Volatility and Long Term Relations in Equity Markets: Empirical Evidence from Germany, Switzerland, and the UK

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Abstract

The aim of this paper is twofold. First it aims to compare several GARCH family models in order to model and forecast the conditional variance of German, Swiss, and UK stock market indexes. The main result is that all GARCH family models show evidence of asymmetric effects. Based on the "out of sample" forecasts I can say that for each market considered there is a model that will lead to better volatility forecasts. Secondly a long run relation between these markets was investigated using the cointegration methodology. Cointegration tests show that DAX30, FTSE100, and SMI indexes move together in the long term. The VECM model indicates a positive long run relation among these indexes, while the error correction terms indicate that the Swiss market is the initial receptor of external shocks. One of the main findings of this analysis is that although the UK, Switzerland and Germany do not share a common currency, the diversification benefits of investing in these countries could be very low given that their stock markets seem to move together in the lung term.

JEL Classification: C22, C53, G15, G17

Keywords: Stock Returns; Volatility; GARCH models; Cointegration

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1. Introduction

This work investigates several aspects of the German, Swiss and UK equity markets, namely the volatility phenomenon as well as the long term relations among these markets. Modelling and forecasting volatility has been broadly investigated in recent years: the main reason is that volatility is a measure of the risk connected with the financial markets, so trying to forecast it can be extremely useful in order to take good investment decisions[1]. On the other side volatility may negatively affect economic performance of advanced economies (Mala and Reddy, 2007) so it is useful to detect this phenomenon especially in advanced economies like German which is considered as the economic engine of Europe. Why extend this study particularly to the UK and Switzerland? We want to see if market volatility in these countries is quite similar to the German market although the UK has not adopted the Euro and Switzerland is not part of the European Union (EU). Given that the assumption of constant volatility is often violated in financial markets, one way to model such patterns is to allow the volatility to depend upon its history: time-varying volatility of financial markets returns can be described by GARCH (generalized autoregressive conditional heteroskedasticity) family models. So this methodology is going to be used in order to study the volatility phenomenon. The other aim of this study is to detect whether financial markets considered here are integrated. Fratzscher (2001) showed that countries adopting the Euro currency in January 1999, have benefited in terms of stronger financial integration among their equity markets because of the elimination of currency risks among them. Is it possible to think of Germany, UK and Switzerland as having integrated financial markets given that they do not share either a common currency or membership to the EU regarding Switzerland? Before giving an answer to this question we need to define the concept of financial integration. There are different definitions of financial integration and among them, one in particular is based on long term relations among equity markets: if this long term trend among financial markets exists, then they are integrated. This last study will be conducted by using the cointegration methodology developed by Johansen and Juselius (1990).

This paper is organised as follows. Section 2 provides a brief review of the empirical literature on both stock market volatility and integration. The econometric modelling is set out in detail in Section 3. Section 4 describes the data and descriptive statistics on the three equity markets considered here. Section 5 reports the results and Section 6 concludes.

[1] As pointed out by Mala e Reddy (2007), stock market volatility has several negative implications, among them a negative effect on consumer spending. A fall in stock markets may reduce consumer confidence and thus drive down consumer spending. This could lead firms to reduce production as well as investors to sell stock and shares of those firms with a negative effect on the overall index.

2. Empirical literature on volatility and financial integration

This section aims to give some recent findings from the empirical literature relative to volatility and long term relations among financial markets. Only studies will be highlighted which used GARCH family models as well as cointegration methodology as an econometric framework in order to focus this paper on a well defined research field characterized by using this methodology.

Many financial time series exhibit periods of unusually large volatility, follows by periods of relative tranquillity (Campbell et al., 1997). Such a phenomenon has been identified with the term "volatility clustering". Another interesting phenomenon is that "bad news" seems to have a more pronounced effect on volatility than "good news". This last phenomenon is also known in financial literature as "asymmetric volatility". What does this mean precisely? This phenomenon has been stylized by financial literature with the term asymmetric volatility: in order to explain it, two main explanations have been proposed by current literature. Black (1976) sustained that equity firms tend to be more leveraged when their stock market values go down; an immediate effect is a growth of volatility. On the other hand another explanation about the negative relationship between returns and volatility is based on the so-called "volatility feedback effect". In other words if stock market volatility has a positive relation with the equity premium[2], then stock prices should move in the opposite direction to the level of market volatility. In this way the volatility feedback can describe a negative relationship between volatility and market prices (Pindyck 1984, French et al. 1987, Kim et al. 2004).

These considerations have led to the use of several time varying volatility models to estimate and forecast volatility. In its seminal paper, Engle (1982) proposed to model time varying conditional variance with Autoregressive Conditional Heteroskedasticity (ARCH) models where it is possible to simultaneously model the mean and the variance of a series. Bollerslev (1986) extended Engle's work by developing Generalized ARCH (GARCH) models which may provide a parsimonious alternative to the higher order ARCH process. Both ARCH and GARCH models capture volatility clustering, but they fail to model the asymmetric effect described above. In other words in these models negative and positive news produce the same impact on volatility, this is clearly difficult to accept given that financial markets show evidence of the above described asymmetric effect. In order to overcome these drawbacks, asymmetric volatility models have been developed[3].

[2] That is the excess return that an individual stock market provides over a risk-free rate. The risk-free rate in the market is often quoted as the rate on long-term bonds which are considered risk free because of the low chance that the government will default on its loans.

[3] In these models "bad" and "good" news have a different impact on volatility.

Because of their symmetry, a big negative shock has the same impact on future volatility as a big positive shock of the same magnitude. An interesting extension has been towards asymmetric volatility models, in which good news and bad news have a different impact on future volatility (Verbeek, 2004). Nonlinear extensions of GARCH models such as the Exponential GARCH (EGARCH) model by Nelson (1991), the Asymmetric Power ARCH (PGARCH) model by Ding et al (1993), the Threshold GARCH (TGARCH) model by Glosten et al. (1994) and Zakoian (1994), have been widely used by the empirical literature in order to investigate the relationship between stock market returns and volatility.

Koutmos (1998) used a TGARCH model to investigate whether conditional variance responds asymmetrically to past information. His study considers nine industrialized countries: the results for the UK stock market show that there is asymmetric behaviour of the conditional variance since it rises proportionally more during market declines than during market increases**.** Chen et al. (2001) examined the relationship between stock market returns and volatility in nine international stock markets by using EGARCH techniques. Considering the UK and Switzerland stock market indexes[4], results show evidence of asymmetry given that the leverage factor is statistically significant. Faff et al.(2000) measured the leverage effect by the EGACH and TARCH models by using daily returns data on 32 UK industries. Their results show asymmetric effects in the conditional volatility of returns with respect to good and bad shocks. Bekaert and Wu (2000) examined asymmetric volatility, that is the negative correlation between return and conditional volatility, in the Japanese stock market by using a multivariate GARCH-in-mean model. They found that asymmetry is an important feature of the Nikkey 225 index volatility, in other words the dominant cause of the asymmetry of the Japanese stock market is due to volatility feedback. Najand (2002) examined the ability of linear and non linear models to forecast daily S&P500 index volatility, empirical results show that EGARCH models seem to be the best ones for forecasting stock index price volatility.

Jacobsen e Dannenburg (2003) investigated the volatility of stock returns for several European countries[5] by using daily, weekly and bi-weekly financial series of stock market indexes. Relative to both the UK and German market indexes, results show that GARCH effects are present in the daily, weekly and by-weekly frequencies but not in the monthly data. Koulakiotis et al (2006) by using symmetric and asymmetric GARCH models, found that the relationship between stock market volatility and the expected returns is not significant for the stock market of industrialized countries with the exception of the UK where the coefficient of the relationship between volatility and stock

[4] That study also considered Canada, France, Hong Kong, Italy, Japan, and the USA, but not the German index.

[5] They considered France, Germany, Italy, the Netherlands, the United Kingdom and the United States.

price returns is -6.14[6]. However, Li et al. (2005) found empirical evidence that the significance of that particular relationship depends on the way volatility is estimated by using EGARCH-M models. In fact, using a semiparametric specification of conditional variance, they show that after the 1987 stock market crash, the relationship between stock market returns and volatility is significant in 7 out of 12 international stock markets considered[7], specifically for Germany, the UK and Switzerland the coefficients are very high, respectively -18.81 (significant at 5% level), -19.19 (5%) and -16.67 (5%). Alberg et al. (2008) estimated stock market volatility of the Tel Aviv Stock Exchange (TASE) by using the GARCH model and its asymmetric specifications. The main purpose of the study was to rank the forecasting ability of each model used. They found evidence that the forecasting performance of the EGARCH model is better than the GARCH, TGARCH and APARCH models. Floros (2008) used both symmetric and asymmetric GARCH family models for modelling volatility for two Middle East stock indices. He found strong evidence that the daily returns of the Egyptian CMA Index and the Israeli TASE-100 Index can be characterised by asymmetric GARCH models. All these empirical studies show both the importance of GARCH family models in evaluating relations between returns and stock market volatility as well as different approaches to model financial series by using series with high (daily) or low (monthly) frequencies to break down the sample data in sub-periods. This last approach may also be responsible for obtaining opposite results.

The integration of stock markets has been extensively studied by empirical literature: cointegration methodology is one of the most common econometric frameworks used. The following review of empirical literature aims to point out some of the most recent findings from empirical analysis.

Francis and Leachman (1998) found empirical evidence of a cointegration relationship among major stock indexes of the US, the UK, Germany and Japan (1998). In order to detect the short term dynamics of relations among these markets they use the results from a cointegration analysis in order to build an error correction model (ECM). ECM results indicate that changes in the returns in both the UK and German stock markets have a statistically significant effect on the US stock markets returns. Ng (2000) examined the influence of the US and Japanese equity markets to six Pacific-basin equity markets. She found that the Japanese and the US equity markets have little influence on these markets. One of the main explanations is that returns of the Pacific-Basin markets are strongly influenced by some local forces which seem to be unrelated to the major equity markets considered. Swanson (2003), using both the Engle-Granger (1987) and the Johansen

[6] This means that if stock price volatility increases by 1%, then the stock market returns will decrease by 6.14% with negative persistence.

[7] They considered stock market indexes of the following countries: Australia, Canada, France, Germany, Hong Kong, Italy, Japan , the Netherlands, Singapore, the United Kingdom, the United States, and Switzerland.

(1988) cointegration tests**,** showed the capacity of the US equity market to influence both the German and Japanese equity markets in a positive manner. Similar results about the influence of major financial markets toward smaller markets was pointed out by Cotter (2004) who used the Johansen and Juselius (1990) procedure. He found that the German, UK and USA equity markets strongly affect the Irish market but that the reverse effects are insignificant. Examining both short and long term relations between the US and several Central Europe equity markets by the Johansen cointegration tests (Johansen, 1988), Gilmore and McManus (2002) found that these markets are not cointegrated with the US market indicating the existence of diversification benefits for short and long term investors. Ratanapakorn and Sharma (2002) investigated both the short-term and long-term relationships among five regional indices before and after the 1997 Asian crisis. One of their results showed that, during the crisis, European market Granger caused the US market while this phenomenon was not present before that crisis. In other words these authors want to point out that during the Asian crisis period, globalization increased strongly making more evident links between international financial markets.

Other papers have investigated the existence of a cointegration relations among indices in South East Asia. For example, Manning (2002), using the cointegration approach (which had been originally introduced by Johansen, 1988, Johansen and Juselius 1990, Johansen 1991) showed that a sample of Asian markets had converged before the 1997 Asian crisis: this process was abruptly interrupted by the following crisis.

In all these studies however none investigated both the short run as well as the long run relationship among equity markets of the three European countries here considered after the introduction of the Euro in one of them. Given that the absence of a common currency may induce investors to diversify their financial investments, we may expect the absence of a long term relationship among these financial markets which have their own currencies. So the aim of the second part of the empirical work in this study is going to detect this relationship as well as analyzing the short term behaviour of these markets by using Johansen's methodology.

3. Econometric methodology

In conventional econometric models, the variance of the disturbance term is assumed to be constant. However figure 2 (see section 4) demonstrates that financial time series exhibit periods of large volatility, followed by periods of relative tranquillity. In such circumstances, the assumption of a constant variance (homoskedasticity) is inappropriate, so it is preferable to use models that allow the variance to depend upon its history. The seminal paper in this area is Engle (1982) which proposed the concept of autoregressive conditional heteroskedasticity (ARCH). In ARCH models the variance of the error term at time t depends upon the squared error terms from the previous periods. A useful variant proposed by Bollerslev (1986) is the generalized GARCH (p,q) model, which can be written as:

$$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

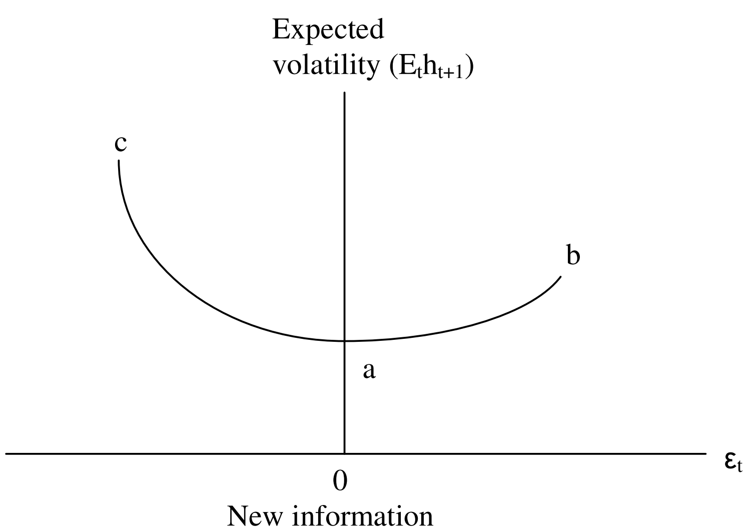
Given that a GARCH (1,1) specification often performs very well (Verbeek, 2004), equation.1 can be written as

$$\sigma_t^2 = \varpi + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

which has only three unknown parameters to estimate, non negativity of σ_t^2 requires that ϖ, α and β are non negative. An important restriction to the GARCH specifications above is their symmetry. That is, a big negative shock has the same impact on future volatility as a big positive shock of the same magnitude. An interesting extension is towards asymmetric volatility models, in which good news and bad news have a different impact on future volatility.

The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage effect. The concept of the leverage effect is captured in figure 1, where "new information" is measured by the size of ε_t. If $\varepsilon_t = 0$, expected volatility $(E_t h_{t+1})$ is 0. On the other side figure 1 assumes that any news increases volatility; however, if the news is good (that is ε_t is positive), volatility increases along line ab. If the news is "bad", volatility increases along line ac. Since line ac is steeper than ab, a positive ε_t will have a smaller effect on volatility than a negative shock of the same size.

Figure 1 – The Leverage Effect



Source: Enders (2004)

Asymmetric GARCH models have been developed in order to take into account the different effect of news on the volatility of stock market returns.

Glosten, Jaganathan, and Runkle (1994) showed how to allow the effects of good and bad news to have different effects on volatility. In a sense, $\varepsilon_{t-1} = 0$ is a threshold so that shocks greater than the threshold have different effects than shocks below the threshold. Consider the threshold-GARCH (TGARCH) specification for the conditional variance as:

$$\sigma_2^t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

where d_{t-1} is a dummy variable that is equal to one if $\varepsilon_{t-1} < 0$ and is equal to 0 if $\varepsilon_{t-1} \leq 0$. In this model, good news, $\varepsilon_{t-1} > 0$ and bad news, $\varepsilon_{t-1} < 0$, have differential effects on the conditional variance, good news has an impact of α_1, while bad news ha an impact of $\alpha + \gamma$. So if $\gamma > 0$, negative shocks (bad news) will have larger effects on volatility than positive shocks (good news), and then we say that there is a leverage effect.

Another model that allows for the asymmetric effect is the exponential GARCH (EGARCH) model (Nelson, 1991). The specification for the conditional variance is stated thus:

$$\log\sigma_2^t = \omega + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta\log\sigma_{t-1}^2 \quad (4)$$

where the presence of leverage effects can be tested by the hypothesis that $\gamma \neq 0$. The impact is asymmetric if $\gamma \neq 0$.

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modelled rather than the variance. This model, is generalized in Ding et al. (1993) with the Power ARCH specification (PGARCH). In the power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry of up to order r, so the standard deviation equation is stated thus:

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

where $\delta > 0$, $|\gamma_i| \leq 1$ for i=1,…,r , $\gamma_i = 0$ for all $i > r$, and $r \leq p$. The symmetric model sets $\gamma_i = 0$ for all i. Note that if $\delta = 2$ and $\gamma_i = 0$ for all i, the PARCH model is simply a standard GARCH specification. As in the previous models, the asymmetric effects are present if $\gamma \neq 0$.

An alternative specification for the conditional volatility process is a component GARCH (CGARCH) model of Ding and Granger (1996) The conditional variance in the CGARCH (1,1) model is stated thus:

$$\sigma_t^2 = \varpi + a\left(\varepsilon_{t-1}^2 - \varpi\right) + \gamma\left(\sigma_{t-1}^2 - \varpi\right) \tag{6}$$

this shows mean reversion to ϖ, which is constant all the time. By contrast, the component model allows mean reversion to a varying level m_t, modelled as:

$$\sigma_t^2 - m_t = \varpi + \alpha\left(\varepsilon_{t-1}^2 - \varpi\right) + \beta\left(\sigma_{t-1}^2 - \varpi\right) \tag{7}$$

$$m_t = \omega + \rho\left(m_{t-1} - \omega\right) + \phi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right) \tag{8}$$

where σ_t^2 is the volatility, while m_t is the time varying long run volatility. Equation 7 describes the transitory component, $\sigma_t^2 - m_t$, while equation 8 describes the long run component m_t. An extension of CGARCH model is an Asymmetric component GARCH model (AGARCH) which combines the component model with the asymmetric TGARCH model. This specification which is going to be used in the next section, introduces asymmetric effects in the transitory equation and estimates models of the form:

$$r_t = x_t \pi + \varepsilon_t \tag{9}$$

$$q_t = \omega + \alpha\left(q_{t-1} - \omega\right) + \gamma\left(\varepsilon_{t-1}^2 + \sigma_{t-1}^2\right) + \theta_1 z_{1t} \tag{10}$$

$$\sigma_t^2 - q_t = \beta\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta_1\left(\varepsilon_{t-1}^2 - q_{t-1}\right)d_{t-1} + \beta_2\left(\sigma_{t-1}^2 - q_{t-1}\right) + \theta_2 z_{2t} \tag{11}$$

Where z represents the exogenous variables and d is the dummy variable indicating negative shocks, $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance.

In the second part of this study we tested for Cointegration between the FTSE100 index and the SMI index by examining the long-term equilibrium relationships between the UK and the Switzerland Stock market indexes. Cointegration is a long-term measure of diversification based on price data and is usually used in order to detect a degree of integration by measuring the stability of long-run relationships across financial markets (Richards, 1995). If there exists a linear combination of two nonstationary series integrated of order one, i.e. I(1), that is stationary., these series are called cointegrated series. Cointegration measure answers the question of a long-term common stochastic trend between a non-stationary time series. If non-stationary series x and y are both integrated of the same order and there is a linear combination of them that is stationary, they are called cointegrated series and the vector of this relationship is called the cointegrating vector. Accordingly, cointegrated series share a common stochastic trend. It follows that these two series will not drift apart too much, meaning that even if they may deviate from each other in the short term, they will revert to a long-term equilibrium. This fact makes cointegration a very powerful approach for portfolio diversification purposes especially for the long term. Meanwhile, cointegration does not imply high correlation; two series can be cointegrated and yet have very low correlations.

Two basic methodologies are evident for testing cointegration: the Engle-Granger and Johansen methodologies. The Engle-Granger (1987) methodology, based on OLS regression, is most suitable for bivariate settings[8] where the choice of a dependent variable is not a question and it can identify only one cointegration vector while there can be more in multivariate analysis. This is why it was decided to use the Johansen cointegration methodology in this present work. This methodology was developed by Johansen (1988) who developed a maximum likelihood procedure which allows one to test for the number of cointegrating relations. Here only will be focused upon a few aspects, further details can be found in Johansen and Juselis (1990) and Johansen (1991).

The starting point of the Johansen procedure is to estimate a vector autoregression (VAR) model using undifferenced data (Enders, 2004) as well as selecting lag length p using the both the Akaike (AIC) and Schwarz (SC) information criterion, that is the following equation:

$$Y_t = c + \sum_{i=1}^{p} \Delta Y_{t-1} + \varepsilon_t \qquad (12)$$

where Y_t is a column vector of all the endogenous variables in the system (here the log price indexed), c is a vector of constants, ε_t is a vector of innovations, and p is the number of lags of variables in the system.

The second step involves the determination of the number of cointegrating relations in the VAR model identified above. In order to get this result, the Johansen methodology (1991) provides two statistics to determine the number of cointegration vectors: Trace and Maximum Eigenvalue statistics. Johansen and Juselius (1990) say that Trace statistic tests the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations, where n is the number of variables in the system for r = 0,1,2,…, n-1. The Maximum Eigenvalue statistics tests the null hypothesis of r cointegrating relations against the alternative of r+1 cointegrating relations for r=0,1,2,…, n-1. In some cases Trace and Maximum Eigenvalue statistics may yields different results.

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[8] Engle and Granger (1987), building upon the representation theorem of Granger (1983), introduce a two-step procedure where first an ordinary least squares (OLS) regression is estimated on the integrated of order one data and then residuals of the regression are checked for stationarity. Granger's representation theorem (1983) suggests that in a bivariate system I(1) series x and y, if lagged x improves the estimation of y, then x is said to Granger cause y. "Granger causality" suggests a lead-lag relationship between time series and there may be "Granger causality" between asset prices without the presence of a cointegrationg vector. However, cointegration analysis implies a Granger (1983) casual flow between the integrated assets.

The third step is based on the Granger Representation Theorem, that is if the variables in the VAR, which represent the long-run dynamics between those variables, are found to be co-integrated, then there must exist an associated error-correction model (ECM), which can be built by imposing as restrictions the number of cointegration relations previously identified. In this way the VAR is transformed in a Vector Error Correction Model (VECM) which can be used in order to show any short-run dynamics between variables as well as to distinguish between the short-run and the long run relationship among the variables. The VECM representation of equation 12 is of the following form:

$$\Delta Y_t = \sum_{J=1}^{k-1} \Gamma_j \Delta Y_{t-j} + \alpha\beta^{'} Y_{t-k} + \mu + \varepsilon_t \tag{13}$$

with Δ denoting the first difference operator, Γ_j are coefficient matrices (j = 1,2, …,k), β is the cointegrating matrix of r cointegrating vectors β_1, $\beta_2,\ldots,\beta_k$, which represent estimates of the long-run cointegrating relationship between the variables in the system, while α is the matrix of error coefficients that measure the speed at which the variables adjust to their equilibrium values. It must be pointed out that the value of the speed of adjustment is expected to be less than one in absolute terms in order to guarantee both the stability of the system and for the variables in the long-run regression to be co-integrated. The sign of adjustment parameters indicate the direction of the adjustment process. This means that if the system deviates from its long-term path, the sign and the magnitude of the adjustment parameter would indicate the direction of adjustment and speed at which the variables parameters adjust in the short-term in order to go back to its long-term equilibrium path. The Johansenn and Juselis methodology provides likelihood estimates of α and $\beta^{'}$

4. Data

The observation period goes from January 3, 1999 to September 23, 2008 for a total of 2447 observations on the German stock market (i.e. DAX30), UK Stock market (i.e. the FTSE 100 Index) and the Swiss Stock Market (i.e. Swiss Market Index). All time series are closing prices obtained from Yahoo.Finance. The reason for using daily data is based on the consideration that lower frequency data (such as weekly or monthly) may lack part of the information relative to interactions between markets which are contained instead in daily data (Voronkova, 2004). Levels for each of the three stock market indexes are presented in figure 2. In this paper, returns of each stock market index (fig.3) have been computed using the prices log difference, that is $r_t = \ln(P_t) - \ln(P_{t-1})$. Tab. 1 shows the statistical characteristics of returns of each stock market index. The analysis reveals that only the DAX30 index had a positive mean during the investigation period. The German stock market is the most volatile (with a standard deviation equals to 0.0153) while the British is least (standard deviation equals to 0.0116). The maximum return is observed for DAX (7,4%) while the minimum is observed for FTSE100 (5,9%). All daily returns have a negative skewness implying that the distribution has a long left tail. Stock market returns also exhibit an excess of kurtosis implying that returns do not follow a normal distribution. The last characteristic can be seen clearly in figure 4, which indicates quantiles of stock market returns with respect to normal distribution quantiles: we may also note that quantiles of returns do not lie along the red line, in other words these returns do not have a normal distribution. The Jarque-Bera test (tab. 1) confirms such a result by rejecting the null hypothesis of a normal distribution for index returns. These characteristics of the returns are in line with a set of stylized facts about financial series with have been pointed out by Pagan (1996).

Table 1 – Summary statistics for daily returns

Index	N. obs	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera Test	p-value
Dax	2447	7.32e-05	0.075	-0.074	0.0153	-0.082	5.771	785.65	0.00
Ftse100	2447	-3.73e-05	0.059	-0.056	0.0116	-0.145	5.439	615.074	0.00
Smi	2447	-3.17e-05	0.064	-0.057	0.0119	-0.046	6.75	1440.4	0.00

Table 2 reports the correlation coefficients between market index returns. Examination of the correlations reveal that FTSE100 and SMI indexes have higher pairwise correlation between each other[9].

Table 2 – Pairwise correlation matrix of stock market indexes

	DAX30	FTSE100	SMI
DAX30	1.00	-	-
FTSE100	0.897	1.00	-
SMI	0.890	0.913	1.00

[9] Correlations can show whether and how pairs of variables are related: it must be noted that high (low) correlations do not necessarily imply high (low) dependence.

Figure 2 – Daily data for the DAX30, FTSE100 and SMI indexes

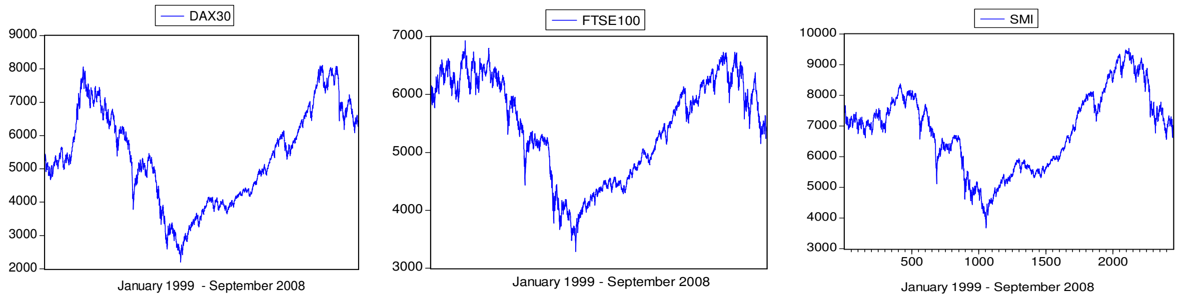


Figure 3 – Returns for the DAX30, FTSE100 and SMI Stock market indexes

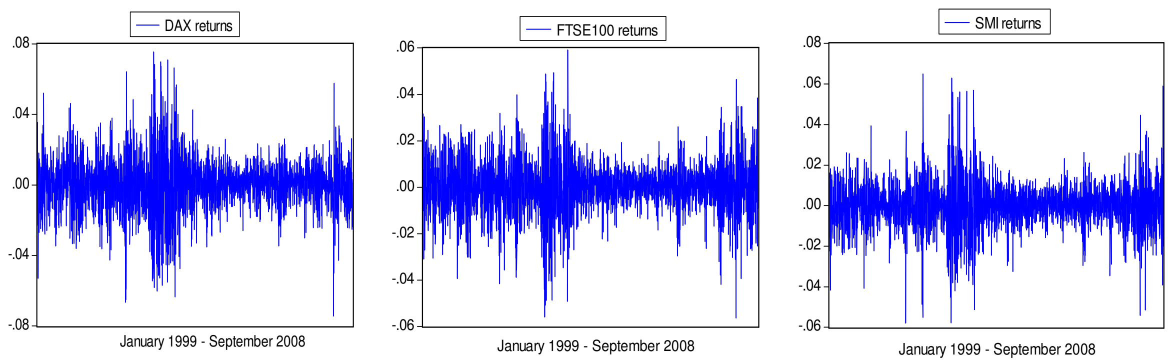
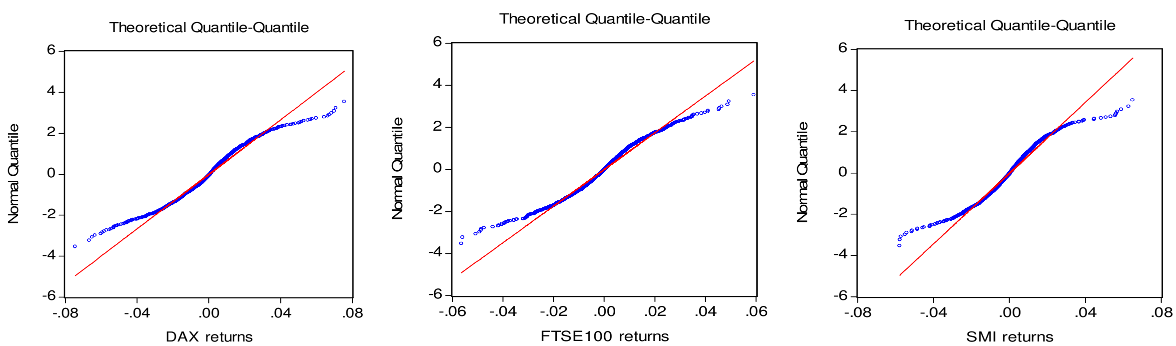


Figure 4 – Q-Q normal plot about return normal distribution of each index



5. Empirical results

This section aims to show the main findings which have been obtained by using either GARCH family models as well as the cointegration analysis.

5.1 Modelling Volatility

In order to model and forecast volatility, the first 2300 observations for each stock market index were used for modelling, the last 147 observations where kept out of sample in order to be used for forecasting volatility.

For each conditional volatility model, we estimated ARMA(p,q) models, using the AIC and SC (see Appendix A). We chose the model with lower values. Sometimes these criteria gave different results, in that case we selected the model following the SC criterion because it usually indicates a more parsimonious one (Enders, 2004). Considering the DAX index returns, the EGARCH model was estimated using a MA(1) model, TGARCH was modelled using an ARMA (1,1) model, AGARCH was estimated using a MA(1) model, finally PGARCH model was estimated using an ARMA (2,2) model. Considering the FTSE100 index returns, the EGARCH equation was modelled using a mean equation given by an AR (1) model. The TGARCH equation was estimated using an AR(1) model. An AR(1) was chosen to model the PGARCH model, finally an AR(2) was chosen to estimate the conditional mean equation of the AGARCH model. Moving to the SMI returns, the EGARCH equation was modelled with an AR(1), the TGARCH with an AR(1), the PGARCH with an AR(1) and finally the AGARCH with an ARMA(2,1). All models estimated are characterized by both mean and volatility equations. Here only volatility equations will be presented since we are interested in analysing specifically the conditional volatility results given by each conditional volatility equation.

Table 3 reports the parameter estimates of all conditional volatility models defined in the previous section. Considering the DAX30 index, the EGARCH model shows a negative and significant γ parameter, this means that positive shocks generate less volatility than negative shocks (bad news). Also the TGARCH leverage effect is significant, in addition bad news has an impact of 0.139 (that is the sum of α and γ). We may note in the case the TGARCH model that the estimate of α is smaller that the coefficients of γ, this implies that negative shocks do not have a great impact on conditional volatility than positive shocks of the same magnitude. Furthermore the PGARCH model confirms that asymmetric effects are present for DAX30 given that the coefficients of γ are positive and significant. Finally the AGARCH shows a transitory leverage effect (that is $\gamma > 0$) which is statistically significant.

For FTSE100 stock returns, the EGARCH model shows a negative and significant γ coefficient, indicating the existence of the leverage effect in returns during the sample period. Also the coefficient β of lagged conditional variance is significantly positive and less than one, indicating that the impact of "old" news on volatility is significant: the magnitude of the coefficient is especially high for the FTSE100 Index, indicating a long memory in the variance.

The results of the estimation of the AGARCH(1,1) model show the presence of transitory leverage effects ($\gamma > 0$) in the conditional variance. The sum of variables in the transitory equation will have an impact on the short run volatility, because that sum is greater than the unity, it means that in the short run there is no steady state. However, the estimates of the persistence in the long run component (that is the sum of coefficients β, β_1, β_2) give a value equal to 0.158, indicating that the long run component converges quickly to the steady state. Also for the TGARCH the leverage effect is positive, this means that negative shocks will have a greater impact on volatility than positive shocks. The results of the estimation of PGARCH(1,1) model indicate that the asymmetric effects are positive and significant. Moving to the Swiss Market Index, all GARCH family model coefficients of lagged conditional variance are positive, significant and less than one for most specifications. Strong GARCH effects are apparent for EGARCH and PGARCH specifications. The EGARCH model indicates a negative and significant γ parameter, showing the existence of the leverage effects. In the PGARCH and TGARCH specification the estimate of α is smaller than the estimate of γ, this means negative shocks do not have a greater impact on conditional volatility than positive shocks of the same magnitude. In addition bad news has an impact of 1.068 (PGARCH) and 0.153 (TGARCH). In the AGARCH model, the coefficient γ is greater than zero, indicating the presence of transitory leverage effects in the conditional variance.

The Ljung-Box Q-statistics indicate that the autocorrelations of the residuals are not statistically significant at the normal levels of significance for all GARCH family models estimated.

Table 3 - Conditional volatility equations for GARCH family models

	DAX30 Stock Index returns			
	AGARCH(1,1)	EGARCH(1,1)	PGARCH(1,1)	TGARCH(1,1)
ω	0.0002***	-0.313***	3.17e-05	2.70E-06***
	(0.00)	(0.00)	(0.409)	(0.00)
β	-0.139***	0.977***	0.910***	0.905***
	(0.00)	(0.00)	(0.00)	(0.00)
β_1	0.113***	-	-	-
	(0.00)			
β_2	-0.529***	-	-	-
	(0.00)			
α	0.988***	0.154***	0.074***	0.020***
	(0.00)	(0.00)	(0.00)	(0.00)
γ	0.094***	-0.084***	0.534***	0.119***
	(0.00)	(0.00)	(0.00)	(0.00)
Q-statistic (4)	3.643	3.562	-	1.742
	(0.303)	(0.313)		(0.418)
Q-statistic (8)	10.367	11.946	8.4451*	8.577
	(0.169)	(0.102)	(0.077)	(0.199)
Q-statistic (12)	11.908	13.444	10.085	10.371
	(0.371)	(0.265)	(0.259)	(0.409)
	FTSE100 Stock Index Returns			
ω	6.41E-05	-0.240***	0.0003	1.49E-06***
	(0.00)	(0.00)	(0.183)	(0.00)
β	-0.053***	0.983***	0.938***	0.918***
	(0.00)	(0.00)	(0.00)	(0.00)
β_1	0.166**	-	-	-
	(0.00)			
β_2	0.883***	-	-	-
	(0.00)			
α	0.992***	0.105***	0.061***	-0.0018

	(0.00)	(0.00)	(0.00)	(0.845)
γ	0.037***	-0.111***	0.999***	0.134***
	(0.00)	(0.00)	(0.00)	0.00
Q-statistic (4)	3.361*	3.745	3.876	3.932
	(0.07)	(0.290)	(0.275)	(0.269)
Q-statistic (8)	8.377	5.059	5.086	5.156
	(0.21)	(0.653)	(0.649)	(0.641)
Q-statistic (12)	19.01**	6.075	6.289	6.314
	(0.04)	(0.868)	(0.853)	(0.852)

SMI Stock Index returns				
	AGARCH(1,1)	EGARCH(1,1)	PGARCH(1,1)	TGARCH(1,1)
ω	0.0002***	-0.306***	0.0004	2.11E-06***
	(0.00)	(0.00)	(0.197)	(0.00)
β	-0.135***	0.975***	0.924***	0.908***
	(0.00)	(0.00)	(0.00)	(0.00)
β_1	0.115***	-	-	-
	(0.00)			
β_2	1.056***	-	-	-
	(0.00)			
α	0.992***	0.104***	0.068***	-0.011
	(0.00)	(0.00)	(0.00)	(0.198)
γ	0.155***	-0.131***	0.999***	0.164***
	(0.00)	(0.00)	(0.00)	(0.00)
Q-statistic (4)	2.463	4.105	4.338	3.784
	(0.117)	(0.250)	(0.227)	(0.285)
Q-statistic (8)	5.557	7.839	7.878	7.189
	(0.352)	(0.347)	(0.343)	(0.409)
Q-statistic (12)	12.677	14.149	14.392	14.145
	(0.176)	(0.225)	(0.212)	(0.225)

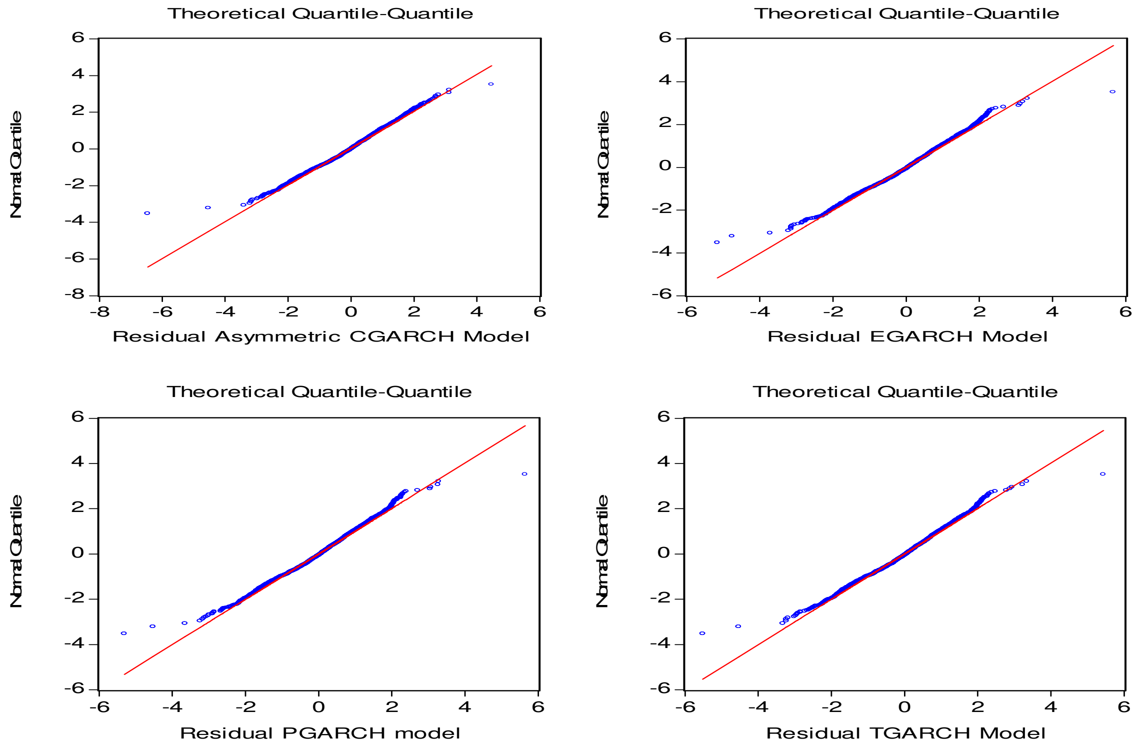
Note : For GARCH family model coefficients values in brackets are p-values. The Ljung-Box Q-statistic, Q(n), is a test statistic for the null hypothesis that there is no autocorrelation up to order n, value in brackets are p-values.

One way of further examining the distributions of the residuals is to plot the quantiles. If the residuals are normally distributed, the points in the QQ plots should lie along a straight line[10]. The plots (fig.5) indicate that it is primarily great negative shocks that are driving the departure of normality for all GARCH models estimated.

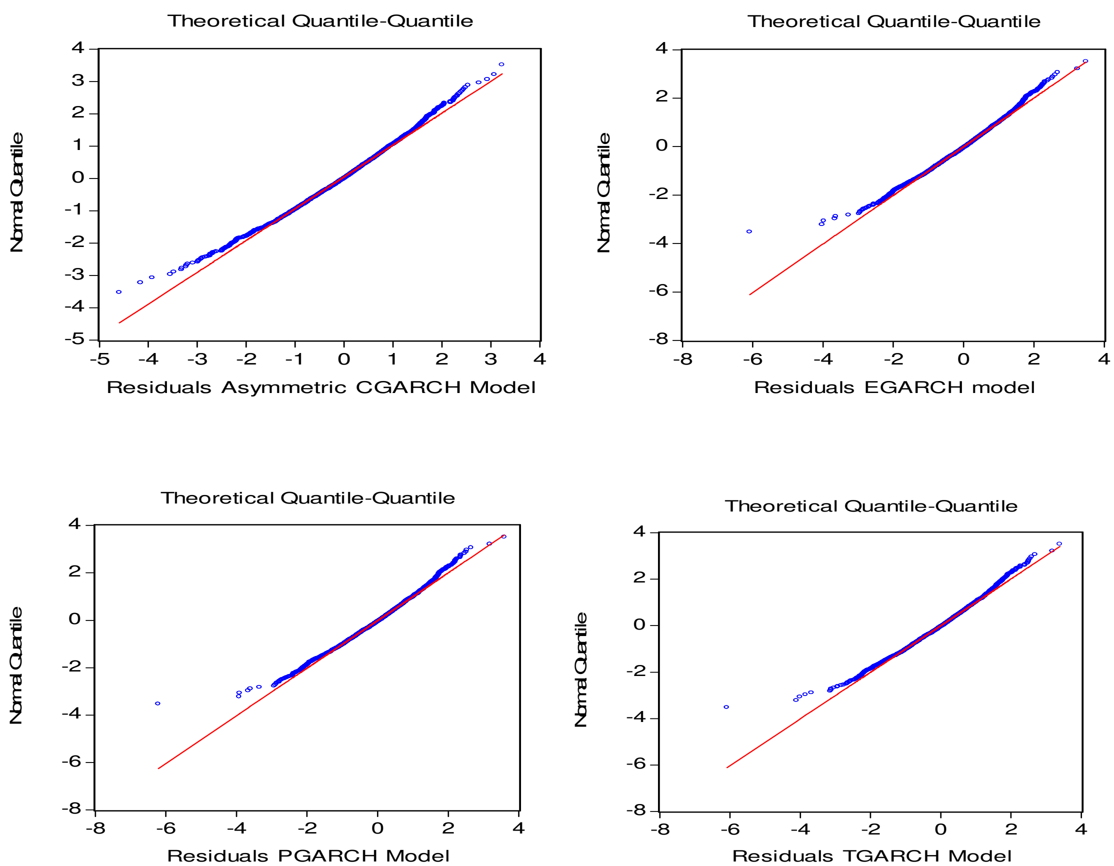
[10] The quantile-quantile (QQ) plot is a simple yet powerful tool for comparing two distributions (Cleveland, 1994). This view plots the quantiles of the chosen series against the quantile of another series or a theoretical distribution. If the two distributions are the same, the QQ plot should lie on a straight line. If the QQ plot does not lie on a straight line, the two distributions differ along some dimensions. The pattern of deviation from linearity provides an indication of the nature of a mismatch.

Figure 5 – Quantile-Quantile (QQ) Plot

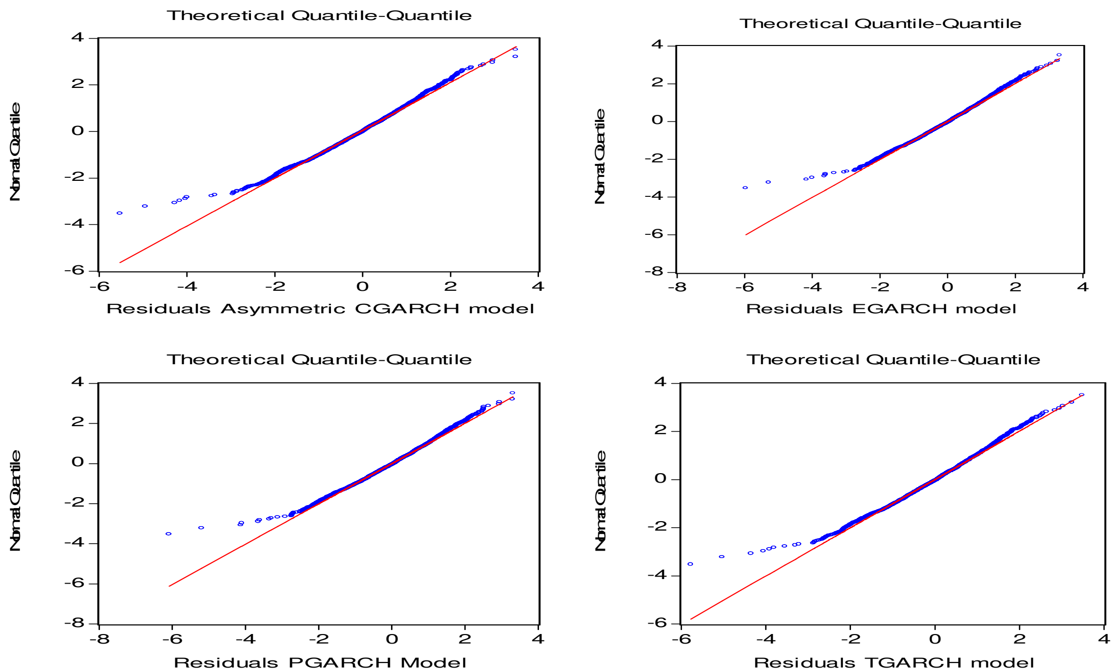
DAX30 Index



FTSE Index



SMI Index



Finally, in order to test whether there are any remaining ARCH effects in the residuals a Lagrange Multiplier test (Engle, 1982) for autoregressive conditional heteroschedasticity (ARCH) in the residual was carried out[11] : if the variance equation is correctly specified, there should be no ARCH in the standardized residuals. Results (tab.4) show little evidence of remaining ARCH effects for all models estimated with some exceptions for the PGARCH and TGARCH relative to DAX returns.

Table 4 - Remaining ARCH effects

DAX stock market returns				
	AGARCH(1,1)	EGARCH(1,1)	PGARCH(1,1)	TGARCH(1,1)
ARCH LM Test	0.006 (0.936)	2.367 (0.123)	4.262 (0.038)	6.414 (0.01)
FTSE stock market returns				
	AGARCH(1,1)	EGARCH(1,1)	PGARCH(1,1)	TGARCH(1,1)
ARCH LM Test	1.182 (0.276)	0.932 (0.334)	2.164 (0.141)	0.043 (0.835)
SMI stock market returns				
	AGARCH(1,1)	EGARCH(1,1)	PGARCH(1,1)	TGARCH(1,1)
ARCH LM Test	1.961 (0.161)	1.439 (0.230)	1.631 (0.201)	2.968 (0.084)

Note: P-value in the parentheses

[11] The ARCH LM test is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order q in the residual, we ran the following regression: $e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_t^2 - s \right) + v_t$, where e is the residual. This is a regression of the squared residuals on a constant and lagged squared residual up to order q. The software used in this work, that is EViews5, reports two test statistics from this test regression. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Obs*R-squared statistic is Engle's LM statistic, computed as the number of observations times the R-squared from the test regression. Here we have reported only the Engle's LM statistic.

5.2 Forecasting Volatility of Stock market returns

In order to see how the estimated models might fit real data, we examined forecasts for out-of-sample data by using the last 147 observation of each index market series. Since the actual volatility is unobserved, we will use the squared return series of each Market Index[12] as a proxy for the realized volatility. A plot of the proxy against the forecasted volatility provides an indication of the ability of GARCH models to track variations in market volatility (see figure 6).

At this point it is necessary to evaluate the quality of each volatility model estimated. The GARCH family models to make accurate predictions of the volatility can be measured by the value of the coefficient of determination R^2 coming from regressing squared returns on the volatility forecast, that is:

$$r_t^2 = a + bh_t^2 + u_t \quad (14)$$

This regression may be strongly influenced by extreme values of r_t^2. As pointed out by Hansen and Lunde (2001) in order to overcome these drawbacks, Pagan and Schwert (1990) as well as Engle and Patton (2000) suggested the following regression:

$$\log r_t^2 = a + b \log h_t^2 + u_t \quad (15)$$

this seems to be less sensitive to extreme values, because severe mispredictions are given less weight than is the case of eq. 14.

In order to define the best model in terms of ability to forecast for each index, following the results (tab.5) of equation 15, we may that for the DAX30 index the TGARCH model seems to have a higher ability to forecast DAX30 volatility better. The PGARCH model seems to be the best model to forecast volatility of the FTSe100 index. While both EGARCH and PGARCH models could be used in order to forecast SMI index volatility.

Table 5 – R^2 coefficients for each GARCH family models estimated

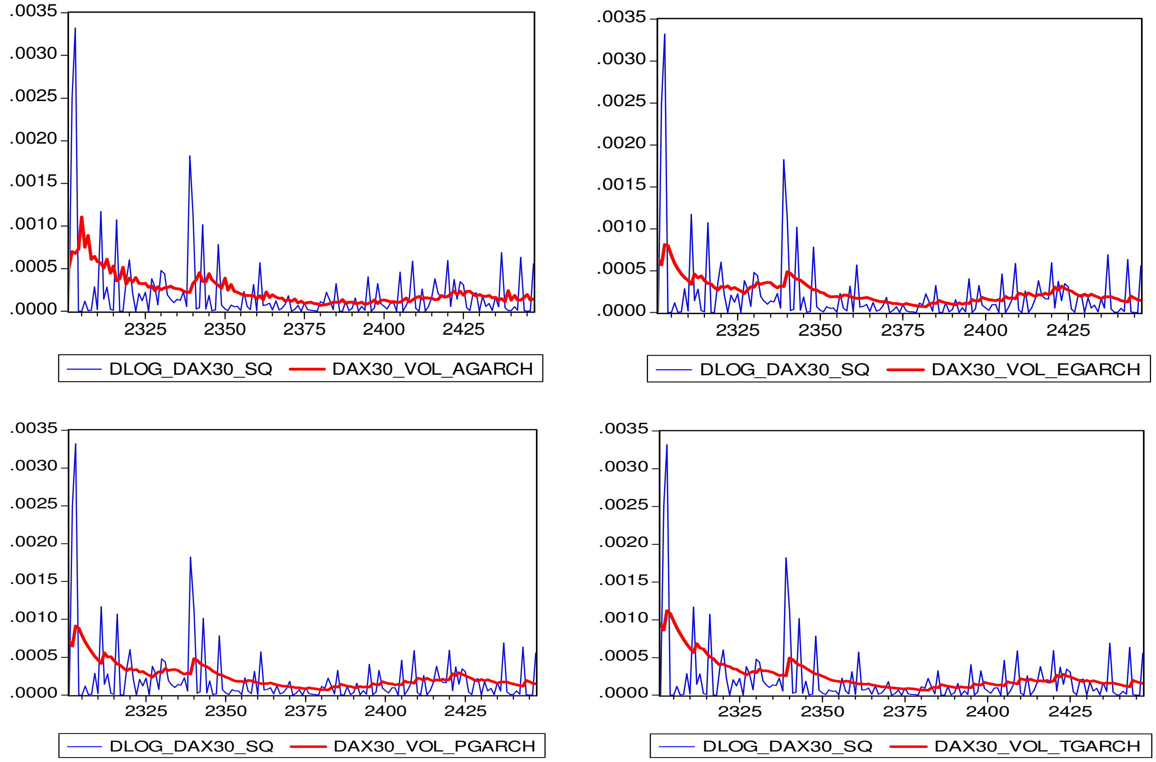
Index	AGARCH	EGARCH	PGARCH	TGARCH
DAX30	0.1396	0.14750	0.1494	**0.1568**
FTSE100	0.1155	0.1251	**0.1264**	0.1209
SMI	0.1210	**0.1362**	**0.1362**	0.1304

Note: Selected models by the coefficient of determination R^2 are in bold

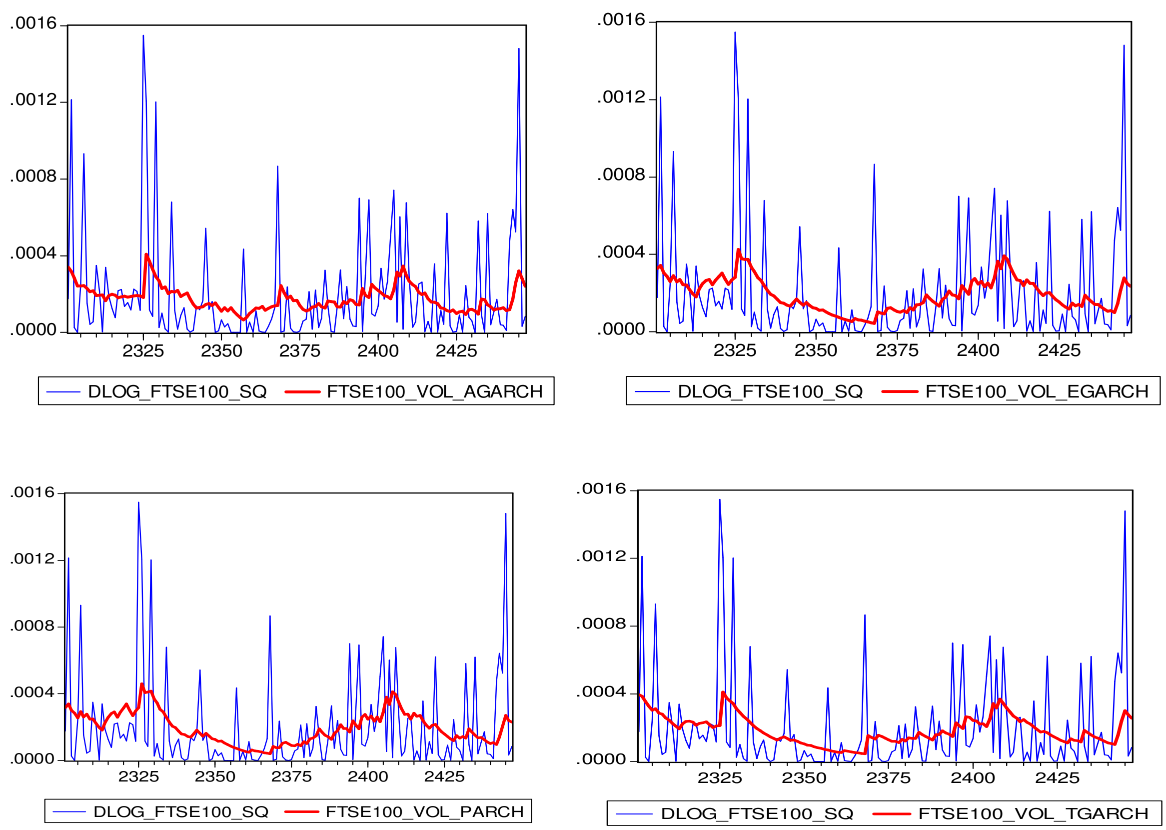
[12] The squared return series for DAX30 has been named as "Dlog_DAX30_sq", for the FTSE100 Stock market index the variable takes the name "Dlog_FTSE100_sq", and for the SMI the variable takes the name "Dlog_SMI_sq".

Figure 6 – Forecasting volatility

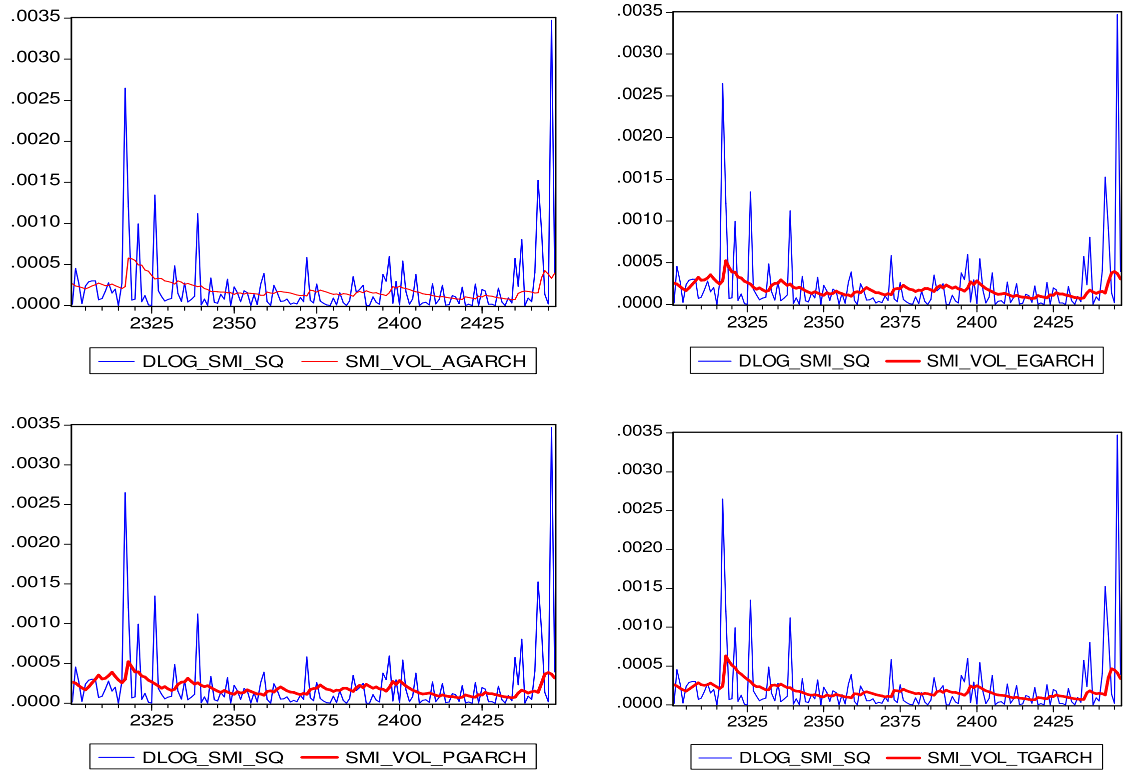
DAX30 Stock Market forecasted volatility



FTSE100 Stock Market forecasted volatility



SMI Stock Market Index forecasted volatility



5.3 Cointegration analysis

This section shows the results of the cointegration analysis by using the Johansen and Juselius methodology. The variables selected for the Cointegration analysis are presented in table 6. LDAX30, LFTSE100, and LSMI were transformed from indices: to arrive at the stationary variables, all variables are converted into natural logarithms and their first differences are taken: table 7 provides the summary statistics for the variables in their first differences.

Table 6 – Definitions of variables and time series transformations

Variables	Definitions of variables
LDAX30	Natural logarithm of daily-end closing prices on the German DAX30 stock market index
LFTSE100	Natural logarithm of daily-end closing prices on the UK FTSE100 stock market index
LSMI	Natural logarithm of daily-end closing prices on the SMI stock market index
Transformation	Definitions of Transformations
$\Delta LDAX30_t = LDAX30_t - LDAX30_{t-1}$	Daily return on the German Stock market
$\Delta LFTSE100_t = LFTSE100_t - LFTSE100_{t-1}$	Daily return on the UK Stock market
$\Delta LSMI_t = LSMI_t - LSMI_{t-1}$	Daily return on the Swiss Stock market

Table 7 – Descriptive statistics

Variables in first differences	Mean	Std Dev	Minimum	Maximum
$\Delta LDAX30_t$	7.32e-05	0.0153	-0.0743	0.0755
$\Delta LFTSE_t$	-3.73e-05	0.0116	-0.0563	0.059
$\Delta LSMI_t$	-3.17e-05	0.0119	-0.0578	0.0648

Cointegration requires the variables to be integrated of the same order. So, we test the variables for unit roots to verify their stationarity. We do this through the ADF test and the Phillips-Peron test: these tests are applied to levels and first differences where the model includes a constant. The test results (tab.8) indicate that the null hypothesis cannot be rejected for each of the two price series. Then, unit root tests are performed on each of the price index series in log first differences: the null hypothesis can be rejected for each of the time series, this means that the series are integrated of order one. The finding that each price series is non-stationary implies that each of the observed markets is weakly efficient.

Table 8 – Unit roots test on the Stock Market Indexes

Unit Root test with intercept				
	ADF Test		Phillips-Perron Test	
	t-statistic	P-value	t-statistic	P-value
LDAX30	-1.234	0.661	-1.205	0.674
LFTSE100	-1.367	0.599	-1.526	0.520
LSMI	-1.326	0.619	-1.415	0.576
ΔDAX30	-51.182***	0.00	-51.173***	0.00
ΔLFTSE	-11.20***	0.00	-53.55***	0.00
ΔLSMI	-12.64***	0.00	-49.36***	0.00

The null Hypothesis (Ho) for the ADF test is that the time series has a unit root, the same hypothesis is considered by the Phillip-Perron Test. The critical level for the ADF test and Philips-Perron Test: -3.43 (1%), -2.86%(5%), -2.56(10%). In the Phillip-Perron Test as a method of spectral estimate the Bartlett-Kernell was used (that is the default method given by the Eview5 software), while the width band used is that given by default (that is the Newey-West). The Akaike Information Crietria (AIC) has been used in the ADF in order to select the optimal number of lags: EViews5 software gives a maximum lag equal to 26. One/Two/Three stars indicate that we reject the null hypothesis with the following significant levels: 10%, 5% and 1%.

According to the test results shown above, indexes are nonstationary on level but they become stationary when their first difference is taken. The second step of the Johansen-Juselius methodology is to specify the appropriate lag length of the VAR system. AIC and SC select respectively a VAR(8) and a VAR (7), because SC usually selects the parsimonious one then a VAR (7) is chosen.

The next step is to use Johansen cointegration tests in order to obtain the cointegration rank. The Trace Statistics (i.e. λ_{trace}) are detailed in table 9 for the various hypotheses. Since 47.599 exceeds the 5 percent critical value of the λ_{trace} statistic, it is possible to reject the null hypothesis of no cointegrating vectors and accepting the alternative of one or more cointegrating vectors. Since 13.625 is less than 5 percent of the critical value of 15.494, we cannot reject the null hypothesis at

this significant level; so in this case the λ_{trace} indicates no more than one cointegrating vector at the 5 percent level. The Maximum Eigenvalue statistic (i.e. λ_{max}) confirms the results of the λ_{trace} statistic.
The primary finding obtained from the Johansen cointegration tests is that a stationary long-run relationship exists between the three European equity markets. Thus, there is a tendency for the FTSE100, DAX30 and SMI markets to move together in the long term.

Table 9 – Results and critical values for the λ_{trace} and λ_{max} test

H_o	H_1	λ_{trace}	$CV_{(trace, 5\%)}$	λ_{max}	$CV_{(max, 5\%)}$
r = 0	r > 0	47.599**	29.797	33.974**	21.131
r ≤ 1	r > 1	13.625	15.494	11.404	14.264
r ≤ 2	r > 2	2.221	3.841	2.221	3.841

Note: the Critical Value (i.e. CV) are taken from Osterwald-Lenum (1992), which differ slightly from those reported in Johansen and Juselius (1990). ** denotes rejection of the null hypothesis at the 5% level.

The next step requires building a VECM model with the cointegration rank selected by the previous step.
In order to evaluate the relationship between the German, Swiss and UK stock markets, several VECM models with p = 1-12 as well as a constant were built: the lag lengths for the series in the VECM are determined according to the SIC and AIC. It was found that the model with p = 6 has the lowest SC, while the p = 8 model has the lowest AIC. Because SC usually selects the most parsimonious a VECM(6) model was chosen with cointegrating rank = 1.
Normalizing cointegrating coefficients with respect to LDAX30, the cointegrating vector is given as $\beta' = (1.00, -1.041 , -0.60, -5.755)$. Results are shown in the equation below:

$$LDAX30 = 5.755 + 1.041\ LFTSE100 + 0.60\ LSMI \qquad (16)$$

Since a double logarithmic functional form is used here, the coefficients in β' can be interpreted as long-term elasticities. The coefficient on LSMI means that a 1% increase in the SMI index leads to, on average, a 0.60 increase in the DAX30 index, while if the FTSE100 index increases by 1% then the DAX30 increases by 1.041%. In the cointegration relationship both LFTSE100 and LSMI are also significant (with a t-statistic respectively equals to -3.72 and -2.53). Therefore the validity of this model is supported. We may conclude that the DAX30 index has a positive long-term relationship with both the Swiss as well as the UK stock markets.
The error correction parameter is sometimes called the speed of adjustment and it indicates how quickly the economy moves back to the long run equilibrium after a shock. In table 10, we can see that the error correction term that is not significant belongs to the SMI index only. This means that this index is weakly exogenous to the system. The weak exogeneity of the index further implies that

the market is the initial receptor of external shocks. The adjustment back to equilibrium can be inferred from the signs and magnitude of the coefficients. The negative sign means that the respective index will pose shocks to the other indices in the observed region. In this sense, the DAX30 index will give the greatest negative impact on the other observed European markets, since it has the greatest error term coefficient.

Table 10 - VECM (6) estimated results

Variables	ΔLDAX30	ΔLFTSE100	ΔLSMI
Error correction term α	-0.016**	-0.005**	-0.002
	(-5.348)	(-2.132)	(-0.828)
R-squared	0.159	0.114	0.023
F-statistic	24.251	16.542	3.073
Log likelihood 21915.17			
AIC -17.911			
SC -17.761			

Note: values in brackets are t-statistics, ** significant at 5% level for the null hypothesis of zero coefficients.

The above results indicate that there is integration among equity markets of analysed countries although their differences were previously exposed. There are several potential financial and non financial sources which may explain this integration. Among the financial sources we may find the liberalisation of capital flow barriers among EU countries here analysed, anyway this explanation should be valid only relative to the UK and German stock markets given that these countries are members of the EU[13] On the other hand, among other sources of financial integration that are not financial in nature we may find business cycle similarities among these countries which could lead to greater financial integration[14].

Although Germany is a member of the European Union as well as Euroarea, the UK is not a member of the Euroarea, Switzerland is not a member of the European Union, following our empirical results we may say that their financial markets are integrated as well as sharing a common trend in the long term. We may also note that a strong financial integration among these markets means that there are fewer opportunities to diversify portfolios for those investors within these countries. In other words, because of financial integration, investors are not able to earn extra returns in the long term[15]. However, this last explanation has a point of weakness given that the

[13] Cotter (2004) points out that driving forces of increasing equity market integrations can be considered as harmonisation of regulatory and market structures as well as the removal of capital control barriers.

[14] Ragunathan et al. (1999) suggest that financial markets are more likely to be integrated in the expansionary phases of business cycle. In other words different economies may be more or less integrated depending on the business cycle phase they are experiencing.

[15] As pointed out by Hardouvelis et al. (1999), since stock markets become more integrated and the diversification benefits tend to be reduced, investors may decide to shift the focus of diversification from a national level to an industrial level. In other words we may say that international competition shifts from a national level to an industrial level.

exchange rate risks among these countries is still present[16] so the diversification benefits of investing in these countries could still be convenient given the different currency that they use (Hardouvelis et al, 1999). It could be interesting to detect how much the exchange rate is still important for investors who operate in advanced economies like those considered in the present work. Another point we need to emphasize this study is that negative shocks can be transmitted from larger markets (like the German and the British ones) toward a small market like the Swiss one. Policy makers, especially those of the European Union, should be concerned with the existence of integration among these markets because it could suggest that all these markets could be treated as a single market one. This means that regulatory legislation at a European Union level should take into account its effects on non Euroarea countries.

6. Conclusion

Stock returns show evidence of volatility clustering, that is great changes in returns tend to be followed by great changes and small changes by small changes. This means that the variance tends to change over time. In order to study this phenomenon, the goal of this paper was modelling and forecasting volatility of several European stock market indexes as well as analysing the existence of long run relations among them. The stylized facts such the asymmetric effects of bad and good news were analyzed using GARCH family models which capture these characteristics. I used nine years of daily data on the DAX30, FTSE100, and SMI index to illustrate the existence of asymmetric effects as well as a long run relationship. Among the main results of this paper, we may point out that all GARCH family models show evidence of asymmetric effects. Considering EGARCH, PGARCH, and TGARCH, the estimated β coefficients are quite big near the typical value around 0.9; this means that old news has a quite persistent effect on volatility. On the other hand only for PGARCH and TGARCH models the sum of the coefficients α and β is less than one, implying that, although it takes a long time, the volatility process does return to its mean. Each model estimated has been used in order to forecast future volatility of each index. As suggested by Engle and Patton (2001) the R^2 coefficient has been used in order to find the model that forecasts future volatility better for each index. Results from R^2 coefficient evidence that the DAX30 index is forecasted better by a TGARCH model, the FTSE100 index volatility can be forecast specifically

[16] Fratzscher (2001), points out that exchange rate uncertainty is one of the main reasons for the segmentation of financial markets. By adopting a common currency the Euro area countries have raised the degree of financial integration among them. On the other hand he suggests that a less volatile and predictable exchange rate may reduce the degree of market segmentation: so this could be one of the explanations of the integration among the financial markets considered in this study. It must be said that theory offers ambiguous conclusions about the relationship between exchange rate and international correlations among financial markets. One of these conclusions suggest that international correlation among financial market increases, when exchange rates are more volatile ((Bodart and Reding, 1999)

using a PGARCH model, while both EGARCH and PGARCH models can be used alternatively to forecast SMI index volatility.

Cointegration analysis shows evidence of a long run relation between German, Swiss, and UK market indexes. The cointegration vector shows evidence that the DAX30 index has a positive long run relationship with both the Swiss and the UK stock markets. On the other hand the error correction parameters are statistically significant for the DAX and the FTSE stock market index. For the SMI index the error correction term is not significant, this means that the Swiss market is the initial receptor of external shocks. These results have important implications for investors given that the long term relationship among these markets show that there are fewer opportunities to diversify portfolios within Germany, Switzerland and the UK, thus providing incentives to focus more on diversifying across sectors. Implications are also relevant for policy makers; financial integration among these markets means that Germany, Switzerland, and the UK stock index are interdependent and subject to spillovers resulting from endogenous and exogenous shocks. Such interdependence may require supervisors and market overseers to increasingly adopt a Euro-area approach when they are called to regulate these different stock markets.

Appendix A

This appendix shows results of the estimated ARMA model which have been used to model the mean equation in GARCH family models. Models selected by the AIC and SC are in bold.

Table 1A – DAX returns: estimates of the ARMA(p,q) model for the AGARCH mean equation, 1-2300 obs

	AIC				SC		
		q				q	
p	0	1	2	P	0	1	2
0	-	-5.8739	-5.8728	0	-	**-5.8539**	-5.8503
1	-5.8737	**-5.8762**	-5.8750	1	-5.8538	-5.8537	-5.8500
2	-5.8721	-5.8756	-5.8746	2	-5.8496	-5.8506	-5.8471

Table 2A – DAX returns: estimates of the ARMA(p,q) model for the EGARCH mean equation, 1-2300 obs

	AIC				SC		
		q				q	
p	0	1	2	P	0	1	2
0	-	-5.8909	-5.8907	0	-	**-5.8759**	-5.8732
1	-5.8909	**-5.8932**	-5.8923	1	-5.8759	-5.8757	-5.8723
2	-5.8920	-5.8927	-5.8918	2	-5.8745	-5.8727	-5.8694

Table 3A – DAX returns: estimates of the ARMA(p,q) model for the PGARCH mean equation, 1-2300 obs

	AIC				SC		
		q				q	
p	0	1	2	P	0	1	2
0	-	-5.8944*	-5.8955*	0	-	-5.8770*	-5.8756*
1	-5.8944*	-5.8969*	-5.8960*	1	-5.8769*	-5.8769*	-5.7936*
2	-5.8955*	-5.8964*	**-5.8956**	2	-5.8756*	-5.8739*	**-5.8706**

*Convergence not achieved after 500 iterations

Table 4A – DAX returns: estimates of the ARMA(p,q) model for the TGARCH mean equation, 1-2300 obs

	AIC				SC		
		q				q	
p	0	1	2	P	0	1	2
0	-	-5.8937	-5.8907	0	-	-5.8787	-5.8732
1	-5.8938	**-5.8964**	-5.8923	1	-5.8788	**-5.8789**	-5.8723
2	-5.8949	-5.8959	-5.8951	2	-5.8774	-5.8759	-5.8726

Table 5A – FTSE100 returns: estimates of the ARMA(p,q) model for the AGARCH mean equation, 1-2300 obs

	AIC			SC			
		q				q	
p	0	1	2	P	0	1	2
0	-	-6.4503	-6.4429	0	-	-6.4303	-6.4274
1	-6.4501	-6.4526	-6.4508	1	-6.4301	-6.4301	-6.4259
2	**-6.4529**	-6.4523	**-6.4529**	2	**-6.4304**	-6.4274	-6.4225

Table 6A – FTSE100 returns: estimates of the ARMA(p,q) model for the EGARCH mean equation, 1-2300 obs

	AIC			SC			
		q				Q	
p	0	1	2	P	0	1	2
0	-	-6.4683	-6.4679	0	-	-6.4533	-6.4504
1	-6.4685	-6.4696*	-6.4688	1	**-6.4535**	-6.4522*	-6.4488
2	**-6.4696**	-6.4688	-6.4695*	2	-6.4521	-6.4489	-6.4471*

*Convergence not achieved after 500 iterations

Table 7A – FTSE100 returns: estimates of the ARMA(p,q) model for the PGARCH mean equation, 1-2300 obs

	AIC			SC			
		q				q	
p	0	1	2	P	0	1	2
0	-	-6.4692	-6.4611	0	-	-6.4517	-6.4436
1	-6.4692	-6.4706	-6.4697	1	**-6.4518**	-6.4506	-6.4472
2	**-6.4707**	-6.4704	-6.4706	2	-6.4507	-6.4479	-6.4456

Table 8A – FTSE100 returns: estimates of the ARMA(p,q) model for the TGARCH mean equation, 1-2300 obs

	AIC			SC			
		q				q	
p	0	1	2	P	0	1	2
0	-	-6.4613	-6.4611	0	-	-6.4463	-6.4436
1	-6.4616	**-6.4630**	-6.4621	1	**-6.4466**	-6.4455	-6.4421
2	-6.4623	-6.4628	-6.4626	2	-6.4448	-6.4428	-6.4401

Table 9A – SMI returns: estimates of the ARMA(p,q) model for the AGARCH mean equation, 1-2300 obs

	AIC			SC			
	q				q		
p	0	1	2	P	0	1	2
0	-	-6.4076	-6.4100	0	-	-6.3876	-6.3875
1	-6.4071	-6.4105	**-6.4151**	1	-6.3872	-6.3880	-6.3901
2	-6.4112	-6.4144	-6.4090	2	-6.3888	**-6.3895**	-6.3815

Table 10A – SMI returns: estimates of the ARMA(p,q) model for the EGARCH mean equation, 1-2300 obs

	AIC			SC			
	q				q		
p	0	1	2	P	0	1	2
0	-	-6.4415	-6.4407	0	-	-6.4265	-6.4232
1	-6.4418	-6.4419	-6.4419	1	**-6.4269**	-6.4254	-6.4219
2	-6.4413	**-6.4436**	-6.4429	2	-6.4238	-6.4237	-6.4204

Table 11A – SMI returns: estimates of the ARMA(p,q) model for the PGARCH mean equation, 1-2300 obs

	AIC			SC			
	q				q		
p	0	1	2	P	0	1	2
0	-	-6.4436	-6.4428	0	-	-6.4261	-6.4228
1	-6.4438	-6.4442	-6.4434	1	**-6.4263**	-6.4242	-6.4209
2	-6.4433	-6.4455	**-6.4446**	2	-6.4233	-6.4231	-6.4197

Table 12A – SMI returns: estimates of the ARMA(p,q) model for the TGARCH mean equation, 1-2300 obs

	AIC			SC			
	q				q		
p	0	1	2	P	0	1	2
0	-	-6.4331	-6.4322	0	-	-6.4181	-6.4148
1	-6.4335	-6.4341	-6.4321	1	**-6.4185**	-6.4166	-6.4121
2	-6.4331	**-6.4355**	-6.4347	2	-6.4156	-6.4155	-6.4122

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