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Spillover effect: A study for major capital markets and Romania capital market

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Content

1 Abstract

In this dissertation paper we focus our attention on the tail risk and how different capital markets are influencing each other. Previous studies have detected return and volatility across countries during crises periods. Using the well –know Value at Risk (VaR) measure for heavy tailed financial returns, our objective is to detect if the information for a negative shock in a foreign market helps the forecast of the behavior of another market. We calculate 1 day, 95% and 99% Value at Risk for major US stock indices- S&P 500, NASDAQ 100, DJ INDUSTRIALS, and major European stock indices –CAC 40, FTSE100, and DAX30 and for Romanian stock index-BET. The VaR for each index is calculated the following techniques: Historical Simulation, Variance Approach and Extreme Value Theory.

Spillover effects being the influence of one market on others, is examined using the Granger causality, for daily changes of the VAR series.

2 Introduction

Recent studies in finance have highlighted the importance of rare events in assets pricing and portfolio choice. These rare events might be in the form of a large change in investment returns a stock market crash, major defaults or the collapse of risky asset prices.

Potential financial crises always create panic at institutional level. Their impact might be catastrophic and the financial institutions will not enough have regulatory or economic capital to cover the material risks and potential losses.

Recent empirical evidence suggests that the financial returns are heavy-tailed. Heavy tails is translated in the probability mass is concentrated at the tails of the marginal probability distributions. If the heavy tails are not considered, extreme losses occur more frequently and the magnitude of losses is larger than expected.

As a general practice in the financial institutions, the losses are split into three categories and each one is covered by a certain protection method: expected loss – covered by provisions is risk spread, unexpected losses – covered by the economic capital and extreme losses – covered by capital but more over by insurance. If the extreme losses occur more frequently and the financial institutions do not expect them, their financial costs may increase exponentially.

In this paper dissertation we focus our attention from risk considered in term of volatility to risk considered in term of extreme losses with low probability of being exceeded. This means tail risk. We approach it through Value at Risk measure for risk management. Our objective is to determine whether this kind of risk, presents spillover effects across the markets.

An important milestone in the development of VaR models was J.P. Morgan's decision in 1994 to develop its VaR methodology. RiskMetrics is a methodology that incorporates in a simple way the key facts on time series and risk. Also, Value at Risk is one of the methods used to calculate and allocate regulatory and economic capital for all the material risks (e.g. credit risk, market risk, operational risk, liquidity risk, etc) that may impact the activity of a financial institution.

This dissertation paper is organized as follows. Section 3 reviews the literature treating financial spillover effects. Section 4 presents the parametric and non-parametric methods to estimate and evaluate VaR models. Section 5 describes the spillover methodology. Section 6 details the data series used in the calculations and the methodologies their selves applied on the data selected. Also, the annexes present daily log returns graphics, statistics and histogram and output of GARCH normal and GARCH student.

3 Literature review

The global crash of stock markets in October 1987 increased research interest into how financial disturbances transmit from one market to another.

Hamao, Masulis and Ng (1990) studied the existence of price change and price volatility effects across three major international stock markets: Tokyo, London and New York. The analysis utilizes daily opening and closing prices. In order to explore these pricing relationship they estimate the Nikkei, FTSE, and S&P indexes daily return processes with a GARCH-M model. Price volatility spillovers was detected in the period following October 1987 crash from both London and New York to the Tokyo stock market and New York to London. No price volatility spillover effects in other directions are found for the pre-October 1987 period.

Sang Jin Lee, 2006 investigate the volatility spillover effect among six Asian country stock markets and the US using GARCH (1,1) model. He found that there are significant volatility spillover effects within these countries, especially the regionally close five countries Hong Kong, South Korea, Japan, Singapore and Taiwan experienced more links among them. Also he observed that the volatility spillover effects increased after Asian financial crisis.

Robert F. Engle, Wen-Ling Lin and Takatoshi Ito, 1994 investigate empirically how returns and volatilities of stock indices are correlated between the Tokyo and the New York markets. Using intra-daily data to decompose daily returns in daytime and overnight returns, they estimated two models (aggregate shock model and signal-extraction mode) Then, both models were compared with GARCH-M model of Hamao, Masulis and Ng.(1990).They found that cross-market interdependence in returns and volatilities was bi-directional Tokyo (New York) daytime returns are correlated with New York (Tokyo) overnight returns.

International stock market have different trading hours and the use of close to close return underestimate return correlation. Martin Martens and Ser-Huang Poon, 2000 studied the daily correlation dynamics between the US and two European countries: France and the UK. First they evaluated two returns synchronization procedure: Riskmetrics method and a

GARCH-based method proposed by Burns et al.(1998). Second they studied daily dynamic and spillover effects on the conditional variance, correlation and covariance for stock index returns. They find that there exists a clear difference between spillover and a contemporaneous correlation. Besides volatility spillover effect from the US to another countries detected in previous studies, they found a reverse volatility spillover effect from the Europe to the US.

4 Value at risk

Financial activity is unstable and risky. The risk of losses arising from adverse movements in market prices or rates is called market risk. Value at Risk (VaR) provides a different approach to market risk: it is a measure of investment portfolio loss potential.

VaR has been defined as the maximum expected loss over a given horizon period at a given level of confidence from adverse market movements. It assumes that the portfolio is not managed during this time. The confidence level is the probability that the loss is not greater than predicted by VaR. The significance level of VaR is the probability that is associated with a VaR measurement. It corresponds to the frequency with which a given level of loss is expected to occur.

More formally, from a statistical point of view, VaR describes the quantile of the projected distribution and losses over the target horizon. If "α" is the selected confidence level, VaR correspond to the "1-α" lower- tail level.

Hence,

$$\Pr(\Delta_h \Pi_t < -VaR_{\alpha,h}) = \alpha \quad (3.1),$$

where the loss or profit for a portfolio that is left unmanaged over a risk horizon of h days is: $\Delta_h = \Pi_{t+h} - \Pi_t$.

Price movements are measure relative to some initial price. Price changes in percent are referred to as return. In VaR calculation daily return are typically used. In some cases the square root of return is employed so that the h-day VaR is simply taken as $\sqrt{h}$ times the 1-day VaR;

$$\mathrm{VaR}_{\alpha,h} = \sqrt{h}\ \mathrm{VaR}_{\alpha,1} \quad (3.2)$$

One often proposed alternative to VaR is called expected shortfall. Expected Shortfall is defined as expected loss in greater than given cutoff level. Cutoff level is often chosen to correspond to VaR. Formally expected shortfall is given by Artzner et al., 1999).

$$\mathrm{ES} = -\mathrm{E}\left[x / x \le -VaR\right] \quad (3.3)$$

Expected shortfall given an idea about the magnitude of losses when losses greater than predicted by VaR occur. The recent practices in financial institutions imply that this is more accurate method for allocating capital. Instead of using VaR methods to determine economic capital for the institution and for the business areas, the risk management has been started to use expected shortfall. It is a conservative approach that demonstrates the willingness of the institutions to cover better against the potential expected, unexpected and extreme losses.

Approaches to VaR may be categorized to into two large categories:

- **Non parametric methods** use no assumptions about the distributions of returns. The estimation of VaR is based solely on empirical distributions of return. Historical Simulation is classified under this category.
- **Parametric methods** make some assumptions about the distributions of return. This implies selection and calculation of parameters used, estimation of the portfolio distribution and finally VaR calculation.

3.1 Historical Simulation

This is the most common and the simplest non-parametric method to estimate VaR that requires only minimal distributional assumption.

The basic idea behind historical simulation of VaR is very straightforward: one simply uses real historical data to build an empirical density for the portfolio P&L. Historical data are collected usually on a daily basic covering several years. The first simulation trial assume that the percentage changes in each market variables are the same as those on the first day covered by the data base; the second simulation trial assumed that the percentage changes are the same as those on the second day and so on. Finally the historical VaR measure is the percentile of the empirical distribution corresponding to the confidence level of these distributions.

The number of data points to be included in the empirical distribution is often referred to as “window size”.

Advantages of HS include its conceptual simplicity: there is no need to estimate distribution parameters such as volatilities and correlations. Regarding to assumptions about return distributions, HS is free from model and makes it possible to accommodate heavy tails. A drawback with HS is that is cannot predict losses that occur less frequently than in the sampling period. This causes high variance in extreme statistics. Therefore extreme loss predictions require employing a window size of substantial length.

Very long historic data periods may contain a number of extreme market events from far in the past are not necessarily relevant to "current" normal circumstances.

3.2 Variance /Covariance Approach

It is a parametric method based on the assumption that the return are normally distributed.

VaR is defined as:

$$VaR_{\alpha,h} = Z_{\alpha}\,\sigma_t - \mu_t, \quad (3.4)$$

Where Z_{α} is the α^{th} percentile of the standard normal density

This method is know as the Delta - Normal Method and it is particularly easy to implement, but can be subject a number of criticism. A first problem is the existence of fat tails in the distribution of return on most financial assets.. In this situation a model based on a normal distribution would underestimate the proportion of outliers and hence the true value at risk.

Another problem is that the method inadequately measures the risk of non-linear instruments such as options and mortgages. For those type of instruments, Delta- Gamma (DG) method may be used. We can improve the quality of the linear approximation by adding terms in the Taylor expansion of the valuation function. This method takes the variance of both sides of the quadratic approximation.

The standard deviation is calculated using the following three approaches

- Moving average (MA) technique
- Exponential Weighted Moving Average (EWMA) technique
- GARCH techniques.

Each of the listed techniques will be detailed in the next subsections.

3.2.1 Moving Average (MA)

Simple moving averages of fixed length have also been used to estimate and forecast unconditional volatility and correlation. A typical length is 20 trading days (about a calendar month) or 60 trading days (about a calendar quarter).

The volatility estimated for returns r_t over M days is constructed as follow:

$$\sigma^2{}_t = (1/M)\sum_{i=1}^{M} r^2{}_{t-i} \quad (3.5)$$

Each day the forecast is updated by adding information from the preceding day and dropping information from (M+1)

Long term predictions should be unaffected by short term phenomena such as volatility clustering so it is appropriate to take the average over a long historic period. Short-term predictions should reflect a current market condition which means that only the immediate past return should be used.

3.2.2 Exponential Weighted Moving Average (EWMA) technique

It is a more realistic technique that allows measuring small changes in time-series parameters. In order to capture the dynamic features of volatility it is use an exponential moving average of historical observations, where the latest observations carry the highest weight in volatility estimate.

The variance is given by:

$$\sigma^2{}_t = (1-\lambda)\sum_{i=1}^{\infty} \lambda^{i-1} r^2{}_{t-i} \quad (3.6)$$

The RiskMetrics methodology adopted EWMA technique to estimate variance and covariance of risk factor.

The formula above can be written in a recursive form:

$$\sigma^2 = (1-\lambda)r_{t-1}{}^2 + \lambda\sigma^2{}_{t-1} \quad (3.7)$$

The exponential moving average weighted model depends on the parameter λ - which is often referred to decay factor. This parameter determines the relative weight of past observations. RiskMetrics chose the optimal decay factor, for the daily data, set $\lambda = 0.94$ and for one month set $\lambda = 0.97$. This corresponds to 74 respectively 151 past data points.

3.2.3 GARCH (Generalized Autoregressive Conditional Heteroskedasticity)

Many financial time series such as stock prices, exchange rate, display volatility clustering, that is period in which their prices show wide swings for an extended time period followed by periods in which there is relative calm.

How we can model this "varying variance"? The Autoregressive Conditional Heteroskedastic (ARCH) model originally developed by Engle in 1982 explicitly recognizes this type of temporal dependence. Heteroscedasticity or unequal variance may have an autoregressive structure in that heteroscedasticity observed over different periods may be autocorrelated.

A useful generalization of this model is the GARCH parameterization introduced by Bollerslev (1986). As per Engle (2001) this model is also a weighted average of past squared residuals, but is has declining weights that never go completely to zero.

A general GARCH (p,q) model is given by Bollerslev, 1986, and the equations specified for this model are:

The conditional mean $y_{t/t-1}$ it is take as constant $y_t = \mu_t + \varepsilon_t$

Conditional variance equation:

$$\sigma_t{}^2 = \varpi + \sum_{j=1}^{p} \beta_j \sigma_{t-j}{}^2 + \sum_{i=1}^{q} \alpha_i r^2{}_{t-j} \quad (3.8)$$

Where

p and q are the number of lags included in the conditional variance and squared returns respectively.,

r_t is the continuously compounded return between day t and t-1

σ^2 is the variance distribution of day t

$\varpi, \beta_1 ...., \beta_q, \alpha_1, ..., \alpha_q$ are the model parameters.

Also, the following restrictions apply:

$$\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0 \text{ and } \sum_{i=1}^{\max(p,q)} (\alpha_i \beta_j) < 1$$

The coefficients α_i measure the persistence of returns. If α_i is high then volatility reacts fast to changes in the market. The β_j measures the persistence of variance.

The first number in parentheses "p" refers to how many autoregressive lags, or ARCH terms, appear in the equation, while the second number "q" refers to how many moving average lags are specified which often called the number of GARCH terms.

Many previous studies showed that is unnecessary to include more than one lag in the conditional variance estimate for financial returns.

3.3 Extreme Value Theory (EVT)

The motivation for the use of extreme value theory is that the stock distribution is not normal. Empirical observations have shown that the distributions is fat-tail; that there are significant probabilities for the stock returns to be high or low, much more so than predicted by the normal distribution.

The EVT is concerned with the shape of the cumulative distribution function for the value x beyond a cutoff point u. The cumulative distribution function belongs to the following family:

$$F(y) = 1 - (1 + \xi y)^{-1/\xi} \qquad \xi \neq 0 \quad (3.9)$$

$$F(y) = 1\text{-}\exp(-y) \qquad \xi = 0 \quad (3.10)$$

The distributions are defined as the generalized Pareto distribution because it subsumes other known distributions including the Pareto and normal distributions as special case.

The normal distribution corresponds to $\xi = 0$ in which case the tail disappears at an exponential speed. For typical financial data $\xi > 0$ implies heavy tails that disappears more slowly.

In order to determine the VaR, the following necessary steps have to be considered:

- The standardized portfolio returns are given from the following formula:

$$z_t = \frac{r_t}{\sigma_t} \quad (3.11)$$

- It is choose a threshold “u” to represent the 95th, 99th percentile.
- Let y = x + u; The ξ is estimated by the simple Hill estimator as defined bellow. When the tail parameter ξ is positive then the return distributions is fat tailed.

$$\xi = 1/T_u \sum_{i=1}^{T_u} \ln \frac{y_i}{u} \quad (3.12)$$

- The VaR from the EVT combined with the variance model is calculated as:

$$\mathrm{VaR}_{\alpha,t} = \sigma_t u \left(\frac{\alpha}{T_u/T} \right)^{-\xi} \quad (3.13)$$

3.4 Back Testing

The VaR models estimated should be accompanied by validation. Model validation is a general process of checking whether a model is adequate. In the financial institutions this process can be carried out in two ways either internally by independent parties from the model development or by an external advisor.

Back testing is a formal statistical framework that consist of verifying that actual losses are in line with projected losses, for a given back testing period the estimated VaR are compared to the observed returns on day to day basis. VaR measure is violated when the negative return on portfolio or security exceeds the corresponding VaR measure.

Suppose that we are calculating a 1- day (1-α%) VaR , where (1-α%) is the confidence level. Unconditional coverage back testing involves checking if the fractions of violations obtained for the particular VaR model is significantly different from the fraction α%.

When the model is perfectly calibrated the number of observations falling outside VAR should be in line with the confidence level.

Kupiec (1995) develops approximate 95 percent confidence regions for such a test. The choice of the confidence region for the test is not related to the quantitative level α selected for VaR. This confidence level refers to the decision rule to accept or reject the model.

These regions are defined by the tail points of the log-likelihood ratio:

$$LR_{uc} = -2\ln\left[(1-\alpha)^{T-N}\alpha^{N}\right] + 2\ln\left\{\left[1-(N/T)\right]^{T-N}(N/T)^{N}\right\} \quad (3.14)$$

Where T is the total number of observations of the sample and N is the number of days that a violation is observed.

The LR_{uc} is asymptotically distributed chi-square with one degree of freedom under the null hypothesis that α is the probability. It is reject the null hypothesis if $LR_{uc} > 3.84$ (critical value).

5 Spillover

5.1 Unit Roots tests

In order to proceed to the implementation of our methodology and examine the spillover effects our series must be stationary.

If a time series is stationary its mean variance and autocovariance (at various lags) remain the same no matter at what point we measure them. In this way we can conclude that the series are not depending on time.

A process Y_t is the stationary in the following conditions hold:

1. $E(Y_t) = \mu < \infty$ (constant mean);
2. Cov $(Y_t, Y_{t-k}) = \gamma_k < \infty$ (covariance at la "k", depend on "k" but not on t).

If k=o we obtain γ_0 which is simply the variance of Y $(=\sigma^2)$. The second condition implies that a stationary process has a constant variance.

A non- stationary process arises when one of the conditions for stationarity does not hold.

Testing for unit-roots means testing the hypothesis:

$$H_0 : \rho = 1$$

$$\text{Vs } H_1 : |\rho| < 1$$

in the following random walk model.

$$Y_t = \rho Y_{t-1} + u_t, \quad -1 \leq \rho \leq 1 \text{ where } u_t \text{ is a white noise error term}$$

We know that if $\rho = 1$, this is, in the case of the unit root.

A series Y_t integrated of order "d" it must be differenced at least "d" times in order to make it stationary.

If a time series is non-stationary we can study its behavior only for the time period under consideration. The set of time series data will therefore be for a particular episode. As a consequence it is not possible to generalize it to other time period.

A non-stationarity series is characterized by a drift parameter that increase with time. The variance and covariance would also not be stable in time. We want to check if the drift is stochastic or deterministic. If the trend in time series is completely predictable and not variable we call it a deterministic trend, whereas if it is not predictable we call it a stochastic trend.

The unit root tests can be performed using two methods. The first one takes care of the deterministic part, focusing on the existence of a unit root through Augmented Dickey-Fuller (1981) test. The second methods focus on the stochastic part of the drift trough the test of Philips-Perron.

5.2 Granger causality

Regressions analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation, but in regressions involving times series data and the situation maybe somewhat different.

Granger causality is a technique for determining whether one time series is useful in forecasting another. Testing Granger causality involves using F –tests to test whether lagged information on a variable Y provides any statistically significant information about a variable X in the presence of lagged X.

If variable X (Granger) causes variable Y, then changes in X should precede changes in Y. Therefore in a regression of Y on other variables (including its own past value) if we include past or lagged value of X and its significantly improves the prediction of Y , then we can say that X (Granger) causes Y. A similar definition applies if Y (Granger) causes X.

It is important to note that the statement “Y Granger causes X” does not imply that X is the effect or the result of Y.

In order to test for Granger causality across two variables X_t and Y_t we run bivariate regressions with a lag length set as k. These are called unrestricted regressions:

$$X_t = c_1 + \sum_{i=1}^{p} \alpha_{1i} X_{t-i} + \sum_{i=1}^{p} \beta_{1i} Y_{t-i} + \varepsilon_{1t} \quad (5.1)$$

$$Y_t = c_1 + \sum_{i=1}^{p} \alpha_{2i} X_{t-i} + \sum_{i=1}^{p} \beta_{2i} Y_{t-1} + \varepsilon_{2t} \quad (5.2)$$

For the first equation The Granger causality is examined by testing the null hypothesis whether all β_{1i} are equal to zero.

Ho: $\beta_{11} = \beta_{12} = \ldots.. = \beta_{1k} = 0$

That is we perform a Wald test with Wals statistics:

W= $\frac{(SSR_R - SSR_{UR})}{SSR_{UR} /(n-2k-1)}$ which is asymptotically distributed as χ^2 under H_0

If we assume that errors ε_{1t} are independent and identically normally distributed we have an exact finite sample F-statistic:

F= $\frac{W}{q} = \frac{(SSR_R - SSR_{UR})/k}{SSR_{UR} /(n-2k-1)}$

Where SSR_{UR} - is the residual sum of squares of the unrestricted regression above, SSR_R is the residual sum of square of the restricted regression which is the regression without the lags of Y_t. If the ADF and PP unit root test have verified that the series on levels are non stationary and the first differences are stationary (first integrated) then the Granger causality tests are performed across the first differences of the series.

6 Result and Discussion

6.1 Data series

In this paper dissertation we studied the major US and European stock indices and Romanian representative index: NASADAQ 100, Dow Jones Industrial Average DJINDUS, The Standard & Poor's 500 (S&P 500) for the United States, CAC 40 for France, DAX 30 for Germany, FTSE100 for the United Kingdom and BET for Romania. It is use daily stock market closing price, daily data for the last ten years 22/09/1997-30/05/2008

In order to estimate VaR models it is calculate daily continuously compounded returns of each index using the formula:

$$r_t = \ln \frac{P_t}{P_{t-1}} \quad (6.1)$$

Where r_t is the continuously compounded return between day t-1 and t and P_t is the index price at day t.

Here we should note that the use of daily closing prices leads to an underestimation of the true correlations between stock markets and hence underestimates the true risk associated with a portfolio of such assets. Also we have mentioned that efficient markets hypothesis suggests that information is quickly and efficiently incorporated into stock prices.

As we can see in the Appendix the diagram of daily log-returns clearly display the volatility clustering phenomenon: large changes in index value tend to cluster.

6.2 Statistics

The next two tables detail the statistics obtained for the seven stock indexes.

	BET	NASDAQ_100	DJINDUS
Mean	0.000791	0.0001511	0.000174
Median	0.000435	0.0011926	0.000413
Maximum	0.176253	0.1325464	0.061547
Minimum	-0.2077	-0.1016841	-0.07455
Std. Dev.	0.018958	0.0180046	0.011095
Skewness	-0.04071	0.0498227	-0.20902

Kurtosis	16.86964	6.8307005	6.961061
Jarque-Bera	20832.44	1645.2417	1777.515
Probability	0.000	0.000	0.000

Table 1: Descriptive statistics for the daily log return of the indices for the period 22/09/1997 -30/05/2008.

	S_P_500	**CAC_40**	**DAX_30**	**FTSE_100**
Mean	0.000144	0.000192	0.000213	6.91E-05
Median	0.000489	0.000459	0.000854	0.000394
Maximum	0.055744	0.070023	0.075527	0.059038
Minimum	-0.07113	-0.07678	-0.07433	-0.05637
Std. Dev.	0.011531	0.014265	0.015751	0.011763
Skewness	-0.07571	-0.12714	-0.1524	-0.13899
Kurtosis	5.933356	5.732981	5.548385	5.283189
Jarque-Bera	966.6401	853.5214	743.5263	594.7102
Probability	0.000	0.000	0.000	0.000

Table 2: Descriptive statistics for the daily log return of the indices for the period 22/09/1997-30/05/2008.

As per the values from the above two tables, we observe that our daily returns of the indexes do not follow the normal distribution. This is sustained by the following:

- **Skewness moment** is different from 0 and in almost in all the cases being negative. The negative values imply the leverage effect – the negative correlation between changes in the volatility and the changes in the market price.
- **Kurtosis moment** registers values quite high and it exceeds the value of 3 which shows the normality of the distribution;
- **Jarque-Bera (JB) statistics** must show non-significance in order for the daily returns to follow the normal distribution. In our case, as the value of the probability from the above tables shows, the JB statistics is significant.

Therefore, as FAMA mentioned in his 1965 article, our indexes display leptokurtosis, meaning that there are too many values near the mean and too many out in the extreme tails. This is translated as heavy tail phenomenon. Also, this demonstrates volatility clustering meaning that large changes may tend to be followed by large changes, but of random sign, whereas small changes tend to be followed by small changes.

In order to study the spillover effect of the tail risk, we estimate the daily VaR series using the following non and parametric techniques detailed below and 95% and 99% confidence level.

6.3 Historical Simulation

The method of historical simulation is based on the assumption that the distribution of the returns is constant over the sample period and the future is sufficiently like the past. This considers also the non-normality of the distribution, fat tail and skewness different from 0.

In order to calculate the VaR as per the historical simulation, we have used two sizes of past observation: 100 and 250 days. The daily VaR is calculated as the percentile of the indexes series using the last 100 and 250 daily returns and 95 and 99% confidence level. For each index, the process is repeated for all the days using the rolling window of the same number of observations (100 and 250).

6.4 Delta-Normal Approach

Before calculating the Value at Risk we have estimated the volatility using three methods: moving average, EWMA and GARCH

For the moving average technique we have used a moving window of fixed length for estimating the volatility over 10 days, 20 days and 60 days.

We have also estimated the daily volatility following an exponentially weighted moving average over the past 74 days using a decay factor of 0.94. According to RiskMetrics a decay factor of 0.94 corresponds to a 1% tolerance level and 74 days of historical data.

We have used the RiskMetrics formula as defined below:

$$\sigma^2 = (1-\lambda) r_{t-1}{}^2 + \lambda \sigma^2{}_{t-1} \quad (6.2)$$

6.5 GARCH

The GARCH methods were also used to determine the daily volatility to be included in the Delta-Normal VaR..

All seven markets have some autocorrelations which are indicated by Ljung –Box statistics and ARCH effect which is implied by ARCH LM test, which means that GARCH model is appropriate to analyze those series.

Hence we estimate a GARCH type model that consists of two equations:

The first is the conditional mean equation:

$$r_t = \mu_t + \varepsilon_t \quad (6.3)$$

where r_t is the daily log return, μ_t is the mean of the return distribution and ε_t is the residual value.

The second equation is the conditional variance equation as it was defined:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}{}^2 + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} \quad (6.4)$$

r_t is the continuously compounded return between day t and t-1, σ^2 is the variance distribution of day t and α_i and β_i are the coefficients that measure the persistence of returns and variance.

In every case the best GARCH model accepted is a GARCH (1, 1) as we can see in the appendix. In order to select the most appropriate GARCH higher model have been estimated and we have compared the Akaike and Schwarz statistics produced by each model for each index. We choose the model that produces the lowest Schwarz statistics.

Also we estimate two GARCH models for each index one under the assumption that the errors of the mean equation follow the Normal distribution and the second under the assumption that the errors follow the Student's t distribution.

The equation for the GARCH (1,1) model is:

- Mean equation: $r_t = \mu_t + \varepsilon_t$ (6.5)

- Variance equation: $\sigma_t^{\ 2} = \alpha_0 + \alpha_1 r_{t-1}^{\ \ 2} + \beta_1 \sigma_{t-1}^{\ \ 2}$ (6.6)

.As a result all the coefficients are significant at 5% probability level. In the Appendix we detailed the GARCH output estimations.

Since the variance has been estimated we then calculate 1 day 95% and 99% VaR according to the Delta-Normal method.

6.6 EVT

In order to calculate the extreme value theory VaR, the generalized Pareto distribution was applied. This distribution counts other distributions including Pareto and normal distributions.

ξ is a key parameter in our distributions. An $\xi = 0$ corresponds to a normal distribution while an $\xi > 0$ entails heavy tails. ξ is estimated by Hill estimator as described at (3.12) formulae.

As listed bellow, ξ for all the indexes and methods is more than 0 demonstrating once again the fat tail of the indexes.

S&P ξ	**95**	**99**	**DJINDUS ξ**	**95**	**99**
MA(10)	0,873739	0,834302	**MA(10)**	0,609743	0,272561
MA(20)	0,887254	0,334582	**MA(20)**	0,629297	0,305806
MA(60)	0,946735	0,752213	**MA(60)**	0,999635	1,123182
EWMA	4,826161	2,845424	**EWMA**	6,484068	5,481972
NASDAQ ξ	**95**	**99**	**DAX ξ**	**95**	**99**
MA(10)	0,568145	0,257056	**MA(10)**	0,528118	0,068633
MA(20)	0,617452	0,29738	**MA(20)**	0,552788	0,062541
MA(60)	0,954129	0,861468	**MA(60)**	0,296996	0,087011
EWMA	4,766432	2,652726	**EWMA**	3,837795	1,507284
FTSE ξ	**95**	**99**	**CAC ξ**	**95**	**99**
MA(10)	0,557953	0,241958	**MA(10)**	0,510517	0,194532
MA(20)	0,584293	0,275665	**MA(20)**	0,535125	0,207019
MA(60)	0,953114	0,859596	**MA(60)**	0,804967	0,298043
EWMA	6,981758	18,63721	**EWMA**	3,368116	1,365778
BET ξ	**95**	**99**			

MA(10)	0,873739	0,834302
MA(20)	0,887254	0,334582
MA(60)	0,946735	0,752213
EWMA	4,826161	2,845424

Table 3 ξ value for all the indexes

6.7 Back Testing Results

The adequacy of VaR models is verified by means of back testing. It involves comparing the measures with the returns. As per Jorrion (2002), the problem is that since VaR is reported only at a specified confidence level, it is expected the figure to be exceeded in some instances, for example in 5% of the observations at the 95% confidence level. Also a 6 to 8% could occur and this may be interpreted as bad luck. However, if the frequency of deviations is from 10% to 20%, then there is a problem with the VaR model.

We perform the Kupiec test in order to accept or reject each VaR model. The rate of violations are calculated for each back testing period and compared to the target rate of violations. For VaR at 95% confidence level the target rate of violations is 5% and for VaR 99% the target rate of violations is 1%. The rate of violations which differs from the target rate of violations indicates that the VaR model is biased.

All the VaR series determined with the above mentioned methods were backtested for the last 250 days.

The next two tables present the value of the Kupiec test for 95% and 99% confidence level. After calculating the tests we choose the series to be used further in the calculations. For selecting the series we have applied the following assumption/judgment:

- If there were more than two accepted VaR models, we have selected the median value. The reason behind this decision was related to the capital adequacy decision. If the VaR is too high then the capital requirement will be high. Consequently, if the accepted VaR is too low, then the capital requirements may be too low and potential risks and impact may not be covered.

- If there were only two accepted VaR models, we have used a conservative approach, meaning that we have selected the highest VaR.

95%			
Index	**Method**	**LR-UC**	**Average VaR**
BET	Delta Normal HS (100)	3.0905329	0.0276308
	Delta Normal MA (10)	1.1382542	0.0320058
	Delta Normal MA (20)	1.1382542	0.0324269
	EVT MA(10)	1.1382542	0.0340828
	EVT MA(20)	1.1382542	0.0325120
	EVT MA(60)	0.0213240	0.0384520
	Delta Normal Garch	1.1382542	0.0337270
CAC	Delta Normal MA (10)	0.4960553	0.0260029
	Delta Normal MA (20)	0.9513567	0.0257010
	EVT MA(10)	0.1971196	0.0281309
	EVT MA(20)	0.1826969	0.0267166
	Delta Normal Garch	0.5633529	0.0257855
DAX	Delta Normal MA (10)	0.1826969	0.0284093
	Delta Normal MA (20)	0.0213240	0.0280818
	EVT MA(10)	0.0213240	0.0299647
	EVT MA(20)	0.5633529	0.0290922
	Delta Normal Garch	1.9441361	0.0281159
DJINDUS	Delta Normal MA (10)	0.0213240	0.0203952
	Delta Normal MA (20)	0.0213240	0.0201946
	EVT MA(10)	0.1971196	0.0211605
	EVT MA(20)	0.0213240	0.0203006
	EVT MA(60)	0.5633529	0.0285154
FTSE	Delta Normal MA (10)	0.0207919	0.0214809
	Delta Normal MA (20)	0.0207919	0.0213600
	EVT MA(10)	0.0213240	0.0226490
	EVT MA(20)	0.0207919	0.0212196
	EVT MA(60)	1.5402866	0.0287126
NASDAQ	Delta Normal MA (10)	1.1382542	0.0322451
	Delta Normal MA (20)	0.5633529	0.0319142
	EVT MA(20)	0.5633529	0.0301694
S&P	Delta Normal MA (10)	0.1971196	0.0213185

95%			
Index	**Method**	**LR-UC**	**Average VaR**
	Delta Normal MA (20)	0.4960553	0.0211155
	EVT MA(10)	0.0213240	0.0200892
	EVT MA(20)	0.1826969	0.0202222
	EVT MA(60)	0.9513567	0.0281317

Table 4 – 95% VaR Backtesting results

99%			
Index	**Method**	**LR-UC**	**Average VaR**
BET	Delta Normal MA (20)	1.9568098	0.0386976
	EVT MA(60)	1.1764911	0.1593860
	Delta Normal Garch	0.7691384	0.0402432
CAC	Delta Normal MA (20)	1.9568098	0.0305890
	Delta Normal Garch	1.9568098	0.0306895
DAX	Delta Normal MA (10)	1.9568098	0.0338125
	Delta Normal Garch	0.7691384	0.0334637
DJINDUS	Delta Normal MA (20)	1.9568098	0.0240397
	EVT MA(60)	1.1764911	0.0428615
FTSE	EVT MA(60)	1.1764911	0.0744080
	Delta Student Garch	1.1764911	0.0503621
NASDAQ	Delta Normal MA (10)	0.7691384	0.0383607
	Delta Normal MA (20)	0.7691384	0.0379673
S&P	Delta Normal Garch	0.0207919	0.0253649

Table 5 – 99% VaR Backtesting results

After calculating the Value at Risk using different techniques we reach the following conclusion about these. Extreme Value Theory estimates better the 95% VaR while the 99% VaR estimation is split between Delta Normal Garch, EVT and Delta Normal Moving Average. Also, the GARCH models with normal distributions have much more better performance than GARCH models with Student distributions for the residuals.

In the next two tables we present the statistics of the indexes' VaR approaches that were selected to continue the study.

VaR 95	FTSE	NASDAQ	S_P	BET	CAC	DJINDUS	DAX
Mean	-0.02006	-0.03196	-0.02104	-0.03205	-0.0263	-0.01995	-0.02783
Median	-0.018	-0.02764	-0.01916	-0.0269	-0.02354	-0.01819	-0.02411
Maximum	-0.00388	-0.01002	-0.00584	-0.00612	-0.01	-0.00705	-0.01235
Minimum	-0.07076	-0.10775	-0.07067	-0.15358	-0.07893	-0.05714	-0.08308
Std. Dev.	0.009954	0.017376	0.010218	0.018121	0.012844	0.009034	0.012739
Skewness	-1.72562	-1.40808	-1.37807	-2.54379	-1.54594	-1.43645	-1.51809
Kurtosis	7.336156	5.116781	5.594731	14.44459	5.48355	5.513321	5.113575
Jarque-Bera	3242.813	1310.449	1512.893	16562.03	1660.584	1538.39	1444.972
Probability	0	0	0	0	0	0	0

Table 6 –1 day VaR 95% Statistics

Var 99%	BET	CAC	DAX	NASDAQ	S_P	DJINDUS	FTSE
Mean	-0.03956	-0.03066	-0.03347	-0.03854	-0.02107	-0.04327	-0.07547
Median	-0.03361	-0.02733	-0.02871	-0.0334	-0.01965	-0.03949	-0.0682
Maximum	-0.01912	-0.0143	-0.00777	-0.00792	-0.01034	0.030277	0.024931
Minimum	-0.30017	-0.08382	-0.11508	-0.15043	-0.05512	-0.09354	-0.15724
Std. Dev.	0.021337	0.01326	0.018513	0.022203	0.007823	0.016497	0.03043
Skewness	-3.84977	-1.50508	-1.52248	-1.61881	-1.24881	-0.43668	-0.41739
Kurtosis	29.4584	5.18723	5.449221	6.351097	4.806293	3.51433	2.344639
Jarque-Bera	80172.56	1461.805	1612.31	2292.423	1003.121	108.4641	118.9238
Probability	0	0	0	0	0	0	0

Table 7–1 day VaR 99% Statistics

6.8 Spillovers: Results and discussion

6.8.1 Unit Root Test

In order to proceed to the causality and next examinations, we have to see if the series are stationary or non-stationary. This issue is studied through Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. More explicitly, the scope of the tests is to identify if the mean variance and autovariance are the same no matter the point of measuring.

The next table details the ADF and PP tests for Unit Root in the 1 day, 95% and 99% VaR series of the indexes. The probabilities reported correspond to t-statistics and sustain the null hypothesis that a series has a unit root.

Unit Root 1 day-95 %				
Index	ADF(intercept)	ADF(intercept & trend)	PP(intercept)	PP(intercept & trend)
BET	0.0001	0.0006	0	0
NASDAQ 100	0.1049*	0.0905*	0.0062	0.0036
DJINDUS	0	0.0001	0.0001	0.0002
S&P 500	0.0001	0.0001	0.0001	0.0001
CAC40	0.0005	0.001	0.0015	0.0032

DAX 30	0.0086	0.0203	0.0017	0.0036
FTSE 100	0	0	0	0
Unit Root 1 day-99 %				
Index	ADF(intercept)	ADF(intercept & trend)	PP(intercept)	PP(intercept & trend)
BET	0	0	0	0
NASDAQ 100	0	0	0	0
DJINDUS	0.8572*	0.995*	0.5873*	0.986*
S&P 500	0.0001	0.0002	0.0001	0.0001
CAC40	0.002	0.006	0.0012	0.003
DAX 30	0.0016	0.0027	0	0.0001
FTSE 100	0.7741*	0.9945*	0.4048*	0.9028*

Table 8 – ADF and PP tests

Using the ADF and PP tests unit root tests, we came to the following conclusion for the 95% VaR series:

- BET, DJINDUS, S&P500, CAC40, DAX30 and FTSE100 present stationary
- NASDAQ100 are non-stationary since it has a unit root. Therefore the null hyphotesis of the existence of a unit root is significant at 5% probability level.

Also, the results identified for the 99% VaR series are:

- BET, NASDAQ100, S&P500, CAC40 and DAX30 present stationarity
- The null hypothesis of root existence is significant for DJINDUS and FTSE100.

6.8.2 Spillovers: Granger Causality

The first way to detect spillover of tail risk across the seven indices is by examining the bivariate Granger causality. The VaR series present non-stationary, hence we use the changes of VaR in order our series to become stationary.

With Granger causality we detect that an index faced the previous days causes the tail risk of another index the next day.

We perform the Granger causality test by running bivariate regressions for all possible pairs (X,Y):

$$\Delta X_t = c_1 + \sum_{i=1}^{k} \alpha_i \Delta X_{t-i} + \sum_{i=1}^{k} \beta i \Delta Y_{t-i} + \varepsilon_t \quad (6.7)$$

$$\Delta Y_t = c_1 + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} + \sum_{i=1}^{k} \beta i X_{t-i} + \varepsilon_t \quad (6.8)$$

Where ΔX_t si ΔY_t is the daily change in the 1-day 95%, or 99% VaR from time t-1 to time t and ε_t are residuals.

The bivariate regressions for all possible pairs are performed in a VAR model.

We choose the appropriate number of lags k according to Schwarz criterion and accept the VAR model that produces the lowest Schwarz statistic.

Bivariate Granger causality tests for daily changes of 1 day, 95% VaR			
Direction of causality	$\chi^2 - Stat$	**Lag**	**Probability**
Δ(DAX30)→ Δ(CAC40)* Δ (CAC40) → Δ (DAX30)*	32.3514 55.12735	1 1	0.000 0.000
Δ (DJINDUS)→ Δ (CAC40) Δ (CAC)→ Δ (DJINDUS)**	3.357153 4.620183	1 1	0.0669 0.0316
Δ (BET)→ Δ (CAC40) Δ (CAC40)→ Δ (BET)	0.044183 1.329493	1 1	0.8335 0.2489
Δ (FTSE100)→ Δ (CAC40)* Δ (CAC40)→ Δ (FTSE100)*	12.23927 21.02623	2 2	0.0022 0.000
Δ (NASDAQ100→ Δ (CAC40)* Δ (CAC40)→ Δ (NASDAQ100)	11.7987 6.079004	2 2	0.0027 0.0479
Δ (S&P500)→ Δ (CAC40) Δ (CAC40)→ Δ (S&P5000	1.387263 0.003572	1 1	0.2389 0.9523
Δ (DJINDUS)→ Δ (DAX30)* Δ (DAX30)→ Δ (DJINDUS)	18.9568 5.720779	2 2	0.0001 0.0572
Δ (BET)→ Δ (DAX30) Δ (DAX30)→ Δ (BET)	0.07673 0.027769	1 1	0.7818 0.8677
Δ (FTSE100)→ Δ (DAX30) Δ (DAX30)→ Δ (FTSE100)**	2.389277 5.959815	1 1	0.1222 0.0146
Δ (NASDAQ100)→ Δ (DAX30)** Δ (DAX30)→ Δ (NASDAQ100)	7.027932 4.147972	2 2	0.0298 0.1257
Δ (S&P500)→ Δ (DAX30)	0.530851 0.019988	1 1	0.4662 0.8876

Bivariate Granger causality tests for daily changes of 1 day, 95% VaR			
Direction of causality	$\chi^2 - Stat$	**Lag**	**Probability**
Δ (DAX30)→ Δ (S&P500)			
Δ (BET)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (BET)	0.908031 0.928986	2 2	0.6351 0.6285
Δ (FTSE100)→ Δ (DJINDUS)* Δ (DJINDUS)→ Δ (FTSE100)**	797.9625 6.109692	1 1	0.000 0.0134
Δ (NASDAQ100)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (NASDAQ100)	2.098071 0.159211	1 1	0.1475 0.6899
Δ (S&P500)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (S&P500)	0.650056 0.664697	1 1	0.4201 0.4149
Δ (FTSE100)→ Δ (BET) Δ (BET)→ Δ (FTSE100)	2.405535 0.689678	2 2	0.3004 0.7083
Δ (NASDAQ100)→ Δ (BET) Δ (BET)→ Δ (NASDAQ100)	2.407223 3.92642	2 2	0.3001 0.1404
Δ (S&P500)→ Δ (BET) Δ (BET)→ Δ (S&P500)	1.614928 0.441757	1 1	0.2038 0.5063
Δ (NASDAQ100)→ Δ (FTSE100)** Δ (FTSE100)→ Δ (NASDAQ100)*	4.296985 260.6101	1 1	0.0382 0.000
Δ (S&P500)→ Δ (FTSE100) Δ (FTSE100)→ Δ (S&P500)*	1.43562 454.5139	1 1	0.2308 0.000
Δ (S&P500)→ Δ (NASDAQ100) Δ (NASDAQ100)→ Δ (S&P500)	0.716394 2.209311	1 1	0.3973 0.1372

Table.10 Bivariate Granger causality between the daily changes of the 1 day, 95% VaR of the various indices. The k lags used in each model are specified by Schwarz criterion. Chi-square and the respective probability correspond to the null hypothesis, which mwans that ΔY does not Granger cause ΔX. * indicates rejection of the null hypothesis and significant Granger causality at 1% probability level.** indicates rejection of the null hypothesis and significant Granger causality at 5% probability level.

As we can observe from the above regressions among the 95% VaR series

- at 1% probability level, there is a spillover effect from FTSE100 to CAC 40, DJINDUS, NASDAQ100, S&P500; from FTSE100 to CAC 40; from DAX 30 to CAC40 and CAC40 to DAX30, from NASDAQ100 to CAC40
- at 5% probability level, there is a spillover effect from DAX30 to FTSE100, from NASADQ100 to DAX30, FTSE100, from DJINDUS to FTSE 100.

The next table details the observations for the 99% VaR series.

Bivariate Granger causality tests for daily changes of 1 day, 99% VaR			
Direction of causality	$\chi^2 - Stat$	**Lag**	**Probability**
Δ(DAX30)→ Δ(CAC40) Δ (CAC40) → Δ (DAX30)	0.209 0.907344	1 1	0.6475 0.3408
Δ (DJINDUS)→ Δ (CAC40) Δ (CAC)→ Δ (DJINDUS)	0.0063 0.306902	1 1	0.9367 0.5796
Δ (BET)→ Δ (CAC40) Δ (CAC40)→ Δ (BET)	0.2011 0.030373	1 1	0.6538 0.8616
Δ (FTSE100)→ Δ (CAC40) Δ (CAC40)→ Δ (FTSE100)	0.0573 0.002298	1 1	0.8109 0.9618
Δ (NASDAQ100→ Δ (CAC40) Δ (CAC40)→ Δ (NASDAQ100)	2.6428 2.885356	2 2	0.2668 0.2363
Δ (S&P500)→ Δ (CAC40) Δ (CAC40)→ Δ (S&P5000	0.6456 0.052308	1 1	0.4217 0.8191
Δ (DJINDUS)→ Δ (DAX30) Δ (DAX30)→ Δ (DJINDUS)	2.0097 3.061968	1 1	0.1563 0.0801
Δ (BET)→ Δ (DAX30) Δ (DAX30)→ Δ (BET)	0.2185 0.024298	1 1	0.6402 0.8761
Δ (FTSE100)→ Δ (DAX30) Δ (DAX30)→ Δ (FTSE100)**	1.595 5.3775	1 1	0.2066 0.0204
Δ (NASDAQ100)→ Δ (DAX30)* Δ (DAX30)→ Δ (NASDAQ100)	18.5304 0.415055	2 2	0.0001 0.8126
Δ (S&P500)→ Δ (DAX30) Δ (DAX30)→ Δ (S&P500)	0.5381 1.327055	1 1	0.4632 0.2493
Δ (BET)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (BET)*	0.860197 25.96176	1 1	0.3537 0.000
Δ (FTSE100)→ Δ (DJINDUS)** Δ (DJINDUS)→ Δ (FTSE100)**	5.831881 4.952479	1 1	0.0157 0.0261
Δ (NASDAQ100)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (NASDAQ100)	3.410554 1.02707	2 2	0.1817 0.5984

Bivariate Granger causality tests for daily changes of 1 day, 99% VaR			
Direction of causality	$\chi^2 - Stat$	Lag	Probability
Δ (S&P500)→ Δ (DJINDUS) Δ (DJINDUS)→ Δ (S&P500)	0.99278 0.753073	1 1	0.3191 0.3855
Δ (FTSE100)→ Δ (BET)* Δ (BET)→ Δ (FTSE100)	33.59425 0.14533	1 1	0.000 0.703
Δ (NASDAQ100)→ Δ (BET) Δ (BET)→ Δ (NASDAQ100)	0.938395 0.980291	2 2	0.6255 0.6125
Δ (S&P500)→ Δ (BET) Δ (BET)→ Δ (S&P500)	0.035712 0.358795	1 1	0.8501 0.5492
Δ (NASDAQ100)→ Δ (FTSE100) Δ (FTSE100)→ Δ (NASDAQ100)	0.342058 1.288006	1 1	0.5586 0.2564
Δ (S&P500)→ Δ (FTSE100) Δ (FTSE100)→ Δ (S&P500)**	2.231709 4.52143	1 1	0.1352 0.0335
Δ (S&P500)→ Δ (NASDAQ100) Δ (NASDAQ100)→ Δ (S&P500)	2.442924 0.469478	1 1	0.1181 0.4932

Table.11 Bivariate Granger causality between the daily changes of the 1 day, 99% VaR of the various indices. The k lags used in each model are specified by Schwarz criterion. Chi-square and the respective probability correspond to the null hypothesis, which mwans that ΔY does not Granger cause ΔX. * indicates rejection of the null hypothesis and significant Granger causality at 1% probability level.** indicates rejection of the null hypothesis and significant Granger causality at 5% probability level.

As we can observe from the above regressions among the 99% VaR series:

- at 1% probability level there is a spillover effect from NASDAQ100 to DAX 30, from DJINDUS and FTSE100 to BET
- at 5% probability level there is a spillover effect from DAX30 to FTSE100, from FTSE100 to DJINDUS, S&P 500 and from DJINDUS to FTSE100,

7 Conclusion

In our research we have dealt with spillover of tail risk. We have approach tail risk through the risk measure of Value at Risk and perform an application on seven major stock indices**:** NASADAQ 100, Dow Jones Industrial Average DJINDUS, The Standard & Poor's 500 (S&P 500) for the United States, CAC 40 for France, DAX 30 for Germany, FTSE100 for the United Kingdom and BET for Romania.

We have used as data series the daily closing prices of each stock index for the last 10 years and we calculated VaR through various methods: historical simulation of the last 100 and 250 observations, and the variance approach. We have estimated variance as a moving average, an exponentially weighted moving average and a GARCH model for each index. In addition we have introduced extreme value theory in order to predict the non-normality of the distribution of the stock returns. After we had estimated variance we calculated 1 day, 95% and 99% VaR series for each index.

We used the back-testing in order to accept or reject the Var methods produced. We finally accepted for each index that one which produces the median value of VaR.

Then, the next step was to detect the spillover effects.

In order to use the VaR series we have first checked them for unit roots through the Augmented Dickey- Fuller and Phillips Perron test. Because the series have proved to be non-stationary we have used the first differences in our following research.

We have performed bivariate Granger causality test for the daily changes of 95% VaR and 99% VaR. Causality have observed significant across various indices.

Our results are in concordance with to the results of another study on spillovers: US indices have the greatest effect across the indices in particular DJ INDUSTRIALS and NASDAQ100 have the greatest effect across the indices.

Another interesting result is that FTSE100 plays a significant role since it leads many other markets. Also we have found a causal relationship between DAC30 and CAC 40 to

European market. Martin Martens and Ser-Huang Poon, 2000 studied the daily correlation dynamics between the US and two European countries: France and the UK, and found a reverse volatility spillover effect from the Europe to the US.

Also we observed that there is a spillover effects from US and European market to Romanian market, especially from DJINDUS and FTSE 100.

Comparing the two different levels of risk (95 % and 99%) we observe that the 95% VaR has as a result more spillover across the market, on the other hand 99% VaR has as a result the spillover effects from US and European market to Romanian market. AS we mentioned before the FTSE100 have presented a important influence to European and US market.

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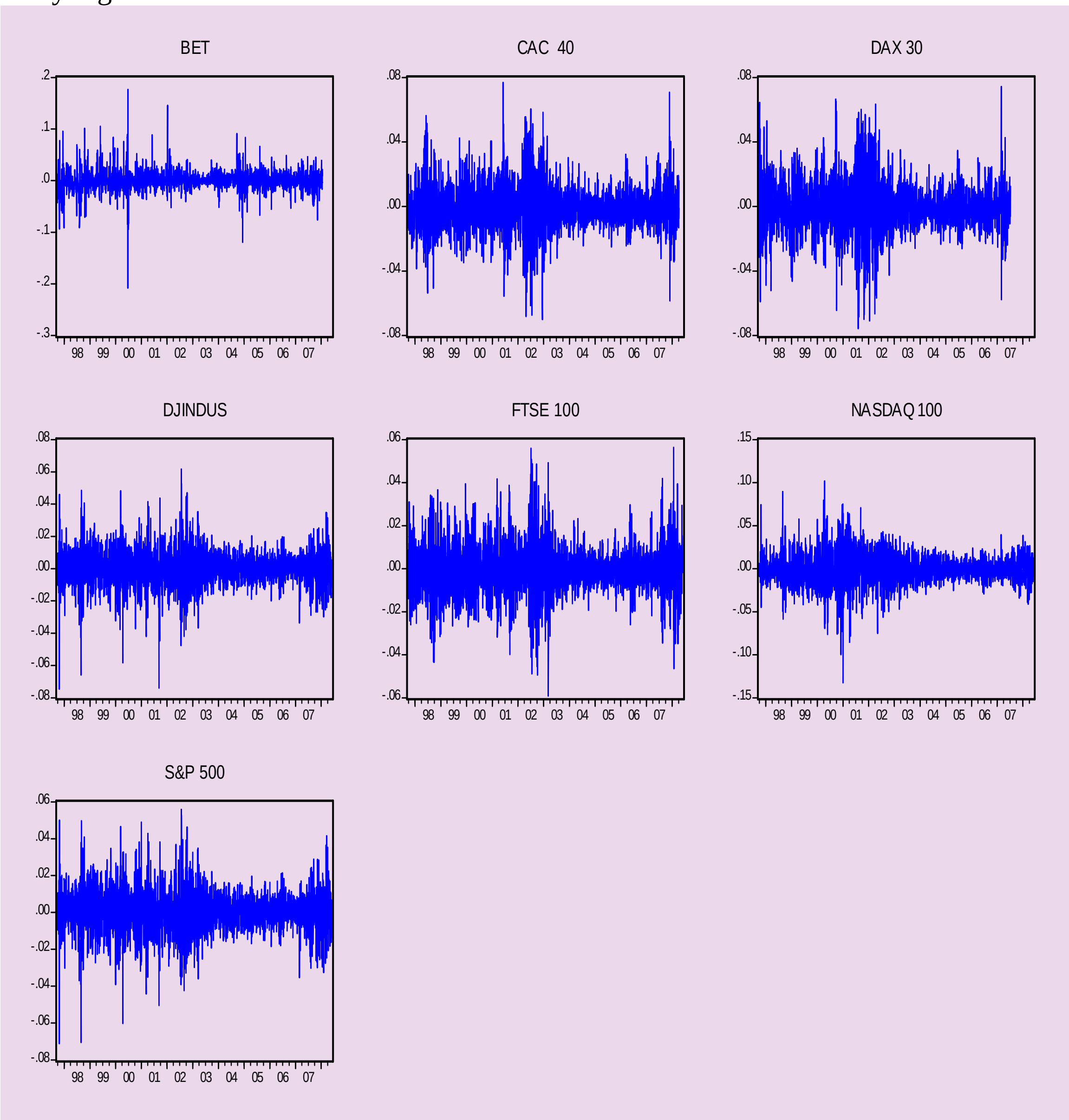
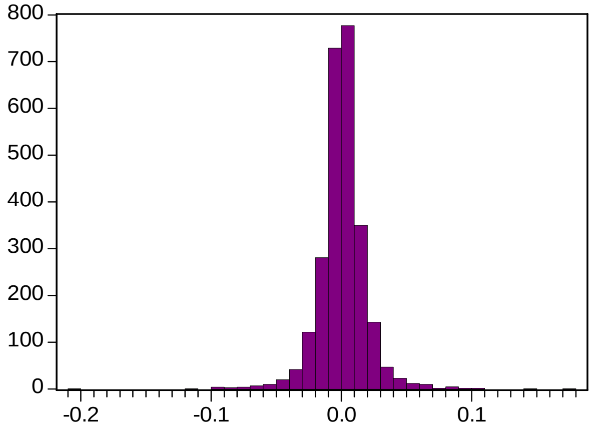
Annex I

Daily log returns of the indexes

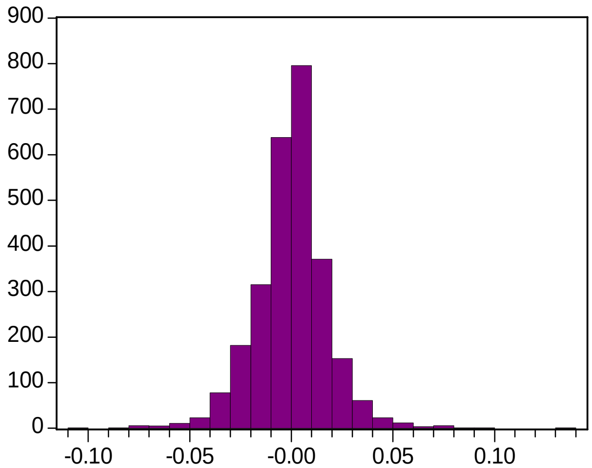


Annex II



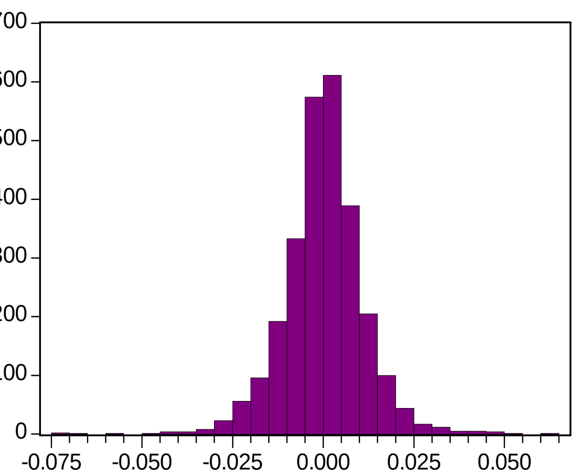
Series: BET
Sample 9/22/1997 5/30/2008
Observations 2599

Mean	0.000791
Median	0.000435
Maximum	0.176253
Minimum	-0.207703
Std. Dev.	0.018958
Skewness	-0.040712
Kurtosis	16.86964
Jarque-Bera	20832.44
Probability	0.000000



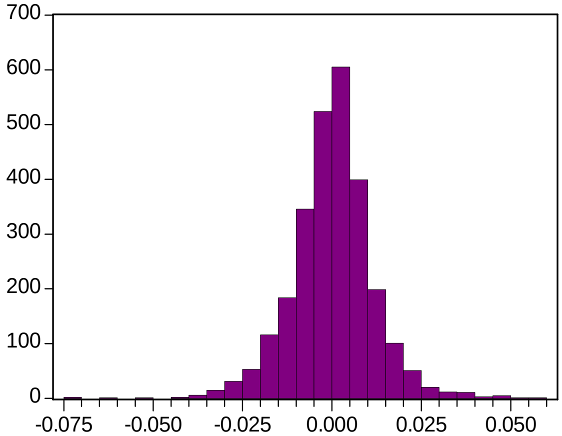
Series: NASDAQ_100
Sample 9/22/1997 5/30/2008
Observations 2689

Mean	0.000151
Median	0.001193
Maximum	0.132546
Minimum	-0.101684
Std. Dev.	0.018005
Skewness	0.049823
Kurtosis	6.830700
Jarque-Bera	1645.242
Probability	0.000000

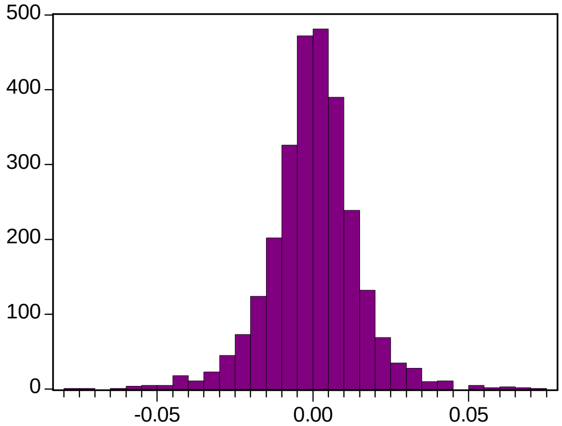


Series: DJINDUS
Sample 9/22/1997 5/30/2008
Observations 2689

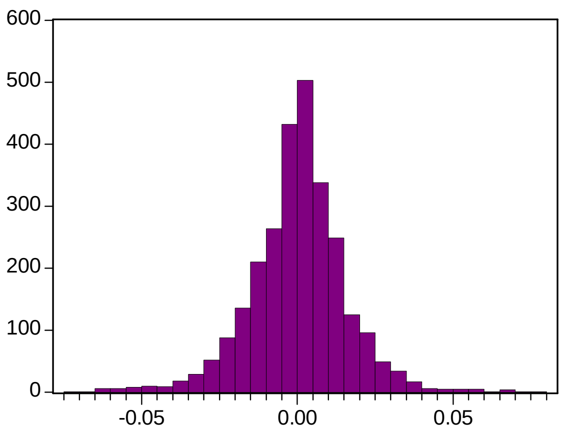
Mean	0.000174
Median	0.000413
Maximum	0.061547
Minimum	-0.074549
Std. Dev.	0.011095
Skewness	-0.209022
Kurtosis	6.961061
Jarque-Bera	1777.515
Probability	0.000000



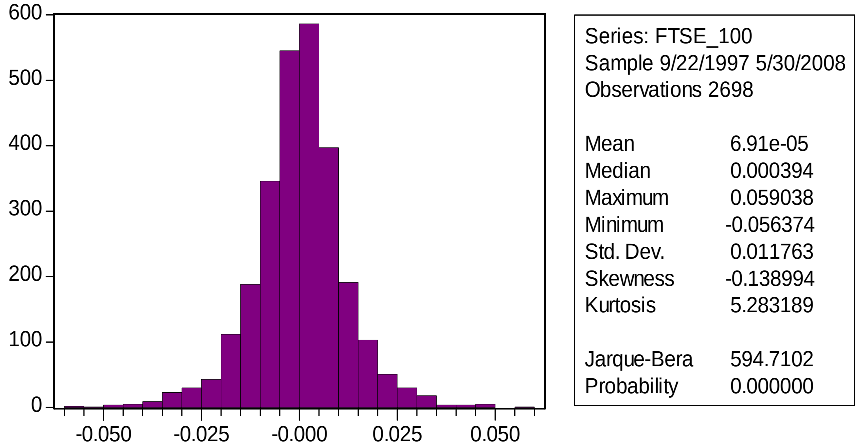
Series: S_P_500	
Sample 9/22/1997 5/30/2008	
Observations 2689	
Mean	0.000144
Median	0.000489
Maximum	0.055744
Minimum	-0.071127
Std. Dev.	0.011531
Skewness	-0.075708
Kurtosis	5.933356
Jarque-Bera	966.6401
Probability	0.000000



Series: CAC_40	
Sample 9/22/1997 5/30/2008	
Observations 2719	
Mean	0.000192
Median	0.000459
Maximum	0.070023
Minimum	-0.076781
Std. Dev.	0.014265
Skewness	-0.127138
Kurtosis	5.732981
Jarque-Bera	853.5214
Probability	0.000000



Series: DAX_30	
Sample 9/22/1997 5/30/2008	
Observations 2709	
Mean	0.000213
Median	0.000854
Maximum	0.075527
Minimum	-0.074335
Std. Dev.	0.015751
Skewness	-0.152396
Kurtosis	5.548385
Jarque-Bera	743.5263
Probability	0.000000


600
500
400
300
200
100
0
-0.050
-0.025
-0.000
0.025
0.050
Series: FTSE_100
Sample 9/22/1997 5/30/2008
Observations 2698
Mean 6.91e-05
Median 0.000394
Maximum 0.059038
Minimum -0.056374
Std. Dev. 0.011763
Skewness -0.138994
Kurtosis 5.283189
Jarque-Bera 594.7102
Probability 0.000000

Annex II

Estimate output GARCH (1, 1) model, a Normal distributions for the residuals is assumed. The dataset is used the period: 22.09.1997-30.05.2008

Dependent Variable: CAC_40

Method: ML - ARCH

Sample: 9/22/1997 5/30/2008

Included observations: 2719

Convergence achieved after 10 iterations

Variance backcast: ON

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000614	0.000211	2.902937	0.0037
		Variance Equation		
C	1.85E-06	4.35E-07	4.266316	0.0000
RESID(-1)^2	0.086682	0.008315	10.42524	0.0000
GARCH(-1)	0.905647	0.008973	100.9319	0.0000

R-squared	-0.000876	Mean dependent var	0.000192
Adjusted R-squared	-0.001982	S.D. dependent var	0.014265
S.E. of regression	0.014279	Akaike info criterion	-5.952767
Sum squared resid	0.553580	Schwarz criterion	-5.944076
Log likelihood	8096.787	Durbin-Watson stat	2.015960

Dependent Variable: DAX_30
Method: ML - ARCH (Marquardt) - Normal distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2709
Convergence achieved after 9 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000797	0.000225	3.548178	0.0004
		Variance Equation		
C	2.47E-06	5.07E-07	4.865161	0.0000
RESID(-1)^2	0.095393	0.009372	10.17871	0.0000
GARCH(-1)	0.895166	0.010085	88.76405	0.0000

R-squared	-0.001374	Mean dependent var	0.000213
Adjusted R-squared	-0.002484	S.D. dependent var	0.015751
S.E. of regression	0.015770	Akaike info criterion	-5.798616
Sum squared resid	0.672736	Schwarz criterion	-5.789898
Log likelihood	7858.225	Durbin-Watson stat	2.028826

Dependent Variable: BET
Method: ML - ARCH
Sample: 9/22/1997 5/30/2008
Included observations: 2599
Convergence achieved after 16 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001057	0.000255	4.147628	0.0000
	Variance Equation			
C	1.75E-05	1.26E-06	13.83018	0.0000
RESID(-1)^2	0.239017	0.012819	18.64490	0.0000
GARCH(-1)	0.739899	0.010265	72.07900	0.0000

R-squared	-0.000198	Mean dependent var	0.000791
Adjusted R-squared	-0.001354	S.D. dependent var	0.018958
S.E. of regression	0.018971	Akaike info criterion	-5.418405
Sum squared resid	0.933957	Schwarz criterion	-5.409382
Log likelihood	7045.217	Durbin-Watson stat	1.773981

Dependent Variable: DJINDUS
Method: ML - ARCH
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 10 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000457	0.000175	2.611683	0.0090
	Variance Equation			
C	1.43E-06	2.17E-07	6.597722	0.0000
RESID(-1)^2	0.088605	0.006018	14.72214	0.0000
GARCH(-1)	0.902656	0.006967	129.5651	0.0000

R-squared	-0.000650	Mean dependent var	0.000174
Adjusted R-squared	-0.001768	S.D. dependent var	0.011095
S.E. of regression	0.011105	Akaike info criterion	-6.394447
Sum squared resid	0.331110	Schwarz criterion	-6.385675
Log likelihood	8601.333	Durbin-Watson stat	2.050237

Dependent Variable: NASDAQ_100
Method: ML - ARCH
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 13 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000585	0.000236	2.475148	0.0133
		Variance Equation		
C	1.93E-06	3.62E-07	5.330591	0.0000
RESID(-1)^2	0.080760	0.005800	13.92474	0.0000
GARCH(-1)	0.914563	0.006206	147.3744	0.0000

R-squared	-0.000581	Mean dependent var	0.000151
Adjusted R-squared	-0.001699	S.D. dependent var	0.018005
S.E. of regression	0.018020	Akaike info criterion	-5.579834
Sum squared resid	0.871863	Schwarz criterion	-5.571062
Log likelihood	7506.086	Durbin-Watson stat	2.006275

Dependent Variable: S_P_500
Method: ML - ARCH
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 13 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000416	0.000181	2.300384	0.0214
	Variance Equation			
C	1.61E-06	2.36E-07	6.839206	0.0000
RESID(-1)^2	0.085452	0.006076	14.06359	0.0000
GARCH(-1)	0.904782	0.007204	125.5935	0.0000

R-squared	-0.000556	Mean dependent var	0.000144
Adjusted R-squared	-0.001674	S.D. dependent var	0.011531
S.E. of regression	0.011541	Akaike info criterion	-6.309421
Sum squared resid	0.357618	Schwarz criterion	-6.300649
Log likelihood	8487.016	Durbin-Watson stat	2.078997

Dependent Variable: FTSE_100
Method: ML - ARCH
Sample: 9/22/1997 5/30/2008
Included observations: 2698
Convergence achieved after 9 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000343	0.000167	2.060023	0.0394
		Variance Equation		
C	1.16E-06	3.13E-07	3.694323	0.0002
RESID(-1)^2	0.093418	0.010155	9.199521	0.0000
GARCH(-1)	0.899959	0.010211	88.13828	0.0000

R-squared	-0.000544	Mean dependent var	6.91E-05
Adjusted R-squared	-0.001658	S.D. dependent var	0.011763
S.E. of regression	0.011772	Akaike info criterion	-6.351354
Sum squared resid	0.373359	Schwarz criterion	-6.342607
Log likelihood	8571.977	Durbin-Watson stat	2.071658

Annex IV

Estimate output GARCH (1, 1) model, a Student's t distributions for the residuals is assumed. The dataset is used the period: 22.09.1997-30.05.2008

Dependent Variable: CAC_40
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2719
Convergence achieved after 15 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000683	0.000205	3.332876	0.0009
	Variance Equation			
C	1.53E-06	5.10E-07	2.992211	0.0028
RESID(-1)^2	0.081474	0.010218	7.973883	0.0000
GARCH(-1)	0.912479	0.010530	86.65149	0.0000
T-DIST. DOF	12.93118	2.341526	5.522543	0.0000

R-squared	-0.001185	Mean dependent var	0.000192
Adjusted R-squared	-0.002661	S.D. dependent var	0.014265
S.E. of regression	0.014284	Akaike info criterion	-5.964956
Sum squared resid	0.553751	Schwarz criterion	-5.954092
Log likelihood	8114.357	Durbin-Watson stat	2.015337

Dependent Variable: DAX_30
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2709
Convergence achieved after 18 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000885	0.000220	4.026782	0.0001
	Variance Equation			
C	1.81E-06	5.81E-07	3.112627	0.0019
RESID(-1)^2	0.090883	0.011427	7.953289	0.0000
GARCH(-1)	0.903402	0.011666	77.44138	0.0000
T-DIST. DOF	13.15146	2.376775	5.533321	0.0000

R-squared	-0.001819	Mean dependent var	0.000213
Adjusted R-squared	-0.003300	S.D. dependent var	0.015751
S.E. of regression	0.015777	Akaike info criterion	-5.810058
Sum squared resid	0.673035	Schwarz criterion	-5.799161
Log likelihood	7874.724	Durbin-Watson stat	2.027925

Dependent Variable: BET
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2599
Convergence achieved after 14 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000747	0.000242	3.093669	0.0020
	Variance Equation			
C	3.32E-05	5.68E-06	5.837365	0.0000
RESID(-1)^2	0.348179	0.046323	7.516302	0.0000
GARCH(-1)	0.620693	0.031896	19.45977	0.0000
T-DIST. DOF	3.971797	0.339789	11.68903	0.0000

R-squared	-0.000005	Mean dependent var	0.000791
Adjusted R-squared	-0.001547	S.D. dependent var	0.018958
S.E. of regression	0.018973	Akaike info criterion	-5.549194
Sum squared resid	0.933777	Schwarz criterion	-5.537915
Log likelihood	7216.178	Durbin-Watson stat	1.774323

Dependent Variable: DJINDUS
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 17 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000477	0.000162	2.939650	0.0033
	Variance Equation			
C	8.83E-07	3.04E-07	2.904833	0.0037
RESID(-1)^2	0.070741	0.009502	7.444772	0.0000
GARCH(-1)	0.923860	0.009920	93.13277	0.0000
T-DIST. DOF	8.649945	1.088722	7.945041	0.0000

R-squared	-0.000745	Mean dependent var	0.000174
Adjusted R-squared	-0.002236	S.D. dependent var	0.011095
S.E. of regression	0.011107	Akaike info criterion	-6.426224
Sum squared resid	0.331141	Schwarz criterion	-6.415259
Log likelihood	8645.058	Durbin-Watson stat	2.050044

Dependent Variable: NASDAQ_100
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 20 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000669	0.000232	2.882274	0.0039
	Variance Equation			
C	1.19E-06	4.51E-07	2.636664	0.0084
RESID(-1)^2	0.068497	0.009005	7.606395	0.0000
GARCH(-1)	0.929276	0.009088	102.2484	0.0000
T-DIST. DOF	14.04246	2.274178	6.174739	0.0000

R-squared	-0.000826	Mean dependent var	0.000151
Adjusted R-squared	-0.002318	S.D. dependent var	0.018005
S.E. of regression	0.018025	Akaike info criterion	-5.593231
Sum squared resid	0.872077	Schwarz criterion	-5.582266
Log likelihood	7525.099	Durbin-Watson stat	2.005782

Dependent Variable: S_P_500
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2689
Convergence achieved after 17 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000485	0.000168	2.885451	0.0039
	Variance Equation			
C	9.26E-07	3.24E-07	2.856397	0.0043
RESID(-1)^2	0.072860	0.009800	7.434765	0.0000
GARCH(-1)	0.922441	0.010066	91.63756	0.0000
T-DIST. DOF	8.792205	1.090346	8.063682	0.0000

R-squared	-0.000876	Mean dependent var	0.000144
Adjusted R-squared	-0.002367	S.D. dependent var	0.011531
S.E. of regression	0.011545	Akaike info criterion	-6.341298
Sum squared resid	0.357732	Schwarz criterion	-6.330334
Log likelihood	8530.876	Durbin-Watson stat	2.078334

Dependent Variable: FTSE_100
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 9/22/1997 5/30/2008
Included observations: 2698
Convergence achieved after 15 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000436	0.000167	2.612540	0.0090
	Variance Equation			
C	1.09E-06	3.60E-07	3.028079	0.0025
RESID(-1)^2	0.093246	0.011726	7.952099	0.0000
GARCH(-1)	0.900905	0.011585	77.76587	0.0000
T-DIST. DOF	15.48143	3.768227	4.108411	0.0000

R-squared	-0.000971	Mean dependent var	6.91E-05
Adjusted R-squared	-0.002458	S.D. dependent var	0.011763
S.E. of regression	0.011777	Akaike info criterion	-6.358199
Sum squared resid	0.373518	Schwarz criterion	-6.347264
Log likelihood	8582.210	Durbin-Watson stat	2.070774