filtering or a Monte Carlo method since the density function for the model has no closed form and neither does the likelihood function.

4. ARCH-type models

4.1 Univariate models

As mentioned earlier, the explicit modeling of time variation in second- and higher-order moments began relatively recently. The linear **ARCH (q)** was the first model of this class introduced by Engle (1982). Poon and Granger (2001) mention that Engle's ARCH later extended to GARCH by Bollerslev has influenced 45 papers included in their review.

The general structure of the model is the following:

Let r_t be the log return of an asset at time index t and let us consider the conditional mean and conditional variance of r_t given the information set $\Im_{t-1}$:

$$\mu_t = E(r_t \mid \Im_{t-1}) \text{ and } \sigma_t^2 = Var(r_t \mid \Im_{t-1}) = E[(r_t - \mu_t)^2 \mid \Im_{t-1}]$$

Assuming that r_t follows a time series model such as stationary ARMA (p,q) we get the model: $r_t = \mu_t + \varepsilon_t$, $\mu_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$, where r_t, p, q are non-negative integers. Therefore, $\sigma_t^2 = Var(r_t \mid \Im_{t-1}) = Var(\varepsilon_t \mid \Im_{t-1})$. The manner in which σ_t^2 evolves over time distinguishes one volatility model from another.

ARCH supposes that the conditional variance, σ_t^2, is a linear function of past squared values of the process ε_t, the mean-corrected asset return.

$$\varepsilon_t = \sigma_t \eta_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = \alpha_0 + \alpha(L)\, \varepsilon_t^2$$

$$\text{with } \alpha_0 > 0 \text{ and } \alpha_i \geq 0 \text{ for } i > 0$$

where $\{\eta_t\}$ is a sequence of iid random variables with mean zero and variance one. Under the ARCH model, large past shocks tend to be followed by other large shocks, allowing for the modeling of the so called "volatility clustering" in returns.

The simplest model of this class is ARCH(1) model:

$$\varepsilon_t = \sigma_t \eta_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \quad \text{with } \alpha_0 > 0 \text{ and } \alpha_1 \geq 0$$

The unconditional mean of ε_t is zero because $E(\varepsilon_t) = E[E(\varepsilon_t \mid \Im_{t-1}] = E[\sigma_t E(\varepsilon_t)] = 0$.

The unconditional variance of ε_t is:

$$Var(\varepsilon_t) = E[E(\varepsilon_t^2 \mid \Im_{t-1}] = E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2) = \alpha_0 + \alpha_1 E(\varepsilon_{t-1}^2).$$

Because ε_t is a stationary process with $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = Var(\varepsilon_{t-1}) = E(\varepsilon_{t-1}^2)$, we have:

$$Var(\varepsilon_t) = \alpha_0 + \alpha_1 Var(\varepsilon_{t-1}) \text{ and } Var(\varepsilon_t) = \frac{\alpha_0}{1-\alpha_1},$$

$0 \leq \alpha_1 \leq 1$ (to ensure nonnegativity of variance).

In order to study the tail behavior of ε_t we need to calculate its fourth moment. $E(\varepsilon_t^4) = E[E(\varepsilon_t^4 \mid \Im_{t-1})\} = 3E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^2 = 3E[\alpha_0^2 + 2\alpha_0\alpha_1 \varepsilon_{t-1}^2 + \alpha_1^2 \varepsilon_{t-1}^4]$, under the normality assumption of ε_t. If ε_t is fourth-order stationary with $m_4 = E(\varepsilon_t^4)$, then we have

$$m_4 = 3E[\alpha_0^2 + 2\alpha_0\alpha_1 \operatorname{Var}(\varepsilon_t) + \alpha_1^2 m_4] = 3\alpha_0^2 \left(1 + 2\frac{\alpha_1}{1-\alpha_1}\right) + 3\alpha_1^2 m_4.$$

Consequently:

$$m_4 = \frac{3\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)}.$$

Therefore α_1 must satisfy the condition $(1 - 3\alpha_1^2)>0$, i.e. $0 \le \alpha_1^2 \le 1/3$.

The unconditional kurtosis of ε_t is $\frac{E(e_t^4)}{[\operatorname{Var}(e_t)]^2} = \frac{3\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)} \text{ x } \frac{(1-\alpha_1)^2}{\alpha_0^2} =$

$3\frac{1-\alpha_1^2}{1-3\alpha_1^2} > 3$.

Thus the excess kurtosis of ε_t is positive and the tail distribution of ε_t is heavier than that of a normal distribution. The shock ε_t of a Gaussian ARCH (1) model is more likely than a Gaussian white noise series to produce "outliers", which is consistent with the empirical evidence of "fat tails".

ARCH models allow positive and negative shocks to have the same effect on volatility because σ_t^2 depends on the square of the previous shocks. This contrasts with empirical studies that suggest asymmetry, i.e. that positive and negative shocks have a different impact on volatility. Furthermore, ARCH models impose restrictions on the values of the coefficients. For example, α_1^2, as stated above, must lie in the interval [0, 1/3] in order to have a finite fourth moment. Another weakness is that ARCH models require the estimate of a very large number of parameters in order to adequately describe the volatility process (in higher order ARCH). Bollerslev (1986) proposed an extension of this type of models, known as **Generalized ARCH** model. Using the same notation as before, a GARCH(p,q) is:

$$\varepsilon_t = \sigma_t \eta_t, \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 = \alpha_0 + \alpha(L)\,\varepsilon_t^2 + \beta(L)\,\sigma_t^2$$

with $\alpha_0>0$, $\alpha_i \ge 0$, $\beta_j \ge 0$ and $\sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i) < 1$. The latter constraint implies that the unconditional variance of ε_t is finite. The simplest model is GARCH (1,1):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad 0 \le \alpha_1, \beta_1 \le 1, \ (\alpha_1 + \beta_1)<1$$

A large ε_{t-1}^2 and σ_{t-1}^2 gives rise to a large σ_t^2, generating the well-known behavior of volatility clustering. Furthermore, it can be shown that

$$\frac{E(\alpha_t^4)}{[Var(\alpha_t)]^2} = \frac{3[1-(\alpha_1+\beta_1)^2]}{1-(\alpha_1+\beta_1)^2-2\alpha_1^2} > 3, \qquad (\alpha_1 + \beta_1)^2 + 2\alpha_1^2 < 1$$

Similar to ARCH models, the tail distribution of a GARCH (1,1) process is heavier than that of a normal distribution.

- If the forecast origin is h, for 1-step ahead forecast of a GARCH(1,1) model we have: $\sigma_{h+1}^2 = \alpha_0 + \alpha_1 \varepsilon_h^2 + \beta_1 \sigma_h^2$, where ε_h and σ_h are known at time index h. Therefore the 1-step ahead forecast is

$$\sigma_h^2(1) = \alpha_0 + \alpha_1 \varepsilon_h^2 + \beta_1 \sigma_h^2.$$

For multistep forecasts we use $\varepsilon_t^2 = \sigma_t^2 \eta_t^2$ and thus the volatility equation becomes:

$$\sigma_{t+1}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_t^2 + \alpha_1 \sigma_t^2 (\eta_t^2 - 1)$$

When t=h+1the equation becomes

$$\sigma_{h+2}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_{h+1}^2 + \alpha_1 \sigma_{h+1}^2 (\eta_{h+1}^2 - 1)$$

Since $E(\eta_{h+1}^2 - 1 | \Im_{t-1}) = 0$, the 2-step ahead volatility forecast becomes:

$$\sigma_h^2(2) = \alpha_0 + (\alpha_1+\beta_1)\, \sigma_h^2(1).$$

In general:

$$\sigma_h^2(l) = \alpha_0 + (\alpha_1+\beta_1)\, \sigma_h^2(l-1), \quad l>1.$$

By repeated substitutions, the l-step ahead forecast can be written as

$$\sigma_h^2(l) = \frac{\alpha_0[1-(\alpha_1+\beta_1)^{l-1}]}{1-\alpha_1-\beta_1} + (\alpha_1 + \beta_1)^{l-1} \sigma_h^2(1).$$

Therefore, $\sigma_h^2(l) \rightarrow \frac{\alpha_0}{1-\alpha_1-\beta_1}$ as $l \rightarrow \infty$, provided that $\alpha_1+\beta_1 < 1$.

It is shown in this way that the multistep ahead volatility forecasts of a GARCH(1,1) model converge to the unconditional variance of ε_t as the forecast horizon increases to infinity, provided that $Var(\varepsilon_t)$ exists.

- By recursively substituting for the lagged variance we can express the conditional variance as a weighted average of the lagged squared residuals :

$$\sigma_t^2 = \frac{\alpha_0}{1-\beta} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} \varepsilon_{t-j}^2$$

It is obvious that this model downweights more distant lagged squared errors.

- Let $\omega_t = \varepsilon_t^2 - \sigma_t^2$, so that $\sigma_t^2 = \varepsilon_t^2 - \omega_t$ and by plugging into the equation of the GARCH model, we have:

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i)\varepsilon_{t-i}^{\ 2} + \omega_t - \sum_{i=1}^{p} \beta_j \omega_{t-j}$$

the squared errors follow a heteroskedastic ARMA (p,q) process. The Autoregressive root which governs the persistence of volatility shocks is the sum $(\alpha_i + \beta_i)$.

The sizes of the parameters α and β determine the short-run dynamics of the resulting volatility series . Large GARCH coefficients β indicate that shocks to conditional variance take a long time to die out, so volatility is “persistent”. Large GARCH error coefficients α mean that volatility reacts quite intensely to market movements.

If the autoregressive polynomial of a GARCH(p,q) model has a unit root, i.e. $\alpha_1+\ldots+\alpha_q+\beta_1+\ldots+\beta_p = 1$ then we have the **IGARCH** model. A key feature of IGARCH models is that the impact of past squared shocks $\omega_{t-i} = \varepsilon_{t-i}^2 - \sigma_{t-i}^2$ for i>0 on ε_t^2 is persistent. An IGARCH(1,1) model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + (1- \alpha_1)\, \varepsilon_{t-1}^2, \quad 0<\alpha_1<1$$

The unconditional variance of ε_t is not defined under the IGARCH model.
When $(\alpha_i + \beta_i) = 1$, then by repeated substitutions in the equation

$$\sigma_h^2(l) = \alpha_0 + (\alpha_1+\beta_1)\, \sigma_h^2(l-1), \quad l>1$$

we have $\sigma_h^2(l) = \sigma_h^2(1) + (l-1)\,\alpha_0$. The effect of $\sigma_h^2(1)$ on future volatility is also persistent and the volatility forecasts form a straight line with slope equal to α_0. Currencies and commodities tend to have volatilities that do not mean-revert.

As shown in Nelson (1990a) and Bougerol and Picard(1992) the IGARCH model is strictly stationary and ergodic, though not covariance stationary.

If volatility changes are transitory, no significant changes in the discount factor or the price of a stock as determined by the net present value will occur. Formal tests for a unit root in variance have been performed by several authors and the null hypothesis of a unit root is typically not rejected. French et al (1987) find a unit root in the variance of S&P daily index, Chou(1988) finds a unit root in the volatility of NYSE value-weighted index and Pagan and Schwert(1990) find one in the variance of U.S. stocks.
Lamoureux and Lastrapes (1990) suggest that the observed high persistence of shocks to the conditional variance is a sign of structural change in the statistical process generating the variance.

Very often it is empirically observed or assumed that the expected return of an asset is related to its expected volatility, i.e. there is a compensation for bearing risk. The **GARCH in mean** (Engle, Lilien, Robins, 1987) model can take this fact into account. A simple GARCH(1,1)-M model can be written as

$$r_t = \mu + c\,\sigma_t^2 + \varepsilon_t, \quad \varepsilon_t = \sigma_t \eta_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\,\varepsilon_{t-1}^2 + \beta_1\,\sigma_{t-1}^2$$

where μ and c are constant. The parameter c is called risk premium parameter. A positive c indicates that the return is positively related to the asset's volatility. The formulation of the GARCH-M model implies that there are serial correlations in the returns series r_t. These serial correlations are introduced by those in volatility process $\{\sigma_t^2\}$. The existence of risk premium is therefore another reason for the serial correlations of historical stock returns.

Unlike the traditional GARCH, where one can get consistent estimates of the conditional mean parameters even in the presence of misspecified conditional variance estimates, a consistent estimation of the ARCH-M model requires that the full model be correctly specified.

The importance of ARCH models in finance is to a great degree attributed to the fact that the tradeoff between risk and return is crucial in financial theory. Three prominent theories in asset pricing have all found implementations using ARCH models: CAPM of Sharpe, Lintner, Mossin and Merton, Consumption-based CAPM of Breeden and Lucas and APT of Ross, Chamberlain and Rotschild.

CAPM suggests a linear relationship between the return and variance of the market portfolio. The ARCH-M model provides a tool for the estimation of this relationship. The relationship between conditional variance and excess returns is the coefficient of relative risk aversion. Applications of this model, as French et al(1987) and Chou (1988), generally result in positive estimates of the risk aversion parameter, which ranges from 1 to 4,5.

The parameter of estimate in the ARCH-M model is found to be sensitive with respect to different model specifications. Baillie and DeGennaro (1990) show that by changing the conditional distribution from Normal to Student-t, the parameter of conditional variance entering the mean equation changes from significant at 5% level to insignificant and of either sign. Furthermore, Glosten et al. (1991) find that the sign of the ARCH-M coefficient is sensitive to the instruments that are added to the mean and variance equations of the model.

The linear GARCH (p,q) is unable to capture the negative relation between current returns and future volatility. The conditional variance is only linked to past conditional variance and squared innovations, hence the sign of shocks plays no role in affecting the volatilities. This was one of the primary motivations for the EGARCH class of models. In these, volatility depends not only on the magnitude but also on the signs of past shocks in returns. Nelson (1991) proposed the **Exponential GARCH** (EGARCH) that allows for asymmetric effects of positive and negative asset returns.

$$\log \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i (\varphi z_{t-i} + \gamma[|z_{t-i}| - E|z_{t-i}|] + \sum_{j=1}^{p} \beta_i \log \sigma_{t-1}{}^2$$

where z_t are the standardized residuals: $z_t = \frac{\varepsilon_t}{\sigma_t}$.

Unlike the linear GARCH (p,q) model, there are no restrictions on the parameters α_i and β_i to ensure nonnegativity of the conditional variances. If $\alpha_i\varphi<0$, the variance tends to rise (fall) when ε_{t-1} is negative (positive) in accordance with the empirical evidence for stock returns. Assuming that z_t is iid normal, it follows that ε_t is covariance stationary provided all the roots of the autoregressive polynomial $\beta(\lambda) = 1$ lie outside the unit circle.

Taylor (1986) and Schwert(1989) assume that the conditional standard deviation is a distributed lag of absolute residuals, as in : $\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i |\varepsilon_{t-i}| + \sum_{j=1}^{p} \beta_j \sigma_{t-j}$, suggesting another ARCH-type model, the **Absolute value GARCH**.

Higgins and Bera(1992) nest the above GARCH formulation in the class **of non-linear ARCH (NARCH)** models:

$$\sigma_t^\gamma = \alpha_0 + \sum_{i=1}^{q} \alpha_i |\varepsilon_{t-i}|^\gamma + \sum_{j=1}^{p} \beta_j \sigma_{t-j}{}^\gamma$$

This relation can be further modified by setting

$$\sigma_t^\gamma = \alpha_0 + \sum_{i=1}^{q} \alpha_i |\varepsilon_{t-i} - \kappa|^\gamma + \sum_{j=1}^{p} \beta_j \sigma_{t-j}{}^\gamma \text{ for some non-zero } \kappa,$$

the innovations in σ_t^γ will depend on the size as well as the sign of lagged residuals, thereby allowing for leverage effects in stock return volatility. This formulation with $\gamma=2$ is a special case of Sentana' s (1991) quadratic GARCH (QGARCH) model in which σ_t^2 is modeled as a quadratic form in the lagged residuals (we will refer to this model later). A simple version of this model termed **asymmetric ARCH (AARCH)** was proposed by Engle(1990) . In the first order case the AARCH model becomes:

$$\sigma_t^2 = \alpha_0 + \alpha\varepsilon_{t-1}{}^2 + \delta\, \varepsilon_{t-1} + \beta\, \sigma_{t-1}{}^2$$

If $\delta<0$, then asymmetry is present.

Treshold GARCH (T-GARCH) is due to Zakoian (1991) and also allows for good and bad news to have different impact on conditional variance. The volatility equation in this model is:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \; \varepsilon_{t-1}^2 + \gamma \; \varepsilon_{t-1}^2 \, d_{t-1} + \sum_{j=1}^{p} \beta_i \; \sigma_{t-1}^2$$

where $d_{t-1} = 1$ if $\varepsilon_{t-1} <0$ and $d_{t-1} = 0$ otherwise.

Good news have an impact of α while bad news have an impact of α+γ. If $\gamma \neq 0$, the news impact is asymmetric.

GJR-GARCH model has been proposed by Glosten, Jagannathan and Runkle (1993). It modifies the conditional variance equation of the GARCH(1,1) model so as to allow for asymmetry. Specifically, GJR-model augments the variance equation of the GARCH(p,q) model with a variable equal to the product of S_t^- and ε_{t-1}^2, where S_t^- is a dichotomous dummy variable that takes the value of unity if ε_{t-1} is negative and zero otherwise. The conditional variance equation becomes:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \, \varepsilon_{t-1}^2 + \beta_1 \, \sigma_{t-1}^2 + \gamma \, S_t^- \, \varepsilon_{t-1}^2$$

It is obvious that this model allows for the coefficients of ε_{t-1}^2 to take different values corresponding to positive and negative shocks.

An alternative representation of this model is the following:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} [\, \alpha_i \; + \gamma_i I_{\{\varepsilon_{t-1}^2 > 0\}} \,] \; \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, \sigma_{t-j}^2$$

Engle and Ng (1993) study the effect of new information on the next period's variance. They introduce the concept of "News Impact Curve" so as to a measure how information is incorporated in volatility estimates. Keeping constant the information dated t-2 and earlier, one can examine the implied relation between ε_{t-1} (innovation in volatility in the previous moment) and the variance in time t, for alternative volatility models. This curve is called "News Impact Curve" and for the GARCH model it is a quadratic centered on $\varepsilon_{t-1}=0$. For the EGARCH it has its minimum at $\varepsilon_{t-1}=0$ and is exponentially increasing in both directions but with different parameters. If a negative innovation causes more volatility than a positive one, the GARCH model will underpredict the volatility following bad news and overpredict the volatility following good news. Furthermore, if large innovations cause more volatility than would be allowed by a quadratic function, the GARCH model will also underpredict volatility after a large shock. These observations lead to at least three new diagnostic tests for volatility models: sign-bias test, negative-sign-bias test and positive-sign-bias test.

Using Japanese daily stock return data for the sample period 1980-1988, the authors estimate the News Impact Curve for GARCH, EGARCH, AGARCH, VGARCH, GJR models and a partially non-parametric ARCH estimated model. The best models appear to be GJR and EGARCH giving, for reasonable values of surprises, similar forecasts as the partially non-parametric model.

Volatility Switching GARCH generalizes GJR-GARCH(1,1) and originates from the fact that the asymmetric behavior of conditional variance depends not only on the sign but on the dimension of the shock as well. The equation for conditional variance of the VS-GARCH(1,1) model is

$$\sigma_t^2 = (\alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2)(1 - S_t^-) + (\varphi_0 + \varphi_1 \varepsilon_t^2 + \gamma \sigma_{t-1}^2) S_t^-$$

Finally, **Q-GARCH** is originally due to Sentana (1995) and the equation for conditional variance is

$$\sigma_t^2 = \alpha_0 + \gamma_1 \varepsilon_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The term $\gamma_1 \varepsilon_{t-1}$ is added to the simple GARCH(1,1) model and allows for the asymmetric impact of positive and negative shocks. The equation can be rewritten as:

$$\sigma_t^2 = \alpha_0 + (\frac{\gamma_1}{\varepsilon_{t-1}} + \alpha_1) \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

If γ_1 is negative, the impact of negative shocks is larger that the impact of positive shocks. Moreover, the asymmetry of the impact varies as the dimension of the shock varies, in particular the asymmetric impact decreases as the dimension of the shock increases.

Hentschel (1995) treats the variance equation as a law of motion for the Box-Cox transformation and suggests that the following equation can nest all popular GARCH models:

$$\frac{\sigma_t^{l} - 1}{\lambda} = \omega + \alpha \sigma_{t-1}^{\lambda} f^{v}(\varepsilon_t) + \beta \frac{\sigma_{t-1}^{l} - 1}{\lambda}$$

where $f(\varepsilon_t) = |\varepsilon_t - b| - c(\varepsilon_t - b)$

By appropriately choosing the parameters λ, v, b and c, one can get almost every GARCH model as shown in the table:

λ	v	b	c	GARCH-MODEL
0	1	0	free	EGARCH (Nelson, 1991)*
1	1	0	$\lvert c\rvert \le 1$	TGARCH (Zakoian, 1991)
1	1	free	$\lvert c\rvert \le 1$	Absolute value GARCH (Taylor, 1986/Schwert, 1989)
2	2	0	0	GARCH (Bollerslev, 1986)
2	2	free	0	Non-linear-Asymmetric GARCH (Engle & Ng, 1993)
2	2	0	free	GJR-GARCH (Glosten, Jagannathan &Runkle, 1993)
free	λ	0	0	Nonlinear GARCH (Higgins & Bera, 1992)
free	λ	0	$\lvert c\rvert \le 1$	Asymmetric power ARCH (Ding, Granger & Engle, 1993)

*using L'Hopital ' s rule

The quadratic GARCH model of Sentana (1991) cannot be nested in this framework.

Hentschel applies the family of GARCH-M models to daily excess returns on U.S. equities, spanning the period January 1926 to December 1990 and estimates the unrestricted model which nests the GARCH models. The standard GARCH is rejected in favor of a model in which conditional standard deviation depends on the shifted absolute value of the shocks raised to the power three halves and past standard deviations.

As already mentioned, GARCH-type models have been extensively used in stock return data applications regarding: individual stock returns, index returns and futures markets returns. Most empirical implementations of GARCH(p,q) adopt low orders for the number of lags, p and q. Typically GARCH(1,1), GARCH(1,2) or GARCH(2,1) are adopted (e.g. French et al, 1987; Akgiray, 1989; Baillie and DeGennaro, 1990).

Pagan and Schwert (1990) compare alternative models for monthly stock volatility using U.S. data for the period 1834-1925. They use the following models: two-step conditional variance, GARCH(1,2), EGARCH(1,2), Markov switching-regime, Non-parametric Kernel and non-parametric Fourier method. Judging from the within-sample predictive power of the models, EGARCH model has the greatest explanatory power since it can reflect the asymmetric relation between volatility and past returns. However non-parametric procedures tend to give better explanations than parametric ones in sample. In out-of-sample prediction experiments non-parametric models fare worse and even with such an extended sample cannot overcome their inherent inefficiency. Augmenting GARCH and EGARCH models with terms suggested by non-parametric methods yields significant increases in explanatory power. A second result of the data analysis is that data taken over long periods cannot be assumed to be covariance stationary, e.g. before and after the Great Depression.

ARCH models have also been used in interest rate and foreign exchange markets. The first explicit ARCH formulation in the field of modeling volatility clustering in interest rate data is attributed to Weiss (1984) who estimates ARCH models on a set of 16 different macroeconomic time series, including monthly AAA corporate bond yields, and finds significant ARCH effects. Among many studies in foreign exchange markets, we mention Andersen and Bollerslev (1998), while West and Cho (1995) use weekly exchange rates of USD against the currencies of Canada, France, Germany, Japan and United Kingdom for the period 1973-1989 and compare the forecasting performance of the following volatility models: univariate homoskedastic (which sets the conditional variance equal to the sample mean of lagged residuals), GARCH(1,1) and IGARCH(1,1), autoregressive and a nonparametric estimator derived using a Gaussian kernel. Exchange rate returns appear to have zero conditional means and fat tails and exhibit serial correlation. The results can be summarized as following: Firstly, as expected, out-of-sample RMSEs are larger than in sample RMSEs. Second, surprisingly, RMSEs do not increase at longer horizons. Comparing alternative models, IGARCH appears to be the most consistent performer. However, in general, the choice of the best model varies from country to country and horizon to horizon. In a conventional test of efficiency, based on the regression of squared residuals on the forecasted volatility, none of the tests is found to perform well.

4.2 Multivariate GARCH models

We may have a vector of asset returns whose conditional covariance matrix evolves over time. Suppose we have N assets with return innovations $\eta_{i.t-1}$, i=1,2…,N. We stack these innovations into a vector η_{t+1}= [$\eta_{i,t+1}$ … $\eta_{N,t+1}$] ' and define $\sigma_{ii,t}$ = Var ($\eta_{i,t+1}$) and $\sigma_{ij,t}$ = Cov ($\eta_{i,t+1}$, $\eta_{j,t+1}$); Hence Σ = [$\sigma_{ij,t}$] is the conditional covariance matrix of all the returns.

It is often convenient to stack all the nonredundant elements of Σ_t (on and below the diagonal) into a vector. The operator which performs this stacking is known as the vech operator: vech (Σ_t) with N(N+1)/2 elements.

VECH model of Bollerslev et al (1988) writes the covariance matrix as a set of univariate GARCH models. Each element of Σ_t follows a univariate GARCH model driven by the corresponding element of the cross-product matrix $\eta_t \eta_t'$.

$$VECH(\Sigma_t) = C + A\, VECH(\eta_t, \eta_{t-1}') + B\, VECH(\Sigma_{t-1}), \quad \eta_t \mid \Psi_{t-1} \sim N(0,H_t),$$

where C is an (N(N+1)/2) vector containing the intercepts in the conditional variance and covariance equations, A and B are N(N+1)/2 * N(N+1)/2 matrices containing the parameters on the lagged disturbance squares or cross-products and on the lagged variances or covariances respectively. The implied conditional covariance matrix is always positive definite if the matrices of the parameters C, A and B are all positive definite. The model has three parameters for each element of Σ_t thus 3N(N+1)/2 in all.
This models, however, does not allow for and co-persistence in variance, neither for asymmetries.

BEKK model of Engle and Kroner(1995) guarantees the positive definiteness of Σ_t by working with quadratic forms rather than the individual elements of Σ_t.

$$\Sigma_t = C'C + B' \Sigma_{t-1} B + A' \eta_t \eta_t' A$$

where C is a lower triangular matrix with N(N+1)/2 parameters, B and A are square matrices with N^2 each, for a total parameter count $(5N^2+N)/2$. Weak restrictions on A and B guarantee that Σ_t is always positive definite.

Bollerslev (1990) has proposed a **Constant Correlation model** in which each asset return variance follows a univariate GARCH(1,1) model and the covariance between any two assets is given by a constant-correlation coefficient multiplying the conditional standard deviation of returns:

$$\sigma_{ii,t} = \omega_{ii} + \beta_{ii}\, \sigma_{ii,t-1} + \alpha_{ii}\, \eta_{it}^2$$

$$\sigma_{ij,t} = \rho_{ij} \sqrt{\sigma_{ii,t}\, \sigma_{jj,t}}$$

N(N+5)/2 parameters

It gives a positive definite covariance matrix provided that the correlations ρ_{ij} make up a well-defined correlation matrix and the parameters ω_{ii}, β_{ii} and α_{ii} are positive.

A special case of the BEKK model is the **single-factor GARCH**(1,1) model of Engle et al(1990). In this model we define N-vectors λ and w αand scalars α and β and then have:

$$\Sigma_t = C'C + \lambda\lambda' [\beta\, \omega' \, \Sigma_{t-1}\, w + \alpha\, (w' \eta_t)^2]$$

It is convenient to set iw=1, i is vector of ones. The vector w can be thought of as a vector of portfolio weights. We define: $\eta_{pt} = w' \eta_t$ and $\sigma_{ij,t} = \omega_{ij} + \lambda_i \lambda_j \sigma_{pp,t}$ and

$\sigma_{pp,t} = \omega_{pp} + \beta\, \sigma_{pp,t-1} + \alpha\, \eta_{pt}^2$

The covariance of two asset returns moves through time only with the variance of the portfolio return which follows a univariate GARCH(1,1) model. The single-factor GARCH(1,1) model is a special case of the BEKK where matrices A and B have rank one: $A=\sqrt{\alpha}\, \omega\, \lambda'$ and $B= \sqrt{\beta}\, \omega\, \lambda'$. It has $(N^2 +5N +2)/2$ parameters. The model can be extended forward to allow for multiple factors or a higher-order GARCH structure.

Finally, the **orthogonal GARCH** model is a generalization of the factor GARCH model introduced by Engle et al(1990) to a multi-factor model with orthogonal factors. It allows k*k GARCH covariance matrices to be generated from just m univariate GARCH models. Normally, m, the number of principal components, will be much less than k, the number of variables in the system. This is so that extraneous “noise” is excluded from the data and the volatilities and correlations produced become more stable. In the orthogonal GARCH model the m*m diagonal matrix of variances of the principal components is a time-varying matrix denoted by D_t, and the time-varying covariance matrix V_t of the original system is approximated by

$$V_t = A\, D_t\, A'$$

where A is the k*m matrix of rescaled facto weights. This model is called orthogonal GARCH when the diagonal matrix D_t of variances of principal components is estimated using a GARCH model. This representation will give positive semi-definite matrix at every point in time, even when the number m of principal components is much less than the number k of variables of the system. Of course, the principal components are only unconditionally uncorrelated, but the assumption of zero conditional correlations has to be made, otherwise it misses the whole point of the model, which is to generate large GARCH covariance matrices from GARCH volatilities alone. The degree of accuracy that is lost by making this assumption is investigated by a thorough calibration of the model, comparing the variances and covariances produced with those from other models such as EWMA or, for small systems, with full multivariate GARCH.

4.3 Sources ARCH effects

An interesting issue is what causes the ARCH effect, i.e. the serial correlation, in financial time series. One possible explanation is the presence of a serially correlated news arrival process. Bollerslev and Domowitz (1991) have shown how the actual market mechanisms may themselves result in temporal dependence in volatility of transaction prices with a particular automated trade execution system inducing a very high degree of persistence in the variance process.

Lamoureux and Lastrapes (1990b) argue that the ARCH is a manifestation of clustering in trading volumes. They introduce the contemporaneous trading volumes in the GARCH(1,1) equation at individual firm's level and they discover that the lagged squared residuals are no longer significant. A simultaneity problem, however, may bias their results, as several other studies have documented contemporaneous correlations between volume and price data. At macroeconomic level, relevant economic variables driving stock volatilities have been proposed by various researchers. Campbell (1987) and Glosten et al (1991) have found that nominal interest rates are significant determinants of volatility. Other studies report that dividend yields, business cycle and financial crises drive stock volatilities.

4.4 Weakness and perspectives for ARCH models

The class of ARCH/GARCH models are just one of the existing parametric methods existing in the literature. Their applications have been extensive, however they are not without weaknesses. Some stylized facts in volatility modeling that are not captured by ARCH/GARCH models (Poon and Granger, 2001) are the following:

- Standardized residuals from ARCH/GARCH models still display large kurtosis, even when Student-t distribution is used to construct the likelihood function. That is, conditional heteroskedasticity alone cannot account for all excess kurtosis.
- The null hypothesis of a unit root in variance is not rejected in several studies based on different stock market data (for example French at al, 1987; Pagan and Schwert, 1990)
- GARCH effect disappears when large shocks are controlled for (Aggarwal, Inclan and Leal, 1999)

Futhermore, Figlewski (1997) mentions the following weaknesses:

- ARCH models require a large number of data points for robust estimation which requires estimating a large number of parameters
- the larger the number of parameters and the data points, the better the model will tend to fit in-sample and the quicker it will tend to fail out-of-sample (this, however, is a general problem affecting all models)

- ARCH models are not designed to make forecasts over long horizons, as they are unable to incorporate any new information from the unknown future disturbances and after some periods ahead they converge to the long run variance at a rate that depends on the values of the parameters.

However, one should recognize that ARCH models offered new tools for measuring risk and its impact on returns as well as for pricing and hedging non-linear assets such as options. Another application is in the field of credit risk management. A variety of studies, such as Christoffersen and Diebold (2000) and Christoffersen, Hahn and Inoue (2001), examined the usefulness of volatility models in computing Value at Risk and compare these methods with the exponential smoothing approach favored by Riskmetrics.

Engle (2002), twenty years after the publication of the ARCH model, recognizes that the number of relevant surveys and applications is vast, but he also identifies that there are still promising areas for future research. In particular, he mentions the following "new frontiers" for ARCH models.

- High Frequency data volatility models

The study of volatility models at intraday frequency is a natural extension of daily models. So far, High Frequency models focus on regularly spaced observations but it is desirable that models for irregularly spaced data (tick data or ultra-high frequency data) be found, for which the frequency of trades arrivals, the existence of spreads and other economic variables may be important for forecasting volatility. Andersen et al (2001) and Andersen and Bollerslev (1998) build models upon intra-daily realized volatility and use this measure to improve daily volatility forecasts.

The class of fractionally integrated GARCH models (FIGARCH) was proposed by Baillie, Bollerslev and Mikkelsen (1996) and aims at modeling the long memory in volatility series. Similarly to the ARFIMA models for the conditional mean, a shock in the conditional variance in the FIGARCH models is transitory, i.e. it dies out at a slow hyperbolic rate of decay. FIGARCH models provide an added flexibility for understanding the long-run dependencies. Bollerslev and Mikkelsen (1996) use daily S&P data and demonstrate that US stock market volatility is best described by a mean-reverting fractionally integrated process and that FIGARCH and FIEGARCH models have the best fit compared to traditional GARCH models. Martens (2002) uses S&P100 index-futures prices and 5-minute returns to forecast daily stock market volatility. Modeling the volatility of overnight returns in a different way from the volatility of intraday returns leads to optimal forecasting performance. Martens and Zein (2002) indicate that volatility forecasts based on historical intraday returns do provide good volatility forecasts that can compete with implied volatility and even outperform it. They use data from futures and options on futures on S&P 100 and JY/USD exchange rate and 5-min returns for floor trading and 30-min returns for overnight trading. The daily realized standard deviation is modeled as a fractionally integrated process. Oomen (2001) uses high frequency FTSE-100 stock index data and models the realized volatility as an Autoregressive Fractionally Integrated Moving Average (ARFIMA) process, which is found to outperform conventional GARCH-type models. ARFIMA can account for the long memory property of the logarithmic realized variance, however it is a complicated and data-intensive method.

- Multivariate models

As computation becomes cheaper and quicker, the potential for building large time-varying conditional covariance and correlation matrices increases. Correlations can also be estimated on intraday basis, however, as frequency increases, the asynchronicity of trades and returns leads to a serious underestimate of comovements. This requires a solution.

- Options Pricing and Hedging

An issue of future research is the pricing of options when the underlying asset follows a GARCH model. Furthermore, several papers both options and underlying asset data to estimate both the risk neutral and objective densities with more complex time series properties in an attempt to understand the skew in index options volatilities.

- Application of ARCH models to the broad class of non-negative processes

The Multiplicative Error Model (MEM) which specifies an error that is multiplied times the mean and which is used in the family of ARCH and GARCH models themselves, can be expanded and used in various financial applications based on non-negative time series.

- Use of Monte Carlo to examine non-linear properties of any model that can be estimated

The volatility of volatility (VoV) for several conditional volatility models can be estimated via Monte Carlo simulation, enabling comparisons even for GARCH models for which no analytic results are available. Furthermore, simulation methods can be utilized in order to estimate stochastic volatility models.

Finally, it should be noted that traditional GARCH models are discrete-time approaches to volatility modeling. However, many models in asset pricing and risk management are developed in a continuous time framework. Therefore, many studies examine GARCH models and their properties in continuous time. Nelson (1990) shows that GARCH(1,1) model and EGARCH converge to continuous time diffusion processes as the sample interval goes to zero. Nelson (1992) and Nelson and Foster (1999) also show that ARCH models fitted to high frequency data provide optimal and consistent estimates of the true volatility underlying a given observation system. Drost and Werker (1996) aim at extending the discrete time GARCH processes to GARCH diffusions and GARCH jump-diffusions. They demonstrate that in order to estimate continuous time GARCH processes it suffices to estimate the discrete time GARCH parameters for the available data frequency.

5. Forecasting Volatility

Poon and Granger (2001) mention that at the time of writing their study there were 72 published and working papers that compared the forecasting performance of volatility models.

The ultimate goal of a volatility model is to provide accurate volatility forecasts. If volatility is constant and returns are iid then the unconditional variance of returns over a long horizon can be derived from a single multiple of single period variance. But this is not likely to be the case. While a point forecast becomes very noisy as the forecast horizon tends to infinity, a cumulative forecast becomes more accurate because volatility is mean-reverting.

Akgiray (1989) was the first to use the GARCH model to forecast volatility. He finds that GARCH(1,1) outperforms the other historical price models (simple historical average, white noise process, EWMA model, ARCH) in every subperiod and for every evaluation measure.

Christoffersen and Diebold (1998) develop a model-free procedure for assessing volatility forecastability across horizons and they find that it decays quickly with the horizon. They examine asset return forecastability as a function of the horizon over which returns are computed. Equity return volatility appears to be significantly forecastable for horizons of less than 10 days. The same result holds for exchange rates as well. Consistently with existing evidence, they also find that bond markets offer more volatility forecastability as far ahead as 15-20 trading days. Their results are consistent with academic studies such as West and Cho (1995) who find that volatility forecasts in foreign exchange markets are not of much importance beyond a 5-day horizon. Furthermore, they also agree with studies documenting slow decay in long-lag autocorrelations of squared or absolute returns, which indicates long-memory volatility dynamics and forecastability of volatility at very long horizons (Andersen and Bollerslev (1997)). This studies, however, tend to work with very high frequency data and thus forecastability of volatility many steps into the future does not necessarily indicate forecastability beyond 10 or 20 days.

The sample frequency does not improve the forecast accuracy of the mean but if data are sampled more frequently vast improvements in volatility estimates can be made (Andersen and Bollerslev, 1998). On the other hand, as frequency gets ultra high, other problems such as non-synchronous trading and bid-ask spreads can appear, that can cause spurious autocorrelation.

In the other extreme, Figlewski (1997) finds that forecast error is doubled in size when daily instead of monthly data are sampled in order to forecast volatility over 24 months.

Any estimator of a parameter of the current or future return distribution has a distribution itself. A point forecast of volatility is just the expectation of the distribution of the volatility estimator, but in addition to the expectation of the distribution of the estimator one might also estimate the standard deviation of the distribution of the estimator, that is the standard error of the volatility forecast. A process volatility is never observed; even ex post we can only know an estimate, the realization of the process volatility that actually occurred. The only observation is on the market return. A 1-day ahead volatility forecast is the standard deviation of the 1-day return, so a 1-day forecast should be compared with the relevant 1-day return.

GARCH volatility term structures

The real strength of the GARCH model is that volatility forecasts for any maturity may be obtained from the estimated model. Term structure forecasts constructed from GARCH models mean-revert to the long-term level of volatility at a speed that is determined by the estimated GARCH parameters.

The first step is to construct forecasts of instantaneous forward volatilities-that is the volatility of r_{t+j} made at time t for every step ahead j. For example, in the GARCH(1,1) model the 1-day forward forecast is

$$\sigma_{t+1}^2 = \omega + \alpha \varepsilon_t^2 + \beta \sigma_t^2$$

and the j-step ahead forecasts are computed iteratively as

$$\sigma_{t+j}^2 = \omega + (\alpha + \beta)\sigma_{t+j-1}^2$$

(the unexpected return at time t+j is unknown for i>0, but $E(\varepsilon_{t+j}^2) = \sigma_{t+j}^2$

Putting $\sigma_{t+j}^2 = \sigma^2$ for all j gives the steady-state variance estimate

$$\sigma^2 = \omega / (1-\alpha-\beta)$$

and this determines the long-term volatility level to which GARCH(1,1) term structure forecasts converge if $\alpha + \beta < 1$.

To construct a term structure of volatility forecasts from any GARCH model, first note that the log return at time t over the next h days is $r_{t,h} = \sum_{j=1}^{h} \mathbf{r}_{t+j}$

Since $V_t(r_{t,h}) = \sum_{j=1}^{h} \mathbf{V_t}(\mathbf{r}_{t+i}) + \sum_{\mathbf{i}} \sum_{\mathbf{j}} \mathbf{cov}(\mathbf{r}_{t+i}, \mathbf{r}_{i+j})$

the GARCH forecast of h-period variance is the sum of the instantaneous GARCH forecast variances, plus the double sum of the forecast autocovariances between returns. The double sum will be very small compared to the first sum on the right-hand side of the equation-indeed, in the majority of cases the conditional mean equation in a GARCH model is simply a constant, so the double sum is zero. Hence we ignore the second term and construct h-day forecasts simply by adding the j-step-ahead GARCH variance forecasts. These are square-rooted and annualized with the appropriate factor to give GARCH h-day volatility forecasts. (for a GARCH model based on daily returns with A daily returns per year, the annualizing factor for the h-day forecast is A/h).

Confidence Intervals for Volatility Forecasts

The covariance matrix of the parameter estimates in a GARCH model can be used to generate GARCH confidence intervals for conditional variance. For example, the variance of the one-step-ahead variance forecast in a GARCH(1,) model is

$$V_t(\hat{\sigma}_{t+1}^2) = V_t(\hat{\omega}) + V_t(\hat{\alpha})\varepsilon_t^4 + V_t(\hat{\beta})\hat{\sigma}_t^4 + 2\,\mathrm{cov}_t(\hat{\omega},\hat{\alpha})\varepsilon_t^2 + 2\,\mathrm{cov}_t(\hat{\omega},\hat{\beta})\hat{\sigma}_t^2 + +2\mathrm{cov}_t(\hat{\alpha},\hat{\beta})\varepsilon_t^2\,\hat{\sigma}_t^2$$

Forecasting performance evaluation

Most empirical studies estimate a number of different models and then evaluate them on the basis of their forecasting performance.

- Among the most popular statistics to evaluate and compare forecast errors are the following:

MEAN ERROR : $\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)$

MEAN ABSOLUTE ERROR: $\frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2 - \sigma_t^2\right|$

ROOT MEAN SQUARED ERROR: $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2}$

MEAN ABSOLUTE PERCENTAGE ERROR: $\frac{1}{T}\sum_{t=1}^{N}\left|\frac{\hat{\sigma}_t^2 - \sigma_t^2}{\sigma_t^2}\right|$

where $\hat{\sigma}_t^2$ is the forecast from a specific conditional variance equation and σ_t^2 is the subsequent realized volatility for the corresponding horizon.

Much of the literature on volatility forecasting uses the root mean square error (RMSE) criterion. But while a RMSE may be fine for assessing price forecasts, or any forecasts that are of the mean parameter, there are problems with using the RMSE criterion for volatility forecasting. In fact, the “minimize the RMSE” criterion is equivalent to the “maximize the likelihood” criterion when the likelihood function is normal with a constant volatility. Hence RMSEs are applicable to mean predictions rather than variance or covariance predictions. Despite this fact, the RMSE is often used to compare the forecast of variance with the appropriate squared return. The difference between the variance forecast and the squared return is taken as the forecast error. These errors are squared and summed over a long post-sample period, and then square-rooted to give post-sample RMSEs. However, these RMSE tests will normally give poor results, because although the expectation of the squared return is the variance, there is a very large standard error around this expectation. That is, the squared returns will jump about excessively while the variance forecasts remain more stable. The reason for this is that the return, r_t, is equal to $\sigma_t z_t$, where z_t is a standard normal variate, so the squared return yields very noisy measurements due to excessive variation in z_t^2.

Furthermore, the above mentioned error statistics assume that the loss function is symmetric. However, in many financial applications over- and under-predictions of volatility are not of the same importance.

- The asymmetry in the loss function can be accounted for using an error statistic which penalizes under-predictions more heavily and is called the Mean Mixed Error (MME(U)):

MME(U)= $\frac{1}{T}\left[\sum_{T=1}^{O}\left|\hat{\sigma}_T^{\,2}-\sigma_T^{\,2}\right|+\sum_{T=1}^{U}\sqrt{\left|\hat{\sigma}_T^{\,2}-\sigma_T^{\,2}\right|}\right]$, where O is the number of over-predictions and U is the number of under-predictions.

Similarly, the above statistic can be redefined so as to weight over-prediction more heavily:

$$\text{MME(O)}=\frac{1}{N}\left[\sum_{T=1}^{O}\sqrt{\left|\hat{\sigma}_T^{\,2}-\sigma_T^{\,2}\right|}+\sum_{T=1}^{U}\left|\sigma_T^{\,2}-\sigma_T^{\,2}\right|\right]$$

Other statistics that appear in the literature are Theil-U and LINEX, defined as following:

$$\text{Theil-U}=\frac{\sum_{i=1}^{N}(\hat{x}_i-x_i)^2}{\sum_{i=1}^{N}(\hat{x}_i^{\,BM}-x_i)^2}$$

The Theil-U statistic standardizes the prediction error by the error from a benchmark model used to remove the effect of any scalar transformation applied to x. (e.g. Random walk model that assumes that the best forecast of the next period's volatility is this period's volatility). One advantage of this statistic is that it is invariant to scalar transformation. However, it is symmetric.

$$\text{LINEX} = \frac{1}{N}\sum_{i=1}^{N}[\exp\{-\alpha(\hat{x}_i - x_i)\} + \alpha(\hat{x}_i - x_i) - 1]$$

In the LINEX loss function, positive errors are valued differently from negative ones, according to the sign of α (a positive value of α penalizes under-predictions more heavily). If α>0 the function is approximately linear for overpredictions and exponential for underpredictions. One argument in favor of LINEX function is that it provides the analytical solution for the optimal prediction under conditional normality. However, the choice of α is subjective.

- Another common statistical measure of accuracy for a volatility forecast is the *likelihood of the return*, given the volatility forecast. That is, the value of the probability density at that point. Suppose that we want to compare the accuracy of two different volatility forecasting models. Suppose model A generates a sequence of volatility forecasts, $\{\hat{\sigma}_{t+1}, \ldots, \hat{\sigma}_{t+T}\}_A$ and model B generates a sequence of volatility forecasts $\{\hat{\sigma}_{t+1}, \ldots, \hat{\sigma}_{t+T}\}_B$. For model A we compare each forecast $\hat{\sigma}_{t+j}$ with the observed return on that day, r_{t+j}, by recording the likelihood of the return. The out-of-sample likelihood of the whole sequence of forecasts is the product of all the individual likelihoods, and we can denote this L_A. Similarly, we can calculate the likelihood of the sample given the forecasts made with the model B, L_B. If over several such post-sample predictive tests, model A consistently gives higher likelihoods than model B, we can say that model A performs better than B.

Different volatility forecasting models may be ranked by the value of the out-of-sample likelihood, but the effectiveness of this method does not rely on the correct specification of the return distributions. It is unlikely that a given forecasting model will be more accurate according to all possible statistical and operational evaluation criteria as well as in all underlying market conditions.

- Another popular evaluation metric is obtained via the ex-post squared return - volatility regression:

$$r_{t+1/m}^{2} = \alpha + \beta\, \sigma_{t+1/m}^{2} + u_{t+1/m}$$

If the volatility model is correctly specified, then α and β should equal zero and one respectively. The coefficient of multiple determination, R^2, from this regression is often interpreted as a direct assessment of the variability of the ex-post volatility that can be explained by the estimates generated by a model.

However, as Andersen and Bollerslev (1998b) indicate, the use of R^2 as a guide to the accuracy of volatility forecasts is problematic. Financial applications focus on the future volatility and not on the subsequent realized volatility. Under the null hypothesis that a specific estimated model constitutes the correct specification, the true variance is by definition identical to the model's volatility forecast. Thus, in this case R^2 simply measures the extent of noise in squared returns relative to the mean which is given by the (true) conditional variance.

If the regression is used as a diagnostic for potential misspecification then an alternative measure of the realized volatility should be utilized. The use of observed squared returns for this purpose is justified to the extent that these provide an unbiased estimator of the underlying latent volatility. However, realized squared returns are poor estimators of day-by-day movements in volatility, as the idiosyncratic component of daily volatility is large. In other words, it is unclear how to interpret R^2 unless we establish a benchmark for the value expected under the null hypothesis of correct model specification.

This fact has been ignored in a number of studies that attribute the systematically low R^2s to the poor forecasting performance of ARCH models. Andersen and Bollerslev further indicate that with conditional Gaussian errors the R^2 from a correctly specified GARCH(1,1) model is bounded from above by 1/3, while with conditional fat-tailed errors the upper bound becomes even lower.

Consequently, low R^2s are a direct implication of standard volatility models and reflect the inherent noise in the realized squared returns when they are regarded as a measure for the underlying latent volatility factor.

Andersen and Bollerslev suggest increasing sampling frequency as a way of constructing more accurate ex-post volatility measurements.

- In many practical applications, each model is able to capture only a limited amount of information contained in the series of interest. An appealing strategy is forecast combination or forecast encompassing. A forecast encompassing test allows us to verify whether a single forecast generated by a specific model incorporates all the information included in forecasts generated by alternative models. The forecasts $\hat{\sigma}_t^{\alpha}$ and $\hat{\sigma}_t^{b}$ generated by two models a and b respectively are confronted in the following regression:

$$\hat{\sigma}_t = a_{\alpha}\hat{\sigma}_t^{\alpha} + a_b\hat{\sigma}_t^{b} + \varepsilon$$

If $(a_\alpha, a_b) = (0,1)$ then model b encompasses model a, i.e. incorporates all the information available in the series. If this is not the case, both models include useful information on $\hat{\sigma}_t$.

Finally, it should be emphasized that all ARCH models assume variance stationarity and perform badly when the series is not stationary. The source of nonstationarity could be, for example, instability due to many subperiods used in a study and a relative short estimation period in each subperiod. This can explain some contradictory results that have appeared in several studies. The simpler methods (like historical average, moving average, exponential smoothing and exponentially weighted moving average) are not adaptive. Their volatility structure does not respond quickly to returns shocks. GARCH is more adaptive. Volatility is separated into volatility due to past shocks and volatility carried forward due to persistence. Therefore shocks in returns can be quickly incorporated into forecasts. Furthermore GJR GARCH and QGARCH are even more adaptive, because they allow the volatility persistence to change relatively quickly when returns change sign. Overall, the simpler methods tend to provide larger volatility forecasts than the more sophisticated models. GJR (and QGARCH) has the tendency to underforecast because it is the quickest to revert from a high volatility to a low volatility state.

In empirical studies models that allow for volatility asymmetry perform best. Brailsford and Faff (1996) prefer GJR to GARCH, Pagan and Schwert (1990) prefer EGARCH to GARCH and Engle and Ng(1993) show that EGARCH and GJR perform best.

6.Emerging Stock Markets

The liberalization of international financial markets is a relative recent phenomenon. For example, in Japan and United Kingdom many barriers to international investments were lifted only at the beginning of 1980s. One of the arguments against liberalization appears to be that investment flows towards emerging markets would be extremely volatile in response to changing economic conditions, leading to high volatility in stock prices. The following table presents the liberalization events in some emerging economies.

Country	Opening Date	Degree of openness
Argentina	October 1991	fully open
Brazil	May 1991	100% of non-voting preferred stock, 49% of voting preferred stock
Chile	December 1988	25% of shares of listed companies
Mexico	May 1989	30% of banks, 100% for other stocks
Malaysia	December 1988	30% for banks and institutions, 100% for remaining stocks
Thailand	December 1988	investable up to 49%
Philippines	October 1989	investable up to 40%

Predicting volatility in emerging markets is important for determining the cost of capital and for evaluating direct investment and asset allocation decisions. At the beginning of the 1990s structural changes and liberalization policies were implemented in most of these countries, leading to an accelerated growth in their capital markets. Sophisticated research in them has been possible only during the last years, due to the development of these markets and the availability of reliable time series data. At the beginning of the 1990s structural changes and liberalization policies were implemented in most of these countries, leading to an accelerated growth in their capital markets. The interest of empirical studies is directed towards the comovements, the dynamic linkages, the co-integration and the volatility spillovers in these markets.

Harvey(1995),using data from more than 800 equities from 20 emerging markets of the world for the period 1976-1992, finds that these markets offer higher average returns and are characterized by higher volatility. Serial correlation is found to be much higher than for developed market returns. Inclusion of emerging market assets in a mean-variance efficient portfolio will significantly reduce portfolio variability and increase expected returns. Over the half of predictable variance in the emerging market returns can be traced to local information. Koutmos G. (1997)investigates the dynamics of stock returns in six emerging markets in the Pacific Basin area (Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand) using daily data for a sample covering the period 12/17/1987 to 9/13/1991. Returns are modeled using an exponential Autoregressive process for the conditional mean and a Threshold GARCH (p,q) for the conditional variance, assumes the Generalized Error Distribution instead of the Normal. He finds that returns appear to have remarkably similar characteristics to those of developed markets, in particular:

⇨ stock prices have a unit root in their univariate representation
⇨ high past innovations of either sign are associated with high future volatility (volatility clustering)
⇨ negative innovations increase volatility more than positive ones (asymmetry)
⇨ standardized residuals are far from normally distributed
⇨ the first order autocorrelation of index stock returns is negatively related to the level of volatility.

Probably the most known characteristic of emerging markets is their higher volatility compared to that of more developed ones. DeSantis and Imrohoroglu (1997) investigate whether emerging market volatility changes over time, how frequent large price changes in emerging markets are, whether there exists a positive relation between market risk and expected returns and what source of risk is priced (local or international) and, finally, whether financial liberalization affected market volatility and to which direction. Using weekly data for the period from December1988 to May 1996 for 15 emerging markets and 4 developed ones as benchmark, they find that:

- volatility is time-varying, persistent and exhibits clustering
- unconditional volatility in emerging markets is higher than that of developed markets. In most cases, higher average returns appear to be associated with a higher level of volatility.
- conditional distributions of returns have "fat tails" and the measure of kurtosis is higher than that of developed markets.
- For Asian markets the price of covariance risk is not statistically significant at either the regional or global level. For Latin America, however, it is statistically significant both regionally and globally.
- There does not appear to be an obvious relation between the opening of financial markets and market volatility. For three out five countries examined, the implied unconditional volatility is larger before the liberalization than after. The estimated kurtosis does not appear to be affected by liberalization.

A possible explanation for this fact can be that the number of securities included in IFC (International Finance Corporation) indices increased over time and higher degree of diversification is likely to have induced reduction in volatility. Alternatively, it has been suggested that liberalization induces greater participation by foreign investors who broaden the market, make it more efficient and reduce the effect of "flow shocks".

Bekaert and Harvey (1997)use a sample of monthly stock returns denominated in USD, extending from January 1976 to December 1992, for twenty emerging markets from the IFC. They confirm the existence of nonnormality and the high unconditional volatility (from 18% for Jordan to 104% for Argentina) for these countries. They utilize a world factor model of conditional variance using the GJR model and they find that the average proportions of variance attributable to world factors are generally small and that in 11 of 17 countries that experienced capital market liberalization, the influence of world factor increases after liberalization. However, they mention that liberalization is a gradual process and it is unlikely that one can capture its impact by a before-and-after snapshot.

They identify and explain four sources of the greater volatility dispersion in emerging markets, namely: i) asset concentration inherent in the IFC index for each country, ii)degree of development and market integration in each country, iii) microstructure characteristics such as the heterogeneity of traders' information set as well as liquidity and iv) macroeconomic factors, such as inflation variability (proxied by the variability of exchange rate fluctuations) and political risk (based on credit ratings). They estimate a pooled time series cross sectional regression in order to examine the explanatory power of these variables. Some of their results include the following:

- volatility of changes in exchange rate plays an important role in explaining equity return volatility (not surprisingly since returns are measured in USD)
- very significant negative relation exists between the size of the trade sector and volatility. More open economies have lower volatilities.
- for the other variables the results vary according to the country and to the significance level.

In order to investigate the impact of liberalization on volatility, they introduce dummy variables in the cross sectional analysis. They break the volatility into four pieces: before (more than 30 months prior to liberalization), pre (30 to 6 months prior), mid (6 months prior to 3 months after) and post (4 months after until the end of the sample) and they find that post liberalization volatility is lower, even after controlling for all of the specifications of the potential influence on the time-series and cross-section of volatility.

Aggarwal, Inclan and Leal (1999)examine 10 of the largest emerging markets and global indices according to IFC. They use an iterated cumulative sums of squares (ICSS) algorithm to identify the points of sudden changes in the variance of returns in each market and how long this change lasts and then examine global and local events during this period. They find that the high volatility of emerging markets is characterized by sudden changes in variance and is mainly associated with country-specific rather than global events. The October 1987 crash appears to be the only global event to have increased volatility in several markets. Furthermore, the periods of high volatility appear to be common to returns measured in local currency and dollar - adjusted returns. They cannot say that liberalization does not affect volatility, however, there seems to be a gradual and smooth adjustment rather than a shock. When variance changes are accounted for in the GARCH(1,1) estimation, the values of GARCH coefficients are reduced and most of them become no longer significant. However, determining the shifts in volatility is not possible ex ante and the change dummies cannot be incorporated in an ex ante model.

Edwards and Susmel (2001)examine volatility dependence and contagion using weekly stock data for indices denominated in USD for Brazil, Argentina, Chile, Mexico and Hong Kong and for the period August 1989 to October 1999. They implement both univariate and bivariate switching volatility models to identify breakpoints in an ARCH model of conditional variance and to explore whether there are comovements in stock market volatility across countries. They find strong evidence of state-varying volatility during the 1990s in Latin America stock markets. The univariate analysis shows that high-volatility episodes are, in general, short-lived and tend to be associated with common international crises. From the bivariate analysis it is inferred that joint high volatility periods appear as a respond to exogenous events influencing both countries. They find that Latin American markets have interdependent volatility processes and in general their results are more supportive of interdependence than of contagion in stock market volatility.

7.Volatility spillovers and causality-in-variance

Hamao et al (1990) divide daily close-to-close returns into their close-to-open and open-to-close components, in order to analyze separately the spillover effects on the opening price and on prices after the opening of trading. They test for spillovers in conditional mean and volatility across countries using correlation analysis and the inclusion of lagged returns and estimated squared residuals from the other stock markets in the ARCH models.

In order to examine spillover effects in open-to-close stock returns, they first employ an MA(1)-GARCH(1,1)-M model and then introduce an exogenous variable into the conditional mean and conditional variance equations that capture the potential volatility spillover effect from the previously open foreign market into the domestic market. Using data for the period 1/4/1985 to 31/3/1988, they find evidence of volatility spillovers from New York to Tokyo, from London to Tokyo and from New York to London for the period after the 1987 Crash, but not for the previous period.

Another methodology widely used in the literature for detecting volatility spillovers utilizes multivariate GARCH parameterizations.

Theodossiou and Lee(1993), using a multivariate GARCH-M model, find that the US market is the major “exporter” of volatility. Susmel and Engle (1994) examine price and volatility spillovers between New York and London using hourly returns and find that these spillovers are small and of short duration.

Koutmos and Booth (1995) explicitly model potential asymmetries that may exist in the volatility transmission mechanism, using a multivariate (for three markets) extension of Nelson’s Exponential GARCH. The multivariate GARCH is suited to test the possibility of asymmetries in the volatility transmission mechanism because it allows own market and cross market innovations to exert an asymmetric impact on the volatility in a given market. Their conditional covariance specification assumes constant correlation coefficients. They first estimate the model restricting all cross-market coefficients to be zero and this model is used as a benchmark and also estimate the model with no parametric restrictions and identify spillovers among markets. Investigating spillover effects across the New York, Tokyo and London markets, they conclude that volatility spillovers in a given market are much more pronounced when the news arriving from the last market to trade is bad. They find evidence of volatility spillovers from New York to London and Tokyo, from London to New York and Tokyo and from Tokyo to London and New York, with an asymmetric transmission mechanism.

Caporale et al (2000) examine causality links between United States, European Japanese and South East Asia stock markets estimating three bivariate GARCH models for which a BEKK representation is adopted. They then test for the relevant zero restrictions on the conditional variance parameters by means of likelihood ratio tests, using appropriately computed critical values.

This equation models the dynamic process of the second moment as a linear function of its own past values as well as past values of the squared innovations, both of which allow for own-market and cross-market influences in the conditional variance. The important feature of this specification is that it allows the conditional variances and covariances of the two series to influence each other, therefore it allows testing of the null hypothesis of no volatility spillover effect in one or even both directions. The likelihood ratio test compares the maximum value of the likelihood function under the assumption of correct null hypothesis of no Granger causality from one variable to the other to the maximum value of the unrestricted likelihood function.

Causality links appear to become unidirectional following the onset of a crisis, running from the markets in turmoil to the others.

Brooks and Henry (2000) find that a multivariate asymmetric GARCH formulation can explain almost all of the non-linear causality between equity markets. Firstly they utilize a non-linear Granger causality test and find evidence of causality among the markets under examination. Afterwards, they specify a time series model that adequately captures these features of the data, i.e. captures the asymmetries in the variance-covariance matrix (own variance asymmetry, cross-variance asymmetry and covariance asymmetry). Their paper seeks to examine the relationship between the US, Japanese and Australian stock markets and their results demonstrate among others that the return on Australian equities is caused by events in the US equity market and that there is no significant evidence of a lead/lag link between the US and Japanese markets

Ng (2000) examines the nature of volatility spillovers from Japan and the US to six Pacific Basin equity markets. She utilizes a bivariate GARCH(1,1) model for the Japanese and US returns. Innovations in Japan and the US are allowed to influence the equity return of a Pacific-Basin market through the error term. Three different parameterizations for the mean and volatility spillover parameters are employed. The first one assumes that the parameters remain constant through time. The second allows liberalization events to affect the parameters and the third one lets the parameters be driven by some local information variables which might capture time variation in correlation. Ng concludes that both regional and world factors are important for market volatility in the Pacific-Basin region and that their relative importance is influenced by important liberalization events, fluctuations in currency returns, size of trade etc.

Miyakoshi (2003) constructs a volatility spillover model that deals with the US shock as an exogenous variable in a bivariate EGARCH for Japan and Asian markets. He concludes that only the influence of US is important for Asian market returns; there is no influence from Japan. The volatility of Asian markets is influenced more by the Japanese market than by the US. there exists an adverse influence of volatility from the Asian market to the Japanese market.

The third branch in the field of causality-in-variance detecting involves the methodology proposed by Cheung and Ng (1996), which will be implemented in this study.

This test for causality-in-variance is an extension of Wiener-Granger causality in mean, based on the cross-correlation function (CCF). It is a two-stage procedure. The first stage involves the estimation of univariate time series models that allow for time variation in both conditional mean and conditional variance. In the second stage the resulting series of squared residuals standardized by conditional variances are constructed. The cross-correlation function of these squared-standardized residuals is then used to test the null hypothesis of no causality in variance. This test is robust to distributional assumptions.

Consider two stationary and ergodic time series, X_t and Y_t. Let I_t be two information sets defined by $I_t = \{X_{t-j}, j \geq 0\}$ and $J_t = \{X_{t-j}, Y_{t-j}, j \geq 0\}$.
Y_t is said to cause X_{t+1} in variance if

$$E\{(X_{t+1} - \mu_{x,t+1})^2 | I_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t\}$$

where $\mu_{x,t+1}$ is the mean of X_{t+1} conditioned on I_t.
Feedback in variance occurs if X causes Y and Y causes X. There is instantaneous causality in variance if

$$E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t + Y_{t+1}\}$$

Additional structure is required in order to make the general causality concept applicable in practice. Suppose X_t and Y_t can be written as

$$X_t = \mu_{x,t} + \sqrt{h_{x,t}}\, \varepsilon_t$$

$$Y_t = \mu_{y,t} + \sqrt{h_{y,t}}\, \zeta_t$$

Where $\{\varepsilon_t\}$ and $\{\zeta_t\}$ are two independent white noise processes with zero mean and unit variance. Their conditional means and variances are given by

$$\mu_{z,t} = \sum_{i=1}^{\infty} \varphi_{z,i}\,(\theta_{z,\mu})\, Z_{t-i}$$

$$h_{z,t} = \varphi_{z,0} + \sum_{i=1}^{\infty} \varphi_{z,i}\ \{(Z_{t-i} - \mu_{z,t-i})^2 - \varphi_{z,0}\}$$

where $\theta_{z,w}$ is a $p_{z,w}$ x 1 parameter vector; W=μ,h; $\varphi_{z,i}\,(\theta_{z,\mu})$ and $\varphi_{z,i}\,(\theta_{z,h})$ are uniquely defined functions of $\theta_{z,\mu}$; and Z= X, Y.

Let U_t and V_t be the squares of the standardized innovations,

$U_t = ((X_t - \mu_{x,t})^2 / h_{x,t}) = \varepsilon_t^2$

$V_t = ((Y_t - \mu_{y,t})^2 / h_{y,t}) = \zeta_t^2$;

$r_{uv}(k)$ be the sample cross-correlation at lag k,

$$r_{uv}(k) = c_{uv}(k)\,(c_{uu}(0)\,c_{vv}(0))^{-1/2},$$

where $c_{uv}(k)$ is the kth lag sample cross covariance given by

$c_{uv}(k) = T^{-1} \sum (U_t - \overline{\mathbf{U}})\,(V_{t-k} - \overline{\mathbf{V}})$, k=0, ±1, ±2, …

and $c_{uu}(0)$ and $c_{vv}(0)$ are the sample variances of U and V respectively. Since $\{U_t\}$ and $\{V_t\}$ are independent, the existence of their second moments implies

$$\begin{pmatrix} \sqrt{\mathbf{T}}\,\mathbf{r_{uv}(k)} \\ \sqrt{\mathbf{T}}\,\mathbf{r_{uv}\ (k')} \end{pmatrix} \rightarrow \text{AN}\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}\right),\ k \neq k'.$$

As in the test for causality in mean, this expression suggests that the CCF of squared standardized residuals can be used to detect causal relations and identify patterns of causation in the second moment. The utility of the CCF has certain advantages over some possible alternative tests for causality in variance. For instance, compared with a multivariate method, the CCF approach does not involve simultaneous modeling of both intra- and inter-series dynamics, and hence it is relatively easy to implement. Further, the proposed test has a well-defined asymptotic distribution and is asymptotically robust to distributional assumptions. However, it is not designed to detect causation patterns that yield zero cross-correlations.

Since both U_t and V_t are unobservable, their estimators have to be used to test the hypothesis of no causality in variance. The sample correlation coefficient $\hat{r}_{uv}(k)$ computed from the consistent estimates of the conditional means and variances of X_t and Y_t in place of $r_{uv}(k)$. The property of $\hat{r}_{uv}(k)$ is given by:

(Theorem) $\sqrt{\mathbf{T}}\,(\hat{r}_{uv}(k_1), \ldots, \hat{r}_{uv}(k_m))$ converge to $N(0, I_m)$ as $T \rightarrow \infty$, where $k_1, \ldots, k_m$ are m different integers, if:

(i) both $E(\varepsilon_t^8)$ and $E(\zeta_t^8)$ exist, and

(ii) for all θ in an open convex neighborhood $N(\theta^0)$ of θ^0 and for all T, $\sqrt{\mathbf{T}}\,\partial^2 c_{AB}(k) / \partial\theta_i\,\partial\theta_j$ exists and is bounded in probability for $\theta_i, \theta_j \in \theta$ and for A, B = U, V.

Given the asymptotic behavior of $\hat{r}_{uv}(k)$, a normal test statistic or a chi-square test statistic can be constructed to test the null hypothesis of noncausality. To test for a causal relationship at a specified lag k, we can compare $\sqrt{\mathbf{T}}\,\hat{r}_{uv}(k)$ with the standard normal distribution. Alternatively, a chi-square test statistic defined by $S = T \sum_{\mathbf{i=j}}^{\mathbf{k}} \hat{\mathbf{r}}_{\mathbf{uv}}(i)^2$, which has a chi-square distribution with (k-j+1) degrees of freedom, can be used to test the hypothesis of no causality from lag j to lag k. The choice of j and k depends on the specification of alternative hypotheses. When there is no a priori information on the direction of causality, we may set –j=k=m. The parameter m should be large enough to include the largest nonzero lag that may appear in the causation pattern. When a uni-directional causality pattern, say, Y_t does not cause X_t, is considered, we set j=1 and k=m.

Remarks:

- causality in the mean of X_t and Y_t can be tested by examining $\hat{r}_{\varepsilon\zeta}(k)$, the univariate standardized residual CCF, using the test statistic that also converges to the standardized normal distribution
- the existence of serial correlation in ε_t and ζ_t or in U_t and V_t can affect the size of the proposed tests for causality in mean and variance. Therefore the model specified in the first stage should "accurately" account for the serial autocorrelation in the data.
- The existence of causality in mean violates the independence assumption and hence may affect the CCF test. This, however, depends on the model specification. For example, in a GARCH model, the conditional variance is driven by the squared innovations. As the causality in mean is associated with causality in the innovation term, it is likely that the former can have an effect on the size of the causality-in-variance test. Its conditional mean, however, does not necessarily depend on the second moment of the process. Hence the causality in variance may have a possible, but smaller, effect on the causality-in-mean test. For the above-mentioned reasons, causality-in-mean and causality-in-variance should be determined simultaneously

Cheng and Ng apply the CCF test to a) daily index returns on Japan Nikkei 225 Index and US S&P index and b) 15-min returns on the S&P500 index futures and the corresponding returns on the underlying index. They find that the US stock index causes the Japanese stock index in variance, while a feedback appears in the variance of the 15-min stock index and futures returns.

8. Data and Descriptive Statistics

The data set consists of daily index closing prices, in local currency and United States Dollar, of 14 Emerging Equity markets and 4 developed ones, namely of the following:

Emerging Equity Markets:

- Latin America: BOVESPA Price index (Brazil), IGPA Index (Chile), IGBL Lima Stock Exchange Index (Peru), IPC Bolsa Index (Mexico) and Merval Price Index (Argentina)
- East Asia: Shangai Stock Exchange Composite Index (China) and Philippines Stock Exchange Composite Index (Philippines)
- South Asia: Bangkok S.E.T Index (Thailand) and Kuala Lumpur Composite Index (Malaysia)
- Europe: RTS Index (Russia), Budapest (BUX) Index (Hungary) and Warsaw general Index (Poland)
- Mideast/ South Africa: Israel TA100 Index (Israel) and FTSE/JSE All Share Index (South Africa)

Developed Equity Markets:

Standard and Poor's 500 Composite Index (U.S.), Nikkei 225 Stock Average (Japan), FTSE 100 (U.K.) and DAX30 Performance (XETRA) Index (Germany).

The characterization of markets as emerging is based on the International Finance Corporation classification. Some markets, as Czech Republic, Turkey, Egypt and Morocco are not included in the sample due to unavailability of sufficient data, while representative Asian markets where chosen on the basis of market capitalization. Some preliminary data about these stock markets are presented on table 1.

Table 1: Stock market data about the markets analyzed

	MARKET CAPITALIZATION				**VALUE TRADED**		**TURNOVER RATIO**		**LISTED DOMESTIC COMPANIES**	
	$ millions		% of GDP		% of GDP		value of shares traded as % of capitalization			
	1990	2000	1990	1999	1990	1999	1990	2000	1990	2000
Argentina	3,268	166,068	2.3	29.6	0.6	2.7	33.6	4.8	179	127
Brazil	16,354	226,152	3.5	30.3	1.2	11.6	23.6	43.5	581	459
Chile	13,645	60,401	45.0	101.1	2.6	10.2	6.3	9.4	215	258
China	*2,028*	590,991	*0.5*	33.4	*0.2*	38.1	*158.9*	15.3	14	1,086
Hungary	*505*	12,021	*1.5*	33.7	*0.3*	29.7	*6.3*	90.7	*21*	60
Israel	3,324	64,081	6.3	63.3	10.5	15.3	95.8	36.3	216	654
Malaysia	48,611	116,935	110.4	184.0	24.7	61.4	24.6	44.6	282	795
Mexico	32,725	125,204	12.5	31.8	4.6	7.5	44.0	32.3	199	179
Peru	812	10,562	3.1	25.8	0.4	4.4	19.3	12.6	294	230
Philippines	5,927	51,554	13.4	62.8	2.7	25.7	13.6	15.8	153	230
Poland	*144*	31,279	*0.2*	19.1	*0.0*	7.2	*89.7*	49.9	*9*	225
Russian Federation	*244*	38,922	*0.0*	18.0	--	0.7	--	36.9	*13*	249
South Africa	137,540	204,952	122.8	200.2	7.3	55.6	--	33.9	732	616
Thailand	23,896	29,489	28.0	46.9	26.8	33.5	92.6	53.2	214	381
Germany	335,073	*1,432,190*	*22.2*	67.8	*21.4*	64.3	139.3	*107.5*	413	933
Japan	2,917,679	*4,456,937*	98.2	104.6	54.0	42.5	43.8	*52.5*	2,071	*2,470*
United Kingdom	848,866	*2,933,280*	85.9	203.4	28.2	95.6	33.4	*51.9*	1,701	*1,945*
United States	3,059,434	*16,635,114*	53.2	181.8	30.5	202.9	53.4	*123.5*	6,599	*7,651*

Data Source: Standard & Poor's *Emerging marlkets Factbook 2000* and World Bank's national accounts

The period under investigation extends from 1/9/1995 to 15/3/2004, for a total of 2227 observations. The sample is divided in two subperiods: 1/9/1995 to 31/12/1999 and 1/1/2000 to 15/3/2004 and each one is examined separately. All data are obtained from Datastream and all calculations and estimations were performed using Eviews4.0. Stock returns are defined as percentage logarithmic differences of closing prices between two consecutive days, i.e. $R_t = \ln(P_t/P_{t-1})$ (continuously compounded stock returns). The study is performed for own currency and U.S. dollar-denominated returns, however the results of own currency analysis are not reported since they are qualitatively similar. When market returns are dollar denominated, investors are assumed to be unhedged against foreign currency risk.

Figure 1 plots the closing prices and the equivalent returns on the indices over the sample period.

Figure 1: Index closing prices and daily continously compounded returns

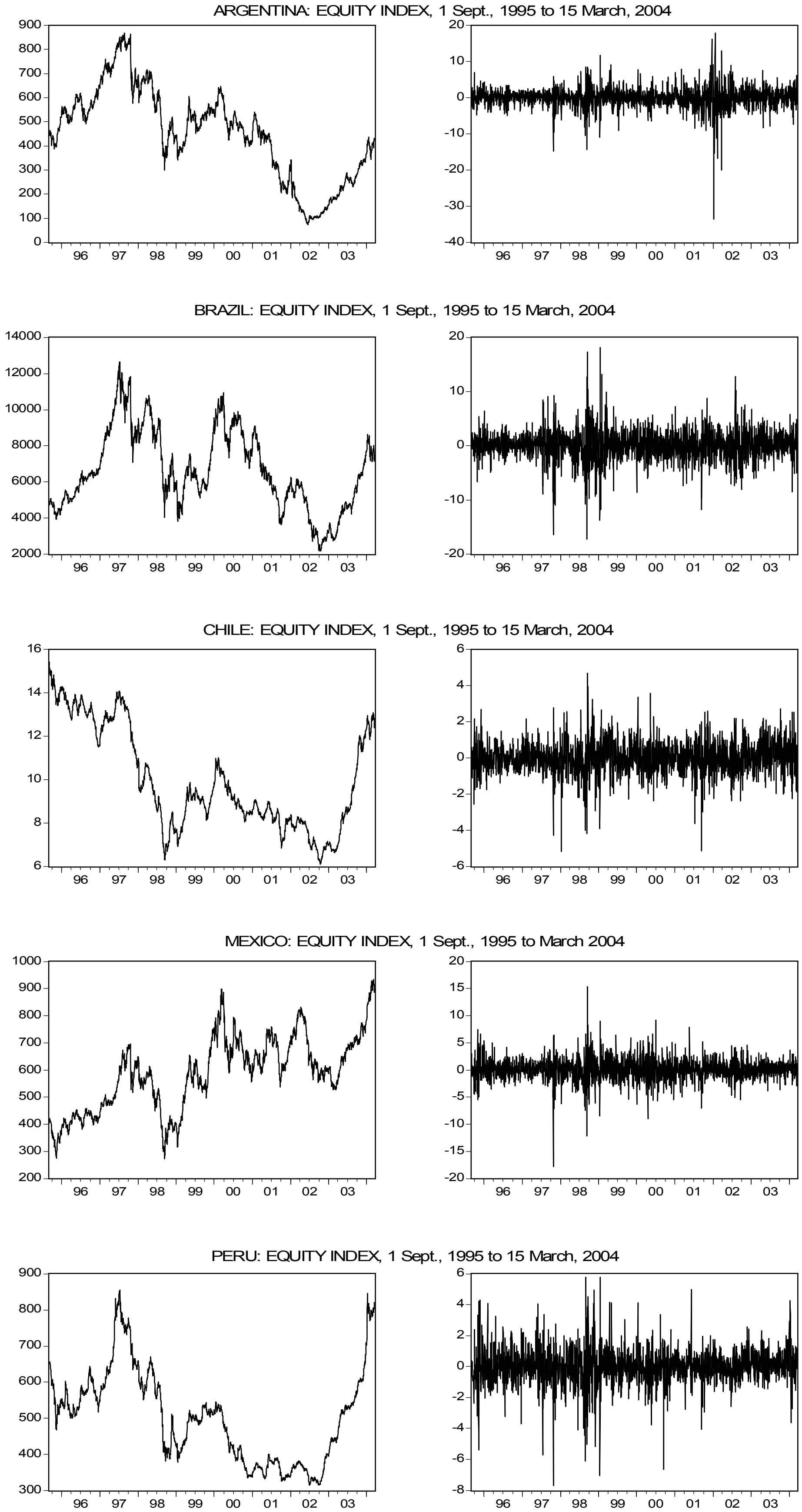
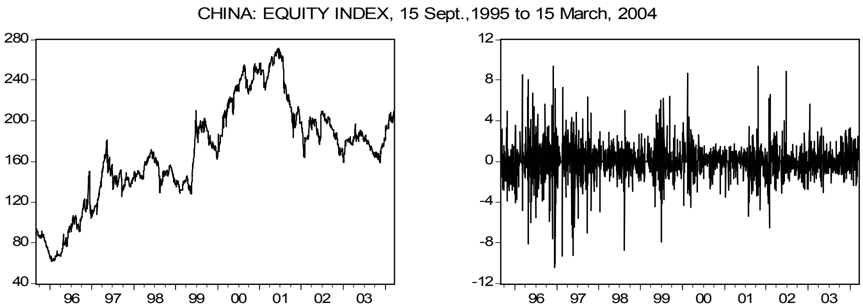
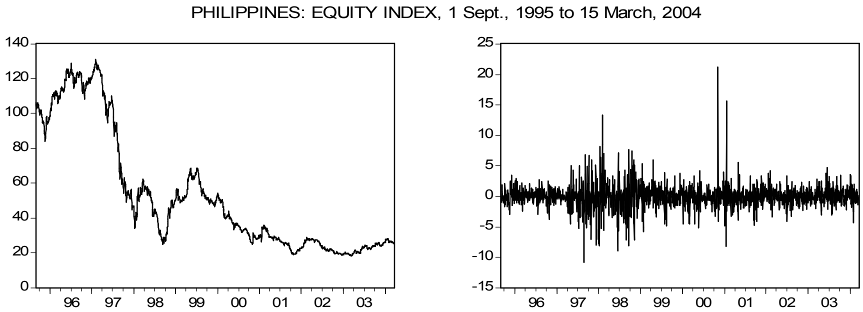
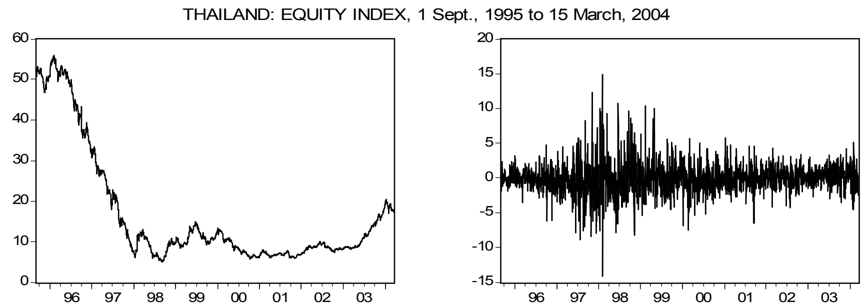


Figure 1 (continued)







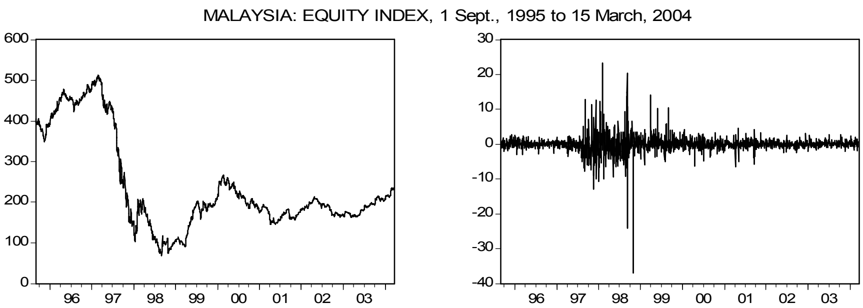
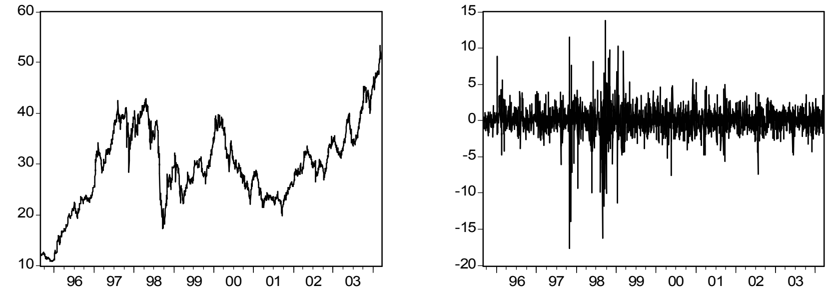
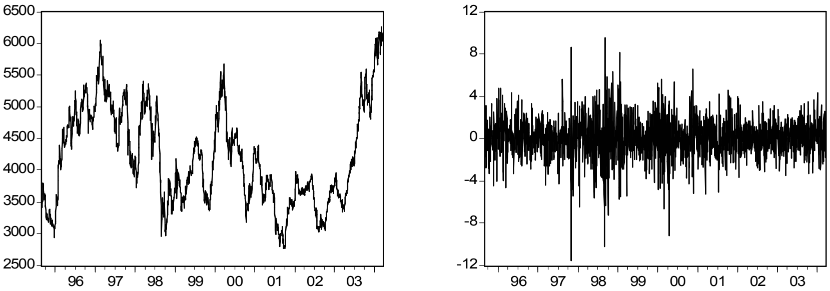


Figure 1 (continued)

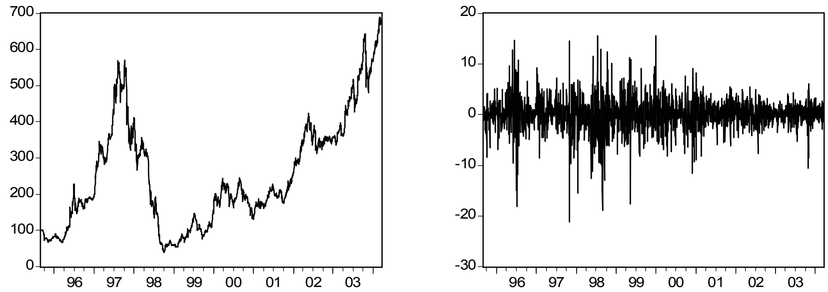
HUNGARY: EQUITY INDEX, 1 Sept., 1995 to 15 March, 2004



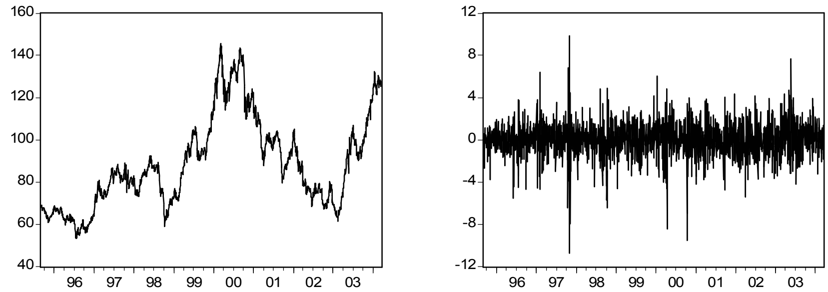
POLAND: EQUITY INDEX, 1 Sept., 1995 to 15 March, 2004



RUSSIA: EQUITY INDEX, 1 Sept., 1995 to 15 March, 2004



ISRAEL: EQUITY INDEX, 1 Sept., 1995 to 15 March, 2004



SOUTH AFRICA: EQUITY INDEX, 1 Sept., 1995 to 15 March, 2004

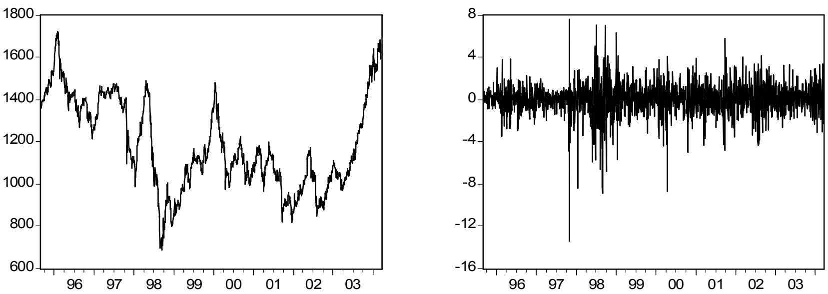


Figure 1 (continued)

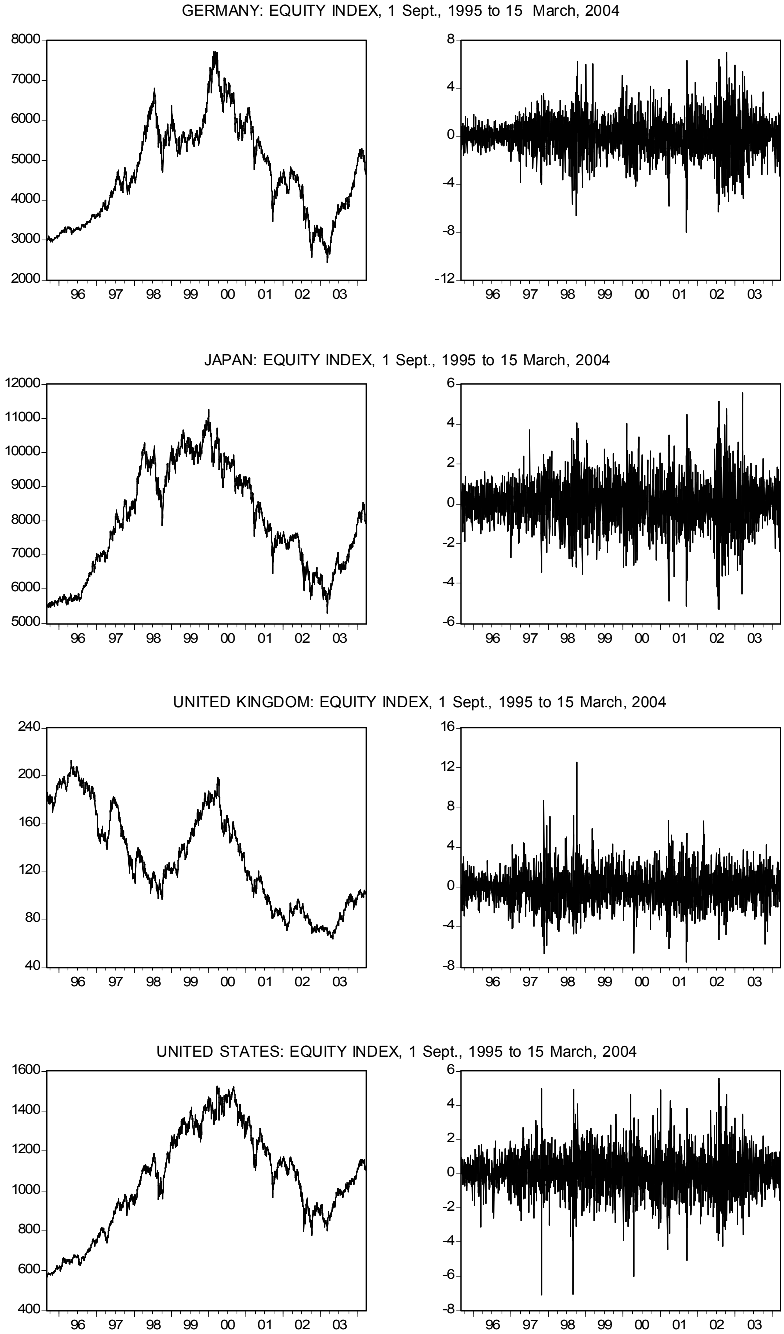


Table 2: Summary Descriptive statistics

	ARGENTINA		BRAZIL		CHILE		MEXICO		PERU	
STATISTICS	USD	Local currency	USD	Local currency	USD	Local currency	USD	Local currency	USD	Local currency
OVERALL SAMPLE : 1/9/1995 – 15/3/2004										
Mean	-0.0027	0.0452	0.0199	0.0702	-0.0095	0.0098	0.0358	0.0610	0.0101	0.0294
Std. Dev.	2.5909	2.3477	2.6401	2.3726	0.8743	0.6845	1.9143	1.6587	1.1201	1.0555
Maximum	17.7900	16.1165	18.0182	28.8176	4.6592	4.4666	15.2900	12.1536	5.7751	5.4197
Minimum	-33.6501	-17.2292	-17.2301	-17.2292	-5.1794	-3.7734	-17.8779	-14.3138	-7.6684	-6.6599
Skewness	-1.2693	-0.0939	-0.1528	0.4443	-0.1811	0.1009	-0.1727	0.0214	-0.2919	-0.1091
Kurtosis	22.2909	8.3106	8.4764	17.7792	5.8770	6.7623	10.6049	9.8602	8.6871	8.4520
LB(5)	20.544[a]	14.898[b]	22.862[a]	7.0893	188.04[a]	338.50[a]	47.635[a]	26.762[a]	109.77[a]	120.21[a]
LB(10)	30.948[a]	37.261[a]	41.250[a]	37.264[a]	210.51[a]	363.86[a]	55.25[a]	32.286[a]	116.73[a]	128.92[a]
$LB^2(5)$	101.73[a]	233.91[a]	587.97[a]	242.73[a]	191.03[a]	306.61[a]	256.74[a]	236.12[a]	385.11[a]	389.62[a]
LB^2 (10)	232.39[a]	402.24[a]	766.94[a]	307.41[a]	258.73[a]	568.95[a]	336.87[a]	350.06[a]	520.29[a]	558.69[a]
JB	35113.87	2619.11	2790.38	20332.34	779.92	1316.71	5375.34	4365.28	3031.51	2761.37
1ST SUBSAMPLE : 1/9/1995 – 31/12/2000										
Mean	0.0176	0.0177	0.0627	0.1190	-0.0399	-0.0135	0.0554	0.0921	-0.0197	0.0194
Std. Dev.	2.1734	2.1720	2.7969	2.7227	0.8759	0.7732	2.1050	1.7924	1.2970	1.2290
Maximum	11.6389	11.5650	18.018	28.8176	4.6592	4.4666	15.2900	12.1536	5.7751	5.4197
Minimum	-14.7136	-14.7649	-17.2301	-17.2292	-5.1794	-3.7734	-17.8779	-14.3138	-7.6684	-6.6599
Skewness	-0.69852	-0.6949	-0.2146	0.6270	-0.1902	0.1384	-0.2914	0.0361	-0.2779	-0.0911
Kurtosis	9.8739	9.8429	10.4715	19.1483	6.9475	6.6330	11.8638	11.4236	7.5103	7.3520
LB(5)	6.6538[c]	6.9699[c]	6.8664[c]	6.0227[c]	135.65[a]	178.48[a]	28.546[a]	9.6443[c]	60.001[a]	65.816[a]
LB(10)	28.510[a]	28.925[a]	32.085[a]	36.958[c]	154.58[a]	200.23[a]	51.859[a]	26.452[a]	62.010[a]	68.192[a]
$LB^2(5)$	195.46[a]	196.68[a]	342.58[a]	119.65[a]	133.64[a]	141.18[a]	147.52[a]	132.72[a]	204.31[a]	184.8[a]
LB^2 (10)	307.06[a]	309.53[a]	450.97[a]	149.41[a]	201.53[a]	285.32[a]	192.02[a]	191.9[a]	268.67[a]	261.88[a]
JB	2315.75	2295.69	2637.04	12351.9	740.52	625.07	3715.20	3341.15	972.37	882.28
2ND SUBSAMPLE: 1/1/2000 – 15/3/2004										
Mean	-0.0238	0.07392	-0.0264	0.0177	0.0251	0.0359	0.0149	0.0283	0.0412	0.0386
Std. Dev.	2.9629	2.5177	2.4654	1.9419	0.8695	0.5770	1.6973	1.5095	0.8965	0.8405
Maximum	17.7900	16.1165	12.7279	2.7784	3.5718	2.7784	9.1400	7.0199	4.9786	4.2868
Minimum	-33.6501	-11.2907	-11.7854	-2.3258	-5.1481	-2.3258	-9.0110	-8.2673	-6.6251	-5.8872
Skewness	-1.4347	0.2971	-0.0771	0.1019	-0.1687	0.1019	0.0514	-0.0300	0.8058	-0.1012
Kurtosis	23.5578	7.1285	4.7836	5.1611	4.7987	5.1611	5.9834	5.8029	11.2775	8.204
LB(5)	15.629[a]	8.8777[c]	26.294[a]	7.3646[c]	62.904[a]	153.12[a]	19.535[a]	21.398[a]	54.267[a]	61.019[a]
LB(10)	33.276[a]	19.376[b]	33.541[a]	14.367[c]	73.156[a]	155.95[a]	27.423[a]	28.345[a]	74.268[a]	85.507[a]
$LB^2(5)$	42.186[a]	71.614[a]	141.94[a]	46.539[a]	56.449[a]	141.60[a]	41.120[a]	83.856[a]	84.066[a]	112.30[a]
LB^2 (10)	99.685[a]	134.79[a]	171.46[a]	54.817[a]	68.445[a]	172.41[a]	55.832[a]	134.10[a]	105.68[a]	148.02[a]
JB	19640.0	793.04	146.10	214.78	152.66	214.78	406.22	358.29	3241.66	1236.35

All returns are percentages: $R_t = \ln(P_t/P_{t-1})*100$. The sample includes 2227 daily observations. LB(n) is the Ljung-Box statistic for up to n lags (distributed as χ^2 with n degrees of freedom). $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags. JB is the Jarque-Bera test statistic for normality (distributed as χ^2 with two degrees of freedom).

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table 2 presents some basic descriptive statistics for the return series, in local currency and in U.S. dollars, for the full sample and for the two subsamples. A comparative analysis of the characteristics of these markets shows the following: for the Latin American countries, returns in local currency were higher than returns in dollars. Furthermore, these markets were more volatile in dollars than in local currency, as shown by the standard deviation of their returns. With the exception of Mexico, in all the other four Latin markets returns in dollars were lower than the equivalent return on S&P index. The most profitable market appears to have been Mexico, offering an average daily return of 0.0358% in dollars, while the highest return in local currency was offered

TABLE 2 (continued)

STATISTICS	CHINA USD	CHINA Local currency	PHILIPPINES USD	PHILIPPINES Local currency	THAILAND USD	THAILAND Local currency	MALAYSIA USD	MALAYSIA Local currency
Mean	0.0392	0.0389	0.0646	-0.0299	-0.0245	-0.0298	-0.0245	-0.0056
Std. Dev.	1.6728	1.6728	1.8216	1.5635	2.1470	1.8581	2.2298	1.7977
Maximum	9.4031	9.4009	21.2658	16.1776	14.8199	11.3495	23.4081	20.8173
Minimum	-10.4326	-10.4376	-10.8941	-9.7441	-14.0712	-10.0280	-37.0102	-24.1533
Skewness	-0.1441	-0.1453	1.0974	0.9149	0.4758	0.5435	-1.2961	0.5643
Kurtosis	9.7933	9.7944	18.8800	15.9763	8.7136	7.0483	57.3813	40.9550
LB(5)	14.955[b]	14.961[b]	124.65[a]	74.363[a]	52.463[a]	42.116[a]	42.145[a]	51.351[a]
LB(10)	28.175[a]	28.166[a]	137.48[a]	84.001[a]	72.924[a]	62.480[a]	65.571[a]	58.531[a]
$LB^2(5)$	433.48[a]	434.22[a]	126.23[a]	65.848[a]	568.54[a]	343.95[a]	103.46[a]	983.13[a]
LB^2 (10)	520.54[a]	521.26[a]	158.53[a]	86.004[a]	806.86[a]	518.05[a]	153.53[a]	1013.1[a]
JB	4288.08	4289.53	23836.15	15928.38	3111.93	1629.736	274915	133732.2
	1[st] SUBSAMPLE : 1/9/1995 – 31/12/2000							
Mean	0.0560	0.0556	-0.0613	-0.0224	-0.1250	-0.0891	-0.0564	-0.0192
Std. Dev.	1.9658	1.9629	2.0362	1.7281	2.5511	2.1252	2.9561	2.3045
Maximum	9.3794	9.3790	13.3649	9.6657	14.8196	11.3495	23.4081	20.8173
Minimum	-10.4326	-10.4376	-10.8941	-9.7441	-14.0712	-10.0280	-37.0102	-24.1533
Skewness	-0.4168	-0.4177	0.0215	0.0683	0.6793	0.8767	-1.0470	0.5867
Kurtosis	8.0351	8.0379	7.8996	7.6346	7.9454	6.8925	36.4558	29.5802
LB(5)	19.097[a]	19.104[a]	88.481[a]	55.424[a]	40.736[a]	32.493[a]	21.130[a]	32.475[a]
LB(10)	30.912[a]	30.893[a]	98.537[a]	61.628[a]	51.002[a]	43.988[a]	37.168[a]	38.801[a]
$LB^2(5)$	260.78[a]	19.104[a]	222.85[a]	164.88[a]	254.80[a]	148.65[a]	43.507[a]	483.29[a]
LB^2 (10)	295.98[a]	30.893[a]	376.99[a]	241.54[a]	342.50[a]	238.3[a]	46.489[a]	493.2[a]
JB	1226.43	1227.88	1130.38	1012.23	1238.45	858.14	52906.5	33329.5
	2[ND] SUBSAMPLE: 1/1/2000 – 15/3/2004							
Mean	0.0195	0.0195	-0.0498	-0.0373	0.0307	-0.0140	0.0072	0.0351
Std. Dev.	1.3033	1.3033	1.5494	1.3752	1.6247	1.8101	1.0450	1.5319
Maximum	9.4031	9.4009	21.2658	16.1776	5.7322	6.6255	4.4999	5.3417
Minimum	-6.5458	-6.5433	-8.2395	-6.1911	-7.4683	-9.8735	-6.3486	-7.3454
Skewness	0.8058	0.8044	3.6009	2.5874	-0.2745	-0.0581	-0.4925	-0.3348
Kurtosis	11.2775	11.2668	48.8188	34.7498	4.7250	4.9939	8.1617	5.0912
LB(5)	4.3399[c]	4.3547[c]	34.814[a]	17.953[a]	18.958[a]	14.553[b]	40.564[a]	40.628[a]
LB(10)	5.7129[c]	5.837[c]	39.603[a]	27.206[a]	32.740[a]	28.905[a]	44.897[a]	44.963[a]
$LB^2(5)$	41.771[a]	41.810[a]	24.063[a]	6.7743[c]	207.44[a]	195.14[a]	108.22[a]	108.00[a]
LB^2 (10)	59.598[a]	59.616[a]	24.114[a]	6.9456[c]	229.84[a]	212.98[a]	112.16[a]	111.92[a]
JB	3241.66	3233.14	98060.4	47171.27	149.39	181.84	1258.72	219.79

by Brazil (0.0702%). By contrast, the lowest return in dollars was that of Argentina (-0.0027%) and in local currency that of Chile (0.0098%).

The Asian markets have been more volatile in USD than in local currency, with the exception of China, for which the standard deviation of returns is almost identical in the two cases. The highest mean return in dollars was the one offered by Philippines (0.06465%) which was also higher than the mean return offered by any of the four developed markets. In local currency, China offered a mean return of 0.0389% which also exceeds the mean returns of the developed markets in local currency.

All three European markets offered positive mean returns. Russia offered an average return of 0.0858%, which is the highest among all markets under investigation. The pattern of more volatile returns in dollars than in local currency is also found here.

TABLE 2 (continued)

STATISTICS	HUNGARY USD	HUNGARY Local currency	POLAND USD	POLAND Local currency	RUSSIA* USD	ISRAEL USD	ISRAEL Local currency	SOUTH AFRICA USD	SOUTH AFRICA Local currency
OVERALL SAMPLE : 1/9/1995 – 15/3/2004									
Mean	0.0641	0.8514	0.0256	0.0455	0.0858	0.0282	0.0458	0.0070	0.0340
Std. Dev.	1.9221	1.8671	1.7331	1.5903	3.0538	1.4993	1.3571	1.4313	1.2116
Maximum	13.8502	13.6162	9.5323	7.8933	15.5568	9.8327	9.6117	7.5952	7.2656
Minimum	-17.6267	-18.0339	-11.5662	-10.2864	-21.1025	-10.7957	-10.3815	-13.4372	-12.6283
Skewness	-0.8695	-0.9156	-0.2098	-0.2212	-0.4409	-0.3988	-0.3347	-0.8334	-0.8437
Kurtosis	15.5549	16.2646	6.4797	6.3143	8.7211	7.9345	8.9381	11.0322	12.6786
LB(5)	25.838[a]	19.364[a]	38.355[a]	33.363[a]	37.570[a]	19.925[a]	15.037[a]	33.113[a]	49.757[a]
LB(10)	34.53[a]	31.123[a]	59.909[a]	44.646[a]	52.173[a]	33.868[a]	24.982[a]	46.380[a]	57.167[a]
$LB^2(5)$	276.20[a]	339.99[a]	398.08[a]	340.63[a]	296.15[a]	147.69[a]	131.79[a]	434.01[a]	499.09[a]
$LB^2(10)$	363.88[a]	460.11[a]	496.21[a]	425.74[a]	487.69[a]	293.55[a]	331.41[a]	491.05[a]	482.56[a]
JB	14900.45	16630.55	1139.44	1037.02	3107.996	2317.48	3312.13	6241.644	8952.54
1st SUBSAMPLE : 1/9/1995 – 31/12/2000									
Mean	0.0926	0.1519	0.0218	0.0674	0.04965	0.0479	0.0756	-0.0003	0.0456
Std. Dev.	2.2645	2.2299	1.8935	1.7490	3.6447	1.4291	1.3444	1.5040	1.2143
Maximum	13.8502	13.6162	9.5323	7.8933	15.5568	9.8327	9.6117	7.5952	7.2656
Minimum	-17.6267	-18.0339	-11.5662	-10.2864	-21.1025	-10.7957	-10.3815	-13.4372	-12.6283
Skewness	-0.9962	-1.1085	-0.2560	-0.3257	-0.3749	-0.5710	-0.4084	-1.1582	-1.5067
Kurtosis	15.0611	15.1525	6.6756	6.3089	7.6357	10.6046	11.5303	14.3134	18.9648
LB(5)	20.269[a]	17.655[a]	34.205[a]	45.325[a]	33.692[a]	7.0381[c]	3.7273[c]	26.470[a]	28.900[a]
LB(10)	28.486[a]	28.164[a]	50.286[a]	66.918[a]	45.330[a]	17.921[b]	15.161[c]	41.719[a]	37.465[a]
$LB^2(5)$	132.15[a]	162.78[a]	242.10[a]	196.92[a]	116.55[a]	122.54[a]	114.43[a]	262.5[a]	288.36[a]
$LB^2(10)$	167.76[a]	212.22[a]	299.35[a]	237.65[a]	187.88[a]	258.36[a]	294.17[a]	289.64[a]	304.41[a]
JB	7036.23	7184.88	648.46	535.50	1038.29	2784.24	3457.55	6279.04	12428.06
2ND SUBSAMPLE: 1/1/2000 – 15/3/2004									
Mean	0.0348	0.0157	0.0295	0.0239	0.1227	0.0062	0.0135	0.0152	0.0227
Std. Dev.	1.4907	1.3965	1.5522	1.4086	2.2933	1.5696	1.3706	1.3539	1.2100
Maximum	5.6473	6.0043	6.5150	6.4434	9.1205	7.7036	6.5684	5.7539	5.8894
Minimum	-7.5437	-6.8735	-9.2092	-8.4678	-11.5316	-9.5268	-8.4246	-8.7293	-7.9481
Skewness	-0.2660	-0.0226	-0.1108	-0.0306	-0.2532	-0.2532	-0.2589	-0.3619	-0.1530
Kurtosis	4.9683	4.9182	5.2338	5.4338	5.9308	5.9308	6.4755	5.5199	6.1429
LB(5)	18.362[a]	9.2636[c]	6.7926[c]	2.1608[c]	5.9136[c]	14.630[b]	13.878[b]	10.435[c]	25.767[a]
LB(10)	23.966[a]	22.096[b]	11.786[c]	3.1362[c]	11.804[c]	24.549[a]	20.313[b]	16.770[c]	29.911[a]
$LB^2(5)$	46.754[a]	32.238[a]	75.491[a]	85.419[a]	190.30[a]	50.955[a]	48.148[a]	71.777[a]	68.731[a]
$LB^2(10)$	74.385[a]	67.884[a]	95.615[a]	116.11[a]	252.56[a]	71.227[a]	67.922[a]	108.05[a]	91.149[a]
JB	189.51	167.81	229.69	270.19	403.26	403.26	562.84	313.34	24.86

*The price index for Russia is dollar-denominated

Finally, Israel and South Africa offered positive average returns in dollars of 0.0282% and 0.0070% which are lower than returns in the local currency. Among all the emerging markets under investigation, the most volatile in dollars appears to have been Russia (standard deviation of 3.0538%) followed by Argentina (2,5909%), while the less volatile have been Chile (0.8743%) and Peru(1.1201%). In local currency, the highest standard deviation characterized Brazil (2.3477%) and Argentina ()2.3477%) and the lower Chile (0.6845%) and Peru(1.0555%). With the exception of Chile, Peru and Israel, the rest of emerging markets were more volatile than the developed ones.

With regard to skewness, with the exception of Philippines and Thailand, returns in dollars have negative skewness coefficient, i.e. are skewed to the left. In local currency, the returns of Brazil, Chile, Mexico, Philippines, Thailand and Malaysia are skewed to the right, while the rest of the distributions are negatively skewed. In

TABLE 2 (continued)

STATISTICS	GERMANY USD	GERMANY Local currency	UNITED KINGDOM USD	UNITED KINGDOM Local currency	JAPAN USD	JAPAN Local currency	UNITED STATES USD(Local currency)
OVERALL SAMPLE : 1/9/1995 – 15/3/2004							
Mean	0.0198	0.0238	0.0168	-0.0211	-0.0269	-0.0211	0.0302
Std. Dev.	1.5753	1.6749	1.1567	1.1828	1.6634	1.4691	1.1947
Maximum	7.0407	7.5526	5.5699	5.9025	12.5711	7.6604	5.5732
Minimum	-7.9934	-8.8746	-5.3089	-5.8853	-7.5163	-7.2339	-7.1127
Skewness	-0.1145	-0.1327	-0.1258	-0.1560	0.2953	0.0184	-0.0970
Kurtosis	5.2312	5.3767	5.0526	5.4097	5.9579	4.9646	5.8222
LB(5)	7.7234	6.2899	35.353[a]	30.375[a]	7.8349	8.9028	5.5936
LB(10)	16.103	16.666	47.561[a]	49.656[a]	12.223	12.094	11.531
$LB^2(5)$	595.35[a]	619.62[a]	621.96[a]	733.16[a]	119.40[a]	121.56[a]	234.89[a]
LB^2 (10)	1225.4[a]	1272.5[a]	1101.8[a]	1334.5[a]	204.27[a]	231.23[a]	387.61[a]
JB	466.61	530.49	396.64	547.64	843.84	358.13	742.25
1st SUBSAMPLE : 1/9/1995 – 31/12/2000							
Mean	0.0747	0.1001	0.0635	0.0602	-0.0004	0.0038	0.0847
Std. Dev.	1.2475	1.3761	0.9681	0.9931	1.6742	1.4068	1.0431
Maximum	6.3016	7.2363	-0.0179	4.3450	12.5711	7.6604	4.9886
Minimum	-6.6163	-7.8931	4.2277	-3.6613	-6.6665	-5.9570	-7.1127
Skewness	-0.1176	-0.3389	4.0431	-0.0844	0.5965	0.1249	-0.4783
Kurtosis	6.5010	6.2350	-3.5341	4.6918	7.4067	5.5321	8.1277
LB(5)	8.6399[c]	8.0421[c]	21.600[a]	24.893[a]	8.2304[c]	13.943[b]	5.2284[c]
LB(10)	24.392[a]	29.591[a]	29.527[a]	34.252[a]	15.496[c]	16.996[c]	16.684[c]
$LB^2(5)$	148.54[a]	229.61[a]	97.813[a]	220.63[a]	67.149[a]	119.94[a]	86.930[a]
LB^2 (10)	350.03[a]	489.09[a]	207.96[a]	398.89[a]	115.54[a]	218.89[a]	139.55[a]
JB	579.72	514.39	71.03	136.10	981.37	304.82	1281.11
2ND SUBSAMPLE: 1/1/2000 – 15/3/2004							
Mean	-0.0344	-0.0712	-0.0214	-0.0337	-0.0531	-0.0472	-0.0258
Std. Dev.	1.8527	1.9089	1.3038	1.3241	1.6452	1.5312	1.3311
Maximum	7.0407	7.5526	5.5699	5.9025	6.6986	7.2217	5.5732
Minimum	-7.9934	-8.8746	-5.3089	-5.8853	-7.5163	-7.2339	-6.0052
Skewness	-0.0579	0.0114	-0.1379	-0.1344	-0.0273	-0.0588	0.1440
Kurtosis	4.1753	4.6789	4.8461	5.3098	4.3739	4.4804	4.5714
LB(5)	4.5285[c]	8.9916[c]	22.025[a]	20.955[a]	2.9393[c]	1.2329[c]	3.9376[c]
LB(10)	14.253[c]	23.410[a]	44.094[a]	46.048[a]	4.1096[c]	5.4198[c]	5.6846[c]
$LB^2(5)$	270.70[a]	291.69[a]	342.67[a]	382.69[a]	56.545[a]	35.626[a]	137.07[a]
LB^2 (10)	549.08[a]	602.71[a]	585.82[a]	694.78[a]	101.77[a]	68.126[a]	218.46[a]
JB	63.58	128.51	158.83	246.51	86.18	100.54	116.35

developed markets, return distributions are skewed to the left with the exception of Japan.

Kurtosis coefficients are larger than 3 in all cases, indicating that stock return distributions are leptokurtic.

The above mentioned characteristics can justify the values of the Jarque-Bera statistic that rejects normality of returns at the 1% significance level for all markets.

The presence of intertemporal dependencies in returns and squared returns, a common empirical finding, is tested by Ljung-Box Q-statistics that test the null hypothesis of no autocorrelation up to order k. It follows a chi-square distribution with k degrees of freedom. Table 2 presents the LB Q-statistic of standardized returns and squared returns. They show that the null hypothesis of white noise residuals can be rejected at the 1% level. The values of the autocorrelation statistics are consistent with the persistence in the squared returns, in other words with the volatility clustering often observed in financial series. They indicate strong second-moment time dependencies.

These findings are typical of stock return series and are also in accordance with Bekaert & Harvey(1997), Koutmos (1997) and DeSantis & Imrohoroglou (1997).

Table 3 shows the t-statistics resulting from Unit Root Tests performed on the return series in dollars. Augmented Dickey Fuller and Phillips-Perron tests are performed and the results show that the null hypothesis of a unit root in the series can be rejected at the 1% level for all markets.

Table 3 : Unit root test for daily returns (in USD)

COUNTRY	ADF	PP
ARGENTINA	-21.002	-44.226
BRAZIL	-21.514	-42.826
CHILE	-17.003	-37.355
MEXICO	-20.687	-41.102
PERU	-18.497	-38.927
CHINA	-19.575	-47.760
PHILIPPINES	-21.340	-36.771
THAILAND	-20.592	-40.918
MALAYSIA	-20.812	-43.348
HUNGARY	-21.764	-44.438
POLAND	-21.064	-41.298
RUSSIA	-20.495	-41.711
ISRAEL	-22.136	-44.427
SOUTH AFRICA	-20.571	-42.076
GERMANY	-21.972	-46.845
UN. KINGDOM	-24.294	-46.649
JAPAN	-21.817	-49.222
USA	-22.539	48.169

MacKinnon critical values for rejection of hypothesis of a unit root are the following:
1% critical value: -3.9676
5% critical value: -3.4144
10%critical value: -3.1290
The null hypothesis is rejected if the t-statistic is smaller than the critical value.

Finally, table 4 shows the historic correlations of the emerging markets under investigation with the major developed markets for the overall sample period.

Table 4 : Historic correlations between emerging and developed markets

EMERGING MARKET	GERMANY	JAPAN	UNITED KINGDOM	UNITED STATES
ARGENTINA	0.211	0.063	0.210	0.313
BRAZIL	0.326	0.087	0.300	0.442
CHILE	0.343	0.126	0.327	0.324
MEXICO	0.389	0.120	0.362	0.535
PERU	0.273	0.1315	0.267	0.221
CHINA	-0.015	0.0304	-0.0306	-0.0301
PHILIPPINES	0.079	0.191	0.115	0.050
THAILAND	0.127	0.222	0.141	0.043
MALAYSIA	0.071	0.193	0.116	-0.004
HUNGARY	0.332	0.218	0.322	0.140
POLAND	0.289	0.232	0.286	0.136
RUSSIA	0.239	0.139	0.247	0.135
ISRAEL	0.284	0.119	0.270	0.208
SOUTH AFRICA	0.416	0.270	0.435	0.210

The last table that gives information about the characteristics of returns is table 5 that shows the results of a type of test that is very useful for volatility models specification.

In order to examine the asymmetric impact of positive/negative and small/large innovations on volatility and how well a model captures it, Engle and Ng (1993) proposed some diagnostic tests. These tests, based on the news impact curve implied by the particular ARCH-type model used, are (i) the sign-bias test, (ii) the negative-size-bias test and (iii) the positive-size-bias test.

Each of these test statistics examine whether squared standardized residuals are indeed independent and identically distributed. The sign-bias test explores the impact of positive and negative innovations on volatility not predicted by the model. The squared standardized residuals are regressed against a constant and a dummy variable S_t that takes the value of unity if ε_{t-1} (the error from the conditional mean equation) is negative and zero otherwise. The test is based on the t-statistic of the dummy variable coefficient.

The negative-size-bias test explores how well the model captures the impact of small and large negative innovations. It is defined a s the t-ratio of the coefficient of $S_t\varepsilon_{t-1}$ in the regression of squared standardized residuals against a constant and $S_t\varepsilon_{t-1}$. The positive-size-bias test examines possible biases associated with small and large positive innovations. The squared standardized residuals are regressed against a constant and $(1-S_t)\varepsilon_{t-1}$. Again the t-statistic of $(1-S_t)\varepsilon_{t-1}$ coefficient is the test statistic. Finally, the model can be subject to all of these tests at once by running a single regression and testing that all the coefficients are equal to zero. This can be the TR^2 or the F statistic for the regression. However individual tests are more powerful.

In summary, defining $v_t= \varepsilon_t/\sigma_t$, where σ_t is the estimated conditional standard deviation, as the standardized residuals, the regressions for each test will be:

Sign bias : $v_t^2 = a + b\, S_t + u_t$, where u_t is an i.i.d. process

Negative size bias: $v_t^2 = a + b\, S_t\, \varepsilon_{t-1} + u_t$

Positive-size bias: $v_t^2 = a + b\, (1-S_t)\, \varepsilon_{t-1} + u_t$

Joint test: $v_t^2 = a + b_1\, S_t + b_2\, S_t\, \varepsilon_{t-1} + b_3\, (1-S_t)\, \varepsilon_{t-1} + u_t$

These diagnostic test statistics can also be used as summary statistics on the raw data to explore the nature of conditional heteroskedasticity in the data series without first imposing a volatility model and this is how they are used in the present step. In this case ε_t and v_t will be defined as $\varepsilon_t = y_t - \mu$ and $v_t= \varepsilon_t / \sigma$, where μ and σ are the unconditional mean and standard deviation of the series y_t respectively.

Table 5 : Volatility specification tests based on the news impact curve

COUNTRY	SIGN BIAS (t-values)	NEGATIVE SIZE BIAS (t-values)	POSITIVE SIZE BIAS (t-values)	JOINT TEST (F-test)
OVERALL SAMPLE				
ARGENTINA	0.4404	-2.4415[b]	1.8973	4.3218[a]
BRAZIL	3.9047[a]	-12.2797[a]	2.1975[b]	66.2122[a]
CHILE	1.6952	-8.5143[a]	2.4683[b]	38.3084[a]
MEXICO	1.6755	-5.7411[a]	2.8909[a]	19.7222[a]
PERU	1.4718	-9.5936[a]	5.1619[a]	57.2825[a]
CHINA	1.5054	-11.0288[a]	3.7580[a]	59.7071[a]
PHILIPPINES	-04162	-4.5466[a]	7.7638[a]	36.7444[a]
TAIWAN	2.2139[b]	-6.5853[a]	-0.1945	16.5127[a]
INDIA	0.9624	5.9281[a]	1.8142	18.8823[a]
THAILAND	-1.0827	-3.6248[a]	10.0547[a]	52.2849[a]
MALAYSIA	0.6021	-3.6633[a]	9.2400[a]	41.2102[a]
HUNGARY	2.6105[a]	-12.2863[a]	3.037[a]	68.0589[a]
POLAND	2.1001[b]	-10.8624[a]	1.9277	55.5612[a]
RUSSIA	1.9223	-10.0648[a]	4.3549[a]	55.7228[a]
ISRAEL	2.3800[b]	-6.4438[a]	-0.4009	15.2666[a]
SOUTH AFRICA	2.7156[a]	-14.5998[a]	-0.1590	85.9637[a]
GERMANY	3.1135[a]	-9.5830[a]	0.5934	37.6864[a]
UN. KINGDOM	2.4115[b]	-9.0594[a]	1.6165	38.6550[a]
JAPAN	-1.2904	-0.7102	2.9196[a]	4.1787[a]
USA	2.7507[a]	-8.5500[a]	-0.9134	28.4570[a]

This table reports the results of tests for the asymmetric effect of new information on standardized residuals developed by Engle & Ng (1993). All t-statistics refer to the coefficient b in the following regressions:

Sign bias : $v_t^2 = a + b\,S_t + u_t$ Negative size bias: $v_t^2 = a + b\,S_t\,\varepsilon_{t-1} + u_t$

Positive-size bias: $v_t^2 = a + b\,(1-S_t)\,\varepsilon_{t-1} + u_t$

Joint test: $v_t^2 = a + b_1 S_t + b_2 S_t\,\varepsilon_{t-1} + b_3 (1-S_t)\,\varepsilon_{t-1} + u_t$

where u_t is an i.i.d. process and S_t is a dummy variable that takes the value of 1 if ε_{t-1} is negative and zero otherwise.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

As can be seen from table 5, the negative-size-bias is highly significant, with the exception on Japan, indicating that large negative innovations cause more volatility than small ones. In the cases where positive-size-bias is significant, positive innovations appear to increase volatility regardless of size. Finally, sign-bias-test is significant in some cases, which can be evidence of the fact that positive and negative innovations have an asymmetric impact on volatility. These facts that give a first idea about the type of volatility models that will be more suitable. In particular, they indicate that in the majority of cases a “good” model should allow for asymmetries caused by the sign and/or the size of past innovations.

9. Mean and Variance Models
9.1 Mean equation specification

A GARCH model consists of two equations. The first is the conditional mean equation and the second is the conditional variance equation. The procedure followed in this section is the following: first, an ARMA model that can remove linear dependence from the data is selected for each series and its residuals are examined. Second, GARCH-type models are specified for each series and mean and variance equations are jointly estimated. Third, the fitted models are checked, compared and evaluated.

Before proceeding to GARCH models estimation it is important to choose an ARMA(p,q) model that adequately models the conditional mean of the series, assuming constant variance. The aim of the step is the selection of a model that removes all the serial correlation from the data. However, the parameterization should be kept as simple as possible. Otherwise, estimation problems might appear when mean and variance equation are jointly estimated. Table 6 presents the ARMA terms required for each series to become no longer serially correlated, as well as some estimation output information. It is clear than an AR(1) model suffices to remove the serial correlation in most markets, however different ARMA(p,q) models were required in some cases. In the step of mean and variance equation estimation some mean equation coefficients might appear to be non significantly different from zero, leading to a different (usually more simple) parameterization of the series mean.

Table 6 reports the results from the Breusch-Godfrey serial correlation LM test that checks residuals for remained serial correlation up to an order p. The LM statistic is asymptotically distributed as chi-square distribution with p degrees of freedom. The null hypothesis of no serial correlation up to order p is accepted at the 1% significance level for all markets.

ARCH LM test tests the null hypothesis of no ARCH effect up to order q in the residuals. It is based on an auxiliary regression and checks the joint significance of squared residuals coefficients. It is asymptotically distributed $\chi^2(q)$. The null hypothesis of no heteroskedasticity cannot be accepted for any of the markets.

Finally, White's test for heteroskedasticity is also based on an auxiliary regression and the statistic is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of slope coefficients in the test regression.

The statistical significance of Q-statistics and the rejection of the null hypothesis of no heteroskedasticity by both the ARCH LM test and White's test, suggest that the variance of the series should be parameterized and not assumed to be constant.

Table 6 : Mean equation specification results for overall sample

	ARGENTINA	BRAZIL	CHILE	MEXICO	PERU	CHINA
Relevant ARMA terms	AR(1), AR(2)	AR(1)	ARMA(1,2)	AR(1), AR(2)	ARMA(2,2)	AR(1)
Log likelihood	-5266.66	-5307.57	-2777.17	-4752.80	-3352.90	-4301.52
Durbin-Watson	2.003	1.991	2.002	1.995	1.998	1.999
Akaike info criterion	4.738	4.772	2.499	4.114	3.019	3.868
Schwarz criterion	4.746	4.777	2.510	4.122	3.032	3.873
Breusch-Godfrey test						
LM statistic	4.411	4.158	2.159	2.107	0.2929	0.080
Probability	0.110	0.125	0.339	0.348	0.863	0.960
White heteroskedasticity test						
Test statistic	14.949	216.256	87.128	99.471	195.560	171.011
Probability	0.004	0.000	0.000	0.000	0.000	0.000
ARCH-LM test						
LM statistic	158.408	322.497	157.632	217.454	191.679	286.227
Probability	0.000	0.000	0.000	0.000	0.000	0.000

	PHILIPPINES	THAILAND	MALAYSIA	HUNGARY	POLAND	RUSSIA
Relevant ARMA terms	AR(1), AR(2)	AR(1)	AR(2),AR(4), MA(1),MA(2)	AR(1), AR(3)	AR(1)	AR(1)
Log likelihood	-4425.21	-4833.73	-4908.72	-4596.87	-4361.63	-5623
Durbin-Watson	2.000	2.008	1.951	2.002	1.999	2.000
Akaike info criterion	3.982	4.346	4.422	4.138	3.922	5.056
Schwarz criterion	3.989	4.351	4.435	4.146	3.927	5.061
Breusch-Godfrey test						
LM statistic	0.109	2.713	5.746	3.480	0.017	1.010
Probability	0.900	0.257	0.056	0.175	0.991	0.603
White heteroskedasticity test						
Test statistic	123.947	170.785	52.191	226.986	258.825	214.910
Probability	0.000	0.000	0.000	0.000	0.000	0.000
ARCH-LM test						
LM statistic	126.145	376.868	73.297	253.139	302.100	287.514
Probability	0.000	0.000	0.000	0.000	0.000	0.000

	ISRAEL	S. AFRICA	GERMANY	U.K.	JAPAN	USA
Relevant ARMA terms	AR(1), AR(2)	AR(1)	AR(1)	AR(1), AR(2), MA(1)	AR(1)	AR(1)
Log likelihood	-4052.22	-3940.86	-4168.14	-3467.23	-4286.67	-3552.64
Durbin-Watson	1.999	2.003	1.998	2.002	2.002	1.999
Akaike info criterion	3.646	3.544	3.748	3.121	3.854	3.195
Schwarz criterion	3.654	3.549	3.753	3.131	3.860	3.200
Breusch-Godfrey test						
LM statistic	0.506	3.664	2.431	2.095	4.312	3.095
Probability	0.776	0.160	0.296	0.350	0.115	0.212
White heteroskedasticity test						
Test statistic	152.240	377.611	99.009	221.361	7.735	92.158
Probability	0.000	0.000	0.000	0.000	0.020	0.000
ARCH-LM test						
LM statistic	187.882	402.660	417.391	385.478	115.75	181.272
Probability	0.000	0.000	0.000	0.000	0.000	0.000

9.2 GARCH models estimation

Among the various GARCH specifications available in the literature, the following models were selected: (symmetric) *GARCH(p,q)* proposed by Bollerslev (1986), Nelson's *EGARCH(1,1)*, GJR by Glosten et al(1993) or *Threshold ARCH* by Zakoian(1994) and *ARCH-in-mean* formulations based on the model of Engle et al.(1987). This selection is justified by the fact that these models allow for a simple and robust parameterization of the conditional variance; they have been widely used in previous studies, therefore results can be comparable and third they allow for checking the assumption of symmetric and asymmetric responses of variance. Furthermore, a number of research papers (e.g. French et al., 1987; Akgiray, 1989; Baillie and DeGennaro,1990) have proved that simple parameterizations, such as the GARCH(1,1), perform remarkably well in a variety of circumstances.

GARCH models to be estimated for each market:

Mean equation	$y_t = x_t * \gamma + \varepsilon_t$, $\varepsilon_t = z_t * \sigma_t$, $z_t \sim$ i.i.d. $E(z_t)=0$ $Var(z_t)=1$
(symmetric) GARCH(p,q)	$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$
Threshold GARCH(p,q)	$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_i \sigma_{t-1}^2$, $d_t=1$ if $\varepsilon_{T-1}<0$, 0 otherwise
Exponential GARCH(p,q)	$\log \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i (\varphi z_{t-i} + \gamma[\lvert z_{t-i}\rvert - E\lvert z_{t-i}\rvert] + \sum_{j=1}^{p} \beta_i \log \sigma_{t-1}^2$
GARCH-in-Mean	$y_t = x_t * \gamma + \sigma_t^2 + \varepsilon_t$, where σ_t^2 can have any of the previous parameterizations

The widely used Normal distribution is used for the estimation of all models, while a GARCH(1,1) model with Student-t distributed errors is also estimated for comparative purposes.

Assuming that the mean of the series is given by:

$y_t = x_t \gamma + \varepsilon_t$, where $\varepsilon_t = z_t \sigma_t$, z_t i.i.d. process with $E(z_t)=0$ and $Var(z_t)=1$,

then if z_t is normally distributed then the likelihood function becomes:

$$\log f(\varepsilon_t \sigma_t^{-1}) = -0.5 [\sum_{t=1}^{T} \log (2\pi + 0.5 \varepsilon_t^2 \sigma_t^{-2})]$$

However, it is widely recognized that return distributions tend to have "fatter" tails than the normal distribution. Although the unconditional distribution for ε_t in the GARCH(p,q) models with conditionally normal errors has fatter tails than the normal, for many financial time series it does not adequately account for leptokurtosis. That is, the standardized residuals often appear to be leptokurtic. Bollerslev (1987) suggest using a standardized Student-t distribution with the degrees of freedom being estimated. Nelson suggest using the Generalized Error distribution. In the first case the distribution function becomes:

$$f(\varepsilon_\tau \mid F_{t-1}) = \Gamma\left(\frac{1}{2}(v+1)\right)\left[\Gamma\left(\frac{1}{2}v\right)\right]^{-1}[(v-2)]^{-1/2}\left[1+\varepsilon_t^2(v-2)^{-1}\right]^{-(v+1)/2}$$

where G is the gamma distribution and v is the degrees of freedom that can either be preset or estimated along with the other parameters in the model.

In the case of GED distribution:

$$f(\varepsilon_t) = \frac{v\exp\left(-\frac{1}{2}|\varepsilon/\lambda|^v\right)}{\lambda\, 2^{(1+v^{-1})}\Gamma(v^{-1})}, \quad \text{where } \lambda = [2^{-(2/v)}\,\Gamma(1/v)/(3/v)]^{1/2}.$$

When v=2 it produces a normal density while v> (<2) is more thin (fat) tailed than a normal.

Following Bollerslev (1986), GARCH model parameters are estimated by maximum likelihood, an estimation procedure that is widely used because it almost always produces consistent, asymptotically normal and efficient estimates. The general idea is to choose estimates of the parameters θ to maximize the likelihood of the data under an assumption about the shape of the distribution of the data generation process.

Most estimation algorithms are iterative, that is, the parameter estimates are updated using a scheme: $\theta_{i+1} = \theta_i + \lambda_i\,\delta_i$, where λ_i is a step length and δ_i is a direction vector, chosen so that the likelihood of the data under θ_{i+1} is greater than the likelihood under θ_i. The gradient descent methods that are used for GARCH model estimation define the direction vector in terms of the gradient of the likelihood function and the Hessian matrix of second derivatives of the likelihood function, both evaluated at θ_i.

For a normal symmetric GARCH model, the log-likelihood of a single observation r_t is : $l_t = -\frac{1}{2}[\ln\sigma_t^2 + (\varepsilon_t^2/\sigma_t^2)]$, where μ is the mean and σ^2 is the variance of the data generation process. Σl should be maximized with respect to the variance parameters. Denoting the variance parameters by θ, in the case of a GARCH(1,1) model the parameters are $\theta = (\omega, \alpha, \beta)'$. Then the first derivatives may be written :

$$\partial l_t / \partial\theta = (1/(2\sigma_t^2))\,[(\varepsilon_t^2/\sigma_t^2)]$$

where the gradient vector is

$$g_t = \partial\sigma_t^2 / \partial\theta$$

These derivatives may be calculated recursively, taking the ordinary least squares estimate of unconditional variance as pre-sample estimates of ε_t^2 and σ_t^2 and calculating the gradient vectors by the recursion

$$g_t = z_t + \beta\, g_{t-1},$$

where $z_t = (1, \varepsilon_{t-1}^2, \sigma_{t-1}^2)$. Solving the first-order conditions $\partial_t/\partial\theta=0$ yields a set of non-linear equations in the parameters that may be solved using some quasi-Newton variable metric algorithm such as the Davidon-Fletcher-Powell (DFP) or the Bernt-Hall-Hall-Hausman (BHHH) that is recommended by Bollerslev (1986). The BHHH iteration is

$$\theta_{i+1} = \theta_i + \lambda_i\, H_t^{-1}\, g_i,$$

where λ_i is a variable step length chosen to maximize the likelihood in the appropriate direction, H_t is the Hessian matrix $\Sigma(g_t g_t')$ and $g_t = \Sigma g_t$, both evaluated at θ_i. The iteration is deemed to have converged when the gradient vector g is zero. This algorithm was used in the present study.

Convergence problems might arise because the more parameters in the GARCH model the "flatter" the likelihood function becomes, therefore the more difficult it is to maximize. In that case a different set of estimates may be obtained when the starting values for the iteration are changed. In order to ensure that the estimates correspond to a global optimum of the likelihood function one would have to run the model with many starting values and each time record the likelihood of the optima. If this type of convergence problem is encountered, one should use a more parsimonious parameterization of the GARCH model, if possible.

Convergence problems with GARCH models can also arise because the gradient algorithm used to maximize the likelihood function has hit a boundary. If there are obvious outliers in the data it is very likely that the iteration will return the value 0 or 1 for either the alpha or the beta parameter (or both) in the GARCH(1,1) models. It may be safe to remove a single outlier if the circumstances that produced the outlier are thought to be unlikely to happen in future. Alternatively the boundary problem might be mitigated by changing the starting values of the parameters, or changing the data set so that the likelihood function has a different gradient at the beginning of the search. otherwise the model specification will have to be changed. A sure sign of using the wrong GARCH model is when the iteration refuses to converge at all, even after having checked the data for outliers, changed the starting values or chosen a different data period.

In the present study convergence did not cause problems, however, as explained later, all models were re-estimated for two sub-samples of the original data set, i.e. with different starting values and amount of data, so as to be checked for stability and robustness.

Each of the abovementioned models was estimated for each market jointly with the mean equation that was specified earlier (table 6). The estimation started from a limited number of lags p and q. In the cases where residual diagnostic tests showed that the estimated models did not capture all the ARCH effects, higher order models were estimated.

Tables A1-A18 in the Appendix report the estimated mean and the variance equations coefficients for each market. The next part of each table includes diagnostic tests for the residuals of the series. If a model is correctly specified, the residuals should be i.i.d. random variables with mean zero and variance one (and follow the assumed distribution with the estimated scale parameter or degrees of freedom). The standardized residuals generated by each model are checked with Ljung-Box Q-statistics, ARCH LM test and normality tests.

The in-sample-performance (or goodness-of-fit) criteria presented are the Akaike Information criterion, the Schwarz information criterion and the log Likelihood value.

Furthermore, some descriptive statistics for the resulting conditional variance series are presented in the last part of each table. The last two columns show the estimation output from a GARCH(1,1) model assuming that the residuals follow a Student-t distribution with the degrees of freedom being estimated. After having estimated the models for each country, the model with the best in-sample performance was selected, on the basis of Akaike Information criterion, Schwarz information criterion and the log Likelihood value.

Table 7 presents the selected model for each country for the overall sample period. It is worth noting that EGARCH(1,1) and TGARCH(1,1) are the prevailing models, indicating that variance models allowing for leverage and asymmetry are preferred to the symmetric ones. However, with the exception of Israel, South Africa and Thailand, a symmetric GARCH(1,1) suffices to remove ARCH effects as is shown by the ARCH LM test and Ljung-Box statistics. Its in-sample performance, however, is inferior to that of EGARCH, TARCH and GARCH models of higher lag order.

EGARCH(1,1) model was selected for Philippines, South Africa, Germany and United States. In all four cases the leverage coefficient (γ) is negative and statistically significant, indicating the existence of leverage effect in equity return volatility. Leverage effect does not appear to be statistically significant in the cases of Argentina, Peru, China, Thailand, Russia, Israel and Japan. For the rest of the markets, however, even if a different parameterization is finally selected, the statistical significance of γ demonstrates the existence of leverage effects. Furthermore, Threshold GARCH performed best for Argentina, Brazil, Mexico, Peru, Israel, UK and Japan.

The TARCH term is positive and statistically different from zero, which shows that bad news has a larger impact on conditional variance (asymmetry). For the remaining countries (Chile, China, Malaysia, Hungary, Poland and Russia), a symmetric GARCH(p,q) model with lags ranging from 1 to 3 fared best.

The standardized residuals diagnostics indicate the existence of excess kurtosis in standardized residuals that is a common empirical finding. As mentioned earlier, the shocks of Gaussian GARCH models have fatter tails than the Normal distribution, however, GARCH models are not able to capture all the excess kurtosis. For this reason, GARCH models have also been estimated with the assumption of Student-t distribution. The excess kurtosis, although reduced in most cases, could not be absolutely modelled.

Table 7 : Selected ARMA-GARCH models for overall sample period

	ARGENTINA	BRAZIL	CHILE	MEXICO	PERU
	TARCH(1,1)	**TARCH(2,1)**	**GARCH(2,2)**	TARCH(1,1)	**TARCH(1,1)**
Mean equation					
constant-c	0.0437[c]	0.0418[c]	0.0001[c]	0.0261[c]	0.0013[c]
	(1.0608)	(0.9666)	(0.0592)	(0.7882)	(0.6538)
AR(1) coefficient	0.0706[a]	0.1197[a]	0.9312[a]	0.1449[a]	1.0841[a]
	(2.8946)	(5.7513)	(27.2015)	(6.7021)	(21.9960)
AR(2) coefficient					-0.1454[a]
					(-5.0570)
MA(1) coefficient			-0.6562[a]		-0.8949[a]
			(-15.3957)		(-22.0331)
MA(2) coefficient			-0.2024[a]		
			(-6.9181)		
GARCH-M coef.					
Variance equation					
constant- ω	0.1019[b]	0.3349[a]	0.0018[c]	0.1196[a]	0.1173[a]
	(2.0248)	(5.2163)	(1.3890)	(4.1387)	(3.8002)
ARCH terms:					
α_1	0.056024[c]	-0.049826[a]	0.184229[a]	0.010176[c]	0.156385[a]
	(1.5027)	(-5.6586)	(4.5278)	(0.9230)	(4.4091)
α_2		0.078297[a]	-0.169453[a]		
		(3.9895)	(-4.4452)		
GARCH terms:					
β_1	0.899381[a]	0.814146[a]	1.491754[a]	0.874278[a]	0.694352[a]
	(35.3664)	(31.2742)	(10.5285)	(34.6670)	(11.9352)
β_2			-0.508697[a]		
			(-3.8020)		
EGARCH terms:					
α					
β					
γ					
TARCH terms:					
γ	0.062632[c]	0.2092[a]		0.169820[a]	0.1246[c]
	(1.3618)	(5.7645)		(3.7319)	(1.3665)
Akaike criterion	4.4130	4.4698	2.3619	3.8823	2.8002
Schwarz criterion	4.4284	4.4877	2.3850	3.8977	2.8207
Log likelihood	-4901.32	-4963.45	-2618.63	-4313.16	-3105.82
Stand.Res.Diagnostics					
$LB^2(5)$	3.6451	4.2319	1.0320	3.4332	3.4007
	(0.602)	(0.517	(0.794)	(0.634)	(0.493)
$LB^2(10)$	8.2076	13.753	4.2300	8.3521	4.1928
	(0.609)	(0.185)	(0.836)	(0.594)	(0.898)
Skewness	-0.435	-0.2338	-0.0120	-0.0651	-0.1744
Kurtosis	7.550	4.2571	4.8821	5.3141	6.0788
JB statistic	1989.03	166.736	342.40	498.04	889.69
ARCH-LM test					
LM statistic	8.256	13.5804	4.1373	8.1186	4.1886
Probability	0.603	0.1930	0.9409	0.6172	0.9384
Summary statistics for cond. variance series					
Mean	7.094	6.870	0.724	3.657	1.247
Standard deviation	10.796	7.8624	0.508	4.167	1.424
Maximum	151.944	72.649	6.647	60.692	17.335
Minimum	1.389	0.4621	0.191	0.371	0.375
Skewness	6.571	4.262	3.431	6.267	4.839
Kurtosis	61.247	25.932	24.051	60.271	34.075

This table presents the maximum likelihood estimates of mean and variance equations of the models selected based on the in-sample performance. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table 7 (continued)

	CHINA	***PHILIPPINES***	***THAILAND***	***MALAYSIA***
	GARCH(2,2)	**EGARCH(1,1)**	**GARCH(3,3)**	**GARCH(2,2)**
Mean equation				
constant-c	0.0210[c]	-0.0797[a]	0.0068[c]	0.0289[a]
	(0.7200)	(-3.1674)	(0.2121)	(1.3669)
AR(1) coefficient		0.1769[a]	0.1076[a]	0.1537[a]
		(3.4331)	(4.5704)	(5.2896)
AR(2) coefficient				
GARCH-M coef.				
Variance equation				
constant- ω	0.4693[a]	-0.0989[a]	0.1015[a]	0.0010[c]
	(3.8227)	(-2.7114)	(2.7981)	(0.6729)
ARCH terms:				
α_1	0.235931[a]		0.061928[a]	0.155553[a]
	(4.8381)		(3.7489)	(3.8544)
α_2	0.114371[a]		0.096348[a]	-0.146722[a]
	(2.7750)		(5.4460)	(-4.0290)
α_3			0.071260[a]	
			(3.9461)	
GARCH terms:				
β_1	-0.148448[a]		-0.788683[a]	1.630172[a]
	(-3.2892)		(-13.7390)	(9.2380)
β_2	0.643605[a]		0.678964[a]	-0.639324[a]
	(12.0758)		(26.4446)	(-3.8618)
β_3			0.862524[a]	
			(14.6144)	
EGARCH terms:				
α		0.1638[a]		
		(3.4933)		
β		0.9824[a]		
		(183.121)		
γ		-0.0760[b]		
		(-2.0117)		
TARCH terms:				
γ				
Akaike criterion	3.6056	3.6547	4.0341	3.4439
Schwarz criterion	3.6210	3.6701	4.0572	3.4619
Log likelihood	-4007.08	-4059.92	-4478.98	-3824.42
Stand.Res.Diagnostics				
$LB^2(5)$	2.4129	2.0162	8.8683	2.0551
	(0.790)	(0.847)	(0.114)	(0.841)
$LB^2(10)$	4.8305	2.4786	14.034	4.1180
	(0.902)	(0.991)	(0.171)	(0.942)
Skewness	0.3531	1.4095	0.1593	-0.084
Kurtosis	10.2391	23.829	4.4882	10.6136
JB statistic	4906.91	40959.8	214.765	5376.79
ARCH-LM test				
LM statistic	4.6854	2.3962	13.923	4.1010
Probability	0.9111	0.9923	0.1765	0.9426
Summary statistics for cond. variance series				
Mean	2.869	3.129	4.595	4.898
Standard deviation	3.368	3.043	4.790	11.986
Maximum	41.345	18.526	48.659	226.61
Minimum	0.418	0.456	0.594	0.307
Skewness	5.031	2.231	3.678	8.684
Kurtosis	39.343	8.004	24.032	116.42

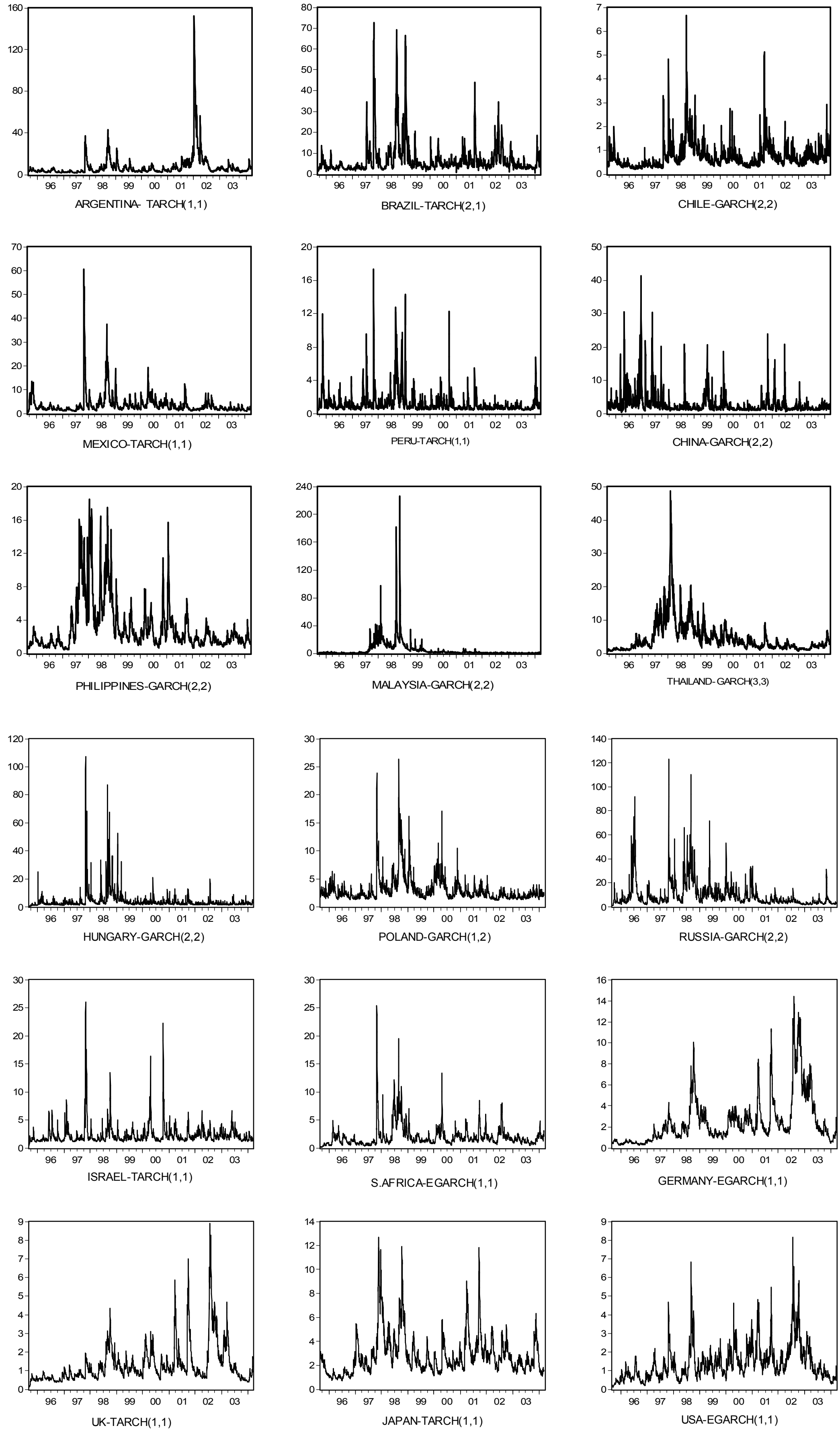
Table 7 (continued)

	HUNGARY	***POLAND***	***RUSSIA***	***ISRAEL***	***SOUTH AFRICA***
	GARCH(2,2)	**GARCH(1,2)**	**GARCH(2,2)**	**TARCH(1,1)**	**EGARCH(1,1)**
Mean equation					
constant-c	0.0866[a]	0.0373[c]	0.1616[a]	0.0309[c]	0.0545[b]
	(2.8710)	(1.2471)	(3.8804)	(1.0935)	(2.3682)
AR(1) coefficient	0.1328[a]	0.1493[a]	0.1294[a]	0.1058[a]	0.1277[a]
	(4.7307)	(6.3692)	(5.1933)	(4.3469)	(5.1814)
GARCH-M coef.					
Variance equation					
constant- ω	0.0136[c]	0.0530[a]	0.0216[C]	0.1799[a]	-0.1343[a]
	(1.1866)	(2.7355)	(1.1279)	(4.2818)	(-4.7784)
ARCH terms:					
α_1	0.318202[a]	0.156621[b]	0.1950[a]	0.053777[b]	
	(2.8787)	(3.0819)	(4.3618)	(2.1359)	
α_2	-0.303267[a]	-0.103979[b]	-0.1778[a]		
	(-2.8441)	(-2.1457)	(-4.3558)		
GARCH terms:					
β_1	1.427451[a]	0.928389[a]	1.6248[a]	0.804952[a]	
	(9.5929)	(53.2966)	(11.5210)	(3.1114)	
β_2	-0.445297[a]		-0.6436[a]		
	(-3.1827)		(-5.1008)		
EGARCH terms:					
α					0.1995[a]
					(5.0110)
β					0.9620[a]
					(112.128)
γ					-0.0955[a]
					(-3.4654)
TARCH terms:					
γ				0.119704[a]	
				(3.1114)	
Mean annual.volatility					
Akaike criterion	3.8179	3.7641	4.7364	3.5146	3.2474
Schwarz criterion	3.8359	3.7795	4.7543	3.5300	3.2628
Log likelihood	-4238.58	-4179.70	-5262.29	-3902.29	-3606.81
Stand.Res.Diagnostics					
$LB^2(5)$	1.3028	7.185	1.2735	2.8740	19.336
	(0.935)	(0.207)	(0.938)	(0.719)	(0.002)
$LB^2(10)$	3.4625	12.595	10.642	14.070	22.336
	(0.968)	(0.247)	(0.386)	(0.170)	(0.013)
Skewness	-0.3717	-0.1035	-0.1336	-0.345	-0.2590
Kurtosis	8.6405	4.1324	5.5664	5.230	5.5305
JB statistic	2999.51	122.82	617.25	505.40	618.59
ARCH-LM test					
LM statistic	3.4284	12.718	10.643	14.255	20.014
Probability	0.9694	0.239	0.385	0.1616	0.0291
Summary statistics for cond. variance series					
Mean	3.851	2.912	9.565	2.270	1.991
Standard deviation	6.440	2.139	10.942	1.841	2.010
Maximum	107.330	26.389	123.108	26.033	25.448
Minimum	0.252	1.137	0.7544	0.524	0.165
Skewness	8.035	3.887	3.828	5.677	4.460
Kurtosis	91.648	25.970	25.549	51.006	35.469

Table 7 (continued)

	GERMANY	UNITED KINGDOM	JAPAN	UNITED STATES
	EGARCH(1,1)	TARCH(1,1)	TARCH(1,1)	EGARCH(1,1)
Mean equation				
constant-c	0.0366[c]	0.0090[c]	-0.0287[c]	0.0233[c]
	(1.5497)	(1.3076)	(0.3485)	(0.2407)
AR(1) coefficient		0.7260[a]		
		(5.3843)		
AR(2) coefficient		-0.0815[a]		
		(-3.3744)		
MA(1) coefficient		-0.6993		
		(-5.1720)		
GARCH-M coef.				
Variance equation				
constant- ω	-0.0982[a]	0.0225[a]	0.0381[a]	-0.0590[a]
	(-5.4447)	(4.3213)	(2.8686)	(-3.7042)
ARCH terms:				
α_1		0.014248[c]	0.042159[a]	
		(1.2190)	(3.0629)	
α_2				
GARCH terms:				
β_1		0.922149[a]	0.919123[a]	
		(72.7372)	(68.0016)	
β_2				
EGARCH terms:				
α	0.1340[a]			0.0817[a]
	(5.247)			(3.9417)
β	0.9892[a]			0.9756[a]
	(333.53)			(215.557)
γ	-0.0561[a]			-0.1256[a]
	(-3.5679)			(-6.8226)
TARCH terms:				
γ		0.0874[a]	0.0548[b]	
		(4.1891)	(2.5695)	
Mean annual.volatility				
Akaike criterion	3.3978	2.9017	3.7358	2.9643
Schwarz criterion	3.4106	2.9222	3.7486	2.9771
Log likelihood	-3776.83	-3218.70	-4153.00	-3294.32
Stand.Res.Diagnostics				
$LB^2(5)$	11.403	7.9566	9.5835	3.2079
	(0.044)	(0.093)	(0.088)	(0.668)
$LB^2(10)$	14.232	11.894	12.915	5.08
	(0.163)	(0.219)	(0.228)	(0.886)
Skewness	-0.0655	-0.1870	0.0828	-0.3323
Kurtosis	3.6361	3.5554	4.1889	4.455
JB statistic	39.129	41.553	133.64	164.70
ARCH-LM test				
LM statistic	16.635	11.7785	13.0883	4.7497
Probability	0.145	0.3001	0.2187	0.9072
Summary statistics for cond. variance series				
Mean	2.496	1.309	2.817	1.391
Standard deviation	2.324	1.061	1.698	0.962
Maximum	14.399	8.896	12.697	8.154
Minimum	0.283	0.121	0.743	0.137
Skewness	2.093	2.835	2.135	1.938
Kurtosis	7.824	13.707	9.234	8.565

Figure 2 : Estimated conditional variances using the selected models of table 7.



- **Stability of GARCH coefficients**

When utilizing long periods of data, one should always consider whether major market events that occurred several years before should influence estimates and forecasts today and whether the estimated parameters are stable. Lamoureux and Lastrapes (1990) were among the first to point out that the high persistence of shocks to conditional variance (in the case of a GARCH(1,1) model this is demonstrated by the sum of coefficients $\alpha_1+\beta_1$ being close to one) is a sign of structural change in variance.

For the markets under investigation, the coefficients from a symmetric GARCH(1,1) model are presented in table 8. Although different models might have been selected for each market (see table7), GARCH(1,1) coefficients can offer an idea of coefficients stability and variance persistence. The sum of the coefficients is very close to 1 for many countries, while for Malaysia and Germany the sum indicates that the GARCH(1,1) model is integrated and long-term variance is not defined. This might indicate that the model is not well specified for the data and should be reestimated using a different historical period or a different (asymmetric) GARCH model.

Table 8 : GARCH(1,1) coefficients for each market for the overall sample

EQUITY MARKET	ω	α_1	β_1	$\alpha_1+\beta_1$	Long term variance
ARGENTINA	0.0896	0.0866	0.9035	0.9901	9.223
BRAZIL	0.2048	0.1264	0.8463	0.9727	7.535
CHILE	0.0288	0.1215	0.8431	0.9646	0.814
MEXICO	0.1572	0.1264	0.8330	0.9594	3.871
PERU	0.1157	0.2210	0.6946	0.9156	1.371
CHINA	0.2647	0.1894	0.7210	0.9104	2.984
PHILIPPINES	0.0832	0.1293	0.8577	0.987	6.627
THAILAND	0.0197	0.0542	0.9428	0.997	6.767
MALAYSIA	0.0039	0.0475	0.9558	1.003	-
HUNGARY	0.3237	0.2319	0.6907	0.9226	4.191
POLAND	0.1373	0.0981	0.8533	0.9514	0.144
RUSSIA	0.2458	0.1592	0.8293	0.9885	0.249
ISRAEL	0.1407	0.1058	0.8321	0.9379	0.150
S. AFRICA	0.0261	0.0896	0.9020	0.9916	3.148
GERMANY	0.0061	0.0734	0.9277	1.001	-
UK	0.0268	0.0966	0.8845	0.9811	1.424
JAPAN	0.0390	0.0713	0.9165	0.9878	3.224
US	0.0154	0.0710	0.9207	0.9917	1.893

Andreou and Ghyzels(2002) apply three types of tests for break-points in conditional variance dynamics (namely the ones proposed by Kokoszka and Leipus, Lavielle and Mouline and Inclan and Tiao) and, examining the markets of UK, Hong Kong, US and Japan for the period 4/1/1989-19/10/2001, they find that the Asian Crisis period appears to be a common break in all stock indices, that is revealed in different months of 1997. In July-August 1997 they detect the first change-points associated with the Asian crisis in UK and Hong Kong, followed by the October 1997 change-point in the S&P500 as well as the Nikkei. A second common break detected in the stock indices is associated with the Russian crisis. In July 1998 they detect change-points in the FTSE and S&P500, followed by the August 1998 break in the Nikkei. Under the single change point hypothesis the Asian crisis period appears to have been a common break point.

The detection of breaking points for each market individually is beyond the scope of this study. However, the breaking points detected in the literature cannot be ignored, and for this reason the initial sample has been divided into two parts (1/9/1995 to 31/12/1999 and 1/1/2000 to 15/3/2004) and all GARCH models have been reestimated for each period separately. Rolling estimation of GARCH coefficients has shown that the stability of the parameters and of the long-term variance is improved substantially when the two subperiods are examined separately. Furthermore, the following tables, 9 and 10, indicate that the two subsamples differ with respect to the long-term variance implied by the GARCH(1,1) model and to the persistence in variance.

Table 9 : GARCH(1,1) coefficients for each market for the first sub-sample(1/9/95-31/12/99)

EQUITY MARKET	ω	α_1	β_1	$\alpha_1+\beta_1$	Long term variance
ARGENTINA	0.2210	0.1565	0.8002	0.9567	5.103
BRAZIL	0.1604	0.1669	0.8196	0.9865	11.138
CHILE	0.0288	0.1565	0.8175	0.974	1.107
MEXICO	0.1572	0.1757	0.8007	0.9764	1.288
PERU	0.1154	0.2383	0.6857	0.924	1.518
CHINA	0.2647	0.2216	0.6645	0.8861	8.779
PHILIPPINES	0.0361	0.1706	0.8361	1.0067	-
THAILAND	0.0197	0.0410	0.9593	1.0003	-
MALAYSIA	0.0039	0.0505	0.9550	1.0055	-
HUNGARY	0.3237	0.3483	0.6243	0.9726	11.81
POLAND	0.1373	0.1255	0.8001	0.9256	1.845
RUSSIA	0.2458	0.2058	0.7661	0.9719	8.685
ISRAEL	0.1407	0.1226	0.8048	0.9274	1.938
S. AFRICA	0.0261	0.1885	0.8059	0.9944	4.660
GERMANY	0.0061	0.0958	0.8884	0.9842	0.386
UK	0.0268	0.0378	0.9544	0.992	4.887
JAPAN	0.0391	0.0761	0.9188	0.9949	7.666
US	0.0154	0.0790	0.9101	0.9891	1.412

Table 10:GARCH(1,1)coefficients for each market for the second sub-sample(1/1/00-15/3/04)

EQUITY MARKET	ω	α_1	β_1	$\alpha_1+\beta_1$	Long term variance
ARGENTINA	0.0783	0.0601	0.9321	0.9922	10.038
BRAZIL	0.5697	0.0916	0.8095	0.9011	5.760
CHILE	0.0322	0.0649	0.8912	0.9561	0.733
MEXICO	0.0198	0.0214	0.9688	0.9902	2.020
PERU	0.1309	0.1964	0.6462	0.8426	0.831
CHINA	0.2537	0.1689	0.6835	0.8524	1.718
PHILIPPINES	0.4545	0.1020	0.7006	0.8023	2.298
THAILAND	0.2502	0.1310	0.7684	0.8994	2.487
MALAYSIA	0.0779	0.1065	0.8183	0.9248	1.035
HUNGARY	0.3280	0.1327	0.7217	0.8544	2.252
POLAND	0.0522	0.0442	0.9302	0.9744	2.039
RUSSIA	0.1529	0.1297	0.8455	0.9752	6.165
ISRAEL	0.1416	0.0834	0.8577	0.9411	2.404
S. AFRICA	0.0970	0.0894	0.8588	0.9482	1.872
GERMANY	0.0554	0.0958	0.8884	0.9842	3.506
UK	0.0488	0.1172	0.8532	0.9704	1.648
JAPAN	0.1221	0.0563	0.8984	0.9547	2.695
US	0.0236	0.0767	0.9105	0.9872	1.843

The following pages present the selected models for the two subsamples. It is striking that not only the coefficient values but also the conditional variance parameterizations differ across the three periods. Only for South Africa and United Kingdom is the GARCH model the same in all cases (EGARCH(1,1) and TARCH(1,1) respectively). This facts underlines the importance of the quantity of the data and the historical period chosen for the estimation. In general, as pointed in Alexander (2001) , there exists a tradeoff between having sufficient amount of data that will guarantee convergence and parameter stability and having so much data that the estimated models do not reflect current conditions.

This is a consideration that depends on the purposes and the forecasting horizon of any particular occasion. For example, for a short forecasting horizon it might be better to remove single outliers or start the estimation sample after extraordinary events (a crash or a crisis) that are not likely to be repeated during the periods of interest.

Table 11 : Selected models for the first sample period (1/9/1995 to 31/12/1999)

	ARGENTINA	BRAZIL	CHILE	MEXICO	PERU
	GARCH(2,2)	**TARCH(1,1)**	**TARCH(1,1)**	**EGARCH(1,1)**	**TARCH(1,1)**
Mean equation					
constant-c	0.1257[a]	0.1170[b]	-0.0307[c]	0.0351[c]	-0.0009[c]
	(2.6609)	(2.1221)	(-1.6013)	(0.7582)	(-0.033)
AR(1) coefficient	0.1081[a]	0.1069[a]	0.3339[a]	0.1856[a]	0.2138[a]
	(3.0480)	(3.4827)	(10.8307)	(6.2277)	(6.1521)
GARCH-M coef.					
Variance equation					
constant- ω	0.005530[c]	0.253365[a]	0.020443[a]	-0.124951[a]	0.152754[a]
	(0.6948)	(4.4501)	(2.7574)	(-2.8493)	(3.0259)
ARCH terms:					
α_1	0.190499[a]	0.007591[c]	0.095320[a]		0.160208[a]
	(2.8888)	(0.4253)	(3.8787)		(3.4288)
α_2	-0.185545[a]				
	(-2.8716)				
GARCH terms:					
β_1	1.646825[a]	0.823522[a]	0.834274[a]		0.682514[a]
	(16.7490)	(27.9409)	(24.5887)		(9.4161)
β_2	-0.653261[a]				
	(-7.0077)				
EGARCH terms:					
α				0.241128[a]	
				(3.1034)	
β				0.9482[a]	
				(51.7505)	
γ				-0.1648[a]	
				(-3.2868)	
TARCH terms:					
γ		0.2494[a]	0.0980[c]		0.682514[a]
		(4.4865)	(1.6313)		(9.4161)
Akaike criterion	4.1005	4.3805	2.2555	3.9753	3.0852
Schwarz criterion	4.1316	4.4072	2.2822	4.0020	3.1119
Log likelihood	-2307.73	-2466.82	-1267.23	-2238.09	-1735.60
Stand.Res.Diagnostics					
$LB^2(5)$	3.2089	11.154	3.7499	2.9180	3.9084
	(0.668)	(0.048)	(0.586)	(0.713)	(0.563)
$LB^2(10)$	10.211	16.432	6.7687	5.6330	5.8870
	(0.422)	(0.089)	(0.747)	(0.845)	(0.825)
Skewness	-0.440	-0.312	0.0106	-0.0480	-0.167
Kurtosis	5.493	4.401	4.2881	4.5267	5.613
JB statistic	329.36	110.8	78.078	110.09	326.44
ARCH-LM test					
LM statistic	10.207	16.301	6.654	5.781	6.161
Probability	0.422	0.091	0.757	0.833	0.801
Summary statistics for cond. variance series					
Mean	4.507	7.648	0.729	4.243	1.700
Standard deviation	5.088	11.176	0.707	5.062	1.939
Maximum	48.109	96.808	5.463	73.967	19.711
Minimum	1.168	0.894	0.171	0.328	0.282
Skewness	4.367	3.845	3.017	5.996	4.052
Kurtosis	27.793	20.845	13.991	59.334	23.875

This table presents the maximum likelihood estimates of mean and variance equations of the models selected based on the in-sample performance. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table 11 (continued)

	CHINA GARCH(2,2)	PHILIPPINES EGARCH(1,1)	THAILAND GARCH(3.2)	MALAYSIA EGARCH(1,1)
Mean equation				
constant-c	0.0310[c]	-0.0437[c]	-0.0756[c]	0.0061[c]
	(0.6375)	(-1.2998)	(-1.6163)	(0.1635)
AR(1) coefficient		0.2638[a]	0.1525[a]	0.0927[b]
		(7.4573)	(4.7873)	(1.9891)
GARCH-M coef.				
Variance equation				
constant- ω	0.925765[a]	-0.166071[a]	00019302[c]	-0.052014[b]
	(3.5959)	(-6.0297)	(1.7272)	(-2.4620)
ARCH terms:				
α_1	0.246963[a]		0.027889[c]	
	(5.1885)		(1.9256)	
α_2	0.131806[b]		0.047483[a]	
	(2.4209)		(4.1341)	
α_3				
GARCH terms:				
β_1	-0.209960[a]		0.826788[a]	
	(-3.0476)		(68.1905)	
β_2	0.616643[a]		-0.836224[a]	
	(10.5661)		(-51.8764)	
β_3			0.935429[a]	
			(50.7192)	
EGARCH terms:				
α		0.240474[a]		0.074884[a]
		(6.2148)		(2.6614)
β		0.983848[a]		1.000277[a]
		(162.359)		(370.19)
γ		-0.074571[b]		-0.046509[a]
		(-2.2899)		(0.0089)
TARCH terms:				
γ				
Akaike criterion	3.9458	3.7101	4.3298	4.0856
Schwarz criterion	3.9725	3.7368	4.3654	4.1123
Log likelihood	-2223.42	-2088.38	-2436.20	-2300.35
Stand.Res.Diagnostics				
$LB^2(5)$	2.4178	6.1842	10.680	3.0075
	(0.789)	(0.289)	(0.058)	(0.699)
$LB^2(10)$	3.4044	8.5363	13.436	4.1108
	(0.970)	(0.577)	(0.200)	(0.942)
Skewness	-0.0576	-0.0725	0.3166	-0.1711
Kurtosis	7.6275	4.3223	4.7147	12.595
JB statistic	1008.86	83.24	157.19	4337.02
ARCH-LM test				
LM statistic	3.3879	8.3151	15.9068	3.8554
Probability	0.9707	0.5980	0.1023	0.9536
Summary statistics for cond. variance series				
Mean	4.026	3.910	6.620	9.118
Standard deviation	4.111	4.200	6.051	11.606
Maximum	41.249	22.565	43.327	49.352
Minimum	0.006	0.301	0.545	0.242
Skewness	4.344	1.821	2.088	1.383
Kurtosis	28.915	6.008	9.799	3.847

Table 11 (continued)

	HUNGARY	POLAND	RUSSIA	ISRAEL	SOUTH AFRICA
	GARCH(1,2)	**TARCH(1.1)**	**GARCH(1,2)**	**GARCH(3.1)**	**EGARCH(1,1)**
Mean equation					
constant-c	0.0783[c]	0.0061[c]	0.1171[c]	0.0775[b]	0.0740[b]
	(1.7007)	(0.1300)	(1.6607)	(2.1185)	(2.4435)
AR(1) coefficient	0.1662[a]	0.2234[a]	0.1789[a]	0.0855[b]	0.1600[a]
	(4.3573)	(6.7924)	(4.9055)	(2.5362)	(4.0869)
GARCH-M coef.					
Variance equation					
constant- ω	0.025464[c]	0.251121[a]	0.395703[b]	0.157407[a]	-0.194199[a]
	(1.7001)	(2.9902)	(2.3083)	(2.9797)	(-4.6824)
ARCH terms:					
α_1	0.608880[a]	0.062047[b]	0.269187[a]	0.118595[a]	
	(2.9919)	(2.2493)	(3.1080)	(3.3141)	
α_2	-0.566810[a]		-0.126581[c]		
	(-2.8556)		(-1.4252)		
GARCH terms:					
β_1	0.959309[a]	0.805406[a]	0.839155[a]	1.250605[a]	
	(64.0317)	(15.6097)	(19.6686)	(6.0936)	
β_2				-0.902913[a]	
				(-3.4887)	
β_3				0.453876[a]	
				(3.4867)	
EGARCH terms:					
α					0.279724[a]
					(4.7380)
β					0.962064[a]
					(89.8235)
γ					-0.092296[b]
					(-2.0306)
TARCH terms:					
γ		0.105661[c]			
		(1.6090)			
Akaike criterion	4.0202	3.8960	5.1350	3.3804	3.1550
Schwarz criterion	4.0470	3.9227	5.1617	3.4116	3.1817
Log likelihood	-2263.44	-2193.31	-2892.71	-1901.27	-1775.02
Stand.Res.Diagnostics					
$LB^2(5)$	2.0975	3.0082	0.6762	2.2416	6.5374
	(0.835)	(0.699)	(0.984)	(0.815)	(0.257)
$LB^2(10)$	2.7998	9.8915	9.8937	14.262	10.514
	(0.986)	(0.450)	(0.450)	(0.161)	(0.397)
Skewness	-0.4323	-0.1039	-0.0558	-0.5482	-0.449
Kurtosis	9.2316	4.1026	5.8052	5.7238	7.252
JB statistic	1861.98	59.22	370.78	405.57	888.7
ARCH-LM test					
LM statistic	2.7837	9.8298	10.5128	13.9520	9.2736
Probability	0.9860	0.4555	0.3967	0.1751	0.5063
Summary statistics for cond. variance series					
Mean	5.962	3.354	13.709	2.012	2.221
Standard deviation	12.422	2.830	14.566	1.949	3.173
Maximum	182.256	29.939	137.171	33.094	35.361
Minimum	0.176	1.444	1.219	0.523	0.131
Skewness	7.463	4.587	3.444	7.8521	4.937
Kurtosis	76.638	30.831	19.536	97.478	39.305

Table 11 (continued)

	GERMANY	UNITED KINGDOM	JAPAN	UNITED STATES
	EGARCH(1,1)	TARCH(1,1)	EGARCH(1,1)	TARCH (1,1)
Mean equation				
constant-c	0.0713[a]	0.0486[c]	-0.020[c]	0.0794[a]
	(2.7352)	(1.8212)	(-0.496)	(3.2689)
AR(1) coefficient		0.0614[b]		
		(2.034)		
GARCH-M coef.				
Variance equation				
constant- ω	-0.0752[a]	0.00638[c]	-0.084968[a]	0.024801[a]
	(-3.6217)	(1.7255)	(-4.4926)	(3.6420)
ARCH terms:				
α_1		0.010142[c]		-0.018654[c]
		(0.6933)		(-0.8238)
α_2				
GARCH terms:				
β_1		0.963724[a]		0.912242[a]
		(75.774)		(39.9426)
β_2				
EGARCH terms:				
α	0.09925[a]		0.119285[a]	
	(3.6295)		(4.5639)	
β	0.996991[a]		0.992310[a]	
	(378.508)		(210.55)	
γ	-0.013151[c]		-0.060933[a]	
	(-0.6094)		(-2.8882)	
TARCH terms:				
γ		0.03919[b]		0.1654[a]
		(2.0399)		(3.7021)
Mean annual.volatility				
Akaike criterion	2.9467	2.6395	3.6540	2.7277
Schwarz criterion	2.9689	2.6662	3.6763	2.750
Log likelihood	-1659.90	-1484.03	-2059.56	-1536.17
Stand.Res.Diagnostics				
$LB^2(5)$	5.6326	4.9796	9.6048	5.1593
	(0.344)	(0.418)	(0.087)	(0.397)
$LB^2(10)$	8.7656	7.9692	12.027	6.3422
	(0.554)	(0.643)	(0.283)	(0.786)
Skewness	-0.0671	-0.1471	0.261	-0.567
Kurtosis	3.8737	3.6219	4.039	4.879
JB statistic	36.795	22.27	63.778	227.03
ARCH-LM test				
LM statistic	8.9952	8.4237	91.132	5.991
Probability	0.5325	0.5875	0.7254	0.816
Summary statistics for cond. variance series				
Mean	1.577	0.922	2.784	1.133
Standard deviation	1.438	0.518	1.856	1.087
Maximum	8.619	3.246	11.766	10.994
Minimum	0.250	0.1474	0.4633	0.194
Skewness	1.971	1.598	1.382	4.087
Kurtosis	7.375	5.933	5.221	25.444

Table 12: Selected models for the second sample period (1/1/2000 to 15/3/2004)

	ARGENTINA	BRAZIL	CHILE	MEXICO	PERU
	GARCH(1,2)	EGARCH(1,)	GARCH(1,2)	EGARCH(1,)	GARCH(2,1)
Mean equation					
constant-c	0.1633[c]	-0.0146[c]	0.0013[c]	0.0193[c]	0.0432[b]
	(1.3523)	(-0.219)	(0.3383)	(0.4297)	(1.959)
AR(1) coefficient	-0.8044[a]	0.1337[a]	0.6539[a]	0.0967[a]	0.1559[a]
	(-7.7679)	(4.4631)	(3.6767)	(3.1742)	(4.7415)
AR(2) coefficient			0.2538[a]		
			(1.7877)		
MA(1) coefficient	0.8082[a]		-0.4392[a]		
	(7.6778)		(-2.5823)		
MA(2) coefficient			-0.3930[a]		
			(-3.3593)		
GARCH-M coef.					
Variance equation					
constant- ω	0.1890[a]	0.0167[c]	0.0113[c]	-0.0140[c]	0.1300[b]
	(7.8345)	(0.3514)	(1.3773)	(-0.8982)	(2.182)
ARCH terms:					
α_1	-0.0197[a]		0.195045[a]		0.223395[b]
	(-79.899)		(3.7620)		(2.2610)
α_2	0.104180[a]		-0.163328[a]		
	(15.7167)		(-3.0851)		
GARCH terms:					
β_1	0.890016[a]		0.952860[a]		0.153412[c]
	(161.54)		(40.4116)		(1.2878)
β_2					0.466796[a]
					(4.1874)
EGARCH terms:					
α		0.117239[a]		0.034685[c]	
		(2.663)		(1.8811)	
β		0.93604[a]		0.984343[a]	
		(45.154)		(196.95)	
γ		-0.09999[a]		-0.066673[a]	
		(-3.406)		(-3.951)	
TARCH terms:					
γ					
Akaike criterion	4.709	4.542	2.460	3.744	2.484
Schwarz criterion	4.741	4.569	2.501	3.771	2.512
Log likelihood	-2571.41	-2480.94	-1336.87	-2044.12	-1351.87
Stand.Res.Diagnostics					
$LB^2(5)$	2.0627	9.6802	2.0441	1.1404	2.1755
	(0.724)	(0.085)	(0.563)	(0.950)	(0.824)
$LB^2(10)$	4.7581	12.689	6.554	3.0459	3.5738
	(0.855)	(0.242)	(0.585)	(0.980)	(0.965)
Skewness	-0.3799	-0.0224	-0.2280	0.024	-0.409
Kurtosis	7.7241	3.7345	4.5868	4.747	6.266
JB statistic	1044.57	24.708	124.265	139.41	516.29
ARCH-LM test					
LM statistic	4.809	13.428	6.791	2.937	3.536
Probability	0.903	0.200	0.744	0.982	0.965
Summary statistics for cond. variance series					
Mean	8.434	5.912	0.720	2.872	0.799
Standard deviation	11.036	2.819	0.335	1.940	0.626
Maximum	118.92	28.821	5.363	18.243	9.637
Minimum	0.0009	2.234	0.346	0.769	0.376
Skewness	5.255	2.614	4.309	3.168	5.463
Kurtosis	36.966	13.654	42.843	18.614	51.906

This table presents the maximum likelihood estimates of mean and variance equations of the models selected based on the in-sample performance. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table 12 (continued)

	CHINA	PHILIPPINES	THAILAND	MALAYSIA
	EGARCH(1,1)	EGARCH(1,1)-M	TARCH(1,1)-M	TARCH(1,1)
Mean equation				
constant-c	-0.0280[c]	-0.3333[a]	0.3276[A]	0.0159[c]
	(-0.8182)	(-2.9263)	(2.7573)	(0.6024)
AR(1) coefficient		0.1130[c]	-0.3129[a]	0.1989[a]
		(1.6854)	(-3.9704)	(5.4491)
AR(2) coefficient			-0.6143[a]	
			(-7.1887)	
MA(1) coefficient			0.3625[a]	
			(5.001)	
MA(2) coefficient			0.7122[a]	
			(9.3887)	
GARCH-M coef.		0.1385[a]	-0.1218[a]	
		(2.6730)	(-2.7810)	
Variance equation				
constant- ω	-0.0484[c]	-0.0800[c]	0.1899[a]	0.0346[b]
	(-1.6811)	(-1.8928)	(3.4151)	(2.3820)
ARCH terms:				
α_1			0.041107[b]	0.013272[c]
			(2.2841)	(0.7334)
α_2				
α_3				
GARCH terms:				
β_1			0.820060[a]	0.905707[a]
			(22.1215)	(28.8725)
β_2				
β_3				
EGARCH terms:				
α	0.075163[c]	0.168163[b]		
	(1.6484)	(2.4725)		
β	0.988920[a]	0.952668[a]		
	(81.2249)	(35.4738)		
γ	-0.063918[b]	-0.094429[c]		
	(-2.3117)	(-1.7866)		
TARCH terms:				
γ			0.1255[a]	0.0928[b]
			(2.2841)	(2.4859)
Akaike criterion	3.1953	3.5344	3.662	2.757
Schwarz criterion	3.2181	3.2987	3.708	2.784
Log likelihood	-1746.02	-1924.57	-1993.36	-1503.68
Stand.Res.Diagnostics				
$LB^2(5)$	6.5230	1.0763	4.4469	8.5393
	(0.259)	(0.956)	(0.217)	(0.129)
$LB^2(10)$	8.2577	1.3710	10.222	12.361
	(0.604)	(0.999)	(0.250)	(0.262)
Skewness	0.2093	2.2700	0.006	-0.284
Kurtosis	7.5052	30.866	3.809	6.327
JB statistic	934.93	36304.6	29.883	520.01
ARCH-LM test				
LM statistic	7.9413	1.2906	11.1061	11.350
Probability	0.6345	0.9994	0.3493	0.330
Summary statistics for cond. variance series				
Mean	1.589	2.282	2.381	1.067
Standard deviation	0.903	1.525	1.369	0.788
Maximum	5.562	14.583	13.288	6.029
Minimum	0.433	0.800	1.132	0.434
Skewness	1.645	2.978	3.481	2.880
Kurtosis	6.030	15.528	20.434	12.797

Table 12 (continued)

	HUNGARY	POLAND	RUSSIA	ISRAEL	SOUTH AFRICA
	TARCH(1,1)	GARCH(1,1)	TARCH(1,1)	TARCH(1,1)	EGARCH(1,1)
Mean equation					
constant-c	0.0308^{c}	0.0355^{c}	0.1782^{a}	0.0069^{c}	0.0224^{c}
	(0.7387)	(0.8774)	(3.1897)	(0.1596)	(0.6162)
AR(1) coefficient		0.0976^{a}		0.1078^{a}	0.075^{b}
		(2.9723)		(3.4617)	(2.4624)
GARCH-M coef.					
Variance equation					
constant- ω	0.3146^{a}	0.0522^{b}	0.1918^{a}	0.1820^{a}	-0.0286^{c}
	(2.7253)	(2.0971)	(2.6655)	(3.1228)	(-1.1188)
ARCH terms:					
α_1	0.037932^{c}	0.044209^{a}	0.099180^{a}	0.022^{c}	
	(1.3885)	(3.0848)	(2.897)	(1.0345)	
α_2					
GARCH terms:					
β_1	0.74695^{a}	0.930261^{a}	0.833588^{a}	0.8357^{a}	
	(9.9817)	(47.046)	(21.984)	(22.634)	
β_2					
EGARCH terms:					
α					0.0802^{b}
					(2.2890)
β					0.9294^{a}
					(55.553)
γ					-0.1378^{a}
					(-4.9096)
TARCH terms:					
γ	0.1422^{b}		0.0627^{c}		
	(2.3858)		(1.1362)		
Mean annual.volatility					
Akaike criterion	3.5731	3.6058	4.3069	3.6505	3.3208
Schwarz criterion	3.5959	3.6286	4.3297	3.6779	3.3482
Log likelihood	-1953.06	-1969.21	-2355.18	-1992.68	-1812.15
Stand.Res.Diagnostics					
$LB^2(5)$	3.4983	9.7343	3.7939	9.6263	4.313
	(0.624)	(0.083)	(0.579)	(0.087)	(0.505)
$LB^2(10)$	8.4628	15.305	5.4038	14.923	7.2941
	(0.584)	(0.121)	(0.863)	(0.135)	(0.697)
Skewness	-0.204	-0.044	-0.350	-0.132	-0.056
Kurtosis	3.930	3.874	4.145	4.428	3.527
JB statistic	47.139	35.268	82.355	96.347	13.270
ARCH-LM test					
LM statistic	8.708	15.560	5.386	16.371	7.469
Probability	0.559	0.112	0.863	0.089	0.680
Summary statistics for cond. variance series					
Mean	2.229	2.389	5.409	2.472	1.768
Standard deviation	1.156	1.494	4.485	1.591	0.925
Maximum	14.145	12.374	32.773	20.832	10.028
Minimum	1.312	1.140	1.340	1.192	0.576
Skewness	4.159	3.340	2.449	5.030	2.509
Kurtosis	29.21	16.969	10.181	41.257	14.005

Table 12 (continued)

	GERMANY	UNITED KINGDOM	JAPAN	UNITED STATES
	TARCH(1,1)	TARCH(1,1)	GARCH(1,2)	EGARCH(1,1)
Mean equation				
constant-c	-0.0469[c]	-0.0374[c]	-0.0213[c]	-0.0369[c]
	(-1.0435)	(-1.2189)	(-0.4714)	(-1.1265)
AR(1) coefficient				
GARCH-M coef.				
Variance equation				
constant- ω	0.0489[a]	0.0369[a]	0.1443[b]	-0.0305[c]
	(3.1163)	(3.7087)	(2.1013)	(-1.8484)
ARCH terms:				
α_1	-0.003648[c]	-0.011152[c]	-0.044713[a]	
	(-0.2704)	(-0.6508)	(-6.8190)	
α_2			0.121884[a]	
			(4.9515)	
GARCH terms:				
β_1	0.918900[a]	0.905789[a]	0.870102[a]	
	(60.0379)	(48.7245)	(22.2771)	
β_2				
EGARCH terms:				
α				0.046347[b]
				(2.2435)
β				0.981130[a]
				(229.802)
γ				-0.120848[a]
				(-6.4404)
TARCH terms:				
γ	0.141009[a]	0.1624[a]		
	(5.1955)	(4.6437)		
Mean annual.volatility				
Akaike criterion	3.8377	3.1284	3.7809	3.2056
Schwarz criterion	3.8605	3.1512	3.8037	3.2284
Log likelihood	-2098.06	-1706.26	-2063.18	-1751.69
Stand.Res.Diagnostics				
$LB^2(5)$	12.644	7.5252	1.5568	5.2399
	(0.027)	(0.184)	(0.906)	(0.387)
$LB^2(10)$	15.593	10.621	9.3013	8.9004
	(0.112)	(0.388)	(0.504)	(0.542)
Skewness	-0.079	-0.160	-0.073	-0.037
Kurtosis	2.911	3.071	3.815	3.365
JB statistic	1.502	4.933	31.286	-6.356
ARCH-LM test				
LM statistic	17.110	11.189	9.798	8.158
Probability	0.0719	0.3429	0.4583	0.6133
Summary statistics for cond. variance series				
Mean	3.434	1.676	2.724	1.718
Standard deviation	2.839	1.441	1.147	1.037
Maximum	16.899	11.573	10.540	7.610
Minimum	0.666	0.374	0.187	0.226
Skewness	2.036	2.801	2.478	1.373
Kurtosis	7.231	13.03	11.763	5.733

10. Causality-in-Variance patterns

The second part of this empirical application involves the implementation of Cheung and Ng's (1996) procedure for detecting causality-in-variance. The direction of causality is restricted: we are seeking causality spillovers (in mean and in variance) from the developed markets to the emerging ones.

The sample cross-correlations of standardized residuals and squared standardized residuals of the models estimated in the previous part are calculated and presented in table A19 of the Appendix. The "lag" refers to the number of periods each developed market data lag emerging market data. A "lead" is given by a negative lag. As explained in part 7, the cross correlation multiplied by the square root of the number of observations in the sample gives a test statistic that is asymptotically normally distributed. Table 13 below summarizes the significant correlations between pairs of markets.

Table 13 : Summary of causality patterns for the overall sample

(causality **to**) Emerging markets		(causality **from**) Developed markets			
		US	Japan	UK	Germany
ARGENTINA	Mean	-3,0	0	-3,0	-4,0
	Variance	-4,-2,0	-1	-4,-2,0	0
BRAZIL	Mean	-1,0	-4.0	-4,-3,0	-4,0
	Variance	-2,0		0	-4,0
CHILE	Mean	-5,0	0	0	-5,0
	Variance	-4,0	-5,-1	-3,-2,0	-4,0
MEXICO	Mean	-3,0		-2,0	-2,0
	Variance	0	0	-3,-2,0	-2
PERU	Mean	-1,0	-1	-3,0	-4,-1,0
	Variance	0	-2,-1	-2,0	-4,0
CHINA	Mean	0		-4,-2,-1	-1
	Variance	-4,0		-4	-4
PHILIPPINES	Mean	-1,0	-1,0	-1,0	-1,0
	Variance	-1	0		
THAILAND	Mean	-3,-1,0	-1,0	-3,-2,-1,0	-3,-2,-1,0
	Variance	-5,-1	-1,0	-5,-3,-1	-3,-1
MALAYSIA	Mean	-3,-1	-3,0	-1,0	-4,-1,0
	Variance	-1	0		
HUNGARY	Mean	-2,-1	-3,0	-4,-3,-1,0	-1,0
	Variance	-1,0	-3	-3	-3,0
POLAND	Mean	-3,-2,-1,0	0	-2,-1,0	-1,0
	Variance	-3,-1,0	0	-3,-1,0	-3,-1,0
RUSSIA	Mean	-1,0	0	-4,-3,-1,0	-4,-1,0
	Variance	-1,0	0	-3,0	0
ISRAEL	Mean	-4,-3,-1,0	0	-3,-1,0	-4,-3,0
	Variance	-4,-1,0		-5,-4,-3,0	0
S. AFRICA	Mean	-1,0	0	-2,-1	-1,0
	Variance	-1,0	0	-3,-1,0	-4,-2,-1,0

This summary is based on the sample cross-correlations reported in table A19 . 0 indicates contemporaneous correlation, while k indicates the presence of correlation at lag k

Based on the sample cross-correlation causation patterns, the respective models are reconstructed by adding the relevant exogenous variables (the developed market's lagged return-for the mean equation- or squared return-for the variance equation) to the original models. The augmented models are reestimated, non-significant coefficients are dropped and the resulting models are presented in table 14. The maximum likelihood values and the Akaike and Schwarz criteria indicate that the new models perform better than the original models in-sample. The variables added have explanatory power with respect to the relevant mean and volatility equations. Besides, they can reveal information about the flow of return and volatility from developed markets to emerging ones. The same procedure is repeated for the two subsamples and the augmented models are given in tables 15 and 16.

For the overall sample, there is evidence of causality-in-variance from Germany to Argentina, Brazil, Mexico, Thailand and Israel; from UK to Argentina, Mexico, Hungary and S.Africa; from Japan to Argentina, Chile, Philippines, Thailand and Malaysia and finally from US to Argentina, Brazil, China, Malaysia, Hungary, Poland and Russia. US market appears to be the major exporter of volatility, since it influences the largest number of emerging markets, with a number of lags ranging from 0 to -4.

As can be deduced from the estimation results, mean and variance causality do not have the same patterns, i.e. one developed market may cause an emerging one in-mean but not in-variance and vice-versa. For example, in the overall sample, Chile is caused in-mean by Germany, UK and US but in-variance it is caused only by Japan; Israel and S. Africa appear to be caused-in-mean by all four developed markets, while in variance they are caused by Germany and UK.

Geographical proximity appears to influence mean returns more than volatility. For example, Hungary, Poland and Russia are caused-in-mean by Germany and United Kingdom, while variance causality is mainly driven by US. Chile is caused-in-variance solely by Japan.

Finally, Peru is not caused-in-variance by any of the developed markets.

The number of lags in causality relations should be interpreted with caution due to existing time differences. For example, During the regular trading hours of the New York stock market, markets in East Asia have already completed their trading day. Thus, investors in Asia will have information on the previous day’s stock price movements in New York before the commencement of trading of their own market. Thus, causality-in-variance at lag 0 should be interpreted as evidence of the US market causing the Asian market. Furthermore, Asian-Pacific markets are open when European markets are closed. Therefore, these markets can neither influence Asia-Pacific markets contemporaneously. Malaysia and Thailand close some hours after the Japanese market has closed. Therefore, contemporaneous causality between them (on the same calendar day) means that Japanese index movements affects the closing price of these markets.

In the first subsample, Germany is the leader in volatility spillover effects and causes, among others, all three European emerging markets and S. Africa. Causality patterns are not the same as in the overall sample, while Peru and Malaysia do not appear to be caused-in-variance by any of the suggested explanatory variables.

In the second subsample, US appear to be the major exporter of variance, although UK and Japan also influence a large number of markets.

Some variance causality patterns remain stable across the three sample periods. These are, namely, from Germany to Brazil, from Germany to S.Africa, from UK to Argentina and from US to Hungary.

The volatility transmission mechanism can either be explained as the natural consequence of the real and financial interrelations between economies or (and) as a result of the action of institutional investors (portfolio interpretation). Furthermore, as noted in Brooks and Henry(2000) the existence of lead/lag links is not necessarily inconsistent with the weak form of the efficient market hypothesis and does not directly imply excess returns will exist. The long-run availability of such excess returns is the condition which would have to be fulfilled for a violation of the efficient markets hypothesis.

Table 14: Estimates of augmented models using exogenous variables-overall sample

	ARGENTINA		BRAZIL		CHILE		MEXICO	
	Lags	**TARCH(1,1)**	**Lags**	**TARCH(2,1)**	**Lags**	**GARCH(2,2)**	**Lags**	**TARCH(1,1)**
Mean equation								
constant-c		-0.0098[c] (-0.259)		-0.0102[c] (-0.278)		-0.0113[c] (-0.903)		0.8800[a] (12.283)
AR(1) coefficient		0.0462[b] (2.202)		0.0879[a] (4.643)		0.2957[a] (6.065)		-0.0548[c] (-0.8922)
MA(1) coefficient						-0.058[c] (-1.099)		
MA(2) coefficient						-0.0216[c] (-0.881)		
GARCH-M coef.								
R_{GER}	-4	0.0537[b] (2.037)	0	0.1768[a](4.192)	0	0.051[a](3.459)		
			-4	0.0779[a](2.667)	-5	0.0351[a](3.587)		
R_{UK}	0	0.2127[c] (5.615)	0	0.1804[a](3.484)	0	0.0885[a] (4.77)		
R_{JAP}								
R_{US}	0	0.0537[b] (2.037)	0	0.6916[a](15.52)	0	0.1469[a] (7.937)		
Variance equation								
constant- ω		0.0803[a] (5.593)		0.2772[a] (4.178)		0.0018[c] (1.224)		-0.0024[c] (-0.007)
ARCH terms:								
α_1		0.0669[a](13.553)		-0.0101[c] (-0.665)		0.1804[a] (4.637)		0.1236[c] (0.887)
α_2						-0.1565[a] (-4.076)		
GARCH terms:								
β_1		0.8966[a](167.33)		0.5711[a] (5.817)		1.2290[a] (6.797)		0.5365[a] (3.008)
β_2				0.1621[c] (1.1714)		-0.2613[c] (-1.533)		
EGARCH terms:								
α								
β								
γ								
TARCH terms:								
γ		0.0489[a] (4.979)		0.2738[a] (3.524)				1.5591[a] (2.695)
$(R_{GER})^2$	0	0.0321[a] (5.091)	0	0.0989[b](1.952)			-2	-0.0643[a] (-3.901)
$(R_{UK})^2$	-4	-0.0446[a] (-3.445)					0	0.9362[a] (3.365)
$(R_{JAP})^2$	-1	-0.0086[b] (-2.033)			-1	0.0012[b] (1.828)		
$(R_{US})^2$	0	0.0613[a] (3.621)	0	0.1021[a](3.285)				
	-4	-0.0546[a] (-3.444)						
Akaike criterion		4.2275		4.2000		2.2047		2.1097
Schwarz criterion		4.2634		4.2333		2.2433		3.9866
Log likelihood		-4682.78		-4653.20		-2433.42		-4425.67
Stand.Res.Diagnostics								
$LB^2(5)$		4.0769		4.4213		1.6044		1.1352
		(0.538)		(0.490)		(0.658)		(0.951)
$LB^2(10)$		9.0169		6.9288		3.9077		1.9702
		(0.531)		(0.474)		(0.865)		(0.997)
Skewness		-0.3398		-0.1165		-0.043		4.843
Kurtosis		6.8725		3.6311		4.3135		43.244
JB statistic		1431.20		41.91		160.36		158781
ARCH-LM test								
LM statistic		9.214		8.978		3.849		2.003
Probability		0.511		0.534		0.953		0.996
Summary statistics for cond. variance series								
Mean		6.257		5.104		0.603		4.527
Standard deviation		10.280		5.331		0.384		8.910
Maximum		145.01		68.983		5.073		267.73
Minimum		0.137		1.155		0.148		0.173
Skewness		6.701		4.143		21.896		17.134
Kurtosis		62.497		28.621		26576.6		418.54

This table presents the maximum likelihood estimates of mean and variance equations of the models augmented with explanatory variables indicated by cross-correlation functions. R_{GER}, R_{UK}, R_{JAP}, R_{US} are the returns of Germany, United Kingdom, Japan and United States markets respectively, while $(R_{GER})^2$, $(R_{UK})^2$, $(R_{JAP})^2$, $(R_{US})^2$ are the returns squared. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level,[b] Denotes significance at 5% level,[c] Denotes significance at above 10% levels

Table 14 (continued)

	PERU Lags	PERU TARCH(1,1)	CHINA Lags	CHINA GARCH(2,2)	PHILIPPINES Lags	PHILIPPINES EGARCH(1,1)	THAILAND Lags	THAILAND GARCH(3,3)
Mean equation								
constant-c		0.0163[c] (0.9199)		0.0197[c] (0.719)		-0.0486[c] (-1.804)		0.0118[c] (0.3801)
AR(1) coefficient		0.1632[a] (6.6518)		0.016[c] (0.560)		0.1956[a] (96.649)		0.0992[a] (4.9196)
AR(2) coefficient		0.0405[b] (1.7701)						
GARCH-M coef.								
R_{GER}	0	0.096[a] (5.448)	-1	0.0362[a] (2.581)	0	0.0462[a] (2.632)		
					-1	0.1180[a] (3.328)		
R_{UK}							0	0.0986[a] (3.100)
							-1	0.0669[b] (2.198)
							-3	0.0882[a] (3.686)
R_{JAP}					0	0.0778[a] (4.287)	0	0.1799[a] (7.982)
R_{US}	0	0.0971[a] (4.204)	0	-0.0419[b](-2.04)	-1	0.1645[a] (5.765)	-1	0.1168[a] (3.928)
	-1	0.0866[a] (4.887)						
Variance equation								
constant- ω		0.0971[a] (3.962)		0.0063[b] (2.031)		-0.1601[a] (-4.736)		0.0519[b] (2.536)
ARCH terms:								
α_1		0.1909[a] (4.814)		0.2087[a] (4.688)				0.0562[a] (4.667)
α_2				-0.2024[a] (-4.680)				0.0558[a] (5.184)
α_3								0.0655[a] (5.047)
GARCH terms:								
β_1		0.6957[a] (12.912)		1.5604[a] (17.824)				0.3212[a] (5.835)
β_2				-0.5682[a] (-6.629)				-0.2738[a] (-4.783)
β_3								0.7514[a] (17.135)
EGARCH terms:								
α						0.2338[a] (5.420)		
β						0.9625[a] (114.46)		
γ						-0.0958[b] (-1.897)		
TARCH terms:								
γ		0.0857[c] (1.080)						
$(R_{GER})^2$							-1	0.0109[a] (2.635)
							-3	-0.0178[a](-6.584)
$(R_{UK})^2$								
$(R_{JAP})^2$					0	0.0069[a] (3.972)	0	0.0307[a] (3.617)
$(R_{US})^2$			0	-0.001[b](-1.921)				
Akaike criterion		2.7140		3.574		3.564		3.971
Schwarz criterion		2.7396		3.600		3.593		4.015
Log likelihood		-3007.99		-3966.90		-3954.95		-4397.39
Stand.Res.Diagnostics								
$LB^2(5)$		2.9835		2.1738		0.7856		7.1624
		(0.703)		(0.825)		(0.978)		(0.209)
$LB^2(10)$		4.3834		3.0056		1.3085		12.774
		(0.928)		(0.981)		(0.999)		(0.237)
Skewness		-0.150		0.246		1.399		0.203
Kurtosis		6.214		8.177		23.092		4.695
JB statistic		966.12		2507.98		38155.3		281.56
ARCH-LM test								
LM statistic		4.568		2.884		1.269		13.222
Probability		0.918		0.984		0.999		0.211
Summary statistics for cond. variance series								
Mean		1.166		2.779		2.927		4.317
Standard deviation		1.344		3.062		3.175		4.550
Maximum		14.297		40.184		22.187		51.433
Minimum		0.298		0.362		0.399		0.006
Skewness		4.468		4.729		2.749		3.986
Kurtosis		28.919		37.845		11.287		28.448

Table 14 (continued)

	MALAYSIA		HUNGARY		POLAND		RUSSIA	
	Lags	GARCH(1,1)	Lags	GARCH(1,1)	Lags	GARCH(1,2)	Lags	GARCH(2.2)
Mean equation								
constant-c		0.0365[C] (1.643)		0.0803[a] (2.830)		0.0245[c] (0.8423)		0.1283[a] (2.937)
AR(1) coefficient		0.14819[A] (5.352)		0.1117[a] (4.346)		0.1212[a] (5.2744)		0.1149[a] (4.9053)
GARCH-M coef.								
R_{GER}			0	0.1937[a] (6.837)	0	0.1663[a] (5.424)	0	0.1140[b] (2.51)
R_{UK}			0	0.1719[a] (4.487)	0	0.0976[b] (2.410)	0	0.2089[a](3.553)
R_{JAP}	0	0.1154[a] (6.619)	0	0.0763[a] (3.709)	0	0.0909[a] (4.269)	0	0.0820[b] (2.420)
	-3	0.0369[b] (2.401)						
R_{US}	-1	0.1472[a] (6.480)	-1	0.1891[a] (5.932)	-1	0.2945[a] (9.849)	0	0.1160[b] (1.989)
			-2	-0.0636[b] (-2.222)	-2	-0.0821[a] (-2.97)	-1	0.2360[a] (5.322)
Variance equation								
constant- ω		-0.0028[c] (-0.513)		0.2189[b] (2.313)		0.0488[b] (2.426)		0.2776[b] (2.359)
ARCH terms:								
α_1		0.0482[a] (3.322)		0.1697[a] (4.969)		0.1045[a] (3.468)		0.1711[a] (4.759)
α_2						-0.0695[b] (-2.206)		-0.027[c] (-0.432)
GARCH terms:								
β_1		0.9518[a] (63.180)		0.7156[a] (13.010)		0.9427[a] (55.000)		0.7976[b] (2.498)
β_2								0.0246[c] (0.0938)
EGARCH terms:								
α								
β								
γ								
TARCH terms:								
γ								
$(R_{GER})^2$								
$(R_{UK})^2$			-3	-0.0463[b] (-2.096)				
$(R_{JAP})^2$	0	0.0059[b] (2.538)						
$(R_{US})^2$	-1	-0.0031[b] (-2.000)	0	0.1178[b] (2.243)	0	0.0647[a] (2.664)	0	0.1888[b] (2.172)
					-3	-0.065[a] (-2.803)	-3	-0.1739[a] (-2.764)
Akaike criterion		3.3938		3.6579		3.6055		4.658
Schwarz criterion		3.4195		3.6887		3.6389		4.693
Log likelihood		-3762.24		-4053.78		-3994.55		-5163.38
Stand.Res.Diagnostics								
$LB^2(5)$		4.7081		1.0967		2.8809		1.0576
		(0.453)		(0.954)		(0.718)		(0.958)
$LB^2(10)$		6.7540		4.1091		9.2303		13.872
		(0.748)		(0.942)		(0.510)		(0.179)
Skewness		0.176		-0.054		0.094		-0.139
Kurtosis		9.908		7.264		4.044)		5.326
JB statistic		4432.87		1685.83		104.34		508.56
ARCH-LM test								
LM statistic		6.422		4.132		9.322		13.871
Probability		0.778		0.941		0.501		0.189
Summary statistics for cond. variance series								
Mean		4.940		2.976		2.313		8.541
Standard deviation		10.161		3.936		1.135		9.473
Maximum		84.559		52.996		14.110		89.102
Minimum		0.206		0.691		0.820		0.584
Skewness		4.048		6.325		3.243		3.610
Kurtosis		23.024		55.044		21.889		20.507

Table 14 (continued)

	ISRAEL		SOUTH AFRICA	
	Lags	**TARCH(1,1)**	**Lags**	**EGARCH(1,1)**
Mean equation				
constant-c		0.0174[C] (0.659)		0.0600[a] (3.1019)
AR(1) coefficient		0.0513[B] (2.246)		0.0390[c] (0.0927)
GARCH-M coef.				
R_{GER}	0	0.0951[a] (3.462)	0	0.2797[a] (16.913)
R_{UK}	0	0.1358[a] (3.833)	-1	0.0617[b] (2.362)
R_{JAP}	0	0.0452[a] (2.754)	0	0.0677[a] (4.996)
R_{US}	0	0.1453[a] (4.603)	-1	0.2213[a] (9.412)
	-1	0.201[a] (7.406)		
	-3	0.0593[b] (2.226)		
Variance equation				
constant- ω		0.1253[a] (3.351)		0.0442[a] (2.973)
ARCH terms:				
α_1		0.0683[b] (2.534)		0.1310[a] (4.893)
α_2				
GARCH terms:				
β_1		0.8085[a] (23.549)		0.7771[a] (4.893)
β_2				
EGARCH terms:				
α				
β				
γ				
TARCH terms:				
γ		0.0654[c] (1.879)		
$(R_{GER})^2$	0	0.0189[b] (2.487)	0	0.0521[a] (3.002)
			-2	-0.0324[a] (-2.056)
$(R_{UK})^2$			0	0.0374[b] (2.164)
$(R_{JAP})^2$				
$(R_{US})^2$				
Akaike criterion		3.3811		3.0058
Schwarz criterion		3.4145		3.0366
Log likelihood		-3745.13		-3330.48
Stand.Res.Diagnostics				
$LB^2(5)$		2.9653		3.7311
		(0.705)		(0.589)
$LB^2(10)$		10.394		5.9631
		(0.407)		(0.818)
Skewness		-0.322		-0.192
Kurtosis		5.723		5.009
JB statistic		725.29		387.87
ARCH-LM test				
LM statistic		10.400		5.788
Probability		0.406		0.832
Summary statistics for cond. variance series				
Mean		1.947		1.528
Standard deviation		1.377		1.537
Maximum		18.417		21.304
Minimum		0.771		0.259
Skewness		4.578		4.953
Kurtosis		36.056		45.033

Table 15: Estimates of augmented models using exogenous variables-first subsample

	ARGENTINA		BRAZIL		CHILE		MEXICO	
	Lags	**GARCH(2,2)**	**Lags**	**TARCH(1,1)**	**Lags**	**TARCH(1,1)**	**Lags**	**EGARCH(1,1)**
Mean equation								
constant-c		0.0265^{c} (0.633)		-0.0068^{c} (-0.135)		-0.0551^{a} (-2.970)		-0.0558^{c} (-1.366)
AR(1) coefficient		0.0680^{b} (2.386)		0.0575^{b} (2.036)		0.3017^{a} (10.267)		0.1353^{a} (4.962)
GARCH-M coef.								
R_{GER}			0	0.1557^{b} (2.389)	0	0.0624^{a} (2.949)	0	0.1362^{a} (2.752)
			-4	0.1257^{b} (2.341)				
R_{UK}	0	0.1504^{b} (2.533)	0	0.1573^{b} (2.075)	0	0.0834^{a} (3.193)	0	0.2057^{a} (3.247)
R_{JAP}								
R_{US}	0	0.7944^{a} (14.933)	0	0.7358^{a} (11.379)	0	0.1717^{a} (6.727)	0	0.6914^{a} (15.005)
	-2	-0.100^{b} (-2.008)						
Variance equation								
constant- ω		0.2293^{b} (2.488)		0.2184^{a} (3.851)		0.0151^{b} (2.226)		-0.1008^{a} (-2.596)
ARCH terms:								
α_1		0.2061^{a} (4.802)		0.0049^{c} (0.255)		0.0828^{a} (3.394)		
α_2		0.0838^{c} (1.887)						
GARCH terms:								
β_1		-0.0507^{c} (-0.807)		0.7665^{a} (19.477)		0.8246^{a} (21.629)		
β_2		0.6338^{a} (8.790)						
EGARCH terms:								
α								0.1675^{a} (3.311)
β								0.9259^{a} (37.602)
γ								-0.1148^{a} (-4.170)
TARCH terms:								
γ				0.268^{a} (4.781)		0.0704^{c} (1.470)		
$(R_{GER})^2$			-4	0.1594^{b} (2.417)	-2	0.0134^{b} (2.269)		
$(R_{UK})^2$	0	0.2225^{b} (2.119)						
	-3	0.2686^{a} (2.694)						
$(R_{JAP})^2$								
$(R_{US})^2$							0	0.0319^{b} (2.375)
Akaike criterion		3.8276		4.1756		2.1194		3.6960
Schwarz criterion		3.8811		4.2247		2.1640		3.7406
Log likelihood		-2144.85		-2339.86		-1185.36		-2076.44
Stand.Res.Diagnostics								
$LB^2(5)$		2.4956		1.6518		1.1697		1.6057
		(0.777)		(0.895)		(0.948)		(0.901)
$LB^2(10)$		9.3614		6.8838		7.4781		3.7006
		(0.498)		(0.736)		(0.680)		(0.960)
Skewness		-0.346		-0.101		0.170		0.229
Kurtosis		5.017		3.841		3.779		3.881
JB statistic		213.68		35.173		34.018		46.533
ARCH-LM test								
LM statistic		8.517		6.550		7.059		3.555
Probability		0.578		0.767		0.719		0.965
Summary statistics for cond. variance series								
Mean		3.525		5.688		0.597		3.114
Standard deviation		3.745		7.397		0.482		4.656
Maximum		38.438		72.568		3.972		58.102
Minimum		0.238		1.126		0.137		0.474
Skewness		3.802		3.908		2.547		7.031
Kurtosis		23.040		23.419		11.491		62.376

This table presents the maximum likelihood estimates of mean and variance equations of the models augmented with explanatory variables indicated by cross-correlation functions. R_{GER}, R_{UK}, R_{JAP}, R_{US} are the returns of Germany, United Kingdom, Japan and United States markets respectively, while $(R_{GER})^2$, $(R_{UK})^2$, $(R_{JAP})^2$, $(R_{US})^2$ are the returns squared. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level, [b] Denotes significance at 5% level, [c] Denotes significance at above 10% levels

Table 15 (continued)

	Lags	PERU TARCH(1,1)	Lags	CHINA GARCH(2,2)	Lags	PHILIPPINES EGARCH(1,1)	Lags	THAILAND GARCH(3,2)
Mean equation								
constant-c		-0.0322[c] (-1.093)		0.0327[c] (0.729)		-0.0735[b] (-2.104)		-0.1152[b] (-2.369)
AR(1) coefficient		0.2076[a] (5.936)				0.2298[a] (7.262)		0.1529[a] (4.870)
GARCH-M coef.								
R_{GER}	0	0.0662[b] (2.121)			0	0.1114[a] (3.043)		
					-1	0.1443[a] (4.028)		
R_{UK}	0	0.1125[b] (2.277)					0	0.2695[a] (4.799)
R_{JAP}								
R_{US}	0	0.1764[a] (3.1657			-1	0.2539[a] (6.160)	-1	0.2179[a] (3.4815)
Variance equation								
constant- ω		0.1550[a] (2.684)		1.1199[a] (3.746)		-0.1765[a] (-6.132)		-0.0106[c] (-0.459)
ARCH terms:								
α_1		0.1594[a] (3.313)		0.2676[a] (5.158)				0.0362[b] (2.203)
α_2				0.1630[a] (2.729)				0.0420[a] (2.605)
GARCH terms:								
β_1		0.6934[a] (9.175)		-0.2585[a] (-3.125)				0.9638[a] (45.601)
β_2				0.5666[a] (9.135)				-0.9661[a] (-33.415)
β_3								0.8919[a] (29.510)
EGARCH terms:								
α						0.2406[a] (5.991)		
β						0.9747[a] (134.27)		
γ						-0.0838[a] (-2.624)		
TARCH terms:								
γ		0.0968[c] (1.074)						
$(R_{GER})^2$								
$(R_{UK})^2$								
$(R_{JAP})^2$			0	-0.0152[a] (-9.086)	-3	-0.0140[a] (-3.597)		
			-1	-0.0111[b] (-2.056)	-5	0.0186[a] (4.234)		
$(R_{US})^2$							-1	0.1794[a] (3.178)
Akaike criterion		3.0261		3.941		3.633		4.2745
Schwarz criterion		3.0662		3.976		3.682		4.3235
Log likelihood		-1699.28		-2216.81		-2032.6		-2401.96
Stand.Res.Diagnostics								
$LB^2(5)$		1.5209		2.3300		4.8950		11.714
		(0.911)		(0.802)		(0.429)		(0.039)
$LB^2(10)$		3.9146		3.5498		7.2494		15.547
		(0.951)		(0.965)		(0.702)		(0.113)
Skewness		-0.212		-0.048		-0.076		0.377
Kurtosis		5.969		7.375		4.119		4.968
JB statistic		423.37		901.25		59.881		209.06
ARCH-LM test								
LM statistic		4.110		3.419		7.168		18.150
Probability		0.942		0.969		0.709		0.0524
Summary statistics for cond. variance series								
Mean		1.486		3.918		3.608		5.930
Standard deviation		1.410		4.2129		4.074		5.098
Maximum		11.938		43.331		27.896		42.972
Minimum		0.2878		0.024		0.269		0.414
Skewness		3.624		4.507		2.108		2.107
Kurtosis		19.117		30.881		7.716		10.784

Table 15 (continued)

	MALAYSIA		HUNGARY		POLAND		RUSSIA	
	Lags	EGARCH(1,1)	Lags	GARCH(1,2)	Lags	TARCH(1,1)	Lags	GARCH(1.2)
Mean equation								
constant-c		-0.0221[c] (-0.530)		0.0614[c] (1.610)		-0.0484[c] (-1.127)		-0.0380[c] (-0.543)
AR(1) coefficient		0.0861[c] (1.866)		0.1456[a] (4.081)		0.2034[a] (6.351)		0.1654[a] (4.794)
GARCH-M coef.								
R_{GER}			0	0.3202[a] (5.470)	0	0.1665[a] (3.303)	0	0.2930[a] (3.322)
					-1	0.2242[a] (5.252)		
R_{UK}	0	0.1565[a] (2.608)	0	0.1672[a] (2.725)	0	0.1559[b] (2.499)	0	0.2736[b] (2.333)
			-5	-0.1112[a] (-2.634)			-4	0.2140[b] (2.389)
R_{JAP}								
R_{US}	-1	0.2055[a] (4.103)	-1	0.2094[a] (3.837)	-1	0.4547[a] (8.705)	-1	0.5276[a] (5.303)
			-3	0.1274[a] (2.673)	-2	-0.2983[a] (-5.843)		
Variance equation								
constant- ω		-0.0498[b] (-2.355)		0.3189[b] (2.226)		0.3599[a] (2.664)		0.4325[b] (2.032)
ARCH terms:								
α_1				0.3064[a] (4.621)		0.0824[b] (2.195)		0.2300[a] (4.447)
α_2				-0.0317[c] (-0.598)				
GARCH terms:								
β_1				0.3643[a] (3.708)		0.6733[a] (7.487)		0.4185[c] (1.671)
β_2								0.2962[c] (1.332)
EGARCH terms:								
α		0.0720[b] (2.493)						
β		1.0005[a] (411.066)						
γ		-0.0407[cb] (-2.218)						
TARCH terms:								
γ						0.0554[c] (0.995)		
$(R_{GER})^2$			0	0.2868[a] (3.156)	0	0.1613[a] (4.352)	0	0.2727[b] (1.966)
			-3	0.3557[a] (2.699)	-5	-0.0519[a] (-2.830)		
$(R_{UK})^2$			-3	-0.2007[a] (-5.855)				
$(R_{JAP})^2$								
$(R_{US})^2$			-1	0.2891[b] (2.194)				
Akaike criterion		4.0536		3.812		3.6660		5.0437
Schwarz criterion		4.0893		3.879		3.7241		5.0928
Log likelihood		-2280.29		-2129.47		-2049.15		-2828.63
Stand.Res.Diagnostics								
$LB^2(5)$		3.6253		2.1084		2.2377		0.7929
		(0.605)		(0.834)		(0.815)		(0.977)
$LB^2(10)$		5.1291		12.608		10.366		15.481
		(0.882)		(0.246)		(0.409)		(0.115)
Skewness		-0.148		0.033		0.087		0.212
Kurtosis		13.306		5.511		3.820		5.274
JB statistic		5000.72		295.91		32.983		251.26
ARCH-LM test								
LM statistic		4.7077		12.674		10.270		17.460
Probability		0.9098		0.242		0.417		0.064
Summary statistics for cond. variance series								
Mean		8.832		4.123		2.475		12.384
Standard deviation		11.020		6.496		1.398		12.625
Maximum		44.126		80.483		12.484		91.196
Minimum		0.219		0.026		0.789		1.283
Skewness		1.306		5.765		3.023		2.875
Kurtosis		3.522		48.044		15.752		13.212

Table 15 (continued)

	Lags	ISRAEL GARCH(3,1)	Lags	SOUTH AFRICA EGARCH(1,1)
Mean equation				
constant-c		-0.0169[c] (-0.440)		0.0169[c] (0.629)
AR(1) coefficient		0.0495[c] (1.539)		0.1313[a] (3.971)
GARCH-M coef.				
R_{GER}			0	0.1792[a] (5.3428)
R_{UK}	0	0.1780[a] (4.133)	0	0.1865[a] (4.3794)
	-3	0.1274[a] (3.061)		
	-5	0.1042[a] (3.004)		
R_{JAP}				
R_{US}	0	0.1286[a] (3.172)	-1	0.1815[a] (6.149)
	-1	0.3148[a] (7.763)	-2	-0.0620[b] (-1.962)
	-4	-0.1058[a] (-3.042)		
Variance equation				
constant- ω		0.0792[a] (2.826)		-0.2237[a] (-3.213)
ARCH terms:				
α_1		0.0781[a] (2.889)		
α_2				
GARCH terms:				
β_1		0.6774[a] (6.730)		
β_2		0.7933[a] (18.109)		
β_3		-0.6134[a] (-8.311)		
EGARCH terms:				
α				0.2525[a] (3.1393)
β				0.9225[a] (29.838)
γ				-0.0887[b] (-2.385)
TARCH terms:				
γ				
$(R_{GER})^2$			0	0.0887[a] (5.0367)
			-1	-0.0620[a] (-3.430)
$(R_{UK})^2$	0	0.0921[a] (2.881)		
	-3	-0.0582[a] (-2.817)		
$(R_{JAP})^2$				
$(R_{US})^2$				
Akaike criterion		3.2416		2.925
Schwarz criterion		3.3086		2.978
Log likelihood		-1808.41		-1637.75
Stand.Res.Diagnostics				
$LB^2(5)$		5.9030		3.5701
		(0.316)		(0.613)
$LB^2(10)$		13.283		5.6549
		(0.208)		(0.843)
Skewness		-0.4004		-0.2834
Kurtosis		5.9016		6.0125
JB statistic		424.73		441.65
ARCH-LM test				
LM statistic		13.019		5.1551
Probability		0.222		0.8805
Summary statistics for cond. variance series				
Mean		1.748		1.977
Standard deviation		1.480		7.317
Maximum		14.815		176.02
Minimum		0.276		0.204
Skewness		4.309		18.290
Kurtosis		28.256		392.932

Table 16: Estimates of augmented models using exogenous variables-second subsample

	ARGENTINA		BRAZIL		CHILE		MEXICO	
	Lags	**GARCH(1,2)**	**Lags**	**EGARCH(1,1)**	**Lags**	**GARCH(1,2)**	**Lags**	**EGARCH(1,1)**
Mean equation								
constant-c		0.0411^{c} (0.712)		-0.0071^{c} (-0.124)		0.0272^{c} (0.999)		0.0454^{c} (1.284)
AR(1) coefficient		0.0192^{c} (0.280)		0.1357^{a} (5.553)		-0.2421^{c} (-1.716)		0.0389^{c} (1.245)
AR(2) coefficient		-0.0116^{c} (-0.161)				0.1484^{c} (1.691		
MA(1) coefficient						-0.1055^{c} (-1.362)		
MA(2) coefficient								
GARCH-M coef.								
R_{GER}	0	0.1679^{a} (4.212)	0	0.2906^{a} (6.172)			0	0.1589^{a} (5.732)
	-2	0.0621^{b} (1.968)						
	-4	0.0804^{b} (2.576)						
R_{UK}	-2	0.1256^{a} (5.002)						
R_{JAP}	-4	-0.0484^{b} (-2.061)					-3	0.0517^{b} (2.325)
R_{US}	0	0.3543^{a} (6.602)	0	0.6364^{a} (10.232)	0	0.2072^{a} (13.262)	0	0.5244^{s} (13.120)
			-3	0.1519^{a} (3.298)	-1	0.1747^{a} (6.109)	-1	0.0969^{b} (2.443)
Variance equation								
constant- ω		0.3257^{a} (5.505)		0.090^{c} (1.817)		0.0068^{c} (1.457)		0.0125^{c} (1.013)
ARCH terms:								
α_1		0.0953^{c} (1.821)				0.2036^{a} (3.859)		
α_2		0.0497^{c} (0.714)				-0.1713^{a} (-3.158)		
GARCH terms:								
β_1		0.8277^{a} (20.296)				0.9576^{a} (54.141)		
β_2								
EGARCH terms:								
α				0.0584^{c} (1.253)				-0.0164^{c} (-0.997)
β				0.8492^{a} (22.829)				0.9975^{c} (1578.94)
γ				-0.1495^{a} (-4.974)				-0.0121^{c} (-0.904)
TARCH terms:								
γ								
$(R_{GER})^2$			0	0.0205^{a} (4.549)				
$(R_{UK})^2$	-1	-0.0637^{a} (-10.33)						
$(R_{JAP})^2$								
$(R_{US})^2$							0	0.0245^{a} (4.227)
							-4	-0.0248^{a} (-4.134)
Akaike criterion		4.6068		4.2168		2.3147		3.2991
Schwarz criterion		4.6709		4.2625		2.3649		3.3450
Log likelihood		-2499.05		-2294.51		-1255.16		-1789.32
Stand.Res.Diagnostics								
$LB^2(5)$		3.0107		8.5769		1.5231		5.5516
		(0.556)		(0.127)		(0.677)		(0.352)
$LB^2(10)$		4.9806		12.182		3.7588		12.209
		(0.836)		(0.273)		(0.878)		(0.271)
Skewness		-0.5735		-0.0633		-0.2830		-0.1024
Kurtosis		8.4219		3.4546		4.8778		5.0980
JB statistic		1396.19		10.14		175.35		202.18
ARCH-LM test								
LM statistic		5.000		13.465		4.035		10.530
Probability		0.891		0.198		0.945		0.395
Summary statistics for cond. variance series								
Mean		8.230		4.664		0.637		1.774
Standard deviation		13.029		4.176		0.348		1.157
Maximum		159.85		43.054		5.761		12.842
Minimum		0.004		1.473		0.269		0.784
Skewness		5.921		4.445		4.582		3.266
Kurtosis		47.922		28.076		49.955		22.871

This table presents the maximum likelihood estimates of mean and variance equations of the models augmented with explanatory variables indicated by cross-correlation functions. R_{GER}, R_{UK},R_{JAP},R_{US} are the returns of Germany, United Kingdom, Japan and United States markets respectively, while $(R_{GER})^2$, $(R_{UK})^2$, $(R_{JAP})^2$, $(R_{US})^2$ are the returns squared.

Table 16 (continued)

		PERU		CHINA		PHILIPPINES		THAILAND
	Lags	**GARCH(2,1)**	**Lags**	**EGARCH(1,1)**	**Lags**	**EGARCH(1,1)-M**	**Lags**	**TARCH(1,1)-M**
Mean equation								
constant-c		0.0518[c] (1.698)		-0.0182[c] (-0.520)		-0.2908[b] (-2.551)		0.0426[c] (0.566)
AR(1) coefficient		0.1943[a] (5.114)		0.0545[a] (3.083)		0.1077[c] (1.650)		0.4141[b] (2.226)
AR(2) coefficient								0.0643[c] (0.389)
GARCH-M coef.						0.1267[b] (2.343)		-0.0066[c] (-0.192)
MA(1) coefficient								-0.4051[b] (-2.163)
MA(2) coefficient								0.0016[c] (0.010)
R_{GER}							0	0.087[a] (3.935)
							-3	0.0541[b](2.051)
R_{UK}	0	0.1558[a] (5.964)			-1	0.1113[a] (2.851)		
R_{JAP}	0	0.0497[a] (3.634)	-1	-0.0554[b](-2.576)	0	0.1419[a] (4.793)		
R_{US}							-1	0.1582[a](3.900)
Variance equation								
constant- ω		0.2817[a] (3.641)		-0.0595[c] (-1.929)		-0.0827[c] (-1.690)		0.1932[a] (2.898)
ARCH terms:								
α_1		0.2590[a] (2.776)						0.0655[b] (2.142)
α_2								
α_3								
GARCH terms:								
β_1		0.1252[c] (1.235)						0.7446[a] (15.274)
β_2		0.4280[a] (4.032)						
β_3								
EGARCH terms:								
α				0.0878[c] (1.851)		0.1687[b] (2.031)		
β				0.9884[a] (80.282)		0.9521[a] (24.903)		
γ				-0.0702[a] (-2.605)		-0.0915[c] (-1.725)		
TARCH terms:								
γ								0.1375[a] (2.738)
$(R_{GER})^2$								
$(R_{UK})^2$	0	0.0294[a] (2.729)						
$(R_{JAP})^2$							-3	0.0334[b](2.001)
$(R_{US})^2$	-3	-0.0114[a](-8.830)						
Akaike criterion		2.3767		3.1713		3.4820		3.6159
Schwarz criterion		2.4225		3.2032		3.5232		3.6799
Log likelihood		-1286.53		-1727.71		-1893.95		-1962.09
Stand.Res.Diagnostics								
$LB^2(5)$		0.6767		4.5783		0.9862		2.8647
		(0.984)		(0.469)		(0.964)		(0.413)
$LB^2(10)$		1.2827		5.9638		1.2638		5.1033
		(0.999)		(0.818)		(1.000)		(0.746)
Skewness		-0.235		0.191		2.476		-0.033
Kurtosis		6.371		7.107		34.403		3.547
JB statistic		526.82		775.65		46028.46		13.854
ARCH-LM test								
LM statistic		1.287		5.804		1.186		5.580
Probability		0399		0.831		0.999		0.849
Summary statistics for cond. variance series								
Mean		0.741		1.604		2.125		2.394
Standard deviation		0.650		1.069		1.379		1.546
Maximum		10.803		7.905		14.226		16.273
Minimum		0.013		0.358		0.644		0.899
Skewness		6.062		2.381		3.433		3.876
Kurtosis		67.596		10.712		20.131		25.350

The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses. $LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models.

[a] Denotes significance at 1% level,[b] Denotes significance at 5% level,[c] Denotes significance at above 10% levels

Table 16 (continued)

	MALAYSIA		HUNGARY		POLAND		RUSSIA	
	Lags	**TARCH(1,1)**	**Lags**	**TARCH(1,1)**	**Lags**	**GARCH(1,1)**	**Lags**	**TARCH(1,1)**
Mean equation								
constant-c		0.0117[c] (0.412)		0.0286[c] (0.777)		0.0581[c] (1.499)		0.1935[a] (3.686)
AR(1) coefficient		0.2224[a] (6.409)				0.0398[c] (1.327)		
GARCH-M coef.								
R_{GER}	-2	-0.0327[b] (-2.390)	0	0.2467[a] (11.547)	0	0.2087[a] (8.868)	0	0.1203[a] (3.395)
	-5	0.0352[b] (2.299)			-3	0.0538[b] (2.421)		
R_{UK}	-3	-0.0541[a] (-2.894)			-4	-0.0593[b] (-2.059)		
R_{JAP}			-3	-0.0377[b] (-2.223)				
R_{US}	-1	0.1715[a] (7.228)	-1	0.2053[a] (6.409)	-1	0.2212[a] (6.733)	0	0.1634[b] (2.469)
							-1	0.2461[a] (5.390)
Variance equation								
constant- ω		0.1634[a] (5.578)		0.8777[a] (3.990)		0.0302[c] (1.479)		0.1837[b] (2.177)
ARCH terms:								
α_1		0.1139[a] (3.192)		0.0067[c] (0.225)		0.0271[b] (2.243)		0.1139[a] (3.050)
α_2								
GARCH terms:								
β_1		0.5804[a] (10.861)		0.3473[a] (2.578)		0.9436[a] (51.506)		0.8482[a] (18.361)
β_2								
EGARCH terms:								
α								
β								
γ								
TARCH terms:								
γ		0.1492[b] (2.576)		0.1258[b] (2.215)				
$(R_{GER})^2$	0	0.0078[a] (2.673)						
$(R_{UK})^2$								
$(R_{JAP})^2$			-1	-0.0446[a] (-7.986)	-3	0.0081[b] (2.137)		
$(R_{US})^2$	-1	0.0167[a] (4.763)	0	0.1143[a] (3.149)	0	0.0888[b] (2.081)		
					-1	-0.0897[b] (-2.180)		
Akaike criterion		2.6761		3.3961		3.4507		4.2426
Schwarz criterion		2.7310		3.4419		3.5056		4.2746
Log likelihood		-1447.81		-1844.31		-1872.12		-2315.87
Stand.Res.Diagnostics								
$LB^2(5)$		1.7501		4.5738		7.2313		2.1951
		(0.883)		(0.470)		(0.204)		(0.822)
$LB^2(10)$		3.5266		9.1120		14.387		3.4828
		(0.966)		(0.522)		(0.156)		(0.968)
Skewness		-0.024		-0.196		0.050		-0.5787
Kurtosis		6.196		3.773		4.119		5.0662
JB statistic		464.52		34.270		52.527		255.92
ARCH-LM test								
LM statistic		3.624		8.753		14.097		3.696
Probability		0.962		0.555		0.168		0.959
Summary statistics for cond. variance series								
Mean		0.973		1.823		1.965		4.820
Standard deviation		0.849		0.776		0.993		3.498
Maximum		9.424		10.780		9.062		23.346
Minimum		0.423		0.002		0.844		1.555
Skewness		5.229		3.847		2.824		2.215
Kurtosis		38.342		29.336		14.219		8.545

Table 16 (continued)

	ISRAEL		SOUTH AFRICA	
	Lags	TARCH(1,1)	Lags	EGARCH(1,1)
Mean equation				
constant-c		0.0317[c] (0.786)		0.0623[c] (1.950)
AR(1) coefficient		0.0633[b] (2.041)		-0.0175[c] (-0.599)
GARCH-M coef.				
R_{GER}	0	0.1670[a] (5.873)	0	0.2563[a] (13.419)
	-4	0.0579[b] (2.471)	-1	0.0723[a] (2.902)
			-4	0.0441[b] (2.429)
R_{UK}			0	-0.0575[b] (-2.200)
R_{JAP}				
R_{US}	0	0.1795[a] (3.994)	-1	0.2304[a] (6.437)
	-1	0.1719[a] (5.458)		
Variance equation				
constant- ω		0.0936[b] (2.571)		-0.0733[b] (-2.242)
ARCH terms:				
α_1		0.0320[c] (1.441)		
α_2				
GARCH terms:				
β_1		0.8722[a] (24.043)		
β_2				
EGARCH terms:				
α				0.1014[b] (2.341)
β				0.9377[a] (45.632)
γ				-0.0795[a] (-2.628)
TARCH terms:				
γ		0.0918[b] (2.469)		
$(R_{GER})^2$	0	0.0159[a] (2.599)	0	0.0158[a] (3.375)
			-4	-0.0140[a] (-2.945)
$(R_{UK})^2$				
$(R_{JAP})^2$				
$(R_{US})^2$	-4	-0.0267[b] (-2.256)		
Akaike criterion		3.5049		3.0515
Schwarz criterion		3.5598		3.1110
Log likelihood		-1901.68		-1650.07
Stand.Res.Diagnostics				
$LB^2(5)$		9.7007		4.0815
		(0.162)		(0.538)
$LB^2(10)$		13.745		10.754
		(0.185)		(0.377)
Skewness		-0.219		-0.017
Kurtosis		4.612		3.650
JB statistic		127.03		19.298
ARCH-LM test				
LM statistic		13.916		10.659
Probability		0.176		0.384
Summary statistics for cond. variance series				
Mean		2.138		1.320
Standard deviation		1.259		0.632
Maximum		13.822		5.765
Minimum		0.690		0.543
Skewness		3.291		2.240
Kurtosis		20.855		10.873

11. Forecasting performance

As mentioned earlier, the ultimate purpose of a volatility model is to provide accurate forecasts of volatility across relevant horizons. The models developed so far have been evaluated on the basis of their in-sample performance. However, the real test for them would be a comparison of out-of-sample performance, i.e. of their predicting ability. Furthermore, most of the literature using the two step procedure of cross-correlation function is constrained to the detection of causality patterns and the reestimation of the models including the explanatory variables (e.g.Cheung & Ng,1996; Hu et.al, 1997;Kanas & Kouretas, 2000).

In this part the augmented models will be compared to the initial ones on the basis of their one-step-ahead forecasting performance. The procedure is designed as follows:

- The ARMA-GARCH models are estimated for each market for an initial 3yr period (1/1/2000 to 1/1/2003) and based on their in-sample performance the best of them is selected.
- Using a rolling sample of 3 years that moves by 1 day each time, the models coefficients are updated daily and the 1-day-ahead forecast of volatility is derived.
- The proxy for the measurement of volatility is the squared daily return. The criticism on the properties of squared return as an estimator of variance has been established in the literature, however what matters here is the relative forecasting performance of the simple and the extended models based on the same proxy. Furthermore, the availability of high frequency data that could constitute a better estimator of daily volatility for the markets under examination, is not satisfactory.
- Comparing each forecast variance to the corresponding realization we can get the Root mean Squared Error of the model.
- Utilizing the Cross correlation Function, mean and volatility causality patterns from developed to emerging markets in the initial sample are identified.
- The models for the initial sample are reestimated making use of the explanatory variables identified in the previous step.
- Using the same rolling sample 1-day-ahead forecasts of daily volatility of the augmented models are constructed and then compared to each realization, giving the Root Mean Squared Error.
- Each RMSE is divided by the RMSE derived by using the Random Walk model for forecasting daily volatility (assumes that the best forecast of today’s volatility is yesterday’s volatility).
- The two RMSEs are compared.

This procedure gives the results summarized in table 17.

Table 17: Results of forecasting performance evaluation

EQUITY MARKET	ARMA-GARCH MODEL	EXPLANATORY VARIABLES		RMSE of INITIAL MODEL	RMSE OF AUGMENTED MODEL
		MEAN	VARIANCE		
ARGENTINA	C-GARCH(1.2)	R_{GER}, $R_{GERM}(-4)$, $R_{JAP}(-4)$,$R_{UK}(-2)$, R_{US}	$R_{JAP}^2(-5)$, $R_{UK}^2(-1)$	0.7214	0.7432
BRAZIL	AR(1)-EGARCH(1,1)	R_{GER}, R_{US}	R_{GERM}^2	0.7572	**0.7518**
CHILE	AR(1)-TARCH(1,1)	R_{GER}, R_{US}, $R_{US}(-1)$, $R_{US}(-5)$	$R_{GERM}^2(-4)$, $R_{JAP}^2(-5)$, $R_{US}^2(-5)$	0.7312	**0.7135**
MEXICO	AR(1)-EGARCH(1,1)	$R_{GER}(-4)$, R_{US}	R_{US}^2, $R_{US}^2(-4)$	0.7366	**0.7062**
PERU	ARMA(1,1) TARCH(1,1)	R_{UK}, $R_{UK}(-1)$	--	0.9895	0.9981
CHINA	C-EGARCH(1,1)	$R_{JAP}(-1)$, $R_{UK}(-3)$	--	0.7039	**0.7037**
PHILIPPINES	C-EGARCH(1,1)-M	$R_{UK}(-1)$	R_{JAP}^2	0.7612	**0.7582**
THAILAND	ARMA(4,4)-GARCH(2,2)	R_{GER}, $R_{GER}(-1)$	--	0.7834	**0.7815**
MALAYSIA	AR(1)-EGARCH(1,1)	$R_{GER}(-5)$, $R_{US}(-1)$	$R_{GERM}^2(-3)$	0.7723	**0.7687**
HUNGARY	AR(1)-EGARCH(1,1)	R_{GER}, $R_{GER}(-5)$, $R_{JAP}(-2)$, $R_{US}(-1)$	R_{US}^2	0.7113	**0.7094**
POLAND	AR(1)-EGARCH(1,1)	R_{GER} ,$R_{US}(-1)$	--	0.7087	**0.7044**
RUSSIA	C-TARCH(1,1)	R_{GER} ,$R_{US}(-1)$	--	0.7424	**0.7406**
ISRAEL	AR(1)-EGARCH(1,1)	R_{GER}, $R_{GER}(-4)$, R_{US} , $R_{US}(-1)$	R_{GERM}^2, $R_{US}^2(-3)$	0.6955	**0.6945**
S.AFRICA	AR(1)-EGARCH(1,1)	R_{GER} $R_{GER}(-1)$, $R_{GER}(-4)$	R_{GERM}^2, $R_{GERM}^2(-4)$	0.7114	**0.7091**

The table summarizes the results of the forecasting performance comparison described in section 11

With the exception of Argentina and Peru (for which no explanatory variables were statistically significant in variance equation), in the rest of the markets the RMSE criterion favors the augmented models.

It is obvious however that this procedure gives only a rough approximation of the predicting ability of the resulting models, since it is based on the horizon of 1-day only and on the symmetric criterion of RMSE. Furthermore, the performance might have been improved if the causality patterns were re-detected as the sample was rolled forward. This, however, would result in a very complex model with little practical value. In this part the aim has been to get a first idea of the predicting properties of the new models.

12. Conclusions-Remarks

The aim of this study was the examination of the heteroskedastic behavior of emerging stock markets and of its relation to that of major developed markets. The methodology followed was the implementation of some widely used GARCH models for the estimation of the conditional variance equation and the selection of the model that better captures the characteristics of variance. Variance equations were estimated jointly with mean equations for each market and the resulting residual series were shown to reject autocorrelation and heteroskedasticity. The models that were favored where mostly those that allowed for asymmetry, i.e. for negative/positive and large/small innovations to have a different impact on volatility, a property that has been confirmed repeatedly in the literature.

Variance equation parameters were shown to be sensitive to the data period chosen, probably because the sample period included major international events, such as the Asian the Russian crises, that have been shown to have caused a breaking point in volatility processes. The division of the initial sample into two subsamples showed that the characteristics of variance in the two periods were different and that persistence in variance may be attributed to the heterogeneity of the data. Therefore the amount of data used and the historic period chosen should always be seriously considered.

The second part of the study has been dedicated to causality-in-variance patterns. The direction of causality has been restricted: whether and to what extend developed markets cause emerging ones in-variance. Using the Cheung and Ng(1996) cross-correlation-function test we pinpointed the sources of causality spillovers and the relevant lags. The exogenous variables were introduced into the original mean and variance equations and all models were reestimated. The resulting models performed best in-sample and out-of-sample, as shown by a first approximation. With few exceptions, the sources of volatility were not stable throughout the period under examination and the developed markets that caused an emerging one in mean did not always cause the same market in-variance. It is important, however, that lead/lag relations can help construct better models and more accurate forecasts.

The literature about volatility estimating and forecasting is vast. New models and improved estimation techniques are proposed very often. ARCH-type models, though not free of weaknesses, have been successful due to their desirable properties and empirical goodness of fit. They can capture persistence in volatility, mean-reverting behavior of volatility and asymmetry. Some of the issues that remain open to research are the estimation of GARCH models with high frequency data, the appropriate measurement of the realization of volatility process and the modeling of time varying higher moments.

On the other hand, Cheung and Ng methodology for detecting causality-in-variance is only one of the existing in the literature. It is not without limitations. The most important one probably is its inability to detect causation patterns that yield zero cross-correlations. A comparison between the causality patterns detected by this methodology and other formulations, such as multivariate GARCH models, would be interesting. Furthermore the causality examination can be extended to issues, such as the time required for stock prices to absorb the volatility transmitted and whether there is any economic reason why a specific developed market is more influential than others with respect to volatility spillovers.

As a final remark, the study suggests that appropriate GARCH models estimated using the most relevant data period can remove heteroskedasticity from the data and properly reflect the characteristics of volatility, while, volatility causation patterns revealed by the two-stage procedure improve the explanatory power and the forecasting performance of GARCH models.

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Appendix

Table A1: Estimated models for ARGENTINA , overall sample period

	A R G	*E N*	*T I*	*N A*		
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0894[b]	0.0865[b]	0.0890[b]	0.0838[b]	0.1012[c]	0.0437[c]
	(2.1728)	(2.1048)	(2.1639)	(2.024)	(1.4914)	(1.0608)
AR(1) coefficient	0.0564[b]	0.0548[b]	0.0559[b]	0.0556[b]	0.0568[b]	0.0706[a]
	(2.2872)	(2.1526)	(2.2440)	(2.2386)	(2.2785)	(2.8946)
GARCH-M coef.					-0.0028[c]	
					(-0.1894)	
Variance equation						
constant- ω	0.0896[c]	0.0753[c]	0.1056[c]	0.1740[c]	0.0884[c]	0.1019[b]
	(1.7712)	(1.7136)	(1.8042)	(1.8551)	(1.7688)	(2.0248)
ARCH terms:						
α_1	0.086687[a]	0.126289[a]	0.103901[a]	0.126749[a]	0.086119[a]	0.056024[c]
	(3.4623)	(2.5898)	(3.2564)	(4.1500)	(3.4666)	(1.5027)
α_2		-0.050269[c]		0.046680[c]	0.904182[a]	
		(-1.0144)		(1.2334)	(32.2963)	
GARCH terms:						
β_1	0.903599[a]	0.915746[a]	0.666670[c]	0.028041[c]		0.899381[a]
	(31.9818	(35.0081)	(1.7816)	(0.2567)		(35.3664)
β_2			0.218055[c]	0.781743[a]		
			(0.6144)	(7.9510)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.062632[c]
						(1.3618)
Akaike criterion	4.4213	4.4208	4.4217	4.4195	4.4224	4.4130
Schwarz criterion	4.4341	4.4362	4.4371	4.4375	4.4378	4.4284
Log likelihood	-4913.75	-4912.23	-4910.99	-4907.53	-4911.79	-4901.32
Stand.Res.Diagnostics						
$LB^2(5)$	6.5424	8.2801	7.4423	7.4294	6.7363	3.6451
	(0.257)	(0.141)	(0.190)	(0.191)	(0.241)	(0.602)
$LB^2(10)$	10.760	12.230	11.508	7.9658	11.043	8.2076
	(0,376)	(0.270)	(0.319)	(0.380)	(0.354)	(0.609)
Skewness	-0.464	-0.468	-0.4700	-0.484	-0.467	-0.435
Kurtosis	7.155	7.039	7.143	7.183	7.163	7.550
JB statistic	1681.14	1635.01	1672.57	1708.99	1687.18	1989.03
ARCH-LM test						
LM statistic	10.722	12.017	11.417	10.836	10.941	8.256
Probability	0.3795	0.2839	0.3259	0.370	0.362	0.603
Summary statistics for cond. variance series						
Mean	6.935	6.918	6.935	7.004	6.937	7.094
Standard deviation	9.504	9.543	9.533	10.061	9.466	10.796
Maximum	120.560	164.604	139.881	167.036	119.680	151.944
Minimum	1.396	1.386	1.391	1.366	1.389	1.389
Skewness	5.728	6.300	5.884	6.600	5.707	6.571
Kurtosis	47.094	63.633	51.306	67.553	46.771	61.247

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis.
The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table A1(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0743[c]	0.0772[c]	0.1737[b]	0.1108[a]	0.1500[a]
	(1.0758)	(0.1045)	(1.7767)	(3.1007)	(2.6903)
AR(1) coefficient	0.0698[a]	0.0689[a]	0.0638[a]	0.0514[a]	0.0514[b]
	(2.8083)	(2.9007)	(2.6974)	(2.5547)	(2.5592)
GARCH-M coef.	-0.0077[c]		-0.0291[c]		-0.0088[c]
	(-0.5628)		(-1.4054)		(-0.9089)
Variance equation					
constant- ω	0.0984[b]	-0.0967[c]	-0.1004[a]	0.1741[a]	0.1718[a]
	(1.9930)	(-2.5195)	(-2.7787)	(3.9420)	(3.9417)
ARCH terms:					
α_1	0.055467[c]			0.113527[a]	0.112701[a]
	(1.5081)			(5.6828)	(5.6916)
α_2					
GARCH terms:					
β_1	0.900669[a]			0.874428[a]	0.875667[a]
	(36.0572)			(50.5540)	(51.3137)
β_2					
EGARCH terms:					
α		0.1727[a]	0.1753[a]		
		(3.5886)	(3.6831)		
β		0.9838[a]	0.9854[a]		
		(86.0741)	(97.4178)		
γ		-0.0432[c]	-0.0447[c]		
		(-1.0257)	(-1.1049)		
TARCH terms:					
γ	0.0626[c]				
	(1.3795)				
Degrees of freedom				3.632	3.623
Akaike criterion	4.4141	4.4336	4.4336	4.2906	4.2911
Schwarz criterion	4.4321	4.4489	4.4516	4.3060	4.3091
Log likelihood	-4901.53	-4926.38	-4925.43	-4795.25	-4764.79
Stand.Res.Diagnostics					
$LB^2(5)$	3.7692	6.5414	6.5864	2.9906	2.9135
	(0.583)	(0.257)	(0.253)	(0.701)	(0.713)
$LB^2(10)$	8.6507	10.828	11.838	12.728	11.936
	(0.566)	(0.371)	(0.296)	(0.239)	(0.289)
Skewness	-0.4359	-0.5445	-0.5188	-0.5444	-0.5464
Kurtosis	7.5319	9.1573	8.7413	7.5822	7.5659
JB statistic	1973.66	3624.87	3155.80	2057.43	2044.38
ARCH-LM test					
LM statistic	8.665	11.048	12.067	13.705	12.987
Probability	0.5641	0.353	0.2805	0.1868	0.2243
Summary statistics for cond. variance series					
Mean	7.077	6.701	6.698	7.509	7.419
Standard deviation	10.667	7.223	7.296	10.388	10.163
Maximum	150.604	85.578	87.155	153.465	149.066
Minimum	1.371	1.068	1.054	0.174	0.171
Skewness	6.560	4.143	4.398	6.430	6.350
Kurtosis	61.282	28.427	31.778	60.791	59.451

Table A2: Estimated models for BRAZIL , overall sample period

	B R A Z I L					
Parameters / Criteria	GARCH(1,1)	GARCH(2,2)	GARCH(3,3)	GARCH(3,2)	GARCH(3,2)-M	TARCH(2,1)
Mean equation						
constant-c	0.1320[a]	0.1325[a]	0.1404[a]	0.1332[a]	0.0875[c]	0.0418[c]
	(3.2152)	(3.2221)	(3.456)	(3.2557)	(1.2719)	(0.9666)
AR(1) coefficient	0.1045[a]	0.1059[a]	0.1063[a]	0.1051[a]	0.1008[a]	0.1197[a]
	(4.4493)	(4.5126)	(4.5919)	(4.4721)	(4.3907)	(5.7513)
GARCH-M coef.					0.0101[c]	
					(0.7940)	
Variance equation						
constant- ω	0.2048[a]	0.2768[c]	0.7255[a]	0.0274[c]	0.0258[b]	0.3349[a]
	(4.0106)	(0.4900)	(4.1475)	(1.3906)	(2.3075)	(5.2163)
ARCH terms:						
α_1	0.126474[a]	0.116443[a]	0.106558[a]	0.145814[a]	0.093587[a]	-0.049826[a]
	(4.9224)	(3.1785)	(3.3336)	(4.0561)	(3.3685)	(-5.6586)
α_2		0.052589[c]	0.195814[a]	-0.126250[a]	-0.072380[b]	0.078297[a]
		(0.1509)	(4.2638)	(-3.6561)	(-2.3551)	(3.9895)
α_3			0.153274[a]			
			(3.9011)			
GARCH terms:						
β_1	0.846349[a]	0.544908[c]	-0.713796[a]	1.706493[a]	2.2298[a]	0.814146[a]
	(34.05472)	(0.2051)	(-5.9633)	(6.1566)	(26.6684)	(31.2742)
β_2		0.249305[c]	0.564672[a]	-0.852205[c]	-1.8410[a]	
		(0.1114)	(8.7671)	(-1.6597)	(-11.1437)	
β_3			0.600509[a]	0.122239[c]	0.586671[a]	
			(5.9977)	(0.4765)	(6.7541)	
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.2092[a]
						(5.7645)
Akaike criterion	4.5043	4.5058	4.5009	4.5004	4.5008	4.4698
Schwarz criterion	4.5171	4.5237	4.5240	4.5209	4.5239	4.4877
Log likelihood	-5006.10	5003.48	-4996.08	-4996.48	-4995.91	-4963.45
Stand.Res.Diagnostics						
$LB^2(5)$	16.329	14.052	10.622	8.4117	6.2566	4.2319
	(0.006)	(0.015)	(0.059)	(0.135)	(0.282)	(0.517
$LB^2(10)$	26.873	24.783	19.151	16.028[c]	11.836	13.753
	(0.003)	(0.006)	(0.038)	(0.099)	(0.296)	(0.185)
Skewness	-0.3376	-0.3370	-0.3132	-0.3193	-0.3192	-0.2338
Kurtosis	4.5935	4.5873	4.4399	4.4870	4.4419	4.2571
JB statistic	277.70	275.59	228.53	242.72	230.44	166.736
ARCH-LM test						
LM statistic	0.0527	23.7036	18.0408	15.8466	11.4052	13.5804
Probability	0.8182	0.0084	0.0542	0.1041	0.3268	0.1930
Summary statistics for cond. variance series						
Mean	7.002	7.003	7.045	6.900	7.0055	6.870
Standard deviation	7.867	7.898	8.228	7.388	7.7303	7.8624
Maximum	88.328	86.922	88.113	87.531	89.053	72.649
Minimum	0.949	1.013	0.907	0.732	1.426	0.4621
Skewness	4.556	4.584	4.785	4.532	4.660	4.262
Kurtosis	30.518	30.752	33.340	32.600	34.066	25.932

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A2(continued)

Parameters / Criteria	TARCH(1,2)-M	EGARCH(1,2)	EGARCH(1,2)-M	GARCH(3,2)-t	GARCH(3,2)-M-t
Mean equation					
constant-c	0.0573[c]	0.0758[c]	0.1151[c]	0.1257[a]	0.1249[b]
	(0.8014)	(1.7433)	(1.4508)	(3.1331)	(2.0260)
AR(1) coefficient	0.1176[a]	0.1131[a]	0.1088[a]	0.0926[a]	0.0925[a]
	(5.6040)	(5.3342)	(5.0261)	(4.3615)	(4.3587)
GARCH-M coef.	-0.0042[c]		-0.0096[c]		0.0002[c]
	(-0.3173)		(-0.9649)		(0.0252)
Variance equation					
constant- ω	0.3402[a]	-0.0788[a]	-0.0857[a]	0.0372[a]	0.0364[a]
	(4.8134)	(-2.8760)	(-3.1402)	(3.3284)	(3.7308)
ARCH terms:					
α_1	-0.049638[a]			0.075144[a]	0.074981[a]
	(-5.6785)			(5.6891)	(5.9877)
α_2	0.079814[a]			-0.046705[a]	-0.047142[a]
	(4.0127)			(-2.7344)	(-3.1786)
GARCH terms:					
β_1	0.8103[a]			2.240708[a]	2.248657[a]
	(29.5199)			(70.138)	(116.328)
β_2				-1.907258[a]	-1.917212[a]
				(-421.187)	(-1142.48)
β_3				0.633621[a]	0.636324[a].
				(25.0607)	(41.0467)
EGARCH terms:					
α		0.0944[b](1.990)	0.0968[b] (2.0441)		
		0.1352[b] (2.374)	0.1373[b] (2.3893)		
β		0.9405[a] (73.296)	0.9428[a] (71.414)		
γ		-0.1812[a] (-5.056)	-0.1809[a] (-5.040)		
		0.0532[c] (1.3324)	0.0529[c] (1.3272)		
TARCH terms:					
γ	0.2139[a]				
	(5.8129)				
Degrees of freedom				6.469	6.464
Akaike criterion	4.4734	4.4748	4.4787	4.4636	4.4645
Schwarz criterion	4.4939	4.4953	4.5018	4.4867	4.4902
Log likelihood	-4966.43	-4970.25	-4973.62	-4952.30	-4952.38
Stand.Res.Diagnostics					
$LB^2(5)$	3.9598	7.3345	7.1230	7.3853	7.2453
	(0.555)	(0.197)	(0.212)	(0.194)	(0.203)
$LB^2(10)$	13.196	15.760	15.166	9.7125	9.5143
	(0.213)	(0.107)	(0.126)	(0.466)	(0.484)
Skewness	-0.2330	-0.1765	-0.1761	-0.0819	-0.0730
Kurtosis	4.2650	4.315	4.342	6.1999	6.2797
JB statistic	168.42	171.97	178.62	952.22	999.66
ARCH-LM test					
LM statistic	12.9500	15.7543	14.8713	16.179	16.227
Probability	0.2264	0.1068	0.1368	0.0946	0.0932
Summary statistics for cond. variance series					
Mean	6.873	6.576	6.586	7.066	7.067
Standard deviation	7.829	6.044	6.030	7.819	7.819
Maximum	72.233	58.511	58.216	90.513	90.490
Minimum	0.462	0.864	0.937	0.037	0.036
Skewness	4.292	3.439	3.447	4.633	4.638
Kurtosis	26.352	19.080	19.122	33.616	33.692

Table A3: Estimated models for CHILE , overall sample period

Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
		C H I L E				
Mean equation						
constant-c	0.0000791[c]	0.0003[c]	0.0001[c]	0.0001[c]	-0.0167[c]	-0.0017[c]
	(0.0377)	(0.1638)	(0.0686)	(0.0592)	(-1.6310)	(-0.7649)
AR(1) coefficient	0.9288[a]	0.9315[a]	0.9303[a]	0.9312[a]	0.9354[a]	0.9309[a]
	(26.0526)	(26.5734)	(26.6538)	(27.2015)	(-1.6310)	(27.9405)
MA(1) coefficient	-0.6530[a]	-0.6632[a]	-0.6570[a]	-0.6562[a]	-0.6607[a]	-0.6540[a]
	(-14.5394)	(-15.2548)	(-14.9812)	(-15.3957)	(-15.8480)	(-15.2280)
MA(2) coefficient	-0.2031[a]	-0.1999[a]	-0.2022[a]	-0.2024[a]	-0.2058[a]	-0.2006[a]
	(-6.9050)	(-6.6864)	(-6.8692)	(-6.9181)	(-7.2430)	(-6.9198)
GARCH-M coef.					0.0258[c]	
					(1.6435)	
Variance equation						
constant- ω	0.0288[a]	0.0128[a]	0.0366[a]	0.0018[c]	0.0287[a]	0.026295[a]
	(3.3667)	(2.0857)	(3.8263)	(1.3890)	(3.3299)	(3.6653)
ARCH terms:						
α_1	0.121550[a]	0.207438[a]	0.153546[a]	0.184229[a]	0.121369[a]	0.075871[a]
	(5.2383)	(4.9171)	(4.5686)	(4.5278)	(5.2630)	(3.8544)
α_2		-0139270[a]		-0.169453[a]		
		(-3.1679)		(-4.4452)		
GARCH terms:						
β_1	0.8431[a]	0.916084[a]	0.510986[c]	1.491754[a]	0.943218[a]	0.853601[a]
	(29.4324)	(38.8289)	(1.6420)	(10.5285)	(29.4300)	(35.2328)
β_2			0.2900[c]	-0.508697[a]		
			(1.0030)	(-3.8020)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.079385[b]
						(2.1687)
Akaike criterion	2.3723	2.3664	2.3708	2.3619	2.3927	2.3669
Schwarz criterion	2.3902	2.3869	2.3913	2.3850	2.3927	2.3874
Log likelihood	-2632.18	-2624.66	-2629.59	-2618.63	-2631.05	-2625.20
Stand.Res.Diagnostics						
$LB^2(5)$	5.7622	8.9711	5.1169	1.0320	4.9665	
	(0.124)	(0.03)	(0.163)	(0.794)	(0.174)	
$LB^2(10)$	8.4034	11.688	7.7332	4.2300	7.5314	
	(0.395)	(0.166)	(0.460)	(0.836)	(0.481)	
Skewness	-0.2203	-0.2028	-0.2191	-0.0120	-0.2618	
Kurtosis	4.9395	4.9582	4.9446	4.8821	5.1744	
JB statistic	366.77	370.76	368.39	342.40	463.78	
ARCH-LM test						
LM statistic	8.2400	11.395	7.6037	4.1373	7.392	7.2006
Probability	0.6054	0.3275	0.6674	0.9409	0.6879	0.7063
Summary statistics for cond. variance series						
Mean	0.732	0.726	0.730	0.724	0.741	
Standard deviation	0.516	0.515	0.516	0.508	0.510	
Maximum	5.548	7.468	6.313	6.647	5.562	
Minimum	0.235	0.213	0.233	0.191	0.232	
Skewness	3.148	3.709	3.273	3.431	3.092	
Kurtosis	18.019	28.892	20.082	24.051	17.864	

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A3(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.0143[c]	-0.0022[c]	-0.0169[c]	-0.0009[c]	-0.0066[c]
	(-1.3975)	(-0.9545)	(-1.6354)	(-0.4767)	(-1.2973)
AR(1) coefficient	0.9372[a]	0.9333[a]	0.9408[a]	0.9329[a]	0.9314[a]
	(31.3202)	(28.367)	(-1.6354)	(28.3726)	(34.5645)
MA(1) coefficient	-0.6629[a]	-0.6587[a]	-0.6665[a]	-0.6739[a]	-0.6740[a]
	(-16.2921)	(-15.9980)	(-17.4619)	(-16.8232)	(-19.1101)
MA(2) coefficient	-0.2038[a]	-0.2001[a]	-0.2052[a]	-0.1952[a]	-0.1941[a]
	(-0.2038)	(-6.9881)	(-7.4533)	(-7.2756)	(-7.7664)
GARCH-M coef.	0.0195[c]				0.0097[c]
	(1.2660)				(1.2652)
Variance equation					
constant- ω	0.0276[a]	-0.2063[a]	-0.2100[a]	0.0307[a]	0.0308[a]
	(3.7064)	(-6.4819)	(-6.4789)	(4.1427)	(4.0320)
ARCH terms:					
α_1	0.077179[a]			0.1217[a]	0.1227[a]
	(3.8819)			(6.7129)	(6.8005)
α_2					
GARCH terms:					
β_1	0.85047[a]			0.8400[a]	0.8383[a]
	(34.3895)			(38.5055)	(38.0588)
β_2					
EGARCH terms:					
α		0.2409[a]	0.2425[a]		
		(6.5443)	(6.5080)		
β		0.9508[a]	0.9468[a]		
		(68.1328)	(64.5992)		
γ		-0.0559[b]	-0.0553[b]		
		(-2.2138)	(-2.1342)		
TARCH terms:					
γ	0.0772[b]				
	(2.0824)				
Degrees of freedom				8.013	8.430
Akaike criterion	2.3673	2.3698	2.370	2.3435	2.3416
Schwarz criterion	2.3904	2.3903	2.393	2.3641	2.3647
Log likelihood	-2624.65	-2628.44	-2627.65	-2595.70	-2594.89
Stand.Res.Diagnostics					
$LB^2(5)$	4.0227	5.5670	4.1431	6.8264	6.6635
	(0.259)	(0.135)	(0.246)	(0.234)	(0.247)
$LB^2(10)$	6.6509	8.2740	6.7795	9.6783	9.3464
	(0.575)	(0.407)	(0.561)	(0.469)	(0.500)
Skewness	-0.1933	-0.1433	0.1815	-0.218	-0.216
Kurtosis	4.823	4.6103	4.8246	4.972	4.965
JB statistic	322.06	248.04	320.87	378.67	375.67
ARCH-LM test					
LM statistic	6.5600	8.1057	6.6489	8.1371	7.9044
Probability	0.7662	0.6185	0.7581	0.6154	06381
Summary statistics for cond. variance series					
Mean	0.7097	0.717	0.687	0.729	0.726
Standard deviation	0.5158	0.446	0.423	0.509	0.509
Maximum	4.6577	4.052	3.910	5.477	5.402
Minimum	0.2304	0.161	0.168	0.030	0.030
Skewness	3.2385	2.510	2.512	3.135	3.108
Kurtosis	17.740	12.576	12.802	17.876	17.498

Table A4: Estimated models for MEXICO , overall sample period

Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
	M E X I C O					
Mean equation						
constant-c	0.0853[a]	0.0855[a]	0.0854[a]	0.0852[a]	0.0134[c]	0.0261[c]
	(2.6713)	(2.6710)	(2.6691)	(2.6539)	(0.2237)	(0.7882)
AR(1) coefficient	0.1439[a]	0.1443[a]	0.1442[a]	0.1459[a]	0.1431[a]	0.1449[a]
	(6.1599)	(6.1791)	(6.1683)	(6.2504)	(6.1058)	(6.7021)
GARCH-M coef.					0.0289[c]	
					(1.5174)	
Variance equation						
constant- ω	0.1572[a]	0.1610[a]	0.1557[a]	0.3026[a]	0.1574[a]	0.1196[a]
	(3.1698)	(2.8456)	(2.8786)	(3.4907)	(3.0366)	(4.1387)
ARCH terms:						
α_1	0.1264[a]	0.123433[a]	0.124437[a]	0.121473[a]	0.126168[a]	0.010176[c]
	(2.9240)	(3.1703)	(3.0497)	(3.1904)	(2.9044)	(0.9230)
α_2		0.004876[c]		0.122474[a]		
		(0.1199)		(3.1904)		
GARCH terms:						
β_1	0.8330[a]	0.830056[a]	0.856066[a]	-0.073245[c]	0.832846[a]	0.874278[a]
	(18.5263)	(15.4208)	(3.0659)	(-0.2369)	(18.1671)	(34.6670)
β_2			-0.0207[c]	0.751410[b]		
			(-0.8140)	(2.4378)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.169820[a]
						(3.7319)
Akaike criterion	3.9198	3.9207	3.9207	3.9216	3.9227	3.8823
Schwarz criterion	3.9326	3.9361	3.9361	3.9396	3.9381	3.8977
Log likelihood	-4355.81	-4355.81	-4355.80	-4355.84	-4358.10	-4313.16
Stand.Res.Diagnostics						
$LB^2(5)$	7.5818	7.4062	7.4732	7.5490	7.3443	3.4332
	(0.181)	(0.306)	(0.188)	(0.183)	(0.196)	(0.634)
$LB^2(10)$	12.584	12.418	12.480	12.665	11.853	8.3521
	(0.248)	(0.258)	(0.254)	(0.243)	(0.295)	(0.594)
Skewness	-0.2085	-0.2063	-0.2072	-0.2064	-0.0592	-0.0651
Kurtosis	6.0153	6.0020	6.0077	5.9530	5.3368	5.3141
JB statistic	859.04	851.31	854.61	824.24	507.56	498.04
ARCH-LM test						
LM statistic	12.2575	12.0716	12.1409	12.2998	11.5032	8.1186
Probability	0.2681	0.2802	0.2757	0.2654	0.3196	0.6172
Summary statistics for cond. variance series						
Mean	3.661	3.660	3.660	3.664	3.656	3.657
Standard deviation	3.779	3.780	3.779	3.797	3.709	4.167
Maximum	46.432	46.249	46.074	48.087	44.044	60.692
Minimum	0.444	0.448	0.443	0.522	1.210	0.371
Skewness	5.791	5.808	5.801	5.830	5.616	6.267
Kurtosis	49.248	49.452	49.361	50.032	46.478	60.271

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A4(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0007[c]	0.0237[c]	0.0814[c]	0.0615[b]	0.0091[c]
	(0.0143)	(0.7022)	(1.3494)	(1.9720)	(0.1603)
AR(1) coefficient	0.1468[a]	0.1502[a]		0.1278[a]	0.1270[a]
	(6.5918)	(6.9670)		(5.9791)	(5.9282)
GARCH-M coef.	0.0117[c]		-0.0081[c]		0.0203[c]
	(0.6733)		(-0.40660		(1.0934)
Variance equation					
constant- ω	0.1256[a]	-0.0802[a]	-0.0863[a]	0.1039[a]	0.1059[a]
	(4.0450)	(-2.9185)	(-2.8860)	(3.9060)	(3.9334)
ARCH terms:					
α_1	0.0107[c]			0.092538[a]	0.0934[a]
	(0.9677)			(6.2073)	(6.2263)
α_2					
GARCH terms:					
β_1	0.8709[a]			0.8800[a]	0.8784[a]
	(33.8848)			(50.1182)	(49.6498)
β_2					
EGARCH terms:					
α		0.1692[a]	0.1693[a]		
		(3.5995)	(3.3583)		
β		0.9554[a]	0.9609[a]		
		(71.1719)	(77.1772)		
γ		-0.1307[a]	-0.1123[a]		
		(-4.0911)	(-3.8778)		
TARCH terms:					
γ	0.1687[a]				
	(3.6685)				
Degrees of freedom				5.675	5.719
Akaike criterion	3.8864	3.8823	3.9062	3.8558	3.8562
Schwarz criterion	3.9044	3.8977	3.9216	3.8712	3.8741
Log likelihood	-4316.69	-4313.09	-4341.62	-4281.74	-4281.09
Stand.Res.Diagnostics					
$LB^2(5)$	3.3468	4.5053	6.4773	3.6538	3.3999
	(0.647)	(0.479)	(0.263)	(0.600)	(0.639)
$LB^2(10)$	8.0577	8.2737	11.787	6.400	6.0084
	(0.623)	(0.602)	(0.300)	(0.781)	(0.815)
Skewness	-0.0592	-0.0752	-0.0653	0.0396	0.0496
Kurtosis	5.3368	5.4415	5.5253	9.0795	9.1752
JB statistic	507.56	554.74	593.09	3428.7	3537.79
ARCH-LM test					
LM statistic	7.7921	8.2037	10.8788	15.744	15.405
Probability	0.6491	0.6089	0.3670	0.1071	0.1179
Summary statistics for cond. variance series					
Mean	3.673	3.481	2.562	3.636	3.626
Standard deviation	4.223	2.987	2.995	3.478	3.4628
Maximum	60.845	42.590	40.036	38.791	37.926
Minimum	1.079	0.308	0.656	0.103	0.105
Skewness	6.249	4.614	4.210	4.973	4.960
Kurtosis	59.391	39.150	32.616	36.139	35.947

Table A5: Estimated models for PERU , overall sample period

Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
		P E R U				
Mean equation						
constant-c	0.0031[c]	0.0029[c]	0.0030[c]	0.0027[c]	0.0114[c]	0.0013[c]
	(1.4808)	(1.4200)	(1.4539)	(1.333)	(1.3698)	(0.6538)
AR(1) coefficient	1.0854[a]	1.0820[a]	1.0826[a]	1.0828[a]	1.0909[a]	1.0841[a]
	(22.8105)	(22.3733)	(22.3988)	(22.8306)	(23.5259)	(21.9960)
AR(2) coefficient	-0.1458[a]	-0.1437[a]	-0.1442[a]	-0.1436[a]	-0.1485[a]	-0.1454[a]
	(-5.1457)	(-5.0378)	(-5.0658)	(-5.0625)	(-5.3182)	(-5.0570)
MA(1) coefficient	-0.8981[a]	-0.8966[a]	-0.8965[a]	-0.8986[a]	-0.9061[a]	-0.8949[a]
	(-22.9753)	(-22.5138)	(-22.503)	(-23.3393)	(-23.1576)	(-22.0331)
GARCH-M coef.					-0.0079[c]	
					(-1.0988)	
Variance equation						
constant- ω	0.1157[a]	0.1025[a]	0.1213[a]	0.0442[c]	0.1155[a]	0.1173[a]
	(3.7444)	(2.7247)	(2.9410)	(0.6647)	(3.7376)	(3.8002)
ARCH terms:						
α_1	0.221011[a]	0.245532[a]	0.234911[a]	0.255336[a]	0.220779[a]	0.156385[a]
	(4.0525)	(3.3698)	(3.1511)	(3.7431)	(4.0456)	(4.4091)
α_2		-0.0451[c]		-0.166268[b]		
		(-0.4709)		(-1.3087)		
GARCH terms:						
β_1	0.6946[a]	0.7249[a]	0.595579[c]	1.208960[c]	0.6945[a]	0.694352[a]
	(11.8142)	(8.7092)	(1.4376)	(1.7927)	(11.8101)	(11.9352)
β_2			0.080988[c]	-0.330096[c]		
			(0.2398)	(-0.6637)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.1246[c]
						(1.3665)
Akaike criterion	2.8052	2.8055	2.8057	2.8054	2.8062	2.8002
Schwarz criterion	2.8231	2.8260	2.8263	2.8285	2.8268	2.8207
Log likelihood	-3112.42	-3111.75	-3112.04	-3110.65	-3112.59	-3105.82
Stand.Res.Diagnostics						
$LB^2(5)$	3.2695	3.4614	3.41496	2.9144	2.9784	3.4007
	(0.514)	(0.484)	(0.491)	(0.572)	(0.561)	(0.493)
$LB^2(10)$	3.9587	4.2006	4.1388	3.4827	3.8413	4.1928
	(0.914)	(0.898)	(0.846)	(0.942)	(0.922)	(0.898)
Skewness	-0.2809	-0.2882	-0.2864	-0.2742	-0.2274	-0.1744
Kurtosis	6.4873	6.5705	6.5427	6.4633	6.3652	6.0788
JB statistic	1156.20	1212.16	1193.49	1139.38	1068.62	889.69
ARCH-LM test						
LM statistic	3.9616	4.2030	4.1461	3.4542	3.8563	4.1886
Probability	0.9490	0.9377	0.9405	0.9686	0.9535	0.9384
Summary statistics for cond. variance series						
Mean	1.246	1.247	1.246	1.247	1.254	1.247
Standard deviation	1.367	1.374	1.370	1.383	1.373	1.424
Maximum	15.595	16.113	15.958	16.092	15.553	17.335
Minimum	0.405	0.394	0.408	0.351	0.4154	0.375
Skewness	4.499	4.637	4.538	4.726	4.5233	4.839
Kurtosis	29.919	32.484	31.243	33.803	30.174	34.075

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A5(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0134[c]	0.0283[c]	0.0137[c]	0.0024[c]	0.0160[c]
	(1.5272)	(1.2646)	(1.5533)	(0.8414)	(1.3568)
AR(1) coefficient	1.0838[a]		1.0856[a]	1.0461[a]	0.9803[a]
	(22.5035)		(20.7720)	(11.1703)	(8.1173)
AR(2) coefficient	-0.1464[a]	0.0594[b]	-0.1495[a]	-0.1271[a]	-0.1159[a]
	(-5.1818)	(2.3912)	(-5.0363)	(-3.9675)	(-3.2498)
MA(1) coefficient	-0.8977[a]	0.1977[a]	-0.8948[a]	-0.8835[a]	-0.8197[a]
	(-22.0768)	(7.4556)	(-20.3927)	(-9.8500)	(-6.9205)
GARCH-M coef.	-0.0114[c]		-0.0113[c]		-0.0128[c]
	(-1.3954)		(-1.4001)		(-1.2632)
Variance equation					
constant- ω	0.1144[a]	-0.2905[a]	-0.2871[a]	0.0870[a]	0.0883[a]
	(3.8919)	(-5.4870)	(-5.5532)	(4.7623)	(4.7987)
ARCH terms:					
α_1	0.154054[a]			0.158446[a]	0.159659[a]
	(4.3861)			(6.3632)	(6.3659)
α_2					
GARCH terms:					
β_1	0.6979[a]			0.771106[a]	0.768694[a]
	(12.4884)			(24.4433)	(24.3336)
β_2					
EGARCH terms:					
α		0.3906[a]	0.3857[a]		
		(5.0752)	(5.1156)		
β		0.8942[a]	0.8999[a]		
		(26.1307)	(28.6152)		
γ		-0.0616[c]	-0.0664[c]		
		(-1.3268)	(-1.4333)		
TARCH terms:					
γ	0.1296[c]				
	(1.4356)				
Degrees of freedom				5.03	5.003
Akaike criterion	2.8007	2.8103	2.8086	2.7153	2.7140
Schwarz criterion	2.8238	2.8283	2.8317	2.7358	2.7371
Log likelihood	-3105.43	-3118.11	-3114.19	-3011.49	-3008.97
Stand.Res.Diagnostics					
$LB^2(5)$	3.2263	2.6024	2.3734	3.6991	3.7419
	(0.521)	(0.626)	(0.667)	(0.593)	(0.578)
$LB^2(10)$	4.2235	3.1857	2.9158	4.4598	4.4624
	(0.896)	(0.956)	(0.968)	(0.924)	(0.924)
Skewness	-0.1066	-0.1650	-0.1004	-0.346	-0.344
Kurtosis	5.9838	6.2359	6.0937	7.135	7.141
JB statistic	829.24	980.42	890.69	1630.80	1634.12
ARCH-LM test					
LM statistic	4.2160	3.1239	2.8859	8.3742	4.3677
Probability	0.9370	0.9783	0.9839	0.5923	0.9292
Summary statistics for cond. variance series					
Mean	1.296	1.217	1.259	1.210	1.209
Standard deviation	1.473	1.207	1.221	1.196	1.200
Maximum	18.062	19.655	19.787	12.253	12.517
Minimum	0.421	0.252	0.275	0.087	0.088
Skewness	4.836	5.215	5.165	3.960	3.994
Kurtosis	34.192	47.658	46.875	22.863	23.299

Table A6: Estimated models for CHINA , overall sample period

	C H I N A					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0171[c]	0.0134[c]	0.0140[c]	0.0210[c]	-0.0539[c]	0.0107[c]
	(0.5565)	(0.4856)	(0.4566)	(0.7200)	(-1.0923)	(0.3749)
GARCH-M coef.					0.0368[c]	
					(1.7911)	
Variance equation						
constant- ω	0.2647[a]	0.0260[b]	0.2678[a]	0.4693[a]	0.2593[a]	0.2651[a]
	(2.9212)	(1.9637)	(3.0327)	(3.8227)	(2.9643)	(2.7806)
ARCH terms:						
α_1	0.189418[a]	0.21082[a]	0.222922[a]	0.235931[a]	0.187324[a]	0.176427[a]
	(4.0299)	(3.7374)	(3.6045)	(4.8381)	(4.0027)	(2.8185)
α_2		-0.154868[a]		0.114371[a]		
		(-2.7285)		(2.7750)		
GARCH terms:						
β_1	0.721070[a]	0.937611[a]	0.279126[c]	-0.148448[a]	0.724826[a]	0.721195[a]
	(14.0684)	(43.0236)	(1.8623)	(-3.2892)	(14.6476)	(13.4320)
β_2			0.409403[a]	0.643605[a]		
			(3.2409)	(12.0758)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0254[c]
						(0.3673)
Akaike criterion	3.6183	3.6074	3.6162	3.6056	3.6175	3.6189
Schwarz criterion	3.6285	3.6202	3.6291	3.6210	3.6304	3.6317
Log likelihood	-4023.21	-4010.11	-4019.92	-4007.08	-4021.38	-4022.88
Stand.Res.Diagnostics						
$LB^2(5)$	2.4008	9.7644	2.8462	2.4129	2.3396	2.4229
	(0.791)	(0.082)	(0.724)	(0.790)	(0.800)	(0.788)
$LB^2(10)$	3.5501	10.664	4.2114	4.8305	3.4267	3.5480
	(0.965)	(0.384)	(0.937)	(0.902)	(0.970)	(0.965)
Skewness	0.3445	0.2225	0.3577	0.3531	0.3444	0.3436
Kurtosis	10.9003	8.3496	10.7226	10.2391	10.9799	10.9922
JB statistic	5833.12	2672.78	5579.09	4906.91	5950.28	5968.26
ARCH-LM test						
LM statistic	3.4437	10.9894	4.1472	4.6854	3.3374	3.4388
Probability	0.9689	0.3583	0.9404	0.9111	0.9723	0.9691
Summary statistics for cond. variance series						
Mean	2.847	2.897	2.861	2.869	2.852	2.847
Standard deviation	3.184	2.970	3.185	3.368	3.287	3.222
Maximum	41.468	33.769	38.183	41.345	47.504	43.922
Minimum	0.957	0.610	0.895	0.418	0.952	0.959
Skewness	5.035	3.838	4.782	5.031	5.594	5.289
Kurtosis	41.357	25.651	36.260	39.343	51.528	45.792

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

[c] Denotes significance at above 10% levels

Table A6(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.0578[c]	0.0957[c]	-0.2792[c]	0.0281[c]	-0.0546[c]
	(-1.1879)	(1.6564)	(-1.7804)	(1.2878)	(-1.1074)
GARCH-M coef.	0.0358[c]				0.0368[c]
	(1.6674)				(1.7968)
			0.1115[c]		
			(1.8134)		
Variance equation					
constant- ω	0.2603[a]	-0.0953[c]	-0.1040[c]	0.2404[a]	0.2598[a]
	(2.8880)	(-1.2924)	(-1.5280)	(4.4891)	(2.9605)
ARCH terms:					
α_1	0.175390[a]			0.342531[a]	0.187968[a]
	(2.8127)			(5.2009)	(4.0050)
α_2					
GARCH terms:					
β_1	0.724751[a]			0.695318[a]	0.724083[a]
	(14.2497)			(22.2167)	(14.6083)
β_2					
EGARCH terms:					
α		0.3089[a]	0.3092[a]		
		(3.8745)	(4.3946)		
β		0.8590[a]	0.8676[a]		
		(13.5271)	(19.0641)		
γ		0.000795[c]	-0.0121[c]		
		(0.0162)	(-0.3393)		
TARCH terms:					
γ	0.0226[c]				
	(0.3423)				
Degrees of freedom					
Akaike criterion	3.6182	3.6492	3.6435	3.4130	3.6179
Schwarz criterion	3.6336	3.6620	3.3589	3.4259	3.6307
Log likelihood	-4021.11	-4056.60	-4049.26	-3790.34	-4018.11
Stand.Res.Diagnostics					
$LB^2(5)$	2.3650	2.7169	2.5690	2.8883	2.8516
	(0.797)	(0.744)	(0.766)	(0.717)	(0.723)
$LB^2(10)$	3.4331	3.5032	3.3138	4.6664	4.6399
	(0.969)	(0.967)	(0.973)	(0.912)	(0.914)
Skewness	0.3431	0.3994	0.9996	0.6635	0.6599
Kurtosis	11.0538	12.807	12.700	14.508	14.4547
JB statistic	6059.86	8980.37	8784.19	12447.83	12331.5
ARCH-LM test					
LM statistic	3.3414	3.4593	3.2716	5.1344	5.1078
Probability	0.9722	0.9684	0.9742	0.8820	0.8838
Summary statistics for cond. variance series					
Mean	2.854	2.627	2.636	3.928	3.935
Standard deviation	3.346	1.936	2.078	5.436	5.399
Maximum	50.127	22.719	30.091	71.771	69.176
Minimum	0.955	0.751	0.810	0.240	0.240
Skewness	5.896	3.730	4.477	5.180	5.034
Kurtosis	57.107	24.718	36.882	43.317	40.952

Table A7: Estimated models for PHILIPPINES , overall sample period

	P H I L I P P I N E S					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0013[c]	-0.0032[c]	-0.0253[c]	-0.10928[c]	-0.0138[c]	-0.0416[c]
	(0.0285)	(-0.0735)	(-0.8106)	(-0.2894)	(-0.2718)	(-1.1917)
AR(1) coefficient	0.2023[a]	0.2085[a]	0.2341[a]	0.2144[a]	0.2023[a]	0.1827[a]
	(5.0119)	(5.6308)	(8.9925)	(6.1835)	(5.1184)	(3.6867)
GARCH-M coef.					0.0078[c]	
					(0.5689)	
Variance equation						
constant- ω	0.0832[a]	0.0985[a]	0.0868[a]	0.1626[a]	0.090771[a]	0.039777[a]
	(5.3265)	(4.2335)	(5.2255)	(3.0711)	(5.2532)	(3.2012)
ARCH terms:						
α_1	0.12931[a]	0.106681[c]	0.109984[a]	0.102077[c]	0.135661[a]	0.027310[c]
	(4.301)	(1.3355)	(2.6234)	(1.4963)	(4.2206)	(0.9501)
α_2		0.041424[c]		0.136800[c]		
		(0.5866)		(1.880632)		
GARCH terms:						
β_1	0.857716[a]	0.8372[a]	1.367530[a]	0.232162[c]	0.8498[a]	0.913038[a]
	(25.4212)	(28.6409)	(6.597866)	(0.6475)	(23.9091)	(40.3696)
β_2			-0.489327[a]	0.504029[c]		
			(-3.057669)	(1.5486)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.110027[a]
						(2.5841)
Akaike criterion	3.6887	3.6888	3.6856	3.6886	3.6924	3.6596
Schwarz criterion	3.7015	3.7042	3.7010	3.7066	3.7078	3.6750
Log likelihood	-4098.709	-4097.896	-4094.26	-4096.66	-4101.81	-4065.33
Stand.Res.Diagnostics						
$LB^2(5)$	0.0460	0.0545	0.1132	0.0518	0.0486	0.3817
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(0.996)
$LB^2(10)$	0.3189	0.3310	0.4117	0.3196	0.3122	0.7831
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
Skewness	2.2398	2.2473	2.2028	2.2365	2.2729	1.5792
Kurtosis	44.3075	44.381	43.689	44.249	45.176	27.800
JB statistic	160049	160629	155289	159597	166826	57944
ARCH-LM test						
LM statistic	0.3181	0.3300	0.4114	0.3185	0.3135	0.7645
Probability	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
Summary statistics for cond. variance series						
Mean	3.452	3.467	3.549	3.461	3.455	3.281
Standard deviation	4.676	4.824	5.605	4.884	4.732	3.529
Maximum	60.044	64.387	77.987	77.868	62.730	21.575
Minimum	0.649	0.658	0.624	0.708	0.7147	0.552
Skewness	5.068	5.319	6.507	5.747	5.308	2.400
Kurtosis	40.870	44.352	62.662	54.328	44.822	8.820

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A7(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.033[c]	-0.0797[a]	-0.1117[a]	-0.0459[b]	-0.0492[c]
	(-0.6778)	(-3.1674)	(-2.7384)	(-1.9149)	(-1.4328)
AR(1) coefficient	0.1817[a]	0.1769[a]	0.1768[a]	0.2113[a]	0.2112[a]
	(3.5573)	(3.4331)	(3.4945)	(9.8400)	(9.8307)
GARCH-M coef.			0.0163[c]		0.0018[c]
			(0.9361)		(0.1319)
Variance equation					
constant- ω	0.0427[a]	-0.0989[a]	-0.1068[a]	0.1390[a]	0.1386[a]
	(2.7604)	(-2.7114)	(-2.6447)	(4.8366)	(4.8326)
ARCH terms:					
α_1	0.031337[c]			0.219093[a]	0.218907[a]
	(0.9767)			(7.0539)	(7.0568)
α_2					
GARCH terms:					
β_1	0.936949[a]			0.756656[a]	0.756930[a]
	(33.9198)			(28.7432)	(28.7812)
β_2					
EGARCH terms:					
α		0.1638[a]	0.1787[a]		
		(3.4933)	(3.5018)		
β		0.9824[a]	0.9786[a]		
		(183.121)	(155.39)		
γ		-0.0760[b]	-0.0775[b]		
		(-2.0117)	(-2.0453)		
TARCH terms:					
γ	0.1142[a]				
	(2.6105)				
Degrees of freedom				4.38	4.38
Akaike criterion	3.6650	3.6547	3.6608	3.4812	3.4821
Schwarz criterion	3.6830	3.6701	3.6787	3.4966	3.5001
Log likelihood	-4070.418	-4059.92	-4065.65	-3865.17	-3865.14
Stand.Res.Diagnostics					
$LB^2(5)$	0.2652	2.0162	1.3609	0.1539	0.1533
	(0.998)	(0.847)	(0.929)	(1.000)	(1.000)
$LB^2(10)$	0.6576	2.4786	1.8246	0.3528	0.3529
	(1.000)	(0.991)	(0.998)	(1.000)	(1.000)
Skewness	1.6233	1.4095	1.4662	2.730	2.731
Kurtosis	28.849	23.829	25.166	56.194	56.213
JB statistic	62925.4	40959.8	46348	265214.7	265410.9
ARCH-LM test					
LM statistic	0.6407	2.3962	1.7565	0.3523	0.3545
Probability	0.9999	0.9923	0.9978	0.9999	0.9999
Summary statistics for cond. variance series					
Mean	3.302	3.129	3.153	3.396	3.396
Standard deviation	3.578	3.043	3.110	5.672	5.671
Maximum	22.41	18.526	19.629	100.567	100.48
Minimum	0.619	0.456	0.443	0.139	0.138
Skewness	2.482	2.231	2.324	7.609	7.604
Kurtosis	9.357	8.004	8.550	90.921	90.798

Table A8: Estimated models for THAILAND, overall sample period

	T H A I L A N D					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(3,2)	GARCH(3,3)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0113[c]	0.0075[c]	0.0051[c]	0.0068[c]	0.0257[c]	-0.0076[c]
	(0.3460)	(0.2312)	(0.1597)	(0.2121)	(0.5410)	(-0.2281)
AR(1) coefficient	0.1123[a]	0.1109[a]	0.1106[a]	0.1076[a]	0.1109[a]	0.1113[a]
	(4.7603)	(4.7398)	(4.7617)	(4.5704)	(4.6890)	(4.7128)
GARCH-M coef.					-0.0050[c]	
					(-0.3505)	
Variance equation						
constant- ω	0.0197[b]	0.0136[b]	0.0313[b]	0.1015[a]	0.0345[a]	0.0287[a]
	(2.3347)	(2.0788)	(2.1682)	(2.7981)	(2.5784)	(2.7024)
ARCH terms:						
α_1	0.054294[a]	0.073658[b]	0.049472[c]	0.061928[a]	0.076208[a]	0.0485[a]
	(5.3604)	(2.5549)	(1.9518)	(3.7489)	(6.0560)	(3.3366)
α_2		-0.032415[c]	0.038962[c]	0.096348[a]		
		(-1.0867)	(1.3524)	(5.4460)		
α_3				0.071260[a]		
				(3.9461)		
GARCH terms:						
β_1	0.942808[a]	0.956615[a]	0.855019[a]	-0.788683[a]	0.918616[a]	0.9314[a]
	(92.9158)	(109.131)	(5.7192)	(-13.7390)	(70.8197)	(74.4611)
β_2			-0.701384[a]	0.678964[a]		
			(-4.2238)	(26.4446)		
β_3			0.752969[a]	0.862524[a]		
			(8.3764)	(14.6144)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0312[c]
						(1.3412)
Akaike criterion	4.0379	4.0381	4.0371	4.0341	4.0457	4.0346
Schwarz criterion	4.0508	4.0535	4.0576	4.0572	4.0611	4.0500
Log likelihood	-4487.25	-4486.40	-4483.31	-4478.98	-4492.86	-4482.59
Stand.Res.Diagnostics						
$LB^2(5)$	13.045	18.868	14.705	8.8683	6.6477	7.1359
	(0.023)	(0.002)	(0.012)	(0.114)	(0.248)	(0.211)
$LB^2(10)$	18.388	22.962	18.275	14.034	12.637	13.645
	(0.049)	(0.011)	(0.050)	(0.171)	(0.245)	(0.190)
Skewness	0.1828	0.1767	0.1775	0.1593	0.1892	0.2158
Kurtosis	4.6853	4.6449	4.6238	4.4882	4.8903	4.7759
JB statistic	175.72	262.445	256.13	214.765	344.429	309.69
ARCH-LM test						
LM statistic	18.7920	23.2688	19.045	13.923	12.7292	14.3173
Probability	0.0429	0.0097	0.0396	0.1765	0.2392	0.1590
Summary statistics for cond. variance series						
Mean	4.617	4.586	4.593	4.595	4.671	4.584
Standard deviation	4.675	4.484	4.596	4.790	4.970	4.581
Maximum	44.861	42.485	45.607	48.659	54.735	45.471
Minimum	0.607	0.589	0.596	0.594	0.716	0.611
Skewness	3.403	3.054	3.288	3.678	4.042	3.339
Kurtosis	20.857	17.165	19.862	24.032	28.626	20.781

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A8(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(2,3)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0237[c]	0.0035[c]	0.0313[c]	-0.0329[c]	-0.0030[c]
	(0.6354)	(0.1034)	(0.5916)	(-1.0566)	(-0.0678)
AR(1) coefficient	0.1111[a]	0.1199[a]	0.1195[a]	0.1036[a]	0.1035[a]
		(5.0246)	(4.9604)	(4.9259)	(4.9453)
GARCH-M coef.	-0.0139[c]		-0.0170[c]		-0.0107[c]
	(-0.9438)		(-1.0950)		(-0.8584)
Variance equation					
constant- ω	0.0420[a]	-0.0068[c]	-0.0986[a]	0.0647[a]	0.1033[a]
	(2.8713)	(-1.8757)	(-6.0340)	(3.9446)	(6.5529)
ARCH terms:					
α_1	0.0608[a]			0.106436[a]	
	(3.6205)			(3.9446)	
α_2					
GARCH terms:					
β_1	0.9114[a]			0.886929[a]	0.8904[a]
	(62.7301)			(64.203)	(65.795)
β_2					
EGARCH terms:					
α		0.1496[b] (2.2579) -0.0639[c] (-0.4980) -0.0767[c] (-1.0552)	0.151327[a] (6.5258)		
β		1.7929[a] (20.805) -0.7929[a] (-9.2004)	0.9893[a] (236.234)		
γ		0.0077[c] (0.8442) -0.0429[c] (0.542) 0.0340[c] (0.3874)	-0.0207[c] (-1.1449)		
TARCH terms:					
γ	0.0435[c]				
	(1.5738)				
Degrees of freedom				5.13	5.13
Akaike criterion	4.0413	4.0347	4.0512	3.9862	3.9865
Schwarz criterion	4.0593	4.0629	4.0691	4.0016	4.0045
Log likelihood	-4489.01	-4475.62	-4497.95	-4426.68	-4426.07
Stand.Res.Diagnostics					
$LB^2(5)$	4.1420	9.2592	10.894	3.4481	3.3010
	(0.529)	(0.099)	(0.054)	(0.631)	(0.654)
$LB^2(10)$	11.250	12.573	18.223	8.7521	8.5087
	(0.338)	(0.249)	(0.051)	(0.556)	(0.579)
Skewness	0.2293	0.1681	0.2432	0.0486	0.0247
Kurtosis	4.9539	4.5086	4.9328	5.9574	6.1373
JB statistic	273.48	221.387	368.115	812.134	913.17
ARCH-LM test					
LM statistic	11.4398	13.4148	18.257	9.9343	10.0207
Probability	0.3242	0.2013	0.0507	0.4462	0.4386
Summary statistics for cond. variance series					
Mean	4.617	4.369	4.496	4.817	4.818
Standard deviation	4.760	3.957	4.031	5.377	5.396
Maximum	52.613	41.420	39.478	65.881	65.453
Minimum	0.737	0.4722	0.560	0.064	0.061
Skewness	3.809	2.2944	2.981	4.581	4.576
Kurtosis	26.572	12.145	17.484	36.466	36.060

Table A9: Estimated models for MALAYSIA , overall sample period

	M A L A Y S I A					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0364[c]	0.0303[c]	0.0359[c]	0.0289[a]	0.0377[c]	0.0105[c]
	(1.5727)	(1.3662)	(1.5574)	(1.3669)	(1.4580)	(0.4685)
AR(1) coefficient	0.1481[a]	0.1382[a]	0.1471[a]	0.1537[a]	0.1505[a]	0.1529[a]
	(5.0759)	(4.6090)	(5.0189)	(5.2896)	(5.117)	(4.8054)
GARCH-M coef.					0.0014[c]	
					(0.1217)	
Variance equation						
constant- ω	0.0039[c]	0.0025[c]	0.0047[c]	0.0010[c]	0.0041[c]	0.0050[c]
	(0.7734)	(0.6995)	(0.6779)	(0.6729)	(0.7667)	(0.9843)
ARCH terms:						
α_1	0.045740[a]	0.159923[a]	0.057812[c]	0.155553[a]	0.048755[a]	0.0220[c]
	(2.9372)	(3.2482)	(1.4436)	(3.8544)	(3.1241)	(1.5714)
α_2		-0.125547[b]		-0.146722[a]		
		(-2.5368)		(-4.0290)		
GARCH terms:						
β_1	0.955893[a]	0.966518[a]	0.654095[c]	1.630172[a]	0.953006[a]	0.9547[a]
	(60.0764)	(71.1049)	(0.7380)	(9.2380)	(59.2264)	(63.931)
β_2			0.290181[c]	-0.639324[a]		
			(0.3404)	(-3.8618)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0495[a]
						(3.1987)
Akaike criterion	3.4719	3.4588	3.4708	3.4439	3.4816	3.4571
Schwarz criterion	3.4847	3.4742	3.4862	3.4619	3.4970	3.4725
Log likelihood	-3857.50	-3842.01	-3855.34	-3824.42	-3867.37	-3840.12
Stand.Res.Diagnostics						
$LB^2(5)$	9.5124	9.9725	9.6505	2.0551	7.5738	9.0223
	(0.090)	(0.076)	(0.086)	(0.841)	0.181)	(0.108)
$LB^2(10)$	11.770	12.222	11.888	4.1180	9.6740	11.620
	(0.348)	(0.270)	(0.293)	(0.942)	(0.470)	(0.355)
Skewness	0.0390	-0.0126	0.0340	-0.084	0.0631	-0.0118
Kurtosis	9.7163	8.9612	9.5667	10.6136	10.446	9.4881
JB statistic	4182.55	3294.63	3998.23	5376.79	5141.84	3902.65
ARCH-LM test						
LM statistic	11.1087	11.4950	11.2427	4.1010	9.0781	10.9956
Probability	0.3491	0.3202	0.3389	0.9426	0.5247	0.3578
Summary statistics for cond. variance series						
Mean	5.232	5.162	5.229	4.898	5.277	5.386
Standard deviation	10.506	11.064	10.470	11.986	10.667	11.637
Maximum	84.233	239.38	100.861	226.61	87.99	117.60
Minimum	0.324	0.305	0.318	0.307	0.318	0.302
Skewness	3.868	7.421	3.885	8.684	4.006	4.611
Kurtosis	21.054	113.47	21.629	116.42	22.569	30.315

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A9(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0105[c]	0.0232[c]	0.0131[c]	0.0123[c]	0.0139[c]
	(0.4685)	(1.0135)	(0.1804)	(0.6562)	(0.6412)
AR(1) coefficient	0.1529[a]	0.1366[a]	0.1417[a]	0.1208[a]	0.1209[a]
	(4.8054)	(4.4293)	(4.3448)	(5.8632)	(5.8673)
GARCH-M coef.			0.0111[c]		-0.0011[c]
			(0.6995)		(-0.1372)
Variance equation					
constant- ω	0.0050[c]	-0.0594[a]	-0.0691[a]	0.0641[a]	0.0641[a]
	(0.9843)	(-3.7082)	(-4.0464)	(4.8553)	(4.8536)
ARCH terms:					
α_1	0.0220[c]			0.1898[a]	0.1898[a]
	(1.5714)			(36.6622)	(6.6553)
α_2					
GARCH terms:					
β_1	0.9547[a]			0.8143[a]	0.8143[a]
	(63.9310)			(45.9435)	(45.915)
β_2					
EGARCH terms:					
α		0.0830[a]	0.0963[a]		
		(3.7184)	(4.0247)		
β		1.0004[a]	0.9997[a]		
		(409.97)	(382.711)		
γ		-0.0368[a]	-0.0380[b]		
		(-2.8400)	(-2.5229)		
TARCH terms:					
γ	0.0495[a]				
	(3.1987)				
Degrees of freedom					
Akaike criterion	3.4571	3.4468	3.4588	3.2796	3.2805
Schwarz criterion	3.4725	3.4622	3.4768	3.2950	3.2985
Log likelihood	-3840.12	-3828.65	-3841.00	-3640.99	-3640.97
Stand.Res.Diagnostics					
$LB^2(5)$	10.712	14.495	11.251	0.5713	0.5716
	(0.057)	(0.013)	(0.047)	(0.989)	(0.989)
$LB^2(10)$	15.709	16.909	13.484	1.5185	1.5172
	(0.108)	(0.076)	(0.198)	(0.999)	(0.999)
Skewness	-0.0118	-0.1156	-0.9160	-0.9162	-0.9137
Kurtosis	9.4881	9.8572	10.5566	48.3565	48.295
JB statistic	3902.65	4364.24	5297.03	191118.5	190342.5
ARCH-LM test					
LM statistic	10.9956	15.6739	12.5308	1.5290	1.5269
Probability	0.3578	0.1093	0.2511	0.9988	0.9988
Summary statistics for cond. variance series					
Mean	5.386	4.945	5.082	5.397	5.406
Standard deviation	11.637	8.701	9.130	16.161	16.188
Maximum	117.60	51.713	58.543	262.743	262.700
Minimum	0.302	0.244	0.236	0.064	0.064
Skewness	4.611	2.609	2.790	8.987	8.972
Kurtosis	30.315	9.550	10.960	108.094	107.67

Table A10: Estimated models for HUNGARY , overall sample period

Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
	H U N G A R Y					
Mean equation						
constant-c	0.0987[a]	0.0794[b]	0.0907[a]	0.0866[a]	0.0637[c]	0.0545[c]
	(3.1912)	(2.5208)	(.8893)	(2.8710)	(1.2471)	(1.7421)
AR(1) coefficient	0.1347[a]	0.1154[a]	0.1251[a]	0.1328[a]	0.1341[a]	0.1377[a]
	(4.8679)	(4.1974)	(4.5543)	(4.7307)	(4.8678)	(5.1765)
GARCH-M coef.					0.0156[c]	
					(0.9926)	
Variance equation						
constant- ω	0.3237[a]	0.0808[a]	0.3699[a]	0.0136[c]	0.3391[a]	0.3540[a]
	(2.8489)	(2.6491)	(2.6931)	(1.1866)	(2.8606)	(2.9856)
ARCH terms:						
α_1	0.231984[a]	0.378491[a]	0.2847[a]	0.318202[a]	0.239664[a]	0.120623[a]
	(3.1866)	(3.0615)	(3.0147)	(2.8787)	(3.2406)	(2.9115)
α_2		-0.298543[b]		-0.303267[a]		
		(-2.4656)		(-2.8441)		
GARCH terms:						
β_1	0.6907875[a]	0.902722	0.3074[c]	1.427451[a]	0.680020[a]	0.6896[a]
	(9.4834)	(31.8220)	(1.5036)	(9.5929)	(9.1457)	(9.6504)
β_2			0.3211[b]	-0.445297[a]		
			(2.1100)	(-3.1827)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.193529[c]
						(1.6684)
Akaike criterion	3.8355	3.8218	3.8303	3.8179	3.8386	3.8253
Schwarz criterion	3.8483	3.8372	3.8457	3.8359	3.8540	3.8407
Log likelihood	-4262.04	-4243.88	-4253.33	-4238.58	-4262.60	-4247.82
Stand.Res.Diagnostics						
$LB^2(5)$	3.1614	5.6219	3.8919	1.3028	2.9026	5.9169
	(0.675)	(0.345)	(0.565)	(0.935)	(0.715)	(0.314)
$LB^2(10)$	4.6572	6.6007	5.2181	3.4625	4.3450	7.3291
	(0.913)	(0.763)	(0.876)	(0.968)	(0.930)	(0.694)
Skewness	-0.4213	-0.4235	-0.3964	-0.3717	-0.4174	-0.3052
Kurtosis	9.6311	8.4604	9.0659	8.6405	9.5449	8.8511
JB statistic	4142.44	2829.45	3467.94	2999.51	4034.05	3207.06
ARCH-LM test						
LM statistic	4.7570	6.7288	5.3577	3.4284	4.4394	7.4249
Probability	0.9068	0.7507	0.8660	0.9694	0.9253	0.6848
Summary statistics for cond. variance series						
Mean	3.827	3.862	3.831	3.851	3.830	3.830
Standard deviation	6.088	6.498	6.116	6.440	6.093	6.544
Maximum	94.435	115.94	87.977	107.330	89.547	97.119
Minimum	0.627	0.343	0.667	0.252	1.135	0.6085
Skewness	7.017	8.349	6.922	8.035	7.010	7.577
Kurtosis	68.842	101.120	66.594	91.648	67.892	79.002

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A10(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0216[c]	0.0797[b]	0.0758[c]	0.0885[a]	0.0066[c]
	(0.4576)	(2.3016)	(1.3230)	(3.1381)	(0.4141)
AR(1) coefficient	0.1397[a]	0.1416[a]	0.1414[a]	0.0759[a]	0.0743[c]
	(5.1789)	(4.6311)	(4.6688)	(3.5291)	(1.5909)
GARCH-M coef.	0.0143[c]		0.0019[c]		0.0755[a]
	(0.8422)		(0.1039)		(3.5115)
Variance equation					
constant- ω	0.3757[a]	-0.1545[a]	-0.1568[a]	0.2231[a]	0.2219[a]
	(3.0332)	(-2.7378)	(-2.7198)	(4.9995)	(4.9654)
ARCH terms:					
α_1	0.122930[a]			0.160315[a]	0.158974[a]
	(2.9631)			(6.3499)	(6.3251)
α_2					
GARCH terms:					
β_1	0.6768[a]			0.776987[a]	0.7785[a]
	(9.3147)			(27.3568)	(27.3474).
β_2					
EGARCH terms:					
α		0.4044[a]	0.4159[a]		
		(4.4548)	(4.5415)		
β		0.8631[a]	0.8568[a]		
		(14.0257)	(13.1763)		
γ		-0.0861[c]	-0.0875[c]		
		(-1.5430)	(-1.5513)		
TARCH terms:					
γ	0.2001[c]				
	(1.6797)				
Degrees of freedom				4.685	4.676
Akaike criterion	3.8278	3.8454	3.849	3.7104	3.7121
Schwarz criterion	3.8458	3.8608	3.867	3.7258	3.7301
Log likelihood	-4249.60	-4272.10	-4275.22	-4119.98	-4119.10
Stand.Res.Diagnostics					
$LB^2(5)$	5.8757[c]	5.4323	5.4981		
	(0.318)	(0.365)	(0.358)		
$LB^2(10)$	7.2030[c]	6.9367	7.2167		
	(0.706	(0.731)	(0.705)		
Skewness	-0.3037	-0.2148	-0.2108	-0.046	-0.578
Kurtosis	8.7784	9.8466	9.714	2.661	11.426
JB statistic	3128.40	4362.94	4196.79	11.463	6710.11
ARCH-LM test					
LM statistic	7.2994	6.8843	7.1175	10.177	11.206
Probability	0.6969	0.7363	0.7143	0.3996	0.3416
Summary statistics for cond. variance series					
Mean	3.853	3.621	3.639	3.644	3.643
Standard deviation	6.707	6.254	6.509	5.146	5.117
Maximum	100.035	194.99	209.87	66.355	65.792
Minimum	1.215	0.426	0.7626	0.224	0.221
Skewness	7.706	17.275	18.393	5.866	5.848
Kurtosis	81.243	449.45	403.36	46.95	46.717

Table A11: Estimated models for POLAND , overall sample period

	P O L A N D					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0437[c]	0.0373[c]	0.0392[c]	0.0516[c]	0.0309[c]	0.0217[c]
	(1.4435)	(1.2471)	(1.3109)	(1.6898)	(0.4336)	(0.6864)
AR(1) coefficient	0.1625[a]	0.1493[a]	0.1577[a]	0.1706[a]	0.1627[a]	0.1647[a]
	(6.8869)	(6.3692)	(6.8041)	(7.2702)	(6.9024)	(7.0514)
GARCH-M coef.					0.0056[c]	
					(0.1998)	
Variance equation						
constant- ω	0.1373[a]	0.0530[a]	0.1633[a]	0.4434[a]	0.1362[a]	0.1299[a]
	(3.2912)	(2.7355)	(0.0033)	(3.6565)	(3.2793)	(3.5709)
ARCH terms:						
α_1	0.098135[a]	0.156621[b]	0.130544[a]	0.126028[a]	0.097743[a]	0.062867[a]
	(3.7689)	(3.0819)	(3.9583)	(4.2553)	(3.7452)	(3.4448)
α_2		-0.103979[b]		0.125272[a]		
		(-2.1457)		(4.2469)		
GARCH terms:						
β_1	0.853307[a]	0.928389[a]	0.336712[c]	-0.208150[a]	0.8540[a]	0.862636[a]
	(25.0766)	(53.2966)	(1.7303)	(-4.6744)	(25.101)	(30.1466)
β_2			0.475091[a]	0.796362[a]		
			(2.6427)	(18.4267)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.056068[c]
						(1.5707)
Akaike criterion	3.7677	3.7641	3.7655	3.7702	3.7688	3.7645
Schwarz criterion	3.7805	3.7795	3.7809	3.7882	3.7842	3.7799
Log likelihood	-4186.61	-4179.70	-4181.27	-4185.54	-4184.92	-4180.14
Stand.Res.Diagnostics						
$LB^2(5)$	10.497	7.185	6.174	4.419	10.486	8.8027
	(0.062)	(0.207)	(0.290)	(0.491)	(0.063)	(0.117)
$LB^2(10)$	16.596	12.595	12.039	10.514	16.568	13.674
	(0.084)	(0.247)	(0.077)	(0.397)	(0.084)	(0.188)
Skewness	-0.0912	-0.1035	-0.1044	-0.0735	-0.0937	-0.0598
Kurtosis	4.2233	4.1324	4.2200	4.1580	4.2279	4.1187
JB statistic	141.82	122.82	141.98	126.28	142.978	117.317
ARCH-LM test						
LM statistic	26.086	12.718	11.834	10.464	16.065	13.393
Probability	0.0971	0.239	0.296	0.400	0.0977	0.2024
Summary statistics for cond. variance series						
Mean	2.914	2.912	2.917	2.882	2.915	2.910
Standard deviation	2.199	2.139	2.202	2.230	2.197	2.240
Maximum	24.556	26.389	25.581	29.079	24.463	24.569
Minimum	1.412	1.137	1.148	1.167	1.141	1.143
Skewness	4.358	3.887	4.088	5.156	4.341	4.339
Kurtosis	30.034	25.970	26.475	42.583	29.791	28.931

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A11(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0146[c]	0.0110[c]	0.0214[c]	0.0386[c]	0.0675[c]
	(0.2072)	(0.3367)	(0.2689)	(1.2633)	(1.0467)
AR(1) coefficient	0.1649[a]	0.1692[a]	0.1689	0.1463[a]	0.1463[a]
	(7.0903)	(6.9864)	(7.0144)	(6.8397)	(6.8307)
GARCH-M coef.	0.0030[c]		-0.0034[c]		-0.0121[c]
	(0.1105)		(-0.1104)		(-0.5070)
Variance equation					
constant- ω	0.1283[a]	-0.0961[a]	-0.0965[a]	0.1548[a]	0.1568[a]
	(3.5196)	(-3.7001)	(-3.6965)	(4.1823)	(4.1926)
ARCH terms:					
α_1	0.061992[a]			0.101805[a]	0.102605[a]
	(3.4073)			(6.2123)	(6.1947)
α_2					
GARCH terms:					
β_1	0.863832[a]			0.845942[a]	0.844462[a]
	(30.2200)			(36.0347)	(35.5932)
β_2					
EGARCH terms:					
α		0.1847[a]	0.1851[a]		
		(4.0596)	(4.0478)		
β		0.9539[a]	0.9538[a]		
		(58.949)	(58.115)		
γ		-0.0430[c]	-0.0433[c]		
		(-1.6612)	(-1.6688)		
TARCH terms:					
γ	0.056263[c]				
	(3.4073)				
Degrees of freedom				6.6847	6.6780
Akaike criterion	3.7652	3.7754	3.7762	3.7391	3.7399
Schwarz criterion	3.7831	3.7908	3.7941	3.7545	3.7579
Log likelihood	-4179.91	-4194.20	-4194.06	-4151.96	-4151.84
Stand.Res.Diagnostics					
$LB^2(5)$	8.886	21.984	21.738	9.3494	11.465
	(0.114)	(0.001)	(0.001)	(0.096)	(0.076)
$LB^2(10)$	13.733	25.996	25.737	15.138	16.637
	(0.185)	(0.004)	(0.004)	(0.127)	(0.083)
Skewness	-0.0612	-0.0511	-0.0508	-0.0740	-0.0935
Kurtosis	4.1235	4.2806	4.2831	4.2436	4.2668
JB statistic	118.379	153.019	153.61	145.54	152.09
ARCH-LM test					
LM statistic	13.509	25.364	25.247	15.031	16.074
Probability	0.196	0.004	0.0048	0.130	0.097
Summary statistics for cond. variance series					
Mean	2.911	2.865	2.866	2.949	2.982
Standard deviation	2.241	1.770	1.768	2.195	2.169
Maximum	24.49	18.674	18.673	24.954	24.592
Minimum	1.142	0.798	0.7957	0.136	0.136
Skewness	4.322	3.290	3.290	4.423	4.220
Kurtosis	28.684	19.256	19.288	31.073	28.377

Table A12: Estimated models for RUSSIA , overall sample period

	R U S S I A					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.1670[a]	0.1607[a]	0.1634[a]	0.1616[a]	0.2153[a]	0.1553[a]
	(3.9336)	(3.8094)	(3.8641)	(3.8804)	(3.3751)	(3.3636)
AR(1) coefficient	0.1338[a]	0.1265[a]	0.1299[a]	0.1294[a]	0.1336[a]	0.1355[a]
	(5.3994)	(5.0995)	(5.2396)	(5.1933)	(5.3774)	(5.4610)
GARCH-M coef.					-.00085[C]	
					(-0.9448)	
Variance equation						
constant- ω	0.2458[a]	0.1938[B]	0.2713[a]	0.0216[C]	0.2475[a]	0.2493[a]
	(3.522)	(3.0281)	(2.6927)	(1.1279)	(3.4097)	(3.4680)
ARCH terms:						
α_1	0.159278[a]	0.199278[a]	0.1798[a]	0.1950[a]	0.1601[a]	0.148982[a]
	(0.000)	(3.4254)	(3.1400)	(4.3618)	(5.1028)	(4.6862)
α_2		-0.068282[C]		-0.1778[a]		
		(-1.1261)		(-4.3558)		
GARCH terms:						
β_1	0.823971[a]	0.8551[a]	0.6105[C]	1.6248[a]	0.8228[a]	0.823662[a]
	(28.3829)	(31.1960)	(1.6657)	(11.5210)	(28.0481)	(28.1110)
β_2			0.1907[C]	-0.6436[a]		
			(0.3040)	(-5.1008)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.019126[c]
						(26.1110)
Akaike criterion	4.7429	.4.7420	4.7428	4.7364	4.7470	4.7435
Schwarz criterion	4.7558	4.7574	4.7582	4.7543	4.7624	4.7589
Log likelihood	-5271.56	-5269.49	-5270.469	-5262.29	-5275.13	-5271.17
Stand.Res.Diagnostics						
$LB^2(5)$	1.955	1.3603	1.2951	1.2735	2.1811	1.8001
	(0.855)	(0.929)	(0.935)	(0.938)	(0.824)	(0.876)
$LB^2(10)$	12.725	11.264	11.695	10.642	13.098	12.856
	(0.239)	(0.337)	(0.309)	(0.386)	(0.218)	(0.232)
Skewness	-0.1585	-0.1823	-0.1753	-0.1336	-0.1567	-0.1362
Kurtosis	5.5732	5.6029	5.5804	5.5664	5.5836	5.5338
JB statistic	623.22	640.46	628.70	617.25	627.96	602.11
ARCH-LM test						
LM statistic	12.635	11.093	11.480	10.643	12.969	12.859
Probability	0.244	0.350	0.321	0.385	0.225	0.231
Summary statistics for cond. variance series						
Mean	9.711	9.6444	9.678	9.565	9.709	9.718
Standard deviation	11.135	10.912	11.004	10.942	11.072	11.242
Maximum	110.413	108.310	106.857	123.108	113.986	110.788
Minimum	1.048	0.995	1.070	0.7544	11.072	1.043
Skewness	3.554	3.557	3.511	3.828	3.558	3.638
Kurtosis	20.445	20.84	19.999	25.549	20.569	21.338

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.

[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A12(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.2076[a]	0.2268[a]	0.3471[a]	0.1499[a]	0.2024[a]
	(3.2055)	(4.1110)	(3.7872)	(3.4732)	(3.2608)
AR(1) coefficient	0.1354[a]	0.1429	0.1375[a]	0.1102[a]	0.1105[a]
	(5.3965)	(5.5708)	(5.1413)	(5.1238)	(5.1381)
GARCH-M coef.	-0.00965[c]		-0.0218[b]		-0.0105[c]
	(-1.0568)		(-1.9599)		(-1.2659)
Variance equation					
constant- ω	0.2520[a]	-0.1277[a]	-0.1352[a]	0.2353[a]	0.2329[a]
	(3.3851)	(-4.1517)	(-4.5779)	(4.1378)	(4.1759)
ARCH terms:					
α_1	0.148808[a]			0.178933[a]	0.179468[a]
	(4.6953)			(7.3817)	(7.4018)
α_2					
GARCH terms:					
β_1	0.822261[a]			0.8171404[a]	0.816243[a]
	(27.9298)			(42.2921)	(42.1506)
β_2					
EGARCH terms:					
α		0.3011[a]	0.2987[a]		
		(6.1447)	(6.2603)		
β		0.9520[a]	0.9566[a]		
		(66.9766)	(71.6066)		
γ		-0.0195[c]	-0.0204[c]		
		(-0.6361)	(-0.6708)		
TARCH terms:					
γ	0.021864[c]				
	(27.9298)				
Degrees of freedom				4.583	4.601
Akaike criterion	4.7482	4.7579	4.7605	4.6607	4.6624
Schwarz criterion	4.7662	4.7733	4.7784	4.6761	4.6803
Log likelihood	-5273.05	-5287.19	-5289.09	-5179.10	-5117.62
Stand.Res.Diagnostics					
$LB^2(5)$	2.0321	4.3677	5.2595	1.009	1.0476
	(0.845)	(0.498)	(0.385)	(0.962	(0.959)
$LB^2(10)$	13.159	14.334	14.919	12.475	12.619
	(0.215)	(0.158)	(0.135)	(0.255)	(0.246)
Skewness	-0.130	-0.061	-0.0605	-0.145	-0.150
Kurtosis	5.535	5.839	5.8016	5.584	5.576
JB statistic	601.91	748.81	729.05	627.41	624.08
ARCH-LM test					
LM statistic	13.153	14.829	15.266	12.427	12.566
Probability	0.215	0.138	0.122	0.257	0.248
Summary statistics for cond. variance series					
Mean	9.710	9.160	9.174	10.283	10.221
Standard deviation	11.161	8.728	8.714	12.158	11.977
Maximum	114.966	84.864	85.982	120.989	121.630
Minimum	1.626	0.934	1.152	0.235	0.239
Skewness	3.649	3.162	3.118	3.594	3.558
Kurtosis	21.554	17.999	17.499	20.881	20.540

Table A13: Estimated models for ISRAEL , overall sample period

	I S R A E L					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0573[b]	0.0608[b]	0.0590[b]	0.0608[b]	0.0075[c]	0.0309[c]
	(2.0691)	(2.1959)	(2.1258)	(2.1953)	(0.1150)	(1.0935)
AR(1) coefficient	0.0989[a]	0.0952[a]	0.0968[a]	0.0952[a]	0.0992[a]	0.1058[a]
	(4.2135)	(4.0395)	(4.1333)	(4.0375)	(4.2531)	(4.3469)
GARCH-M coef.					0.0272[c]	
					(0.8436)	
Variance equation						
constant- ω	0.1407[a]	0.1680[a]	0.1041[a]	0.1681[c]	0.1447[a]	0.1799[a]
	(3.7614)	(3.6198)	(2.8367)	(1.3237)	(3.7550)	(4.2818)
ARCH terms:						
α_1	0.105884[a]	0.068894[b]	0.0777[a]	0.068897[b]	0.108807[a]	0.053777[b]
	(4.7457)	(2.0710)	(2.7621)	(0.0383)	(4.8230)	(2.1359)
α_2		0.057472[c]		0.057521[c]		
		(1.3860)		(0.5393)		
GARCH terms:						
β_1	0.832114[a]	0.800224[a]	1.2238[a]	0.799747[c]	0.827525[a]	0.804952[a]
	(28.0008)	(20.6166)	(5.2158)	(0.9662)	(27.4201)	(3.1114)
β_2			-0.3469[c]	0.000396[c]		
			(-1.7517)	(0.0008)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.119704[a]
						(3.1114)
Akaike criterion	3.5237	3.5225	3.5228	3.5234	3.5264	3.5146
Schwarz criterion	3.5365	3.5279	3.5382	3.5413	3.5418	3.5300
Log likelihood	-3915.13	-3912.79	-3913.21	-3912.79	-3915.41	-3902.29
Stand.Res.Diagnostics						
$LB^2(5)$	7.3251	4.6124	6.2317	4.6109	7.3896	2.8740
	(0.198)	(0.590)	(0.284)	(0.465)	(0.193)	(0.719)
$LB^2(10)$	16.337	12.528	14.900	12.525	16.681	14.070
	(0.090)	(0.251)	(0.136)	(0.251)	(0.082)	(0.170)
Skewness	-0.364	-0.350	-0.356	-0.350	-0.359	-0.345
Kurtosis	5.391	5.260	5.283	5.260	5.387	5.230
JB statistic	579.19	519.45	530.28	519.45	576.06	505.40
ARCH-LM test						
LM statistic	11.6382	12.7362	15.2789	12.7333	17.1385	14.255
Probability	0.0006	0.2387	0.1222	0.2389	0.0713	0.1616
Summary statistics for cond. variance series						
Mean	2.251	2.259	2.261	2.259	2.256	2.270
Standard deviation	1.633	1.696	1.693	1.6969	1.639	1.841
Maximum	26.268	26.686	24.643	26.687	26.049	26.033
Minimum	0.514	0.536	0.484	0.536	0.972	0.524
Skewness	5.542	5.788	5.578	5.788	5.516	5.677
Kurtosis	53.033	57.582	52.397	57.586	52.007	51.006

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A13(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,2)	EGARCH(1,2)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0080[c]	0.0298[c]	0.0101[c]	0.0646[b]	0.0482[c]
	(0.1314)	(1.0563)	(0.1578)	(2.4936)	(0.7987)
AR(1) coefficient	0.1071[a]	0.0961[a]	0.0968[a]	0.0853[a]	0.0852[a]
	(4.3169)	(3.8051)	(3.7536)	(4.0234)	(4.0161)
GARCH-M coef.	0.0125[c]		0.3691[c]		0.0088[c]
	(0.4168)		(0.3691)		(0.2974)
Variance equation					
constant- ω	0.1857[a]	-0.1208[a]	-0.1240[a]	0.1087[a]	0.1094[a]
	(4.1643)	(-3.2637)	(-3.3232)	(3.8373)	(3.8379)
ARCH terms:					
α_1	0.054768[b]			1.091485[a]	0.091727[a]
	(2.1637)			(5.6908)	(5.6827)
α_2					
GARCH terms:					
β_1	0.800237[a]			0.862517[a]	0.861958[a]
	(3.1187)			(37.0162)	(36.8084)
β_2					
EGARCH terms:					
α		0.1345[c] (1.6401)	0.1343[c] (1.6448)		
		0.1164[c] (0.1313)	0.1207[c] (1.5527)		
β		0.9031[a](31.732)	0.9024[a](31.3702)		
γ		-0.1003[b](-2.151)	-0.0970[b] (-2.094)		
		-0.0055[c] (-0.129)	-0.0089[c] (-0.2105)		
TARCH terms:					
γ	0.121294[a]				
	(3.1187)				
Degrees of freedom				5.281	5.280
Akaike criterion	3.5170	3.5179	3.5198	3.4560	3.4569
Schwarz criterion	3.5349	3.5384	3.5429	3.4714	3.4749
Log likelihood	-3903.92	-3905.74	-3906.84	-3837.17	-3837.12
Stand.Res.Diagnostics					
$LB^2(5)$	2.9623	4.4424	4.3594	8.9887	9.0492
	(0.706)	(0.488)	(0.499)	(0.110)	(0.107)
$LB^2(10)$	14.400	17.997	18.087	17.541	17.675
	(0.155)	(0.055)	(0.054)	(0.063)	(0.061)
Skewness	-0.3426	-0.3573	-0.3499	-0.3682	-0.3680
Kurtosis	5.2326	5.2832	5.2735	5.4406	5.4387
JB statistic	505.43	530.68	524.63	602.81	301.876
ARCH-LM test					
LM statistic	14.5284	17.466	17.265	18.707	18.851
Probability	0.1502	0.0646	0.0686	0.0441	0.042
Summary statistics for cond. variance series					
Mean	2.275	2.220	2.227	2.279	2.279
Standard deviation	1.855	1.379	1.402	1.602	1.606
Maximum	26.064	17.084	17.661	23.560	23.610
Minimum	1.018	0.475	0.718	0.108	0.109
Skewness	5.722	3.573	3.676	4.993	5.015
Kurtosis	51.563	25.190	56.520	42.948	43.171

Table A14: Estimated models for SOUTH AFRICA , overall sample period

	SOUTH AFRICA					
Parameters / Criteria	GARCH(1,1)	GARCH(2,3)	GARCH(3,2)	GARCH(3,3)	GARCH(1,1)-M	TARCH(2,3)
Mean equation						
constant-c	0.0744[a]	0.0777[a]	0.0655[a]	0.0801[a]	0.0872[β]	0.0473[β]
	(3.2956)	(3.6208)	(3.0144)	(3.6730)	(-0.1730)	(2.0872)
AR(1) coefficient	0.1222[a]	0.1067[a]	0,1134[a]	0.1129[a]	0.1101[α]	0.1343[α]
	(4.8595)	(4.5221)	(4.8081)	(4.7266)	(4.4333)	(5.4797)
GARCH-M coef.					-0.0038[c]	
					(-0.1730)	
Variance equation						
constant- ω	0.0261[a]	0.0026[c]	0.0063[c]	0.0030[c]	0.0616[α]	0.0175[α]
	(2.5395)	(2.9604)	(1.6198)	(1.1606)	(3.8148)	(2.8607)
ARCH terms:						
α_1	0.089670[a]	0.121671[a]	0.156484[a]	0.112415[c]	0.132416[α]	0.042688[ψ]
	(3.3755)	(2.9604)	(3.8992)	(2.6177)	(5.7570)	(1.7293)
α_2		-0.0464[c]	-0.133738[a]	0.058733[c]		-0.029666[ψ]
		(-0.5224)	(-3.3641)	(1.0918)		(-1.0935)
α_3		-0.0669[c]		-0.162317[c]		
		(-1.2358)		(-4.1848)		
GARCH terms:						
β_1	0.902041[a]	1.6376[a]	1.6222[a]	0.957315[α]	0.843119[α]	1.872073[α]
	(32.9492)	(15.5760)	(6.1783)	(5.0206)	(36.7940)	(14.6605)
β_2		-0.6471[a]	-0.837217[c]	0.6301[β]		-1.556939[α]
		(-6.3882)	(-1.8124)	(2.3152)		(-8.3452)
β_3			0.189485[c]	-0.597884[α]		0.634288[α]
			(0.8353)	(-5.0595)		(7.1222)
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0546[α]
						(3.5591)
Akaike criterion	3.2746	3.2529	3.2594	3.2580	3.2836	3.249
Schwarz criterion	3.2874	3.2735	3.2799	3.2811	3.2990	3.2728
Log likelihood	-3638.00	-3609.33	-3616.48	-3614.003	-3647.02	-3606.40
Stand.Res.Diagnostics						
$LB^2(5)$	28.840[a]	2.7784	15.021	4.7438	7.5244	12.505
	(0.000)	(0.328)	(0.010)	(0.448)	(0.184)	(0.028)
$LB^2(10)$	31.300[a]	6.6042	15.178	7.6148	10.282	13.959
	(0.000)	(0.762)	(0.126)	(0.668)	(0.416)	(0.175)
Skewness	-0.4717	-0.3115	-0.3770	-0.3095	-0.4520	-0.2951
Kurtosis	6.3967	5.4638	5.5293	5.6976	6.6650	5.1380
JB statistic	1152.20	598.50	645.54	709.90	1321.07	456.11
ARCH-LM test						
LM statistic	28.3814	6.5983	15.1111	7.2987	9.5934	12.4314
Probability	0.0015	0.7627	0.1280	0.6969	0.4768	0.2521
Summary statistics for cond. variance series						
Mean	2.113	2.018	2.047	2.000	2.104	2.086
Standard deviation	2.340	2.428	2.229	2.489	2.521	2.457
Maximum	26.875	42.568	36.960	41.585	36.892	36.869
Minimum	0.169	0.142	0.150	0.132	0.484	0.163
Skewness	4.468	7.012	5.743	6.665	6.027	5.200
Kurtosis	32.975	89.932	62.519	74.195	59.388	47.506

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A14(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(3,3)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0802[β]	0.0545[b]	0.0922[b]	0.0720[a]	-0.0864[a]
	(2.2323)	(2.3682)	(2.3002)	(3.4943)	(-2.6351)
AR(1) coefficient	0.1203[α]	0.1277[a]	0.1186[a]	0.0981[a]	0.0987[a]
	(5.0242)	(5.1814)	(4.8993)	(4.4783)	(4.6600)
GARCH-M coef.	-0.0264[Ψ]		-0.0327[c]		-0.0131[c]
	(-1.2205)		(-1.3449)		(-0.6403)
Variance equation					
constant- ω	0.0547[α]	-0.1343[a]	-0.1497[a]	0.0045[b]	0.0330[a]
	(4.2439)	(-4.7784)	(-5.6728)	(2.3334)	(3.6507)
ARCH terms:					
α_1	0.040821[β]			0.144888[a]	0.109943[a]
	(2.0596)			(4.8191)	(7.1107)
α_2				0.028996[c]	
				(0.8629)	
α_3				-0.160786[a]	
				(-5.2903)	
GARCH terms:					
β_1	0.869426[α]			0.871251[a]	0.880770[a]
	(47.7185)			(16.3409)	(62.3966)
β_2				0.669062[a]	
				(177.351)	
β_3				-0.555160[a]	
				(-11.3409)	
EGARCH terms:					
α		0.1995[a]	0.2232[a]		
		(5.0110)	(5.8525)		
β		0.9620[a]	0.9581[a]		
		(112.128)	(94.8733)		
γ		-0.0955[a]	-0.1014[a]		
		(-3.4654)	(-3.5587)		
TARCH terms:					
γ	0.1261[α]				
	(3.3585)				
Degrees of freedom				5.427	5.383
Akaike criterion	3.2643	3.2474	3.2566	3.1945	3.1978
Schwarz criterion	3.2822	3.2628	3.2746	3.2202	3.2158
Log likelihood	3624.57	-3606.81	-3616.06	-3540.72	-3547.39
Stand.Res.Diagnostics					
$LB^2(5)$	6.5698	19.336	11.967	8.7565	12.668
	(0.255)	(0.002)	(0.035)	(0.119)	(0.027)
$LB^2(10)$	9.5826	22.336	15.594	9.9991	17.386
	(0.478)	(0.013)	(0.149)	(0.441)	(0.066)
Skewness	-0.3069	-0.2590	-0.2318	-0.3912	-0.5648
Kurtosis	5.8300	5.5305	5.5239	5.8776	7.0943
JB statistic	777.44	618.59	610.52	824.85	1673.21
ARCH-LM test					
LM statistic	8.7505	20.014	13.0782	7.1133	15.6449
Probability	0.5559	0.0291	0.2193	0.7147	0.1102
Summary statistics for cond. variance series					
Mean	2.113	1.991	1.991	2.078	2.175
Standard deviation	2.673	2.010	2.043	2.452	2.495
Maximum	36.979	25.448	28.514	42.417	20.687
Minimum	0.516	0.165	0.337	0.004	2.495
Skewness	5.907	4.460	4.989	6.785	4.871
Kurtosis	55.511	35.469	44.590	78.999	38.634

Table A15: Estimated models for GERMANY , overall sample period

	G E R M A N Y					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0602[a]	0.0604[a]	0.0601[a]	0.0604[a]	0.0546[c]	0.0404[c]
	(2.6144)	(2.6620)	(2.6494)	(2.6651)	(1.7463)	(0.0833)
GARCH-M coef.					0.0056[c]	
					(0.3385)	
Variance equation						
constant- ω	0.0061[b]	0.0083[b]	0.0030[b]	0.0074[c]	0.0066[c]	0.0084[a]
	(2.0549)	(2.2557)	(1.9910)	(1.9572)	(1.9571)	(2.7743)
ARCH terms:						
α_1	0.073435[a]	-0.008381[c]	0.033924[a]	-0.009832[c]	0.079593[a]	0.035697[b]
	(5.5466)	(-0.4183)	(3.1031)	(-0.4934)	(6.0961)	(2.2408)
α_2		0.102458[a]		0.091878[a]		
		(4.5234)		(3.1859)		
GARCH terms:						
β_1	0.9277[a]	0.907781[a]	1.584592[a]	1.063741[a]	0.921824[a]	0.063833[a]
	(78.243)	(66.9615)	(12.4687)	(4.1246)	(78.2072)	(2.9119)
β_2			-0.617829[a]	-0.144190[c]		
			(-5.2557)	(-0.6028)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0638[a]
						(2.9119)
Akaike criterion	3.4089	3.4030	3.4055	3.4037	3.4150	3.3998
Schwarz criterion	3.4192	3.4158	3.4183	3.4191	3.4279	3.4126
Log likelihood	-3790.15	-3782.57	-3785.37	-3782.40	-3795.98	-3779.06
Stand.Res.Diagnostics						
$LB^2(5)$	8.2141	1.3976	5.0463	1.0891	8.7753	11.953
	(0.145)	(0.925)	(0.410)	(0.955)	(0.118)	(0.035)
$LB^2(10)$	11.531	4.2847	6.5236	3.7916	11.807	13.942
	(0.318)	(0.934)	(0.770)	(0.956)	(0.298)	(0.176)
Skewness	-0.1119	-0.0953	-0.1046	-0.0952	-0.1022	-0.0743
Kurtosis	3.5540	3.4869	3.4866	3.4733	3.5740	3.5935
JB statistic	33.120	25.371	26.029	24.144	34.443	34.721
ARCH-LM test						
LM statistic	12.0658	4.4000	6.7077	3.8626	12.550	14.1455
Probability	0.2806	0.9275	0.7527	0.9533	0.2499	0.1664
Summary statistics for cond. variance series						
Mean	2.593	2.609	2.610	2.609	2.610	2.594
Standard deviation	2.473	2.580	2.580	2.588	2.502	2.564
Maximum	14.865	16.283	15.623	16.182	15.347	15.513
Minimum	0.236	0.220	0.229	0.220	0.227	0.274
Skewness	2.018	2.176	2.179	2.189	2.080	2.076
Kurtosis	7.384	8.322	8.283	8.390	7.723	7.450

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A15(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.0522[c]	0.0366[c]	0.0418[c]	0.0621[a]	0.0531[c]
	(1.7065)	(1.5497)	(1.2712)	(2.7450)	(1.7110)
GARCH-M coef.	-0.0098[c]		-0.0021[c]		0.0074[c]
	(-0.5962)		(-0.1160)		(0.4349)
Variance equation					
constant- ω	0.0086[b]	-0.0982[a]	-0.1079[a]	0.0114[a]	0.0114[a]
	(2.4836)	(-5.4447)	(-3.1389)	(3.4395)	(3.4159)
ARCH terms:					
α_1	0.039055[b]			0.0773[a]	0.077371[a]
	(2.4786)			(6.9930)	(6.9956)
α_2					
GARCH terms:					
β_1	0.925418[a]			0.9221[a]	0.922114[a]
	(81.2945)			(92.0003)	(91.9495)
β_2					
EGARCH terms:					
α		0.1340[a]	0.1464[a]		
		(5.247)	(6.0532)		
β		0.9892[a]	0.9888[a]		
		(333.53)	(289.827)		
γ		-0.0561[a]	-0.0578[a]		
		(-3.5679)	(3.5441)		
TARCH terms:					
γ	0.0699[a]				
	(3.0403)				
Degrees of freedom				10.314	10.379
Akaike criterion	3.4059	3.3978	3.4044	3.4134	3.4140
Schwarz criterion	3.4213	3.4106	3.4198	3.4262	3.4294
Log likelihood	-3784.83	-3776.83	-3783.11	-3790.70	-3790.46
Stand.Res.Diagnostics					
$LB^2(5)$	13.705	11.403	12.583	26.454	25.336
	(0.018)	(0.044)	(0.028)	(0.000)	(0.000)
$LB^2(10)$	15.516	14.232	15.274	28.334	27.135
	(0.114)	(0.163)	(0.122)	(0.002)	(0.002)
Skewness	-0.0642	-0.0655	-0.0542	0.012	0.020
Kurtosis	3.6216	3.6361	3.6686	4.547	4.597
JB statistic	37.379	39.129	42.5608	222.180	236.72
ARCH-LM test					
LM statistic	16.094	16.635	15.9052	14.1513	14.011
Probability	0.096	0.145	0.102	0.166	0.1724
Summary statistics for cond. variance series					
Mean	2.606	2.496	2.514	2.596	2.596
Standard deviation	2.571	2.324	2.354	2.447	2.451
Maximum	15.762	14.399	14.911	14.989	15.029
Minimum	0.270	0.283	0.270	0.011	0.011
Skewness	2.122	2.093	2.149	2.058	2.061
Kurtosis	7.741	7.824	8.127	7.629	7.642

Table A16: Estimated models for UNITED KINGDOM, overall sample period

U N I T E D K I N G D O M						
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0072[a]	0.0140[b]	0.0140[b]	0.014[b]	0.0151[c]	0.0090[c]
	(2.6139)	(1.9783)	(1.9772)	(1.9763)	(0.9892)	(1.3076)
AR(1) coefficient	0.9356[a]	0.7791[a]	0.7798[a]	0.7790[a]	0.7814[a]	0.7260[a]
	(24.9150)	(7.3438)	(7.3292)	(7.3356)	(7.1104)	(5.3843)
AR(2) coefficient	-0.0734[a]	-0.0836[a]	-0.0834[a]	-0.0835[a]	-0.0822[a]	-0.0815[a]
	(-3.0433)	(-3.3982)	(-3.3867)	(-3.3931)	(-3.3170)	(-3.3744)
MA(1) coefficient	-0.9146[a]	-0.7557[a]	-0.7563[a]	-0.7557[a]	-0.7573[a]	-0.6993
	(-30.0242)	(-7.1683)	(-7.1538)	(-7.1605)	(-6.9334)	(-5.1720)
GARCH-M coef.					-0.0007[C]	
					(-0.0560)	
Variance equation						
constant- ω	0.0268[a]	0.0224[a]	0.0179[b]	0.0254[c]	0.0184[a]	0.0225[a]
	(3.6339)	(3.3911)	(2.2043)	(0.8992)	(3.4087)	(4.3213)
ARCH terms:						
α_1	0.096644[a]	0.062111[b]	0.06859[b]	0.061240[b]	0.0813[a]	0.014248[c]
	(5.6809)	(2.0422)	(2.4249)	(2.0157)	(5.4555)	(1.2190)
α_2		0.023631[c]		0.036183[c]		
		(0.4911)		(0.3267)		
GARCH terms:						
β_1	0.884546[a]	0.898001[a]	1.093318[b]	0.752101[c]	0.9056[a]	0.922149[a]
	(49.1458)	(49.0011)	(3.0576)	(0.5818)	(59.935)	(72.7372)
β_2			-0.1749[c]	0.132080[c]		
			(-0.5337)	(0.9099)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0874[a]
						(4.1891)
Akaike criterion	2.9206	2.9163	2.9165	2.9172	2.9197	2.9017
Schwarz criterion	2.9386	2.9369	2.9370	2.9403	2.9403	2.9222
Log likelihood	-3240.78	-3235.01	-3235.22	-3234.94	-3238.80	-3218.70
Stand.Res.Diagnostics						
$LB^2(5)$	6.9952	7.7367	8.2366	7.7276	8.2551	7.9566
	(0.136)	(0.102)	(0.083)	(0.102)	(0.083)	(0.093)
$LB^2(10)$	12.986	13.022	13.478	13.093	14.368	11.894
	(0.163)	(0.162)	(0.142)	(0.158)	(0.110)	(0.219)
Skewness	-0.2144	-0.2184	-0.2180	-0.2193	-0.2108	-0.1870
Kurtosis	3.5336	3.5728	3.5751	3.5705	3.5736	3.5554
JB statistic	43.437	48.100	48.285	48.000	46.983	41.553
ARCH-LM test						
LM statistic	13.0396	13.4391	13.9030	13.4723	14.6357	11.7785
Probability	0.2214	0.2001	0.1774	0.1984	0.1459	0.3001
Summary statistics for cond. variance series						
Mean	1.342	1.328	1.328	1.328	1.337	1.309
Standard deviation	1.112	1.0726	1.071	1.071	1.083	1.061
Maximum	9.063	7.984	8.0753	7.981	8.278	8.896
Minimum	0.121	0.125	0.1071	0.128	0.334	0.121
Skewness	2.894	2.730	2.7250	2.724	2.699	2.835
Kurtosis	13.859	12.420	12.388	12.381	12.193	13.707

This table presents the maximum likelihood estimates of mean and variance equations of each model. The Bollerslev-Wooldrige robust standard errors of the coefficients are given in parentheses.
$LB^2(n)$ is the Ljung-Box statistic of squared stock returns for up to n lags-the corresponding probability is given in parenthesis. The ARCH-LM test tests for remaining ARCH effects of up to order 10 in the standardized residuals of the models. JB is Jarque-Bera statistic for Normality.
[a] Denotes significance at 1% level
[b] Denotes significance at 5% level
[c] Denotes significance at above 10% levels

Table A16(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	0.0169[c]	0.0088[c]	0.0144[c]	0.0203[b]	0.0185[c]
	(0.9940)	(1.3016)	(0.7772)	(2.2694)	(1.3819)
AR(1) coefficient	0.7348[a]	0.7332[a]	0.7176[a]	0.6789[a]	0.6734[a]
	(5.5264)	(5.4915)	(5.1776)	(6.9128)	(6.8182)
AR(2) coefficient	-0.0809[a]	-0.0816[a]	-0.0834[a]	-0.0950[a]	-0.0949[a]
	(-3.3174)	(-3.4585)	(-3.5233)	(-4.2561)	(-4.2571)
MA(1) coefficient	-0.7081[a]	-0.7059[a]	-0.6892[a]	-0.6523[a]	-0.6469[a]
	(-5.3175)	(-5.2788)	(-4.9594)	(-6.6789)	(-6.5802)
GARCH-M coef.	-0.0069[a]				0.0022[c]
	(-0.4816)				(1.3819)
Variance equation					
constant- ω	0.0208[a]	-0.0935[a]	-0.0981[a]	0.0212[a]	0.0214[a]
	(3.9951)	(-5.7908)	(-5.9408)	(3.7347)	(3.7512)
ARCH terms:					
α_1	0.017739[c]			0.078883[a]	0.079094[a]
	(1.4856)			(6.6835)	(6.6799)
α_2					
GARCH terms:					
β_1	0.9207[a]			0.9056[a]	0.905262[a]
	(71.9223)			(69.145)	(68.8710)
β_2					
EGARCH terms:					
α		0.1223[a]	0.1272[a]		
		(5.8295)	(-5.9408)		
β		0.9773[a]	0.9795[a]		
		(197.28)	(198.20)		
γ		-0.0701[a]	-0.0674[a]		
		(-4.4270)	(-4.2357)		
TARCH terms:					
γ	0.0870[a]				
	(5.0982)				
Degrees of freedom				13.256	13.268
Akaike criterion	2.9061	2.9035	2.9068	2.9086	2.9095
Schwarz criterion	2.9292	2.9240	2.9299	2.9291	2.9326
Log likelihood	-3222.688	-3220.76	-3223.37	-3226.38	-3226.42
Stand.Res.Diagnostics					
$LB^2(5)$	6.9949	7.5770	6.0341	9.3345	9.3937
	(0.136)	(0.108)	(0.197)	(0.096)	(0.094)
$LB^2(10)$	11.441	11.655	11.195	14.188	14.141
	(0.247)	(0.233)	(0.263)	(0.165)	(0.167)
Skewness	-0.1784	-0.1895	-0.1747	-0.2057	-0.212
Kurtosis	3.5639	3.5384	3.5273	3.5756	3.583
JB statistic	41.276	40.1911	37.091	46.442	48.196
ARCH-LM test					
LM statistic	11.4157	11.5267	11.2117	14.882	14.867
Probability	0.3260	0.3179	0.3412	0.136	0.1369
Summary statistics for cond. variance series					
Mean	1.340	1.285	1.308	1.325	1.325
Standard deviation	1.090	0.925	0.950	1.055	1.053
Maximum	9.129	7.352	7.522	8.107	8.056
Minimum	0.362	0.111	0.278	0.021	0.021
Skewness	2.833	2.298	2.343	2.678	2.671
Kurtosis	13.652	10.296	10.462	12.089	11.998

Table A17: Estimated models for JAPAN, overall sample period

	JAPAN					
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	-0.0058[c]	0.0011[c]	-0.0018[c]	0.0009[c]	-0.0557[c]	-0.0287[c]
	(-0.1889)	(0.0384)	(-0.0602)	(0.0298)	(-0.8757)	(0.3485)
GARCH-M coef.					0.0230[c]	
					(0.8924)	
Variance equation						
constant- ω	0.0391[a]	0.0546[a]	0.0246[b]	0.0571[b]	0.0393[a]	0.0381[a]
	(2.8487)	(3.0003)	(2.0858)	(2.3929)	(2.8651)	(2.8686)
ARCH terms:						
α_1	0.071311[a]	-0.0041[c]	0.0412[b]	-0.003905[c]	0.071358[a]	0.042159[a]
	(5.6558)	(-02381)	(2.8317)	(-0.2238)	(5.6630)	(3.0629)
α_2				0.098065[a]		
				(-0.2238)		
GARCH terms:						
β_1	0.916564[a]	0.093361[a]	1.440982[a]	0.826668[c]	0.916427	0.919123[a]
	(67.7884)	(4.3501)	(6.6774)	(2.3645)	(67.6710)	(68.0016)
β_2		0.893856[a]	-0.489897[b]	0.061493[c]		
		(52.6187)	(-2.4727)	(0.1912)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.0548[b]
						(2.5695)
Akaike criterion	3.7410	3.7364	3.7393	3.7373	3.7415	3.7358
Schwarz criterion	3.7513	3.7492	3.7521	3.7526	3.7543	3.7486
Log likelihood	-4159.82	-4153.65	-4156.87	-4153.63	-4159.35	-4153.00
Stand.Res.Diagnostics						
$LB^2(5)$	6.8772	0.9361	4.3308	0.9294	7.0736	9.5835
	(0.230)	(0.968)	(0.503)	(0.968)	(0.215)	(0.088)
$LB^2(10)$	10.394	3.8482	6.8315	3.8848	10.722	12.915
	(0.407)	(0.954)	(0.741)	(0.952)	(0.380)	(0.228)
Skewness	0.1018	0.0946	0.0950	0.0965	0.1016	0.0828
Kurtosis	4.2141	4.1961	4.1861	4.1991	4.1895	4.1889
JB statistic	140.56	136.04	133.84	136.82	135.07	133.64
ARCH-LM test						
LM statistic	10.5532	3.8763	6.9870	3.8981	10.8592	13.0883
Probability	0.3933	0.9527	0.7266	0.9518	0.3685	0.2187
Summary statistics for cond. variance series						
Mean	2.840	2.845	2.843	2.845	2.837	2.817
Standard deviation	1.782	1.877	1.833	1.878	1.780	1.698
Maximum	16.176	18.837	15.190	19.638	16.097	12.697
Minimum	0.766	0.762	0.777	0.760	0.762	0.743
Skewness	2.481	2.786	2.577	2.795	2.484	2.135
Kurtosis	11.814	14.601	12.270	14.813	11.820	9.234

Table A17(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(2,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.0622[c]	-0.036[c]	-0.0901[c]	-0.0229[c]	-0.0504[c]
	(0.3368)	(-1.1729)	(-1.3801)	(-0.7722)	(-0.7816)
GARCH-M coef.	0.0158[c]		0.0272[c]		0.0121[c]
	(0.6004)		(1.0236)		(0.4780)
Variance equation					
constant- ω	0.0402[a]	-0.0659[a]	-0.0871[a]	0.0646[a]	0.0651[a]
	(3.0044)	(-2.5934)	(-5.5646)	(3.8090)	(3.8145)
ARCH terms:					
α_1	0.042556[a]			0.073315[a]	0.073482[a]
	(3.0688)			(5.9340)	(5.9393)
α_2					
GARCH terms:					
β_1	0.918012[a]			0.906179[a]	0.905814[a]
	(67.3848)			(63.1927)	(63.0080)
β_2					
EGARCH terms:					
α		0.1082[a]	0.1356[a]		
		(2.7071)	(5.8503)		
β		1.3808[a] (6.044)	0.9813[a]		
		-0.4044[c](-1.826)	(158.869)		
γ		-0.0266[c]	-0.0472[a]		
		(-1.7312)	(-2.9975)		
TARCH terms:					
γ	0.0541[b]				
	(2.5283)				
Degrees of freedom				7.3343	7.354
Akaike criterion	3.7365	3.7377	3.7345	3.7248	3.7255
Schwarz criterion	3.7519	3.7530	3.7499	3.7376	3.7409
Log likelihood	-4152.77	-4154.06	-4150.53	-4136.99	-4136.86
Stand.Res.Diagnostics					
$LB^2(5)$	9.7853	6.7441	12.636	12.263	11.107
	(0.082)	(0.240)	(0.027)	(0.031)	(0.049)
$LB^2(10)$	13.187	10.533	18.044	13.489	12.354
	(0.213)	(0.395)	(0.054)	(0.198)	(0.262)
Skewness	0.0828	0.1134	0.094	-0.1507	-0.208
Kurtosis	4.1724	4.1755	4.143	6.3605	6.874
JB statistic	130.04	132.95	124.69	1055.89	1408.72
ARCH-LM test					
LM statistic	13.3411	10.600	18.1720		
Probability	0.2052	0.3895	0.0521		
Summary statistics for cond. variance series					
Mean	2.817	2.542	2.767	2.873	2.893
Standard deviation	1.708	1.283	1.454	1.699	1.687
Maximum	12.827	9.730	10.846	16.604	16.251
Minimum	0.752	0.605	0.569	0.064	0.065
Skewness	2.164	1.763	1.521	2.644	2.608
Kurtosis	9.378	7.870	6.475	13.228	12.956

Table A18: Estimated models for UNITED STATES, overall sample period

UNITED STATES						
Parameters / Criteria	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)	GARCH(1,1)-M	TARCH(1,1)
Mean equation						
constant-c	0.0685[a]	0.0675[a]	0.0680[a]	0.0690[a]	0.0035[c]	0.0288[c]
	(3.4654)	(3.3799)	(3.4257)	(3.1510)	(0.0944)	(1.4795)
GARCH-M coef.					0.0601[b]	
					(1.9768)	
Variance equation						
constant- ω	0.0154[a]	0.0186[a]	0.0139[c]	0.0295[a]	0.0222[a]	0.0221[a]
	(3.3736)	(3.2685)	(1.7999)	(3.8980)	(3.1251)	(4.5226)
ARCH terms:						
α_1	0.071092[a]	0.045723[c]	0.063142[c]	0.0370[a]	0.085839[a]	-0.021986[c]
	(4.8896)	(1.3416)	(1.8578)	(3.2456)	(5.1298)	(-1.6527)
α_2		0.036154[c]		0.095999[a]		
		(0.9341)		(7.3294)		
GARCH terms:						
β_1	0.920756[a]	0.908322[a]	1.073713[b]	0.2661[c]	0.901820[a]	0.928617[a]
	(68.4376)	(51.3867)	(2.2663)	(1.5519)	(54.3596)	(68.923)
β_2			-0.1441[c]	0.585389[a]		
			(-0.3282)	(3.6497)		
EGARCH terms:						
α						
β						
γ						
TARCH terms:						
γ						0.1560[a]
						(6.0902)
Akaike criterion	3.0222	3.0220	3.0228	3.0201	3.0286	2.9763
Schwarz criterion	3.0325	3.0348	3.0356	3.0355	3.0414	2.9891
Log likelihood	-3359.77	-3358.567	-3359.41	-3355.39	-3365.86	-3307.656
Stand.Res.Diagnostics						
$LB^2(5)$	5.5810	5.0096	5.2767	3.7741	5.5273	5.0260
	(0.349)	(0.415)	(0.383)	(0.582)	(0.355)	(0.413)
$LB^2(10)$	6.3540	5.9611	6.0933	4.9163	6.2358	6.9049
	(0.785)	(0.819)	(0.807)	(0.897)	(0.795)	(0.734
Skewness	-0.4187	-0.4180	-0.4201	-0.3886	-0.4190	-0.3963
Kurtosis	4.8493	4.8402	4.8520	4.6948	4.7758	4.4216
JB statistic	382.27	378.93	383.62	322.46	357.65	245.74
ARCH-LM test						
LM statistic	6.3309	5.9399	6.096	4.817	6.1305	6.4830
Probability	0.7867	0.8202	0.807	0.903	0.8041	0.7731
Summary statistics for cond. variance series						
Mean	1.471	1.475	1.472	1.475	1.475	1.448
Standard deviation	1.075	1.179	1.083	1.113	1.096	1.163
Maximum	7.242	7.381	7.199	8.188	7.689	10.196
Minimum	0.207	0.212	0.207	0.221	0.388	0.211
Skewness	2.144	2.261	2.178	2.312	2.363	2.432
Kurtosis	8.517	9.211	8.707	9.699	9.818	10.859

Table A18(continued)

Parameters / Criteria	TARCH(1,1)-M	EGARCH(1,1)	EGARCH(1,1)-M	GARCH(1,1)-t	GARCH(1,1)-M-t
Mean equation					
constant-c	-0.0042[c]	0.0233[c]	-0.0321[c]	0.0746[a]	0.0701[b]
	(-0.1312)	(0.2407)	(-0.8396)	(3.7476)	(2.0488)
GARCH-M coef.	0.0281[c]		0.0509[c]		0.0041[c]
	(1.0472)		(1.5437)		(0.1460)
Variance equation					
constant- ω	0.0324[a]	-0.0590[a]	-0.0739[a]	0.0156[a]	0.0154[a]
	(4.0841)	(-3.7042)	(-4.3308)	(3.3108)	(3.2526)
ARCH terms:					
α_1	-0.017554[c]			0.064270[a]	0.064260[a]
	(-1.1719)			(6.1470)	(6.1327)
α_2					
GARCH terms:					
β_1	0.907733[a]			0.926434[a]	0.926603[a]
	(56.0415)			(84.9665)	(84.7614)
β_2					
EGARCH terms:					
α		0.0817[a]	0.1019[a]		
		(3.9417)	(4.5530)		
β		0.9756[a]	0.9646[a]		
		(215.557)	(130.47)		
γ		-0.1256[a]	-0.1335[a]		
		(-6.8226)	(-6.9156)		
TARCH terms:					
γ	0.1729[a]				
	(6.0937)				
Degrees of freedom				7.682	7.690
Akaike criterion	2.9840	2.9643	2.9738	2.9848	3.9857
Schwarz criterion	2.9994	2.9771	2.9892	2.9977	3.0011
Log likelihood	-3315.23	-3294.32	-3303.94	-3314.19	-3314.20
Stand.Res.Diagnostics					
$LB^2(5)$	6.0346	3.2079	3.6086	5.1808	5.1440
	(0.303)	(0.668)	(0.607)	(0.394)	(0.399)
$LB^2(10)$	7.8084	5.08	5.2916	6.3768	6.3565
	(0.648)	(0.886)	(0.871)	(0.783)	(0.784)
Skewness	-0.3866	-0.3323	-0.3400	-0.3559	-0.354
Kurtosis	4.3537	4.455	4.1609	5.0605	5.069
JB statistic	225.43	164.70	167.92	440.21	443.41
ARCH-LM test					
LM statistic	7.5194	4.7497	5.0668	7.2298	7.2387
Probability	0.6756	0.9072	0.8866	0.7035	0.7027
Summary statistics for cond. variance series					
Mean	1.467	1.391	1.405	1.455	1.456
Standard deviation	1.238	0.962	1.003	1.031	1.032
Maximum	11.580	8.154	8.921	6.815	6.808
Minimum	0.324	0.137	0.214	0.015	0.0154
Skewness	2.752	1.938	2.198	2.062	2.059
Kurtosis	13.244	8.565	10.180	8.082	8.063

TABLE A19:Cross correlation in the levels and squares of standardized residuals resulting from the models reported in table 7.

Lag k	ARGENTINA-US $\hat{r}_{\varepsilon\zeta}(k)$	ARGENTINA-US $\hat{r}_{uv}(k)$	ARGENTINA-JAPAN $\hat{r}_{\varepsilon\zeta}(k)$	ARGENTINA-JAPAN $\hat{r}_{uv}(k)$	ARGENTINA-UK $\hat{r}_{\varepsilon\zeta}(k)$	ARGENTINA-UK $\hat{r}_{uv}(k)$	ARGENTINA-GERMANY $\hat{r}_{\varepsilon\zeta}(k)$	ARGENTINA-GERMANY $\hat{r}_{uv}(k)$
-5	0.0206	0.0072	0.0054	-0.0060	0.0206	0.0072	0.0083	-0.0049
-4	0.0307	-0.0385[b]	0.0346	-0.0284	0.0307	-0.0385[b]	0.0425[b]	0.0196
-3	0.0466[b]	0.0257	-0.0094	-0.0114	0.0466[b]	0.0257	0.0094	0.0134
-2	0.0080	0.0575[a]	0.0046	-0.0001	0.0080	0.0575[a]	0.0192	0.0227
-1	-0.0080	-0.0244	0.0058	0.0436[b]	-0.0080	-0.0244	-0.0091	-0.0252
0	0.2268[a]	0.0984[a]	0.0517[a]	-0.0168	0.2268[a]	0.0984[a]	0.2155[a]	0.0512[a]
1	0.1334[a]	0.0113	0.1299[a]	0.0607[a]	0.1334[a]	0.0113	0.1162[a]	0.0349[b]
2	-0.0183	0.0014	0.0021	0.0055	-0.0183	0.0014	-0.0003	0.0008
3	0.0059	0.0119	0.0025	-0.0199	0.0059	0.0119	0.0168	0.0058
4	0.0054	-0.0217	0.0207	0.0177	0.0054	-0.0217	0.0299	-0.0333
5	-0.0227	0.0294	0.0091	0.0038	-0.0227	0.0294	-0.0158	0.0183

Lag k	BRAZIL-US $\hat{r}_{\varepsilon\zeta}(k)$	BRAZIL-US $\hat{r}_{uv}(k)$	BRAZIL-JAPAN $\hat{r}_{\varepsilon\zeta}(k)$	BRAZIL-JAPAN $\hat{r}_{uv}(k)$	BRAZIL-UK $\hat{r}_{\varepsilon\zeta}(k)$	BRAZIL-UK $\hat{r}_{uv}(k)$	BRAZIL-GERMANY $\hat{r}_{\varepsilon\zeta}(k)$	BRAZIL-GERMANY $\hat{r}_{uv}(k)$
-5	0.0039	0.0130	-0.0273	0.0212	0.0124	0.0066	0.0339	0.0055
-4	0.0325	-0.0188	0.0531[a]	-0.0055	0.0459[b]	-0.0142	0.0638[b]	0.0582[a]
-3	0.0309	0.0127	0.0270	0.0023	0.0363[b]	0.0051	0.0165	0.0158
-2	-0.0232	0.0360[b]	0.0168	0.0105	-0.0141	0.0180	0.0048	0.0027
-1	0.0408[b]	-0.0045	-0.0166	0.0025	-0.0047	-0.0015	0.0325	0.0211
0	0.4366[a]	0.3073[a]	0.0903[a]	0.0208	0.2916[a]	0.2586[a]	0.3213[a]	0.1543[a]
1	0.0353[b]	-0.0087	0.1640[a]	0.1007[a]	0.1403[a]	0.0104	0.1049[a]	0.0214
2	0.0038	0.1308[a]	0.0391[a]	0.0330	-0.0440[b]	-0.0014	0.0161	0.0259
3	-0.0108	0.0450[b]	-0.0223	0.0052	0.0048	0.0183	0.0325	0.0591[a]
4	0.0113	0.0325	0.0138	0.0389[a]	-0.0338	0.0094	0.0184	-0.0051
5	-0.0054	0.0222	0.0251	0.0206	-0.0154	0.0168	-0.0204	0.0073

Lag k	CHILE - US $\hat{r}_{\varepsilon\zeta}(k)$	CHILE - US $\hat{r}_{uv}(k)$	CHILE - JAPAN $\hat{r}_{\varepsilon\zeta}(k)$	CHILE - JAPAN $\hat{r}_{uv}(k)$	CHILE - UK $\hat{r}_{\varepsilon\zeta}(k)$	CHILE - UK $\hat{r}_{uv}(k)$	CHILE - GERMANY $\hat{r}_{\varepsilon\zeta}(k)$	CHILE - GERMANY $\hat{r}_{uv}(k)$
-5	0.0558[a]	-0.0282	0.0200	0.0395[b]	0.0063	-0.0179	0.0558[a]	-0.0282
-4	-0.0080	0.0505[a]	-0.0008	-0.0108	0.0087	0.0005	-0.0080	0.0505[a]
-3	0.0091	0.0300	0.0032	0.0002	0.0099	0.0357[b]	0.0091	0.0300
-2	-0.0217	0.0198	-0.0179	0.0011	-0.0020	0.0912[a]	-0.0217	0.0198
-1	0.0033	0.0043	-0.0111	0.0424[b]	0.0029	0.0121	0.0033	0.0043
0	0.3089[a]	0.1258[a]	0.0980[a]	0.0294	0.3005[a]	0.1469[a]	0.3089[a]	0.1258[a]
1	0.0734[a]	0.0089	0.1381[a]	0.0848[a]	0.0692[a]	0.0081	0.0734[a]	0.0089
2	0.0094	0.0058	-0.0192	-0.0045	0.0180	0.0041	0.0094	0.0058
3	0.0155	0.0398[b]	0.0001	0.0111	-0.0006	0.0226	0.0155	0.0398[b]
4	0.0089	-0.0221	0.0106	0.0100	0.0048	0.0069	0.0089	-0.0221
5	-0.0261	-0.0028	0.0227	-0.0062	-0.0197	0.0000	-0.0261	-0.0028

The “lag” refers to the periods the developed market data lag the emerging marktet data, a lead is given by a negative lag, while correlation at lag 0 gives evidence of feedback.

$\hat{r}_{\varepsilon\zeta}(k)$ is the cross correlation of standardized residuals of the ARMA-GARCH models

$\hat{r}_{uv}(k)$ is the cross correlation of squared standardized residuals of the ARMA-GARCH models

$\sqrt{T}\,\hat{r}_{uv}(k)$ is asymptotically normally distributed

[a] Denotes significance at 1% level

[b] Denotes significance at 5% level

TABLE A19 (continued)

	MEXICO - US		MEXICO - JAPAN		MEXICO - UK		MEXICO - GERMANY	
Lag k	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0270	-0.0041	-0.0135	-0.0012	0.0269	-0.0162	0.0125	0.0115
-4	0.0183	0.0094	-0.0140	-0.0156	-0.0055	-0.0001	0.0176	0.0078
-3	-0.0388[b]	-0.0117	0.0144	0.0164	-0.0263	0.0887[a]	-0.0095	-0.0070
-2	-0.0307	0.0172	0.0109	0.0327	0.0510[a]	0.1661[a]	-0.0425[b]	0.0375[b]
-1	-0.0064	0.0329	-0.0083	0.0057	-0.0235	-0.0086	-0.0102	0.0011
0	0.1108[a]	0.4311[b]	-0.0182	0.0081	-0.0579[a]	0.1080[a]	-0.0375[b]	0.0287
1	0.0388[b]	0.0248	-0.0247	0.0511[a]	-0.0205	-0.0093	-0.0434[b]	0.0338
2	-0.0017	0.0197	0.0156	0.0173	0.0234	-0.0110	-0.0026	0.0087
3	0.0257	0.0048	-0.0131	-0.0048	-0.0034	-0.0025	0.0193	0.0280
4	-0.0072	0.0114	-0.0155	-0.0090	0.0159	0.0002	0.0118	-0.0071
5	0.0078	0.0009	0.0222	-0.0041	0.0103	-0.0074	0.0346	-0.0169

	PERU - US		PERU - JAPAN		PERU - UK		PERU - GERMANY	
Lag k	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	-0.0035	-0.0028	-0.0042	0.0176	0.0045	-0.0211	-0.0011	0.0145
-4	0.0036	0.0262	0.0195	-0.0189	0.0181	0.0013	0.0375[b]	0.0672[a]
-3	0.0171	-0.0033	-0.0078	0.0088	0.0378[b]	0.0025	0.0266	-0.0102
-2	-0.0146	0.0139	0.0222	0.0032	-0.0091	0.0864[a]	-0.0183	0.0029
-1	0.1318[a]	0.0092	0.0074	-0.0380[b]	0.0298	0.0068	0.0378[b]	-0.0222
0	0.2333[a]	0.1811[a]	0.1178[a]	0.0287	0.2805[a]	0.1152[a]	0.2837[a]	0.1000[a]
1	-0.0248	0.0403[b]	0.1001[a]	0.0120	0.0113	0.0141	0.0318	0.0127
2	-0.0087	0.0050	-0.0085	0.0058	-0.0200	0.0260	-0.0215	0.0056
3	-0.0234	0.0174	0.0058	0.0147	-0.0268	0.0221	-0.0151	0.0019
4	0.0044	0.0261	0.0109	0.0589[a]	0.0157	-0.0041	0.0057	0.0025
5	-0.0006	-0.0026	0.0055	0.0166	-0.0268	-0.0119	-0.0447[a]	0.0088

	CHINA - US		CHINA - JAPAN		CHINA - UK		CHINA - GERMANY	
Lag k	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0189	0.0040	-0.0057	-0.0097	0.0266	0.0050	0.0182	0.0289
-4	0.0325	0.0368[b]	0.0119	0.0142	0.0475[b]	0.0384[b]	0.0330	0.0351[b]
-3	-0.0259	0.0016	0.0184	-0.0089	-0.0055	-0.0093	-0.0198	0.0006
-2	-0.0103	0.0003	-0.0435[b]	-0.0005	0.0409[b]	0.0225	0.0111	-0.0183
-1	0.0223	-0.0058	0.0439[b]	-0.0151	0.0383[b]	0.0045	0.0460[b]	-0.0201
0	-0.0360[a]	0.0425[b]	0.0294	-0.0037	-0.0402[b]	0.0025	-0.0254	-0.0153
1	-0.0128	-0.0041	-0.0219	0.0026	-0.0303	0.0223	-0.0140	0.0113
2	-0.0012	-0.0019	-0.0169	0.0161	0.0079	0.0031	-0.0246	-0.0034
3	-0.0245	-0.0364[a]	0.0194	-0.0043	-0.0204	-0.0237	0.0383[b]	-0.0049
4	-0.0395[a]	0.1046[a]	0.0279	-0.0161	-0.0153	0.0214	-0.0282	0.0240
5	-0.0091	0.0026	-0.0245	0.0181	-0.0072	-0.0070	-0.0165	0.0082

	PHILIPPINES - US		PHILIPP. - JAPAN		PHILIPP. - UK		PHILIPP. - GERMANY	
Lag k	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0178	-0.0032	-0.0049	-0.0208	-0.0098	-0.0179	0.0056	-0.0071
-4	0.0220	0.0132	0.0173	-0.0238	-0.0022	0.0228	0.0348	0.0291
-3	0.0304	-0.0188	0.0216	0.0290	-0.0061	-0.0089	0.0036	-0.0255
-2	0.0227	-0.0012	-0.0169	-0.0145	0.1833[a]	-0.0125	0.0238	0.0033
-1	0.2253[a]	0.0416[b]	0.0401[b]	-0.0033	0.1265[a]	0.0269	0.1953[a]	0.0188
0	0.0712[a]	-0.0002	0.1927[a]	0.0854[a]	0.0094	0.0161	0.1073[a]	-0.0133
1	0.0100	-0.0108	0.0330	-0.0121	-0.0186	-0.0115	-0.0098	-0.0193
2	-0.0327	0.0161	-0.0036	-0.0039	0.0059	-0.0114	-0.0174	0.0106
3	0.0112	0.0107	-0.0448[b]	0.0009	0.0125	-0.0161	0.0226	-0.0059
4	-0.0145	0.0339	0.0091	-0.0027	-0.0255	0.0121	-0.0044	-0.0078
5	-0.0026	-0.0049	-0.0060	0.0100	0.0094	0.0161	-0.0205	0.0065

TABLE A19 (continued)

Lag k	THAILAND - US		THAILAND - JAPAN		THAILAND - UK		THAILAND - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	-0.0078	0.0414[b]	0.0340	-0.0261	-0.0008	0.0376[b]	0.0183	0.0251
-4	0.0395	-0.0261	0.0262	-0.0196	0.0203	0.0127	0.0340	0.0030
-3	0.0639[a]	0.0083	0.0342	-0.0239	0.0453[b]	0.0737[a]	0.0384[b]	0.0568[a]
-2	0.0432	0.0243	0.0345	-0.0027	0.0531[b]	0.0233	0.0529[a]	0.0207
-1	0.1664[a]	0.1645[a]	0.0400[b]	0.0434[b]	0.1093[a]	0.0555[a]	0.1112[a]	0.0636[a]
0	0.0443[b]	0.0191	0.2154[a]	0.1407[a]	0.1368[a]	0.0004	0.1367[a]	0.0056
1	-0.0006	0.0419[a]	0.0162	-0.0076	-0.0064	0.0181	-0.0047	-0.0063
2	-0.0076	-0.0053	0.0084	0.0281	-0.0146	0.0227	-0.0263	-0.0041
3	0.0032	-0.0133	-0.0317	0.0203	-0.0134	0.0057	0.0102	0.0242
4	-0.0243	0.0146	-0.0013	0.0117	0.0231	-0.0139	0.0242	-0.0193
5	0.0270	0.0129	0.0024	-0.0233	-0.0483[a]	-0.0185	-0.0127	-0.0132

Lag k	MALAYSIA - US		MALAYSIA - JAPAN		MALAYSIA - UK		MALAYSIA - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0146	0.0194	-0.0101	-0.0015	0.0250	-0.0089	0.0501	-0.0014
-4	0.0072	0.0058	0.0146	0.0012	0.0133	0.0115	0.0387[b]	0.0053
-3	0.0513[a]	0.0046	0.0371[a]	0.0230	0.0288	-0.0027	0.0211	-0.0102
-2	-0.0112	0.0058	0.0139	-0.0066	-0.0098	0.0028	-0.0137	0.0265
-1	0.2116[a]	0.0823[a]	0.0106	0.0240	0.1154[a]	0.0332	0.1328[a]	0.0136
0	0.0045	-0.0029	0.2216[a]	0.1003[a]	0.1066[a]	0.0169	0.0692[a]	0.0209
1	0.0043	0.0094	0.0154	0.0069	-0.0183	-0.0009	0.0054	-0.0218
2	-0.0199	-0.0054	0.0119	-0.0021	-0.0334	-0.0120	-0.0233	-0.0086
3	0.0285	0.0225	-0.0195	0.0013	0.0227	0.0032	0.0292	0.0024
4	0.0020	-0.0121	0.0112	0.0049	0.0003	-0.0101	0.0146	0.0009
5	0.0006	-0.0020	0.0019	-0.0162	-0.0075	0.0100	-0.0173	-0.0226

Lag k	HUNGARY - US		HUNGARY - JAPAN		HUNGARY - UK		HUNGARY - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0150	0.0285	-0.0018	-0.0173	0.0011	0.0019	-0.0147	0.0103
-4	-0.0222	-0.0185	0.0188	0.0101	-0.0400[b]	0.0344	-0.0177	-0.0122
-3	-0.0128	0.0263	-0.0550[a]	0.0442[b]	-0.0749[a]	0.1490[a]	-0.0052	0.1054[a]
-2	-0.0370[b]	-0.0086	-0.0147	-0.0048	-0.0151	-0.0122	-0.0152	-0.0105
-1	0.1125[a]	0.3549[a]	0.0097	0.0261	-0.0572[a]	0.0143	-0.0563[a]	0.0180
0	0.0101	0.0419[b]	-0.0422[b]	0.0156	-0.0470[b]	0.0012	-0.0655[a]	0.0608[a]
1	-0.0055	-0.0121	0.0105	0.0039	0.0231	-0.0122	0.0308	0.0156
2	-0.0252	0.0246	-0.0014	0.0002	-0.0402[a]	0.0152	0.0015	-0.0115
3	-0.0257	0.0188	-0.0230	-0.0145	0.0212	0.0072	-0.0001	-0.0189
4	0.0304	0.0068	-0.0128	-0.0042	-0.0180	-0.0095	0.0019	-0.0095
5	-0.0071	-0.0127	0.0280	-0.0013	0.0259	-0.0118	0.0115	-0.0051

Lag k	POLAND - US		POLAND - JAPAN		POLAND - UK		POLAND - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0014	-0.0003	-0.0306	0.0003	-0.0237	0.0146	0.0000	0.0617
-4	0.0022	0.0068	0.0212	-0.0165	0.0011	0.0304	0.0003	-0.0115
-3	0.0378[b]	0.0418[b]	0.0112	0.0267	0.0230	0.0839[a]	0.0267	0.0856[a]
-2	-0.0546[a]	0.0207	-0.0095	-0.0030	-0.0399[b]	0.0109	-0.0292	-0.0130
-1	0.3060[a]	0.2903[a]	-0.0053	0.0060	0.1451[a]	0.0522[a]	0.1669[a]	0.0413[b]
0	0.1372[a]	0.0726[a]	0.2015[a]	0.1526[a]	0.2530[a]	0.0780[a]	0.2668[a]	0.1271[a]
1	0.0216	0.1067[a]	0.0768[a]	0.0135	0.0141	0.0356[b]	0.0362[b]	-0.0080
2	-0.0410[b]	-0.0157	-0.0032	0.0343	0.0064	0.0073	-0.0013	-0.0105
3	0.0235	-0.0096	-0.0047	-0.0110	-0.0377[b]	0.0271	-0.0269	-0.0045
4	0.0247	0.0190	0.0345[b]	0.0379[b]	0.0314	0.0288	0.0157	0.0421[b]
5	0.0154	0.0149	-0.0129	-0.0179	-0.0157	-0.0099	0.0075	-0.0159

TABLE A19 (continued)

Lag k	RUSSIA - US		RUSSIA - JAPAN		RUSSIA - UK		RUSSIA - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	0.0160	-0.0090	0.0281	0.0125	-0.0029	-0.0057	0.0072	-0.0105
-4	0.0218	-0.0063	0.0010	-0.0139	0.0633[a]	0.0127	0.0387[b]	-0.0124
-3	0.0378	-0.0062	0.0290	0.0151	0.0515[a]	0.0721[a]	0.0304	0.0229
-2	-0.0091	-0.0294	0.0065	0.0259	-0.0051	0.0215	0.0231	0.0260
-1	0.1915[a]	0.1779[a]	-0.0200	-0.0184	0.0696[a]	0.0301	0.0591[a]	0.0086
0	0.1376[a]	0.0723[b]	0.1292[a]	0.0641[a]	0.2465[a]	0.0721[a]	0.2258[a]	0.0707[a]
1	-0.0121	0.0015	0.0693[a]	0.0172	0.0033	-0.0048	0.0156	0.0083
2	0.0034	0.0611[b]	0.0266	0.0246	0.0107	0.0356[b]	0.0217	-0.0268
3	0.0165	0.0427[b]	0.0187	0.0103	0.0014	-0.0062	0.0323	0.0001
4	-0.0063	-0.0339	0.0044	0.0467[b]	-0.0038	0.0141	-0.0335	-0.0361[b]
5	-0.0080	0.0303	0.0345[b]	0.0117	-0.0296	-0.0514[a]	-0.0229	0.0047

Lag k	ISRAEL - US		ISRAEL - JAPAN		ISRAEL - UK		ISRAEL - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	-0.0229	-0.0022	-0.0007	-0.0340	-0.0032	0.0447[b]	0.0180	0.0284
-4	-0.0412[b]	0.0729[a]	0.0051	0.0161	0.0247	0.0830[b]	0.0475[b]	0.0253
-3	0.0417[b]	-0.0069	0.0308	0.0006	0.0445[b]	0.0360[b]	0.0377[b]	-0.0074
-2	-0.0226	0.0231	-0.0016	0.0014	-0.0179	-0.0287	-0.0237	-0.0175
-1	0.2277[a]	0.1279[a]	-0.0195	0.0230	0.0513[a]	0.0284	0.0702	0.0326
0	0.1906[a]	0.0536[a]	0.1197[a]	-0.0327	0.2633[a]	0.0545[a]	0.2595[a]	0.0911[a]
1	0.0261	0.0253	0.0938[a]	0.0894[a]	0.0158	-0.0070	0.0493[b]	-0.0210
2	0.0304	0.0195	-0.0255	0.0246	0.0305	0.0050	0.0286	0.0062
3	0.0004	0.0065	-0.0127	-0.0076	-0.0090	0.0170	0.0151	0.0122
4	-0.0061	-0.0089	0.0202	0.0522[a]	0.0066	-0.0267	0.0193	0.0046
5	0.0095	0.0052	0.0224	0.0082	0.0150	-0.0052	0.0126	-0.0008

Lag k	SOUTHAFRICA - US		S. AFRICA - JAPAN		S. AFRICA - UK		S. AFRICA - GERMANY	
	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$	$\hat{r}_{\varepsilon\zeta}(k)$	$\hat{r}_{uv}(k)$
-5	-0.0095	-0.0065	-0.0150	0.0089	-0.0173	-0.0116	-0.0005	-0.0143
-4	0.0060	0.0209	0.0249	-0.0029	0.0138	0.0178	0.0382	0.0534[a]
-3	-0.0143	0.0252	-0.0258	0.0179	-0.0130	0.0793[a]	-0.0105	0.0120
-2	-0.0215	0.0146	0.0100	-0.0028	0.1157[a]	0.0244	-0.0082	0.0510[a]
-1	0.3064[a]	0.1664[a]	-0.0427	-0.0066	0.4123[a]	0.0681[a]	0.1277[a]	0.0642[a]
0	0.1852[a]	0.1092[a]	0.2353[a]	0.0826[a]	-0.0050	0.2037[a]	0.3916[a]	0.1872[a]
1	0.0018	0.0383[b]	0.0789[a]	0.0059	0.0069	-0.0164	0.0104	-0.0082
2	0.0052	0.1230[a]	0.0210	0.0241	0.0022	0.0133	0.0024	0.0052
3	0.0092	0.0438[b]	0.0211	0.0069	-0.0196	-0.0067	0.0403[b]	0.0150
4	-0.0158	0.0389[b]	0.0342	0.0684[a]	-0.0073	0.0245	-0.0163	0.0432[b]
5	0.0304	-0.0081	-0.0233	0.0094	-0.0050	-0.0085	-0.0198	-0.0127