Modeling the Egyptian Stock Market Volatility Pre- and Post Circuit Breaker

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Abstract

Circuit breakers (price limits and trading halts) are regulatory instruments aiming to reduce severe price volatility and provide markets with a cooling-off period. This paper investigates the impact of price limits on volatility dynamics in the Egyptian Stock Exchange. A variety of mean and variance specifications in GARCH type models (GARCH, GJR, and APARCH) and four different error distributions (Normal, Student-*t*, GED, and Skewed-*t*) are utilized. Results from examining a split sample suggest significant changes in the time varying volatility process. Results prior to the imposition of price limits exhibit leptokurtosis; yet show no sign of the widely cited leverage effect. Results after the imposition of price limits display both leptokurtosis and the leverage effect.

نمذجة تذبذبات أسعار البورصة المصرية قبل وبعد تطبيق نظام الحدود السعرية

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الملخص

الحدود السعرية وإيقاف التداول هي أدوات نظامية، تهدف إلى الحد من التذبذبات الحادة في الأسعار، وتنعم معها الأسواق بفترة من الهدوء. تحقق هذه الورقة من أثر الحدود السعرية على حركة التذبذب في البورصة المصرية. وقد تم استخدام مجموعة متنوعة من توصيفات الوسط الحسابي والتباين لنماذج الانحدار الذاتي المعمم المشروط بتذبذبات التباين GARCH، نموذج جلوستن جاناثان ورانكل GJR، ونموذج الانحدار الذاتي المشروط بتذبذبات التباين غير متناسق القوى APARCH، وباستخدام أربعة توزيعات مختلفة للأخطاء التوزيع الطبيعي normal، توزيع ستودنت ت student، التوزيع المعمم للأخطاء GED، وتوزيع ت غير المتماثل skewed-t. تشير النتائج المحققة من اختبار عينة مشتقة إلى معنوية التغيرات في عملية التذبذبات بتوقيتات مختلفة. كما أن النتائج السابقة على تطبيق حدود سعرية تثبت وجود أثر الذيول السميكة leptokurtosis، بينما لم تظهر آثار كبيرة لأثر الرافعة leverage effect بينما أوضحت النتائج التالية لتطبيق الحدود السعرية ظهور كلا الأثرين.

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Introduction

Circuit breakers (price limits and trading halts)[1], with all their multi-dimensional complexities, have started to interest economists within the last decade or so. Unfortunately, there is no agreement on whether circuit breakers are effective tools or not. Also, to date, most of the existing literature do not aid in resolving this issue.

"Our ignorance is unfortunate because circuit breakers can have very significant effects upon markets" (Harris, 1998). Whether these effects are positive or negative [2] is debatable. Regulators clearly need to know more about these effects if they are to make optimal decisions on whether or not to apply circuit breakers to their stock exchanges. And if they do apply them, they need to know which ones are the most effective.

Many financial asset markets have daily price limits on individual assets. U.S. futures markets are perhaps the best-known example, followed by emerging equities markets.[3] Advocates of limits claim that they reduce price volatility in two ways: (a) Firstly, they give participants a "time out" or cooling-off period to digest information and help markets avoid unwanted price fluctuations; and (b) Secondly, the limits literally set a ceiling and a floor for the price to move within a trading day. Critics, on the other hand, assert that limits may have several adverse effects on the market. Empirical literature criticizing price limits has concentrated on three different hypotheses: (a) Volatility spillover; (b) Delayed price discovery; and (c) The trading interference hypotheses.

This article examines the effects of price limits on the Egyptian Stock Exchange (ESE)[4] where a tight symmetric 5% daily limit was imposed during most of the period between 1997-2001. Unlike other studies, this paper does not research on the effectiveness of price limits in the ESE. Rather, it tests their impact on the time-varying market volatility process. Data used include daily adjusted closing prices for two major market indices that allow the comparison of the time-varying volatility process during the limit time period with an earlier no-limit time period, January 3, 1993 through January 31, 1997. A variety of GARCH models (GARCH, APARCH, JGR) is used with different density specifications (Normal, Student-*t*, Skewed Student-*t*, and GED) to examine empirically whether estimated volatility changes significantly as a result of the imposition of symmetric price limits.

After examining a split sample, results suggest significant changes in the time- varying volatility process. Empirical results, prior to the imposition of price limits, exhibit leptokurtosis yet show no sign of the widely cited leverage effect. Following the imposition of price limits, results display both leptokurtosis and the leverage effect. Economically, this indicates that regulatory and/or structural shifts in the market lead to a different conditional volatility model structure.

Literature

While there is a growing literature on the effectiveness of circuit breaker mechanisms,[5] this paper focuses on the theoretical and empirical studies of financial time series. Financial time series, unlike other series, usually exhibit a set of peculiar characteristics. Firstly, volatility clustering is often observed, i.e., large changes tend to be followed by large changes and small changes tend to be followed by small changes; (see Mandelbrot, 1963 for early evidence). Secondly, financial data often exhibit leptokurtosis. In other words, the distribution of their returns tends to be fat-tailed, i.e., the kurtosis exceeds the kurtosis of a standard Gaussian distribution (see Mandelbrot, *op. cit;* or Fama, 1965). Moreover, the so-called "leverage effect," initially noted by Black (1976), refers to the fact that changes in stock prices tend to be negatively correlated with changes in volatility, i.e., volatility is higher after negative shocks than after positive shocks of the same magnitude.

Over the past two decades, enormous effort has been devoted to modeling and forecasting the movement of stock returns and other financial time series. Seminal work in this area of research may be attributed to Engle (1982), who introduced the standard Autoregressive Conditional Heteroskedasticity (ARCH) model. Engle's process proposes

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(1) According to Harris (1998): "All circuit breakers limit trading activity in some way. Trading halts stop trading when prices have moved, or will imminently move, by some pre-specified amount. Trading resumes after some time interval. Price Limits require all trade prices to be within a certain range."

(2) Empirically, some researchers have concluded that circuit breakers reduce volatility (Ma, Rao, and Sears (1989a; 1989b). Others find that volatility increases (Mecagni and Sourial , 1999; Lee, Ready and Seguin, 1994). Still, others find that trading restrictions have little effect in the long run (Lauterbach and Ben-Zion, 1993; Santoni and Liu, 1993; Overdahl and McMillan, 1997.)

(3) For example: Austria, Belgium, Egypt, France, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, Spain, Switzerland, Taiwan, Thailand and Turkey among others.

(4) Mecagni and Sourial (1999) using a normal and symmetric GARCH-in mean specification tested for the same effect. Their results provide evidence that price limits negatively impacted the market by: reducing the welfare of investors, reducing efficiency and increasing market volatility.

(5) For a detailed literature survey, see Harris (1998).

to model time-varying conditional volatility using past innovations to estimate the variance of the series. Empirical evidence shows that high ARCH orders have to be selected in order to catch the dynamics of the conditional variance. This argument gave rise to the Generalized ARCH (GARCH) model of Bollerslev (1986), which introduces the time-varying volatility process as a function of both past disturbances and past volatility. Today, the ARCH and GARCH literature have grown immensely and its applications have expanded from stock returns to interest rates, foreign exchange, inflation and so on. Excellent survey papers by Bollerslev, Chou, and Kroner (1992), as well as, Bollerslev, Engle and Nelson (1994) cite more than 200 papers on this subject. The ability to estimate and forecast financial market volatility has expanded even further because of its importance in the portfolio selection and asset management processes. This is in addition to its importance in the pricing of primary and derivative assets.

Although most researchers agree that volatility is predictable in many asset markets, they differ on how this volatility predictability should be modeled within an ARCH/GARCH context. As a result, a variety of new extensions were produced, some of which were motivated by pure theory, whereas others were simply empirical trial-and-error suggestions. The most interesting of these approaches targeted the structural form of the GARCH model by allowing for "asymmetries" to capture the aforementioned "leverage effect." Among the most widely applied models are the Exponential GARCH (EGARCH) of Nelson (1991); the so-called (GJR) of Glosten, Jagannathan and Runkle (1993); and the Asymmetric Power ARCH (APARCH) of Ding, Granger and Engle (1993).[6]

Another area heavily researched in the GARCH domain is the method of estimation. GARCH models are estimated using a Maximum Likelihood (ML) approach.[7] The logic of ML is to interpret the density as a function of the parameters set, conditional on a set of sample outcomes. This function is called the *likelihood function*. As noted earlier, financial time-series often exhibit non-normality patterns, i.e., excess kurtosis and skewness. Bollerslev and Wooldridge (1992) propose a Quasi Maximum Likelihood (QML) method that is robust to departures from normality. Indeed Weiss (1986) and Bollerslev and Wooldridge (1992) show that under the normality assumption, the QML estimator is consistent if the conditional mean and the conditional variance are correctly specified. This estimator, however, is inefficient, with the degree of inefficiency increasing as departure from normality increases. This penalty imposed for not knowing the true conditional density results in failure to capture the fat-tails property of high-frequency financial time series (Engle and Gonzalez-Rivera, 1991). Consequently, this has led to the use of non-normal distributions to better model excessive third and fourth moments.

It is expected that excess kurtosis and skewness displayed by the residuals of conditional heteroscedasticity models will be reduced when a more appropriate distribution is used. Bollerslev (1987); Baillie and Bollerslev (1989); Kaiser (1996); and Beine, Laurent, and Lecourt (2000), among others, use Student-*t* distribution while Nelson (1991) and Kaiser (*op. cit*) suggest the Generalized Exponential Distribution (GED). Other propositions include mixture distributions such as the normal-lognormal (Hsieh, 1989) or the Bernoulli-normal (Vlaar and Palm, 1993). Finally, to better capture skewness, Fernandez and Steel (1998) and Lambert and Laurent (2000; 2001) use a skewed student-*t* distribution.

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(6) Other famous asymmetric GARCH models include the Threshold GARCH (TGARCH) of Zakoian (1994), the Quadratic GARCH (QGARCH) of Sentana (1995), the Volatility Switching ARCH (VS-ARCH) of Fornari and Mele (1996), and the Logistic Smooth Transition ARCH (LST-ARCH) of Gonzales-Rivera (1996) and Hagerud (1996).

(7) As an alternative to ML and Quasi Maximum Likelihood (QML) estimation, GARCH models can also be estimated directly with Generalized Method of Moments (GMM). This was suggested and implemented by Glosten, Jagannathan and Runkle (1993).

Empirical Methodology

Models

Let the adjusted closing price of a market index at time t be denoted by P_t. Stock market returns, R_t, through out this paper is defined as continuously compounded or (log) returns at time t. R_t measured as the natural log difference in the closing market index between two consecutive trading days {ln {$|P_t|$ / $|P_{t-1}|$ } = ln (P_t) - ln (P_{t-1})} and are assumed to follow the AR(p)-process:

$$R_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i R_{t-i} + \varepsilon_t \qquad (1)$$

where ε_t denotes a discrete-time stochastic process taking the form:

$$\varepsilon_t = z_t \sigma_t \qquad (2)$$

where $z_t \sim iid(0,1)$, and σ_t is the conditional variance of return at time t, whose dynamics are to be modeled using ARCH/GARCH type specifications.

Bollerslev's (1986)[(8)] GARCH model assumes that the conditional variance is generated by:

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (3)$$

where γ,α, and β are non-negative constants.

For the GARCH process to be defined, it is required that $\alpha > 0$.

The first asymmetric GARCH type model is the GJR model of Glosten, Jagannathan and Runkle (1993)[(9)]. Its generalized version is given as:

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \omega_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (4)$$

where, S_t^- is an indicator function that takes the value of one when $\varepsilon_{t-1} < 0$ and zero otherwise. It may be seen clearly that this model assumes the impact of ε_t^2 on the conditional variance σ_t^2 is different when ε_t is positive or negative. In sum, it assumes that negative shocks have a higher impact than positive ones.

Ding, Granger, and Engle (1993) propose the Asymmetric Power ARCH (APARCH). The APARCH model may be expressed as:

$$\sigma_t^\delta = \gamma_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \tau_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \qquad (5)$$

where, $\delta > 0$ and $-1 < \tau_i < 1$ ($i = 1,\ldots,q$). This model's strength arises from the fact that it couples the flexibility of a varying exponent with the asymmetry coefficient (to take the "leverage effect" into account).

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(8) It is straightforward to show that Bollerslev's (1986) GARCH model is based on the infinite ARCH model introduced by Engle (1982).

(9) The Threshold GARCH (TGARCH) model of Zakoian (1994) is very similar to the GJR but models the conditional standard deviation instead of the conditional variance.

To summarize, the shocks (news) of the aforementioned asymmetric volatility models capture the leverage effect by allowing either the slope of the two sides of the news impact curve(10) to differ or the center of the news curve to locate at a point where ε_{t-i} is positive. In the standard GARCH model, this curve is a quadratic function centered on ε_{t-i} = 0. GJR captures asymmetry because its news impact curve has a steeper slope on its negative side than on its positive one. Finally, APARCH detects the asymmetry by allowing its news impact curve to be centered at a positive ε_{t-i}.(11)

Estimation Methodology and Density Assumptions

To estimate the parameters of these models, a maximum likelihood (ML) approach is used. The innovations z_t is assumed to be following a conditional distribution. Hence, a log-likelihood function is considered for maximization using a standard numerical method. Again, it may be expected that excess kurtosis and skewness displayed by the residuals of GARCH models are reduced when a more appropriate distribution is used. The next few paragraphs will describe the different densities used in this paper and provide their log-likelihood functions.

The normal distribution is the most widely used when estimating GARCH models. Given both the mean equation in Equation 1, the variance equation for any of the models presented in Equations 3, 4 and 5, and the stochastic process of the innovations given by Equation 2, the log-likelihood function for the standard normal distribution is given by:

$$L_{normal} = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t\right] \qquad (6)$$

where T is the number of observations.

For a Student-t distribution, the log-likelihood is:

$$L_{student-t} = T\left\{\ln\Gamma\left(\frac{\upsilon+1}{2}\right) - \ln\Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2}\ln\left[\pi(\upsilon-2)\right]\right\}$$

$$-0.5\sum_{t=1}^{T}\left\{\ln\sigma_t^2 + (1+\upsilon)\ln\left[1+\frac{z_t^t}{\upsilon-2}\right]\right\} \qquad (7)$$

Furthermore, the GED log-likelihood function of a normalized random error is:

$$L_{GED} = \sum_{t=1}^{T}\left[\ln(\upsilon/\lambda_\upsilon - 0.5\left|\frac{z_t}{\lambda_\upsilon}\right|^{\upsilon} - (1+\upsilon^{-1})\ln(2) - \ln\Gamma(1/\upsilon) - 0.5\ln(\sigma_t^2)\right]$$

where $$\lambda_\upsilon = \sqrt{\frac{\Gamma\left(\frac{1}{\upsilon}2^{\frac{-2}{\upsilon}}\right)}{\Gamma\left(\frac{3}{\upsilon}\right)}} \qquad (8)$$

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(10) Engle and Ng (1993) performed a comparison among the standard GARCH model and the EGARCH, GJR, and APARCH. They suggest an increasing metric by which to analyze the effect of news on conditional heteroskedasticity. Holding constant the information dated at t-2, they examined the implied relation between ε_{t-1} and σ_t. They call this curve, with all lagged conditional variances evaluated at the level of the unconditional variance of the stock return, *the news impact curve* because it relates past return shocks (news) to current volatility. This curve measures how new information is incorporated into volatility estimates using the various proposed models.

(11) For a more detailed discussion, see Engle and Ng (1993) and for methods of extrapolating news impact curves for a wide variety of models, see Hentschel (1995).

The previous two densities account for fat tails, but do not take into account asymmetries. Lambert and Laurent (2001) applied and extended the skewed Student-*t* density proposed by Fernandez and Steel (1998) to a GARCH framework:

$$L_{SkStudent} = T\left\{\ln\Gamma\left(\frac{\upsilon+1}{2}\right) - \ln\Gamma\left(\frac{\upsilon}{2}\right) - 0.5\ln[\pi(\upsilon-2)] + \ln\left(\frac{2}{\xi+\frac{1}{\xi}}\right) + \ln(s)\right\}$$
$$-0.5\sum_{t=1}^{T}\left\{\ln\sigma_t^2 + (1+\upsilon)\ln\left[1+\frac{(sz_t+m)^2}{\upsilon-2}\xi^{-2I_t}\right]\right\} \qquad (9)$$

where $I_t = 1$ if $z_t \geq -\frac{m}{s}$ or -1 if $z_t < -\frac{m}{s}$

$$m = \frac{\Gamma\left(\frac{\upsilon+1}{2}\right)\sqrt{\upsilon-2}}{\sqrt{\pi}\,\Gamma\left(\frac{\upsilon}{2}\right)}\left(\xi-\frac{1}{\xi}\right) \quad \text{and} \quad s = \sqrt{\left(\xi^2+\frac{1}{\xi^2}-1\right)-m^2}.$$

See Lambert and Laurent (2001) for further details.

Specification Tests

To estimate the unknown parameters of the models, iterative numerical methods with the help of software, are required. These procedures are usually time-consuming, especially if the code must be written, and if the model in question explains the data badly, the estimation might not converge. This is why specification tests play a crucial role. They investigate whether or not a certain model might have been the data-generating process of a time series. Following the recommendations of Wooldridge (1991) and Hagerud (1997), a "bottom-up" strategy is used when performing specification tests. In other words, specifying the conditional mean is the initial step. Once the conditional mean is formulated and estimated satisfactorily, tests for the conditional variance specification are initiated.

When attempting to specify the conditional mean, only possible autocorrelations in the returns are tested for.(12) To test for autocorrelation, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are employed, in addition to a test developed by Richardson and Smith (1994),(13) which is a robust version of the standard Box-Pierce (1970) procedure. If $\hat{\rho}_i$, is the estimated autocorrelation between the returns at time *t* and *t-i,* then the (RS) is formulated as:

$$RS(k) = T\sum_{i=1}^{k}\frac{\hat{\rho}_i^2}{1+c_i} \qquad (10)$$

(12) Other studies have tested for "day-of-the-week effects" and the possibility of the conditional variance as the explanatory variable of the returns. These specifications are not considered in this study.

(13) Cited in Hagerud (1997).

where c_i is an adjustment factor for heteroskedasticity and is calculated as:

$$c_i = \frac{\text{cov}\left[\overline{r_t^2}, \overline{r_{t-i}^2}\right]}{\text{var}[r_t]^2} \qquad (11)$$

where $\overline{r_t^2}$ is the demeaned return at time *t*. Under the null of no autocorrelation, this test is distributed χ^2 with *k* degrees of freedom. If the null cannot be rejected, it can be deduced that the specification of the conditional mean in (1) is equal to a constant plus a residual. On the other hand, if the null is rejected, an AR(1) model is estimated on the series. Furthermore, to ensure that this AR(1) specification has captured all the autocorrelation, Equation 10 is applied on the estimated residuals of the AR(1) process. The residual testing using Equation 10 is compared to a χ^2 distribution with *k*-1 degrees of freedom. If the null cannot be rejected, it is concluded that returns are generated by an AR(1) model. If the null is rejected, the testing continues with higher- order AR models until the null cannot be rejected.

Once the conditional mean equation has been specified, tests for the presence of heteroskedasticity are performed. The most widely cited and used test for this purpose is the LM test of no ARCH of Engle (1982)[(14)]. The test procedure is to run an OLS regression on Equation 1 after having calculated the "correct" lags from the Richardson and Smith test in Equation 10 and save the residuals. Then, regress the squared residuals on a constant and *p* lags and test $T{*}R^2$ on a χ^2 distribution with *p* degrees of freedom.

If the null of no ARCH(*q*) cannot be rejected, the investigation continues with tests for asymmetric GARCH. The fact that negative return shocks cause more volatility than positive return shocks of the same magnitude, tells us that the standard GARCH model will underpredict the amount of volatility following bad news and overpredict it following good news. These observations suggest testing for whether it is possible to predict the squared normalized residuals by variables observed in the past, which are not included in the volatility model being used. If these variables can predict the squared normalized residuals, then the variance model is misspecified. The sign bias test proposed by Engle and Ng (1993) considers a dummy variable S_{t-i}^-, which takes the value of one when ε_{t-i} is negative and zero otherwise. This test examines the impact of positive and negative return shocks on volatility not predicted by the model under consideration. The general derived form of the test using a slightly different notation than Engle and Ng (*op. cit*) is:

$$v_t^2 = \underline{z}_{0t}\underline{\vartheta}_0 + \underline{z}_{at}\underline{\vartheta}_a + u_t \qquad (12)$$

where, $\underline{z}_{0t}$ is a *k x 1* vector of explanatory variables of the model hypothesized under the null,[(15)] $\underline{\vartheta}_0$ is the *k x 1* vector of parameters under the null. $\underline{\vartheta}_a$ is a *m x 1* vector of additional parameters corresponding to $\underline{z}_{at}$, which is a *m x 1* vector of missing explanatory variables. $v_t \equiv \varepsilon_t / \sigma_{0t}$, where, σ_{0t} is the conditional standard deviation vector estimated using the hypothesized model under the null and finally, u_t is the residual.

Theoretically, the right hand side of Equation 12 should have no explanatory power at all. To actually perform the sign bias test $\underline{z}_{at}$ is replaced by S_{t-i}^- and an actual regression takes the following form:

$$v_t^2 = a + bS_{t-1}^- + \underline{\beta}' \underline{z}_{0t} + e_t \qquad (13)$$

(14) Engle's (1982) LM test of no ARCH is standard in any statistical or econometric software package.

(15) Usually a symmetric GARCH(1,1).

where, a and b are constant parameters, β is a constant parameter vector, and e_t is the residual. The sign bias test is defined as the t-statistic for the coefficient b in regression Equation 13.

Furthermore, according to Engle and Ng (1993), the sign bias test can also be used on raw data to explore the nature of the time-varying volatility in a time series, without first imposing a volatility model. In this case, ε_t, and v_t would be defined as:

$$\varepsilon_t = R_t - \mu \qquad (14a)$$

$$v_t = \frac{\varepsilon_t}{s} \qquad (14b)$$

where, μ and s are the unconditional mean and standard deviation of the time series R_t, respectively. If b from Equation 13 is statistically significant, then it is justifiable to use Models 4 and 5.

Data

The behavior of the ESE stock returns was analyzed using two major daily aggregate indices.(16) These indices have different composition and therefore worthwhile looking at in order to assess the sensitivity of the empirical results. The indices are:

- ***The Hermes Financial Index*** (HFI) started on July 1, 1992. The HFI is the benchmark of the Egyptian market and is used to monitor the overall market overall performance. HFI tracks the movement of the most active Egyptian stocks traded on the ESE. Although HFI is broad-based, it limits its constituents only to companies that have genuine liquidity in the market, as opposed to those companies that trade only a few sporadic pre-arranged trades. The HFI is capitalization weighted for registered stocks that are openly traded,(17)

- ***The Egyptian Financial Group Index*** (EFGI) started on January 3, 1993, and is capitalization-weighted for registered stocks. EFGI tracks the movement of large capitalization Egyptian companies(18) that are most actively traded on the ESE.

The sample consists of 2237 daily observations on stock returns of the HFI and the EFGI indices. It covers a nine-year period beginning on January 3, 1993 and ending on December 31, 2001. For illustrative purposes, Figure 1 (Appendix) compares the two indices' daily closing values taken across the sample period. Figure 2 (Appendix) looks at the behavior of the EFGI and HFI returns, respectively, over the sample period.

The effect of policy change has been explored by dividing the sample into two parts: pre-and post-imposing the circuit breaker(19). Moreover, a restricted F-Chow test (20) was formulated to test for the significance of the structural change. The result rejects the null hypothesis of no structural change in daily returns, and consequently the sample was partitioned into two sub-samples. The descriptive statistics of both indices (found in Appendix Tables 1, 2 and 3) over the two sub-sample periods highlighting the following:

- Mean returns for the EFG Index are slightly larger than the HFI(21), whereas the Median returns for HFI are larger than EFGI's for the first sub-sample. As for the second sub-sample, the exact opposite occurs.

- Non-conditional variances for both indices increased in the second sub-sample over the first one. Furthermore, there is evidence of volatility clustering (see Figure 2 and that large or small asset price changes tend to be followed by other large or small price changes of either sign (positive or negative). This implies that stock return volatility changes over time. Furthermore, the figures indicate a sharp increase in volatility starting from the year 1997.

- The returns for both indices are positively skewed. The null hypothesis for skewness coefficients that conform with a normal distribution's value of zero has been rejected at the 5% significance level.(22)

- The returns for both indices also display excess kurtosis. The null hypothesis for kurtosis coefficients that conform to the normal value of three is rejected for both indices.(23)

- The high values of Jarque-Bera test for normality decisively rejects the hypothesis of a normal distribution.

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(16) The two indices (EFGI) and (HFI) have been chosen because they represent the largest and most actively traded stocks. They also entail the largest sample information. Other indices cited by Mecagni and Sourial (1999) were not used for reasons as follows: (a) The Capital Market Authority index (CMAI), was not used due to the dominance of infrequently traded stocks which results in a downward bias of index momentum; (b) The Prime Index for Initial Public Offerings (PIPO) was not used because it represents the partially and wholly privatized companies only; and (c) the MSCI and IFC (Global and Investable) indices were not used in this paper since they would entail a sizable loss in sample information. The two indices were started in 1996 and 1997, respectively.

(17) No Over the Counter (OTC) traded stocks.

(18) Companies with a market capitalization that exceeds L.E.500 million.

(19) The sample is divided into two sub-samples: (a) Sub-sample 1 starting from 1/3/93 and ending 1/31/97 just before imposing the price limit regulation in February 1997; and (b) Sub-sample 2 starting after the regulation and ending on December 31 2001.

(20) To carry out the test, the data were partitioned into two sub-samples. Each sub-sample contained more observations than the number of coefficients in the equation so that the equation can be estimated. The Chow breakpoint test compares the sum of squared residuals obtained by fitting a single equation to the entire sample with the sum of squared residuals obtained when separate equations are fit to each sub-sample of the data. E-Views, reports the F-statistic for the Chow breakpoint test. The F-statistic is based on the comparison of the restricted and unrestricted sum of squared residuals and in the simplest case involving a single breakpoint.

(21) A Z-test was conducted to test for significant differences in the means.

(22) The t-stat was calculated in the following matter: (S-0)/se(S), where (S) stands for skewness coefficient and (se(S)) stands for the standard error. Standard error =(6/number of observations)1/2.

(23) The **t-stat** was calculated in the following matter: (K-3)/se(K), where (K) stands for kurtosis coefficient and (se(K)) stands for the standard error. Standard error =(24/number of observations) $^{1/2}$.

- Although the Augmented Dicky-Fuller (ADF) unit root tests strongly reject the hypothesis of non-stationarity,(24) both returns display a degree of time dependence. This can be seen through the Autocorrelation Function (ACF) for both indices. Correlograms (taken over 36 lags) were estimated for the returns on both indices. For the first sub-sample, the correlograms show a pattern of smooth decay typical of stationarity, and a second-order autoregressive process AR(2).(25) The second sub-sample has a sharper decay after the first lag indicating the presence of an AR(1). This has been confirmed using the Richardson and Smith test (1994) calculated on ten autocorrelations. (see Appendix Table 2)
- Engle's (1982) test of no ARCH is calculated for distinct orders (q= 2,5 and 10) (see Appendix Table 3). Both indices show signs of heteroskedasticity in both sub-samples, indicating the legitimacy of using ARCH/GARCH type models.

The statistical results for both indices appear to have very similar characteristics. They both display positive skewness, were found to be deviating from normality, and display a degree of serial correlation. These stylized results of non-conformity to normality are consistent with previous empirical work on the ESE(26) and similar to a number of previous empirical works on mature markets(27).

Finally, Engle and Ng's (1993) sign bias test on the raw data was conducted. The test was performed by estimating Equation 13 using Equations 14a and 14b as proxies for ε_t and v_t. For the first sub-sample, the results show no signs of asymmetry in the data because of the insignificance of *b* in the two regressions for the two indices. On the other hand, for the second sub-sample, *b* is significant for both indices at the 5% level, which in turn, justifies estimating asymmetric GARCH type models.

In sum, looking at the first sub-sample, it may be hypothesized from the specification tests that the simple symmetric GARCH should outperform all other asymmetric GARCH models. Furthermore, given the fact that the residual series exhibited some excess kurtosis, it can also be predicted that a fatter-tailed distribution such as the student-*t*, or maybe a GED, should generate better results than just simply a normal distribution or a more complex asymmetric student-*t*. As for the second sub-sample, the sign bias test on the raw series predicts that asymmetric GARCH models should do a better job in explaining the ESE's dynamics. In addition, both the presence of excess kurtosis and asymmetry tell us that a skewed student-*t* distribution should excel.

Estimation Results

To estimate the parameters of the earlier mentioned models, we use the GARCH ToolBox in MATLAB, as well as, the G@RCH 2.3 Ox programmed package of Laurent and Peters (2001).(28) Models (29) 3, 4,and 5 will only be studied in their most simple structure, when both of the lags, *p* and *q,* are equal to one. Low-order lag lengths were found to be sufficient to model the variance dynamics over very long sample periods.(30)

As already previously mentioned, a maximum likelihood approach is used to estimate the three models with the four underlying error distributions. For the first sub-sample, convergence was not reached for any of the models using the GED distribution. Furthermore, convergence was not reached either for the APARCH model under any of the four distributions. Failures often occur because the series of the conditional variance is given a negative value, or because stationarity conditions on the estimated parameters could not be met[31]. Appendix Tables 4 and 5 present the

(24) While it may appear that the test can be carried out by performing a **t-test**, the t-statistic under the null hypothesis of a unit root does not have the conventional t-distribution. Dickey and Fuller (1979) showed that the distribution under the null hypothesis is nonstandard, and simulated the critical values for selected sample sizes. More recently, MacKinnon (1991) has implemented a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates the response surface using the simulation results, permitting the calculation of Dickey-Fuller critical values for any sample size and for any number of right-hand variables. These MacKinnon critical values for unit root tests were the ones used in this paper.

(25) See Enders (1994).

(26) See, Mecagni and Sourial (1999).

(27) Fama (1965) showed that the distribution of both daily and monthly returns for the Dow Jones depart from normality, and are negatively, leptokurtic, and volatility clustered. Furthermore, Kim and Kon (1994) found the same for the S&P 500. Finally, Peters (2001) showed similar results for two major European stock indices (FTSE 100 and DAX 30). In general, most mature markets were found to have negatively skewed return series. For a more detailed discussion see Harvey and Siddique (1999) or Harvey and Siddique (2000).

(28) The authors would like to thank Prof. Blake LeBaron and Math Works for their support in sharing the upgrades of the MATLAB GARCH ToolBox; Prof. Sebastian Laurent for his immense help and valuable comments with operating the G@RCH 2.3 package. Finally, the authors are thankful to Dean Peter Petri and GSIEF for their financial support.

(29) The EGARCH model of Nelson (1991) was also tried but did not converge in any of the attempts.

(30) French, Schwert, and Stambaugh (1987) analyzed daily S&P stock index data for 1928-1984 for a total of 15,369 observations and required only four parameters in the conditional variance equation (including the constant).

(31) See Hagerud (1997).

estimation results for the first sub-sample's parameters of the GARCH and GJR models, respectively. GJR's use appears to be unjustified for sub-sample 1, since the symmetric coefficients were not significant for both indices.

Since one of the objectives of this study is to jointly investigate which of the GARCH type models and underlying distributions "best" models the conditional variance for the ESE. Three selection criteria for finding the best model and distribution are used: (a) the value of the likelihood function, which is maximized; (b) the BIC [(32)] information criteria of Schwartz; and the AIC[(33)] information criteria of Akaiki, which are both minimized.[(34)]

Appendix Tables 6 to 8 report the log likelihood value, the information criteria, and other useful in-sample statistics.[(35)] Not surprisingly, the models with the most parameters always maximize the likelihood function, in this case, GJR. However, when the number of parameters is given consideration, as in the AIC and BIC, the simple traditional GARCH always outperforms the more parameterized GJR across both indices. This result strengthens the hypothesis drawn earlier from the specification tests that the use of asymmetric models is, for the first sub-sample, unnecessary.

Regarding the densities, the two student-*t* distributions clearly outperform the Gaussian. Again, it is not surprising to see the log-likelihood function increase strongly when using the skewed student-*t* density against the two other symmetric densities. The presence of asymmetry in the density is not needed because in all cases for sub-sample 1 (when using GARCH and GJR), the student-*t* outperforms the skewed-t for both indices (see Appendix Tables 9 and 10).

Both models that converge for the first sub-sample seem to do an adequate job of describing the dynamics of the first and second moments. The Box-Pierce statistics under the null of no autocorrelation, for the residuals and the squared residuals, are, for the most part, non-significant at the ten percent level.

Appendix Tables 11 to 13 present the estimation results for the second sub-sample's parameters of the GARCH, GJR and APARCH models respectively. Both uses of GJR and APARCH appear to be justified for sub-sample 2, since the symmetric coefficients are all significant at the 5% level for both indices.

Looking at the log likelihood values AIC and BIC in Appendix Tables 14-17, the fact that GJR or APARCH models better estimate the series for both indices than the traditional GARCH, may almost be highlighted. However, this conclusion should be cautiously drawn because of the very small differences in values for these tests.

In looking at densities for the second sub-sample, no single distribution stands as being the best.(See Appendix Tables 18 to 20). Yet again, the two Student-*t* distributions clearly outperform the Guassian and the GED distributions for both indices. Unlike the first sub-sample, where the use of asymmetric densities was not needed, in the second sub-sample the usefulness of asymmetry is not clear-cut. If the Skewed Student-*t* density gives better results than the symmetric Student-*t* when modeling the EFGI, the opposite is observed for the HFI. A possible explanation for this deviation is that if skewness is significant in both series, its magnitude might be lower for the HFI.

GARCH, GJR and APARCH for the second sub-sample also do a decent job in describing the dynamics of the first and second moments. The Box-Pierce statistics, under the null of no autocorrelation, for the residuals and the squared residuals are non-significant at the ten percent level.

Conclusion

This paper examines whether the imposition of daily price limits changes the return volatility dynamics. As laboratory, the Egyptian Stock Exchange was used where 5% daily limits were imposed in early 1997.

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(32) $$Schwartz = -2\frac{LogL}{n} + 2\frac{\log(k)}{n}$$

(33) $$Akaiki = -2\frac{LogL}{n} + \frac{k}{n}$$

where, $LogL$ = log likelihood value, n = number of observations and k is the number of estimated parameters.

(34) For a more detailed discussion of AIC and BIC see Green, (2000).

(35) Reported are: the Box-Pierce statistics at lag (l) for both the standardized and squared standardized residuals and the adjusted Pearson goodness-of-fit test that compares the empirical distribution of innovations with the theoretical one.

The study compares different GARCH-type models with different underlying distributional assumptions for the innovations in an effort to understand the data generation process of the series. The comparison focuses on two different aspects, specification tests and in-sample estimates, in order to determine the "best" fitted model. Moreover, the time series is divided into two sub-samples to examine changes in performance of the models as a result of the circuit breaker regulation that affected the trading environment.

The estimation results conform to a series of ex-ante specification tests. For the first sub-sample, the evaluation criteria for the in-sample estimates show that a simple GARCH model with student-*t* innovations outperforms any of the more sophisticated asymmetric models. Regarding the second sub-sample, it was clear that APARCH and GJR gave better estimates over the traditional GARCH. The favorite density was yet again the fat-tailed student-*t* distribution.

The empirical evidence provided in this article confirms Mecagni and Sourial (1999) findings that the symmetric price limits on individual shares failed to dampen volatility in the market. However, this paper adds two more important findings.

- Firstly, regulatory and/or structural shifts in the market results in a different conditional volatility model structure. In other words, the appropriateness of assuming the same underlying volatility model for both *pre* and *post* samples is questioned.

- Secondly, the leverage effect, captured in the post-limit sub-sample, shows Egyptian investors to be very risk-averse (negative shocks tend to have a deeper impact on conditional volatility than positive shocks). With price limits in place, investors find it hard to exit the market, which forces them to advance their trades. This advancement of trades creates a volatility spillover effect on subsequent trading days.

To conclude, in many emerging markets, circuit breakers are implemented with a belief that they will protect the market from harmful volatility and speculation. However, in many cases, circuit breakers end up paving the way for speculative attacks. Thus, to fully evaluate the consequences of circuit breakers such as price limits, it would be important to examine their effects on the overall market efficiency.

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Appendix

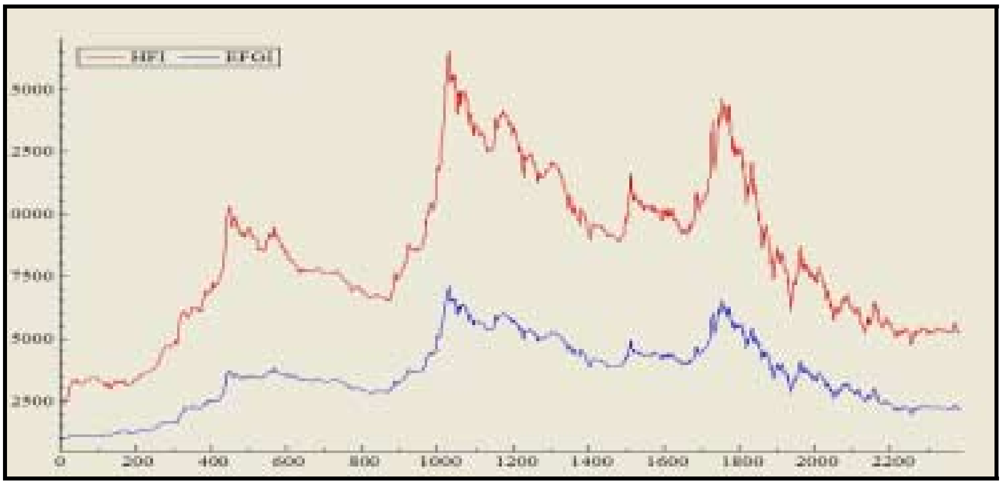

Figure 1. EFGI and HFI daily closing prices
January 3, 1993 to December 31, 2001.

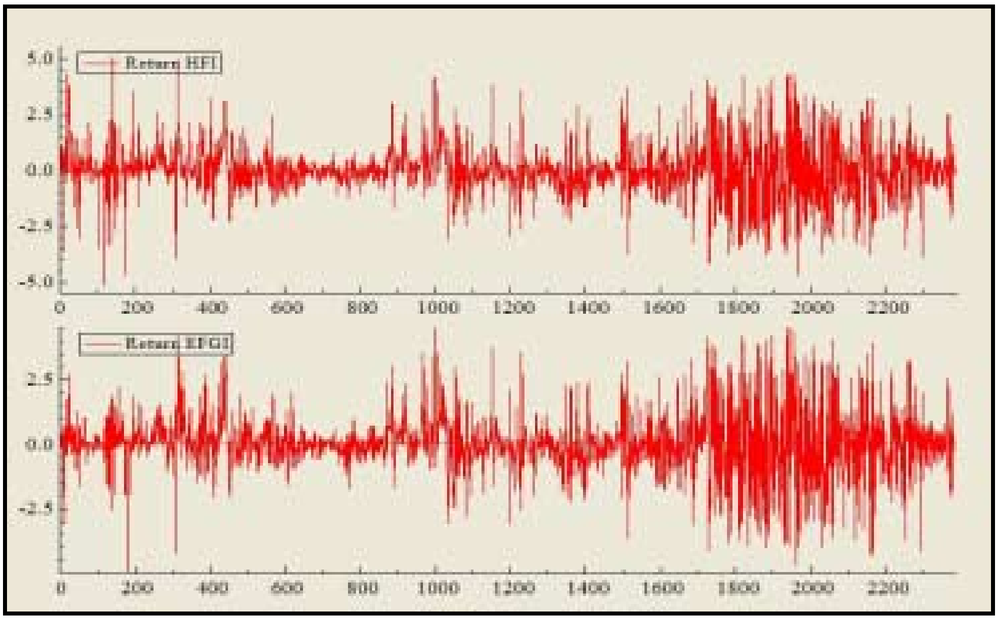

Figure 2. EFGI and HFI daily returns.
January 3, 1993 to December 31, 2001.

Table 1. Descriptive Statistics for Sub-samples 1 and 2

	Sub-sample (1) Jan 3, 1993 – Jan 31, 1997		Sub-sample (2) Feb. 2, 1997 – Dec. 31, 2001	
Descriptive Statistics	**HFI**	**EFGI**	**HFI**	**EFGI**
Mean (%)	0.1717	0.1760	-0.0701	-0.0735
Standard Error	0.0292	0.0254	0.0421	0.0442
Median (%)	0.0527	0.0707	-0.0937	-0.0960
Standard Deviation (%)	0.9321	0.8107	1.3807	1.4493
Variance	0.0087	0.0066	0.0191	0.0210
Kurtosis	9.2774	9.2799	3.9512	3.9083
Skewness	0.4690	0.7587	0.2019	0.1442
Jarque-Berra Normality Test	1706.634	1768.753	422.352	401.385
Augmented Dickey-Fuller Unit Root Test	-10.6552	-10.368	-12.6053	-12.8503
Range	0.1021	0.0941	0.0902	0.0918
Minimum	-5.1527	-4.9213	-4.6796	-4.6910
Maximum	5.0565	4.4893	4.3417	4.4971
Sample Size	1017	1017	1219	1219

Table 2. Results from Tests of Autocorrelation for Sub-samples 1 and 2

Index	***RS(10)*** **on** r_t **(*p-value*)**	***RS(10)*** **on** ε_t **from AR(1) (*p-value*)**	***RS(10)*** **on** ε_t **from AR(2) (*p-value*)**
	Sub-sample (1) Jan 3, 1993 – Jan 31, 1997		
HFI	0.005	0.039	0.172
EFGI	0.003	0.018	0.092
	Sub-sample (2) Feb 2, 1997 – Dec 31, 2001		
HFI	0.041	0.365	-----
EFGI	0.033	0.296	-----

N.B. Column two gives *p-values* for the Richardson and Smith's (1994) test for autocorrelation calculated on the demeaned returns.

Table 3. Results from Tests of No ARCH for Sub-samples 1 and 2

Index	No ARCH (2)	No ARCH (5)	No ARCH (10)	κ(ε)	s(ε)
	Sub-sample (1) Jan 3, 1993 – Jan 31, 1997				
HFI	46.866 (0.000)	23.634 (0.000)	12.890 (0.000)	10.009	0.187
EFGI	59.026 (0.000)	27.540 (0.000)	14.546 (0.000)	9.3512	0.171
	Sub-sample (2) Feb 2, 1997 – Dec 31, 2001				
HFI	135.770 (0.000)	70.150 (0.000)	37.609 (0.000)	4.919	0.253
EFGI	158.290 (0.000)	75.545 (0.000)	40.125 (0.000)	4.008	0.203

Table 4. AR(2)-GARCH (1,1) Estimation Results for Sub-sample 1 from January 3, 1993 to December 31, 1997

	HFI				EFGI			
	Normal	Student-t	GED	Skewed-t	Normal	Student-t	GED	Skewed-t
φ_0	0.0281 (0.0376)	0.0248 (0.0267)	Fail	0.0450 (0.0358)	0.0173 (0.0269)	0.0160 (0.0203)	Fail	0.0137 (0.0266)
φ_1	0.2819 **(0.0373)**	0.2834 **(0.0359)**	Fail	0.2811 **(0.0361)**	0.2296 **(0.0406)**	0.2837 **(0.0358)**	Fail	0.2786 **(0.0358)**
φ_2	0.1270 **(0.0376)**	0.0869 **(0.0338)**	Fail	0.0844 **(0.0339)**	0.0906 **(0.0409)**	0.0527 **(0.0330)**	Fail	0.0508 **(0.0331)**
γ_1	0.0079 (0.00821)	0.0584 (0.0513)	Fail	0.0609 (0.0523)	0.0046 (0.0019)	0.0116 (0.0070)	Fail	0.0124 (0.0083)
α_1	0.3431 **(0.3250)**	0.2527 **(0.2262)**	Fail	0.2539 **(0.2497)**	0.2231 **(0.2116)**	0.1567 **(0.1075)**	Fail	0.1456 **(0.1642)**
β_1	0.6480 **(0.0641)**	0.7418 **(0.1228)**	Fail	0.7422 **(0.1194)**	0.7679 **(0.0119)**	0.8258 **(0.0347)**	Fail	0.8354 **(0.0373)**
υ		2.6442 **(0.3059)**	Fail	2.6113 **(0.3068)**		2.7294 **(0.3478)**	Fail	2.6155 **(0.3448)**
ξ			Fail	-0.0388 (0.0463)			Fail	-0.0734 (0.0441)

Table 5. AR(2)-GJR (1,1) Estimation Results for Sub-sample 1 from January 3, 1993 to December 31, 1997

	HFI				EFGI			
	Normal	Student-t	GED	Skewed-t	Normal	Student-t	GED	Skewed-t
φ_0	0.0242 (0.0359)	0.0348 (0.0246)	Fail	0.0258 (0.0327)	0.0038 (0.0267)	0.0256 (0.0198)	Fail	0.0069 (0.0257)
φ_1	0.2802 **(0.0357)**	0.2759 **(0.0343)**	Fail	0.2742 **(0.0347)**	0.2344 **(0.0384)**	0.2723 **(0.0342)**	Fail	0.2679 **(0.0346)**
φ_2	0.1404 **(0.0359)**	0.0887 **(0.0322)**	Fail	0.0876 **(0.0324)**	0.0945 **(0.0389)**	0.0597 **(0.0312)**	Fail	0.0577 **(0.0313)**

γ_1	0.0016 (0.0009)	0.0595 (0.0365)	Fail	0.0592 (0.0364)	0.0056 **(0.0021)**	0.0153 **(0.0082)**	Fail	0.0149 (0.0082)
α_1	0.0485 **(0.0938)**	0.4618 **(0.2217)**	Fail	0.4726 **(0.2290)**	0.1145 **(0.0197)**	0.3132 **(0.1162)**	Fail	0.3432 **(0.1363)**
β_1	0.9577 **(0.0063)**	0.7098 **(0.0982)**	Fail	0.7091 **(0.0975)**	0.08936 **(0.1234)**	0.8099 **(0.0378)**	Fail	0.8067 **(0.0373)**
ω_1	-0.0140 (0.0104)	-0.1879 (0.1459)	Fail	-0.1905 (0.1485)	-0.0128 (0.0287)	-0.0914 (0.0940)	Fail	-0.0938 (0.1016)
υ		2.7377 **(0.2958)**	Fail	2.7248 **(0.2971)**		2.8401 **(0.3409)**	Fail	2.7675 **(0.3414)**
ξ			Fail	-0.0184 (0.0444)			Fail	-0.0475 (0.0431)

Table 6. Post-estimation Statistics for Sub-sample 1 Using a Normal Distribution

	HFI		EFGI	
	GARCH	**GJR**	**GARCH**	**GJR**
AIC	2.2919	2.2931	1.9779	1.9798
BIC	2.3234	2.3289	2.0094	2.0167
LL	-1044.840	-1043.931	-900.872	-900.773
Q(20)	27.0796	28.3415	27.1476	26.9028
Q^2(20)	27.7842	29.9136	6.8547	6.8535
P(50)	165.4973	156.2279	145.1047	142.2694
P-Val (lag-1)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
P-Val(lag-k-1)	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Table 7. Post-estimation Statistics for Sub-sample 1 Using a Student-t Distribution

	HFI		EFGI	
	GARCH	**GJR**	**GARCH**	**GJR**
AIC	1.9999	2.0016	1.7329	1.7339
BIC	2.0367	2.0417	1.7697	1.7760
LL	-909.983	-908.839	-787.570	-787.027
Q(20)	22.6572	22.4837	22.1934	21.0600
Q^2(20)	51.5792	52.7243	8.0535	7.7841
P(50)	62.4438	59.8266	45.7590	63.7525
P-Val (lag-1)	(0.0939)	(0.1382)	(0.0605)	(0.0766)
P-Val(lag-k-1)	[0.0218]	[0.02891]	[0.0318]	[0.0129]

Table 8. Post-estimation Statistics for Sub-sample 1 Using a Skewed-t Distribution

	HFI		EFGI	
	GARCH	**GJR**	**GARCH**	**GJR**
AIC	2.0019	2.0018	1.7337	1.7348
BIC	2.0439	2.0489	1.7757	1.7821
LL	-909.889	-908.754	-786.903	-786.419
Q(20)	22.5149	22.3562	20.5837	19.6528

Q*²*(20)	52.3955	53.5165	7.8765	7.6543
P(50)	57.4275	54.4831	51.8659	58.4089
P-Val (lag-1)	(0.1912)	0.2738	(0.2678)	(0.1680)
P-Val(lag-k-1)	[0.0457]	[0.0531]	(0.0989)	[0.0301]

Tables 6-8 compare post estimation statistics across models for the specifications that converged with the first sub-sample series. *AIC, BIC* are the Akaike and Schwartz information criteria. *LL*, is the log likelihood value. *Q(20)* and $Q^2(20)$ are respectively the Box-Pierce statistic at lag 20 of the standardized and squared standardized residuals. *P(50)* is the Pearson Goodness-of-fit with 50 cells. P-values of the non-adjusted and adjusted test are given respectively in parentheses and brackets. The period investigated is from Jan 3, 1993 to Dec 31, 1997.

Table 9. Post-estimation Statistics for Sub-sample 1 Using GARCH

	HFI			EFGI		
	Normal	**Student-t**	**Skewed-t**	**Normal**	**Student-t**	**Skewed-t**
AIC	2.2919	1.9999	2.0019	1.9779	1.7329	1.7337
BIC	2.3234	2.0367	2.0439	2.0094	1.7697	1.7757
LL	-1044.84	-909.98	-909.88	-900.87	-787.57	-786.90
Q(20)	27.0796	22.6572	22.5149	27.1476	22.1934	20.5837
Q*²*(20)	27.7842	51.5792	52.3955	6.8547	8.0535	7.8765
P(50)	165.497	62.4438	57.4275	145.1047	45.7590	51.8659
P-Val (lag-1)	(0.0000)	(0.0939)	(0.1912)	(0.0000)	(0.0605)	(0.2627)
P-Val(lag-k-1)	[0.0000]	[0.0218]	[0.0457]	[0.0000]	[0.0318]	[0.0989]

Table 10. Post-estimation Statistics for Sub-sample 1 Using GJR

	HFI			EFGI		
	Normal	**Student-t**	**Skewed-t**	**Normal**	**Student-t**	**Skewed-t**
AIC	2.2931	2.0016	2.0018	1.9798	1.7339	1.7348
BIC	2.3289	2.0417	2.0489	2.0167	1.7760	1.7821
LL	-1043.93	-908.83	-908.75	-900.77	-787.02	-786.42
Q(20)	28.3415	22.4937	22.3562	26.9028	21.0612	19.6528
Q²(20)	29.9136	52.7243	53.5165	6.8535	7.7841	7.6543
P(50)	156.2279	59.8266	54.4831	142.269	63.7525	58.4089
P-Val (lag-1)	(0.0000)	(0.1382)	(0.2738)	(0.0000)	(0.0766)	(0.0168)
P-Val(lag-k-1)	[0.0000]	[0.0289]	[0.0530]	[0.0000]	[0.0129]	[0.0301]

Tables 9 and 10 compare post estimation statistics across distributions for the specifications that converged with the first sub-sample series. *AIC, BIC* are the Akaike and Schwartz information criteria. *LL*, is the log likelihood value. *Q(20)* and $Q^2(20)$ are respectively the Box-Pierce statistic at lag 20 of the standardized and squared standardized residuals. *P(50)* is the Pearson Goodness-of-fit with 50 cells. P-values of the non-adjusted and adjusted test are given respectively in parentheses and brackets. The period investigated is from Jan 3, 1993 to Dec 31, 1997

Table 11. AR(1)-GARCH (1,1) Estimation Results for Sub-sample 2

	HFI				EFGI			
	Normal	**Student-t**	**GED**	**Skewed-t**	**Normal**	**Student-t**	**GED**	**Skewed-t**
φ_0	-0.0436 (0.0343)	-0.0784 (0.0314)	-0.0712 (0.0325)	-0.0495 (0.0344)	-0.0505 (0.0339)	-0.0720 (0.0317)	-0.0671 (0.0328)	-0.0529 (0.0342)
φ_1	0.2974 **(0.0315)**	0.3037 **(0.0312)**	0.02965 **(0.0307)**	0.3120 **(0.0313)**	0.2736 **(0.0310)**	0.2767 **(0.0311)**	0.2754 **(0.0318)**	0.2812 **(0.0311)**
γ_1	0.0585 (0.0129)	0.0332 (0.1060)	0.0442 (0.0125)	0.0337 (0.1067)	0.0532 (0.0122)	0.0351 (0.0109)	0.0435 (0.0122)	0.0353 (0.0110)
α_1	0.3543 **(0.0497)**	0.3810 **(0.0583)**	0.3700 **(0.0577)**	0.3687 **(0.0577)**	0.3409 **(0.0479)**	0.3564 **(0.0544)**	0.3488 **(0.0539)**	0.3467 **(0.0542)**
β_1	0.6575 **(0.0368)**	0.6725 **(0.0384)**	0.6646 **(0.0403)**	0.6812 **(0.0387)**	0.6715 **(0.0366)**	0.6827 **(0.0386)**	0.6773 **(0.0398)**	0.6895 **(0.0393)**
υ		7.7052 **(1.6180)**	1.4717 **(0.0846)**	7.8586 **(1.7111)**		9.8063 **(2.5201)**	1.5809 **(0.0919)**	9.9566 **(2.6137)**
ξ				0.1050 (0.0448)				0.0744 (0.0449)

This table reports results from AR(1)-GARCH (1,1) estimation using different densities. The number of observations was reduced by one hundred for forecast evaluation purposes. Columns 2, 3, 4, 5 are the different model estimations using normal, student, GED and skewed student-t respectively. Asymptotic heteroskedasticity-consistent standard errors are given in parentheses, **(bold)** denoting significance at the 5% level. The period investigated is from February 2, 1997 to Dec 31, 2001.

Table 12. AR(1)-GJR (1,1) Estimation Results for Sub-sample 2

	HFI				EFGI			
	Normal	**Student-t**	**GED**	**Skewed-t**	**Normal**	**Student-t**	**GED**	**Skewed-t**
φ_0	-0.0730 (0.0360)	-0.1066 (0.0325)	-0.0974 (0.0328)	-0.0783 (0.0351)	-0.0754 (0.0357)	-0.0965 (0.0332)	-0.0899 (0.0343)	-0.0776 (0.0353)
φ_1	0.2931 **(0.0314)**	0.2981 **(0.0311)**	0.2911 **(0.0289)**	0.3013 **(0.0311)**	0.2702 **(0.0310)**	0.2739 **(0.0310)**	0.2727 **(0.0320)**	0.2750 **(0.0310)**
γ_1	0.0559 (0.0126)	0.0315 (0.0102)	0.0418 (0.0121)	0.0311 (0.0101)	0.0512 (0.0120)	0.0336 (0.0106)	0.0416 (0.0119)	0.0335 (0.0106)
α_1	0.2921 **(0.0476)**	0.2902 **(0.0538)**	0.2900 **(0.0535)**	0.2804 **(0.0527)**	0.2863 **(0.0476)**	0.2871 **(0.0527)**	0.2847 **(0.0525)**	0.2790 **(0.0519)**
β_1	0.6580 **(0.0363)**	0.6761 **(0.0378)**	0.6664 **(0.0396)**	0.6838 **(0.0378)**	0.6751 **(0.0360)**	0.6868 **(0.0379)**	0.6816 **(0.0391)**	0.6923 **(0.0384)**
ω_1	0.1348 **(0.0587)**	0.1876 **(0.0711)**	0.1708 **(0.0697)**	0.1798 **(0.0685)**	0.1074 **(0.0540)**	0.1374 **(0.0629)**	0.1267 **(0.0614)**	0.1349 **(0.0614)**
υ		7.6317 **(1.5682)**	1.4712 **(0.0835)**	7.8635 **(1.6844)**		9.6895 **(2.4451)**	1.5795 **(0.0911)**	9.9519 **(2.5851)**
ξ				0.1032 **(0.0448)**				0.0747 (0.0447)

This table reports results from AR(1)-GJR (1,1) estimation using different densities. The number of observations was reduced by one hundred for forecast evaluation purposes. Columns 2, 3, 4, 5 are the different model estimations using normal, student, GED and skewed student-t respectively. Asymptotic heteroskedasticity-consistent standard errors are given in parentheses, **(bold)** denoting significance at the 5% level. The period investigated is from February 2, 1997 to Dec 31, 2001.

Table 13. AR(1)-APARCH (1,1) Estimation Results for Sub-sample 2

	HFI				EFGI			
	Normal	**Student-t**	**GED**	**Skewed-t**	**Normal**	**Student-t**	**GED**	**Skewed-t**
φ_0	-0.0682 (0.0378)	-0.1057 (0.0326)	-0.0955 (0.0345)	-0.0752 (0.0366)	-0.0734 (0.0360)	-0.0965 (0.0331)	-0.0893 (0.0345)	-0.0772 (0.0354)
φ_1	0.3007 **(0.0321)**	0.3005 **(0.0313)**	0.2960 **(0.0317)**	0.3042 **(0.0315)**	0.2706 **(0.0312)**	0.2739 **(0.0310)**	0.2731 **(0.0321)**	0.2751 **(0.0310)**
γ_1	0.0654 (0.0142)	0.0356 (0.0124)	0.0491 (0.0144)	0.0361 (0.0122)	0.0554 (0.0136)	0.0333 (0.0122)	0.0440 (0.0137)	0.0342 (0.0122)
α_1	0.3328 **(0.0443)**	0.3620 **(0.0572)**	0.3493 **(0.0535)**	0.3446 **(0.0551)**	0.3275 **(0.0461)**	0.3536 **(0.0573)**	0.3385 **(0.0537)**	0.3408 **(0.0560)**
β_1	0.6870 **(0.0359)**	0.6939 **(0.0433)**	0.6908 **(0.0417)**	0.7062 **(0.0427)**	0.6915 **(0.0403)**	0.6852 **(0.0487)**	0.6918 **(0.0460)**	0.6959 **(0.0485)**
τ_1	0.0978 **(0.0441)**	0.1267 **(0.0466)**	0.1188 **(0.0482)**	0.1256 **(0.0477)**	0.0804 **(0.0411)**	0.0973 **(0.0428)**	0.0926 **(0.0444)**	0.0985 **(0.0434)**
δ	1.4600 **(0.2856)**	1.7215 **(0.3706)**	1.5785 **(0.3430)**	1.6533 **(0.3629)**	1.7186 **(0.3670)**	2.0253 **(0.4770)**	1.8313 **(0.4299)**	1.9451 **(0.4635)**
υ		7.7057 **(1.6078)**	1.4782 **(0.0845)**	7.9737 **(1.7466)**		9.6814 **(2.4453)**	1.5815 **(0.0916)**	9.9763 **(2.6088)**
ξ				0.1063 **(0.0450)**				0.0752 **(0.0449)**

This table reports results from AR(1)-APARCH (1,1) estimation using different densities. The number of observations was reduced by one hundred for forecast evaluation purposes. Columns 2, 3, 4, 5 are the different model estimations using normal, student, GED and skewed student-t respectively. Asymptotic heteroskedasticity-consistent standard errors are given in parentheses, **(bold)** denoting significance at the 5% level. The period investigated is from February 2, 1997 to Dec 31, 2001.

Table 14. Post-estimation Statistics for Sub-sample 2 Using a Normal Distribution

	HFI			EFGI		
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
AIC	3.0126	3.0093	3.0087	3.0881	3.0862	3.0876
BIC	3.0368	3.0362	3.3017	3.1195	3.1101	3.1190
LL	-1680.570	-1677.726	-1676.408	-1722.82	-1720.768	-1720.516
Q(20)	38.7892	40.9358	39.7497	35.6250	38.9075	38.8009
$Q^2(20)$	17.7525	18.5805	18.0303	21.6192	22.3666	22.1063
P(50)	66.6850	49.4093	60.9374	51.1072	56.0223	54.3244
P-Val (lag-1)	(0.0471)	(0.0456)	(0.1178)	(0.0390)	(0.0228)	(0.0278)
P-Val(lag-k-1)	[0.0152]	[0.0232]	[0.0294]	[0.0214]	[0.0087]	[0.0096]

Table 15. Post-estimation Statistics for Sub-sample 2 Using a Student-t Distribution

	HFI			EFGI		
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
AIC	2.9806	2.9754	2.9767	3.0688	3.0660	3.0678
BIC	3.0075	3.0068	3.0126	3.0967	3.0964	3.1037
LL	-1661.667	-1657.744	-1657.503	-1711.00	-1708.451	-1708.451
Q(20)	38.0908	43.9911	43.7125	37.3773	41.8335	41.8408
$Q^2(20)$	20.1930	20.9786	20.6143	23.8263	24.0072	24.0410
P(50)	39.4004	27.5147	37.0769	64.0652	48.1582	46.1921
P-Val (lag-1)	(0.0834)	(0.0994)	(0.0894)	(0.0728)	(0.0507)	(0.0587)
P-Val(lag-k-1)	[0.0628]	[0.0958]	(0.0645)	(0.0202)	[0.0237]	[0.0266]

Table 16. Post-estimation Statistics for Sub-sample 2 Using a GED Distribution

	HFI			EFGI		
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
AIC	2.9888	2.9846	2.9854	3.0752	3.0730	3.0746
BIC	3.0157	3.0160	3.0212	3.1021	3.1044	3.1105
LL	-1666.27	-1662.93	-1662.34	-1714.61	-1712.36	-1712.28
Q(20)	38.2406	43.6063	42.8182	36.384	40.3427	40.2542
$Q^2(20)$	19.1555	19.9843	19.4103	22.8130	23.3187	23.1316
P(50)	39.5791	34.2172	43.0643	50.6604	48.4263	45.5666
P-Val (lag-1)	(0.0829)	(0.0946)	(0.0711)	(0.0407)	(0.0496)	(0.0613)
P-Val(lag-k-1)	[0.0620]	[0.0797]	[0.0382]	[0.0196]	[00229]	[0.0287]

Table 17. Post-estimation Statistics for Sub-sample 2 Using a Skewed-*t* Distribution

	HFI			EFGI		
	GARCH	**GJR**	**APARCH**	**GARCH**	**GJR**	**APARCH**
AIC	2.9774	2.9724	2.9735	3.0682	3.0653	3.0671
BIC	3.0088	3.0083	3.0139	3.0996	3.0912	3.1005
LL	-1658.89	-1655.08	-1654.70	-1709.66	-1707.09	-1707.08
Q(20)	37.0505	43.3402	42.9835	36.5826	41.5144	41.5002
$Q^2(20)$	20.5418	21.5452	21.4203	23.886	24.2280	24.1888
P(50)	40.5621	41.7239	48.9625	44.0474	40.2046	43.4218
P-Val (lag-1)	(0.0799)	(0.0760)	(0.0476)	(0.0673)	(0.0810)	(0.0697)
P-Val(lag-k-1)	[0.0534]	[0.0439]	[0.0156]	[0.0384]	[0.0505]	[0.0327]

Tables 14-17 compare post estimation statistics across models for the specifications that converged with the first sub-sample series. *AIC, BIC* are the Akaike and Schwartz information criteria. *LL*, is the log likelihood value. *Q(20)* and $Q^2(20)$ are respectively the Box-Pierce statistic at lag 20 of the standardized and squared standardized residuals. *P(50)* is the Pearson Goodness-of-fit with 50 cells. P-values of the non-adjusted and adjusted test are given respectively in parentheses and brackets. The period investigated is from February 2, 1997 to Dec 31, 2001.

Table 18. Post-estimation Statistics for Sub-sample 2 Using GARCH

	HFI				EFGI			
	Normal	**Stud-t**	**GED**	**Skew-t**	**Normal**	**Stud-t**	**GED**	**Skewed-t**
AIC	3.0126	2.9806	2.9888	2.9774	3.0881	3.0688	3.0752	3.0682
BIC	3.0360	3.0075	3.0157	3.0088	3.1195	3.0967	3.1021	3.0996
LL	-1680.57	-1661.67	-1666.27	-1658.89	-1722.82	-1711.01	-1714.61	-1709.66
Q(20)	38.7892	38.0908	38.2406	37.0505	35.625	37.3773	36.3840	36.5826
$Q^2(20)$	17.7525	20.1930	19.1555	20.5418	21.6192	23.8263	22.8130	23.886
P(50)	66.6850	39.4004	39.5791	40.5621	51.1072	64.0652	50.6604	44.0474
P-Val	(0.0471)	(0.0834)	(0.0829)	(0.0799)	(0.0390)	(0.0728)	(0.0407)	(0.0673)
P-Val	[0.0152]	[0.0628]	[0.0620]	[0.0534]	[0.0214]	[0.0202]	[0.0196]	[0.0384]

Table 19. Post-estimation Statistics for Sub-sample 2 Using GJR

	HFI				EFGI			
	Normal	**Stud-t**	**GED**	**Skew-t**	**Normal**	**Stud-t**	**GED**	**Skewed-t**
AIC	3.0093	2.9754	2.9846	2.9724	3.0862	3.0660	3.0730	3.0653
BIC	3.0362	3.0068	3.0160	3.0083	3.1101	3.0964	3.1044	3.0912
LL	-1677.73	-1657.74	-1662.93	-1655.079	-1720.77	-1708.45	-1712.35	-1707.09
Q(20)	40.9358	43.9911	43.6063	43.3402	38.9075	41.8335	40.3427	41.5144
$Q^2(20)$	18.5805	20.9786	19.9843	21.5452	22.3666	24.0072	23.3187	24.2280
P(50)	49.4093	27.5147	34.2172	41.7239	56.0223	48.1582	48.4263	40.2046
P-Val	(0.0456)	(0.0994)	(0.0946)	(0.0760)	(0.0228)	(0.0507)	(0.0496)	(0.0810)
P-Val	[0.0232]	[0.0958]	[0.0797]	[0.0439]	[0.0087]	[0.0237]	[0.0229]	[0.0505]

Table 20. Post-estimation Statistics for Sub-sample 2 Using APARCH

	HFI				EFGI			
	Normal	**Stud-t**	**GED**	**Skew-t**	**Normal**	**Stud-t**	**GED**	**Skewed-t**
AIC	3.0087	2.9767	2.9854	2.9735	3.0876	3.0678	3.0746	3.0671
BIC	3.3017	3.0126	3.0212	3.0139	3.1190	3.1037	3.1105	3.1005
LL	-1676.41	-1657.50	-1662.33	-1654.70	-1720.52	-1708.45	-1712.28	-1707.08
Q(20)	39.7497	43.7125	42.8182	42.9835	38.8009	41.8408	40.2542	41.5002
$Q^2(20)$	18.0303	20.6143	19.4103	21.4203	22.1063	24.0410	23.1316	24.1888
P(50)	60.9374	37.0769	43.0643	48.9625	54.3244	46.1921	45.5666	43.4218
P-Val	(0.1178)	(0.0894)	(0.0711)	(0.0476)	(0.0278)	(0.0587)	(0.0613)	(0.0697)
P-Val	(0.0294)	[0.0645]	[0.0382]	[0.0156]	[0.0096]	[0.0266]	[0.0287]	[0.0327]

Tables 18-20 compare post estimation statistics across distributions for the specifications that converged with the first sub-sample series. *AIC, BIC* are the Akaike and Schwartz information criteria. *LL*, is the log likelihood value. *Q(20)* and $Q^2(20)$ are respectively the Box-Pierce statistic at lag 20 of the standardized and squared standardized residuals. *P(50)* is the Pearson Goodness-of-fit with 50 cells. P-values of the non-adjusted and adjusted test are given respectively in parentheses and brackets. The period investigated is from February 2, 1997 to Dec 31, 2001.