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Asymmetric Conditional Volatility on the Romanian Stock Market

- DISSERTATION PAPER-

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ABSTRACT

Recent studies show that a negative shock in stock prices will generate more volatility than a positive shock of similar magnitude. The aim of this paper is to test the hypothesis under which the the conditional variance of stock returns is an asymmetric function of past information. This paper investigates the volatility of the Romanian Stock Market using daily observations from Bucharest Exchange Trading Composite® Index (BET-C) for the period from April 16, 1998 (index launch date) through June 1, 2008 and for a subsample period. Preliminary analysis of the data shows significant departure from normality. Moreover, returns and squared residuals show a significant level of serial correlation which is related to the conditional heteroskedasticity due to the time varying volatility. These results suggest that ARCH and GARCH models can provide good approximation for capturing the characteristics of BET-C. The empirical analysis supports the hypothesis of asymmetric volatility; hence, good and bad news of the same magnitude have different impacts on the volatility level. In order to assess asymmetric volatility we use autoregressive conditional heteroskedasticity specifications known as TARCH and EGARCH. Our results show that the conditional variance is an asymmetric function of past innovations raising proportionately more during market declines, a phenomenon known as the leverage effect.

CONTENTS

I. INTRODUCTION

Two of the most common empirical findings in financial literature are that the distributions of high-frequency asset returns display tails heavier than those of normal distribution and that the squared returns are highly serially correlated. Furthermore, many empirical results indicate that the stock index return presented asymmetric volatility. The findings of Schwert (1990), Nelson (1991), Campbell and Hentschel (1992), Rabemananjara and Zakoian (1993), Engle and Ng (1993), Hentschel (1995), Bekaert and Wu (2000), Wu (2001), and Blair, Poon and Taylor (2002) provided the evidence.

The purpose of my paper is to test whether volatility on the Romanian Stock Market is also asymmetric, in the sense that negative shocks on returns increase the next period's conditional volatility more than positive shocks of equal magnitude.

In order to assess this stylized fact of financial market volatility, I have chosen the series of returns for the Bucharest Exchange Trading Composite Index (BET-C) for the period from April 16, 1998 (index launch date) through June 1, 2008 and a subsample period from November 1, 2004 through June 1, 2008. BET-C is the composite index of BVB market. It is a market capitalization weighted index. BET-C reflects the price movement of all the companies listed on the BVB regulated market, Ist and Iind Category, excepting the SIFs (Financial Investment Companies generated from the romanian privatisation process). The BET-C index is the most comprising index on the Romanian stock market, taking into account the stock price evolution of 55 listed companies[1].

Using the BET-C Index return series, in section IV, I compare the GARCH (1, 1) model with three other volatility models that allow for asymmetry in the impact of news on volatility.

In addition, there is evidence that individual stock also exhibits asymmetric volatility. Black (1976) and Christie (1982) were among the first to document and explain a negative relationship between current individual stock return and future volatility in the US equity markets. The leverage effect is a phrase that describes the asymmetric response of volatility to shocks of differing signs. Black (1976) showed that if the price on day t fell then the volatility on day t + 1 would, on average, be higher than if the price rose by the same amount. Black's

[1] The composition of the index as of July 2008 is available in Figure 1 in Appendix

explanation of this phenomenon stated that a price fall reduces the value of equity and hence increases the debt-to-equity ratio. This increase in leverage raises the riskiness of the firm and an increase in volatility is observed. Christie (1982) tested Black's explanation by looking at the relationship between the asymmetry in equity volatility and the debt-to-equity ratio of firms.

Christie demonstrates that stock price changes and volatility are inversely related, i.e. the elasticity of volatility with respect to the value of equity is negative. He also finds that volatility is an increasing function of financial leverage suggesting that this may be the cause of the negative elasticity of volatility with respect to the value of equity. He found a strong relationship between the leverage effect and the debt-to-equity ratio, but claimed that the debt-to-equity ratio did not fully explain the effect.

If such asymmetries exist in individual stocks returns it is natural to expect that in a cross sectional analysis the size of the asymmetry will be positively related to the degree of financial leverage (i.e, the higher the leverage the more asymmetric the response of volatility to innovations). Otherwise the asymmetric impact of innovations on volatility has to be explained by factors other than the financial leverage.

In Section IV of my paper, I find twelve individual stocks from the Romanian stock market that exhibit asymmetric volatility over the period starting June 1, 2004 to June 1 2008. For each of these companies I calculate four over-the-sample-period mean leverage ratios (two of them based on the book value of equity and the other two on the market value of equity), then employ the cross-section regression method of Koutmos and Saidi (1995) to determine whether the estimated degree of asymmetry, for each stock, is related to some measure of financial leverage.

The rest of the paper is organized as follows: Section II presents a selection of relevant literature on the issues concerning aasymmetry in conditional variance and its determinants. Section III introduces the concepts and models used in the empirical analysis. Section IV describes the data, the actual implementation of the models and discusses the results, while Section V concludes.

II. LITERATURE REVIEW

Recent empirical studies of national stock-index returns have noted several empirical regularities. First, daily stock returns have been found to present autocorrelations. The existence of an AR process has been attributed to nonsynchronous trading (Scholes and Williams, 1977; Lo and MacKinlay, 1990), time-varying short-term expected returns (Fama and French, 1988; Sentana and Wadhwani, 1992), and costs of price adjustment (Amihud and Mendelson, 1987; Damodaran, 1993; Koutmos, 1998).

Second, in multi-country analysis, cross correlations of stock returns have been reported in studies by Hamao et al (1989), Koutmos and Booth (1995), Kim and Rogers (1995), and Chiang (1998). Their findings indicate that national stock returns are significantly correlated and that linkages among international stock markets have grown more interdependent over time. Third, following the approaches by Engle (1982), Bollerslev (1986), French et al (1987), Schwert (1989), Pagan and Schwert (1990), Baillie and DeGennaro (1990), the cumulative evidence indicates that stock volatility exhibits a clustering phenomenon, i.e. large changes tend to be followed by large changes and small changes tend to be followed by small changes. In their review of this market phenomenon, Bollerslev et al (1992) report that the GARCH(1,1) model appears to be sufficient to describe the volatility evolution of stock-return series.

A drawback of standard ARCH-type models is that the estimated coefficients are assumed to be fixed throughout the sample period and fail to take into account the asymmetrical effect between positive and negative shocks to stock returns. This leads to the fourth regularity - an asymmetrical effect is found in studying stock-return series. It has been shown that a negative shock to stock returns will generate greater volatility than will a positive shock of equal magnitude. By extending the research methods proposed by Nelson (1991), Glosten et al (1993), Engle and Ng (1993) and Koutmos (1997, 1998, and 1999) find significant evidence to support the asymmetrical hypothesis of stock-index returns.

More recently, Bekaert and Wu (2000) and Wu (2001) highlight the leverage effect and volatility feedback effect in explaining asymmetrical volatility in response to news and find supportive evidence in Nikkei 225 stocks.

Note that in the specification of the asymmetrical partial-adjustment price model (Amihud and Mendelson, 1987; Damodaran, 1993; Koutmous, 1998), where prices incorporate negative returns faster than positive returns, the news variable is implicitly embedded in the autoregressive process of the mean equation. These models are useful and appropriate if our interest is to focus on examining whether news of negative returns is incorporated into current prices faster than news reflecting positive returns. On the other hand, Bekaert and Wu's model (2000) provides a unified framework to examine asymmetrical volatility in response to news at the firm level and the market level.

The ability to forecast financial market volatility is important for portfolio selection and asset management as well as for the pricing of primary and derivative assets. While most researchers agree that volatility is predictable in many asset markets, they differ on how this volatility predictability should be modeled. In recent years the evidence for predictability has led to a variety of approaches, some of which are theoretically motivated, while others are simply empirical suggestions. The most interesting of these approaches are the "asymmetric" or "leverage" volatility models, in which good news and bad news have different predictability for future volatility. These models are motivated by the empirical work of Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), Nelson (1990), and Schwert (1990). Pagan and Schwert (1990) provide the first systematic comparison of volatility models. This paper builds on their results, focusing on the asymmetric effect of news on volatility.

The importance of a correctly specified volatility model is clear from the range of applications requiring estimates of conditional volatilities. In the valuation of stocks, Merton (1980) shows that the expected market return is related to predictable stock market volatility. French, Schwert, and Stambaugh (1987) and Chou (1988) also find empirical evidence for this relationship. Schwert and Seguin (1990) and Ng, Engle, and Rothschild (1992) show that individual stock return volatility is driven by market volatility, with individual stock return premiums affected by the predictable market volatility. In the valuation of stock options, Hull and White (1987) suggest that stochastic stock return volatility might be the source of some documented pricing biases of the Black-Scholes option-pricing formula. Furthermore, the research of Day and Lewis (1992) shows that implied volatility from the Black-Scholes model cannot capture the entire predictable part of future volatility relative to some GARCH and

EGARCH models. Amin and Ng (1993) show that option valuation under predictable volatility is different from option valuation under unpredictable volatility.

Finally, the predictability of volatility is important in designing optimal dynamic hedging strategies for options and futures (Baillie and Myers (1991) and Engle). The predictability of volatility might also affect the results of event studies (for example, Connolly (1989))

There is a long tradition in finance [see, e.g., Cox and Ross (1976)] that models stock return volatility as negatively correlated with stock returns. Influential articles by Black (1976) and Christie (1982) further document and attempt to explain the asymmetric volatility property of individual stock returns in the United States. The explanation put forward in these articles is based on leverage. A drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility. Although, to many, "leverage effects" have become synonymous with asymmetric volatility, the asymmetric nature of the volatility response to return shocks could simply reflect the existence of time-varying risk premiums [Pindyck (1984), French, Schwert, and Stambaugh, (1987), and Campbell and Hentschel (1992)]. If volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline. Hence the causality is different: the leverage hypothesis claims that return shocks lead to changes in condi-tional volatility, whereas the time-varying risk premium theory contends that return shocks are caused by changes in conditional volatility. Which effect is the main determinant of asymmetric volatility re-mains an open question. Studies focusing on the leverage hypothesis, such as Christie (1982) and Schwert (1989), typically conclude that it cannot account for the full volatility responses. Likewise, the time-varying risk premium theory enjoys only partial success. The volatility feedback story relies first of all on the well-documented fact that volatility is persistent. That is, a large realization of news, positive or negative, increases both current and future volatility. The second basic tenet of this theory is that there exists a positive intertemporal relation between expected return and conditional variance. The increased volatility then raises expected returns and lowers current stock prices, dampening volatility in the case of good news and increasing volatility in the case of bad news.

A survey of the existing literature on asymmetric volatility is offered by Bekaert and Wu (2000)[1] :

Study	Volatility measure	Presence of asymmetry	Explanation
Black (1976)	Gross volatility	Stocks, portfolios	Leverage hypothesis
Christie (1982)	Gross volatility	Stocks, portfolios	Leverage hypothesis
French, Schwert and Stambaugh (1987)	Conditional volatility	Index	Time-varying risk premium theory
Schwert (1990)	Conditional volatility	Index	Leverage hypothesis
Nelson (1991)	Conditional volatility	Index	Unspecified
Campbell and Hentschel (1992)	Conditional volatility	Index	Time-varying risk premium theory
Cheung and Ng (1992)	Conditional volatility	Stocks	Unspecified
Engle and Ng (1993)	Conditional volatility	Index (Japan Topix)	Unspecified
Glosten, Jagannathan and Runkle (1993)	Conditional volatility	Index	Unspecified
Bae and Karolyi (1994)	Conditional volatility	Index	Unspecified
Braun, Nelson and Sunier (1995)	Conditional volatility	Index and stocks	Unspecified
Duffee (1995)	Gross volatility	Stocks	Leverage hypothesis
Ng (1996)	Conditional volatility	Index	Unspecified
Bekaert and Harvey (1997)	Conditional volatility	Index (Emerging Markets)	Unspecified

In recent year, Cheung and Ng (1992), Duffee (1995), Koutmos and Saidi (1995), Kitazawa (2000), and Blair, Poon and Taylor (2002) have also confirmed that the volatility of individual stock exhibits asymmetry. In studying 30 DJIA companies, Koutmos and Saidi (1995) showed that all stock returns exhibit asymmetric volatility in the sense that negative innovations increase volatility more than positive innovations of an equal magnitude with one exception.

[1] This table lists a sample of studies on the relationship between returns and conditional volatility. Conditional volatility studies typically use GARCH models to measure volatility; “gross volatility” typically refers to the standard deviation of daily returns computed over the course of a month. The “unspecified” label in the explanation column means that asymmetry was modeled but the researchers did not specify the exact cause of the asymmetry.

On the average, a negative innovation increases volatility 2.13 times more than a positive innovation. Yoshttsugu Kitazawa (2000) estimated the leverage effect using the EGARCH model for panel data with a large number of stock issues and a small number of daily observations focusing on the Tokyo Stock Exchange. They indicated that the leverage effect is significant in the span from June 22 to 29 in 1998. Blair, Poon and Taylor (2002) estimated the leverage effect of the S&P100 index and all its constituent stocks from an extension of the asymmetric volatility of GJR model. They indicated that the index and the majority of stocks have a greater volatility response to negative returns than to positive returns and the asymmetry is high for the index than for most stocks.

III. METHODOLOGY

1. Models of Predictable Volatility (the GARCH model, the EGARCH model and the TGARCH model)

The first part of my analysis relies on the GARCH model developed by Bollerslev (1986), the Exponential GARCH model introduced by Nelson(1991) and the GJR Threshold GARCH model introduced by Glosten, Jagannathan, and Runkle (1993).

Following Engle and Ng(1993), I also fit to my series of returns a partially non-parametric ARCH model.

Let Y_t be the rate of return of a particular stock or the market portfolio from time t - 1 to time t. Also, let F_{t-1} be the past information set containing the realized values of all relevant variables up to time t - 1. Since investors know the information in F_{t-1} when they make their investment decision at time t - 1, the relevant expected return and volatility to the investors are the conditional expected value of Y_t, given F_{t-1} , and the conditional variance of Y_t, given F_{t-1}. We denote these by m_t and h_t respectively.

That is,

$$m_t = E(y_t / F_{t-1}) \text{ and}$$

$$h_t = Var(y_t / F_{t-1}).$$

Given these definitions, the unexpected return at time t (the shock) is $\varepsilon_t = y_t - m_t$.

Engle (1982) suggests that the conditional variance h_t can be modeled as a function of the lagged ε_t 's. That is, the predictable volatility is dependent on past news. The most detailed model he develops is the pth order autoregressive conditional heteroskedasticity model, the ARCH(p):

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$$

where α_1,..., α_p, and ω to are constant parameters.

The effect of a return shock i periods ago (i < p) on current volatility is governed by the parameter α_i. We would expect that $\alpha_i < \alpha_j$ for i > j. That is, the older the shock, the less effect it has on current volatility. In an ARCH(p) model, an old shock which arrived at the market more than p periods ago has no effect at all on current volatility.

Bollerslev (1986) generalizes the ARCH(p) model to the GARCH(p, q) model, such that :

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}$$

where α_1,..., α_p, β_1,......, β_p, and ω to are constant parameters.

The GARCH model is an infinite order ARCH model. Empirically, the family of GARCH models has been very successful. Of these models, the GARCH (1, 1) is preferred in most cases (survey by Bollerslev et al. (1992)).

The (1,1) in GARCH (1,1) indicates that h_t is based on the most recent observations of ε_t^2, and the most recent estimate of the variance rate. The more general GARCH (p,q) model calculates h_t from the most recent p observations on ε_t^2 and the most recent q estimates of the variance rate. In the GARCH(1, 1) model, the effect of a return shock on current volatility declines geometrically over time. Setting $\omega = \gamma * V_L$, where V_L is the long-run average variance rate and , γ is the weight we apply to it, the GARCH(1,1) model can be written as:

$$h_t = \gamma * V_L + \alpha * \varepsilon_{t-1}^2 + \beta * h_{t-1},$$

Once ω, α and β have been estimated, we can calculate γ as $(1- \alpha - \beta)$. The long-term variance V_L can then be calculated as ω / γ. For a stable GARCH(1,1) process, we require $\alpha + \beta < 1$. Otherwise the weight applied to the long-term variance is negative. The ARCH (or α) effect indicates the short run persistence of shocks, while the GARCH (or β) effect indicates the contribution of shocks to long run persistence (namely, $\alpha + \beta$).

Substituting $\gamma = 1 - \alpha - \beta$ in the above equation, the variance rate estimated at the end of day n-1 for day n is :

$$h_t = (1-\alpha-\beta)V_L + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

$$h_t - V_L = \alpha(\varepsilon_{t-1}^2 - V_L) + \beta(h_{t-1} - V_L)$$

On day (n+k) in the future, we have :

$$h_{t+k} - V_L = \alpha(\varepsilon_{t+k-1}^2 - V_L) + \beta(h_{t+k-1} - V_L)$$

The expected value of ε_{n+k-1}^2 is h_{n+k-1}. Hence :

$$E(h_{t+k} - V_L) = (\alpha+\beta)E(h_{t+k-1} - V_L)$$

, where E denotes the expected value. Using this equation repeatedly yields :

$$E(h_{t+k}) = V_L + (\alpha+\beta)^k (h_t - V_L)$$

This equation forecasts the volatility on day (n+k) using the information available at the end of day n-1. When $\alpha + \beta < 1$, the final term in the equation becomes progressively smaller as k increases. Our forecast of the future variance rate tends towards V_L as we look further and further ahead. This analysis emphasizes the point that we must have $\alpha + \beta < 1$ for a stable GARCH(1,1) process. When $\alpha + \beta > 1$, the weight given to the long-term variance is negative and the process is "mean fleeing" rather than "mean reverting".

Despite the apparent success of these simple parameterizations, the ARCH and GARCH models cannot capture some important features of the data. The most interesting feature not addressed by these models is the leverage or asymmetric effect.

A return $r_{i,t}$ displays asymmetric volatility if :

$$\text{var}\,[r_{i,\,t+1} / I_t,\ \varepsilon_{i,\,t} < 0] - \sigma^2_{i,t} > \text{var}\,[r_{i,\,t+1} / I_t,\ \varepsilon_{i,\,t} > 0] - \sigma^2_{i,t}$$

, where $r_{i,t}$ is the return of the stock of firm i, and :

$$r_{i,\,t+1} = E(r_{i,\,t+1} / I_t) + \varepsilon_{i,\,t+1}$$

$$\sigma^2_{i,t+1} = \text{var}(r_{i,\,t+1} / I_t)$$

In other words, negative unanticipated returns result in an upward revision of the conditional volatility, whereas positive unanticipated returns result in a smaller upward or even a downward revision of the conditional volatility.

This effect suggests that a symmetry constraint on the conditional variance function in past ε_t 's is inappropriate.

Many volatility models have been proposed to incorporate the leverage effect. The two most widely used are the EGARCH (Nelson (1991)) and the GJR (Glosten, Jagannathan and Runkle (1993)) models. The conditional variances in both models depend upon both the signs and magnitudes of the returns, and hence are asymmetric in their response to positive and negative returns.

Nelson proposed the EGARCH model to overcome some weaknesses of the GARCH mode in handling financial time series. The EGARCH model, unlike the linear GARCH models, uses logged conditional variance to relax the positiveness constraint of model coefficients and easily interprets the persistence of shocks as conditional variance. Therefore, it has been extensively cited in literature as the asymmetric GARCH model.

Exponential GARCH (p,q) :

$$\log(h_t) = \omega + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}}$$

, where *r* is the asymmetric level.

Exponential GARCH (1,1) :

$$\log(h_t) = \omega + \beta \cdot \log(h_{t-1}) + \gamma \cdot \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi} \right]$$

, where ω, β, γ, and α are constant parameters.

Nelson's original specification for the log conditional variance is a restricted version of:

$$\log(h_t) = \omega + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} - E\left(\frac{\varepsilon_{t-i}}{h_{t-i}} \right) \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}}$$

, which differs slightly from the specification above. Estimating this model will yield identical estimates except for the intercept term ω , which will differ in a manner that depends upon the distributional assumption and the asymmetry order p . For example, in a p =1 model with a normal distribution, the difference will be $\alpha_{1*}\sqrt{2/\pi}$.

The EGARCH (1,1) model is asymmetric because the level of $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ is included with a coefficient γ. Since this coefficient is typically negative, positive return shocks generate less volatility then negative return shocks, all else being equal.

The EGARCH model differs from the standard GARCH model in three main respects:

1. The EGARCH model allows good news and bad news to have a different impact on volatility, while the standard GARCH model does not

2. The EGARCH model allows big news to have a greater impact on volatility than the standard GARCH model.

3. The EGARCH model imposes no constraints on the parameters to ensure non-negativity of the conditional variance.

GJR (Threshold) GARCH :

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^- \varepsilon_{t-1}^2, \text{ where } S_t^- = 1 \text{ if } \varepsilon_t < 0,\ S_t^- = 0 \text{ otherwise}$$

The variable S^-_{t-1} is a dummy variable equal to one if $\varepsilon_{t-1} > 0$, and equal to zero otherwise, so in this case there are two types of shocks. There is a squared return and there is a variable that is the squared return when returns are negative, and zero otherwise. On average, this is half as big as the variance, so it must be doubled implying that the weights are half as big.

In this model, good news, $\varepsilon_{t-1} > 0$, and bad news , $\varepsilon_{t-1} < 0$, have different effects on the conditional variance; good news has an impact of α, while bad news has an impact of α + γ . If γ > 0, bad news increases volatility, and we say that there is a *leverage effect*. If , γ ≠ 0, the news impact is asymmetric.

The ease of interpretation and application has also made the GJR(p,q) model very popular among financial practitioners. The GARCH model is a special case of the TARCH model where the threshold term is set to zero.

A comparison between the GARCH(1, 1) model and the EGARCH(1, 1) suggests an interesting metric by which to analyze the effect of news on conditional heteroskedasticity. Holding constant the information dated t – 2 and earlier, we can examine the implied relation between ε_{t-1} and h_t. Engle calls 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 to current volatility. This curve measures how new information is incorporated into volatility estimates. In the GARCH model, this curve is a quadratic function centered on $\varepsilon_{t-1} = 0$. That is, positive and negative return shocks of the same magnitude produce the same amount of volatility. Also, larger return shocks forecast more volatility at a rate proportional to the square of the size of the return shock. If a negative return shock causes more volatility than a positive return shock of the same size, the GARCH model underpredicts the amount of volatility following bad news and overpredicts the amount of volatility following good news. Furthermore, if large return shocks cause more volatility than a quadratic function allows, then the standard GARCH model underpredicts volatility after a large return shock and overpredicts volatility after a small return shock.

For the EGARCH, it has its minimum at $\varepsilon_{t-1} = 0$, and is exponentially increasing in both directions but with different parameters.
The news impact curve of the GJR model of Glosten, Jagannathan, and Runkle (1990) is centered at $\varepsilon_{t-1} = 0$, but has different slopes for its positive and negative sides.

2. A Partially Non-Parametric ARCH Model

An alternative approach to estimating the news impact curve is to implement a nonparametric procedure which allows the data to reveal the curve directly. Several approaches are available in the literature, including notably, Pagan and Schwert (1990) and Gourieroux and Monfort (1992). Gourieroux and Monfort essentially specify a histogram for the response of volatility to lags of the news which they estimate by maximum likelihood. In their most successful model however, they introduce a GARCH term to capture the long memory aspects.

Partially Non-parametric ARCH :
We divide the range of $\{ \varepsilon_t \}$ into m intervals with break points τ_i. Let m^- be the number of intervals in the range where ε_{t-1} is negative. Also, let m+ be the number of intervals in the range where ε_{t-1} is positive, so that $m = m^+ + m^-$. We denote these boundaries by the numbers $\{ \tau_{-m}, \ldots, \tau_{-1}, \tau_0, \tau_1, \ldots \tau_m \}$. These intervals need not be equal size, nor do we need the same number on each side of τ_0. For convenience and the ability to test symmetry, we select $\tau_0 = 0$. If we define

P_{it} =1, if $\varepsilon_t > \tau_i$

= 0, otherwise, and

N_{it} =1, if $\varepsilon_t < \tau_{-i}$

= 0 otherwise,

then a piecewise linear specification of the heteroskedasticity function is :

$$h_t = \omega + \beta h_{t-1} + \sum_{i=0}^{m^+} \theta_i P_{it-1}(\varepsilon_{t-1} - \tau_i) + \sum_{i=0}^{m^-} \delta_i N_{it-1}(\varepsilon_{t-1} - \tau_{-i})$$

This functional form, which is really a linear spline with knots at the τ_i's, is guaranteed to be continuous. Between 0 and τ_1 the slope is θ_0 while between τ_1 and τ_2 it is $\theta_0 + \theta_1$, and so forth. Above τ_m, the slope is the sum of all the θ 's. If the partial sums at each point are of the same sign, the shape of the curve is monotonic. To obtain better resolution with larger samples, we increase m. This is an example of the method of sieves approach to nonparametric estimation. A larger value of m can be interpreted as a smaller bandwidth, which will give lower bias and higher variance to each point on the curve.

3. Individual Stocks Cross Sectional Regression

In the second part of this paper, I investigate whether the absolute size of the asymmetry for each of the individual stocks in the selected 12 sample is linked to the financial leverage. I adopt the EGARCH (1,1) specification to test for asymmetric volatility in individual stock returns. Given the data for the returns R_t , estimates for the parameter vector $\theta = (\omega , \beta , \gamma, \alpha)$, for each stock are obtained by maximizing the log-likelihood of the returns over the sample period. The general specification for the mean equation is :

$$R_t = \alpha_1 + \beta_1 * R_{t-1} + \varepsilon_t$$

The term $\beta_1 * R_{t-1}$ is used to account for any autocorrelation that may arise due to nonsynchronous trading . I also augment the mean equation with a number of AR terms in the cases where they appear to be significant. While some authors argue that there is no need for more than one AR term, we find that in some cases higher-order AR terms are also significant. Then, following Koutmos and Saidi (1995) I estimate the following cross section regression :

$$|\gamma_i| = a_1 + a_2*(D/E)_i + a_3*(A)_i + u_i \qquad \text{for } i = 1,\ldots\ldots\ldots\ldots,n$$

,where n is number of stocks, $|\gamma_i|$ is the absolute value of the degree of asymmetry discussed earlier, $(D/E)_i$ is some measure of financial leverage, $(A)_i$ is asset size, u_i is an error term and a_1, a_2 and a_3 are coefficients to be estimated. The variable $(A)_i$ is used to account for heteroskedasticity in u_i due to firm size. A positive and statistically significant a_2 coefficient implies that variations in the asymmetric response of volatility to shocks can be attributed to variations in the debt to equity ratio across firms.

I now turn to the description of the data used and the analysis of the empirical findings.

IV Empirical Data and Results

1.Preliminary data analysis

The empirical part of this paper deals with the daily return rates of the Bucharest Exchange Trading Composite Index (BET-C) for the period starting from April 16, 1998 (index launch date) through June 15, 2008 (2533 obs.) and a subsample period from November 1, 2004 through June 1, 2008 (895 obs.). The data were obtained from the Bucharest Stock Exchange website and the databases of two brokerage companies. The series of the daily stock index has been adjusted for dividends and splits.

Daily returns for the index were calculated as the percent logarithmic difference in the daily stock index, i.e., $R_t = 100*(\ln P_t - \ln P_{t-1})$. The series of continuously compounded index returns obtained this way is stationary (the null of a unit root is clearly rejected) for both data samples, as we can see from the ADF test statistics presented in Table 1 and 2. A graphic representation of the two series of data is given in Figures 1 and 2.

My first analysis of the whole range of data available on the index since its launch date proved unsatisfactory in terms of detecting presence of asymmetric volatility. This proved to be because of the beginning period of the index. A quick view of Figure 2 indicates that the period from 1998 to 2004 was atypicall from the point of view of even an emerging market. The index had very low fluctuations for most of this period, staying mainly in the range of 500 points, then rose slowly towards its launch level of 1000 points. Nevertheless, the standard deviation of the return series was 1.544 (see descriptive statistics Table 3), higher even than the standard deviation of the return series sample between 2004-2008 (which is 1.485, as we can see in the descriptive statistics Table 4) , period in which the index level fluctuated between a minimum of 2.400 points and a maximum of 7.400 points.

Since our focus is on the conditional variance, rather than the conditional mean, I concentrate on the unpredictable part of the stock returns, as obtained through a procedure similar to the one in Engle and Ng (1993). The procedure involves an autoregressive regression which removes the predictable part of the return series**.** Engle and Ng regress their series y_t of daily returns of the Japanese Topix Index on a constant and $y_{t-1}, \ldots y_{t-6}$.

Autocorrelations are correlations calculated between the value of a random variable today and its value some days in the past. Predictability may show up as significant autocorrelations in returns and volatility clustering will show up as significant autocorrelations in squared or absolute returns.

From studying the correlogram of the BET-C daily return series, we see that autocorrelation definitely exists, and there is a significant spike at lag 7. (Table 5). The autocorrelation in index return has been attributed to nonsynchronous trading. An explanation for this phenomenon is offered, for example, in Lo and McKinley (1990). Supposing that the returns to stocks *i* and *j* are temporally independent, but *i* trades less frequently than *j*, if news affecting the aggregate stock market arrives near the close of the market on one day, it is more likely that *j*'s end-of-day price will reflect this information than *i*'s simply because *i* may not trade after the news arrives . Of course, *i* will respond to this information eventually but the fact that it responds with a lag induces spurious cross-autocorrelation between the closing prices of *i* and *j*. As a result, a portfolio consisting of securities *i* and *j* will exhibit serial dependence even though the underlying data-generating process was assumed to be temporally independent

So, to resume with our analysis, denoting by y_t the rate of return of the BET-C index from day t-1 to day t, in order to get the unpredictable part of the return series I regressed y_t on a constant and $y_{t-1}, \ldots y_{t-7}$:

$$y_t = c + \alpha_1 * y_{t-1} + \ldots\ldots + \alpha_7 * y_{t-7} + \varepsilon_t.$$

The results from this mean adjustment regression are available in Table 6 and the correlogram of the residuals obtained from this regression is available in Table 7.

From the Ljung-Box test statistic for twelfth-order serial correlation for the levels, we find no significant serial correlation left in the stock returns series after our adjustment procedure. The coefficients of skewness and kurtosis both indicate that the unpredictable stock returns, the ε's, have a distribution which is skewed to the left and flat tailed.

	RESID01
Mean	-7.59E-17
Median	0.019033
Maximum	6.450684
Minimum	-9.288250
Std. Dev.	1.462429
Skewness	-0.493660
Kurtosis	6.814458

Furthermore, the Ljung-box test statistic for twelfth-order serial correlations in the squares strongly suggests the presence of time-varying volatility (see Table 8).

2. The GARCH model, the EGARCH model and the TGARCH model.

Using the unpredictable stock index returns series as the data series, we estimate the standard GARCH(1, 1) model, as well as two other parametric models which are capable of capturing the leverage and size effects : the Exponential-GARCH(1, 1) and the Threshold GARCH (1,1).

In comparing five models that allow for asymmetric impacts of shocks on volatility, Engle and Ng(1993) find these latter two to have the best parameterisation.

In this paper, I fit the above mentioned models model for all data series by maximizing the log-likelihood function for the model, assuming that ε_t is conditionally normally distributed. The rationale for assuming conditional normality is predominantly ease of computation. However, as shown by Bollerslev and Wooldridge (1992), quasi-maximum likelihood estimators using conditional normality of the error terms yield consistent and asymptotically normal parameter estimates as long as the conditional means and variances are correctly specified, even when the errors are not conditionally normal. All my inference is based on robust standard errors from the maximum likelihood estimation, employing the procedures described in Bollerslev and Wooldridge (1992). All the models are implemented using the EViews econometric software.

First we fit the EGARCH(1,1) model to the period of daily index return observations starting April 16, 1998. The result, presented in Table 9, is indicative of the fact that an asymmetric effect is not statistically significant (the coefficient γ corresponding to the $\varepsilon_{t-1}/\sqrt{ht-1}$ term isn't statistically significant when computing with robust standard errors or asymptotically standard errors), so there is no need to further estimate the TGARCH model. The probable explanation for the result I have obtained was presented in the first part of this section, and the conclusion may be that a GARCH specification is better suited for this data series. The estimation output from a GARCH(1,1)[1] model is :

$$h_t = 0.3592 + 0.3827 * \varepsilon_{t-1}^2 + 0.4754 * h_{t-1}$$

As we can see $\alpha + \beta = 0.8581 < 1$, so the process is stable, the weight applied to the long-run average variance rate $\gamma = 0.1419$ and the level of the long-run variance rate is $V_L = 2.5313$. This corresponds to a volatility of 0.0159 or 1.59% per day.

We now move on modelling the conditional volatility of the sample series of daily BET-C index returns, from November 1, 2004 through June 1, 2008.

As mentioned preaviously, the model specification I use for the mean equation is :

$$Y_t = c + Y_{t-1} + \ldots\ldots\ldots\ldots Y_{t-7} + \varepsilon_t ,$$

$$\varepsilon_t = \eta_t * \sqrt{ht} ,$$

where η_t is a sequence of normally, independently and identically distributed random variables with zero mean and unit variance. ($\eta_t \sim N(0,1)$).

The estimation output(see Table 10) from the GARCH(1,1) model is :

$$h_t = 0.3603 + 0.2945 * \varepsilon_{t-1}^2 + 0.5597 * h_{t-1}$$

[1] A GARCH(1,1) specification for this first series of data yielded higher log likelihood when compared to a GARCH(2,2) model. The (1,2) and (2,1) specifications were also estimated, but the results were unsatisfactory.

(0.000) (0.000) (0.000)

Again we have a stable process, $\alpha + \beta = 0.8581 < 1$, and a long-run volatility rate of 1,57% per day. The estimated parameter for ε_{t-1}^2 in this equation is lower compared to the one obtained when we have fit the GARCH model to the longer series of daily returns, meaning that less weight in the next period's estimation of volatility is attributed to contemporaneous shocks on returns, and more weight is given to the most recent estimation of conditional standard variance.

The EGARCH (1,1) model and TGARCH(1,1) model are estimated with both asymptotic standard errors and robust standard errors.

The estimation results in Table 11 - 14 indicate that the parameters corresponding to the $\varepsilon_{t-1}/\sqrt{ht-1}$ term in the EGARCH is significant and negative using both standard and robust standard errors. The parameter corresponding to the $S_{t-1}^2\ \varepsilon_{t-1}^2$ term in the GJR is significant and positive using both standard and robust standard errors. All these results are consistent with the hypothesis that negative return shocks cause higher volatility than positive return shocks. We can also see that the standard GARCH(1, 1) has a lower log-likelihood than both of these leverage or asymmetric models. The GJR and the EGARCH yield similar log-likelihood.

EGARCH :

$$\log(h_t) = -0.2229 + 0.8285 \cdot \log(h_{t-1}) - 0.1181 \cdot \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + 0.4272 \cdot \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi} \right]$$

TGARCH :

$$h_t = 0.3585 + 0.5729 \cdot h_{t-1} + 0.15988 \cdot \varepsilon_{t-1}^2 + 0.2286 \cdot S_{t-1}^{-}\varepsilon_{t-1}^2$$

In this latter model estimation, the asymmetric effect, $\gamma = 0.2286$, measures the contribution of shocks to both short run persistence, $\alpha + \gamma/2$, and long run persistence $\alpha + \beta + \gamma/2$. The weights now computed on the long-run average, the previous forecast, the symmetric news, and the negative news are (0.0002, 0.5729, 0.1598, 0.1143) respectively. Since $\alpha + \beta + \gamma/2 < 1$, the weight applied to the long-run variance rate is not negative and the process is stable. Clearly the asymmetry is important since the last term would be zero otherwise. In fact, negative returns in this model have more than two times the effect of positive returns on future variances.

The level of significance I obtain for the coefficients of the model terms governing asymmetry is highly significant with asymptotic standard errors (1% level of significance), and significant with robust standard errors (5% level of significance for the EGARCH and slightly over 5% for TGARCH[1]).

Robust t-ratios are designed to be insensitive to departures from normality, especially extreme observations. The effects of significant spikes in volatility on asymptotic t-ratios and robust t-ratios are dramatically different (McAleer and Ng (2002)). Each spike in volatility increases the asymptotic t-ratios but decreases the robust t-ratios, with the magnitudes of the shifts being far greater for the asymptotic t-ratios. The conclusion I draw is that there is asymmetric volatility in the daily BET-C return series for the last 4 years, with the note that it is probably partly determined by the presence of extreme observations. As we could see earlier in this paper, the kurtosis of the unpredictable stock returns series is quite high at 6.81 and that is strong evidence that the extremes are more substantial than would be expected from a normal random variable.

In diagnostic checks, the Ljung-Box test statistic for 15th order serial correlations in the squared normalized residuals is not significant for neither GARCH, EGARCH or TGARCH model specification. From this point of view we can say that all three models appear to have done a good job in explaining the data and largely removing autocorrelation. However, the Ljung-Box test does not have much power in detecting misspecifications related to the leverage or asymmetric effects. In order to compare the models from this point of view, I used diagnostic tests as suggested by Engle and Ng : the Sign Bias Test, the Negative Size Bias Test, and the Positive Size Bias Test. These tests examine whether we can predict the squared normalized residual by some variables observed in the past which are not included in the volatility model being used. If these variables can predict the squared normalized residual, then the variance model is misspecified. The sign bias test considers the variable S_{t-1}^- a dummy

[1] Asymmetric effects in the data are captured by γ , with $\gamma > 0$. Since theory suggests that the coefficient on $S_{t-1}^2\ \varepsilon_{t-1}^2$ cannot be negative, then a one-sided test will reject the zero null hypothesis at the 5% level.

variable that takes a value of one when ε_{t-1}[1] 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 negative size bias test utilizes the variable $S_{t-1}^{-} * \varepsilon_{t-1}$. It focuses on the different effects that large and small negative return shocks have on volatility which is not predicted by the volatility model. The positive size bias test utilizes the variable $S_{t-1}^{+} * \varepsilon_{t-1}$, where $S_{t-1}^{+} = 1 - S_{t-1}^{-}$. It focuses on the different impacts that large and small positive return shocks may have on volatility, which are not explained by the volatility model.

To conduct these tests jointly, we can consider the regression :

$$v_t^2 = a + b_1 S_{t-1}^{-} + b_2 S_{t-1}^{-}\varepsilon_{t-1} + b_3 S_{t-1}^{+}\varepsilon_{t-1} + e_t$$

where, $v_t = \varepsilon_t / \sqrt{h_t}$ is the normalized residual, a , b_1, b_2, and b_3 are constant coefficients and e_t is an i.i.d. error term . The joint test is the LM test for adding the three variables in the variance equation under the maintained specification. The test statistic is equal to T times the R-squared from this regression. If the volatility model being used is correct, then b1 = b2= b3 = 0 and e_t is i.i.d.

The joint diagnostic test result for the EGARCH(1,1) model we have fitted earlier is :

$$v_t^2 = \underset{(0.00)}{1.035} - \underset{(0.67)}{0.084} * S_{t-1}^{-} - \underset{(0.78)}{0.0234} * S_{t-1}^{-} * \varepsilon_{t-1} - \underset{(0.91)}{0.0104} * S_{t-1}^{+} * \varepsilon_{t-1} + e_t$$

For the TGARCH(1,1) :

$$v_t^2 = \underset{(0.00)}{1.039} - \underset{(0.83)}{0.044} * S_{t-1}^{-} - \underset{(0.99)}{0.0006} * S_{t-1}^{-} * \varepsilon_{t-1} - \underset{(0.72)}{0.033} * S_{t-1}^{+} * \varepsilon_{t-1} + e_t$$

For the GARCH (1,1) :

$$v_t^2 = \underset{(0.00)}{1.060} - \underset{(0.66)}{0.059} * S_{t-1}^{-} - \underset{(0.56)}{0.0578} * S_{t-1}^{-} * \varepsilon_{t-1} - \underset{(0.18),}{0.125} * S_{t-1}^{+} * \varepsilon_{t-1} + e_t$$

robust p-values in parantheses.

[2] ε_{t-1} being in turn the series of standardized residuals from the GARCH, EGARCH and TGARCH models

These results are also available in Table 15 in Annexes together with a joint test statistic calculated as $T*R^2$, which asymptotically follows a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects ($b_1 = b_2 = b_3 = 0$).

Although the joint diagnostic test for all three predictable conditional volatility models indicate that the squared normalized residual cannot be predicted by some variables observed in the past which are not included in the volatility model, the generally lower probabilities (and especially much lower rejection probability of b_3=0) in the joint test for the GARCH model indicates that the asymmetric volatility models are better suited to our data series and that the GARCH may leave room for Positive Sign Bias.

Indeed computing the Positive Sign Bias Test alone for the GARCH(1,1) model, in the following form :

$$v_t^2 = a + b_3 * S_{t-1}^+ * \varepsilon_{t-1},$$

yields

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.064243	0.088863	11.97619	0.0000
C(2)	-0.126828	0.059254	-2.140413	0.0326

To conclude, at the 5% level of significance, the GARCH(1,1) estimated for the daily returns series of the BET-C index allows the size of positive shocks to influence volatility more than the size of negative shocks. Such a bias is not encountered when fitting EGARCH or TGARCH models to the data series.

Summary Statistics of the Conditional Variance Estimates

	Mean	Std. Dev	Min.	Max.	Skewness	Kurtosis
ε_t^2 [1]	2.1362	5.1541	1.10e-07	86.271	7.87	98.76
h_t GARCH	2.2557	2.3068	0.7961	29.79	5.35	44.54
h_t EGARCH	2.1782	2.0970	0.5918	36.34	7.24	93.33
h_t TGARCH	2.2649	2.5588	0.7538	38.95	6.47	67.60

[1] ε_t^2 is the squared unpredictable return obtained from the adjustment regression in Part 1 of this section.

As we can see the conditional variance produced by the EGARCH and TGARCH have the highest variation over time . The unconditional variance of the conditional variance (the kurtosis) is lower than the unconditional variance of the squared residual for all three models, a sign that h_t is correctly specified in all cases. Nevertheless the EGARCH and TGARCH models seem to capture the characteristics of the squared returns time series best.

3. The Partially Non-Parametric ARCH Model.

I now turn to the partially non-parametric model introduced by Engle and Ng (1993) and presented earlier in the methodology describing section. I attempt to further explain the volatility process of the BET-C index for the period November 1, 2004 through June 1, 2008 using this method.

Non-parametric models differ from parametric models in that the model structure is not specified a priori but is instead determined from data. The term *nonparametric* is not meant to imply that such models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance. Nonparametric methods are often referred to as *distribution free* methods as they do not rely on assumptions that the data are drawn from a given probability distribution.

As I have preaviously mentioned in Section II, I will work with the unpredictable part of the return series, ε_t , as obtained through an AR(7) mean adjustment regression. The $\{ \varepsilon_t \}$ series is divided into *m* intervals with break points τ_i. Since the purpose of my study is to investigate the impact that return shocks of different signs and magnitudes have on the next period's BET-C index's conditional volatility I study the order statistics of the data series in order to choose the τ_is . Nevertheless, for purposes of symmetry and ability to compare negative with positive return shocks, we will choose $\tau_0 = 0$[1] and the same number of equally spaced intervals on each side of τ_0.

My series of unpredictable returns has its maximum at 0.0645 (that is 6.45% per day - highest return over the sample period) and its minimum at -0.0928 (that is -9.28%). The standard deviation of the series is 0.01462 or 1.462% per day. Based on these order statistics and

[1] Also the median value of the series (0.00019) is quite close to 0, so we would roughly have the same number of observations on each side of τ_0

following Engle and Ng, I choose $\tau_i = i * \sigma$ for $i = 0, \pm 4, \pm 3, \pm 2, \pm 1$, where σ is the unconditional standard deviation of ε_t . Hence the equation to be estimated for the partially nonparametric ARCH model is :

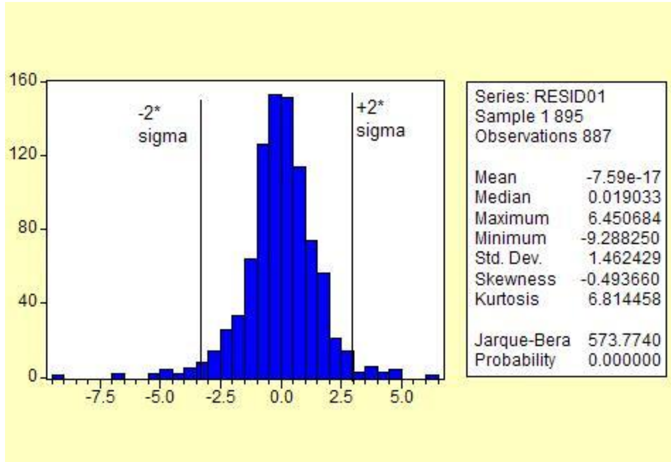
$$h_t = \omega + \beta * h_{t-1} + \sum_{i=0}^{4} \theta_i * P_{it-1} * (\varepsilon_{t-1} - i * \sigma) + \sum_{i=0}^{-4} \delta_i * N_{it-1} * (\varepsilon_{t-1} + i * \sigma) \,,$$

where P_{it-1} is a dummy variable that takes the value of 1 if $\varepsilon_{t-1} > i*\sigma$ and the value of 0 otherwise, and N_{it-1} is a dummy variable that takes the value of 1 if $\varepsilon_{t-1} < -i*\sigma$ and a value of 0 otherwise.

The result of the estimation is (p-values in parenthesis below coefficient estimate) :

$$\begin{aligned}
h_t = {} & 0.0000355 + 0.5779 * h_{t-1} \\
& + 0.00048 * P_{0t-1} * \varepsilon_{t-1} && - 0.00379 * N_{0t-1} * \varepsilon_{t-1} \\
& \quad (0.6809) && \quad (0.0068) \\
& + 0.01534 * P_{1t-1} * (\varepsilon_{t-1} - \sigma) && - 0.01846 * N_{1t-1} * (\varepsilon_{t-1} + \sigma) \\
& \quad (0.0052) && \quad (0.0003) \\
& - 0.0307 * P_{2t-1} * (\varepsilon_{t-1} - 2*\sigma) && - 0.0309 * N_{2t-1} * (\varepsilon_{t-1} + 2*\sigma) \\
& \quad (0.1391) && \quad (0.3136) \\
& + 0.0993 * P_{3t-1} * (\varepsilon_{t-1} - 3*\sigma) && + 0.1408 * N_{3t-1} * (\varepsilon_{t-1} + 3*\sigma) \\
& \quad (0.4421) && \quad (0.0653) \\
& - 0.22008 * P_{4t-1} * (\varepsilon_{t-1} - 4*\sigma) && - 0.1191 * N_{4t-1} * (\varepsilon_{t-1} + 4*\sigma) \\
& \quad (0.6831) && \quad (0.1654)
\end{aligned}$$

As we can see from this estimation output, if we compare the values of the coefficients corresponding to the terms $P_{it-1} * (\varepsilon_{t-1} - i * \sigma)$ to their counterparts $N_{it-1} * (\varepsilon_{t-1} + i * \sigma)$, it is primarily the negative shocks that impact upon volatility, as negative ε_{t-1} 's cause more volatility than positive ε_{t-1} 's of equal absolute size. Moreover, only the coefficients for positive shocks greater than the unconditional standard deviation of the series, σ, seem to inflict statistically significant upon volatility, whereas negative shocks of magnitudes both under and over σ modify the next period's conditional volatility estimate. This finding suggests an asymmetric effect. The negative coefficients of the positive shocks for i=2,4 and the positive coefficient of the negative shock for i=3 are somehow surprising, but they may be driven only by a few outliers, since very few values of the series of data lie beyond the 2 standard deviations border as shown in the histogram figure below.



Thus the nonparametric estimation results indicate that the true slope of the news impact curve as defined in methodology section of this paper is probably steeper on the negative side.

3. A cross sectional analysis of the dependence between the degree of asmmetry and the leverage ratio

For this part of my paper the purpose was to investigate the presence of asymmetric volatility at the level of returns of individual stocks listed on the Bucharest Stock Exchange and, if a sufficient large sample would be found, to then employ the cross-section regression method of Koutmos and Saidi (1995) to determine whether the estimated degree of asymmetry, for each stock, is related to some measure of financial leverage. This investigation was motivated furthermore by the argument of Blair, Poon and Taylor (2000). They state that if asymmetry is absent or a weak effect in the stocks and, furthermore, if the leverage effect cannot explain the asymmetry at the level of individual stocks, than leverage cannot explain the asymmetry in the index, because the leverage level of the index is an aggregate of the leverage levels of individual firms[1].

The dividend and splits adjusted daily returns were obtained from the BSE website and cover the period from June 1, 2004 to June 1 2008.

In studying the daily stock returns for more than 30 companies that are comprised in the BET-C index and for which daily trading volumes have been somewhat significant for the last years,

[1] Bekaert and Wu(2000) provide comparisons of volatility asymmetry between the Nikkei 225 index and a few portofolios of Japanese stocks, based upon multivariate ARCH models.

I discovered only eleven for which estimates for the parameter γ governing asymmetry in an EGARCH(1,1) specification was statistically significant. Among these there are two banks (BRD and TLV), four industrial companies (ALR, ART, ARS,TBM), two pharmaceutical companies (BIO and SCD), two oil industry related companies (PEI and RRC) and one real-estate developer, IMP. In order to enlarge the sample and to get more statistical relevance from a cross-sectional regression on this data, I searched outside the index for a few other companies that have been trading more intensively for the last years.There was just one add-on to the sample, namely DUCL. So the final sample is made up of twelve companies. Although the standard period for which I analyze the daily returns is June 1, 2004 to June 1 2008 for most of the companies in the sample and is made roughly of 1010 observations for each individual company, for three of the companies the period is extended backwards up to 2002 due to significant periods of time in which their price didn't fluctuate due to temporary trading interruptions and which affected significantly a possible asymmetric conditional volatility response to shocks. These companies are ALR and DUCL.

As I mentioned earlier the regression takes the following form :

$$|\gamma_i| = a_1 + a_2{*}(D/E)_i + a_3{*}(A)_i + u_i \quad , \quad \text{for } i = 1,\ldots\ldots\ldots\ldots,n$$

,where n is number of stocks, $|\gamma_i|$ is the absolute value of the degree of asymmetry discussed earlier, $(D/E)_i$ is some measure of financial leverage, $(A)_i$ is asset size, u_i is an error term and a_1, a_2 and a_3 are coefficients to be estimated.

I actually estimate four measures of financial leverage, two of them based on the book value of equity (sum of common stock, capital surplus, retained earnings) and the other two based on the market value of equity (calculated as end-of-the period's price of common stock multiplied by the end-of-the-period's shares of common stock outstanding, where one period represents six months). The length of the period was determined by the availability of biannual financial statements for the analyzed period. Accordingly, the leverage ratios are :

LR1 = long term debt / book value of equity

LR2 = (long term debt+short term debt) / book value of equity

LR3 = long term debt / market value of equity

LR4 = (long term debt+short term debt) / market value of equity.

So there are four regressions to be estimated. I approximate the size of each company by the logarithm of its total assets, denoted (A_i).

Again, since my focus is on the conditional variance, rather than the conditional mean, I concentrate on the unpredictable part of the stock returns series for each stock as obtained through an AR(p) autoregressive regression. The general specification for the mean equation is

$$R_t = \alpha_1 + \beta_1 * R_{t-1} + \varepsilon_t$$

I also augment the mean equation with a number of AR terms in the cases where they appear to be significant. The exact AR specification is indented after the symbol of each stock in the following table. The parameter vectors $\theta_i = (\omega_i, \beta_i, \gamma_i, \alpha_i)$ resulting from fitting an EGARCH (1,1) model to the series of unpredictable returns for each stock are as follows :

	ω	β	γ	α
$BRD_{AR(1)}$	-0.1419	0.8128	-0.0777	0.6179
$TLV_{AR(3)}$	-0.1865	0.9600	- 0.0826	0.4183
$ALR_{AR(1)}$	-0.0393	0.8696	-0.1251	0.6476
$ART_{AR(0)}$	0.1172	0.8756	-0.1599	0.0097
$TBM_{AR(5)}$	-0.1008	0.9129	-0.0967	0.1905
$BIO_{AR(1)}$	-0.0682	0.9819	-0.0345	0.0997
$SCD_{AR(1)}$	-0.0202	0.9405	-0.1317	0.0769
$PEI_{AR(5)}$	-0.0440	0.9342	-0.0936	0.1040
$RRC_{AR(0)}$	0.0123	0.9868	-0.0580	0.0182
$IMP_{AR(0)}$	0.1157	0.5236	-0.0803	0.2719
$ARS_{AR(6)}$	0.1601	0.8186	-0.0809	0.5780
$DUCL_{AR(3)}$	0.3927	0.8390	-0.0503	0.2713

The results from the estimated regressions are as follows :

Included observations: 12
E=C(1)+C(2)*LR1+C(3)*SIZE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.097031	0.123625	0.784882	0.4527
C(2)	-0.004718	0.016934	-0.278600	0.7868
C(3)	-0.000263	0.006186	-0.042438	0.9671

E=C(1)+C(2)*LR2+C(3)*SIZE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.104462	0.124827	0.836858	0.4243
C(2)	0.005423	0.013730	0.394951	0.7021
C(3)	-0.001077	0.006423	-0.167628	0.8706

E=C(1)+C(2)*LR3+C(3)*SIZE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.124587	0.127032	0.980754	0.3523
C(2)	0.012006	0.016728	0.717689	0.4912
C(3)	-0.002059	0.006489	-0.317330	0.7582

E=C(1)+C(2)*LR4+C(3)*SIZE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.162999	0.114477	1.423854	0.188
C(2)	0.015329	0.008914	1.719629	0.119
C(3)	-0.004479	0.005895	-0.759753	0.466

The cross section analysis reveals that, until now, differences in the degree of asymmetry cannot be attributed to differences in the degree of leverage in support of Christie's(1982) and Black's(1976) earlier findings. In his research for the 30 companies making up the DowJonesIndustrialAverage Index, Koutmos (1995) finds a significant positive relationship between the degree of asymmetric volatility and the degree of leverage in only one of the regressions, which uses a leverage measure based on the book-value of equity, with an adjusted R^2 of roughly 16%.

Since the companies in the sample I used are probably the most liquid and most frequently traded from the BET-C index, it can be said that the leverage effect hypothesis was tested under the most favorable circumstances. Further research may test if time-varying risk premiums can explain the asymmetry.

V. Concluding Remarks

The asymmetric response of conditional variance to shocks of differing signs and sizes is a stylized fact of volatility which we meet in international well developed stock markets both at the market index level and at individual stock return level. Recent studies, which find evidence of asymmetric volatility in emerging stock markets, have also been performed.

In studying the evolution of the most comprising index on the Romanian Stock Market, the BET-C Index, I find proof of asymmetric response of the conditional variance of the index to negative and positive shocks, for the latter part of its history, November 1, 2004 through June 1, 2008. I attribute this finding to significant changes in terms of stock market development from the preavious period of April 16, 1998 (index launch date) through to December 2003, as testing for asymmetric volatility for the whole historical period of the BET-C index proves unsatisfactory in terms of detecting asymmetry

In testing for asymmetric volatility, I employ econometric models like the EGARCH, the TGARCH and a partially nonparametric ARCH model as introduced by Engle and Ng (2003). These models seem to capture the characteristics of the unpredictable part of the index return series, as obtained through an AR(7) regression, better than a symmetric GARCH(1,1) specification, for the November 1, 2004 through June 1, 2008 period. On average, I find that negative shocks raise the next period's conditional return variance by more than two times than positive shocks. Using robust t-ratios as introduced by Bollerslev and Woolridge, I find significance for the coefficients of the terms governing asymmetry in the EGARCH and TGARCH models at the 5% level of significance, whilst using asymptotic t-ratios significance is obtained at the 1% level. This may be proof that in part the asymmetry is determined by significant spikes in volatility as shown by McAleer and Ng. The nonparametric approach which allows the data series to unveil the news impact curve directly also shows that it is primarily negative shocks that raise the next period's conditional variance.

In the last part of my paper I test if variations in the degree of financial leverage among a sample of twelve individual stocks from the BET-C index that exhibit asymmetric volatility can explain the variations in the degree of asymmetry. I find no proof of such a dependency so future research should concentrate on the time-varying risk premium theory.

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Figure 1. <u>BET-C Index Composition as of July 2008</u>

Symbol	Company Name	No. of Shares	Ref. Price	Float Factor (FF)	Representation Factor (FR)	Correction Factor (FC)	Weight (%)
BRD	BRD - GROUPE SOCIETE GENERALE S.A.	696,901,518	19.0000	-	0.53	1.000000	20.91
SNP	PETROM S.A.	56,644,108,335	0.4470	-	0.27	1.000000	20.37
ALR	ALRO S.A.	713,779,135	5.6000	-	1.00	1.000000	11.91
TLV	BANCA TRANSILVANIA S.A.	6,110,797,702	0.3310	-	1.00	1.691544	10.20
TGN	S.N.T.G.N. TRANSGAZ S.A.	11,773,844	201.0000	-	1.00	1.000000	7.05
TEL	C.N.T.E.E. TRANSELECTRICA	73,303,142	21.0000	-	1.00	1.000000	4.59
RRC	ROMPETROL RAFINARE S.A.	21,099,276,002	0.0519	-	1.00	1.000000	3.26
ATB	ANTIBIOTICE S.A.	454,897,291	1.2900	-	1.00	1.000000	1.75
IMP	IMPACT DEVELOPER & CONTRACTOR S.A.	2,000,000,000	0.2250	-	1.00	1.000000	1.34
BCC	BANCA COMERCIALA CARPATICA S.A.	1,626,883,176	0.2110	-	1.00	1.174905	1.20
COS	MECHEL TARGOVISTE S.A.	68,850,123	5.1000	-	1.00	1.000000	1.05
OIL	OIL TERMINAL S.A.	582,430,253	0.5750	-	1.00	1.000000	1.00
AZO	AZOMURES S.A.	526,032,633	0.6150	-	1.00	1.000000	0.96
PCL	POLICOLOR S.A.	71,257,475	4.2000	-	1.00	1.000000	0.89
TUFE	TURISM FELIX S.A. BAILE FELIX	496,149,456	0.5700	-	1.00	1.000000	0.84
BIO	BIOFARM S.A.	977,554,909	0.2570	-	1.00	1.120000	0.84
EFO	TURISM, HOTELURI, RESTAURANTE MAREA NEAGRA S.A.	193,114,688	1.4500	-	1.00	1.000000	0.83
DAFR	DAFORA SA	973,577,335	0.2510	-	1.00	1.000000	0.73
OLT	OLTCHIM S.A. RM. VALCEA	323,588,641	0.7550	-	1.00	1.000000	0.73
SCD	ZENTIVA S.A.	416,961,150	0.5750	-	1.00	1.000000	0.71
CMP	COMPA S. A.	218,821,038	0.9550	-	1.00	1.000000	0.62
ART	T.M.K. - ARTROM S.A.	12,268,020	15.5000	-	1.00	1.000000	0.57
ROCE	ROMCARBON SA BUZAU	186,457,267	1.0000	-	1.00	1.000000	0.56
ALU	ALUMIL ROM INDUSTRY S.A.	31,250,000	5.5000	-	1.00	1.000000	0.51
PTR	ROMPETROL WELL SERVICES S.A.	139,095,450	0.5800	-	1.00	2.000000	0.48
BRK	S.S.I.F. BROKER S.A.	208,525,437	0.5450	-	1.00	1.388184	0.47
MPN	TITAN S.A.	408,483,013	0.3800	-	1.00	1.000000	0.46
FLA	FLAMINGO INTERNATIONAL SA	779,050,011	0.1950	-	1.00	1.000000	0.45
ARS	AEROSTAR S.A.	117,136,530	1.2500	-	1.00	1.000000	0.44
CMF	COMELF S.A.	23,412,940	6.0000	-	1.00	1.000000	0.42
SOCP	SOCEP S.A.	343,425,744	0.3950	-	1.00	1.000000	0.40
PPL	PRODPLAST S.A.	37,847,280	3.2500	-	1.00	1.000000	0.37
COMI	CONDMAG S.A.	172,796,516	0.7050	-	1.00	1.000000	0.36
TBM	TURBOMECANICA S.A.	369,442,475	0.3000	-	1.00	1.000000	0.33
SNO	SANTIERUL NAVAL ORSOVA S.A.	8,657,260	10.4000	-	1.00	1.000000	0.27
AMO	AMONIL S.A.	1,112,658,091	0.0653	-	1.00	1.000000	0.22
VNC	VRANCART SA	632,205,306	0.1030	-	1.00	1.100000	0.21
MECF	MECANICA CEAHLAU	133,257,050	0.4000	-	1.00	1.200000	0.19
CBC	CARBOCHIM S.A.	3,882,399	14.9000	-	1.00	1.000000	0.17
EPT	ELECTROPUTERE S.A.	124,167,954	0.4600	-	1.00	1.000000	0.17
ALT	ALTUR S.A.	721,340,861	0.0689	-	1.00	1.000000	0.15
APC	VAE APCAROM S.A.	73,796,185	0.6600	-	1.00	1.000000	0.15
MJM	MJ MAILLIS ROMANIA S.A.	10,431,728	3.8600	-	1.00	1.000000	0.12
UZT	UZTEL S.A.	2,332,593	16.0000	-	1.00	1.000000	0.11
STZ	SINTEZA S.A.	66,112,590	0.4900	-	1.00	1.000000	0.10
BRM	BERMAS S.A.	19,239,914	1.0700	-	1.00	1.120226	0.07
PEI	PETROLEXPORTIMPORT S.A.	408,697	53.8000	-	1.00	1.000000	0.07
UAM	UAMT S.A.	25,085,447	0.7000	-	1.00	1.000000	0.05
BCM	CASA DE BUCOVINA-CLUB DE MUNTE	121,839,600	0.1410	-	1.00	1.000000	0.05
ARM	ARMATURA S.A.	40,000,000	0.3790	-	1.00	1.000000	0.05
ZIM	ZIMTUB S.A.	4,827,824	2.8900	-	1.00	1.000000	0.04
VESY	VES SA	86,400,000	0.1450	-	1.00	1.000000	0.04

Figure 2. BET-C Index Level and Return Evolution April 16, 1998 - June 15, 2008

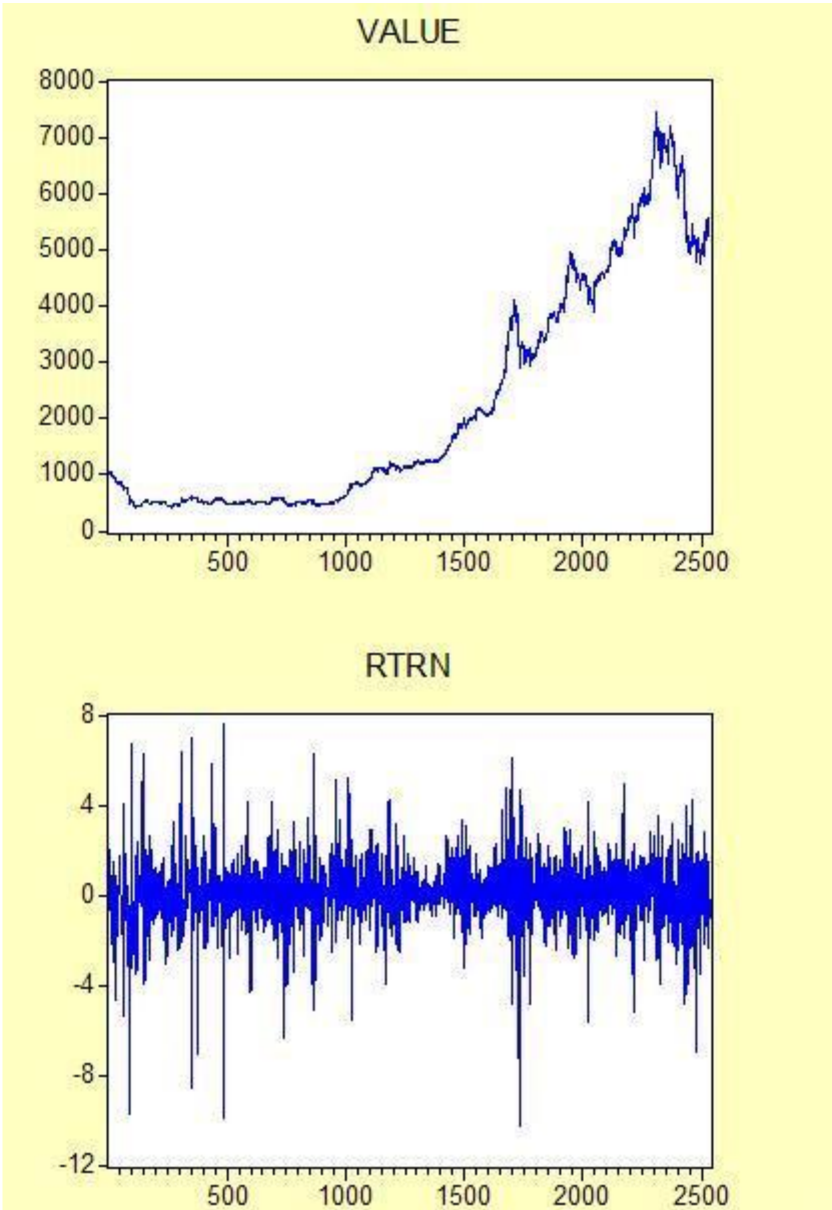

Figure 3 - BET-C Index Level and Return Evolution November 1, 2004 - June 15, 2008

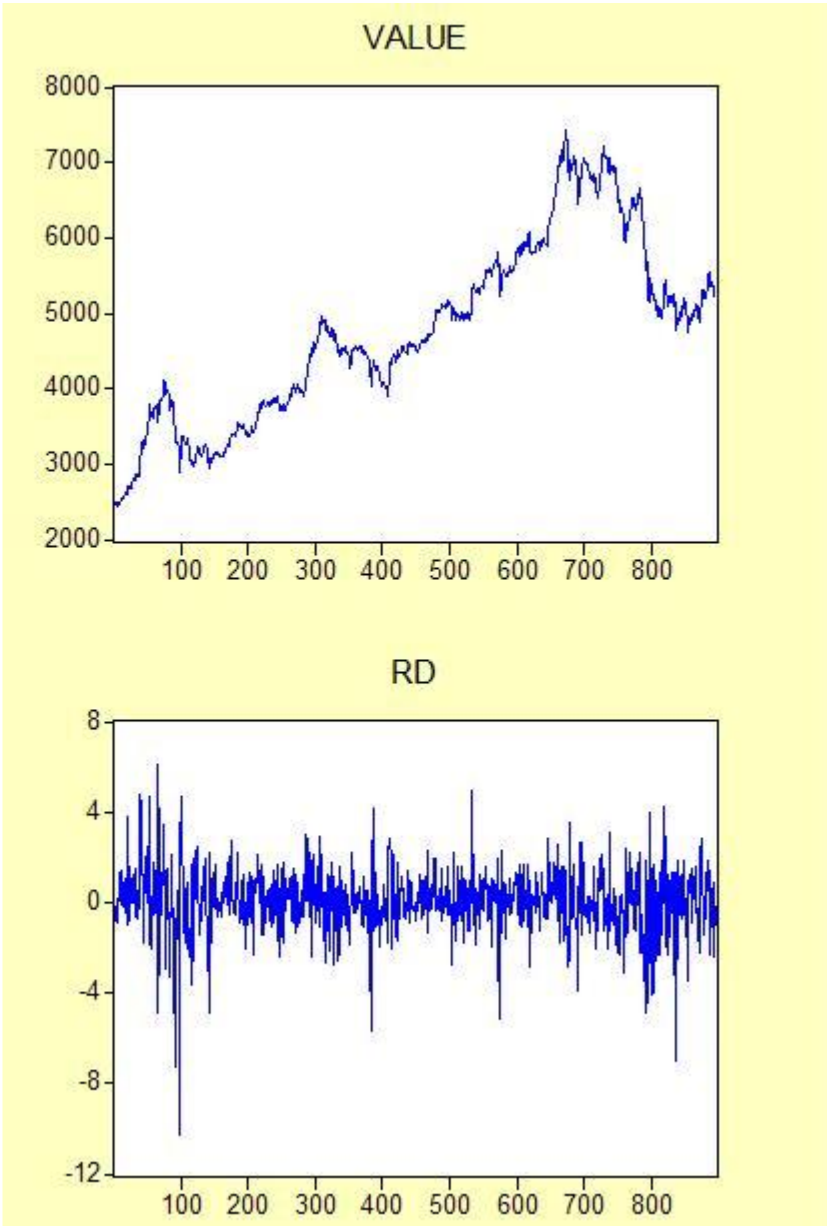

Table 1

Null Hypothesis: RTRN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.97095	0.0000
Test critical values:	1% level	-3.432741	
	5% level	-2.862482	
	10% level	-2.567317	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RTRN)
Method: Least Squares
Date: 07/07/08 Time: 12:45
Sample (adjusted): 3 2532
Included observations: 2530 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RTRN(-1)	-0.821128	0.019564	-41.97095	0.0000
C	0.052800	0.028139	1.876422	0.0607

R-squared	0.410662	Mean dependent var	-0.001181
Adjusted R-squared	0.410429	S.D. dependent var	1.841373
S.E. of regression	1.413871	Akaike info criterion	3.531330
Sum squared resid	5053.553	Schwarz criterion	3.535944
Log likelihood	-4465.133	F-statistic	1761.561
Durbin-Watson stat	2.008545	Prob(F-statistic)	0.000000

Table 2

Null Hypothesis: RD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.62647	0.0000
Test critical values:	1% level	-3.437450	
	5% level	-2.864563	
	10% level	-2.568433	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RD)
Method: Least Squares
Date: 07/07/08 Time: 12:49
Sample (adjusted): 3 895
Included observations: 893 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RD(-1)	-0.886552	0.033296	-26.62647	0.0000
C	0.073056	0.049507	1.475672	0.1404

R-squared	0.443114	Mean dependent var	-0.000969
Adjusted R-squared	0.442489	S.D. dependent var	1.978237
S.E. of regression	1.477083	Akaike info criterion	3.620253
Sum squared resid	1943.961	Schwarz criterion	3.630991
Log likelihood	-1614.443	F-statistic	708.9689
Durbin-Watson stat	2.002002	Prob(F-statistic)	0.000000

Table 3 – Descriptive Statistics for the daily index return series Dec. 22 1998 – Dec. 22 2003

	RD
Mean	0.009580
Median	0.009770
Maximum	7.641450
Minimum	-9.873283
Std. Dev.	1.544575
Skewness	-0.381960
Kurtosis	9.118908

<u>Table 4</u> - Descriptive Statistics for the daily index return series Nov. 1 2004 – Jun. 1 2008

	RD
Mean	0.082190
Median	0.105760
Maximum	6.109019
Minimum	-10.28757
Std. Dev.	1.485044
Skewness	-0.679235
Kurtosis	7.702725

<u>Table 5</u> – Correlogram of daily index returns Nov. 1 2004 – Jun. 1 2008

Correlogram of RD

Date: 07/07/08 Time: 15:00
Sample: 1 895
Included observations: 894

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.113	0.113	11.529	0.001
		2	0.026	0.013	12.122	0.002
		3	0.030	0.026	12.910	0.005
		4	-0.063	-0.070	16.437	0.002
		5	-0.030	-0.016	17.247	0.004
		6	0.008	0.015	17.301	0.008
		7	0.126	0.131	31.658	0.000
		8	0.008	-0.025	31.715	0.000
		9	-0.005	-0.012	31.736	0.000
		10	-0.026	-0.034	32.362	0.000
		11	0.014	0.041	32.536	0.001
		12	0.010	0.012	32.621	0.001
		13	0.041	0.038	34.120	0.001
		14	0.065	0.033	37.966	0.001
		15	0.033	0.024	38.965	0.001
		16	-0.018	-0.025	39.247	0.001
		17	0.037	0.053	40.530	0.001
		18	-0.062	-0.075	44.027	0.001
		19	0.035	0.057	45.124	0.001
		20	0.058	0.036	48.218	0.000
		21	-0.032	-0.045	49.148	0.000
		22	0.005	-0.006	49.173	0.001

Table 6 – Mean Adjustment Regression for daily index returns Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: Least Squares
Date: 07/07/08 Time: 15:24
Sample (adjusted): 9 895
Included observations: 887 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.065934	0.049792	1.324197	0.1858
RD(-1)	0.111228	0.033446	3.325561	0.0009
RD(-2)	0.014437	0.033654	0.428976	0.6680
RD(-3)	0.042194	0.033703	1.251958	0.2109
RD(-4)	-0.072313	0.033637	-2.149818	0.0318
RD(-5)	-0.019633	0.033699	-0.582598	0.5603
RD(-6)	-0.000227	0.033698	-0.006725	0.9946
RD(-7)	0.132081	0.033539	3.938158	0.0001

R-squared	0.036036	Mean dependent var	0.083956
Adjusted R-squared	0.028359	S.D. dependent var	1.489513
S.E. of regression	1.468240	Akaike info criterion	3.614985
Sum squared resid	1894.887	Schwarz criterion	3.658167
Log likelihood	-1595.246	F-statistic	4.694198
Durbin-Watson stat	1.992923	Prob(F-statistic)	0.000035

Table 7 – Correlogram of residuals (unpredictable returns series)

Correlogram of RESID01

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.003	0.003	0.0096	0.922
		2	0.002	0.002	0.0135	0.993
		3	0.004	0.004	0.0266	0.999
		4	-0.007	-0.007	0.0721	0.999
		5	-0.002	-0.002	0.0756	1.000
		6	-0.006	-0.006	0.1069	1.000
		7	0.002	0.002	0.1098	1.000
		8	-0.025	-0.025	0.6627	1.000
		9	-0.006	-0.006	0.6949	1.000
		10	-0.044	-0.044	2.4147	0.992
		11	0.041	0.042	3.9287	0.972
		12	0.004	0.003	3.9405	0.984
		13	0.034	0.034	4.9579	0.976
		14	0.037	0.036	6.2066	0.961
		15	0.037	0.037	7.4156	0.945
		16	-0.019	-0.020	7.7370	0.956
		17	0.041	0.042	9.2688	0.931
		18	-0.061	-0.064	12.655	0.812
		19	0.038	0.042	13.962	0.786
		20	0.050	0.048	16.233	0.702
		21	-0.053	-0.048	18.831	0.596
		22	0.010	0.010	18.921	0.650

<u>Table 8</u> – Correlogram of squared residuals (unpredictable returns series)

Correlogram of SQRESID01

Date: 07/07/08 Time: 16:18
Sample: 1 895
Included observations: 887

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.265	0.265	62.600	0.000
		2	0.150	0.086	82.712	0.000
		3	0.158	0.108	105.12	0.000
		4	0.047	-0.030	107.12	0.000
		5	-0.001	-0.034	107.12	0.000
		6	0.006	-0.003	107.15	0.000
		7	0.162	0.180	130.60	0.000
		8	0.068	-0.003	134.74	0.000
		9	0.007	-0.043	134.79	0.000
		10	0.034	-0.011	135.80	0.000
		11	0.017	0.008	136.07	0.000
		12	0.038	0.054	137.36	0.000
		13	0.052	0.043	139.77	0.000
		14	0.086	0.031	146.38	0.000
		15	0.069	0.011	150.69	0.000
		16	0.020	-0.017	151.04	0.000
		17	0.080	0.069	156.86	0.000
		18	0.043	0.008	158.53	0.000
		19	-0.019	-0.054	158.87	0.000
		20	0.024	0.008	159.40	0.000
		21	0.036	0.017	160.61	0.000
		22	-0.000	-0.014	160.61	0.000

Table 9 – EGARCH(1,1) estimation output for April 16, 1998 - June 15, 2008

Dependent Variable: RTRN
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/07/08 Time: 19:36
Sample (adjusted): 3 2532
Included observations: 2530 after adjustments
Convergence achieved after 23 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.053733	0.024144	2.225519	0.0260
RTRN(-1)	0.241841	0.024590	9.834784	0.0000
	Variance Equation			
C(3)	-0.334781	0.041978	-7.975098	0.0000
C(4)	0.612835	0.065391	9.371853	0.0000
C(5)	-0.037997	0.043123	-0.881118	0.3783
C(6)	0.737439	0.048360	15.24906	0.0000

R-squared	0.028029	Mean dependent var	0.064559
Adjusted R-squared	0.026103	S.D. dependent var	1.436773
S.E. of regression	1.417896	Akaike info criterion	3.286649
Sum squared resid	5074.326	Schwarz criterion	3.300489
Log likelihood	-4151.611	F-statistic	14.55683
Durbin-Watson stat	2.135334	Prob(F-statistic)	0.000000

Table 10 – GARCH(1,1) estimation output for Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/07/08 Time: 16:54
Sample (adjusted): 9 895
Included observations: 887 after adjustments
Convergence achieved after 16 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.121323	0.040928	2.964304	0.0030
RD(-1)	0.145365	0.039839	3.648840	0.0003
RD(-2)	-0.019785	0.039944	-0.495326	0.6204
RD(-3)	0.062331	0.040457	1.540668	0.1234
RD(-4)	-0.062169	0.034314	-1.811801	0.0700
RD(-5)	-0.017366	0.034588	-0.502079	0.6156
RD(-6)	-0.040701	0.047034	-0.865358	0.3868
RD(-7)	0.084285	0.029779	2.830313	0.0047
	Variance Equation			
C	0.360368	0.084719	4.253663	0.0000
RESID(-1)^2	0.294578	0.070534	4.176376	0.0000
GARCH(-1)	0.559725	0.061405	9.115330	0.0000

R-squared	0.028242	Mean dependent var	0.083956
Adjusted R-squared	0.017149	S.D. dependent var	1.489513
S.E. of regression	1.476686	Akaike info criterion	3.453600
Sum squared resid	1910.207	Schwarz criterion	3.512975
Log likelihood	-1520.671	F-statistic	2.545886
Durbin-Watson stat	2.058662	Prob(F-statistic)	0.004961

Table 11 - EGARCH(1,1) estimation output (asymptotic standard errors) for Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/08/08 Time: 06:04
Sample (adjusted): 9 895
Included observations: 887 after adjustments
Convergence achieved after 24 iterations
Variance backcast: ON
LOG(GARCH) = C(9) + C(10)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(11)*RESID(-1)/@SQRT(GARCH(-1)) + C(12)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.077571	0.044481	1.743915	0.0812
RD(-1)	0.155265	0.039450	3.935708	0.0001
RD(-2)	0.004978	0.032746	0.152030	0.8792
RD(-3)	0.062278	0.032013	1.945372	0.0517
RD(-4)	-0.073644	0.033409	-2.204314	0.0275
RD(-5)	-0.018676	0.030418	-0.613981	0.5392
RD(-6)	-0.025853	0.028327	-0.912666	0.3614
RD(-7)	0.067757	0.031815	2.129713	0.0332
	Variance Equation			
C(9)	-0.222903	0.034247	-6.508740	0.0000
C(10)	0.427258	0.047864	8.926477	0.0000
C(11)	-0.118129	0.028934	-4.082649	0.0000
C(12)	0.828568	0.035137	23.58103	0.0000

R-squared	0.028433	Mean dependent var	0.083956
Adjusted R-squared	0.016219	S.D. dependent var	1.489513
S.E. of regression	1.477384	Akaike info criterion	3.442598
Sum squared resid	1909.831	Schwarz criterion	3.507371
Log likelihood	-1514.792	F-statistic	2.327914
Durbin-Watson stat	2.079740	Prob(F-statistic)	0.008048

Table 12 - EGARCH(1,1) estimation output (robust standard errors) for Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/08/08 Time: 06:17
Sample (adjusted): 9 895
Included observations: 887 after adjustments
Convergence achieved after 24 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
LOG(GARCH) = C(9) + C(10)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(11)*RESID(-1)/@SQRT(GARCH(-1)) + C(12)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.077571	0.043258	1.793210	0.0729
RD(-1)	0.155265	0.037538	4.136227	0.0000
RD(-2)	0.004978	0.041221	0.120772	0.9039
RD(-3)	0.062278	0.038912	1.600464	0.1095
RD(-4)	-0.073644	0.032583	-2.260175	0.0238
RD(-5)	-0.018676	0.033189	-0.562724	0.5736
RD(-6)	-0.025853	0.040463	-0.638943	0.5229
RD(-7)	0.067757	0.031359	2.160674	0.0307
	Variance Equation			
C(9)	-0.222903	0.057609	-3.869255	0.0001
C(10)	0.427258	0.080005	5.340389	0.0000
C(11)	-0.118129	0.058967	-2.003316	0.0451
C(12)	0.828568	0.040315	20.55219	0.0000

R-squared	0.028433	Mean dependent var	0.083956
Adjusted R-squared	0.016219	S.D. dependent var	1.489513
S.E. of regression	1.477384	Akaike info criterion	3.442598
Sum squared resid	1909.831	Schwarz criterion	3.507371
Log likelihood	-1514.792	F-statistic	2.327914
Durbin-Watson stat	2.079740	Prob(F-statistic)	0.008048

Table 13 – TGARCH (1,1) estimation output (asymptotic standard errors) for Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/08/08 Time: 06:29
Sample (adjusted): 9 895
Included observations: 887 after adjustments
Convergence achieved after 16 iterations
Variance backcast: ON
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*RESID(-1)^2*(RESID(-1)<0) + C(12)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079710	0.047006	1.695731	0.0899
RD(-1)	0.148769	0.040058	3.713841	0.0002
RD(-2)	-0.014949	0.034987	-0.427280	0.6692
RD(-3)	0.065585	0.032332	2.028448	0.0425
RD(-4)	-0.063802	0.034864	-1.830056	0.0672
RD(-5)	-0.022634	0.030916	-0.732138	0.4641
RD(-6)	-0.037055	0.028389	-1.305253	0.1918
RD(-7)	0.080205	0.033564	2.389624	0.0169
Variance Equation				
C	0.358551	0.071356	5.024857	0.0000
RESID(-1)^2	0.159807	0.040304	3.965011	0.0001
RESID(-1)^2*(RESID(-1)<0)	0.228671	0.066166	3.456036	0.0005
GARCH(-1)	0.572965	0.059345	9.654846	0.0000

R-squared	0.029005	Mean dependent var	0.083956
Adjusted R-squared	0.016798	S.D. dependent var	1.489513
S.E. of regression	1.476949	Akaike info criterion	3.443041
Sum squared resid	1908.707	Schwarz criterion	3.507814
Log likelihood	-1514.989	F-statistic	2.376117
Durbin-Watson stat	2.067436	Prob(F-statistic)	0.006747

Table 14 – TGARCH (1,1) estimation output (robust standard errors) for Nov. 1 2004 – Jun. 1 2008

Dependent Variable: RD
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/08/08 Time: 06:37
Sample (adjusted): 9 895
Included observations: 887 after adjustments
Convergence achieved after 16 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*RESID(-1)^2*(RESID(-1)<0) + C(12)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079710	0.042483	1.876290	0.0606
RD(-1)	0.148769	0.038413	3.872882	0.0001
RD(-2)	-0.014949	0.039836	-0.375272	0.7075
RD(-3)	0.065585	0.038744	1.692780	0.0905
RD(-4)	-0.063802	0.033158	-1.924165	0.0543
RD(-5)	-0.022634	0.034047	-0.664804	0.5062
RD(-6)	-0.037055	0.043111	-0.859518	0.3901
RD(-7)	0.080205	0.029604	2.709291	0.0067
Variance Equation				
C	0.358551	0.079848	4.490439	0.0000
RESID(-1)^2	0.159807	0.061967	2.578894	0.0099
RESID(-1)^2*(RESID(-1)<0)	0.228671	0.123660	1.849191	0.0644
GARCH(-1)	0.572965	0.056560	10.13023	0.0000

R-squared	0.029005	Mean dependent var	0.083956
Adjusted R-squared	0.016798	S.D. dependent var	1.489513
S.E. of regression	1.476949	Akaike info criterion	3.443041
Sum squared resid	1908.707	Schwarz criterion	3.507814
Log likelihood	-1514.989	F-statistic	2.376117
Durbin-Watson stat	2.067436	Prob(F-statistic)	0.006747

Table 15 - Joint Diagnostic Test Estimation Output

GARCH(1,1)……………………………………………………………..

SQRESID07=C(1)+C(2)*NDUM(-1)+C(3)*NDUM(-1)*RESID06(-1)+C(4)
*PDUM(-1)*RESID06(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.060824	0.161705	6.560258	0.0000
C(2)	-0.059752	0.199630	-0.299315	0.7648
C(3)	-0.057867	0.100189	-0.577580	0.5637
C(4)	-0.125010	0.094402	-1.324237	0.1858
Obs*R-squared	0.123100	Prob. Chi-Square(3)		0.988928

EGARCH(1,1)……………………………………………………………….

SQRESID03=C(1)+C(2)*NDUM(-1)+C(3)*NDUM(-1)*RESID02(-1)+C(4)
*PDUM(-1)*RESID02(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.035076	0.155343	6.663163	0.0000
C(2)	-0.084458	0.204087	-0.413832	0.6791
C(3)	-0.023437	0.083367	-0.281133	0.7787
C(4)	-0.010498	0.097212	-0.107994	0.9140
Obs*R-squared	0.049275	Prob. Chi-Square(3)		0.997134

TARCH(1,1)……………………………………………………………...

SQRESID05=C(1)+C(2)*NDUM(-1)+C(3)*NDUM(-1)*RESID04(-1)+C(4)
*PDUM(-1)*RESID04(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.039720	0.161084	6.454522	0.0000
C(2)	-0.044341	0.210665	-0.210479	0.8333
C(3)	-0.000610	0.079362	-0.007682	0.9939
C(4)	-0.033771	0.096390	-0.350359	0.7262
Obs*R-squared	0.042382	Prob. Chi-Square(3)		0.997709

Table 16 – Partial Nonparametric ARCH estimation output

Dependent Variable: RESID01
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/08/08 Time: 18:24
Sample (adjusted): 10 895
Included observations: 886 after adjustments
Convergence achieved after 39 iterations
Variance backcast: ON
GARCH = C(1) + C(2)*GARCH(-1) + C(3)*P0(-1)*RESID01(-1) + C(4)
*N0(-1)*RESID01(-1) + C(5)*P1(-1)*(RESID01(-1)-V) + C(6)*N1(
-1)*(RESID01(-1)+V) + C(7)*P2(-1)*(RESID01(-1)-2*V) + C(8)*N2(
-1)*(RESID01(-1)+2*V) + C(9)*P3(-1)*(RESID01(-1)-3*V) + C(10)
N3(-1)(RESID01(-1)+3*V) + C(11)*P4(-1)*(RESID01(-1)-4*V) +
C(12)*N4(-1)*(RESID01(-1)+4*V)

	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	3.55E-05	8.88E-06	3.993205	0.0001
GARCH(-1)	0.577908	0.059209	9.760404	0.0000
P0(-1)*RESID01(-1)	0.000480	0.001167	0.411258	0.6809
N0(-1)*RESID01(-1)	-0.003797	0.001403	-2.705341	0.0068
P1(-1)*(RESID01(-1)-V)	0.015341	0.005489	2.794794	0.0052
N1(-1)*(RESID01(-1)+V)	-0.018462	0.005042	-3.661351	0.0003
P2(-1)*(RESID01(-1)-2*V)	-0.030733	0.020779	-1.479094	0.1391
N2(-1)*(RESID01(-1)+2*V)	-0.030956	0.030717	-1.007786	0.3136
P3(-1)*(RESID01(-1)-3*V)	0.099330	0.129238	0.768578	0.4421
N3(-1)*(RESID01(-1)+3*V)	0.140875	0.076419	1.843446	0.0653
P4(-1)*(RESID01(-1)-4*V)	-0.220081	0.539121	-0.408222	0.6831
N4(-1)*(RESID01(-1)+4*V)	-0.119167	0.085903	-1.387228	0.1654

R-squared	-0.000000	Mean dependent var	-8.12E-07
Adjusted R-squared	-0.012586	S.D. dependent var	0.014633
S.E. of regression	0.014724	Akaike info criterion	-5.767878
Sum squared resid	0.189488	Schwarz criterion	-5.703046
Log likelihood	2567.170	Durbin-Watson stat	1.992473