UNIVERSITY OF VAASA

FACULTY OF BUSINESS STUDIES

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VOLATILITY PERSISTENCE AND INTER-LINKAGES IN EQUITY MARKETS

Master's Thesis in Accounting and Finance

VAASA 2009

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Year of Completing the Thesis:	2009 Pages: 72

ABSTRACT

Stock market volatility is known to be very persistent, periods of high volatility as well as low volatility tend to last for several months but there is still room left for alternative explanations.

This study focuses on financial markets revisiting the issue of volatility persistence in stock market returns. It attempts to investigate empirically market returns, and volatility persistence in a distinct approach from previous researches and this by testing the memory process and inter-linkages in market volatility with the help of the generalized autoregressive conditional heteroskedastic models (GARCH and CGARCH) and Vector Autoregressive, VAR analysis.

The data used was gathered over a four year period 2005-2009 from Thomson Financial database. It consisted of close prices from major market indices: OMXH, S&P 500, FTSE 500 and TSE. Based on findings from previous studies, two hypotheses were formulated. The first hypothesis compares the accuracy of the complex CGARCH(1,1) to the simple GARCH(1,1) whereas the second hypothesis suggests that shocks in crisis periods are more persistent than in pre-crisis periods. Data for the second hypothesis was divided into two subsamples to cater for the different economic situations (pre-crisis and crisis periods).

Volatility persistence points to existence of short memory in equity markets, shocks to stock market volatility do not last for longer periods. The results also indicate that equity markets are strongly linked and this linkage is stronger in periods when markets are very volatile (crisis). In particular, the results show that U.S. and UK markets are dominant and leading sources of volatility expectations, as the volatility of S&P 500 is found to significantly affect the volatility expectations of UK, Finland and Japan markets.

The findings in this study play a major role in hedging strategies pursued by market participants, risk management and for the pricing of derivative assets.

KEYWORDS: Volatility persistence, Stock returns, CGARCH (1,1), GARCH(1,1**),** Short memory

1. INTRODUCTION

Numerous studies on volatility have been made and all definitions are somewhat different. Michael & Drew (2005) define volatility as conditional and relatively stable through time. Volatility in equity markets also refers to a risk of change and the spread of asset returns, statistically volatility is often measured as the sample standard deviation estimated from market returns. Volatility persistence is not only observed at the aggregate and individual level but also on the market level, therefore it is for this reason that this study concentrates on absolute market returns as volatility proxies. According to Campbell, Lettau, Burton, Malkiel and Xu (2001), aggregate market return is only one component of the return to an individual stock, and although aggregated volatility measures information about an average industry, there still is a great deal of variation across markets.

Considering the role played by volatility shocks in determining persistence, it is therefore important to investors and policy makers to understand and identify the impact of these shocks in asset allocation and risk management through transmission and fluctuations between markets and countries overtime. McCabe, Martin and Tremayne (2003) also define persistence as an indefinite impact of a shock to a series implying that a persistent series contains a permanent component, in which past shocks exert an ongoing effect on the level of series whereas a series that is not persistent contains a transitory component which dies out with time and prices are much less sensitive to the fluctuations in the absolute returns.

Campbell (1990) argues that information on persistence is very useful in explaining movements in expected returns.

In line with volatility persistence, it is important to examine the causal effects in equity markets because neglecting them might lead to underestimated volatility estimates and the issue of interdependencies existing in equity markets through which innovations spread over from one market to another also is investigated. Volatilities in markets tend to be linked in the sense that movements in one asset price may affect others beyond the impact of macroeconomic fundamentals. These volatility relations across asset prices have important practical implication for international investors, multinational firms, risk managers, bank supervision authorities, and monetary policy makers.

Many time-series approaches and methodologies have been adopted to measure volatility transmission, persistence of shocks, cross market inter-linkages and to identify many other relationships within equity markets. Examples of these models are; Regime switching models, Geweke's linear dependence models and a vast lot of GARCH models, although expressed differently, all of them conclude that a certain degree of interdependence exists among these markets. Granger proposes many long memory GARCH models with different specifications for time varying heteroscedastic volatility and long range dependence in equity markets. However, structural breaks in GARCH parameters have been noticed as sources of extreme persistence and when measuring this persistence, much attention should be paid to the sum of these parameters.

1.1. Purpose of the Study

The main objective of this study is to investigate linkages and volatility persistence the equity markets exhibit namely; FTSE-All Share Index, S&P 500, OMX Helsinki and Tokyo Stock Exchange. This is done primarily to demonstrate if findings in this study are in line with previous studies. Many studies have conflicting theories about volatility in these markets.

This study also forms a crucial part in investigating what kind of non linear ARCH type diffusion model is the best specification in describing volatility persistence in equity market returns. Researchers have shown that GARCH models are very useful in modeling temporal behavior of many economic variables and time-varying conditional variances in time-series data. This study uses two ARCH type models, the common

GARCH(1,1) and CGARCH(1,1) to investigate the issue of volatility persistence and its relevance to market interdependencies and how they influence changing market volatility. In addition, this study examines the return volatility-autocorrelation relationship of equity markets in pre-crisis (stable) and crisis periods. Research shows that the dependence is strong during stable periods and weak during volatile periods and it manifests itself as an inverse relationship between the first order autocorrelations and volatility. (Koutmos & Booth 1998: 61)

Finally, this study also aims at capturing the dynamic structure of small markets in relation to their dependence of information shocks by identifying any possible dependence relationships and links between the markets and also to give evidence of any possible lead lag relationships within the markets.

1.2. Justification of the study

Measuring persistence and time-varying volatilities is important for investment diversification strategies, hedging strategies, regulatory policy across financial markets and also in determining an optimal market portfolio for an investor.
To pursue the objectives of this paper and to answer questions about the dynamic character of equity markets, answering these questions is crucial in performing further econometric and time series analysis of the daily price traces, which are used for valuation of market securities and thus, for serious portfolio risk management.

These questions are:

1. How persistent are volatility shocks from one market to another? Are they stable, transitory or long term? Are volatility shocks more persistent in crisis periods than in pre-crisis periods?
2. Do some markets have a tendency to lead others? How do impulses, innovations transfer from one market to another? Are there any feedbacks between the markets?

3. Can the complex Component GARCH (CGARCH) model explain the behavior of volatility shocks in these markets better than the simple GARCH(1,1) model?

1.3. Hypotheses

The main aim of this study is to investigate the nature of volatility persistence in equity markets and any possible inter-linkages that may exist and it is from this point of view that two hypotheses as stated below are formulated.

The first hypothesis is based on Engle and Lee's (1999) GARCH models that were introduced to capture long range dependencies and memory using sample auto correlations and absolute returns in financial markets. GARCH models are known for their ability to capture both the conditional heteroscedasticity in market returns and the structure of serial correlations. When measuring persistence Malik, Ewing and Payne (2005) compared GARCH model results to other models used to control for sudden changes in variance and concluded that the GARCH model considerably reduces the measure of persistence in volatility but at the same time it is sufficient in capturing systematic dynamics of the variance.

H1*: The complex CGARCH (1, 1) model is more accurate than the simple GARCH (1, 1) model in explaining volatility shocks and persistence in equity market returns.*

GARCH(1,1) model is the most frequently used specification because it models volatility with no remaining ARCH effects and incorporates the familiar phenomenon of volatility clustering seen in market returns. With one autoregressive conditional heteroskedasticity (ARCH) term and one GARCH term the model specifies that variance depends on past values of the endogenous variable. (Homan 2009). In addition to the standard GARCH model, the new complex component model (CGARCH) decomposes time-varying conditional volatility into two components namely; a long run component and a short run transitory component which reverts to a trend following a shock.

Volatility shocks in stable periods are expected to be small resulting into low levels of volatility with low market correlation coefficients whereas unstable periods are expected to have large shocks resulting into high levels of volatility with high cross market linkages. In addition, Koutmos and Booth (1998) investigate the relationship between volatility and autocorrelations in stock returns and report that there is an inverse non-linear relationship between first-order autocorrelations and the conditional variance. Periods of high volatility are associated with low correlations and periods with low volatility are linked to high correlations. This condition leads to the second hypothesis as stated below.

H2: *Volatility shocks in crisis periods are more persistent than in the pre-crisis periods.*

1.4. Structure of the thesis

This study comprises two major parts, the Empirical and Theoretical part divided into five chapters. The objective of the theoretical part is to give an overview on the research done relative to this study and to explain the behavior of volatility in equity markets over time.

Chapter one presents the introduction of the topic under study giving a brief review of the theoretical background, the research problem and justification of the study and the hypotheses to be tested in the study. Chapter two presents literature review from previous studies highlighting the characteristic nature of volatility and equity markets. A lot of research has been done on this subject; it is therefore for this reason that this chapter incorporates some of the relevant ideas that give relevant explanations on the persistent nature of volatility, how it is modeled and how it is transmitted from market to market.

Chapter three explains some of the concepts that are vital in volatility and time series analysis. This discussion includes introduction to the market efficiency for instance strong and weak form market efficiency, the concept of random walk theory and the relationship between volatility and risk. All these together give a general picture on the behavioral nature of volatility over time.

Chapter four and five form the empirical part of the study presenting the methodology applied and description of the data and markets under study. Chapter six summarizes these findings and reports the conclusions about the research.

2. LITERATURE REVIEW

Many investors have been affected by the usual daily changes in the value of most major stock indices, such as FTSE and S&P500. Unfortunately the general direction of these changes has been downward. Many researchers in finance ask themselves what the driving force in volatility is and what they have discovered over the last few decades sheds light on the efficiency in equity markets and points to some important implications for economic forecasters and investors. The degree of volatility persistence in equity markets can help investors and forecasters to foresee the path of the economy's growth; In addition, with these changes in the volatility structure, investors now need to hold more stocks in their portfolios in order to diversify the risk.

Schwert (1989) investigated why volatility in stock markets changers over time and he argued that aggregate stock volatility is difficult to explain with the use of stock valuation models especially during times of financial crises, changes in the ex ante volatility of market returns have negative effects on risk-averse investors yet these very changes can have important effects on capital investment, consumption and other business cycle variables such as inflation, industrial production and debt levels in the industrial sector. To an extent, stock market volatility is caused by financial leverage depending on the economic situation: when prices fall during recessions leverage is most likely to increase.

Volatility is a proxy for investment risk, persistence in volatility means that the risk and return trade off changes in a predictable way over the business cycle, for example risk averse investors like lower risk on investment because it means lower uncertainty of future wealth and at the same time investors like higher expected return on investment because of higher expected wealth in future (Bodie, Kane & Marcus 2008).

Koutmos, Knif and Philippatos (2008) model volatility characteristics and the risk-return trade off in European markets with the help of a factor GARCH model, they argue that market portfolio plays a crucial role in asset pricing and all series are conditionally heteroscedastic, past innovations and variances are important determinants of current volatility. The factor model was found to describe successfully the time-varying volatility characteristics, both persistence and asymmetric volatility being the signs of higher volatility leading to higher required rates of return and declining stock prices.

Porteba and Summers (1986) in their study also investigate the impact of volatility shocks on stock market prices; they explore the relationship between changes in stock market return volatility and the fluctuations in stock market prices. Unlike Koutmos, Knif and Philippatos (2008) who assumed leverage in firms, Porteba and Summers assumed otherwise and found that the effect of changes in volatility on the stock market prices is very sensitive to the level of serial correlation, the relationship between returns and volatility changes is negative and shocks to stock market volatility do not last for longer periods implying that stock markets are not highly persistent.

Emerging stock markets are characterised by high volatility from frequent changes in variance. Aggarwal, Inclan and Leal (1999) investigate the factors in which volatility is most persistent and their findings point to local country specific political, social and economic event such as the Marcos-Aquino conflict in the Phillipines, hyper inflation periods in Latin America and the stock market scandal in India. The global events such as the Gulf War and the 1987 crash had a small but insignificant effect on the emerging markets.

Persistence of stock return volatility can also be investigated using learning mechanisms such as the individual and social learning tools. The difference is based on how the expectations across agents change over time. In an agent based artificial stock market, the behaviour of agents is examined and findings suggest that agents in a social leaning mechanism through their interactive behaviour with other agents produces high persistence of return volatility unlike the individual learning mechanism in which there is no direct exchange of ideas and no idea dissemination. So, the variance expectation does not converge (Yamamoto 2005: 2-3, 14).

2.1. Linkages in Equity Markets

Investigating the nature and interdependence between markets is an important task to private and public investors. Early research found that returns in equity markets are highly correlated but does not specify if they are stable through time. These correlations depend on factors that are the primary source of variations in returns (Porteba 1990). As difficult as it is to interpret volatility linkages and their effects across markets in different countries, the recent credit crunch provides a clear example of this. When Wall street plunged, it triggered uncertainty about the U.S financial markets and this was transmitted through to all markets world wide reducing share prices, output and demand in many economies.

Koutmos and Theodossiou (1994) investigate the linkages between the U.S. and Japanese stock markets by testing for dependencies in the first moments of the distribution of stock returns and conclude that there is no evidence that Japanese innovations affect volatility in U.S. and squared residuals show no evidence of linear and non linear dependencies. However, this study contradicted Fun and Shimi's (1989) finding in which they conclude that Japanese markets are followers to other international markets and that the response to a shock from U.S. markets to other markets in the world is very strong.

Over the past years, links between conditional returns of different equity markets have developed and are becoming stronger; this in turn has encouraged globalisation of these markets. Cheeley-Steeley (2000) modelled the interdependence of market volatility using the ARMA(1,1)-GARCH(1,1)-M process and concluded that there is an increase in equity market volatility and returns of major equity markets are highly interdependent and correlated. Along similar lines, Philippatos, Christofi and Christofi (1982) employed correlation analysis of fourteen industrial countries in their study on inter-temporal stability of international stock market relationships and they indicate that indeed there is a stable structure in stock market relationships.

Baele (2005) examines the contagion effect and the extent to which volatility in Western Europe equity markets is increasingly driven by global and regional shocks. He applies the regime switching model to account for the changing economic times and time varying integration and finds that the main factors that intensify shock spillover effects in equity markets are trade integration, market development and price stability. Like many other studies, U.S is found to be the proxy for the world market and its dominant effects are transmitted onto the European equity markets in times of high market volatility. However, Forbes and Rigobon (2002) disagree with the contagion effect in equity markets. In periods of high market volatility (i.e.1987 U.S. market crash) there is no increase in correlation coefficients in these stock markets but there is only a high level of market co-movement which they call interdependence. They define contagion as a significant increase in cross-market co-movement immediately after the shock and if this co movement does not increase significantly then any persisting market correlations between the markets is purely interdependence.

Economists are interested in ascertaining the degree to which financial markets are integrated and the level of causal relationships reflected from one market to the second market. High degree of first order correlation coefficients gives rise to unauthentic inferences about causal relationships in series which can be eliminated by logarithmic transformations. Ripley (1973) applies logarithmic transformation methodology in his study on national stock market indices and suggests that the largest percentage of the movement in the stock index price is unique to the country but also varies widely between countries. He also argues that markets that are more open to capital flows have higher covariance within and in markets in other countries.

2.2. Volatility Modeling

It is not easy to make a choice on which volatility measure to use when modeling volatility this is because there are many proxy volatilities such as stochastic processes, absolute returns and range volatility but GARCH models are by far the most commonly used in capturing volatility persistence and clustering. Bollerslev's GARCH model has been widely applied to study volatility of asset prices and absolute returns and is now a well known tool in the modeling of financial time series. Many ARCH generalizations have been proposed by various researchers, these include: APARCH, FIGARCH, STARCH, SWARCH, TARCH, MARCH, SQARCH and many others. These models examine possible non-linearities, asymmetry and long run memory properties of volatility. (Engle 2004: 407.)

When testing for volatility asymmetries in financial data, the multivariate EGARCH model is highly recommended because it allows for cross market and own market innovations to wield asymmetric impacts on volatility in other equity markets and also does not require any restrictions to ensure that all variances are positive. Koutmos and Booth (1995) examine asymmetric volatility transmissions in stock markets with the help of the EGARCH model and their findings suggest that volatility spillovers from one market to another are very significant and asymmetric implying that stock markets are very sensitive to information from other markets, they also suggest that markets grow more interdependent in times of crisis.

ARCH family models have been implemented with regime switching models where volatility persistence takes on different values depending on whether it is in a high or low state (Poon & Granger 2003: 484). Susmel (2000) applied the switching auto regressive conditional heteroscedastic (SWARCH) model to analyze the behavior of time varying volatility regimes in international stock markets. The model depends on past news and state of the economy.

2.3. Volatility Clustering

Clustering is a feature of heteroscedastic and stochastic processes and also common characteristic to many financial markets; it is described as a market reaction to incoming information with periods of high and low variance. Clustered volatility can also be defined as the consequence of the market being subject to sporadic temporary instability (Lux & Marchesi 1999). The clustering of large changes tends to be followed by large changes of either sign or small changes followed by small changes (Mandelbrot 1963). Volatility clustering is sometimes referred to as the GARCH effect when estimations of GARCH(1,1) models on stock returns yield coefficients that are very close to one (Cont 2007). It also indicates that asset returns should not be correlated, the absence of the linear autocorrelations proves that their dependence is non linear. Furthermore, Cont argues that switching between regimes with different levels of volatility and activity is the leading mechanism to volatility clustering.

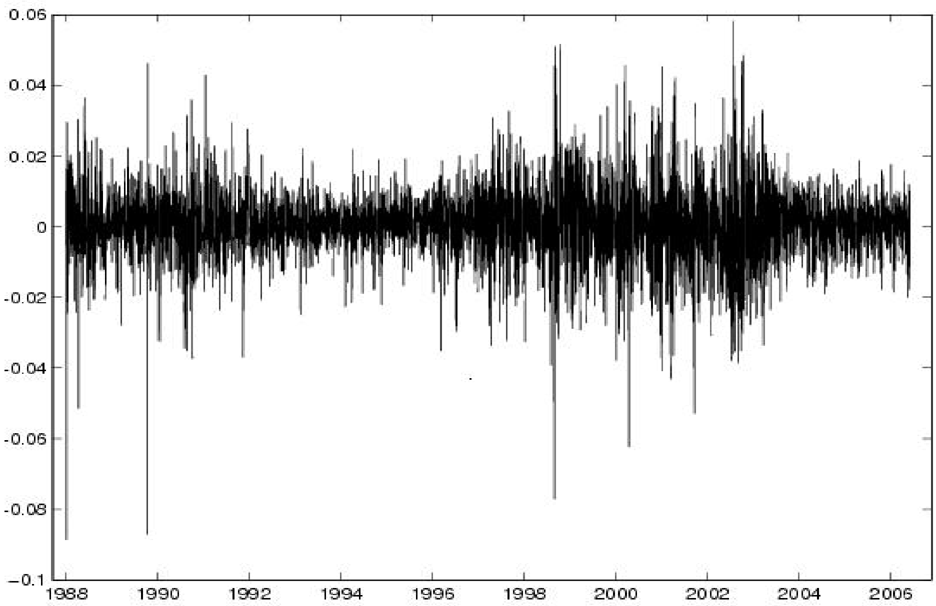

Figure 1. S&P 500 volatility clustering from 1988-2006.

Volatility persistence can also be termed as process caused by arrival of news about economic fundamentals, if information comes in clusters, market returns are very likely to show evidence of ARCH behavior (Engle, Ito & Lin 1990). Testing and analyzing the pattern of volatility clustering is very important because processes exhibiting the ARCH effect have conditional volatility that is much larger than the unconditional variance. During volatile periods, there is a big risk of large losses for processes with ARCH.

Thus not testing for ARCH would lead to sub-optimal portfolio management for investors (Miles 2008: 73-74).

Gaunersdorfer and Hommes (2000) argue that volatility clustering is a phenomenon caused by the interaction between heterogeneous traders; fundamentalists and technical analysts with different strategies and expectations about future asset prices. Fundamentalists believe that asset prices follow a random walk while technical analysts believe that asset prices are predicted in the short run by simple trading rules based on past prices. This interaction between heterogeneous trading rules thus leads to a noisy environment causing unpredictable asset returns and volatility clustering (Gaunersdorfer and Hommes 2000: 1, 16-17).

2.4. Memory in Market Returns

After the deregulation of financial markets in the 1980's, the study of the behavior of equity markets has grown very fast, this is explained by advanced technology for worldwide information transmission and processing the liberalization of capital movements and the securitization of markets. Many studies have come up with a similar finding that volatility in these markets exhibits memory with many pointing to long memory which is also a stylized feature in modeling volatility processes.

For a known fact, asset returns have been found to be uncorrelated over a large number of lags. Low relationships between markets indicate an increasing co-movement of major stock markets and significant interrelations between markets. (Grubel & Fadner 1971). Engel, Ito and Lin (1990) reported the existence of a cross market dynamic effect of news on a short run time path of volatility, such that news revealed at the open time of one market contributed to the return of the next market to open.

Further analyses focusing on volatility spillovers show that the shocks in the volatility are minimal and have duration lasting for about an hour, and also suggest existence of a common time varying volatility is regional rather than worldwide. Booth et al. (1995) find a single common factor generating volatilities on U.S. and UK stock index futures markets. Karolyi (1995) investigated short run dynamics of return and volatility between New York and Toronto exchanges and reported that the size and persistence of return innovations is heavily dependent on how cross markets dynamics in volatility are modeled.

Since the introduction of ARCH models by Engle (1982), volatility persistence has been investigated in detail. It is not only important in forecasting future market movements but is also central to a host of financial issues such as portfolio diversification, risk management, derivative pricing and market efficiency. Although, it is common to find a significant statistical relationship between current measures of volatility and lagged values, it has been very difficult to find models that adequately specify the time series dependencies in volatilities in speculative returns data. Ding, Granger and Engle (1996) show that stock market absolute returns exhibit a long-memory property in which the sample auto-correlation function decays very slowly similar to those of an I(*d*) process. Volatility shocks in time series seem to have very long memory and impact on future volatility over a wide period.

A series is said to have long memory if it displays a slowly declining autocorrelation function, ACF and an infinite spectrum at zero frequency. (Ding & Granger, 1996). Specifically, the series $\{y_t\}_{t=0}^{\infty}$ is said to be a stationary long run memory process if the ACF, $\rho(k)$ behaves as follows:

(1) $$\rho(k) = c|k|^{2d-1} \text{ as } |k| \to \infty$$

Where 0<d<0.5 and c is some positive constant. The left hand side and the right hand side in equation (1) tends to 1 as $|k| \to \infty$. The ACF displays a very slow rate of decay to zero as k goes to infinity and $\sum_{k=-\infty}^{\infty} |\rho(k)| = \infty$. This slow rate of decay can be contrasted to ARMA processes, which have an exponential rate of decay and satisfy the following bound:

(2) $$\left|\rho(k)\right| \leq ba^{k}, 0<b<\infty, 0<a<1$$

And consequently, $\sum_{k=-\infty}^{\infty}\left|\rho(k)\right| < \infty$. A process that satisfies equation (2) is termed as short memory.

Equivalently, long memory can be defined as a spectrum that goes to infinity at the origin. This is,

(3) $$f(\omega) \approx c\omega^{-2d} \text{ as } \omega \to 0$$

A simple example of long memory is the fractionally integrated noise process, I(d), with 0<d<1, which is

(4) $$(1-L)^{d} y_{t} = u_{t}$$

Where L is the lag operator, and $u_t \sim$ iid $(0,\delta^{2})$. This model includes the traditional extremes of a stationary process, I(0) and a non stationary process I(1). The fractional difference operator $(1-L)^{d}$ is well defined for a fractional d, and the ACF of this process displays a hyperbolic decay consistent with equation (1). A model that incorporates the fractional differencing operator is a natural starting point to capture long memory. This is the underlying idea of the ARIMA and CGARCH class of processes.

Another approach used to measure the degree of long memory has been to use semi-parametric methods. This allows one to review the specific parametric form, which is misspecified and could lead to an inconsistent estimate of the long memory parameter.

3. MARKET EFFICIENCY

A time series that exhibits long memory process violates the weak form of efficient market hypothesis developed by Fama (1970); it states that the information in historical prices or returns is not useful or relevant in achieving excess returns. Consequently the hypothesis that prices or returns move randomly (random walk hypothesis) is rejected.

Fama (1970) proposed three forms of market efficiency namely; weak form efficiency, semi-strong efficiency and strong form efficiency.

3.1.1 Weak Form Efficiency

This means that unanticipated returns can not be correlated with the previous unanticipated returns i.e. the market has no memory and the current prices reflect all information contained in the past prices. Under this form of efficiency technical analysis techniques can not be able to consistently produce excess returns, though some forms of fundamental analysis may still provide excess returns. Share prices exhibit no serial dependencies, meaning that there are no “patterns” to asset prices. This implies that future price movements are determined entirely by unexpected information and are therefore random.

3.1.2. Semi-Strong Form Efficiency

Semi-strong market efficiency means that the unanticipated return is not correlated with any publicly available information i.e. prices reflect not only past but all other published information and in an unbiased fashion. It also implies that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns.
To test for semi-strong form efficiency, the adjustments to previously unknown news must be of a reasonable size and must be instantaneous, if there are any such

adjustments it would suggest that investors had interpreted the information in a biased fashion and hence in an efficient manner.

3.1.3. Strong Form Market Efficiency

Strong-form efficiency means that unanticipated return is not correlated with any information i.e. price reflects all existing information, be it publicly available or inside. This would mean that prices would always be fair and no investor would be able to consistently earn excess returns (Brealey & Myers 1988). If there are legal barriers to private information becoming public, as with insider trading laws, strong-form efficiency is impossible, except in the case where the laws are universally ignored.

To test for strong form efficiency, a market needs to exist where investors cannot consistently earn excess returns over a long period. Even if some money managers are consistently observed to beat the market, no refutation even of strong- form efficiency follows: with hundreds of fund managers world wide, even a normal distribution of returns (as efficiency predicts) should be expected to produce a few dozen “star” performers.

The concept of efficient markets was discovered by chance as a by-product. Maurice Kendall (1953) had been studying the behaviour of stock and commodity prices and looking for regular price cycles, but could not find them. Instead he discovered that prices seemed to follow “random walk”, where one day’s price change could not be predicted by looking at the previous day’s price change. The random walk -theory states that stock and commodity price movements will not follow any patterns or trends and that past price movements cannot be used to predict future price movements. There is no systematic correlation between one movement and the subsequent ones (Brealey & Myers 1996).

Often market efficiency is defined with information efficiency. When the markets are informatically efficient all the relevant information is reflected without any delays, i.e. immediately and perfectly to the prices of the security. By examining information efficiency; it is aspired to solve whether the security prices could be predicted whereas market efficiency is aspired to solve whether the observed predictability is economically exploitable.

When markets are efficient investors receive profits only related to the risk they are willing to take. If they wish to have higher returns, they need to accept also higher risk, that is, volatility of the profit. Making money in finance means making a superior return after an adjustment for risk (Shleifer 2000).

The Efficient markets hypothesis and its close counterpart the Random walk theory have been fixtures on the financial economics scene for well over 30 years. But the theories make predictions that do not match the empirical data.

Market efficiency does not say that stock prices are always “correct,” but it does say that stock prices are not mispriced in any kind of “systematic” or predictable way. The random walk theory, which is related to the efficient markets hypothesis, holds that security price changes are independent of one another.

3.2. Random Walk Theory

According to Malkiel (1973), random walk hypothesis is a financial theory stating that stock markets evolve according to a random walk, implying that prices of the stock market cannot be predicted, prices have no memory and move randomly while adjusting to new information as it comes.

Formally, the random walk model can also be expressed as

(5) $$P_t = P_{t-1} + a_t$$

Where P_t the asset price is observed at the beginning of time *t* and a_t is the error term with zero mean and is independent over time. The price change is simply equal to the error term as below.

(6) $$\Delta P_t = P_t - P_{t-1} = a_t$$

Price P_t can also be written as an accumulation of all purely random changes by successive backward substitutions (Mills 1999).

(7) $$P_t = \sum\nolimits_{i=1}^{t} a_i$$

It has been described as "jibing" with the efficient market hypothesis. Economists have historically accepted the random walk hypothesis and have run several tests and continue to believe that stock prices are completely random because of the efficiency of the market. Tests of the theory are done by investigating whether any forecasting is possible. Persistence is found throughout nature, and it should be no great surprise that it appears to some degree in capital markets. New statistical models may help analyze such trends. The main point, however, is that the price activity of the market, assuming it is a complex adaptive system, would be similar to a classic random walk. The new models, however, would appear to do a better job of explaining persistence in returns to the extent that such persistence exists.

3.3. Volatility and the Risk-Return Relationship

Investors and portfolio managers have a certain degree of risk they can bear which has been termed as uncertainty in finance and is sometimes measured as standard deviation. However, volatility is not defined the same way as risk but as standard deviation, σ, of the continuously compounded rate of return in a given period or as variance $\sigma,^2$ estimated from a historical set of observations.

(8) $$\delta^2 = \frac{1}{N-1}\sum_{t=1}^{N}(r_t - \bar{r})^2$$

where $\bar{r}$ is the mean return. The sample standard deviation, δ is the distribution free parameter representing the second moment characteristic of the sample.

Risk and volatility are key components in mean-variance portfolio theory and for the different asset pricing models like the famous CAPM. Increased volatility increases market risk and has several economic costs for example reduced trading activity and market arbitrage. Investors are also forced to postpone investment decisions in periods of uncertainty.

One element that relates between the level of asset prices and memory components of volatility is the risk-return trade off which has been studied using GARCH-type models. Research work has shown that during crisis periods, stocks that co-vary with volatility are those that pay off and these stocks do require a smaller risk premium. Jointly, the risk-return trade off and serial correlation in volatility determine the level of stock prices, the stronger and higher the trade off and serial correlation are, the higher the elasticity of stock prices with respect to volatility. As a result, innovations from volatility die out very fast and affect absolute returns and stock prices in a short time. (Porteba & Summers, 1986). Christensen & Nielsen (2007) examine the relation between risk-return trade off and serial dependence in volatility using the ARFIMA(*p, d, q*) model and their result are consistent with earlier results point to a strong significant risk-return trade off, long memory in volatility and a strong financial leverage effect.

According to the theory of efficient markets, the random walk model is too restrictive. The expected rate of return from time t to $t+1$ of a portfolio with dividends reinvested is assumed to be the sum of the risk-free rate and a risk premium.

If the expected return is constant $E_t[r_{t+1}] = r$ then r_{t+1} is a fair game.

(9) $$E_t[r_{t+1}] = E_t\left[\frac{P_{t+1} + D_t - P_t}{P_t}\right] = r_{f,t} + x_t$$

Where P_t, D_t, $r_{f,t}$, x_t are the stock price, dividend paid, nominal risk-free rate and the risk premium at period *t* respectively.

The link between equity premium and return volatility is expressed with the intertemporal CAPM model which implies a linear relationship between the equity premium and the market return variance.

(10) $$x_t = \delta V_t$$

Where V_t is the instantaneous variance of the market return and δ is the harmonic mean of individual investors' Pratt-Arrow measures of relative risk aversion.

4. METHODOLOGY

4.1. Data Description

This study utilized daily observations from Thomson Financial database for the stock price indices of U.S, London, Japan and Finland. The stock indices used are FTSE ALL SHARE (United Kingdom), OMX HELSINKI (Finland), S&P 500 COMPOSITE (U.S.) and Tokyo Stock Exchange (Japan). For each of the four indices the data set starts from December 24, 2005 to February 17, 2009. Raw data from these indices is expressed in domestic currencies for example FTSE ALL SHARE closing prices in the Great Britain pound (GBP), S&P500 COMPOSITE in US dollars (USD), OMX HELSINKI in Euros (EUR) and Tokyo Stock Exchange in the Japanese Yen (JPY).

Table 1. Firms and European Stock Market Indices.

Stock Index	No. Of Observations
S&P 500 COMPOSITE	1082
OMX HELSINKI (OMXH)	1082
FTSE ALL SHARE	1082
NIKKEI 225 STOCK AVERAGE	1082

Market indices and the number of observations from December 24, 2005 to February 17, 2009.

4.2. Market Description

4.2.1. FTSE All-Share Index

This market was originally called the FT actuaries All-Share index when it was founded in 1962. Two new sub-indices, FTSE 100 and FTSE 250 in the late ‘90’s were then added to this index. It represents the performance of all companies listed on the London

Stock Exchange's major market. At present the market covers over 600 constituents with an approximate value of 98% of UK's market capitalization.

The FTSE All-Share index accounts for 8.11% of the world's equity market capitalization. In this market stocks are free-float weighted to ensure that only the investable opportunity set is included within the index.

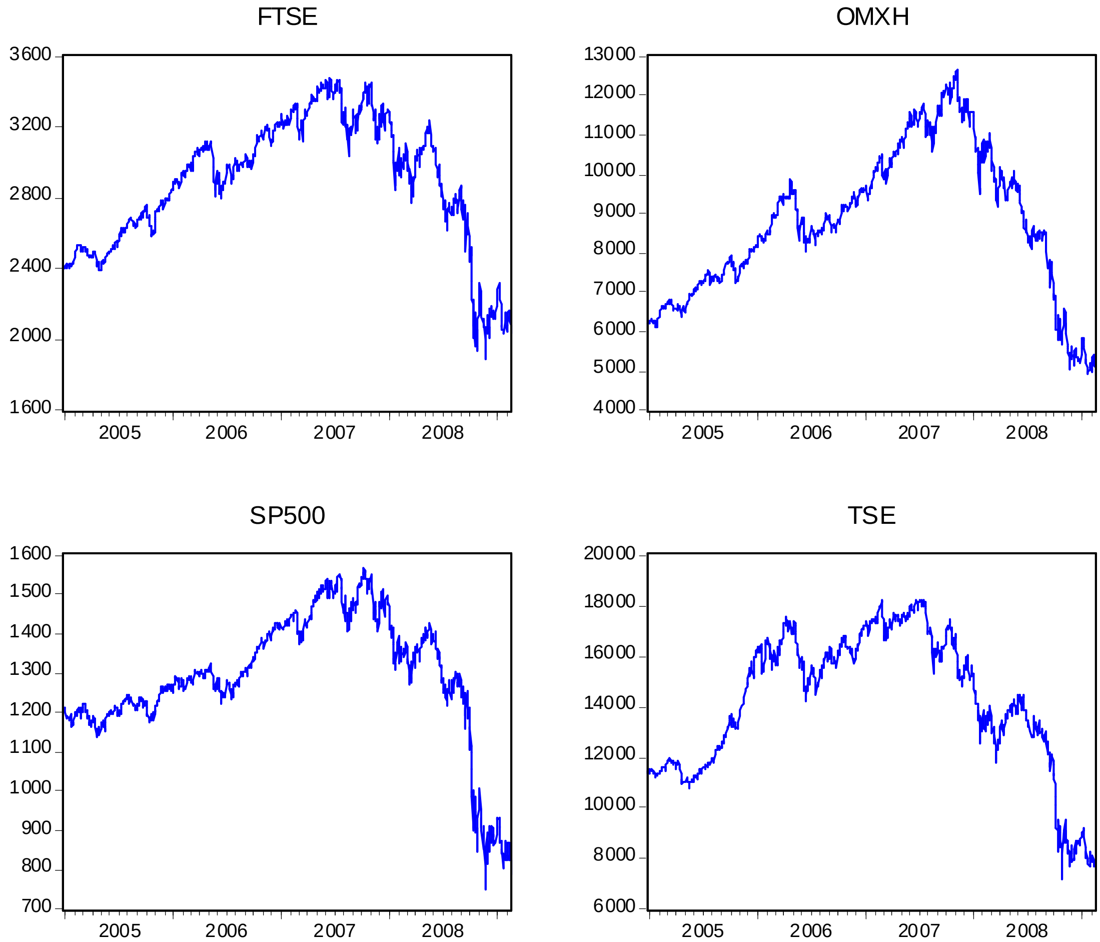

Figure 2. Market series close prices.

4.2.2. S&P 500 Composite Index

The Standard & Poor's composite index founded in 1957 is a value weighted index. Stocks included in this index are those of large public companies that trade on either the New York Stock Exchange or NASDAQ. S&P 500 refers not only to the index but also to the 500 companies that have their common stock included in the index.

It is widely known as the best single gauge of the U.S. equity markets and is also a proxy to the total market although it focuses on the large cap segment of the market.

4.2.3. Tokyo Stock Exchange

The Tokyo Stock Exchange index (TSE) is located in Japan and it is the second largest stock exchange market in the world by market value. By December 2007, this market comprised of 2,414 listed companies with a combined capitalization of 4.3 trillion US dollars. Stocks listed on this index are separated into sections depending on their sizes

4.2.4. OMX Helsinki

OMX Helsinki is a stock exchange located in Finland and is now a part of the NASDAQ OMX Group since February 2008. It operates in eight stock exchanges in the Nordic and Baltic countries.

4.3. Empirical Models

This study used E-views software package for the time series data, econometric multivariate GARCH and Component GARCH (CGARCH) models were used and compared to examine volatility shocks across the markets and to examine the memory components in these markets which in turn explains the degree of volatility persistence of these markets.

4.3.1. GARCH Model

The GARCH parameterization as introduced by Bollerslev (1986) gives parsimonious models that are easy to estimate and successful in predicting conditional variances. The simplest GARCH(1,1) specification used in the study is expressed as below.

(11) $$Y_t = X_t^{'}\theta + \varepsilon_t$$

(12) $$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where the mean equation is written as a function of exogenous variables with an error term. σ_t^2 is the conditional variance based on past information and is written as a function of three terms:

ω : Constant term

ε_{t-1}^2: ARCH term measured as a lag of the squared residual from the mean equation

σ_{t-1}^2: GARCH term (last period's forecast variance)

This model is consistent with the volatility clustering in financial returns data, where large changes in returns are likely to be followed by further large changes. If the lagged variance is substituted on the right hand side of equation (12), then the conditional variance is expressed as a weighted average of all the lagged square residuals:

(13) $$\sigma_t^2 = \frac{\omega}{(1-\beta)} + \alpha\sum_{j=1}^{\infty}\beta^{j-1}\varepsilon_{t-j}^2$$

The GARCH(1,1) variance specification is similar to the sample variance but it down-weights more distant lagged squared errors. The error in the squared returns is given by $\upsilon_t = \varepsilon_t^2 - \sigma_t^2$, substituting it in the variance equation and rearranging terms, the model in terms of errors as:

(14) $$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + \upsilon_t - \beta\upsilon_{t-1}$$

The autoregressive root which governs the persistence of volatility shocks is the sum of α plus β. If this root is close to unity, then shocks die out rather slowly. In addition, the autoregressive root is important in determining the fourth and higher order moments of the unconditional distributions.

4.3.2. Component GARCH Model

Engle and Lee (1999) introduced a flexible alternative, the GARCH model variant, the Component-GARCH (CGARCH) which captures high persistence in volatilities; this model decomposes time-varying conditional volatility into a long-run component, and short run transitory component which reverts to trend following a shock.

The conditional variance in the GARCH(1,1) model below shows mean reversion to

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

ϖ which is a constant for all time. The component model allows mean reversion to a varying level m_t, modeled as:

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

(17) $$m_t = \omega_i + \rho_i(m_{it-1} - \omega_i) + \phi_i(\varepsilon_{it-1}^2 - \sigma_{it-1}^2)$$

σ_t^2 is the volatility, while q_{it} replaces ω and is the time varying long run volatility and $i =$(FTSE, S&P500, TSE, OMXH). Equation (16) describes the transitory component, $\sigma_t^2 - q_t$, which converges to zero with powers of (α+β) where as equation (17) describes the long run component which converges to ω with powers of $\rho.\rho$ typically between 0.99 and 1 so that q_t approaches ω very slowly. Combining the tansitory and permanent equations gives the equation below;

(18) $$\delta^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\varepsilon_{t-1}^2 - (\alpha+\beta)\phi)\varepsilon_{t-2}^2 + (\beta-\phi)\delta_{t-1}^2 - (\beta\rho - (\alpha+\beta)\phi)\delta_{t-2}^2$$

This shows that the component model is a non-linear restricted GARCH (2, 2) model.

4.4. Daily Return Series

The daily market return series R_{it} is defined as the close to close prices on consecutive trading days. The market returns are calculated as the logarithmic difference in the in the daily stock indices.

(19) $$R_{it} = 100(\ln P_{it,close} - \ln P_{it-1,close})$$

Where R_{it} is the return for the series and P_{it} is the closing price for the market series.

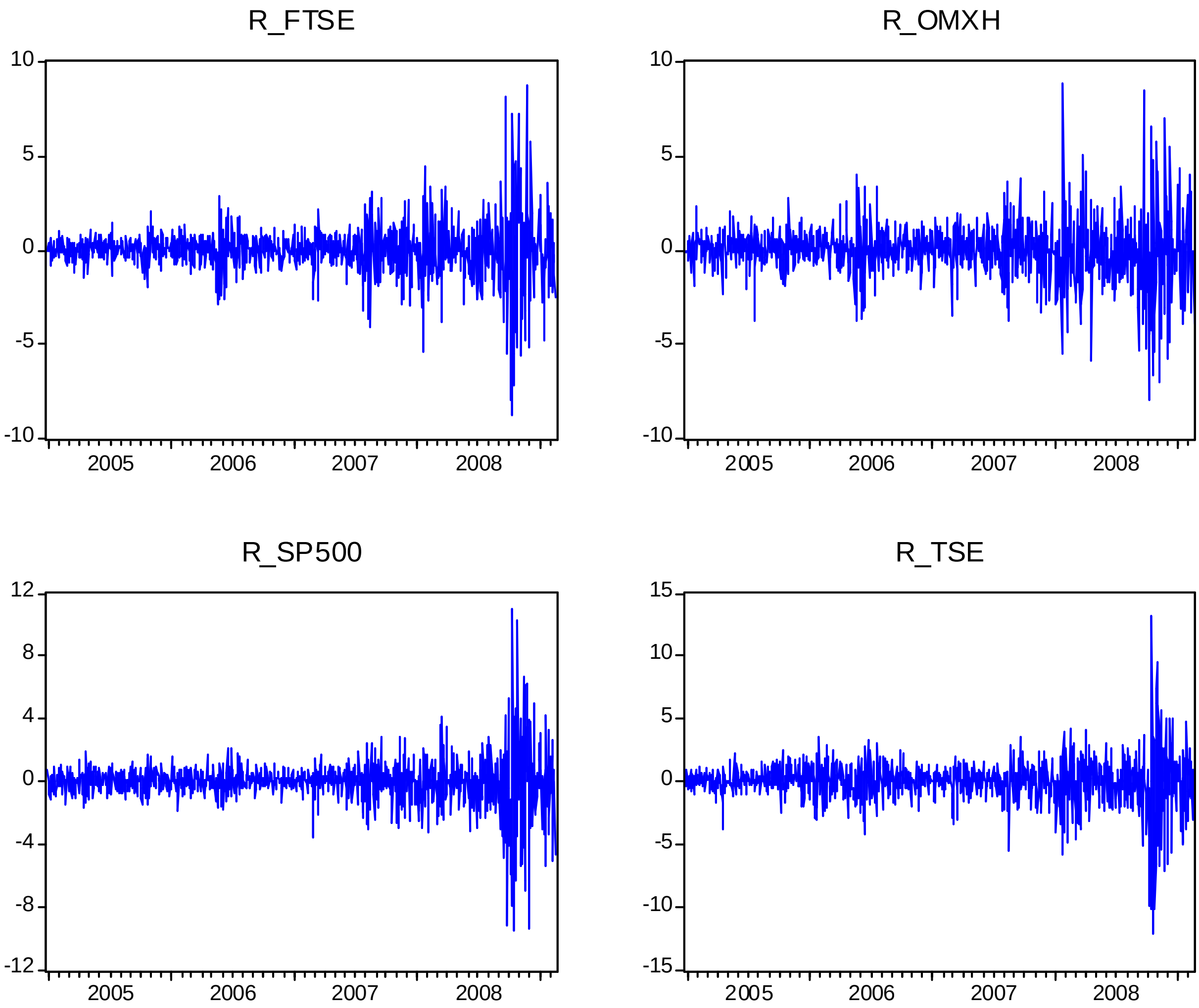

Figure 3. Market Returns.

4.5. Augmented Dickey-Fuller Test

To test for unit roots, the augmented Dickey-Fuller unit root test (1979) and Philips-Perron unit root test which allow for levels and trends are used; the optimal lag lengths are selected based on the Akaike information criterion (AIC).

(20) $$x_t = \theta_o + \phi_1 x_{t-1} + \sum_{j=1}^{k} \delta_j \Delta x_{t-j} + a_t$$

$H_o : \phi_1 = 1$**:** Non stationary (Unit root)

$H_o : \phi_1 < 1$: Stationary (Integrated of order zero)

a_t follows white noise distribution with mean of zero and constant variance i.e. $a_t \sim WN(0, \delta^2)$

4.6. VAR(p) Model

The VAR approach sidesteps the need for structural modelling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. Depending on the stationarity of the series, Vector autoregressive (VAR) modeling as written below with levels of differences will be applied to explain any possible linkages between the series.

(21) $$\sigma_t = \alpha + \sum_{i=1}^{p} \phi_t \sigma_{t-i} + \varepsilon_t$$

Where t=(all the market series) and p denotes the lag order of the system, and δ_t' is a covariance stationary 4x1 vector of volatility time series, α the 4x1 vector of intercepts, and ε_t the 4x1 vector of white noise with zero mean and positive definite covariance matrix, and p denotes the lag order of the system.

The VAR(p) models has also proven to be a useful tool for analysis of term dynamics of several economic time series. The basic VAR model is just a multivariate generalization of the univariate autoregressive (AR) model.

(22) $$\Phi(L) y_t = e_t ,$$

Where $\Phi(L) = I - \Phi_1 L - \Phi_1 L^2 - .... - \Phi_P L^P$ is a matrix polynomial of order p. The vector y_t is assumed to be centered for the sake of simplicity, e_t are random vectors of *m* time series Φ_k are *m x m* matrices (*k*=1,…….,p), and *L* is the lag operator. It is assumed that each vector in e_t are (weak) white noise processes that, however, can be contemporaneously correlated. Formally,

$$E\,(e_t) = 0, \text{ for all } t$$

(23)
$$E\,(e_t\, e_t') = \begin{cases} \Sigma, & if\ \ s = t \\ 0, & if\ s \neq t, \end{cases}$$

Where the prime denotes transpose.

Determination of an appropriate lag order, p for the VAR system which depends on standard lag length criteria is an empirical issue. In this study, the order of the VAR is defined based on the standard length criteria and likelihood ratio tests. In addition, given that the residuals did not exhibit serial correlation additional tools for analyzing casual as well as feedback effects were used to examine cross dependencies amongst the market series.

4.7. Granger Causality and Impulse Response Analysis

Granger causality test, impulse response analysis and Variance decompositions were applied to interpret the estimated VAR (p) system. Granger causality tests identify potential lead-lag relationships between the estimated volatilities and the direction of the causalities.

Impulse response analysis using generalized standard deviation shocks in the volatility of the market series was performed to reveal the persistence of shocks in the system; it was also used to trace the impact of a shock in one market series to another market. The impulse response coefficients can be solved by inverting the VAR coefficient polynomial, giving

(24) $$y_t = \Phi^{-1}(L)e_t = \sum_{k=0}^{\infty}\theta_k e_{t-k} \ ,$$

Where θ_k s are m x m matrices, with θ_0 =*I,* showing the responses of the impulses of e_{t-k} to y_t. A single coefficient $\theta_{ij,k}$ indicates the response of the i^th^ variable to the shock in the j^th^ variable at time point *k.*

However, because the impulses are contemporaneously correlated, it is easier to interpret the results if each series own impulse effects are singled out. This can be accomplished by orthogonalizing the residuals. One of the most applied orthogonalization procedure is the so called Cholesky decomposition such that

(25) $$\Sigma = SS',$$

Where the S is a lower diagonal non singular *m* x *m*. Then the new residual shocks $U_{t-k} = S^{-1}e_{t-k}$ are uncorrelated. In terms of orthogonalized residuals, the VAR co-efficient polynomial equation becomes

(26) $$y_t = \sum_{k=0}^{\infty}\theta_k e_{t-k} = \sum_{k=0}^{\infty}\theta_k SS^{-1}e_{t-k} = \sum_{k=0}^{\infty}\psi_k u_{t-k}$$

Furthermore, because each component in the ***u****-vectors* has unit variances, the squared ij^{th} component, $\psi^2_{ij,k}$, of the ψ_k matrix indicates the fraction of the variance of y_t, the innovation occurred the j^{th} variable at lag k explains. For the sake of convenience these fractions are expressed in percentage terms.

4.7.1. Variance Decompositions

The uncorrelatedness of $u_t S$ allows the error variance of the *S* step ahead forecast of y_{it} to be decomposed into components accounted for by these shocks, or innovations (this is why this technique is usually called innovation accounting).

Because the innovations have unit variances besides the uncorrelatedness, the components of this error variance accounted for by innovations to y_j is given by

(27) $$\sum_{k=0}^{s} \psi_{ij,k}^{2}$$

Comparing this to the sum of innovation responses we get a relative measure how important variable *jS* innovations are in the explaining the variation in variable *i* at different step ahead forecasts, i.e.

(28) $$R_{ij,s}^{2} = 100 \frac{\sum_{k=0}^{s} \psi_{ij,k}^{2}}{\sum_{h=1}^{m} \sum_{k=0}^{s} \psi_{ih,k}^{2}}$$

Thus, while impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decompositions separate the variation in endogenous variable into the component shocks to the VAR.
Letting *s* increase to infinity one gets the portion of the total variance of y_j that is due to the disturbance term ε_j of y_j .

4.8. Geweke's Measures of Linear Dependence

Geweke's measure of linear dependence is used to test for linear feedback from all markets for example if smaller (Japan and Finland) markets are dependant on larger (U.S. and United Kingdom) markets and vice versa.
Geweke suggested a measure of linear feedback between x and y based on the matrices Σ_1 and Σ_{11} as shown below.

(29) $$F_{x \to y} = \ln(|\Sigma_1| / |\Sigma_{11}|),$$

So that the statement “x does not granger cause y” is equivalent to $F_{x \to y} = 0$

Similarly the measure of linear feedback from y to x is defined by

(30) $$F_{y \to x} = \ln(|\Sigma_2| / |\Sigma_{22}|),$$

The measure of linear dependence is defined by $F_{x,y} = F_{x \to y} + F_{y \to x} + F_{x.y}$.

With these estimates, particular dependencies within the markets can be tested as below.

- $H_{01} = F_{x \to y} = 0$: No Granger-causality between the markets (larger to smaller)

(31) $$(T - p)\hat{F}_{x \to y} \sim \chi^2_{mkp}$$

- $H_{02} = F_{y \to x} = 0$: No Granger-causality between smaller markets to larger markets

(32) $$(T - p)\hat{F}_{y \to x} \sim \chi^2_{mkp}$$

- $H_{03} = F_{x.y} = 0$: No instantaneous feedback between the markets

(33) $$(T - p)\hat{F}_{y \to x} \sim \chi^2_{mk}$$

- $H_{04} = F_{y.x} = 0$: No linear dependence between the markets

(34) $$(T - p)\hat{F}_{y \to x} \sim \chi^2_{mk(2p+1)}$$

This is due to the asymptotic independence of the measures $F_{x \to y}$, $F_{y \to x}$ and $F_{x.y}$.

5. EMPIRICAL FINDINGS

Figure 2 indicates that the daily market prices are varying considerably overtime. All market series are non-stationary and are particularly volatile with an increasing pattern and large movements between 2005 to mid 2007. The considerable decline in volatility of the market prices from mid 2007 to date can be explained by the ongoing market crisis world wide. Besides this, Figure 1 indicates that market prices tend to move together very closely.

5.1. Descriptive Statistics

Table 2. Descriptive Statistics.

	FTSE	OMXH	S&P500	TSE
Mean	-0.015536	-0.022953	-0.039148	-0.036650
Median	0.014326	0.018593	0.036229	0.000000
Maximum	8.810746	8.849971	10.95720	13.23458
Minimum	-8.709914	-7.923905	-9.469514	-12.11103
Std. Dev.	1.336039	1.494813	1.469959	1.717081
Skewness	-0.203172	-0.027485	-0.376405	-0.552627
Kurtosis	12.74399	8.524816	15.75390	13.78544
Jarque-Bera	4283.935	1374.969	7352.096	5294.525
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-16.79454	-24.81260	-42.31867	-39.61867
Sum Sq. Dev.	1927.801	2413.222	2333.642	3184.238
Observations	1081	1081	1081	1081

Table 2 reports the descriptive statistics for the daily market returns. The sample means for all the four markets are negative and significantly different from zero with standard deviation rather close to unity. Measures of skewness indicate that the series are all negatively skewed and highly leptokurtic (fat tails) implying that the distribution of these series is non-symmetric which is also an indication of possible ARCH effect. Koutmos (1996), argues that that non linear dependencies are due to the autoregressive conditional heteroskedasticity i.e. volatility clustering in market returns. The large magnitude of the Jarque-bera statistic enables us to reject normality distribution of all the series. Because of the ARCH effect still present in the squared residuals (see graphs in appendix), the series fail to be independently and identically distributed (i.i.d) over time.

Table 3. Contemporaneous Correlations.

	FTSE	OMXH	S&P500	TSE
FTSE	1			
OMXH	0.834648	1		
S&P500	0.519722	0.453792	1	
TSE	0.422207	0.419580	0.106712	1

Correlation structure is one of the important features for investors and portfolio managers since the strategies they employ require a measure of correlation (association). (Koutmos, 1996: 980). The considerable pair wise correlations as reported in Table 3 indicate market expectations of volatility are closely linked across markets and highest between FTSE and OMXH (0.834648).

To remove the ARCH effect before estimating the G(ARCH) models, a conservative strategy of adding AR and MA lags is used when running the autocorrelation and partial autocorrelation functions for each return series until the best specification is achieved when there is no remaining ARCH effects in the series.

After fitting the ARMA terms to all the market series, the resulting conditional mean models are reported in Table 4. Residual autocorrelations and related Q-statistics indicate no further autocorrelation left to the series as explained by the Durbin-watson test (approximately 2 for all series) indicating that these models give virtually a good fit. However, the autocorrelations of the squared residuals suggest that there is still left non linear time dependency into the series which can only be removed with the G(ARCH) models.

Table 4. Choice of AR-MA lags.

	FTSE	OMXH	S&P500	TSE
AR	7	2	2	2
MA	-	2	1	-
Squared residuals	1840.548	2374.933	2250.922	3154.203
Durbin-Watson stat	1.995591	1.982845	1.972141	2.009755
Schwarz criterion	3.428537	3.659174	3.591658	3.929996
Prob(F-statistic)	0.000000	0.001781	0.000000	0.006585

Together with the ARMA specifications, corresponding GARCH(1,1) model is estimated first for all the return series followed by the CGARCH(1,1) model and results compared.

Table 5 reports joint ARMA-GARCH(1,1) model estimates, resulting conditional mean models are ARMA(7,0) for FTSE, ARMA(2,2) for OMXH, ARMA(2,1) for S&P 500 and ARMA(2,0) for TSE. The drift term is significant for all series hence snubbing the random walk theory of market prices. Co-efficients describing conditional volatility are highly significant across all markets indicating that volatility is a function of past normalized residuals and the last period's volatility. The magnitude of α co-efficient which captures the impact an unexpected return has on volatility the next day ranges from 0.0742 for S&P 500 to 0.1334 for FTSE; this means that a return shock in FTSE causes almost twice as much volatility the next day as a return shock in S&P 500. The β co-efficients capture tendency for shocks to persist, these are homogenous for all series and range from 0.8672 for FTSE to 0.9198 for S&P 500. Persistence of shocks measured by the sum of the estimated ARCH and GARCH parameters (α+β) is 1 for FTSE and almost 1 for the remaining series, this indicates that the degree of volatility persistence in equity markets is high and greatest in FTSE hence shocks have a permanent effect on volatility and high persistence is also an indication that negative effects from increased market risk die out more slowly. The estimated Durbin-Watson statistic is approximately two for all market series suggesting that there is no serial correlation amongst the residuals and the mean and variance are well specified.

Results for the ARMA-CGARCH(1,1) model are presented in Table 6, ARMA model orders are unchanged, there is a significant increase in autoregressive parameters as compared to those of the GARCH(1,1) model for instance they are all homogeneous and close to 0.99. Regarding the conditional variance specifications, all parameters are varying but positive and significant(less than those from the GARCH(1,1) estimates).
The conditional variance long run component persistence is generally low for all markets and negative for FTSE and S&P 500. Shocks to the long run component decay very fast, such that a current shock conditions volatility over a short horizon indicating that conditional volatility exhibits short memory. This finding can also be traced from the estimated parameters; the degree of memory in the transitory component is very low ranging from 0.0191 for TSE (lowest) to 0.1359 for FTSE (highest). Persistence of shocks in the transitory component of volatility is measured by the sum of ARCH and GARCH parameters i.e. (α+β) and is very high for all markets: 1.1351, 1.0862, 1.0683 and 1.0185 for FTSE, OMXH, S&P 500 and TSE respectively.
More specifically, long run component half-life decay for volatility shocks is very small and negative, which also means that the shocks decay over a much shorter time horizon.

Residual diagnostics tested using the ARCH-LM tests as reported in Table 7 are used to compare the performance of the GARCH and CGARCH models. For both models the Q-statistics are very insignificant, this leads to rejection of the hypothesis that the residuals and squared residuals are correlated and conclude that there is no serial dependency in the squares of the standard residuals. However, it is noticeable that probability values for the GARCH model are much less than those for the CGARCH model indicating that CGARCH residual diagnostics are cleaner than those for the GARCH model.

Table 5. ARMA-GARCH(1,1) Model.

	FTSE	OMXH	S&P 500	TSE
AR(1)	-0.0592	-0.3696	0.7423	-0.0344
	(0.0340)*	(0.0659)**	(0.1082)	(0.0378)*
AR(2)	-0.0445	-0.9178	0.0528	-0.0345
	(0.0346)*	(0.0551)**	(0.0414)*	(0.0333)*
AR(3)	-0.0342	-	-	-
	(0.0324)*			
AR(4)	0.0146	-	-	-
	(0.0313)*			
AR(5)	-0.0380	-	-	-
	(0.0302)*			
AR(6)	-0.0448	-	-	-
	(0.0320)*			
AR(7)	-0.0135	-	-	-
	(0.0337)*			
MA(1)	-	0.3924	-0.8558	
		(0.0660)**	(0.1008)	
MA(2)	-	0.9157		
		(0.0572)**		
ω	0.0111	0.0257	0.0102	0.0217
	(0.0034)*	(0.0007)*	(0.0023)*	(0.0068)*
α	0.1334	0.0978	0.0742	0.1087
	(0.0173)*	(0.0123)*	(0.0107)*	(0.0128)*
β	0.8672	0.892872	0.9198	0.8873
	(0.0155)*	(0.0142)*	(0.0113)*	(0.0130)*
δ	1.496191	1.471143	1.471143	1.718552
$\alpha+\beta$	1.0005	0.9907	0.9941	0.9960
Log L	-1440.481	-1724.837	-1471.336	-1784.448
Durbin-Watson	2.0011	2.0356	2.0879	1.940559
Schwarz-criterion	2.753941	3.248883	2.772529	3.346430

*Denotes significance at the 5% level and ** denotes significance at 10% level. Standard errors are denoted in parentheses. Log L is the log likelihood.

Table 6. ARMA-CGARCH(1,1) Model.

	FTSE	OMXH	S&P 500	TSE
AR(1)	-0.060748	-0.365408	0.731839	-0.033359
	(0.0335)	(0.0746)**	(0.1084)	(0.0375)*
AR(2)	-0.046477	-0.909691	0.051799	-0.035497
	(0.0347)	(0.0560)	(0.0411)	(0.0328)
AR(3)	-0.035946	-	-	-
	(0.0319)			
AR(4)	0.010751	-	-	-
	(0.0318)*			
AR(5)	-0.036345	-	-	-
	(0.0301)*			
AR(6)	-0.046729	-	-	-
	(0.0323)*			
AR(7)	-0.015540	-	-	-
	(0.0329)*			
MA(1)	-	0.389921	-0.848868	-
		(0.0754)*	(0.1001)	
MA(2)	-	0.907203	-	-
		(0.0582)**		
ω	14.5149	3.0979	1.592	10.65054
	(143.6199)	(2.0892)	(0.9325)	(22.2001)
α	0.9992	0.9926	0.9933	0.9994
	(0.0081)*	(0.0064)*	(0.0046)*	(0.0012)*
β	0.1359	0.0936	0.0749	0.0191
	(0.0183)*	(0.0138)*	(0.0114)*	(0.0258)*
ρ	-0.0083	0.0923	-0.0211	0.0871
	(0.0134)*	(0.0354)*	(0.0105)*	(0.0257)*
φ	-0.9337	-0.2576	-0.9476	0.8948
	(0.0993)**	(0.2451)	(0.0302)*	(0.0284)*
δ	1.339917	1.496191	1.47114	1.71855
$\alpha+\beta$	1.1351	1.0862	1.0683	1.0185
Log L	-1440.197	-1722.532	-1467.996	-1781.754
Durbin-Watson	1.99857	2.03846	2.08036	1.94168
Schwarz-criterion	2.76640	3.25755	2.77928	3.35438

*Denotes significance at the 5% level and ** denotes significance at 10% level.

Standard errors are denoted in parentheses. Log L is the log likelihood.

From these results, it is concluded that the complex CGARCH(1,1) model is the best specification in modeling volatility(two components i.e. short run and long run) as compared to its opponent but persistence of volatility shocks from the GARCH(1,1) model results in half-life decay over a longer time horizon, this leads to rejection of the hypothesis and conclude that the simple GARCH(1,1) model is more accurate than the component GARCH(1, 1) model in explaining the short-run memory volatility persistence in equity market returns.

Table 7. ARCH-LM Test.

GARCH(1,1)	FTSE	OMXH	S&P 500	TSE
Q_1^2	-0.012158	0.034927	-0.046396	-0.030428
F-statistic	0.157978	1.310440	2.312313	0.997520
Obs*R-squared	0.158250	1.311279	2.311643	0.998448
Probability	0.690773	0.252163	0.128408	0.317686
CGARCH(1,1)				
Q_1^2	-0.0091	-0.0114	-0.0390	-0.0233
F-statistic	0.089312	0.138956	1.630086	0.582867
Obs*R-squared	0.089472	0.139196	1.630645	0.583635
Probability	0.765111	0.709395	0.201967	0.445358

The results of the unit root tests for the market series performed with the augmented Dickey-Fuller test (ADF) and Phillips-Perron (PP) are reported in Table 8. The null hypothesis of a unit root is rejected for all the series indicating that the markets are integrated of order zero.

Table 9 reports Akaike’s, Schwarz’s and Hannan-Quinn information criterion and modified likelihood ratio tests for the lag order selection. All the information criteria point to setting p=5, while the Schwarz information criteria suggests p=4. In addition the LR test indicates significant serial correlation in the residuals of the VAR(4) model. Therefore, the VAR(4) system is augmented with an additional lag and the rest of the criteria suggest this specification to be adequate. Therefore, analysis in this paper is based on the VAR(5) system.

Table 8. Unit Root Tests.

Series	ADF test	p value	PP test	p value
FTSE	-16.113*	0.0000	-16.113*	0.0000
OMXH	-32.928*	0.0000	-32.873*	0.0000
S&P 500	-28.866*	0.0000	-28.834*	0.0000
TSE	-25.597*	0.0000	-24.586*	0.0000

*Denotes significance at the 1% level of significance

Table 9. Lag order selection for the VAR(p) system

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6914.055	NA	4.514657	12.85884	12.87735	12.86585
1	-6441.563	940.5914	1.932535	12.01034	12.10292	12.04540
2	-6382.192	117.7485	1.782860	11.92973	12.19157	11.99284
3	-6342.675	78.08030	1.706610	11.88601	12.12673	11.99900
4	-6321.708	61.62065	1.690939	11.87678	12.09638*	11.99988
5	-6290.285	41.27000*	1.643166*	11.84811*	12.23696	11.97718*

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

To analyze behavior of the market interdependence over the last four years, the data set used to estimate cross market correlations was divided into two sub-periods namely: pre-crisis period (sub-period 1) starting from January 03, 2005 to June 15, 2007 and the crisis period (sub-period 2) starting from June 16, 2007 to February 17, 2009.

Table 10 presents the summarized VAR cross market correlation co-efficients between the conditional variances of the returns for the market series over the two sub-periods. In all cases the correlations are statistically significant and positive indicating a high degree of interdependence; this can also be noticed from the rise in the mean cross market correlation coefficients for all the series from 0.42278 in the first sub-period to 0.51653 in the second sub-period.

Table 10. VAR Cross-Market Residual Correlations.

	FTSE	OMXH	S&P 500	TSE	Mean
Subperiod 1 January 2005-June 2007					
FTSE	1				
OMXH	0,718	1			
S&P 500	0,4941	0,4358	1		0,42278
TSE	0,2972	0,2784	0,1155	1	
Subperiod 2 June 2007-Febuary 2009					
FTSE	1				
OMXH	0,8287	1			
S&P 500	0,6835	0,5957	1		0,51653
TSE	0,402	0,3506	0,3135	1	

Looking at the correlation coefficients for specific markets in the pre-crisis period, there is strong evidence of volatility interdependencies from FTSE to all the markets, followed by S&P 500 and OMXH. These findings suggest that market interactions are high with the UK market being the major producer of information and Tokyo being the least. Considering estimates from the second sub-period, the interactions in all markets are positive and much higher than those documented in the pre-crisis period. FTSE is still the driving market with higher and significant correlation coefficients with respect to all the other markets (U.S., Finland and Japan).

A comparison of the results from the pre-crisis and crisis period reveals that equity markets are more interdependent in crisis periods; markets are more sensitive to news originating from UK and U.S. markets. This implies news or innovations in one market have a great impact on the volatility of the next market to trade. This finding thus supports the second hypothesis that volatility in stable periods is small resulting into low levels of volatility with low market correlation coefficients whereas unstable periods are characterized by large persistent shocks resulting into high levels of volatility with high cross market linkages.

It is also clear from the results that the high level of interdependence found between the conditional volatilities is due to the influence of the second sub-period during which volatility interdependence has grown. This implies that in the last two years major equity markets have become increasingly interdependent.

Table 11. Pairwise Granger Causality Tests.

Null Hypothesis:	Obs	F-Statistic	Probability
OMXH --> FTSE	1079	0.98971	0.37202
FTSE --> OMXH		0.95133	0.38655
S&P 500 --> FTSE	1079	137.840	5.2E-54*
FTSE --> S&P 500		3.70903	0.02482**
TSE --> FTSE	1079	1.42178	0.24174
FTSE --> TSE		157.100	1.4E-60*
S&P 500 --> OMXH	1079	94.6621	1.4E-38*
OMXH --> S&P 500		2.09302	0.12382
TSE --> OMXH	1079	2.53416	0.07980**
OMXH --> TSE		100.648	8.6E-41*
TSE --> S&P 500	1079	1.01291	0.36351
S&P 500 --> TSE		310.543	4.E-107*

* and ** denote significance at the 1% and 5% level of significance respectively.

Table 11 reports evidence of bidirectional and unidirectional causality among most of the market volatilities. The probability values indicate that S&P 500 and FTSE market return volatilities Granger cause almost 65% of the other markets with S&P 500 taking the lead.

Examining the same findings using the Block Exogeneity Wald Tests based on the VAR(5) specification as reported in Table 12 points to S&P 500 (U.S.) as the dominant market, the market return volatility of the U.S. markets is found to granger cause the volatility expectations of all the markets. In contrast, the Granger causality tests imply that the volatility prospects of the U.S. markets is not affected by the major equity markets. UK markets also show a fair transmission of volatility to all markets in the exception of US markets. However, the lead-lag relationship is smaller than that of U.S. markets. In addition the results show weak volatility transmission (*p*-values) from Finland and Japan markets.

In general, the granger causality tests point to U.S. markets as the leading source of volatility expectations among the markets.

Table 12. Block Exogeneity Wald Tests.

	Wald Statistic	*p*-Value
Dependent:FTSE		
OMXH	5.043624	0.0803
S&P 500	275.7496	0.0000
TSE	0.070728	0.9653
Dependent:OMXH		
FTSE	14.70223	0.0006
S&P 500	204.3046	0.0000
TSE	2.180852	0.3361
Dependent:S&P 500		
FTSE	3.480475	0.1755
OMXH	0.247130	0.8838
TSE	0.894982	0.6392
Dependent:TSE		
FTSE	19.21490	0.0001
OMXH	2.389961	0.3027
S&P 500	278.9554	0.0000

Table 13. Geweke's Measures of Linear Dependence.

Dependency relation	F	LR	DF	p-val
(FTSE, S&P 500) --> (OMXH, TSE) [X --> Y]	1,4718	1576,3	20	0,0000
(OMXH, TSE) --> (FTSE, S&P 500) [Y--> X]	1,0884	1165,7	20	0,0000
(FTSE, S&P 500) . (OMXH, TSE) [X.Y]	-1,1245	-1204,4	4	N/A
(FTSE, S&P 500) , (OMXH, TSE) [X.Y]	1,4357	1537,6	44	0,0000
No. of observations	1076			
No.of lags	5			
No. of Y variables	2			
No. of X variables	2			
Y = (OMXH, TSE)				
X = (FTSE, S&P 500)				

Geweke's measures of linear dependencies are reported in Table 13 and point to the same inference as in the granger causality tests. The results indicate some evidence of granger causality from smaller markets (OMXH and TSE) to larger markets (UK and U.S.) and vice-versa as seen from the significant probability values. Additionally, the major part of the overall dependency between the blocks is explained by the contemporaneous correlations of the market returns.

To trace the impact of volatility shocks in one market to another, impulse response analysis is utilized and the findings are presented in Figure 4. The main objective of this analysis is to examine the response of the markets' volatility expectations to shocks from S&P 500 and FTSE the leading sources of volatility expectations.
The impulse response function of the volatility of FTSE to a shock in the volatility of S&P 500 indicates that there is a positive significant impact after the contemporaneous day one effect, the volatility of FTSE increases on to day two, and afterwards, the effect reduces and becomes insignificant at day three and completely dies out at the day four effect. Similarly, the impact of volatility from other markets to a shock from S&P 500 behaves in the same way, it increases from the first day effect to the next day and gradually reduces to the day three effect and dies out on day five.

In addition, the impulse response function of volatility of OMXH and TSE to a shock in the volatility of FTSE indicates that after the day one effect, the impact reduces to day two where it becomes insignificant and dies out on the day five effect. However, the response of TSE to the shock from FTSE is more persistent from the contemporaneous day one effect to day two but later dies out at day five.
In brief, the impulse response functions shown in Figure 4 indicate that a shock in the volatility expectations of S&P 500 significantly affect the innovations of the other markets. This finding also supports the result form the granger causality tests.

Finally, variance decomposition analysis is applied to ascertain the relative importance of a market's volatility in affecting other markets in the VAR system. Results of this analysis are reported in Figure 5. Approximately 100% of 1 day and 80% of 2 days variation of FTSE is attributable to innovations from itself. Volatility expectations of S&P 500 appear to have a significant impact on all markets. 20% of variation in OMXH, FTSE and TSE is explained by innovations from S&P 500 whereas 55% variation is solely caused by innovations from itself.

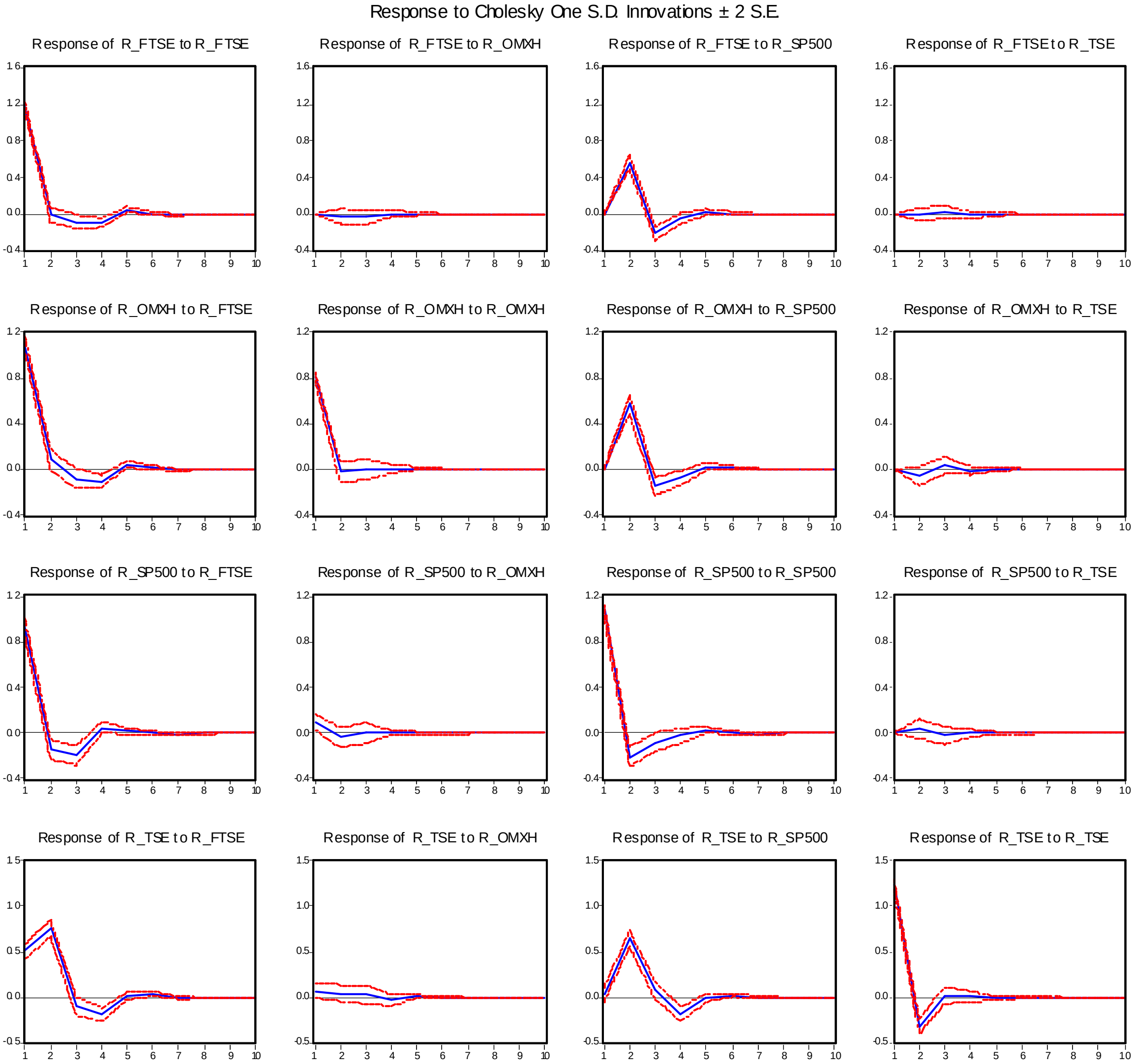

Figure 4. Impulse Response Functions.

Volatility expectations of markets caused by innovations from FTSE appear to be larger than that from S&P 500. 100% of 1 day ahead and 80% of 2 days ahead variation is caused by innovations from within the market itself whereas 65%, 45% and 10% variation of OMXH, S&P 500 and TSE respectively is attributable to innovations from FTSE. However, innovations from TSE do not have any impact on volatility expectations of all the markets. Therefore, variance decompositions suggest that the expected future volatility of OMXH and TSE is significantly affected by innovations from S&P 500 and FTSE with innovations from FTSE (UK) having a more significant effect than those from U.S. markets to the other markets)

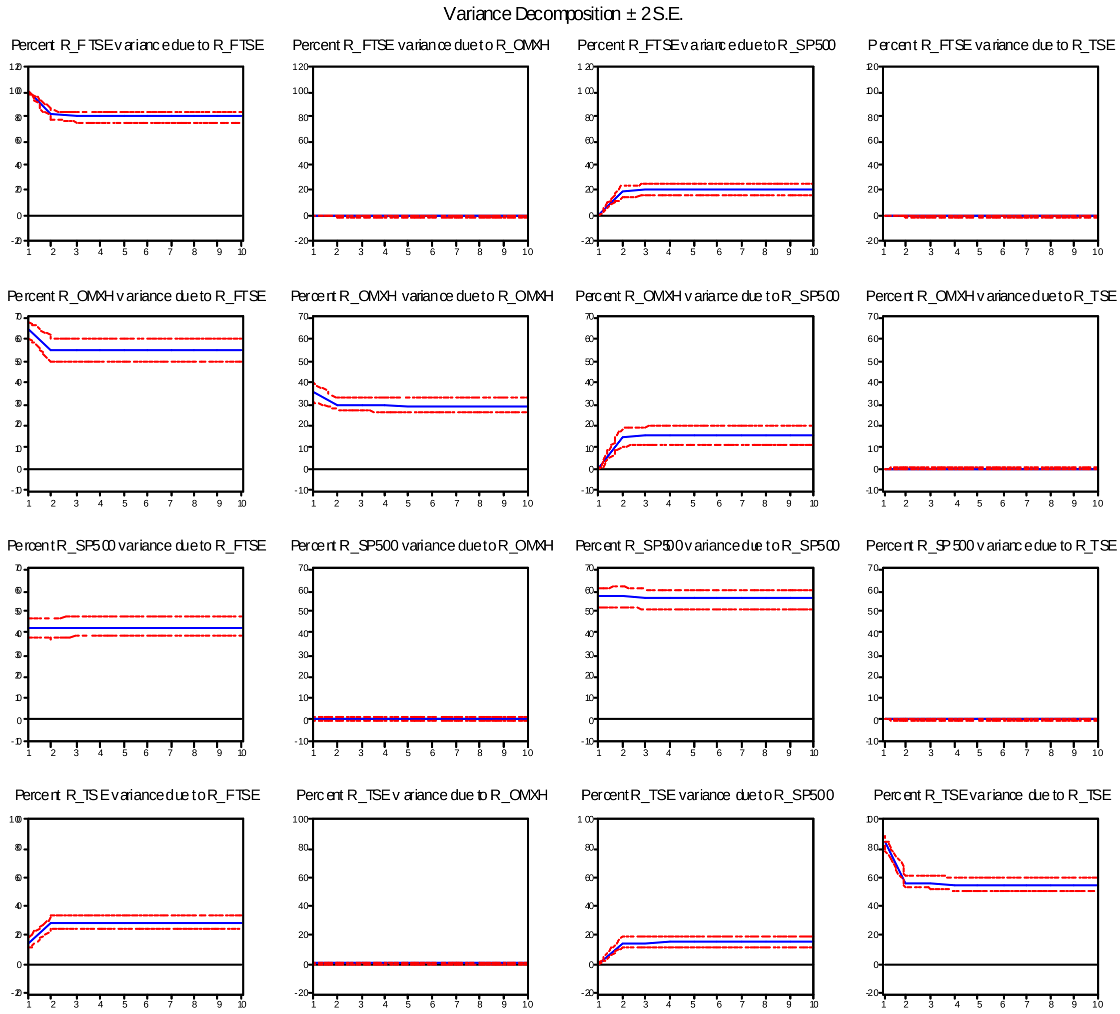

Figure 5. Variance decompositions

6. SUMMARY AND CONCLUSIONS

As has been researched on by many researchers, there are different approaches to measuring and modeling persistence of volatility shocks which play quite a big role in many investment decisions and portfolio management. However there is no definite theory explaining the behavioral of volatility since different methodologies are applied leading to conflicting conclusions.

The main goal of this thesis is to investigate persistence of volatility and any possible interdependencies existing in equity markets. Volatility is modeled using two auto-regressive heteroscedastic models namely; the widely used simple GARCH(1,1) and the component GARCH (CGARCH(1,1)) whereas VAR analysis is used to examine the possible linkages and feedback measures across markets.

Two hypotheses are tested in this study; the first hypothesis compares accuracy of the two GARCH models and the findings lead to rejection of this hypothesis and conclude that the simple GARCH(1,1) model is an adequate and a more appropriate representation of time-varying volatility than the component GARCH(1, 1) model even if the residuals of the CGARCH(1,1) model are cleaner. It is also found that equity markets exhibit short term memory volatility persistence, shock half-life decay is very small and negative and shocks die out very fast. This result confirms the earlier finding of Porteba & Summers (1986) that shocks to stock market volatility do not last for longer periods and that the GARCH(1,1) process is the best in capturing the short-run component of volatility.

The second hypothesis tests how volatile markets are in different economic periods for instance in the pre-crisis and crisis period. With the help of VAR cross-residual correlations, conditional variances of the market returns of the two periods were compared and results show a higher mean correlation between the series in the crisis period than the pre-crisis period leading to rejection of the hypothesis and conclude that volatility shocks in unstable periods are large leading to an increase in market interactions and this is reflected in higher market correlation coefficients

Another element this study focuses on is linkages in equity market volatilities. Vector autoregressive modeling is applied to ascertain the causal dynamics of market return volatilities. Granger causality tests, impulse response analysis and variance decompositions are used to make inference to the VAR estimation results.
The results indicate that equity markets are strongly linked and this linkage is stronger in periods when markets are very volatile (crisis). In particular, the results show that U.S. and UK markets are the dominant markets and leading sources of volatility expectations, as the volatility of S&P 500 is found to significantly affect the volatility expectations of UK, Finland and Japan markets. Moreover, the results suggest that volatility expectations of S&P 500 are not affected by the other markets.

Finally, the modeling procedure applied in this study provides a clear measure on the behavior of market volatility. It remains for future research to examine whether different methods or techniques come up with the same conclusions, this will provide perfection in the modeling of volatility persistence.

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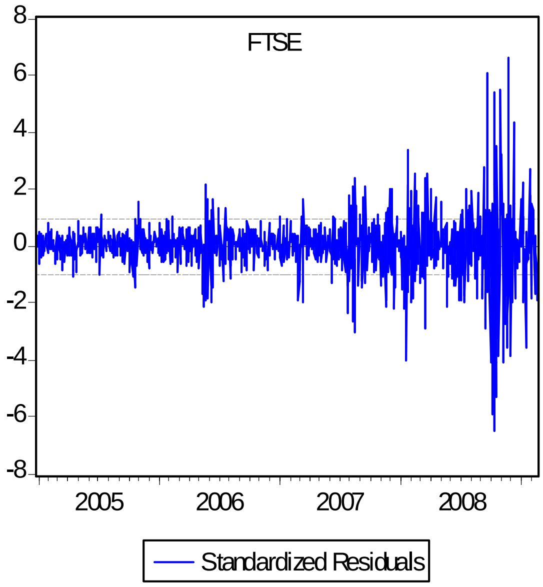
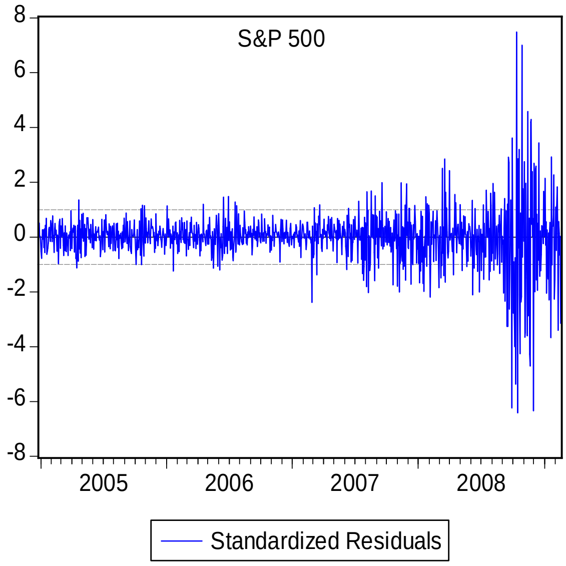
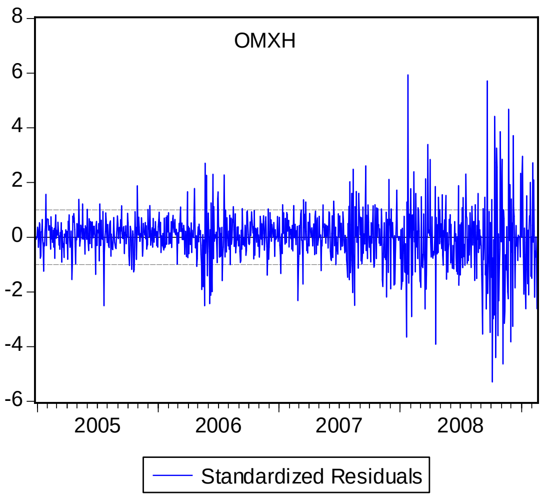
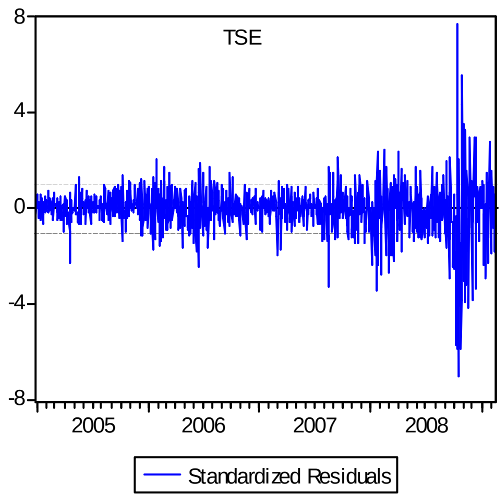
APPENDICES

Appendix 1. Standardized Residuals.

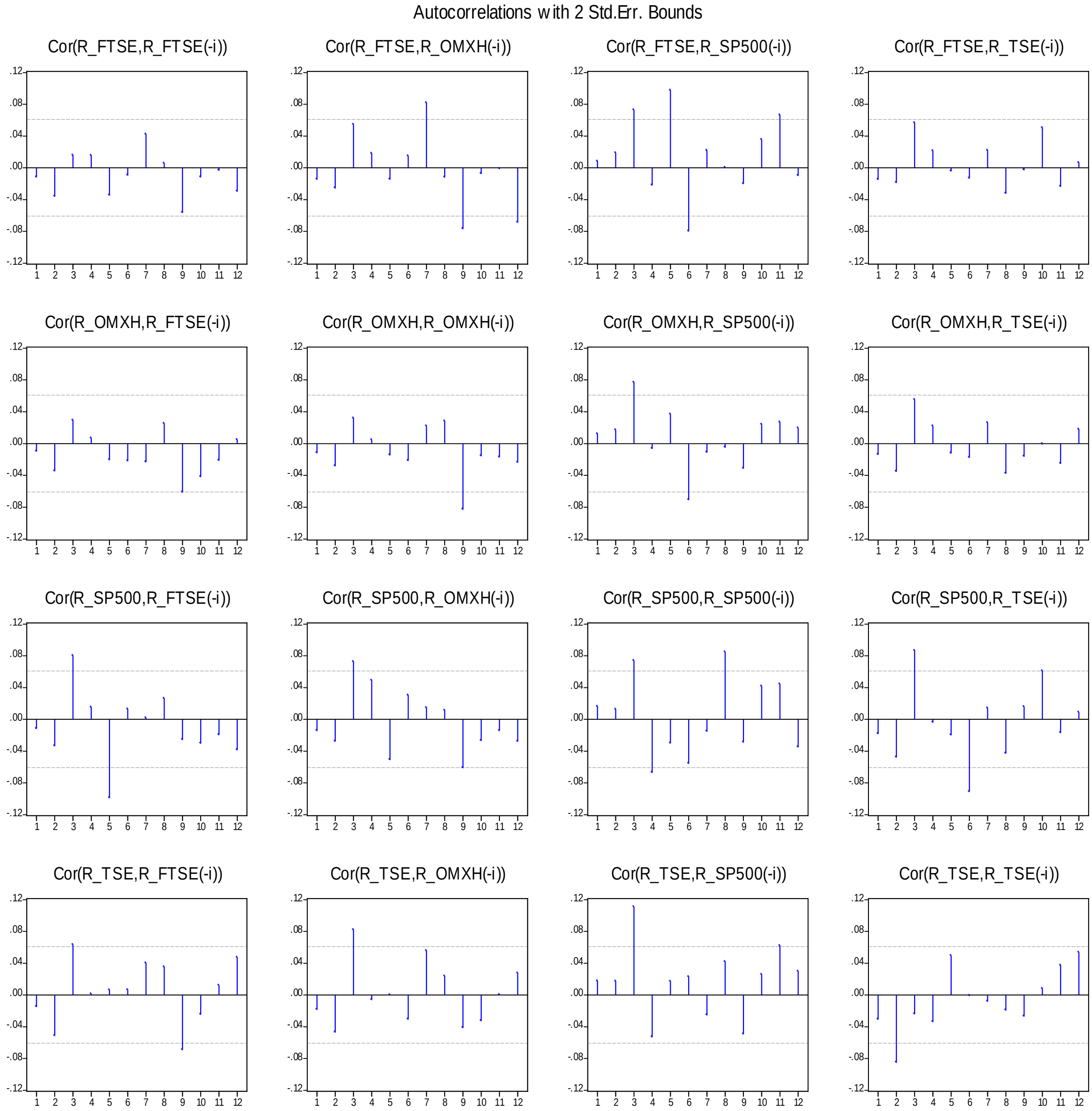








Appendix 2. Standard Error Autocorrelations.



Appendix 3. Vector Autoregression Estimates.

Subsample 1	TSE	OMXH	**Subsample 2**	FTSE	S&P 500
TSE(-1)	-0.252525	-0.048226	FTSE(-1)	-0.202135	0.155637
	(0.03023)	(0.01977)		(0.03385)	(0.05743)
	[-8.35284]	[-2.43973]		[-5.97113]	[2.71018]
TSE(-2)	-0.059274	-0.001549	FTSE(-2)	0.005591	-0.047374
	(0.02548)	(0.01666)		(0.03215)	(0.05453)
	[-2.32636]	[-0.09295]		[0.17391]	[-0.86872]
OMXH(-1)	0.043789	-0.007644	S&P 500(-1)	0.110966	-0.545537
	(0.04691)	(0.03067)		(0.02199)	(0.03730)
	[0.93350]	[-0.24922]		[5.04609]	[-14.6238]
OMXH(-2)	0.094774	0.031514	S&P 500(-2)	0.000895	-0.247162
	(0.04677)	(0.03058)		(0.02241)	(0.03801)
	[2.02620]	[1.03045]		[0.03994]	[-6.50221]
C	-0.013108	-0.002270	C	0.005140	-0.046403
	(0.03800)	(0.02484)		(0.02123)	(0.03601)
	[-0.34497]	[-0.09136]		[0.24211]	[-1.28852]
FTSE	0.395819	0.870705	OMXH	0.661354	0.561934
	(0.04231)	(0.02766)		(0.01650)	(0.02798)
	[9.35622]	[31.4779]		[40.0932]	[20.0813]
S&P 500	0.036498	0.067563	TSE	0.108342	0.096297
	(0.03496)	(0.02286)		(0.01681)	(0.02851)
	[1.04390]	[2.95550]		[6.44604]	[3.37738]
FTSE(-1)	0.391830	0.044433	OMXH(-1)	-0.032859	0.022933
	(0.06120)	(0.04001)		(0.02621)	(0.04447)
	[6.40284]	[1.11049]		[-1.25357]	[0.51573]
S&P 500(-1)	0.404254	0.082738	TSE(-1)	0.056489	0.082769
	(0.04352)	(0.02845)		(0.01737)	(0.02947)
	[9.28963]	[2.90792]		[3.25141]	[2.80829]
FTSE(-2)	-0.015455	-0.033864	OMXH(-2)	-0.048230	0.003268
	(0.05749)	(0.03759)		(0.02617)	(0.04439)
	[-0.26885]	[-0.90097]		[-1.84301]	[0.07362]
S&P 500(-2)	0.148908	0.060651	TSE(-2)	0.005278	0.005539
	(0.04066)	(0.02659)		(0.01428)	(0.02423)
	[3.66199]	[2.28123]		[0.36948]	[0.22856]
R-squared	0.479982	0.706703	R-squared	0.731355	0.361259
Adj. R-squared	0.475113	0.703957	Adj. R-squared	0.728840	0.355278
Sum sq. resids	1655.627	707.7827	Sum sq. resids	517.8381	1490.231
S.E. equation	1.245075	0.814075	S.E. equation	0.696324	1.181248
F-statistic	98.57761	257.3365	F-statistic	290.7511	60.40385
Log likelihood	-1762.019	-1303.553	Log likelihood	-1134.973	-1705.237
Akaike AIC	3.286411	2.436613	Akaike AIC	2.124139	3.181163
Schwarz SC	3.337219	2.487421	Schwarz SC	2.174947	3.231971
Mean dependent	-0.036875	-0.022751	Mean dependent	-0.015971	-0.039874
S.D. dependent	1.718552	1.496191	S.D. dependent	1.337207	1.471143
Determinant resid covariance (dof adj.)		1.024416	Determinant resid covariance (dof adj.)		0.570656
Determinant resid covariance		1.003636	Determinant resid covariance		0.559081
Log likelihood		-3064.027	Log likelihood		-2748.371
Akaike information criterion		5.720162	Akaike information criterion		5.135071
Schwarz criterion		5.821777	Schwarz criterion		5.236687

Appendix 4. Close prices Vs. Returns