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Working Paper 0310

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MODELING AND FORECASTING EGYPTIAN STOCK MARKET VOLATILITY BEFORE AND AFTER PRICE LIMITS

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Abstract

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, EGARCH, 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. In-sample results, prior to the imposition of price limits exhibit leptokurtosis, yet showing no sign of the widely cited leverage effect. In-sample results, after the imposition of price limits display both leptokurtosis and the leverage effect. Out-of-sample forecasts depict the leverage effects, when present, but provide conflicting results regarding the distribution.

تلخيص

تفحـص هذه الورقـة أثـر الحدود السعرية على ديناميكيات التغير فى البورصة المصرية. وقد تم استـخدام مجموعة متنوعة من صيغ المتوسط الحسابى والتباين، فى نماذج GARCH (GARCH, EGARCH, GJR, APARCH)، كما تم استخدام أربعة توزيعات للخطأ (Normal, Student-*t*, GED, and Skewed-*t*). وتشير نتائج اختبار العينة المنفصلة إلى وجود تغيرات واضحة مع تغير الزمن. وقد أظهرت النتائج داخل العينة، قبل فرض الحدود السعرية، وجود تفلطح (leptokurtosis) ، إلا إنها لم تظهر أى اشارة لوجود أثر الرافعة (leverage effect) الذى كثيراً ما تمت الإشارة اليه. أما بالنسبة لنتائج داخل العينة، بعد فرض الحدود السعرية، فقد أظهرت هذه النتائج وجود كل من التفلطح وأثر الرافعة. من جانب آخر، تشير التوقعات بين العينات، عند توافرها، إلى وجود أثر الرافعة؛ إلا إنها تظهر نتائج متباينة فيما يتعلق بالتوزيع.

1. Introduction

Financial time series, unlike other series, usually exhibit a set of peculiar characteristics. First, Mandelbrot (1963) observed that financial returns displayed volatility clustering. Two years later, Fama (1965) demonstrated that financial data exhibit leptokurtosis, or in other words, the distribution of their returns tend to be fat-tailed. Finally, Black (1976) introduced us to the "leverage effect," which simply means that volatility is higher after negative shocks than after positive shocks of the same magnitude.

Over the past two decades, immense efforts have been devoted to modeling and forecasting the movement of stock returns and other financial time series. One of the cornerstones in this area of research can be attributed to Engle (1982), who introduced the standard Autoregressive Conditional Heteroskedasticity (ARCH) model. Engle's process proposed to model time-varying conditional volatility using past innovations to estimate the variance of the series. Bollerslev (1986), seeing that high ARCH orders are sometimes needed to catch the dynamics of the conditional variance, introduced the Generalized ARCH (GARCH) model, which modeled time-varying volatility as a function of both past disturbances and past volatility. Today, the ARCH and GARCH literature has grown enormously 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 importance of estimating and forecasting financial market volatility has expanded even further as a result of its "importance in the portfolio selection and asset management processes, in addition to its importance in the pricing of primary and derivative assets" (Engle and Ng 1993; p.1749).

Engle and Ng (1993) note that although "researchers agree that volatility is predictable in many asset markets, they differ on how this volatility predictability should be modeled" (p.1749) within an ARCH/GARCH context. As a result, a variety of new extensions were produced, some of which were motivated by pure theory, while 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 widespread 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).[1]

Another area heavily researched in the GARCH world is the method of estimation. GARCH models are estimated using a Maximum Likelihood (ML) approach.[2] ML assumes and maximizes a density function[3] for the parameters that are conditional on a set of sample outcomes. Bollerslev and Wooldridge (1992) propose a Quasi Maximum Likelihood (QML) technique that adjusts for small deviations from normality. This technique's estimator, however, is inefficient, as the deviation from normality increases making the "fully efficient ML estimates more preferred" (Bollerslev et al 1992; p.11). Thus there is clearly a penalty imposed for being unaware of the true conditional density. This has consequently led to the use of non-normal distributions to better model excessive third and fourth moments "because it may be expected that excess kurtosis and skewness displayed by the residuals of conditional heteroscedasticity models will be reduced when a more appropriate distribution is used"(Lambert and Laurent 2001; p.3). 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 (1996) suggest the Generalized Exponential

1 Other famous asymmetric GARCH 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).

2 As an alternative to ML and QML estimation, GARCH models can also be estimated directly with Generalized Method of Moments (GMM). This was suggested and implemented by GJR (1991).

3 Known as the Likelihood Function.

Distribution (GED). Other studies include mixture distributions such as the normal-lognormal (Hsieh (1989)) or the Bernoulli-normal (Vlaar and Palm (1993)). Finally, to capture skewness, Fernandez and Steel (1998) and Lambert and Laurent (2000,2001) use a skewed student-*t* distribution.

Asymmetric GARCH models have been used in several empirical papers (e.g., see, Pagan and Schwert (1990); Brailsford and Faff (1996); Hagerud (1997); Franses, Neele, and Van Dijk (1998); or Loudon, Watt, and Yadav (2000)). Furthermore, comparing the effect of adding different densities has been explored on many occasions (e.g., see Hsieh (1989); Baillie and Bollerslev (1989); Lambert and Laurent, (2001)).

This paper adds to the literature in three ways. First, it empirically investigates and tests to what extent asymmetries in the theoretical model, as well as the imposed distributions, might have influenced the data generating process for Egyptian Stock Exchange (ESE) time series.[4] The paper examines four models: GARCH, EGARCH, GJR and APARCH, and introduces a wider variety of densities (Normal, Student-*t*, Skewed Student-*t* and GED). Second, this work attempts to determine the multi-period forecasting abilities of these GARCH-type models and to demonstrate whether they ameliorate when looking at different "actual" volatility proxies. Finally, the paper examines whether the performance of these four models changes significantly as a result of shifts in policies or regulations affecting the trading environment.[5]

The structure of this paper is organized as follows: Section 2 describes the theoretical basics of the models used. In Section 3, the estimation procedures as well as the different densities are discussed. In Section 4, the tests used for the specification of the conditional mean and variances are formulated. The data is described in Section 5. Empirical findings of specification tests, estimations and forecasting are presented in Section 6. In closing a summary and an outlook for further research is given. Detailed tables showing characteristics of the data, the estimation, and the forecast results, as well as several graphs that visualize some properties of the time series, can be found in the appendix.

2. Theoretical Basics

Let the adjusted closing price of a market index at time t be denoted by P_t. Stock market returns R_t throughout this paper are 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:

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

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

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

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

Bollerslev's (1986)[6] simple GARCH model assumes that the time-varying variance is generated by:

4 This is the first such study to examine the ESE.

5 The introduction of symmetric price limits in February of 1997.

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

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

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 model considered is the EGARCH model of Nelson (1991), which looks at the conditional variance and tries to accommodate for the asymmetric relation between stock returns and volatility changes. Nelson implements that by including an adjusting function *g(.)* in the conditional variance equation, which in turn becomes expressed by:

$$\ln \sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_i \ln(\sigma_{t-j}^2) \tag{4}$$

where $z_t = \frac{\varepsilon_t}{\sigma_t}$ is the normalized residual series. The value of $g(z_t)$ is a function of both the magnitude and sign of z_t and is expressed as:

$$g(z_t) = \underbrace{\theta_1 z_t}_{sign} + \underbrace{\theta_2 \left[|z_t| - E|z_t| \right]}_{magnitude} \tag{5}$$

The value $E\left[|z_t|\right]$ changes depending on the assumption made on the unconditional density of z_t. Thus, for the normal distribution:

$$E\left[|z_t|\right] = \sqrt{\frac{2}{\pi}} \tag{6}$$

For the skewed Student-*t* distribution:

$$E\left[|z_t|\right] = \frac{4\xi^2}{\xi + \frac{1}{\xi}} \frac{\Gamma\left(\frac{1+\upsilon}{2}\right)\sqrt{\upsilon - 2}}{\sqrt{\pi}(\upsilon - 1)\Gamma\left(\frac{\upsilon}{2}\right)} \tag{7}$$

where υ denotes the degrees of freedom, $2 < \upsilon \leq \infty$, $\Gamma(.)$ is the gamma function and ξ is a parameter for asymmetry[7].

For the symmetric student-*t* distribution, (7) will apply, with the small adjustment of $\xi = 1$.

Finally, for the GED:

$$E\left[|z_t|\right] = \lambda_\upsilon 2^{\frac{1}{\upsilon}} \frac{\Gamma\left(\frac{2}{\upsilon}\right)}{\Gamma\left(\frac{1}{\upsilon}\right)} \tag{8}$$

Thus, we can conclude that the EGARCH model differs from the standard GARCH model in two main respects. "First, it allows positive and negative shocks to have a different impact on volatility. Second, the EGARCH model allows big shocks to have a greater impact on volatility than the standard GARCH model" (Engle and Ng 1993; p.1753).

7 For more details see Lambert and Laurent (2001).

The GJR model of Glosten, Jagannathan and Runkle (1993)[8], is given by:

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \omega_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (9)$$

where S_t^- is an indicator function that takes the value of one when $\varepsilon_{t-1} < 0$ and zero otherwise. It can 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" (Laurent & Peters; p.31). 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 can be expressed as:

$$\sigma_t^\delta = \gamma_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \tau_i \varepsilon_{t-i} \right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \quad (10)$$

where, $\delta > 0$ and $-1 < \tau_i < 1$ (i = 1,…,q). This model's strength results from the fact that "it couples the flexibility of a varying exponent with the asymmetry coefficient (to take the "leverage effect" into account)" (Laurent and Peters 2002; p.31). The APARCH model includes several other ARCH extensions as special cases[9]:

- The ARCH of Engle (1982), when $\delta = 2$, $\tau_i = 0$ (i= 1,….p) and $\beta_j = 0$ (j= 1,…p).
- The GARCH of Bollerslev (1986), when $\delta = 2$, $\tau_i = 0$ (i= 1,….p).
- The GJR of Glosten, Jaganathan and Runkle (1993), when $\delta = 2$.
- The TARCH of Zakoian (1994) when $\delta = 1$.

Engle and Ng (1993) summarize how 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 to differ or the center of the news curve to locate at a point where ε_{t-i} is positive" [10] (p.1754). In the standard GARCH model, this curve is a quadratic function centered on ε_{t-i} = 0. For the EGARCH, it has its minimum at ε_{t-i} = 0, and exponentially increases in both directions with different parameters. GJR captures asymmetry as 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}.

It is very important to distinguish how asymmetric shocks are incorporated into volatility estimates for the variety of models that are studied. This importance stems from the vitality of volatility predictions on areas such as portfolio selection, asset pricing, and option pricing. Engle and Ng (1993) provide the following example: After a major unexpected price drop, the predictable market volatilities given by different GARCH type models will be highly varied. "Given that predictable

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8 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.

9 See Ding, Granger and Engle (1993) and Laurent and Peters (2002) for developments of these conclusions.

10 Engle and Ng (1993) make a comparison among the standard GARCH model and the EGARCH, GJR, and APARCH and suggest an increasing metric by which to analyze the effect of news on conditional heteroskedasticity. Holding constant the information dated at t-2, they examine the implied relation between εt-1 and σt. 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. See Engle and Ng (1993) for methods of extrapolating news impact curves for a wide variety of models.

market volatility is related to market risk premium, different models will imply very different risk premiums, and hence different risk premiums for individual stocks under a conditional version of the CAPM" (p.1755). Engle and Ng also note that asymmetric shocks "have important implications for option pricing…because stock return volatility is a major factor in determining option prices" (p.1756). All the outlined concerns emphasize the necessity of having a correct understanding of the impact of asymmetries on volatility. By testing the variety of models that were highlighted earlier and examining whether they offer logical solutions to the data, many concerns are answered.

3. Estimations and Density Assumptions

To estimate the parameters of these models, a maximum likelihood (ML) approach is used. "The innovations z_t are assumed to be following a conditional distribution, and hence a log-likelihood function is considered for maximization using standard numerical method" (Hagerud 1997; p.4). 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 run through 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 (1), the variance equation for any of the models presented in (3), (4), (9) and (10), and the stochastic process of the innovations given by (2), the log-likelihood function for the standard normal distribution is given by:

$$L_{normal} = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t\right] \tag{11}$$

where T is the number of observations. For a Student-t distribution, the log-likelihood is:

$$L_{student-t} = T\left\{\ln\Gamma\left(\frac{\upsilon+1}{2}\right) - \ln\Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2}\ln\left[\pi(\upsilon-2)\right]\right\} - 0.5\sum_{t=1}^{T}\left\{\ln\sigma_t^2 + (1+\upsilon)\ln\left[1+\frac{z_t^t}{\upsilon-2}\right]\right\} \tag{12}$$

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

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

$$\text{where } \lambda_\upsilon = \sqrt{\frac{\Gamma\left(\frac{1}{\upsilon}2^{\frac{-2}{\upsilon}}\right)}{\Gamma\left(\frac{3}{\upsilon}\right)}} \tag{13}$$

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:

$$L_{SkStudent} = T\left\{\ln\Gamma\left(\frac{\upsilon+1}{2}\right) - \ln\Gamma\left(\frac{\upsilon}{2}\right) - 0.5\ln\left[\pi(\upsilon-2)\right] + \ln\left(\frac{2}{\xi+\frac{1}{\xi}}\right) + \ln(s)\right\} - 0.5\sum_{t=1}^{T}\left\{\ln\sigma_t^2 + (1+\upsilon)\ln\left[1+\frac{(sz_t+m)^2}{\upsilon-2}\xi^{-2I_t}\right]\right\} \tag{14}$$

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

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

See Lambert and Laurent (2001) for further details.

4. 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 written), and if the model in question explains the data badly, the estimation might not converge" (Hagerud 1997; p.1). For this reason specification tests play a crucial role in investigating whether or not certain models fit the time series data at hand. Following the recommendations of Wooldridge (1991) and Hagerud (1997), a "bottom-up" strategy will be used when performing specification tests. In other words, we will start out by specifying the conditional mean. Once the conditional mean is formulated and estimated satisfactorily, tests for the conditional variance specification are initiated.

Following Hagerud, "when attempting to specify the conditional mean, only possible autocorrelations in the returns are tested for"[11](p.5). To test for autocorrelation, the ACF and PACF are employed, in addition to a test developed by Richardson and Smith (1994),[12] "which is a robust version of the standard Box-Pierce (1970) procedure" (Hagerud 1997; p.5). If $\hat{\rho}_i$, is the estimated autocorrelation between the returns at time *t* and *t-i,* then the (RS) is formulated as:

$$RS(k) = T\sum_{i=1}^{k}\frac{\hat{\rho}_i^2}{1+c_i} \qquad (15)$$

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

$$c_i = \frac{\operatorname{cov}\left[\overline{r_t^2}, \overline{r_{t-i}^2}\right]}{\operatorname{var}[r_t]^2} \qquad (16)$$

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 (15) is applied on the estimated residuals of the AR(1) process. The residual testing using (15) 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. (Hagerud 1997; p.5)

Once the conditional mean equation has been specified, tests for the presence of a time varying variance are implemented. The most widely cited and used test for this purpose is the LM test of no

11 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.

12 This test is cited in Hagerud (1997).

ARCH of Engle (1982)[13]. The test procedure is to run an OLS regression on (1) after having calculated the "correct" lags from the Richardson and Smith test in (15) 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" (Engle and Ng 1993;p.1757). 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 (1993) is:

$$\nu_t^2 = \underline{z}_{0t}\underline{\vartheta}_0 + \underline{z}_{at}\underline{\vartheta}_a + u_t \qquad (17)$$

where, $\underline{z}_{0t}$ is a *k x 1* vector of explanatory variables of the model hypothesized under the null,[14] $\underline{\vartheta}_0$ 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. $\nu_t \equiv \varepsilon_t / \sigma_{0t}$, 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 (17) 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:

$$\nu_t^2 = a + bS_{t-1}^{-} + \underline{\beta}' \underline{z}_{0t} + e_t \qquad (18)$$

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 (18).

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" (p.1760).

In this case, ε_t, and ν_t would be defined as:

$$\varepsilon_t = R_t - \mu \qquad (19a)$$

$$\nu_t = \frac{\varepsilon_t}{s} \qquad (19b)$$

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

14 Usually a symmetric GARCH(1,1).

where, μ and s are the unconditional mean and standard deviation of the time series R_t, respectively. If b from equation (18) is statistically significant, then it is justifiable to use models (3), (4), (9) and (10).

5. Data

The behavior of the ESE stock returns will be analyzed using two major daily aggregate indices.[15] These indices have different composition and are thus worthwhile to examine in order to assess the sensitivity of the empirical results. The indices are:

a. ***The Hermes Financial Index*** (HFI), begun 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 which make only a few sporadic pre-arranged trades. Criteria for inclusion in the index are average daily value traded, average daily number of transactions, total number of days traded during a calendar quarter and market capitalization. The HFI is capitalization weighted for registered stocks that are openly traded,[16] giving higher weights to larger companies, while eliminating cross-ownership among its constituents. The index is calculated on a total return basis, taking into consideration the reinvestment of dividends and is rebalanced quarterly. The index currently contains 34 companies.

b. ***The Egyptian Financial Group Index*** (EFGI), started on January 3, 1993. It is also capitalization-weighted for registered stocks. EFGI tracks the movement of large capitalization Egyptian companies[17] that are most actively traded on the ESE. It is a subset of the Hermes Financial Index (HFI), which in turn limits its constituents to companies that have genuine liquidity in the market, as opposed to those companies that trade only a few sporadic pre-arranged trades. Criteria for inclusion in the EFGI are large market capitalization as well as average daily value traded, average daily number of transactions and total number of days traded during a calendar quarter. The index is also calculated on a total return basis, taking into consideration the reinvestment of dividends. Rebalancing, again, is done on a quarterly basis. EFGI is deemed the investable index and acts as a good indicatior of foreign investment activity. It currently contains 10 companies.

Three other researched, well-cited, and commonly used indices[18]: ***The Capital Market Authority Index*** (CMAI); ***The Prime Index for Initial Public Offerings*** (PIPO); and the ***IFC Global Egypt Index*** are not used. The first, CMAI, is not used because more than 50 percent of the trading value was concentrated in less than 5 percent of its total listed shares. The second (PIPO) and third (IFC) were not used in this paper as this would entail a sizable loss in sample information. The two indices were started in 1996 and 1997, respectively.

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.[19] For illustrative purposes, Figure 1 compares the two used indices' daily closing values taken across the sample period. Furthermore, Figures 2 and 3 look at the behavior of the EFGI and HFI returns, respectively, over the sample period.

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15 The two indices (EFGI) and (HFI) have been chosen because they represent largest and most actively traded stocks. They also entail the largest sample information.

16 No Over the Counter (OTC) traded stocks

17 Companies with a market capitalization that exceeds L.E. 500 million.

18 CMAI and PIPO are researched in Mecagni and Shawky (1999).

19 The data for this study is provided by the Egyptian Financial – Hermes (EFG-Hermes) Group. I would like to thank Mr. Karim Awad and Ms. Heba El-Zoaiby, EFG-HERMES, for their phenomenal support in providing data and adding valuable comments.

Because the main objective of this paper is to examine whether the introduction of the circuit breaker to the ESE affected the data-generation process, it is therefore important that such a significant change be controlled for over time. Here, I explore the effects of a policy change by dividing the sample into two parts: before and after the regulation. To test the soundness of my reasoning,[20] a restricted F-Chow test[21] was formulated. The idea of the breakpoint Chow test is to fit the equation separately for each sub-sample and to examine whether there are significant differences in the estimated equations. A significant difference indicates a structural change in the relationship.

Since the breakpoint test statistics decisively reject the null hypothesis of no structural change in daily returns, the sample was partitioned into two sub-samples. After dividing the sample, we look at the descriptive statistics of both indices (Tables 1 and 2) over the two sub-sample periods and highlight the following:

- Mean returns for the EFG Index are slightly larger than those for the HFI, 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;
- Variability, which can be deduced from looking at the samples' non-conditional variances or standard deviations, is larger for HFI and EFGI in the first and second sub-samples respectively. Variances for both indices increased in the second sub-sample over the first one;
- The returns for both indices are skewed to the right; or in other words, they display positive skewness. The null hypothesis for skewness coefficients that conform with a normal distribution's value of zero has been rejected at the 5 percent 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]
- After looking at the third and fourth moments, it is not surprising that both indices were found to be leptokurtic (fat-tailed). The high values Jarque-Bera test for normality decisively rejects the hypothesis of a normal distribution;
- 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

20 Whether its valid to divide the sample in two sub-samples; with one starting from 1/3/93 and ending 1/31/97 just before imposing the price limit regulation in February 1997, and the other starting after the regulation and ending on 12/31/01.

21 To carry out the test, I partitioned the data 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.

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.

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 one used in this paper.

AR(2).[25] The second sub-sample has a sharper decay after the first lag indicating the presence of an AR(1);

- Finally, Figures 2 and 3 show us that there is evidence of volatility clustering, meaning 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 statistical results for both indices appear to have very similar characteristics. They both display positive skewness, were found to be deviating from normal, and display a degree of serial correlation. These stylized results are very similar to a number of previous empirical works. Fama (1976) showed that the distribution of both daily and monthly returns for the Dow Jones depart from normality, and are skewed, leptokurtic, and volatility clustered. Furthermore, Kim and Kon (1994) found the same for the S&P 500. Finally, Mecagni and Shawki (1999) show similar results in the ESE. They look at the whole sample without partitions.

6. Results

6.1. Specification Tests Results

As mentioned earlier, the search for finding the correct specifications will follow a "bottoms-up" strategy, which means that the conditional first moment will be examined first. Tables 3 and 3' report the results from the Richardson and Smith (1994) test (15), calculated on10autocorrelations. The results indicate that both indices show signs of autocorrelation on a five percent significance level across both sub-samples. In fact, the first sub-sample indicates the presence of an AR(2), whereas in the second sub-sample only an AR(1) can be detected. Since no autocorrelation can be found in the first sub-sample's residual series of the AR(2) specification, we can conclude that, for both indices, the suitable mean equation is (1) with $p = 2$. Moreover, in the second sub-sample the autocorrelation disappears after testing for the AR(1) residuals, the mean specification is (1), yet with $p = 1$, being appropriate.

LeBaron (1992) argues that the magnitude of the serial correlation is sometimes related to volatility, consistent with non-synchronous trading being more severe when volatility and volume are both low. This argument raises a very critical question concerning the data at hand. Is the high serial correlation in the first sub-sample resulting from an "index effect"[26] or from market inefficiencies? To answer this, individual securities were examined and similar results were found that indicated high market inefficiencies during the period. In fact, some securities had even higher order autocorrelations.

Tables 4 and 4' report the results from the Engle's (1982) test of no ARCH. The test is calculated with q equaling two, five and ten. The indices show signs of heteroskedasticity in both sub-samples, indicating the legitimacy of using ARCH/GARCH type models. Tables 4 and 4' also report excess kurtosis for the series of estimated residuals. The fact that excess kurtosis was found to be high indicates that it is unlikely that a GARCH-type model with normal errors can generate the underlying data.

Finally, Engle and Ng's (1993) sign bias test on the raw data was conducted. The test was performed by estimating (18) using (19a) and (19b) as proxies for ε_t and ν_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 2 indices). On the other hand, for the second sub-sample b is significant for both indices at the five percent level, which in turn justifies estimating asymmetric GARCH type models.

25 See Enders (1994).

26 Resulting from the non-trades of some of the component stocks.

In sum, if we look at the first sub-sample we can hypothesize 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 possibly a GED, should generate better results than 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. The validity of the hypotheses given earlier will be tested once the models are estimated and out-of- sample forecasts are conducted.

6.2. 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 (2002).[27] Models (3), (4), (9) and (10) 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.[28]

As was claimed in Section 3, a maximum likelihood approach is used to estimate the four 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 also not reached for the EGARCH and APARCH models under any of the four distributions. These cases are all indicated as failures in the results tables. 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[29]. Tables 5 and 6 present the 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.

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: the value of the likelihood function, which we are maximizing; also the BIC[30] information criteria of Schwartz; and the AIC[31] information criteria of Akaiki, which are both minimized.

Tables 7 to 11 report the log likelihood value, the information criteria, and other useful in-sample statistics.[32] 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.

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27 I 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, I would like to thank Dean Peter Petri and GSIEF for their financial support.

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

29 See Hagerud (1997).

30 $Schwartz = -2\frac{LogL}{n} + 2\frac{\log(k)}{n}$

31 $Akaiki = -2\frac{LogL}{n} + \frac{k}{n}$

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

32 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.

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.

Both models that converged 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 are under the null of no autocorrelation, as the residuals and the squared residuals are for the most part non-significant at the 10 percent level.

As for the second sub-sample, convergence could not be reached with EGARCH, whatever the distribution used. Tables 12 to 14 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 five percent level for both indices.

Looking at the log likelihood values, AIC and BIC in Tables 15-18, we can highlight the fact that GJR or APACH models almost always better estimate the series for both indices than the traditional GARCH. However, this conclusion should be cautiously drawn because of the very small differences in values for these tests. Out-of-sample forecasting should provide better results.

In looking at densities for the second sub-sample, no one distribution has proved to be the best. 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 as 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 10 percent level.

6.3. Forecasting

Laurent and Peters (2002) find estimating an econometric model usually useful in helping to demonstrate the generation process of a time series under study, or finding solutions to economic problems. Yet, they claim: "the main purpose of building a model and estimating it with financial data has always been to produce future forecasts" (p.39). According to Franses and Van Dijk (1998), it is reasonably difficult to select the "best" GARCH model on the basis of specification tests only. For this reason technicians started using out-of-sample forecasting as an alternative approach to selecting the most adequate model. Obviously, "if a volatility model is to be of any use to practitioners in financial markets, it should be capable of generating accurate predictions for the future" (Franses and Van Dijk 1998; p.195).

In this paper we attempt to forecast the conditional variance and compare the performance of the previously discussed models. In the simple GARCH (*p,q*) case the optimal *s*-step-ahead forecast of the conditional variance $h^2_{t+s|t}$ is given by:

$$h^2_{t+s|t} = \hat{\gamma} + \sum_{i=1}^{q} \hat{\alpha}_i \varepsilon^2_{t+s-i|t} + \sum_{j=1}^{p} \hat{\beta}_j \sigma^2_{t+s-j|t} \qquad (20)$$

where $\varepsilon^2_{t+i|t} = \sigma^2_{t+i|t}$ for $i > 0$ and $\varepsilon^2_{t+i|t} = \varepsilon^2_{t+i}$ and $\sigma^2_{t+i|t} = \sigma^2_{t+i}$ for $i < 0$. A closed form solution for $h^2_{t+s|t}$ can be obtained by recursive substitution.

With regards to the asymmetric GARCH type models (EGARCH, GJR, APARCH), the computation of the out-of-sample forecasts might be slightly more complex. The assumption made on the innovation process may have an effect on the forecast.

For example, the *s*-step forecast of the conditional variance of the GJR(*p,q*) is:

$$h^2_{t+s|t} = \hat{\gamma} + + \sum_{i=1}^{q} \left(\hat{\alpha}_i \varepsilon^2_{t-i+s|t} + \hat{\omega}_i S^-_{t-i+s|t} \varepsilon^2_{t-i+s|t} \right) + \sum_{j=1}^{p} \hat{\beta}_j \sigma^2_{t-j+s|t} \tag{21}$$

If $\hat{\omega}_i$ is not zero, one has to compute $S^-_{t-i+s|t}$. By definition, $S^-_{t+i|t} = S^-_{t+i}$ for $i \leq 0$. However, when $i>1$ $S^-_{t+i|t}$ depends on the choice of the distribution of z_t. When the density is symmetric, the probability that ε_{t+i} will be negative is $S^-_{t+i|t} = 0.5$. On the other hand if the underlying error distribution is not symmetric the probability that ε_{t+i} will be negative will depend on the ratio of probability masses above and below the mode.[33]

Finally, the *h*-step-ahead forecast of the APARCH and the EGARCH models are obtained in a similar manner.[34]

Whereas forecasting the future conditional volatility from GARCH models is fairly straightforward, evaluating the forecasts is a more challenging task. In this paper, the GARCH models have been estimated using a sample of *n*-100, where *n* is the sample size. The one hundred excluded observations from the estimation process in each of the two sub-samples are held back for evaluation of the *s*-step-ahead forecasts.

To evaluate the performance of the different models used in forecasting the conditional variance, four widely used statistical criteria are measured:

- Mean Squared Prediction Error (MSPE);
- Adjusted Mean Absolute Percentage Error (AMAPE);
- Theil Inequality Coefficient (TIC);
- Mincer and Zarnowitz R Squared (RS);

The MSPE is:

$$MSPE = \frac{1}{s} \sum_{t=n}^{n+s-1} \left(h^2_t - \sigma^2_t \right)^2 \tag{22}$$

where, *s* is the number of steps ahead, *n* is the sample size, h^2 is the forecasted variance and σ^2 is the ex-post "actual" variance.

The AMAPE is given by:

$$AMAPE = \frac{1}{s+1} \sum_{t=n}^{n+s} \left| \frac{h^2_t - \sigma^2_t}{h^2_t + \sigma^2_t} \right| \tag{23}$$

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33 See Laurent and Peters (2002).

The Theil inequality coefficient is a scaled measure that always lies between zero and one, where zero indicates a perfect fit.

$$TIC = \frac{\sqrt{\frac{1}{s+1}\sum_{t=n}^{n+s}(h_t^2 - \sigma_t^2)^2}}{\sqrt{\frac{1}{s+1}\sum_{t=n}^{n+s}(h_t^2)^2}\sqrt{\frac{1}{s+1}\sum_{t=n}^{n+s}(\sigma_t^2)^2}} \quad (24)$$

Finally, one of the most popular measures to check the forecasting performance of GARCH type models is the Mincer-Zarnowitz regression:

$$\sigma_t^2 = \alpha + \beta h_t^2 + u_t \quad (25)$$

If the conditional variance is correctly specified (and the parameters are known) and $E(h_t^2) = \sigma_t^2$, it follows that α =0 and β =1. The R^2 is measured as a degree of predictability of the GARCH-type model used.

However, a major problem always arises when attempting to evaluate the forecasts of a conditional variance, as σ_t^2 is never observed. To make these forecast evaluation criteria operational, σ_t^2 is replaced by the squared daily returns as the "actual" volatility.

In their econometric text Franses and Van Dijk (1998) observe that, "most of the time, GARCH models provide seemingly poor volatility forecasts, and they explain only very little of the variability of asset returns" (p.195). In other words, the first three evaluation criteria are usually very high, whereas the R^2 of the fourth was never found to exceed five percent. Anderson and Bollerslev (1997) attributed the problem to the improperness of the aforementioned proxy measure. They propose looking at squared returns of higher frequency data with intra-day intervals as low as every five minutes. Because no such data is available for the ESE, the "realized" volatility is assessed through another measure. Based on the recommendations of Prof. Blake LeBaron, a high-low proxy measure is constructed:

$$\sigma_t^2 = \left[\frac{high_t - low_t}{\frac{1}{2}(high_t + low_t)}\right] \quad (26)$$

where, $high_t$ is the highest price at time *t* and low_t is the lowest price.

Unfortunately, high-low data is only available for the studied indices from the year 1997. This means that the forecasts for the first sub-sample will have to be evaluated using the traditional method of squared daily returns. The second sub-sample will use both methods: squared daily returns and equation (26).

The forecasting ability for both sub-samples are reported by ranking both the models, as well as the different densities on a scale from *1……n* (depending on convergence). Table 22 compares the models based on the different specifications. By contrast, Table 23 provides a comparison between the different distributions for both indices in the first sub-sample. The second sub-sample specification and density comparisons evaluated, based on squared daily returns, are shown in Tables 24 and 25, respectively, whereas comparisons based on the high-low volatility index are found in Tables 26 and 27.

When looking at the results from the first sub-sample, the following can be deduced:

34 See Franses and Van Dijk (1998) for derivation and closed form solutions of s-step-ahead forecasts of a variety of asymmetric GARCH models.

- The comparison between the models found in Table 22 strongly supports the use of a simple, traditional GARCH model over the more parameterized asymmetric GJR for HFI. This result complements the in-sample evaluation that was conducted on the estimations. For EFGI the results are mixed. Indeed, when the normal distribution is used, GARCH outperforms GJR, while the exact opposite occurs when the density is a student-*t*;
- The comparison between densities found in Table 23 very strongly supports the use of the normal distribution for both indices. This contradicts what was earlier observed when the estimated models were evaluated. Finally, the fact that the skewed student-*t* distribution performs the most poorly affirms that an asymmetric density should not be considered;
- To understand how close the forecasts are to the squared daily returns in the first sub-sample, one can look at the R squared of equation (25). In particular, the RS is higher when using a simple GARCH. For example, when using a normal distribution, its value is 0.0434 with GARCH versus 0.0407 with GJR for HFI and 0.0646 versus 0.00479 for EFGI[35].

For the second sub-sample, we can conclude the following:

- The comparison between models found in Table 24 strongly supports the use of the APARCH model over the more parsimonious asymmetric GJR and the simple GARCH for the HFI. For EFGI, the results are again mixed. When the normal GED and skewed student-*t* distributions are used, APARCH outperforms all other models; when student-*t* density is employed GARCH, becomes the favorite;
- The comparison between densities found in Table 25 once again strongly supports the use of the normal distribution for both indices. This contradicts what was earlier observed when the estimated models were evaluated;
- The R squared for the regressions that were run on equation (25) for the second sub-sample are still below five percent. This result is similar to those found in other studies. For example Blair, Poon and Taylor (2000) obtained a RS of 0.423 when they forecasted the S&P 100 index using a GJR model and Jorion (1996) reported a RS of 0.024 when he studied daily DM-USD returns.

Finally, when the second sub-sample was evaluated with the high-low proxy in equation (26), disappointing and widely different results were found. These results include:

- The comparison between the models found in Table 26 did not provide us with very clear-cut results. When the normal and skewed student-t distributions are used, GJR outperforms all other models, and then when student-*t* and GED densities are employed APARCH becomes the favorite. One exception to this order, again, occurs for the EFGI series, that is, when GED is utilized GARCH performs the best. These results, as conflicted as they are, do in fact support both the specification tests and in-sample results, earlier reported in this paper;
- The comparison between densities, found in Table 27, disappointingly give very conflicting results. The normal distribution outperforms the rest when GARCH is used, whereas GED becomes the best when GJR is utilized. Finally, when APARCH is used, both the normal and GED perform equally well;
- Even though the high-low proxy evaluation results did not add much information to what was previously observed, we think it has added to the literature in another area. The RS for the regressions that were run on equation (25) have increased significantly; it ranges from 0.0856 - 0.1567. This finding denotes an improvement compared to previous studies using squared daily returns as the "actual" volatility.

7. Conclusion

This paper has presented results from an empirical investigation of two equity return series from the Egyptian Stock Exchange. The study compared varying GARCH-type models with different

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35 Only rankings for the RS for all regressions are reported here due to space considerations.

underlying distributional assumptions for the innovations in an effort to understand the data generation process of the series. The comparison focused on two different aspects, in-sample estimates and out-of-sample forecasts, in order to determine the "best" fitted model. Moreover, the time series was 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 series division and its analysis separately are perfectly timed given the ongoing debate on whether to retain or remove the symmetric price limit bands.

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.

Ex-post forecasting evaluations, when using squared returns, do not enhance the estimation results and leave us with contradictory results. For the first sub-sample, the HFI series demonstrates that the simple GARCH performs the best, whereas the EFGI series gives us conflicting conclusions. Indeed, when the normal distribution is used, GARCH outperforms GJR, while the exact opposite occurs when the density is a student-t. Furthermore, the normal distribution seems to always outperform the student-*t*. Similar conclusions were drawn from the forecasts of the second sub-sample. The APARCH model was favored over the more parsimonious asymmetric GJR and the simple GARCH for the HFI. As for EFGI the results were again mixed. When the normal GED and skewed student-*t* distributions were used, APARCH outperformed all other models, and then when student-*t* density was employed GARCH became the favorite. Even though using the high-low proxy for the "actual" volatility did not strengthen the in-sample density comparison results, it was consistent with both the in-sample and return squared forecasts in suggesting that asymmetry in GARCH models is necessary for the series studied. Furthermore, it showed that studying high-low ranges could be a very promising area of research, which can improve forecasting results.

It was apparent that these differences were depicted when the two sub-samples were examined, indicating significant changes in the time varying volatility process. A series of essential questions arise and should be addressed here: For one, if the ESE were to abolish price limits, would the volatility generation process be similar to the first sub-sample? Certainly not. The results from the first sub-sample should be regarded with extreme caution as a result of the trading frictions and market inefficiencies associated with the market at the time[36]. Also, if the limits were to stay, would the models tested here work for individual securities in the same way that they work for the indices? When price limits are imposed, indices are usually not affected by them unless all the constituting stocks move in tandem and hit the limit. Thus, to fully capture the dynamics of individuals stocks (traded in a limit governed market), limit censored GARCH models should be used[37].

Several directions and extensions could emerge from this study. First, previously mentioned studies could be re-examined using our high-low "actual" volatility proxy to see its validity across the board[38]. Second, based on the recommendations of Bollerslev, Chou, and Kroner (1992), " a comparison of the efficiency of ML, QML, and GMM estimates using different instrument sets would be interesting…" (p. 9). Finally, the ARCH (*q)* and GARCH(*p)* parameters of almost all the models that were estimated when added were very close to unity. This indicates that introducing models with persistent shocks incorporated into them (like IGARCH, FIGARCH and FIAGARCH) might provide superior results.

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36 For more information on the subject see Mecagni and Shawki (1999).

37 This part of the literature is growing and is mostly studies U.S. futures markets. (see Chapter 5 in this thesis)

38 Other methods could not be conducted on the ESE due to data limitations.

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Figure 1: EFGI and HFI Daily Closing Prices January 3, 1993 to March 8 2001

Figure 2: EFGI Returns, January 3, 1993 to March 8 2001

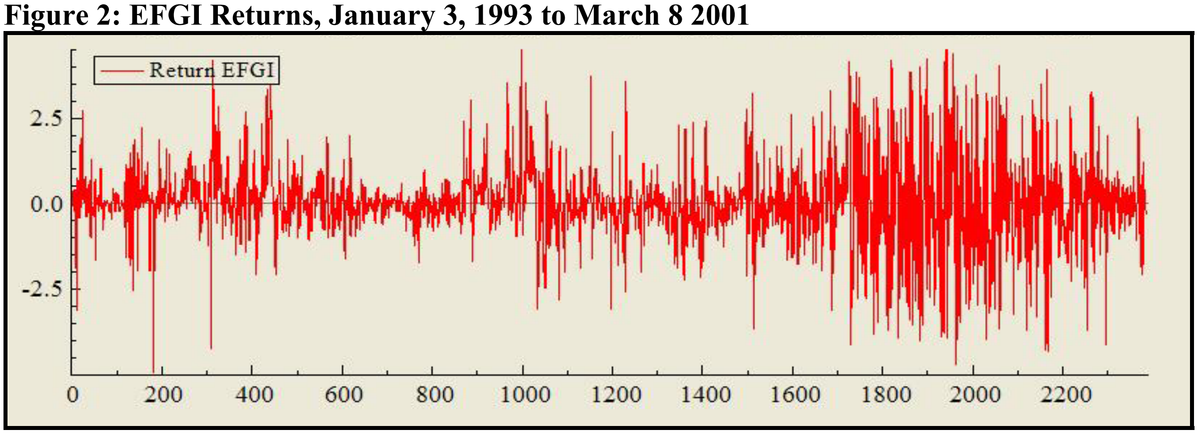

Figure 3: HFI Returns, January 3, 1993 to March 8 2001

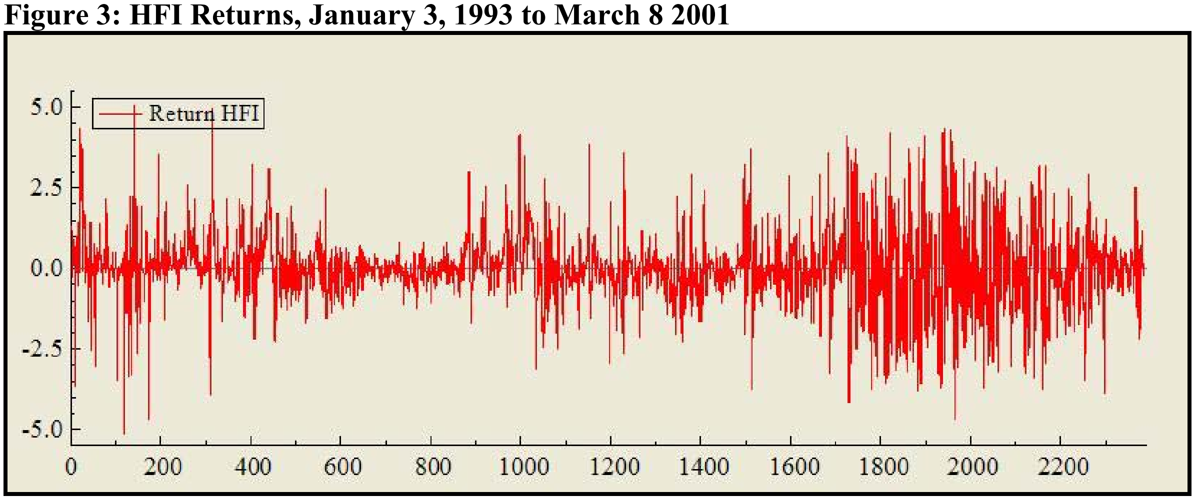

Table 1: Descriptive Statistics for Sub-Sample 1

Descriptive Statistics	HFI	EFGI
Mean (%)	0.1717	0.1760
Standard Error	0.0292	0.0254
Median (%)	0.0527	0.0707
Standard Deviation (%)	0.9321	0.8107
Variance	0.0087	0.0066
Kurtosis	9.2774	9.2799
Skewness	0.4690	0.7587
Jarque-Berra Normality Test	1706.634	1768.753
Augmented Dickey-Fuller Unit Root Test	-10.6552	-10.368
Range	0.1021	0.0941
Minimum	-5.1527	-4.9213
Maximum	5.0565	4.4893
Sample Size	1017	1017

Notes: This table lists the summary statistics for the two ESE indices studied in this paper, HFI and EFGI. The period investigated is from January 3, 1993 to January 31, 1997.

Table 2: Descriptive Statistics for Sub-Sample 2

Descriptive Statistics	HFI	EFGI
Mean (%)	-0.0701	-0.0735
Standard Error	0.0421	0.0442
Median (%)	-0.0937	-0.0960
Standard Deviation (%)	1.3807	1.4493
Variance	0.0191	0.0210
Kurtosis	3.9512	3.9083
Skewness	0.2019	0.1442
Jarque-Berra Normality Test	422.352	401.385
Augmented Dickey-Fuller Unit Root Test	-12.6053	-12.8503
Range	0.0902	0.0918
Minimum	-4.6796	-4.6910
Maximum	4.3417	4.4971
Sample Size	1219	1219

Notes: This table lists the summary statistics for the two ESE indices studied in this paper, HFI and EFGI. The period investigated is from February 2, 1997 to December 31, 2001.

Table 3: Results from Tests of Autocorrelation for Sub-Sample 1

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)
HFI	0.005	0.039	0.172
EFGI	0.003	0.018	0.092

Notes: This table reports results from tests performed to specify the conditional mean equation. Column two gives p-values for the Richardson and Smith's (1994) test for autocorrelation (15), calculated on the demeaned returns. Column three reports p-values for the same statistic, but calculated on estimated residuals from an AR(1) model. Finally, column four reports p-values on estimated residuals from an AR(2) model. All statistics are calculated on10autocorrelations. The period investigated is from January 3, 1993 to January 31, 1997.

Table 3': Results from Tests of Autocorrelation for Sub-Sample 2

Index	RS(10) on rt (p-value)	RS(10) on εt from AR(1) (p-value)	RS(10) on εt from AR(2) (p-value)
HFI	0.041	0.365	-----
EFGI	0.033	0.296	-----

Notes: This table reports results from tests performed to specify the conditional mean equation. Column two gives p-values for the Richardson and Smith's (1994) test for autocorrelation (15), calculated on the demeaned returns. Column three reports p-values for the same statistic, but calculated on estimated residuals from an AR(1) model. Finally, column four reports p-values on estimated residuals from an AR(2) model. All statistics are calculated on10autocorrelations. The period investigated is from February 2, 1997 to December 31, 2001.

Table 4: Results from Tests of ARCH for Sub-Sample 1

Index	No ARCH (2)	No ARCH (5)	No ARCH (10)	$\kappa(\varepsilon)$	$s(\varepsilon)$
HFI	46.866	23.634	12.890	10.009	0.187
	(0.000)	(0.000)	(0.000)		
EFGI	59.026	27.540	14.546	9.3512	0.171
	(0.000)	(0.000)	(0.000)		

Notes: This table reports results from Engle's (1982) test of no ARCH, calculated on different lags. Column two reports test on two squared residuals. Column three gives test results on five squared residuals, whereas column four looks at10squared residuals. Column five reports the coefficient of excess kurtosis calculated on estimated residuals. Finally, column six reports skewness of the estimated residuals. P-values are given in parenthesis. The period investigated is from January 3, 1993 to January 31, 1997.

Table 4': Results from Tests of ARCH for Sub-Sample 2

Index	No ARCH (2)	No ARCH (5)	No ARCH (10)	$\kappa(\varepsilon)$	$s(\varepsilon)$
HFI	135.770	70.150	37.609	4.919	0.253
	(0.000)	(0.000)	(0.000)		
EFGI	158.290	75.545	40.125	4.008	0.203
	(0.000)	(0.000)	(0.000)		

Notes: This table reports results from Engle's (1982) test of no ARCH, calculated on different lags. Column two reports test on two squared residuals. Column three gives test results on five squared residuals, whereas column four looks at10squared residuals. Column five reports the coefficient of excess kurtosis calculated on estimated residuals. Finally, column six reports skewness of the estimated residuals. P-values are given in parenthesis. The period investigated is from February 2, 1997 to December 31, 2001.

Table 5: AR(2)-GARCH (1,1) Estimation Results for Sub-Sample

	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)

Notes: This table reports results from AR(2)-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, with (bold) denoting significance at the 5% level. The period investigated is from January 3, 1993 to September 10, 1996.

Table 6: AR(2)-GJR (1,1) estimation results for sub-sample 1

	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)

Notes: This table reports results from AR(2)-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, with (bold) denoting significance at the 5% level. Asymptotic heteroskedasticity-consistent standard errors are given in parentheses. The period investigated is from January 3, 1993 to September 10, 1996.

Table 7: Post Estimation Statistics for Sub-Sample 1 Using a Normal Distribution

	HFI		EFGI	
	GARCH	**GJR**		**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]

Notes: Tables 7-9 compare post estimation statistics across models for the specifications that converged with the first sub-sample series. AIC, BIC are the Akaike and Swartz information criteria. LL, is the log likelihood value. Q(20) and Q2(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 Sept 10, 1996.

Table 8: 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 9: Post Estimation Statistics for sub-sample 1 using a Skewed-t Distribution

	HFI		EFGI	
	GARCH	**GJR**	**GJR**	**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]

Table 10: 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]

Notes: Table 10-11 compare post estimation statistics across distributions for the specifications that converged with the first sub-sample series. AIC, BIC are the Akaike and Swartz information criteria. LL, is the log likelihood value. Q(20) and Q2(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 Sept 10, 1996.

Table 11: 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
$Q^2(20)$	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]

Table 12: 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	-0.0784	-0.0712	-0.0495	-0.0505	-0.0720	-0.0671	-0.0529
	(0.0343)	(0.0314)	(0.0325)	(0.0344)	(0.0339)	(0.0317)	(0.0328)	(0.0342)
φ_1	0.2974	0.3037	0.02965	0.3120	0.2736	0.2767	0.2754	0.2812
	(0.0315)	**(0.0312)**	**(0.0307)**	**(0.0313)**	**(0.0310)**	**(0.0311)**	**(0.0318)**	**(0.0311)**
γ_1	0.0585	0.0332	0.0442	0.0337	0.0532	0.0351	0.0435	0.0353
	(0.0129)	(0.1060)	(0.0125)	(0.1067)	(0.0122)	(0.0109)	(0.0122)	(0.0110)
α_1	0.3543	0.3810	0.3700	0.3687	0.3409	0.3564	0.3488	0.3467
	(0.0497)	**(0.0583)**	**(0.0577)**	**(0.0577)**	**(0.0479)**	**(0.0544)**	**(0.0539)**	**(0.0542)**
β_1	0.6575	0.6725	0.6646	0.6812	0.6715	0.6827	0.6773	0.6895
	(0.0368)	**(0.0384)**	**(0.0403)**	**(0.0387)**	**(0.0366)**	**(0.0386)**	**(0.0398)**	**(0.0393)**
υ		7.7052	1.4717	7.8586		9.8063	1.5809	9.9566
		(1.6180)	**(0.0846)**	**(1.7111)**		**(2.5201)**	**(0.0919)**	**(2.6137)**
ξ				0.1050				0.0744
				(0.0448)				(0.0449)

Notes: 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, with (bold) denoting significance at the 5% level. The period investigated is from February 2, 1997 to March 8, 2001.

Table 13: 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	-0.1066	-0.0974	-0.0783	-0.0754	-0.0965	-0.0899	-0.0776
	(0.0360)	(0.0325)	(0.0328)	(0.0351)	(0.0357)	(0.0332)	(0.0343)	(0.0353)
φ_1	0.2931	0.2981	0.2911	0.3013	0.2702	0.2739	0.2727	0.2750
	(0.0314)	**(0.0311)**	**(0.0289)**	**(0.0311)**	**(0.0310)**	**(0.0310)**	**(0.0320)**	**(0.0310)**
γ_1	0.0559	0.0315	0.0418	0.0311	0.0512	0.0336	0.0416	0.0335
	(0.0126)	(0.0102)	(0.0121)	(0.0101)	(0.0120)	(0.0106)	(0.0119)	(0.0106)
α_1	0.2921	0.2902	0.2900	0.2804	0.2863	0.2871	0.2847	0.2790
	(0.0476)	**(0.0538)**	**(0.0535)**	**(0.0527)**	**(0.0476)**	**(0.0527)**	**(0.0525)**	**(0.0519)**
β_1	0.6580	0.6761	0.6664	0.6838	0.6751	0.6868	0.6816	0.6923
	(0.0363)	**(0.0378)**	**(0.0396)**	**(0.0378)**	**(0.0360)**	**(0.0379)**	**(0.0391)**	**(0.0384)**
ω_1	0.1348	0.1876	0.1708	0.1798	0.1074	0.1374	0.1267	0.1349
	(0.0587)	**(0.0711)**	**(0.0697)**	**(0.0685)**	**(0.0540)**	**(0.0629)**	**(0.0614)**	**(0.0614)**
υ		7.6317	1.4712	7.8635		9.6895	1.5795	9.9519
		(1.5682)	**(0.0835)**	**(1.6844)**		**(2.4451)**	**(0.0911)**	**(2.5851)**
ξ				0.1032				0.0747
				(0.0448)				(0.0447)

Notes: 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, with (bold) denoting significance at the 5% level. The period investigated is from February 2, 1997 to March 8, 2001.

Table 14: 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	-0.1057	-0.0955	-0.0752	-0.0734	-0.0965	-0.0893	-0.0772
	(0.0378)	(0.0326)	(0.0345)	(0.0366)	(0.0360)	(0.0331)	(0.0345)	(0.0354)
φ_1	0.3007	0.3005	0.2960	0.3042	0.2706	0.2739	0.2731	0.2751
	(0.0321)	**(0.0313)**	**(0.0317)**	**(0.0315)**	**(0.0312)**	**(0.0310)**	**(0.0321)**	**(0.0310)**
γ_1	0.0654	0.0356	0.0491	0.0361	0.0554	0.0333	0.0440	0.0342
	(0.0142)	(0.0124)	(0.0144)	(0.0122)	(0.0136)	(0.0122)	(0.0137)	(0.0122)
α_1	0.3328	0.3620	0.3493	0.3446	0.3275	0.3536	0.3385	0.3408
	(0.0443)	**(0.0572)**	**(0.0535)**	**(0.0551)**	**(0.0461)**	**(0.0573)**	**(0.0537)**	**(0.0560)**
β_1	0.6870	0.6939	0.6908	0.7062	0.6915	0.6852	0.6918	0.6959
	(0.0359)	**(0.0433)**	**(0.0417)**	**(0.0427)**	**(0.0403)**	**(0.0487)**	**(0.0460)**	**(0.0485)**
τ_1	0.0978	0.1267	0.1188	0.1256	0.0804	0.0973	0.0926	0.0985
	(0.0441)	**(0.0466)**	**(0.0482)**	**(0.0477)**	**(0.0411)**	**(0.0428)**	**(0.0444)**	**(0.0434)**
δ	1.4600	1.7215	1.5785	1.6533	1.7186	2.0253	1.8313	1.9451
	(0.2856)	**(0.3706)**	**(0.3430)**	**(0.3629)**	**(0.3670)**	**(0.4770)**	**(0.4299)**	**(0.4635)**
υ		7.7057	1.4782	7.9737		9.6814	1.5815	9.9763
		(1.6078)	**(0.0845)**	**(1.7466)**		**(2.4453)**	**(0.0916)**	**(2.6088)**
ξ				0.1063				0.0752
				(0.0450)				**(0.0449)**

Notes: 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, with (bold) denoting significance at the 5% level. The period investigated is from February 2, 1997 to March 8, 2001.

Table 15: Post Estimation Statistics for Sub-Sample 2 Using a Normal Distribution

	HFI			EFGI		
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
AAa	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]

Notes: Tables 15-18 compare post estimation statistics across models for the specifications that converged with the first sub-sample series. AIC, BIC are the Akaike and Swartz information criteria. LL, is the log likelihood value. Q(20) and Q2(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 March 8, 2001.

Table 16: 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 17: 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]	[0.0229]	[0.0287]

Table 18: 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
Q2(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]

Table 19: 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]

Notes: Table 19-21 compare post estimation statistics across distributions for the specifications that converged with the first sub-sample series. AIC, BIC are the Akaike and Swartz information criteria. LL, is the log likelihood value. Q(20) and Q2(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 March 8, 2001.

Table 20: 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 21: 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]

Table 22: Forecasts Performance-Model Comparison for Sub-Sample 1

	HFI		EFGI	
	Normal			
	GARCH	**GJR**	**GARCH**	**GJR**
MSPE	1	2	1	2
AMAPE	1	2	2	1
TIC	1	2	1	2
RS	1	2	1	2
Total	4	8	5	7
	Student-t			
	GARCH	**GJR**	**GARCH**	**GJR**
MSPE	1	2	2	1
AMAPE	1	2	2	1
TIC	2	1	2	1
RS	1	2	1	2
Total	5	7	7	5
	Skewed-t			
	GARCH	**GJR**	**GARCH**	**GJR**
MSPE	1	2	1	2
AMAPE	2	1	2	1
TIC	2	1	2	1
RS	1	2	1	2
Total	6	6	6	6

Notes: This table compares post estimation forecasts across models for the specifications that converged with the first sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the squared returns.

Table 23: Forecasts Performance-Distribution Comparison for Sub-Sample 1

	HFI					
		GARCH			**GJR**	
	Normal	**Student-t**	**Skewed-t**	**Normal**	**Student-t**	**Skewed-t**
MSPE	1	2	3	1	2	3
AMAPE	1	2	3	1	2	3
TIC	1	2	3	1	2	3
RS	1	2	3	1	2	3
Total	4	8	12	4	8	12
	EFGI					
		GARCH			**GJR**	
MSPE	1	2	3	1	2	3
AMAPE	1	2	3	1	2	3
TIC	1	2	3	1	2	3
RS	1	2	3	1	2	3
Total	4	8	12	4	8	12

Notes: This table compares post estimation forecasts across distributions for the specifications that converged with the first sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the squared returns.

Table 24: Forecasts performance-model comparison for sub-sample 2

	HFI			EFGI		
			Normal			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	2	3	1
AMAPE	2	3	1	2	3	1
TIC	2	3	1	2	3	1
RS	3	2	1	2	3	1
Total	9	11	4	8	12	4
			Student-t			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	1	2	3
AMAPE	2	3	1	1	2	3
TIC	2	3	1	1	2	3
RS	2	3	1	3	1	2
Total	8	12	4	6	7	11
			GED			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	2	3	1
AMAPE	2	3	1	2	3	1
TIC	3	2	1	2	3	1
RS	3	2	1	3	2	1
Total	10	10	4	9	11	4
			Skewed-t			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	3	2	1
AMAPE	3	2	1	3	2	1
TIC	3	2	1	2	3	1
RS	3	2	1	2	3	1
Total	11	9	4	10	10	4

Notes: This table compares post estimation forecasts across models for the specifications that converged with the second sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the squared returns.

Table 25. Forecasts performance-distribution comparison for sub-sample 2

						HFI						
		GARCH				GJR				APARCH		
	Norm	St	GED	Sk	Norm	St	GED	Sk	Norm	St	GED	Sk
MSPE	1	4	2	3	1	4	2	3	1	3	2	4
AMAPE	1	4	2	3	1	4	2	3	1	3	2	4
TIC	1	4	2	3	1	4	2	3	1	4	2	3
RS	1	3	2	4	1	4	2	3	1	3	2	4
Total	4	15	8	13	4	16	8	12	4	13	8	15
						EFGI						
		GARCH				GJR				APARCH		
	Norm	St	GED	Sk	Norm	St	GED	Sk	Norm	St	GED	Sk
MSPE	1	4	2	3	1	4	2	3	1	4	2	3
AMAPE	1	4	2	3	1	4	2	3	1	4	2	3
TIC	1	4	2	3	1	4	2	3	1	4	2	3
RS	1	3	2	4	1	4	2	3	1	4	2	3
Total	4	15	8	13	4	16	8	12	4	16	8	12

Notes: This table compares post estimation forecasts across distributions for the specifications that converged with the second sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the squared returns.

Table 26: Forecasts Performance-Model Comparison for Sub-Sample 2

	HFI			EFGI		
			Normal			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	3	1	2	3	2	1
AMAPE	3	1	2	3	1	2
TIC	3	1	2	3	1	2
RS	1	2	3	1	2	3
Total	10	5	9	10	6	8
			Student-t			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	1	3	2
AMAPE	2	3	1	2	3	1
TIC	2	3	1	2	3	1
RS	3	2	1	3	2	1
Total	9	11	4	8	11	5
			GED			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	2	3	1	1	3	1
AMAPE	2	3	1	1	3	2
TIC	1	3	2	1	3	2
RS	3	2	1	1	2	3
Total	8	11	5	4	11	8
			Skewed-t			
	GARCH	GJR	APARCH	GARCH	GJR	APARCH
MSPE	3	1	2	3	1	2
AMAPE	3	1	2	3	1	2
TIC	3	1	2	3	1	2
RS	3	2	1	3	2	1
Total	12	5	7	12	5	7

Notes: This table compares post estimation forecasts across models for the specifications that converged with the second sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the High-Low proxy in (26).

Table 27: Forecasts Performance-Distribution Comparison for Sub-Sample 2

						HFI						
	GARCH				GJR				APARCH			
	Norm	St	GED	Sk	Norm	St	GED	Sk	Norm	St	GED	Sk
MSPE	1	3	2	4	1	3	2	4	3	2	1	4
AMAPE	3	3	2	4	3	2	1	4	1	2	3	4
TIC	1	3	2	4	3	2	1	4	1	2	3	4
RS	1	4	2	3	1	4	2	3	2	1	3	4
Total	6	13	8	15	8	11	6	15	7	7	10	16
						EFGI						
	GARCH				GJR				APARCH			
	Norm	St	GED	Sk	Norm	St	GED	Sk	Norm	St	GED	Sk
MSPE	1	3	2	4	2	3	1	4	1	2	3	4
AMAPE	3	4	2	3	3	1	2	4	2	1	3	4
TIC	1	3	2	4	1	4	2	3	1	2	3	4
RS	1	4	2	3	1	4	2	3	1	2	3	4
Total	6	14	8	14	7	12	7	14	5	7	12	16

Notes: This table compares post estimation forecasts across distributions for the specifications that converged with the second sub-sample series. The forecasting abilities are reported by ranking the models on a scale from 1…n (depending on convergence). MSPE is Mean Squared Percentage Error, AMAPE is Adjusted Mean Absolute Error, TIC is the Theil Inequality Coefficient and RS is the R Squared of equation (25). The "actual" volatility proxy used here is the High-Low proxy in (26).

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