Scandinavian Stock Exchanges: volatility persistence and propagation. The case of Denmark and Sweden.

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Abstract

This study examines the linkages in stock return volatility between Scandinavian stock exchanges in Stockholm and Copenhagen and those in UK and US. I use three-variable BEKK Multivariate GARCH model as formulated by Engle and Kroner in 1993. The main findings are that there are direct bilateral linkages between Global Financial centers and Scandinavian Markets.

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Introduction

According to “global centre” hypothesis global stock markets play main role in the transmission and propagation of news that is macroeconomic in nature. On his research for the Globalization and World Cities (GaWC) Research Network Pain (2009) claims that New York and London are highly linked by the interactions that arise internally and among the two cities.[1]

“Because networks represented in London also have a presence in many other cities around the world, London is connected to cities world-wide to different degrees depending on the service networks located in them […] Nevertheless these two cities remain the most connected service nodes in the world together with Hong Kong.”

Although there have been several studies on global stock market linkages (Amin, Rao) studies for the developed markets and some emerging markets in Asia such as China and Malaysia, research on the linkages of the Scandinavian markets with the developed markets is limited. The main goal of this thesis is to examine the linkages in return volatility shocks and volatility persistence transmission and propagation between Scandinavian stock markets and developed markets in UK and US. The top 10 cities in the ranking are given in appendix A. The first two main cities are New York and London. In this thesis I will examine linkages between equity markets in New York represented by Dow Jones Industrial Average index (DJI), London Stock Exchange represented by

[1] K. Pain, “London - The Pre-eminent Global City”, *GaWC Research Bulletin 328* (2009) accessed on http://www.lboro.ac.uk/gawc/rb/rb328.html (May 30, 2010).

Financial Times Stock Index (FTSE) and two Scandinavian stock exchange indices Copenhagen OMX Stock Index and Stockholm OMX Stock index. The choice of the two Scandinavian indices is made intentionally as both of them belong to the OMX AB group since 2003, which in turn has been part of NASDAQ OMX Group since 2008.OMX operates eight stock exchanges in Northern Europe.

No Scholar research has been performed on Scandinavian stock markets volatility within the context of the Multivariate Generalized Conditional Heteroskedasticity model which is employed in this paper. First I estimate the model which includes Scandinavian markets and US market, next I examine UK market linkages with the Scandinavian markets.

The rest of the thesis is organized as follows. In the first chapter I discuss the theoretical background for the BEKK-MGARCH model. Second chapter deals with previous research on the topic. In the next chapter I analyze data properties and perform necessary qualitative tests. In the fourth section I discuss methodology used. In the fifth chapter the empirical results are discussed followed by concluding remarks.

Theoretical background

Univariate GARCH

In his influential seminal paper "The Behavior of the Stock Market Prices" Eugene Fama claims that:

"*There is some evidence that large changes tend to be followed by large changes of either sign, but the dependence from this source does not seem to be too important. There is no evidence at all, however, that there is any dependence in the stock-price series that would be regarded as important for investment purposes. That is, the past history of the series cannot be used to increase the investor's expected profits*".[2]

Time series are challenging to forecast and interest lies not only in forecasting time series but also to measure the risk of investment. Variance and standard deviation of the investment is the most common and standard measure of the risk. Variance of the time series is usually not constant, it fluctuates over time. It can be stationary meaning that long-run variance over long horizon is constant. However in the short run, high variance might be followed by periods of small variance. This change in the volatility of the time series is called volatility clustering. The existence of cyclicality or something similar in the variance of the errors of the regression tells us that there is some autoregressive process within the variance, there is some dynamic relationship in the variance of the time series. Reason for that dynamic is heteroskedasticity. Inflation

[2] Eugene Fama, "The Behavior of Stock-market Prices", The *Journal of Business*, Vol. 38, No. 1 (Jan., 1965):87.

behaves differently when the level of heteroskedasticity is weakly observable and behaves different way during periods of strong heteroskedasticity. In macroeconomics, the Autoregressive Conditional Heteroskedasticity (ARCH) is the test used for non-linear dynamics, while in finance ARCH models are standard tools for modeling. ARCH is the special family of the time series models developed by Engle (1982) to model the variance of asset prices in addition to modeling the prices themselves. Initial model is formulated as follows:

$$y_t = y_{t-1} + \cdots \ + y_{t-n} + \varepsilon_t \qquad\qquad \varepsilon_t \sim N(0, \varepsilon_t^2)$$

$$\varepsilon_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \cdots a_\rho \varepsilon_{t-\rho}^2 \qquad (1)$$

We assume that the $E(\varepsilon_t^2) = \varepsilon_t^2$ is the measure of that error variance in the period t. Where y_t is the return series regressed on its past values. Here the model do not assume that error variance is constant over time, so errors are heteroskedastic and measure this sort of heteroskedasticity by the error variance. In ARCH we write the relationship in terms of squared disturbances. However, we cannot measure disturbances directly, we only have residuals, so we use squared residuals as the measure of squared disturbances and which is what Engle (1982) suggested. The process very much resembles autoregressive (AR) model in which dependent variable is regressed on its own past values, i.e. it is AR process and we just use this process for the error variance. However when we speak about time series we can also have a moving average term. Later Engle's student Bollerslev (1986) extended ARCH model to Generalized ARCH model. Bollerslev suggested the generalization of the autoregressive model which corresponds to Autoregressive Moving Average (ARMA) model of the time series. He suggested that instead of modeling the error residual variance, the theoretical variance of the disturbance term be modeled. Bollerslev (1986) wrote the equation in terms of past residuals and past theoretical variances:

$$H_t = \delta_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_\rho\varepsilon_{t-\rho}^2 + b_1\delta_{t-1}^2 + \cdots + b_q\delta_{t-q}^2 \quad \textbf{(2)}$$

Although Engle (1982) and Bollerslev (1986) introduced ARCH/GARCH methodology almost three decades ago, there has been little research using GARCH modeling in application to stock markets.

Multivariate Models

In order to extend univariate model to n-dimensional model we allow the conditional variance covariance matrix of the of the multidimensional random error term to depend on the elements of the past information set. Generalization of the univariate GARCH formulated by Bollerslev, Engle and Wooldridge (1995):

$$VECH(H_t) = C + \sum_{j=1}^{q} A_j vech(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{j=1}^{p} B_j\, vech(H_{t-j})$$

$$\varepsilon_t \mid I_{t-j} \sim N(0, H_t) \qquad (3)$$

H_t is a function of the information set I_{t-1} that allows elements of the variance covariance matrix to depend on lagged values of ε_t and lagged values of the H_t.

vech (..) is the column stacking operator that transforms the lower triangular of the matrix into a vector. The vech allows full set of interactions between series. Main roughback of the model that it requires estimation of N*(N+1)/2 parameters and it becomes non-feasible task. With three variables in the model the number of parameters estimated is $N^2(N+1)^2/2 \quad + N(N+1)/2$ and it growth with the third power of N. Widely used Multivariate GARCH models are the Constant Conditional Correlation model (CCC) developed by Bollerslev (1988) and BEKK (Baba, Engle, Kraft and Kroner) introduced by Engle and Kroner in1995.

Specifics of the CCC model are that each of the series follows univariate GARCH process and each equation can be run separately. Variance matrix is given by constant correlation coefficient φ which is multiplied by conditional standard deviation of the returns:

$$H_t = G_t F G_t$$

$$h_{iit} = a_{i0} + a_{i1}\varepsilon_{it-1}^2 + b_{i1}h_{iit-1}$$

$$h_{ijt} = \varphi_{ij}\sqrt{h_{iit}h_{jjt}} \qquad \forall i \neq j \qquad \textbf{(4)}$$

Where $G_t = diag(h_{1t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}})$ is the N*N diagonal matrix elements and F=$[\varphi_{ij}]$ is N*N matrix of correlation coefficients which are time invariant. The model allows reducing the number of coefficients to be estimated. Another advantage of the CCC-MGARCH model is that it possible to ensure that H_t has positive definiteness of the conditional correlations and variance matrices. Disadvantage of the CCC model is that it allows only for own effects in the conditional variance equation. Because of the restrictions imposed by CCC-MGARCH model basically it is not differentiable from univariate model. One advantage of the BEKK-MGARCH is that they allow for time varying conditional variance as well as variance and do not impose restriction of cross market innovations in the conditional variance equation to be zero which is imposed in case of univariate GARCH and CCC-MGARCH model. BEKK-MGARCH model ensures the positive semi-definiteness condition of the variance covariance matrix. Multivariate GARCH modeling, especially its BEKK specification which is developed recently, has less number of applied research relative to the univariate research. Moreover, the next difficulty in estimating Multivariate GARCH models is that few software packages are capable to estimate full version of the BEKK-MGRACH model which we discuss later in the methodology section. According to Brooks et al.:

”multivariate GARCH models cannot be estimated using the currently available versions of LIMDEP, MATLAB, MICROFIT, SHAZAM or TSP”.[3]

Several packages have routines for estimating only univariate GARCH models. In my research I used RATS (Regression Analysis of Time Series) software package version 6.

[3] Chris Brooks, Simon Burke,Gita Persand, “Multivariate GARCH Models: Software Choice and Estimation Issues”,*Journal of Applied Economerics* ,Vol.18, No 6, (Nov.-Dec., 2003):728

Literature review

There are several influential pieces of research in the field of stock return volatility using univariate, multivariate GARCH and not only using financial data. An empirical application of the univariate GARCH work done by Long (2008). Long examines the stock return volatility in the Vietnam stock market using univariate GARCH. One of the peculiarities of this research is that it takes into account regime changes that occur during last two decades in the Vietnamese society. The consequences of gradual financial liberalization of the stock market and society in general are accounted for by using dummy variables for each event. Specifically, Long found evidence that transition to free market has negative correlation with stock return volatility of the three Vietnamese stock exchanges. However accounting for regime changes reduced persistence of the volatility by almost one third. He concluded for the period of transition estimates that excluding regime change dummies leads to misleading results, and causes less reliable estimation of conditional variance

Due to successful performance of the univariate GARCH models in describing variance covariance matrix of the financial data, studies (Li, Karolyi) extending GARCH to Multivariate dimension has become more popular among applied researchers.

Li (2007) investigates the linkages between two mainland Chinese markets and two mature markets in Hong Kong and in the US. He explores Four-Variable BEKK-MGARCH model proposed by Engle and Kroner (1993) to analyze the markets. He found no relation between stock exchanges between mainland China and the US markets; however, he found unidirectional return spillover from S&P 500 representing US markets to Hong Kong and from Hong Kong to the mainland Chinese markets, which confirmed the hypothesis that return spills over from developed to developing markets. Restricted model that excluded US market showed no relationship between Hong Kong and mainland markets, i.e. the specification that assumes nonexistence of the US market shows that relations between Hong Kong and mainland markets disappear. He suggests that linkages between Hong Kong and those in mainland China have something to do with linkages between S&P 500 and Hang Seng. Li claims that:"Hong Kong has acted as go-between in the information flow"[4]. Moreover he found no relationship between two developing markets, which leads to conclusion that domestic economic parameters do not affect the shaping of the Chinese stock markets. Own past innovations are significant for all four markets and affect volatility, however Li found that own past volatility persistence is smallest for mainland markets indicating that they derive smaller part of their volatility from past volatility.

One of the first papers using MGARCH methodology was written by Karolyi (1995), in which he examines the linkages between Canadian and US markets. He performs his analysis on the basis of relatively old sample between 1981 and 1989. His contribution to the model was that he accounted for weekend effect and for holiday effect, anomalies of the efficient stock market, by including dummies: Hol_t which he used to isolate days after holidays and $WKND_t$ which is one for days following weekends. One of the main findings was that during the late 1980's, the amplitude of the innovations originated in US had decreasing effect on those of Canada. The second main finding was that shocks originating in US have different effect for interlisted and non-interlisted Canadian stocks. It implies that trade barriers for foreign investors in

[4]Hong Li, "International linkages of the Chinese stock exchanges: a multivariate GARCH analysis", *Applied Financial Economics*, 17: 4(2007): 295.

Canada affect the dynamics of the stocks returns responses to shocks that originate in US markets. He concluded that that the effect of the innovations from US market returns for the Canadian market returns and volatility are smaller and less persistent when using MGARCH models compared to vector autoregressive models.

Another research on stock markets using MGARCH was done by Worthington and Higgs (2004) who analyses the volatility transmission among the largest number of countries namely Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand and three developed Asian markets-Japan, Singapore and Hong Kong. The results indicate the presence of significant own-volatility spillover in all markets and it is higher for emerging markets than for developed except for Hong Kong. Japan has the greatest impact in terms of innovations on emerging markets. Volatility persistence in developed countries is lower, which implies that the larger source of volatility for the developed markets is foreign markets, while emerging markets derive their volatility persistence from domestic market.

Rao (2008) uses VAR and MGARCH methodology to examine the volatility propagation across six Middle East emerging markets which show impressive growth in terms of market capitalization, with Kuwait having the highest growth of 724% from 2003 to 2006, while the lowest growth of 131% was discovered in Bahrain. The results indicated the presence of significant own innovations for most of the markets. Own volatility persistence is significant but predominantly negative.

The study by Amin and Imam examines the stock markets of the G-7 countries using VAR-EGARCH.[5] Significant influence of the US markets on other developed markets was detected. Japanese markets are heavily influenced by US, UK and French markets, while other European markets showed dependence from Japanese markets.

Worthington[6] et al. applies MGARCH methodology to examine price volatility among main Australian electricity markets. He identifies the sources and amplitudes of shocks and propagation. His main finding was that also there are natural barriers to the interconnection between electricity markets, shocks and volatility in one market has an influence on the others.

In my thesis I use trivariate BEKK-MGARCH specification to learn linkages between Scandinavian Stock markets in Stockholm and Copenhagen and Global financial center such as New York and London using the latest observable period till April 9 2010.

[5] Abu Saleh M.Muntasir Amin, Mahmood Osman Imam, "Transmission of Stock Return and Volatility Across G-7 Countries", accessed on http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1119543 (May 30, 2010).

[6] Worthington, A. C. Higgs, H. 2003. "A multivariate GARCH analysis of the domestic transmission of energy commodity prices and volatility: A comparison of the peak and off-peak periods in the Australian electricity spot market" Discussion Paper No. 140. [Working Paper] (Unpublished)

Data Description

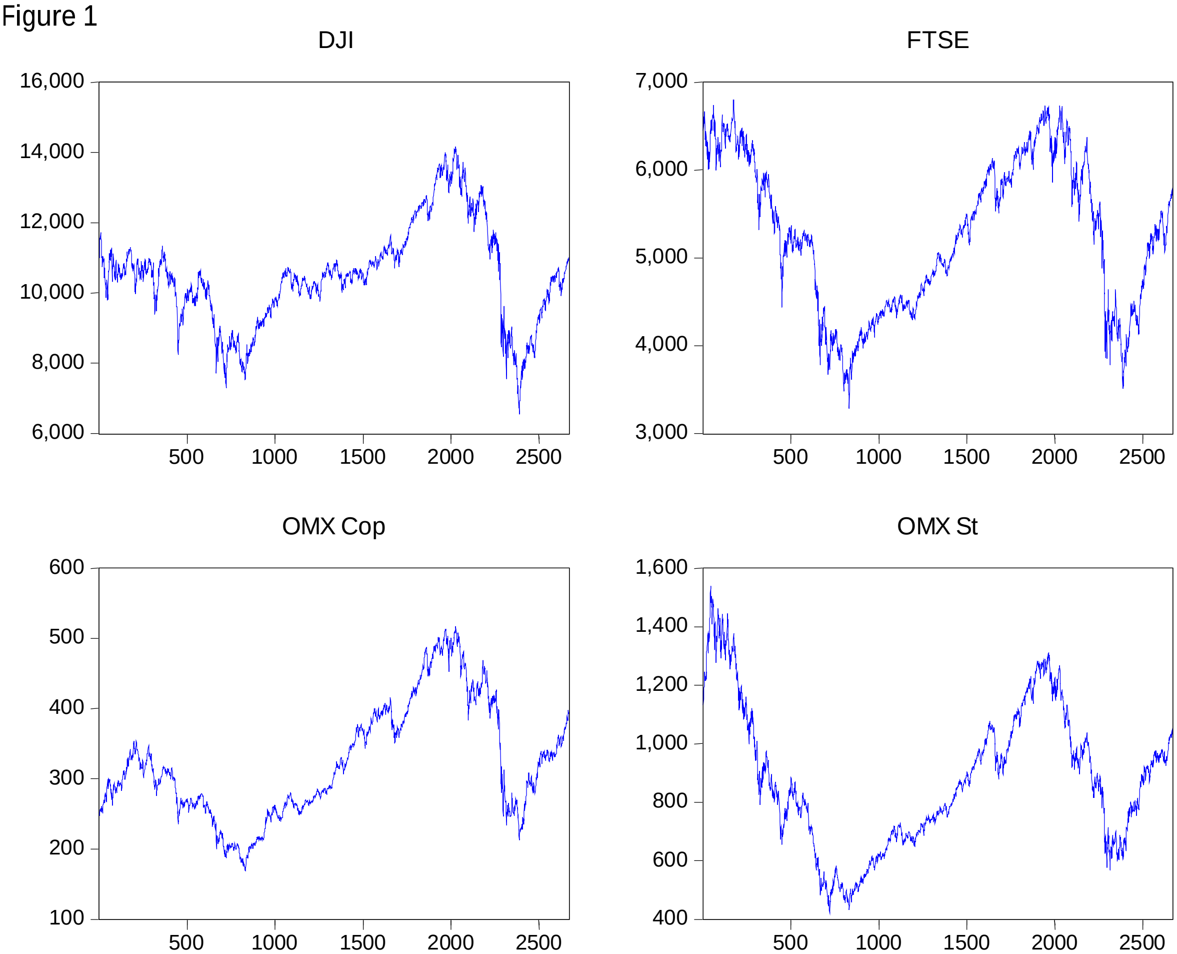
In this study I use stock markets in Copenhagen and Stockholm to represent Scandinavian countries because the Stockholm stock exchange and Copenhagen Stock exchange are mature stock markets in terms of capitalization and turnover. The time series dataset used was downloaded from the Yahoo Finance on April 11 2010. The data consists of daily closing stock market index values of the four stock exchanges, namely London Stock Exchange index(FTSE), OMX Stockholm stock index, OMX Copenhagen Stock index and New York Stock Exchange index(DJI). DJI is a price weighted index that uses 30 largest companies traded in the market. Financial Times Ordinary Share Index is the geometric average of major stocks on the London stock Exchange. OMX Stockholmsborsen All-Share Index includes all listed stocks on the A- and the O-list. The OMX Copenhagen Index is a capitalization-weighted index of the all stocks traded on the Copenhagen Stock Exchange. The index was developed with a base value of 100 as of December 31, 1995.[7]

Dataset includes the time interval encompassing the days starting from 4th January 2000 till 9th April 2010. The sample has 2670 observations and all the data was collected on the same dates over the stock exchange. The sample starts from 4th January 2000 represents the largest period of time where daily observations for all four indices were available. Any missing values due to differences in nonsynchronous trading in countries under observation were replaced by the previous trading day's closing index value. All data taken is in domestic currency terms, which imply that we are hedged against currency exchange rate fluctuations.

[7] Definitions of the Copenhagen Stock index and Stockholm Stock index are taken from Bloomberg.com
http://www.bloomberg.com/apps/quote?ticker=KAX:IND

Figure1 below shows the original series of the four mentioned series. From first sight it seems that all four indices follow similar pattern, but after looking more closely we can see that DJI and OMX Copenhagen move together more closely and simultaneously, while FTSE does the same with OMX Stockholm. One can notice that all markets plunged during crisis in 2001 with Copenhagen and London exchanges facing the highest losses. All indices experienced heavy downturn from august 2007. From the end of 2008 and beginning of 2009 all markets experience growth and recovery.

Figure 1



I perform Augmented Dickey –Fuller test for unit root which outcomes show that all the series are integrated of order 1 and the result is highly robust at 1% significance level. Results reported in table 1 show that all the differenced series are stationary, thus I will use first differences of the log series to capture stochastic properties of the stock indices:

RDJI=log(DJI/DJI{-1})

RFTSE=log(FTSE/FTSE{-1})

ROMXC = log(OMXC/OMXC{-1})

ROMXSt = log (OMXSt/OMXSt{-1})

Where DJI,FTSE,OMXC,OMXSt is the stock index on the day t; DJI{-1}, FTSE{-1}, OMXC{-1}, OMXSt{-1} is the stock index value on the day t-1.

Table 1. ADF test

Null hypothesis: returns are non-stationary	t-statistics	Prob.
RDJI	-40.88499	0.0000
RFTSE	-26.75173	0.0000
ROMXC	-49.96658	0.0001
ROMXSt	-54.30497	0.0001

Kim et al. (1993) claimed that ADF test are not robust in the presence of GARCH errors. Since sample is large and minimum sample requirement of five hundred observations for KPSS test is met, I perform KPSS test to check results of the unit root test. KPSS test confirms the results given by ADF test. Figure 2 shows that all return series have the property of volatility clustering. There are periods of high volatility followed by periods of low volatility. Stockholm and London exchanges have relatively high volatility around the end of 2001 beginning of 2002, and all four series suffer from high volatility around October 2008 and August 2009. Clusters prone to occur simultaneously so heteroskedasticity must be modeled systematically.

Figure 2.Original return series.

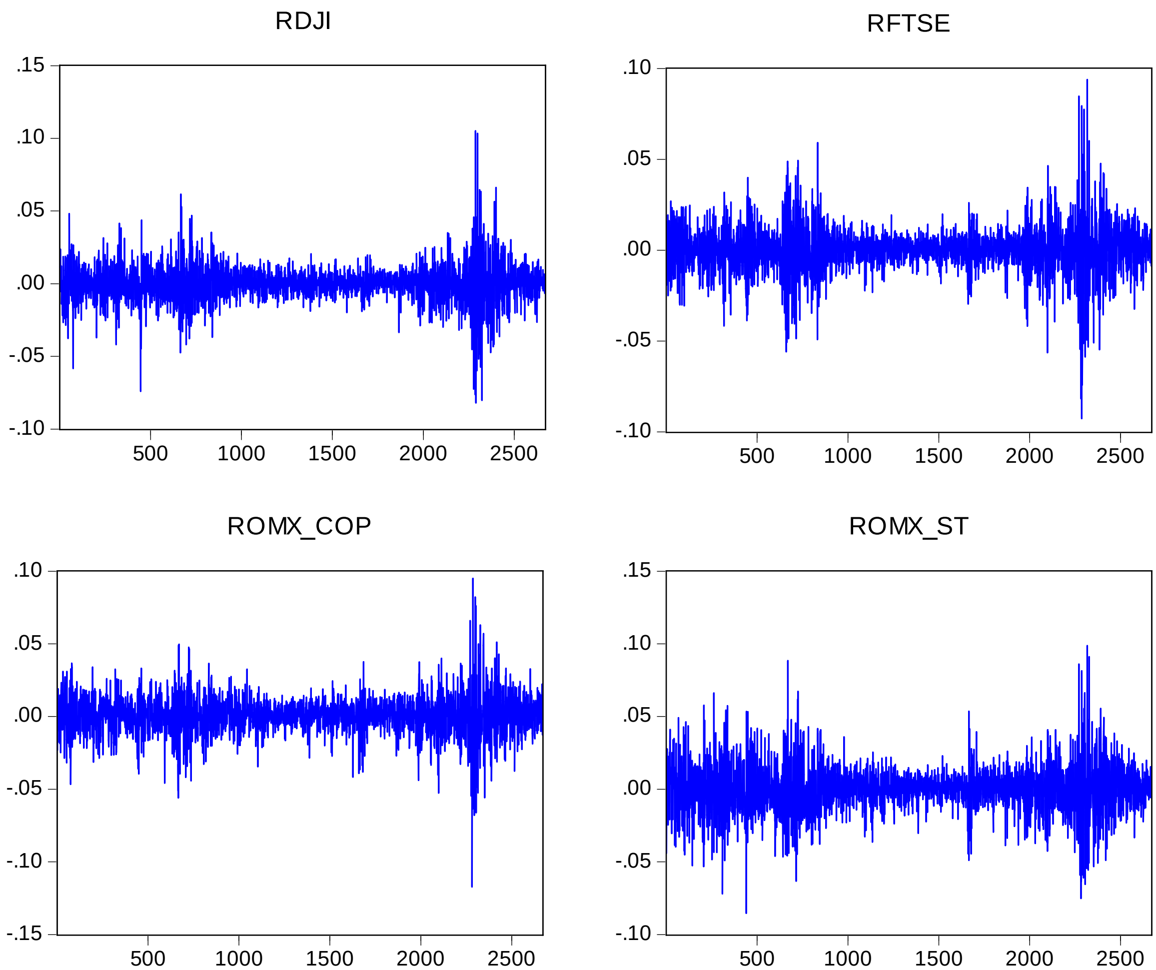


Table 2 reports wide range of descriptive statistics for four return series. Mean, median, standard deviation, skewness, kurtosis, maximum and minimum values are presented.

Table 2.Summary statistics of the return series.

	RDJI	RFTSE	ROMX_COP	ROMX_ST
Mean	1.86E-06	-5.38E-05	0.000166	-4.64E-05
Median	0.000144	0.000000	0.000000	0.000000
Maximum	0.105083	0.093842	0.094964	0.098650
Minimum	-0.082005	-0.092646	-0.117232	-0.085269
Standard deviation	0.012832	0.013112	0.013559	0.016726
Skewness	0.008009	-0.114755	-0.253490	0.122472
Kurtosis	11.00012	9.427252	9.149700	6.119688
Jarque–Bera	7112.249	4599.826	4234.351	1088.186
Probability	0.000000	0.000000	0.000000	0.000000
Observations	2667	2669	2669	2667

All return series are non-normally distributed. Zero hypotheses of normally distributed returns are rejected by highly significant Jarque-Bera statistics. The p-values used to test the hypothesis are all zero. Returns for FTSE and OMXC have negative skewness which is an indication of the fact that negative shocks are dominant for those markets and this two series have longer tails to the left. In contrast returns of DJI and OMXSt have positive skewness. Kurtosis values exceed the kurtosis of normal distribution of 3. In general all return series are leptokurtic, which is common feature of the financial data. These results are consistent with the findings of Fama (1965) when he reported that stock market returns have leptokurtic distribution with fatter tails and kurtosis higher than normal. The performance of the markets measured by the mean is positive for the RDJI and ROMXC, which indicates that over the 10 year period, average returns were positive although very close to zero. Mean of the RFTSE and ROMXSt is negative, which in turn indicates that average returns over the observed period were negative. The median is positive only for RDJI, i.e. there were more days with positive returns than negative, more days when stock exchange was increasing than number of days when it was decreasing. All other stock exchanges have equal numbers of negative and positive days. The range of returns is quite high. The maximum return of 10.5% is characterizes DJI and the lowest of 11.7% is in the OMXC. Non-normal distribution and volatility clustering is the signs that there is autonomous process in the residuals, which can be systematically modeled. Volatility which is measured by standard deviation of the return series is largest on Swedish with value of 1.6% and smallest in US with value of 1.2%. Finally I apply two-step testing procedure developed by Engle (1982) to test for the ARCH/GARCH process in the residual term. I run OLS estimation for each of the return series with constant being an explanatory variable and save the residuals from that estimation. Using squared residuals for the AR process with lag length defined by Akaike information criteria, I test the hypothesis that lagged squared error terms are all equal zero. Results of the test are given in Appendix C. Although from the tables one can see that some of the lags are insignificant, there were lags that are different from zero and they are jointly significant at the 5% significance level. I conclude that there is ARCH process in the residuals, so GARCH models can be used to model the process. GARCH (1, 1) is preferred to ARCH model for the sake of parsimony.

Methodology

The following Tri-variate GARCH model in the style proposed by Engle and Kroner(1993) is used to study the joint processes relating to the stock exchange market's daily rates of return. The estimation of multivariate models similar in style to BEKK-MGARCH is complicated and can lead to difficulties in getting convergence. Kasch-Haroutounian and Price (1998) reported difficulties in obtaining convergence of the four central European stock markets namely Hungary, Czech Republic, Poland and Slovakia. My initial full four-variable multivariate BEKK-GARCH model failed to converge during estimation. Problem with convergence may arise due to that objective function is too flat, or too convoluted in the neighborhood of the actual location, and the gradient does not point to any meaningful dimension. I tried to re-estimate the model by adding sub iteration limits and tried to change starting values. Unfortunaly the actions taken to correct the situation did not help so I estimated tri-variate model.

I present the results of the tri-variate MGARCH (1,1) for Swedish, Danish and US return series in the first case and Swedish, Danish and UK return series in the second estimation. The specification of the tri-variate BEKK is as follows:

$$\boldsymbol{R}_t = \alpha + \boldsymbol{A}\boldsymbol{R}_{t-1} + \varepsilon_t \qquad \boldsymbol{\varepsilon}_t \mid \boldsymbol{I}_{t-1} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{H}_t) \qquad (5)$$

Equation (1) estimates the stock market returns as a VAR(1), the multivariate construction enables us to measure the effects of a shock in lagged return in one market on its own return and that of the other market. $\mathbf{R_t}$ is the 3*1 vector of daily returns at time t and A is a 3*3 matrix of parameters which measure the degree of mean spillover between the markets or, in other words , the diagonal elements measure the effect of own past returns, while off-diagonal elements measure mean spillover across the markets. ε_t is the 3*1 matrix of innovations which has 3*3 variance covariance matrix H_t. I_t represents the information set which is available at time t-1.

$$H_t = CC' + A\varepsilon_t\varepsilon_{t-1}A' + BH_{t-1}B' \qquad (6)$$

In the equation 5, C is the upper triangular matrix of constants, the elements of the symmetric matrix A, a_{ij} measure the effect of innovation in market *i* on market *j*. The diagonal elements measure own innovation effect of market *i*.

Matrix B is symmetric and its elements b_{ij} measure the persistence of conditional volatility spillover between markets, while diagonal elements measure the own volatility persistence. In matrix form this can be expressed as:

$$H_t = \begin{bmatrix} c_{01} & c_{02} & c_{03} \\ 0 & c_{04} & c_{05} \\ 0 & 0 & c_{06} \end{bmatrix}' \begin{bmatrix} c_{01} & c_{02} & c_{03} \\ 0 & c_{04} & c_{05} \\ 0 & 0 & c_{06} \end{bmatrix}$$

$$+\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon_{3,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

$$+\begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \quad (7)$$

Under the assumption of normality, the model can be estimated by maximizing the log-likelihood function for the MGARCH model:

$$L_t = \frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon'_t H_t^{-1}\varepsilon_t$$

$$L = \sum_{t=1}^{T} L_t$$

(8)

Maximization was done by applying the BFGS (Broyden, Fletcher, Goldfarb and Shanno) iteration procedure to maximize the following log-likelihood function L_t

Empirical results

Table 2 below contains the estimated results for the conditional variance equations.

Own ARCH effect

In case of US, Sweden and Finland, own past innovations are significant for Stockholm and New York; however, for Copenhagen it is insignificant. The amplitude of the response to own past shocks is only 0.8% for Copenhagen and 83% for New York. For the second regression that includes UK stock market own ARCH effects are statistically significant for all three markets and magnitude is between 16% and 30% for Copenhagen and Stockholm correspondingly.

Cross ARCH effect

In the case of US, Sweden and Denmark, neither innovations in Sweden market nor US market transmit to the Denmark. However, there is bilateral innovation spillover between US and Sweden. The past shocks in Swedish stock market increase volatility in US market by a small amount of only 0.75%.The effect of US shocks on Swedish market is much higher - 44%.

In case of UK and Scandinavian markets all cross innovation effects are significant. There are bilateral linkages between all markets and UK is the most influential. A 1% shock in UK decreases volatility in the next period by 0.4% and 0.39% in Denmark and Sweden correspondingly.

Own GARCH effects

Own volatility persistence, which are represented by beta coefficients that are on the main diagonal as in the case of ARCH effects are significant only for Sweden and US markets both having value of around 17%,which converts 1% increase in own past volatility to increase in current volatility by 0.17%.

In case of UK all own volatility persistence estimates are significant with the highest persistence of 30% in London.

Cross GARCH effect

US volatility persistence propagates to the Swedish and Danish markets, however in opposite direction there is only propagation of 0.5% from Danish market. There is unidirectional volatility persistence propagation from Sweden to Denmark.

Volatility persistence propagates from UK market to both Scandinavian markets and vice versa. Unidirectional linkages exist between Denmark and Sweden. Danish market has cross volatility persistence which spills over to Sweden market (0.22%).

Table 2. Estimated coefficients for the tri-variate BEKK- MGARCH model for the full sample

	Denmark(i=1)		Sweden(i=2)		US(i=3)	
	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
a_{i1}	0.63190	(0.2262)	0.86942	(0.5579)	0.0101	(0.6092)
a_{i2}	0.00939	(0.0890)	-0.00858	(0.0000)	0.0075	(0.0004)
a_{i3}	0.02255	(0.8299)	-0.44014	(0.0000)	0.8316	(0.0000)
b_{i1}	-0.06382	(0.2610)	0.19330	(0.3215)	0.0054	(0.0398)
b_{i2}	0.00915	(0.0022)	0.17185	(0.0000)	-0.0002	(0.3250)
b_{i3}	0.777561	(0.0009)	-0.23534	(0.0000)	0.1729	(0.0030)

	Denmark(i=1)		Sweden(i=2)		UK (i=3)	
	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
a_{i1}	0.16829	(0.0014)	-0.2353862	(0.0000)	0.0706836	(0.0000)
a_{i2}	-0.00913	(0.0000)	-0.2983257	(0.0000)	0.2929448	(0.0000)
a_{i3}	-0.04300	(0.0046)	-0.3984350	(0.0000)	0.2812429	(0.0000)
b_{i1}	0.23295	(0.0000)	0.2240944	(0.0000)	-0.2308235	(0.0000)
b_{i2}	0.00454	(0.6374)	-0.212468	(0.0000)	0.0546879	(0.0000)
b_{i3}	0.08766	(0.0021)	-0.5833730	(0.00001)	0.3086374	(0.0000)

Results discussed suggest that “global centre” hypothesis does not hold in this case. There is volatility spillover not only from global markets to Scandinavian markets but also movement in the opposite direction. Explanation for this could be that Scandinavian Markets serve as a proxy for other European markets that are not included. It is highly unlikely that US and UK markets are directly influenced by Scandinavian markets; they just serve as representatives of some common European stock market, there may be common European innovations that are also present in Scandinavian Markets. Kroner (1998) in his study of the performance of various multivariate models came to conclusion that results obtained can heavily depend on the choice of a volatility model and restrictions imposed by them.

Conclusion

This study has examined the transmission of the volatility innovations and volatility persistence of the two Scandinavian equity markets in Stockholm and Copenhagen and two global capital markets in New York and London. The study encompassed the period of ten years from 2000 to 2010. A Multivariate Autoregressive Generalized Heteroskedasticity model (MGARCH) was explored to identify the direction, magnitude and persistence of the spillovers. Although volatility spillovers from Global equity markets to those in Scandinavia were not surprising, the bidirectional volatility transmission and persistence is an outcome that was unexpected. Common sense explanation for that is that Scandinavian markets serve as a proxy for the common European market.

This paper could be extended in several ways. One improvement could be to division of the sample to several subsamples to account for periods of high volatility and possible structural breaks. Second approach could be to check existence of the linkages by using other specification. This would allow us to empirically check the linkages although would not be guarantee that results would be meaningful and easy to get due to large set of restrictions imposed on other models rather than on BEKK-MGARCH specification.

Appendix A

Ranking of the cities according to GaWC

	GNC	2008
1	London	100,00
2	New York	99,45
3	Hong Kong	82,16
4	Paris	76,68
5	Singapore	73,63
6	Sydney	72,78
7	Tokyo	72,50
8	Shanghai	70,36
9	Beijing	70,21
10	Milan	68,33

Appendix B

Unit root test for Actual series:

Null Hypothesis: DJI has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.940535	0.3138
Test critical values:	1% level	-3.432613	
	5% level	-2.862426	
	10% level	-2.567286	

Null Hypothesis: FTSE has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.997108	0.2883
Test critical values:	1% level	-3.432611	
	5% level	-2.862425	
	10% level	-2.567286	

Null Hypothesis: OMX_COP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.344858	0.6106
Test critical values:	1% level	-3.432608	
	5% level	-2.862423	
	10% level	-2.567285	

Null Hypothesis: OMX_ST has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.737101	0.4124
Test critical values:	1% level	-3.432610	

	5% level	-2.862424	
	10% level	-2.567285	

Unit root test results for differenced series:

Null Hypothesis: D(DJI) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-40.88499	0.0000
Test critical values:	1% level	-3.432613	
	5% level	-2.862426	
	10% level	-2.567286	

Null Hypothesis: D(FTSE) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.75173	0.0000
Test critical values:	1% level	-3.432611	
	5% level	-2.862425	
	10% level	-2.567286	

Null Hypothesis: D(OMX_COP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-49.96658	0.0001
Test critical values:	1% level	-3.432609	
	5% level	-2.862424	
	10% level	-2.567285	

Null Hypothesis: D(OMX_ST) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-54.30497	0.0001
Test critical values:	1% level	-3.432611	
	5% level	-2.862425	
	10% level	-2.567286	

Appendix C

Dependent Variable: RES_DJI
Method: Least Squares
Date: 05/23/10 Time: 11:35
Sample (adjusted): 10 2670
Included observations: 2651 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_DJI(-1)	-0.024589	0.019450	-1.264269	0.2062
RES_DJI(-2)	0.210729	0.019251	10.94619	0.0000
RES_DJI(-3)	0.038103	0.019459	1.958106	0.0503
RES_DJI(-4)	0.055370	0.019221	2.880684	0.0040
RES_DJI(-5)	0.160387	0.019221	8.344195	0.0000
RES_DJI(-6)	0.151977	0.019469	7.806224	0.0000
RES_DJI(-7)	0.143352	0.019258	7.443625	0.0000
RES_DJI(-8)	0.023592	0.019455	1.212658	0.2254
C	3.94E-05	1.01E-05	3.902380	0.0001

R-squared	0.232057	Mean dependent var	0.000165
Adjusted R-squared	0.229732	S.D. dependent var	0.000522
S.E. of regression	0.000458	Akaike info criterion	-12.53551
Sum squared resid	0.000554	Schwarz criterion	-12.51554
Log likelihood	16624.82	Hannan-Quinn criter.	-12.52828
F-statistic	99.79491	Durbin-Watson stat	2.005266
Prob(F-statistic)	0.000000		

Dependent Variable: SQRES_RFTSE
Method: Least Squares
Date: 05/23/10 Time: 20:53
Sample (adjusted): 10 2670
Included observations: 2661 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQRES_RFTSE(-1)	0.038388	0.019410	1.977694	0.0481
SQRES_RFTSE(-2)	0.136710	0.019423	7.038482	0.0000
SQRES_RFTSE(-3)	0.171430	0.019590	8.750763	0.0000
SQRES_RFTSE(-4)	0.140378	0.019385	7.241579	0.0000
SQRES_RFTSE(-5)	0.225130	0.019385	11.61367	0.0000
SQRES_RFTSE(-6)	0.036319	0.019591	1.853904	0.0639
SQRES_RFTSE(-7)	-0.008212	0.019423	-0.422769	0.6725
SQRES_RFTSE(-8)	-0.026994	0.019409	-1.390796	0.1644
C	4.92E-05	9.79E-06	5.027631	0.0000

R-squared	0.227622	Mean dependent var	0.000172
Adjusted R-squared	0.225292	S.D. dependent var	0.000500
S.E. of regression	0.000440	Akaike info criterion	-12.61714

Sum squared resid	0.000513	Schwarz criterion	-12.59723
Log likelihood	16796.10	Hannan-Quinn criter.	-12.60993
F-statistic	97.69419	Durbin-Watson stat	1.995415
Prob(F-statistic)	0.000000		

Dependent Variable: RES_ROMX_COP
Method: Least Squares
Date: 05/23/10 Time: 11:42
Sample (adjusted): 10 2670
Included observations: 2661 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_ROMX_COP(-1)	0.053864	0.019412	2.774835	0.0056
RES_ROMX_COP(-2)	0.150543	0.019383	7.766831	0.0000
RES_ROMX_COP(-3)	0.025271	0.019600	1.289349	0.1974
RES_ROMX_COP(-4)	0.117517	0.018667	6.295305	0.0000
RES_ROMX_COP(-5)	0.309037	0.018667	16.55518	0.0000
RES_ROMX_COP(-6)	-0.013702	0.019602	-0.699009	0.4846
RES_ROMX_COP(-7)	0.076779	0.019385	3.960841	0.0001
RES_ROMX_COP(-8)	0.025467	0.019411	1.311979	0.1896
C	4.70E-05	1.03E-05	4.584692	0.0000

R-squared	0.247753	Mean dependent var	0.000184
Adjusted R-squared	0.245484	S.D. dependent var	0.000525
S.E. of regression	0.000456	Akaike info criterion	-12.54301
Sum squared resid	0.000552	Schwarz criterion	-12.52310
Log likelihood	16697.48	Hannan-Quinn criter.	-12.53581
F-statistic	109.1799	Durbin-Watson stat	2.004063
Prob(F-statistic)	0.000000		

Dependent Variable: RES_ROMX_ST
Method: Least Squares
Date: 05/23/10 Time: 11:44
Sample (adjusted): 10 2670
Included observations: 2651 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_ROMX_ST(-1)	0.074360	0.019455	3.822165	0.0001
RES_ROMX_ST(-2)	0.091478	0.019498	4.691575	0.0000
RES_ROMX_ST(-3)	0.123761	0.019514	6.342290	0.0000
RES_ROMX_ST(-4)	0.062643	0.019491	3.213903	0.0013
RES_ROMX_ST(-5)	0.132785	0.019494	6.811479	0.0000
RES_ROMX_ST(-6)	0.081184	0.019514	4.160354	0.0000
RES_ROMX_ST(-7)	0.032837	0.019535	1.680945	0.0929
RES_ROMX_ST(-8)	0.013024	0.019461	0.669256	0.5034
C	0.000108	1.50E-05	7.237633	0.0000

R-squared	0.118237	Mean dependent var	0.000279

Adjusted R-squared	0.115567	S.D. dependent var	0.000634
S.E. of regression	0.000596	Akaike info criterion	-12.00945
Sum squared resid	0.000938	Schwarz criterion	-11.98947
Log likelihood	15927.52	Hannan-Quinn criter.	-12.00222
F-statistic	44.28361	Durbin-Watson stat	2.003591
Prob(F-statistic)	0.000000		

RDJI

Heteroskedasticity Test: ARCH

F-statistic	127.8771	Prob. F(4,2654)	0.0000
Obs*R-squared	429.6626	Prob. Chi-Square(4)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/23/10 Time: 20:48
Sample (adjusted): 6 2670
Included observations: 2659 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.03E-05	1.03E-05	6.830249	0.0000
RESID^2(-1)	0.056544	0.019280	2.932796	0.0034
RESID^2(-2)	0.282316	0.019174	14.72370	0.0000
RESID^2(-3)	0.117075	0.019174	6.105963	0.0000
RESID^2(-4)	0.115818	0.019277	6.008007	0.0000

R-squared	0.161588	Mean dependent var	0.000164
Adjusted R-squared	0.160324	S.D. dependent var	0.000521
S.E. of regression	0.000478	Akaike info criterion	-12.45330
Sum squared resid	0.000606	Schwarz criterion	-12.44223
Log likelihood	16561.66	Hannan-Quinn criter.	-12.44929
F-statistic	127.8771	Durbin-Watson stat	2.047473
Prob(F-statistic)	0.000000		

RFTSE

Heteroskedasticity Test: ARCH

F-statistic	152.3994	Prob. F(4,2660)	0.0000
Obs*R-squared	496.8739	Prob. Chi-Square(4)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/23/10 Time: 20:49
Sample (adjusted): 6 2670
Included observations: 2665 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.30E-05	9.81E-06	6.422928	0.0000
RESID^2(-1)	0.080212	0.019147	4.189159	0.0000
RESID^2(-2)	0.184710	0.018771	9.839939	0.0000
RESID^2(-3)	0.210518	0.018772	11.21452	0.0000
RESID^2(-4)	0.157411	0.019147	8.221165	0.0000

R-squared	0.186444	Mean dependent var	0.000172
Adjusted R-squared	0.185221	S.D. dependent var	0.000499
S.E. of regression	0.000451	Akaike info criterion	-12.56957
Sum squared resid	0.000540	Schwarz criterion	-12.55852
Log likelihood	16753.95	Hannan-Quinn criter.	-12.56557
F-statistic	152.3994	Durbin-Watson stat	2.069508
Prob(F-statistic)	0.000000		

Romx_cop
Heteroskedasticity Test: ARCH

F-statistic	121.2160	Prob. F(4,2660)	0.0000
Obs*R-squared	410.8803	Prob. Chi-Square(4)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/23/10 Time: 20:50
Sample (adjusted): 6 2670
Included observations: 2665 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.66E-05	1.06E-05	7.233152	0.0000
RESID^2(-1)	0.104247	0.019150	5.443600	0.0000
RESID^2(-2)	0.210836	0.019135	11.01805	0.0000
RESID^2(-3)	0.110853	0.019136	5.793044	0.0000
RESID^2(-4)	0.156541	0.019149	8.174838	0.0000

R-squared	0.154176	Mean dependent var	0.000184
Adjusted R-squared	0.152905	S.D. dependent var	0.000525
S.E. of regression	0.000483	Akaike info criterion	-12.43016
Sum squared resid	0.000621	Schwarz criterion	-12.41912
Log likelihood	16568.19	Hannan-Quinn criter.	-12.42616
F-statistic	121.2160	Durbin-Watson stat	2.100952
Prob(F-statistic)	0.000000		

Heteroskedasticity Test: ARCH

F-statistic	66.65486	Prob. F(4,2654)	0.0000
Obs*R-squared	242.7365	Prob. Chi-Square(4)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/23/10 Time: 20:51
Sample (adjusted): 6 2670
Included observations: 2659 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000145	1.43E-05	10.10494	0.0000
RESID^2(-1)	0.103306	0.019330	5.344418	0.0000
RESID^2(-2)	0.126822	0.019187	6.609684	0.0000
RESID^2(-3)	0.158068	0.019186	8.238766	0.0000
RESID^2(-4)	0.090900	0.019302	4.709428	0.0000

R-squared	0.091289	Mean dependent var	0.000279
Adjusted R-squared	0.089919	S.D. dependent var	0.000633
S.E. of regression	0.000604	Akaike info criterion	-11.98503
Sum squared resid	0.000967	Schwarz criterion	-11.97396
Log likelihood	15939.10	Hannan-Quinn criter.	-11.98102
F-statistic	66.65486	Durbin-Watson stat	2.026367
Prob(F-statistic)	0.000000		

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