“The extent crisis altered market characteristics: A comparative analysis of GARCH models on Dow Jones and FTSE-100 before and after the current financial crisis.”

Μια εργασία του

Κρουστάλη Ιωάννη

Φοιτητή του

Διατμηματικού Προγράμματος Μεταπτυχιακών Σπουδών στην Οικονομική Επιστήμη

του

Πανεπιστημίου Μακεδονίας

Επιβλέπων: Σουμπενιώτης Δημήτριος, Καθηγητής

Δ.Π.Μ.Σ. στην Οικονομική Επιστήμη
Πανεπιστήμιο Μακεδονίας
Θεσσαλονίκη, Ελλάδα
2010

Table of Contents

1. Introduction

The global economy is still facing an intense financial crisis, which primarily triggered by the subprime mortgage loans markets in the US. The trading of innovative financial products deriving their value from mortgage payments and housing prices increased substantially through the previous years and as a result the bubble burst caused massive losses to market participants, affecting the existence of big and well-known financial institutions. At the same time, investors didn’t price the inherent risks effectively, while financial regulation and supervision in a global context was not sufficient. The “*invisible hand*” theory coined by Adam Smith was thought to resolve the instabilities of the marketplace. However, the situation became particularly risky and in fact credit availability was minimized, consumer confidence decreased, business insolvency problems emerged, global trade reduced and almost all the financial institutions were under immense scrutiny. The impact of financial turbulence to stock markets was particularly harmful, diminishing their values worldwide by trillions of US dollars. In that frame, the Keynesian economics were utilized as a solution to the crisis, activating monetary and fiscal policies by public authorities.

In the years leading up to 2007 new ways to increase the total market turnover were developed, through sophisticated and complex financial instruments. In addition, consumers primarily in the US and the UK were living beyond their means, borrowing money to buy new houses and fund their spending habits. Consequently, asset prices and house prices in particular rose rapidly, while lenders, mainly commercial banks, relaxed the criteria for granting housing loans. The banks in order to find new sources of finance and increase their business, bundled up the poor-quality loans, mixed with some higher-quality mortgages and sold the packages of debt to other financial institutions in a process known as securitization. By July 2007 the housing market in the US started a free-fall and accordingly the value of mortgage-backed securities was decreasing dramatically. In fact, nobody could accurately determine the wealth losses for the investors that had acquired asset backed securities and inevitably the markets abruptly lost the two ingredients vital to keep them vibrant, certainty and trust.

Banks first stopped lending to each other, then sought to repair their finances by cutting back on lending to their customers. Borrowing became harder and more expensive to arrange, while LIBOR and EURIBOR rates hit historical high levels. In addition, fears for rising inflation were an extra problem for most economies[1], which could not allow Central Banks to cut further interest rates so as to boost liquidity. The early efforts of FED and other public authorities to regulate financial market and prevent the likely crash of the system failed. Inevitably, major companies in home construction and mortgage lending faced severe difficulties, while financial institutions such as Washington Mutual, Morgan Stanley, AIG, Merrill Lynch and HBOS which engaged in securitization were at the edge of failure. In the end, leading companies went bankrupt and massive company bailouts took place by the US government.

In fact, the relative stability of fundamental macroeconomic variables in the US and UK in the middle of the last decade was thought to be the necessary condition for decreased market volatility and investment opportunities with low risk. Nevertheless, the advent of the crisis not only turned bearish stock markets but more importantly increased significantly market volatility and the associated uncertainty about future market dynamics. There were several large "Monday" drops in stock markets worldwide during 2008, including one in January, one in August, one in September and another in early October. In addition, intraday volatility showed considerable breadths, even for 'heavy' indices and blue chips. As of October 2008, stock markets in North America, Europe and the Asia-Pacific region had all fallen by about 30% since the beginning of the year. Particularly, the Dow Jones Industrial Average had fallen about 37% since January 2008, while on 6 October the FTSE-100 index had its largest one day points fall (7.86%) since it was established.

The overarching objective of the present paper is to examine the volatility patterns of main US and the UK stock market indices *before* and *during* the current financial crisis, applying various econometric models suggested in the literature. Moreover, we perform a comparative assessment between Dow Jones and FTSE-100 in order to identify potential similarities of the markets' reaction to the crisis. The paper aims to propose the specifications that fit better the data set in the alternative sub-samples and the extent the crisis affected their explanatory power. Specifically,

[1] In February 2008, Reuters reported that global inflation was at historic high levels due to the excess money supply by central banks in order to tame financial crisis.

the paper is structured as follows: the next section depicts the results of previous studies in the field. The third section presents a preliminary data set analysis and a description of the selected econometric methods. The fourth section records the empirical results for the stock markets under consideration, analyzes the significance of the prevailing models and assesses how the crisis affected both the two markets. Finally, the fifth section discusses the conclusions of the paper and suggests items for further research.

2. Literature review

Stock market volatility comprises a particular popular research field in the literature and in fact a number of empirical studies have been conducted with the intension of identifying the appropriate models to capture volatility. Volatility is unobservable in financial markets and is measured trough standard deviation or variance of returns, which can be directly considered as a measure of risk of the numerous financial assets. The early financial time series models assumed that the conditional variance of asset returns is constant overtime. However, empirical evidence demonstrated that the above assumption is violated (Enders, 2004; Kim and Kon 1994; Lau *et al.*, 1990; Hangerman, 1978; Fama, 1965). Engle (1982) was the pioneer of Auto Regressive Conditional Heteroskedasticity (ARCH) model indicating that conditional variance can be expressed as a function of lagged error terms, while Bollerslev (1986) proposed a development of Engle's approach, the Generalized ARCH (GARCH) model which additionally allows conditional variance lags enter in the function. The simple GARCH model was further developed and many extensions and alternative specifications such us Exponential GARCH (Nelson, 1991), Threshold GARCH (Glosten *et al.*, 1993) and GARCH-M (Engle and Bollerslev, 1986) were proposed in order to better capture the characteristics of return series. Indeed, these models have been proved sufficient enough in capturing properties of time-varying stock return volatility relative to other non-GARCH models (Akgiray, 1989). Although there is no consensus among researchers about the superior model in volatility modeling, the above family of models constitutes the prevailing approach.

More than a few researchers suggest that a simple GARCH(1,1) model is sufficient enough to capture volatility in almost all the empirical applications without the need of more complicated models. In particular, Akgiray (1989) applied a GARCH(1,1) model on daily stock returns series of value-weighted and equal-weighted indices obtained from the Center for Research in Security Prices (CRSP) during an extensive period (from 1963 to 1986) indicating satisfactory fitting on the data set, while Bollerslev *et al.* (1992) provided an overview of some extensions of ARCH type models in a study of empirical applications depicting insignificant usefulness from complex specifications. Moreover, DeSantis and Imrohoroglu (1997) employed a simple GARCH model in order to examine the returns' volatility characteristics of emerging markets[2], revealing that volatility exhibits clustering, high persistence and predictability, while was found to be in enough higher levels than in more mature markets. On the contrary, particular extensions of the simple GARCH models applied in many empirical studies seem to provide robust results, capturing better volatility. More specifically, Alles and Murray (2001) examined the pattern of returns and volatility on Irish equity market over a period of deregulation, indicating the inclusion of external volatility; hence the application of GARCH-M models provided more precise findings. Similarly, Song *et al*. (1998) focused on the Chinese capital market after the economic reform and proposed the GARCH-M(1,1) as superior to explain the pattern of volatility of two primary stock markets (Shanghai and Shenzhen Stock Exchanges), while he found evidence of volatility transmission between the two markets. Choudhry (1996) used also the GARCH-M model with the intention to study volatility, risk premia and the persistence of shocks in six emerging stock markets[3] before and after the 1987 crash, founding evidence of changes which varied between the individual markets in the ARCH parameters, the risk premium and volatility persistence after the crash. It should be underlined that the above studies which suggest that GARCH-M models explain in a more efficient way markets' volatility patterns are referred to periods when significant events took place. The fact that volatility tends to react asymmetrically to opposite stock price movements led many researchers to employ asymmetric GARCH specifications in order to overcome the disadvantages of simple GARCH models. Nelson (1991) suggested the Exponential GARCH (EGARCH) model, while Glosten *et al.* (1993) developed the Threshold GARCH (TGARCH) specification, as better capturing the asymmetric impact of shocks to volatility. Empirical evidence from the studies of Alberg *et al.* (2008), Caiado (2004)[4] and Koutmos *et al.* (1993) examining the Tel Aviv, Lisbon and Athens Stock Exchanges respectively, supports the fact that asymmetric GARCH models densities improve significantly the overall estimation for measuring conditional variance. Similar results for the Athens stock exchange depicted Apergis

[2] They use the weekly series from 1988 to 1996 in here regional groups including Latin American, Mid-east Europe and Asia.

[3] He examined Argentina, Greece, India, Mexico, Thailand and Zimbabwe capital markets.

[4] It should be noted that Caiado (2004) found significant asymmetric shocks in daily stock returns, but not in weekly returns. He also found that some weekly return series' properties are substantially different from the corresponding daily returns, while the persistence in conditional volatility is different for some of the subperiods referred.

and Eleptheriou (2001), while Siourounis (2001) underlined the significance of political instability in the volatility level of the examined stock market. However, according to the study of Haroutounian and Price (2001) there is weak evidence of asymmetry for four stock markets of central Europe (Hungary, Poland, Czech Republic and Slovakia).

Considering the major stock markets of US and UK which are in the center of the present study as well, many empirical researchers attempted to analyze their volatility patterns, presenting contradicting results (Chappel *et al.*, 1998; Francis and Leachman, 1996; Bollerslev *et al.*, 1992). A prominent piece of paper in the field has been provided by Harris *et al.* (2004), who modeled the conditional distribution of daily returns of five principal stock markets[5] (including US and UK) using the skewed generalized-*t* (SGT) distribution. That particular methodology allows a wide range of skewness and kurtosis and empirical results showed that the use of SGT distribution offers a substantial improvement in the fit of both GARCH and EGARCH models. However, Curto *et al.* (2007) found that the GARCH(1,1) model with conditional stable Paretian distribution provides a better fit to describe the volatility of returns in US equity market. Contrarily, Tavares *et al.* (2008) applied asymmetric and symmetric GARCH specifications[6] on daily returns from the US and the UK capital markets, suggesting that asymmetric models including EGARCH(1,1) and TGARCH(1,1,1) clearly outperform the simple GARCH(1,1) for both indices. Obviously, the examination of volatility in the markets under consideration presents various and often conflicting results, while the current financial crisis probably altered enough more the markets characteristics. In that frame, our intention is to provide robust findings for both capital markets through a comparative assessment of alternative specifications that have been used extensively in the literature.

[5] They examined the stock markets of US, UK, Germany, Canada and Japan.
[6] They allowed several types of distribution for the return series such us Student's *t* and stable Paretian.

3. Data and methodology

3.1. Data analysis

The main objective of the present study is to propose suitable specifications for modeling volatility of the US and the UK stock markets; hence the nature of the data set should be investigated. In this section, we analyze the data set and its descriptive statistics, which in turn demonstrate the appropriate models that should be performed.

The data source is daily returns[7] of fundamental stock market indices from the US and the UK. In particular, we take into consideration the performance of Dow Jones and FTSE-100 from July 2004 to April 2009 in order to capture the effects of the financial crisis to the capital markets since its burst. The initial samples for both the two indices are further divided considering as breaking point July 2007, since the certain point of time is thought to be the beginning of the crisis. The objective of this data split up is to compare the fitness of particular GARCH-type models on data before and during the crisis, in order to examine the extent that the current crisis altered market fundamentals. In addition, the prevailing models of each sub-period are further compared with the corresponding specification estimated from the initial sample periods.

The daily returns (R_t) of the selected market indices are computed as logarithmic price[8] (P_t) relatives:

$$R_t = \ln P_t - \ln P_t - 1 = \ln(P_t / P_t - 1) \tag{1}$$

In case where price index series P_t follow a random walk, the return series R_t can be seen as a white noise process[9]. However, empirical evidence indicates that the distribution of stock returns is not normally distributed, exhibiting features such as, skewness, leptokurtosis and volatility clustering (Kim and Kon, 1994; Fama, 1965).

In fact, the graphical representation of returns depicts volatility clustering[10] for both Dow Jones and FTSE-100, while volatility increases dramatically after the crisis

[7] It should be pointed out that the prevailing methodology in the literature is to use daily data (Harris *et al.* 2004; Siourounis, 2002; Alles and Murray, 2001; Haroutounian and Price, 2001), since high frequency data allows for more accurate ex-post volatility measurements (Andersen and Bollerslev, 1998).

[8] Data obtained from http://finance.yahoo.com.

[9] A white noise process indicates that return series should be identically and independently distributed with zero mean and constant variance.

[10] Volatility clustering indicates that large returns are expected to follow large returns.

burst[11] (Figures 1 and 2). Therefore, returns variance is not constant overtime and modeling attempts should take into account heteroskedasticity.

Figure 1: Daily returns of Dow Jones

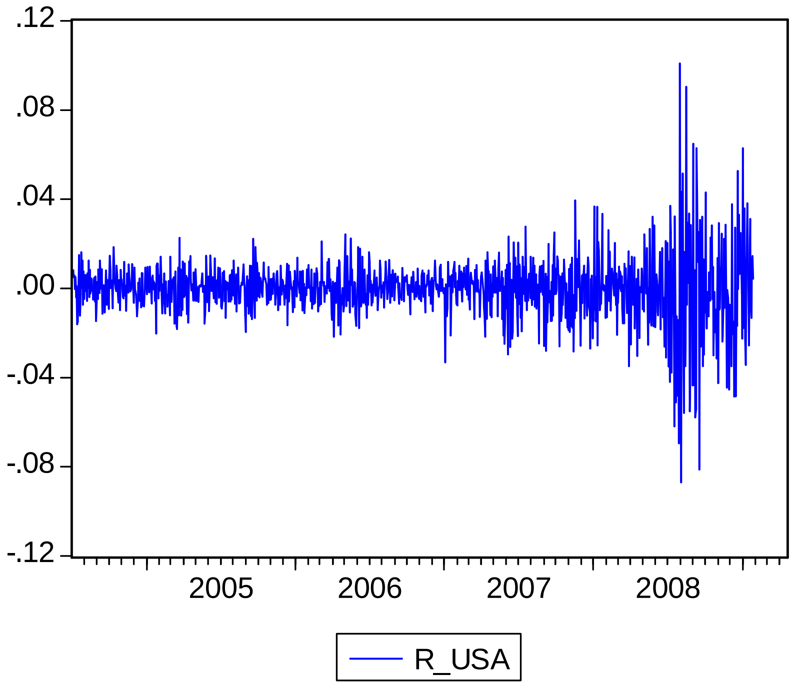
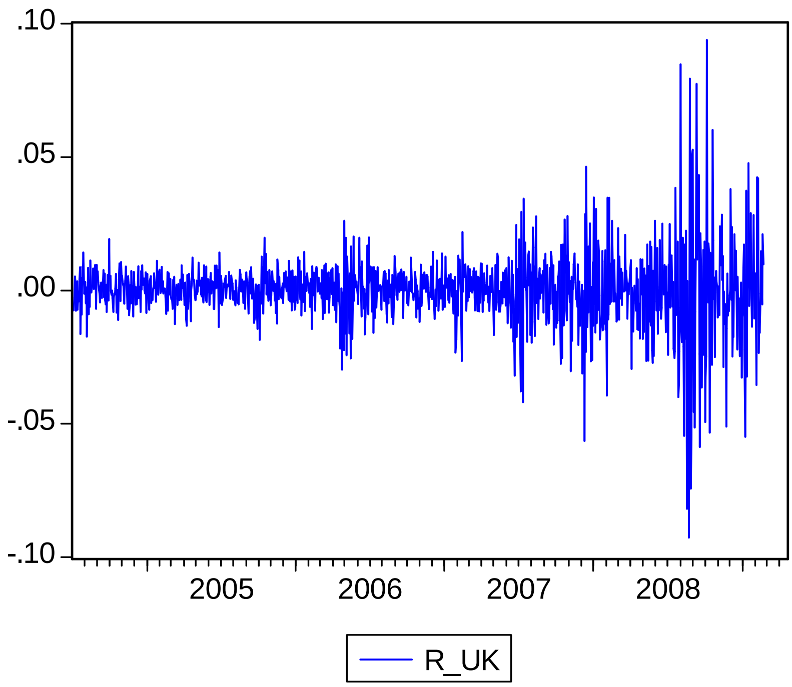


Figure 2: Daily returns of FTSE 100



[11] This phenomenon seems to be more immediate for the FTSE-100 index.

In order to signify the distribution characteristics of the examined indices return series, the skewness and kurtosis test statistics[12] are performed. Table 1 presents the preliminary statistics of the whole samples, the pre and post-crisis samples for Dow Jones and FTSE-100.

Table 1
Preliminary statistics

Statistics (1)	Dow Jones (2)	FTSE-100 (3)	Dow Jones (4)	FTSE-100 (5)	Dow Jones (6)	FTSE-100 (7)
	Entire period		***Pre-crisis***		***Post-crisis***	
Observations	1191	1209	738	754	453	455
Mean	-4.62E-05	-6.05E-05	0.000571	0.000538	-0.001052	-0.001053
Std. Dev.	0.014153	0.013797	0.007321	0.006786	0.020937	0.020702
Skewness	-0.107656	-0.112382	-0.238674	-0.384525	0.055746	0.062438
Kurtosis	11.47	12.83194	3.822631	4.742703	6.21919	6.654869
Jarque-Bera	3562.446	4872.151	27.81593	113.9939	195.8397	253.5423
(p-value)	*0.000*	*0.000*	*0.000001*	*0.000*	*0.000*	*0.000*

Preliminary statistics clearly indicate non-normality of the returns, since the values of skewness and kurtosis deviate from the normal. The non-normality is further confirmed by the Jarque-Bera test statistics, since the corresponding *p-value* rejects the null-hypothesis of normality.

3.2. Methodology

Taking into account the characteristics of the data series, the family of Generalized Autoregressive Conditional Heteroskedastic (GARCH) models (Bollerslev, 1986) has been proven to be particularly appropriate to model time-varying volatility. These models capture the three most common features in return series which are fat tails, excess kurtosis and volatility clustering. The primary objective is the determination of the mean equation and in that line different models including autoregressive (AR), moving average (MA) and ARMA models are employed[13] (Li *et al*,, 2005; Harris *et al.*, 2004, Siourounis, 2002). The next Table 2 demonstrates the best fit specification for each return series mean equation.

[12] Skewness measures the asymmetry while the kurtosis the peakedness of the probability distribution. A normal distribution time series should present zero (0) value for skewness and three (3) for kurtosis.
[13] By using Schwarz and Akaike information criteria, we try to find which model fits best each sample.

Table 2
Optimal mean equation specifications

Return Series	Mean Equation Specification
Dow Jones-pre	ARMA(1,1)
FTSE-100-pre	c + εt
Dow Jones-post	AR(2)
FTSE-100-post	c + εt
Dow Jones-whole	AR(2)
FTSE-100-whole	MA(1,1)

Before applying the GARCH-type models, the existence of ARCH effects should be confirmed and for that reason the Lagrange Multiplier and Ljung-Box tests are employed (Tsay, 2005; McLeod and Li, 1983; Siourounis, 2002; Haroutounian and Price, 2001; Choudhry, 1996; Engle, 1982). For the former we run the OLS estimated squared residuals (e_t^2) of the mean equation on their lags as follows:

$$e_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + ... + \gamma_q e_{t-q}^2 \qquad (2)$$

Then, we test[14] the null hypothesis that $\gamma_0=\gamma_1=\ldots=\gamma_q=0$, the rejection of which indicates the evidence of ARCH(q) effects. The latter tests[15] with Ljung-Box *Q(m)-statistics* for cumulative autocorrelation in the e_t^2 series. The two procedures are applied concurrently for the entire six (6) samples, in order to be able to apply the GARCH specifications.

Under the presence of ARCH effects and due to the violation of the classical linear model basic assumptions, the appropriate methodology for the estimation of GARCH models is the maximum-likelihood instead of the least square. Empirical evidence analyzed previously presents conflicting findings about the performance of alternative GARCH models; thus, intending to present a more multidimensional approach this study attempts to model volatility applying comparatively various models that have been used in the literature and through a comparative assessment provide the best ones.

[14] The test statistic is estimated by multiplying *R-square* of the equation (2) least square estimation by the number of observations, and follows a χ^2 distribution with q degrees of freedom.
[15] The null hypothesis is that the first m lags of autocorrelation function of the squared residuals (e_t^2) are equal to zero.

More specifically, we simultaneously model the mean and variance of Dow Jones and FTSE-100 return series considering firstly the GARCH(p,q) in which the conditional variance is given by:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=j}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

Then, we employ the GARCH-M(p,q)[16] which is specified as follows:

$$R_t = m + \delta\sigma_t^2 + \varepsilon_t \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

where m is the mean specification. We also estimate the GARCH-M(p,q) by replacing σ_t^2 in (4) with σ_t.

Finally, we apply the asymmetric[17] GARCH-type models, TGARCH(p,1,q) and EGARCH(p,q)[18] in which the conditional variance is given by equations (6) and (7) respectively:

$$\sigma_t^2 = \alpha_0 + \sum_{i}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j}^{p} \beta_j \sigma_{t-j}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{6}$$

$$I_{t-1} = 1 \; if \;\; \varepsilon_{t-1} < 0 \; and \; I_{t-1} = 0 \; otherwise$$

$$\ln\sigma_{t-1}^2 = \alpha_0 + \sum_{j=1}^{p} \beta_j \ln\sigma_{t-j}^2 + \sum_{i=1}^{q} \left[a_i \frac{|\,\varepsilon_{t-i}\,|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right] \tag{7}$$

For all the above models the p=1 and q=1 specification found to be optimal[19]. Additionally, it should be underlined that the estimation of the models is conducted with maximum likelihood function using normal distribution for the error term.

In order to determine the best fit data model among the various ARCH type specifications we conduct the required diagnostic testing. The best fit model is

[16] Engle, Lilien and Robins (1987) proposed GARCH-M model which allows the introduction of the conditional variance in the mean equation.

[17] Asymmetric specifications allow different effects of negative and positive return shocks on the volatility.

[18] TGARCH and EGARCH proposed by Glosten *et al.* (1993) and Nelson (1991) respectively.

[19] We used Schwarz and Akaike information criteria to select the optimal p and q.

eventually identified considering the diagnostic and Ljung-Box tests, which examine normality[20] and autocorrelation[21], respectively, in standardized residuals (Enders, 2004; Siourounis, 2002; Haroutounian and Price, 2001; Song, 1998; Choudhry, 1996).

4. Empirical results

The next paragraphs present the empirical results of GARCH models for Dow Jones and FTSE-100, while for each index three sub-sections are introduced according to the examined time period. Effectively, GARCH models can be applied since there is strong evidence of ARCH effects in all the six samples, considering that both Lagrange Multiplier and Ljung-Box tests strongly indicate heteroskedasticity. In particular, the *LM-statistic* of the former is highly significant and the *Q-statistics* of the latter testing for cumulative autocorrelation up to 6th, 12th and 24th lags of squared residual series are highly significant[22] as well.

4.1. Dow Jones

4.1.1. Pre-crisis period

Table 3 presents the results from five alternative models employed in order to estimate volatility of Dow Jones for the period from July 2004 to June 2007. In addition, Table 4 depicts the diagnostic checking in standardized residuals of each GARCH model.

[20] Theoretically, the standardized residuals are ideally expected to have mean zero and a variance of unity, indicating that they are normally distributed. Properly specified GARCH models should be able to reduce the excess skewness and kurtosis present in the return series. Indeed, the model of which the skewness coefficient is as close to 0, the kurtosis coefficient is as close to 3 and Jarque-Bera statistic is as low as possible is considered to be the best fit data model.

[21] We employ the Ljung-Box test in the squared standardized residuals, since the best fit model should not have autocorrelation in standardized residual series and any other remaining ARCH effects.

[22] The *Q-statistics p-values* are equal to zero.

Table 3
GARCH models estimates for Dow Jones (pre-crisis)

	Variance Equation				Mean Equation			
	α_0	α_1	β_1	γ	a_0	a_1	b_1	δ
GARCH(1,1)	5.19e-06*** (2.87e-06)	0.053736** (0.022623)	0.849415* (0.071874)		0.000586** (0.000266)	0.439834 (0.655629)	-0.465874 (0.650309)	
GARCH-M(1,1) SD	3.31e-06 (2.25e-06)	0.044834** (0.020115)	0.892556* (0.059609)		-0.001469 (0.002736)	0.682137* (0.163473)	-0.74666* (0.151083)	0.292110 (0.385356)
GARCH-M(1,1) CV	3.34-06 (2.25e-06)	0.046060** (0.020925)	0.891122* (0.060102)		0.017180 (0.012705)	-0.397309 (0.791042)	0.422167 (0.782121)	0.001670 (0.001281)
TGARCH(1,1,1)	1.65e-06* (3.09e-07)	-0.014439 (0.011233)	0.936003* (0.011843)	0.120495* (0.018553)	0.000189 (0.000207)	0.626141* (0.168795)	-0.701849 (0.151066)	
EGARCH(1,1)	-0.197324* (0.034341)	0.073817* (0.018815)	0.984626* (0.003003)	-0.10505* (0.016892)	-0.000152 (0.000220)	0.560513** (0.220560)	-0.62683* (0.204771)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

Table 4
Diagnostics in the squared standardized residuals

	Skewness	Kurtosis	Jarque-Bera	Q(6)	Q(12)	Q(24)
GARCH(1,1)	-0.375798	4.114639	55.49965 (*0.000*)	0.556	0.159	0.449
GARCH-M(1,1) SD	-0.423788	4.117375	60.40059 (*0.000*)	0.444	0.172	0.409
GARCH-M(1,1) CV	-0.370062	4.041952	50.16049 (*0.000*)	0.482	0.134	0.414
TGARCH(1,1,1)	-0.458832	4.218426	115.3640 (*0.000*)	0.209	0.112	0.387
EGARCH(1,1)	-0.565710	4.726546	211.2781 (*0.000*)	0.390	0.087	0.364

In parentheses are reported the *p-values*. The three last columns present the Ljung-Box *Q-statistics p-values.*

Taking into account the above empirical results, all the applied GARCH models fail to capture the asymmetry and leptokurtotic characteristics of the original pre-crisis return series, since Skweness, Kurtosis and Jarque-Bera statistics of the standardized residuals further deviate from the normal values. However, according to the Ljung-Box *Q-statistics*, all the employed GARCH-type specifications reduce the inter-temporal dependence of squared standardized residuals since the Q(6), Q(12) and Q(24) statistics *p-values* (Table 4) indicate insignificant autocorrelation at 5%

importance level[23]. In this context, GARCH(1,1) seems to be preferable, presenting significant constant term in the mean equation at 5%, while in variance equation the coefficients α_0, α_1 and β_1 are significant at 10%, 5% and 1% importance level, respectively. Furthermore, the coefficient for the lagged conditional variance denotes that 84% of past volatility carries on in the next period, while the sum of coefficients $\alpha_1+\beta_1$ is close to unity (0,913), indicating that volatility shocks on stock prices are quite persistent.

4.1.2. Post-crisis period

The empirical results for the period from July 2007 to April 2009 are presented in Table 5, while Table 6 presents the diagnostic checking.

Table 5

GARCH models estimates for Dow Jones (post-crisis)

	Variance Equation				Mean Equation			
	α_0	α_1	β_1	γ	a_0	a_1	a_1	δ
GARCH(1,1)	7.23e-06***	0.104051*	0.877933*		-0.00045	-0.1750*	-0.11610**	
	(4.01e-06)	(0.033048)	(0.038475)		(0.00055)	(0.05755)	(0.048565)	
GARCH-M(1,1) SD	5.96e-06	0.104286*	0.880626*		-0.00150	-0.1778*	-0.11773**	0.062701
	(4.15e-06)	(0.032709)	(0.038630)		(0.002002)	(0.059635)	(0.049356)	(0.125325)
GARCH-M(1,1) CV	6.03-06	0.104473*	0.880216*		-0.000876	-0.17816*	-0.1178***	1.297565
	(4.14e-06)	(0.032782)	(0.038723)		(0.000905)	(0.059535)	(0.049318)	(2.738566)
TGARCH(1,1,1)	6.35e-06*	-0.026363	0.924515*	0.158893*	-0.000739	-0.16077*	-0.12801*	
	(2.07e-06)	(0.022600)	(0.023480)	(0.038444)	(0.000528)	(0.055811)	(0.045775)	
EGARCH(1,1)	-0.291365*	0.116824**	0.975247*	-0.10804*	-0.00117**	-0.16808*	-0.11662**	
	(0.083060)	(0.047274)	(0.007891)	(0.030717)	(0.000545)	(0.055647)	(0.046421)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

[23] The null hypothesis of zero autocorrelation cannot be rejected at 5% importance level.

Table 6
Diagnostics in the squared standardized residuals

	Skewness	Kurtosis	Jarque-Bera	Q(6)	Q(12)	Q(24)
GARCH(1,1)	-0.192760	2.931413	2.88 (*0.236*)	0.027	0.059	0.167
GARCH-M(1,1) SD	-0.184805	2.966811	2.58 (*0.274*)	0.027	0.057	0.135
GARCH-M(1,1) CV	-0.186702	2.967090	2.64049 (*0.267*)	0.025	0.057	0.136
TGARCH(1,1,1)	-0.177216	2.902806	2.53 (*0.281*)	0.015	0.030	0.126
EGARCH(1,1)	-0.253187	2.887791	5.055 (*0.079*)	0.035	0.065	0.224

In parentheses are reported the *p-values.* The three last columns present the Ljung-Box *Q-statistics p-values.*

Contrary to the pre-crisis period all the estimated models success to explain the asymmetric and leptokurtotic characteristics of post-crisis return distributions to a certain extent (Table 6), since the squared residuals follow distributions which are close to normal. However, the Ljung-Box *Q-statistics* indicate that the estimated models fail to capture the short-term autocorrelation in the Dow Jones return series[24]. In this frame, EGARCH(1,1) seems to be the worst model while the TGARCH(1,1,1) found to fit best the data.

Focusing on TGARCH(1,1,1) specification, coefficients AR(1) and AR(2) of the mean equation are negative and statistically significant at 1% importance level (Table 5). Considering the variance equation, the coefficient β_1 is statistically significant implying that 92% of past volatility carries on in the next period, while the so-called asymmetric effect parameter γ is also highly significant implying evidence of asymmetry in the Dow Jones returns after the crisis. In particular, conditional variance is higher in the presence of negative innovations, indicating that markets become more nervous when negative shocks take place. As an actual fact, small investors get panic from negative shocks and sell their stocks in order to avoid higher losses. This finding is in accordance with Koutmos (1998), who also applied a TGARCH model on data from nine developed capital markets including US and UK.

[24] The Ljung-Box *Q-statistics* indicate evidence of 6^{th} and 12^{th} order autocorrelation for all the models.

4.1.3. Entire period

Similarly with the above sub-sections, we run the GARCH family models for the period from July 2004 to April 2009 (Table 7) and the corresponding diagnostic checking (Table 8).

Table 7

GARCH models estimates for Dow Jones (entire period)

	Variance Equation				Mean Equation			
	α_0	α_1	β_1	γ	a_0	a_1	a_2	δ
GARCH(1,1)	7.22e-07	0.074013*	0.924159*		-0.00063*	-0.06437**	-0.08919*	
	(4.58e-07)	(0.015041)	(0.015485)		(0.000211)	(0.031793)	(0.030369)	
GARCH-M(1,1) SD	1.23e-06*	0.077711*	0.914076*		-0.000615	-0.07374**	-0.09155*	-0.020649
	(4.03e-07)	(0.012944)	(0.014616)		(0.000682)	(0.033693)	(0.031895)	(0.073663)
GARCH-M(1,1) CV	1.22-06*	0.077724*	0.914108*		0.00049***	-0.07364**	-0.09142*	-0.703429
	(4.00e-07)	(0.012980)	(0.014642)		(0.000301)	(0.033652)	(0.031731)	(2.291325)
TGARCH(1,1,1)	1.52e-06*	-0.015099	0.938379*	0.120323*	0.000155	-0.0610***	-0.08617*	
	(2.92e-07)	(0.011163)	(0.011780)	(0.018734)	(0.000222)	(0.032452)	(0.030667)	
EGARCH(1,1)	-0.188643*	0.072964*	0.985582*	-0.10226*	0.000186	-0.06579**	-0.08227*	
	(0.034154)	(0.019480)	(0.002937)	(0.016942)	(0.000222)	(0.032501)	(0.030740)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

Table 8

Diagnostics in the squared standardized residuals

	Skewness	Kurtosis	Jarque-Bera	Q(6)	Q(12)	Q(24)
GARCH(1,1)	-0.456581	4.246836	118.3285 (*0.000*)	0.440	0.224	0.480
GARCH-M(1,1) SD	-0.432431	4.112236	98.34292 (*0.000*)	0.316	0.109	0.287
GARCH-M(1,1) CV	-0.431778	4.108476	97.81737 (*0.000*)	0.313	0.106	0.275
TGARCH(1,1,1)	-0.455931	4.220010	114.9325 (*0.000*)	0.216	0.118	0.327
EGARCH(1,1)	-0.564987	4.714834	208.9418 (*0.000*)	0.456	0.080	0.293

In parentheses are reported the *p-values.* The three last columns present the Ljung-Box *Q-statistics p-values.*

The diagnostic checking indicates that almost all the employed models are able to capture the structure of the squared return autocorrelation[25]. Considering the skewness and kurtosis values (Table 8), the models can explain to a significant extent the corresponding skewness and excess kurtosis observed in the original series. However, it is clear that the GARCH in mean models and especially the GARCH-M(1,1) CV outperform the others.

Taking into examination the coefficients of the prevailing model, both AR(1) and AR(2) of the mean equation are negative and altogether with the ARCH and GARCH coefficients of the variance equation are statistically significant (Table 7). The sum of coefficients ($\alpha_1+\beta_1$) is very close to unity (0.9918) indicating that shocks to volatility are very persistent, which in turn affects the development of stock prices (Poterba and Summers, 1986). Furthermore, the presence of conditional variance (proxy of risk) in the mean equation of the model provides a way to directly study the explicit trade-off between risk and expected return. In this basis, the coefficient δ is usually called risk premium parameter. The empirical results indicate insignificant[26] risk premium parameter (δ) for the Dow Jones returns and as a consequence standard deviation can not be used as proxy of risk. This result is inconsistent with the theory of a positive (non-zero) risk premium on stock indices, which states that higher returns are related with higher levels of risk. The situation becomes further complicated considering that empirical evidence suggests conflicting findings. Indicatively, Chan *et al.* (1991) found insignificant relation between the returns on the S&P 500 index and its conditional variance, while Scruggs (1998) suggested significant and positive risk premium in the US capital market. In addition, Glosten *et al.* (1993) claimed that across time there is no agreement about the relation between risk and return within a given period of time. Investors may not require a high risk premium if risky time periods coincide with periods when investors are better able to bear particular types of risk. Moreover, if the future seems risky investors may want to save more in the present, which in turn lowers the demand for larger premium. Hence, Glosten *et al.* (1993) imply that both a positive and a negative relationship between current return and current variance (risk) are possible.

---

[25] Unique exemption constitutes the significant 12th order autocorrelation in the standardized residuals generated from the EGARCH(1,1) model.

[26] Empirical results also indicate insignificant risk premium parameter in Dow Jones returns for both pre-crisis and post-crisis period.

4.2. FTSE-100

4.2.1. Pre-crisis period

Table 9 presents the results from five alternative models employed in order to estimate volatility of FTSE-100 index for the pre-crisis period, while Table 10 depicts the diagnostic checking.

Table 9

GARCH models estimates for FTSE-100 (pre-crisis)

	Variance Equation				Mean Equation	
	α_0	α_1	β_1	γ	c	δ
GARCH(1,1)	3.00e-06* (1.07e-06)	0.09501* (0.02349)	0.83994* (0.03970)		0.000655* (0.00022)	
GARCH-M(1,1) SD	2.87e-06* (1.02e-06)	0.08999* (0.02242)	0.84423* (0.03767)		-0.000923 (0.00128)	0.259107 (0.20749)
GARCH-M(1,1) CV	2.91e-06* (1.03e-06)	0.09062* (0.02262)	0.84270* (0.03784)		3.21e-05 (0.00055)	16.38077 (13.0931)
TGARCH(1,1,1)	2.84e-06* (7.32e-07)	-0.04927** (0.02344)	0.882742* (0.03114)	0.195743* (0.04059)	0.00039*** (0.00022)	
EGARCH(1,1)	-0.496877* (0.144699)	0.07377*** (0.03766)	0.956398* (0.01346)	-0.14678* (0.02541)	0.000311 (0.00023)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

Table 10

Diagnostics in the squared standardized residuals

	Skewness	**Kurtosis**	**Jarque-Bera**	**Q(6)**	**Q(12)**	**Q(24)**
GARCH(1,1)	-0.353934	3.604784	27.23326 (*0.000*)	0.103	0.035	0.321
GARCH-M(1,1) SD	-0.354946	3.612037	27.60067 (*0.000*)	0.122	0.034	0.321
GARCH-M(1,1) CV	-0.356509	3.612037	27.74046 (*0.000*)	0.122	0.032	0.317
TGARCH(1,1,1)	-0.371987	3.355766	21.36540 (*0.000*)	0.315	0.257	0.636
EGARCH(1,1)	-0.395974	3.412490	25.04939 (*0.000*)	0.259	0.234	0.577

In parentheses are reported the *p-values.* The three last columns present the Ljung-Box *Q-statistics p-values.*

Taking into account the basic statistics of standardized residuals (Table 10), it is notable that they follow distributions closer to normal compared with the distributions of the original FTSE-100 returns. Indeed, GARCH type models are able to capture the asymmetry and the leptokurtotic characteristics of FTSE-100 for the period prior to the crisis, contrary to the case of Dow Jones. Taking into account the Ljung-Box test, the asymmetric GARCH specifications are able to eliminate the inter-temporal dependence of squared residuals, while according to the total diagnostic checking, the TGARCH(1,1,1) seems to be the best data fit model. Table 9 reveals evidently that both the mean and the variance equations of the model present entirely statistically significant coefficients. The highly significance of the asymmetric effect parameter (γ) confirms the value of skewness of the FTSE-100 pre-crisis return series (see Table 1) and implies evidence of asymmetry, in line with the case of Dow Jones index for the post crisis period.

4.2.2. Post-crisis period

The results from the examined models from July 2007 to April 2009 are presented in Table 11, while Table 12 depicts the diagnostic checking in standardized residuals.

Table 11
GARCH models estimates for FTSE-100 (post-crisis)

	Variance Equation				Mean Equation	
	α_0	α_1	β_1	γ	c	δ
GARCH(1,1)	1.02e-05** (4.14e-06)	0.120108* (0.029663)	0.859970* (0.030728)		-0.000321 (0.000764)	
GARCH-M(1,1) SD	1.09e-05** (4.92e-06)	0.132520* (0.032237)	0.845159* (0.034820)		-0.00508** (0.002479)	0.29911** (0.149227)
GARCH-M(1,1) CV	1.11e-05** (4.93e-06)	0.132200* (0.032283)	0.845087* (0.034882)		-0.001791 (0.001175)	5.264637 (3.254002)
TGARCH(1,1,1)	9.70e-06* (2.44e-06)	-0.04807** (0.019735)	0.898324* (0.020118)	0.261956* (0.042933)	-0.00137*** (0.000737)	
EGARCH(1,1)	-0.323569* (0.077672)	0.07593*** (0.042001)	0.966851* (0.007969)	-0.17899* (0.022892)	-0.00164** (0.000737)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

Table 12
Diagnostics in the squared standardized residuals

	Skewness	Kurtosis	Jarque-Bera	Q(6)	Q(12)	Q(24)
GARCH(1,1)	-0.182129	4.009020	21.81734 (*0.000*)	0.513	0.429	0.701
GARCH-M(1,1) SD	-0.214679	3.926036	19.75250 (*0.000*)	0.528	0.461	0.657
GARCH-M(1,1) CV	-0.204075	3.974420	21.15903 (*0.000*)	0.505	0.443	0.637
TGARCH(1,1,1)	-0.291527	3.498021	11.14708 (*0.003*)	0.187	0.097	0.212
EGARCH(1,1)	-0.297437	3.553663	12.52040 (*0.001*)	0.641	0.358	0.556

In parentheses are reported the *p-values.* The three last columns present the Ljung-Box *Q-statistics p-values.*

Considering the diagnostic checking, the TGARCH(1,1,1) model provides the best fit estimations of the FTSE-100 returns' volatility for the post-crisis period, similarly with the period prior to the crisis for the same index and after the crisis for Dow Jones. However, the particular specification is less efficient than the other employed models in capturing the presence of autocorrelation of FTSE-100 index, since is the unique case in which the Ljung-Box diagnostic test indicates significant 12^{th} order autocorrelation at 10% importance level (Table 12). Comparing the pre-crisis TGARCH estimation with the respective post-crisis, ARCH and GARCH coefficients take similar values and the asymmetric effect parameter increases considerably (Tables 9 and 11). The latter finding implies that the asymmetric impact of negative shocks on FTSE-100 index becomes more intensive after the beginning of the crisis.

4.2.3. Entire period

Finally, Table 13 shows the results for the whole sample and Table 14 presents the diagnostic checking.

Table 13
GARCH models estimates for FTSE-100 (entire period)

	Variance Equation				Mean Equation		
	α_0	α_1	β_1	γ	a_0	b_1	δ
GARCH(1,1)	8.44e-07** (3.29e-07)	0.110925* (0.014415)	0.889081* (0.013467)		0.000538* (0.000199)	-0.08978* (0.029775)	
GARCH-M(1,1) SD	8.73e-07* (3.38e-07)	0.114631* (0.014974)	0.884910* (0.013858)		0.000453 (0.000515)	-0.088155* (0.030974)	0.014109 (0.065237)
GARCH-M(1,1) CV	8.78e-07* (3.39e-07)	0.114908* (0.014943)	0.884596* (0.013818)		0.000503** (0.000244)	-0.088052* (0.030926)	0.835496 (2.240613)
TGARCH(1,1,1)	1.19e-06* (2.40e-07)	-0.015567 (0.012233)	0.920717* (0.011553)	0.161505* (0.015114)	0.000206 (0.000206)	-0.076411** (0.030008)	
EGARCH(1,1)	-0.19613* (0.022812)	0.086790* (0.021659)	0.986279* (0.002351)	-0.13773* (0.013316)	0.000132 (0.000213)	-0.05748*** (0.029357)	

*, ** and *** Denotes significance in the 1%, 5% and 10% level respectively. In parentheses are reported the standard errors.

Table 14
Diagnostics in squared standardized residuals

	Skewness	Kurtosis	Jarque-Bera	Q(6)	Q(12)	Q(24)
GARCH(1,1)	-0.379284	3.765789	58.52860 (*0.000*)	0.104	0.014	0.112
GARCH-M(1,1) SD	-0.376677	3.789908	60.02172 (*0.000*)	0.091	0.016	0.119
GARCH-M(1,1) CV	-0.376999	3.784251	59.62200 (*0.000*)	0.092	0.017	0.120
TGARCH(1,1,1)	-0.423125	3.723203	62.42272 (*0.000*)	0.518	0.034	0.139
EGARCH(1,1)	-0.402428	3.626128	52.38146 (*0.000*)	0.435	0.060	0.215

In parentheses are reported the *p-values.* The three last columns present the Ljung-Box *Q-statistics p-values.*

Although for both the two previously examined sub-samples of FTSE-100 the TGARCH(1,1,1) specification appears to be superior, the succeeding model for the entire sample seems to be EGARCH(1,1). Finding which also differs from the present study's results for the entire sample of Dow Jones return series, where the non-asymmetric GARCH-M(1,1) specification found to outperform the others.

Considering the diagnostic checking values, the standardized residuals of the model follow the closer to the normal distribution; in addition EGARCH(1,1) is the most efficient model in capturing the presence of autocorrelation in FTSE-100 returns (Table14). Both ARCH and GARCH coefficients of the EGARCH specification are statistically significant (Table 13) while the asymmetric effect parameter (γ) is also significant, indicating higher conditional variance in the presence of negative innovations. The latter finding is consistent with more than enough empirical studies for developed and developing capital markets (Tavares *et al.*, 2008; Floros, 2008), indicating significant asymmetric effect parameter. In fact, stock markets tend to react more nervously on negative shocks relative to positive announcements.

5. Conclusions and proposals for further research

This overarching objective of the present paper is to examine the extent the current financial crisis altered the stock market characteristics in the US and the UK. In this context, we provide an empirical investigation of the returns' volatility before and after the crisis outbreak. Particularly, the intention is to demonstrate which models fit more efficiently the Dow Jones and FTSE-100 indices volatility in each period. The investigation is conducted by means of GARCH-type models applied to daily Dow Jones and FTSE-100 returns from July 2004 to April 2009. The preliminary analysis of data sets suggests the rejection of normal distribution and strong evidence of ARCH effects in both indices under consideration. These findings of data characteristics are consistent with previous studies of developed and developing capital markets and justify the application of the employed GARCH-type models.

Both symmetric and asymmetric specifications including GARCH(1,1), GARCH-M(1,1), TGARCH(1,1) and EGARCH(1,1) are carried out. As far as Dow Jones is concerned the analysis implies that for the period before the crisis the applied models are unable to capture return series characteristics. The examination of the period after the crisis outbreak demonstrates the TGARCH(1,1,1) specification as better fit the data, while the GARCH-M specification found to be the second best fit model. The analysis of the entire sample suggests that the GARCH in mean model outperforms the others. These findings render apparent the intense presence of asymmetric effects after the crisis in the US stock market, while adding up the pre-crisis returns in the estimated data set the necessity of the asymmetric specifications is eliminated. The fact that investors present more asymmetric behaviour after the crisis and react more nervously to negative shocks further supported by the increased value of the asymmetric parameter (γ) of the TGARCH specification. With regard to FTSE-100 the TGARCH(1,1,1) model fits best both the pre-crisis and the post-crisis data despite the dramatic increase of volatility during the latter. However, it captures more efficiently the asymmetric and leptokurtotic characteristics of the post-crisis returns. Furthermore, the estimations of the asymmetric effect parameter indicate that investors behave more asymmetrically after the crisis outbreak, as in the case of the US stock market. The other asymmetric specification EGARCH(1,1) outperforms the others when the entire sample is examined. In addition, the EGARCH model also fits very efficiently the post-crisis returns. Indeed, there are significant asymmetric reactions to negative innovations from the UK stock market participants not only in the post-crisis but also during the pre-crisis period.

Taking into examination the GARCH and GARCH-M models, empirical evidence for both Dow Jones and FTSE-100 suggests that shocks to volatility are becoming more persistent after the crisis blast, since the sum of the estimated ARCH and GARCH coefficients ($\alpha_1+\beta_1$) of the above models is closer to unity during the relevant period. This finding almost certainly is due to the observed nervousness in the UK and US capital markets caused from the crisis outbreak. Evidently, the financial crisis affected severely investors' behavior and they begun to overreact to several market events. Furthermore, the empirical results are contradictive regarding the presence of risk premium in both the two capital markets during the post-crisis period, while before the crisis in neither market risk premium is required. However, results indicate that in UK after the crisis investors begun to ask for higher returns in order to participate in the risky market environment which formed.

All in all, the present study tries to provide a multidimensional investigation of the two major stock markets of the world. However, there are many questions that are not addressed. First of all, it is very interesting to explore by means of GARCH models how the financial crisis affected the returns' patterns of other mature or emerging capital markets and consequently the behaviour of the investors who participate in them. Furthermore, useful conclusions could be provided by the comparison of the present study’s results with respective findings from the examination of past crises’ effects. Lastly, another interesting extension of the present study is the investigation of the employed GARCH models’ ability to provide out sample forecasts, in order to find the specification which forecasts more satisfactorily the US and the UK market volatility.

References

Akgiray, V. (1989) Conditional heteroskedasticity in time series of stock returns: evidence and forecasts, *Journal of Business*, 62, 55-80.

Alberg, D., Shalit, D. and Yosef, R. (2008) Estimating stock market volatility using asymmetric GARCH models, *Applied Financial Economics*, 18, 1201-1208.

Alles, L. and Murray, L. (2001) An examination of return and volatility patterns on the Irish equity market, *Applied Financial Economics*, 11, 137-146.

Andersen, T.G. and Bollerslev Price T. (1998) Answering the skeptics: Yes standard volatility models do provide accurate forecasts, *International Economic Review*, 39, 885-905.

Apergis, N. and Eleptheriou, S. (2001) Stock returns and volatility: evidence from the Athens Stock Exchange Market Index, *Journal of Economics and Finance*, 25, 50-61.

Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity, *Journal of* Econometrics, 31, 301-27.

Bollerslev, T., Chou, R.Y. and Kroner, K.F. (1992) Arch modeling in finance: a review of the theory and empirical evidence, *Journal of Econometrics*, 52, 5-59.

Caiado, J. (2004) Modelling and forecasting the volatility of the Portuguese stock index PSI-20, *Portuguese Journal of Management Studies*, 1, 3-21.

Chan, K., Chan, K.C. and Karolyi, G.A. (1991) Intraday volatility in the stock index and stock index futures markets, *Review of Financial Studies*, 4, 657-84.

Chappel, D., Padmore, J. and Pigdeon, J. (1998) A note on ERM membership and the efficiency of the London Stock Exchange, *Applied Economics Letters*, 5, 19.

Chortareas, G.E., McDermott, J.B. and Ritsatos, T.E. (2000) Stock Market Volatility in an Emerging Market: Further Evidence from the Athens Stock Exchange, *Journal of Business Finance and Accounting*, 27(7&8), 983-1002.

Choudhry, T. (1996) Stock market volatility and the crash of 1897: evidence from six emerging markets, *Journal of International Money and Finance*, 15, 969-981.

Curto, J.D., Pinto, J.C. and Tavares, G.N. (2007) Modeling stock markets' volatility using GARCH models with Normal, Student's *t* and stable Paretian distributions, *Springer*: *Statistical papers*, 50, 311-321.

De Santis, G.D. and Imrohoroglu, S. (1997) Stock returns and volatility in emerging financial markets, *Journal of International Money and Finance*, 16, 561-579.

Enders, (2004) *Applied Econometrics time series*, 2nd Ed, International ed. Hoboken, N.J. Wiley.

Engle, R. and Bollerslev, T. (1986) Modelling the persistence of conditional variances, *Econometric Reviews*, 5, 1-50.

Engle, R. and Mustafa, C. (1992) Implied ARCH Models from Options Prices, *Journal of Econometrics*, 52, 289-311.

Engle, R. (1982) Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, 50, 987-1008.

Engle, R., Lilien, D. and Robbins, R. (1987) Estimating the time varying risk premia in the term structure: the ARCH-M model, *Econometrica*, 55, 391-407.

Fama, E.F. (1965) The behavior of stock market prices, *Journal of Business*, 38, 34-105.

Floros, C. (2008) Modelling volatility using GARCH models: evidence from Egypt and Israel, *Middle Eastern Finance and Economics*, 2, 31-41.

Francis, B.B. and Leachman, L.L. (1996) The Volatility and Transmission of Equity Returns Among the G7 countries: The Post-Bretton Woods Experience, *International Review of Applied Economics*, 10, 289-303.

Glosten, L., Jagannathan, R. and Runkle, D. (1993) Relationship between the expected value and volatility nominal excess returns on stocks, *Journal of Finance*, 48, 1779-802.

Hangerman, R.L. (1978) Note: More evidence on the distribution of security returns, *The Journal of Finance*, 33, 1213-1221.

Haroutounian, M.K. and Price, S. (2001) Volatility in the transition markets of Central Europe, *Applied Financial Economics*, 11, 93-105.

Harris, R., Kucukozmen, C. and Yilmaz, F. (2004) Skewness in the conditional distribution of daily equity returns, *Applied Financial Economics*, 14, 195-2002.

Kim, D. and Kon, S.J. (1994) Alternative models for the conditional heteroskedasticity of stock returns, *Journal of Business*, 67, 563-598.

Koutmos, G., Negakis, C. and Theodossiou, P. (1993) Stochastic behaviour of the Athens stock exchange, *Applied Financial Economics*, 3, 119-126.

Koutmos, G. (1998) Asymmetries in the conditional mean and the conditional variance, *Journal of Financial Markets, Institutions and Money*, 7, 221-234.

Lau, A., Lau, H., and Wingender, J. (1990) The distribution of stick returns: New evidence against the stable model, *Journal of Business and Economic Statistics*, 8, 217-23.

Li, Q., Yang, J., Hsiao, C. and Chang, Y.J. (2005) The relationship between stock returns and volatility in international stock markets, *Journal of Empirical Finance*, 12, 650-665.

McLeod, A.I. and Li, W.K. (1983) Diagnosis checking ARMA time series models using squared-residual autocorrelation, *Journal of Time Series Analysis*, 4, 269-273.

Nelson, D. (1991) Conditional heteroskedasticity in asset returns: a new approach, *Econometrica*, 59, 347-70.

Poterba, L. and Summers, L. (1986) The Persistence of Volatility and Stock Market Fluctuations, *American Economic Review*, 76, 1142-1151.

Scruggs, J.T. (1998) Resolving the Puzzling Intertemporal Relation between the Market Risk Premium and Conditional Market Variance: A Two-Factor Approach, *Journal of Finance*, 53, 575-603.

Siourounis, G.D. (2002) Modelling volatility and testing for efficiency in emerging capital markets: the case of the Athens stock exchange, *Applied Financial Economics*, 12, 47-55.

Song, H., Liu, X. and Romilly, R. (1998) Stock Returns and Volatility: an empirical study of Chinese stock markets, *International Review of Applied Economics*, 12, 129-139.

Tavares, A., Curto, J.D. and Tavares, G.N. (2008) Modeling heavy tails and asymmetry using ARCH-type models with stable paretian distribution, *Nonlinear Dynamics, Springer*, 51(1), 231-243.

Tsay, L.S. (2005) *Analysis of Financial time series*, 2nd ed. Hoboken, N.J. Wiley.