MULTIVARIATE VOLATILITY AND SPILLOVER EFFECTS IN FINANCIAL MARKETS CASE STUDY USA AND MAJOR EUROPEAN STOCK MARKETS

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Abstract
This Paper Examine the Spillover Effect between USA and Major European Stock Markets .This issue is carried out through DCC form of EGARCH model by Nelson 1991. The empirical evidence suggests that there is spillover effect from London market to New York, Pairs and Frankfurt stock markets, Within the Europe Stock Markets there are unidirectional volatility spillover effect from Frankfurt to Paris and from Paris to London. Volatility increases induced by bad news are transmitted more strongly than volatility declines.

Key Words: Spillover, Multivariate, GARCH, DCC, EGARCH, Major European Countries.

I. Introduction

In the age of massive globalization, economies become increasingly integrated. Globalization involves the liberalization of financial markets, which can be in the form of removal of capital barriers to investment. International stock markets, under ever-expanding globalization, have been experiencing an increasing interdependency or interaction with one another as a result of information spillovers among stock markets. Understanding this interaction is very important for determining asset allocations, pricing domestic securities, implementing global hedging strategies, (Ng,2000). Spillover effect is a result or the effect of return and volatility of larger stocks that have spread to other smaller stocks, or vice ver The existence of volatility spillovers implies that one large shock increases the volatilities not only in its own asset or market but also in other assets or markets as well. Volatility is often related the rate of information flow (Ross, 1989). If information comes in clusters, asset returns or prices may exhibit volatility even if the market perfectly and instantaneously adjusts to the news. Thus, study on volatility spillover can help understanding how information is transmitted across equity markets. As a consequence, current literature has increasingly focused on the spillover effect and volatility (Kim,2009; Beirne,et.al.,2010;Mukherjee and Mishra,2010;Park,et.al.,2010;Singh, Kumar,andPandey,2010). The recent study has been addressed to the investigation spillover effect among USA and major European stock markets in terms of conditional second moments of the distribution of returns, referring to volatility spillovers.

The analysis is carried out through Dynamic Conditional Correlation (DCC) of Engle (2002) and Exponational Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) of Nelson (1991). We preferred the EGARCH-M model which could provide more accurate results as the exponential GARCH-M model accommodated an asymmetric relationship between stock price returns and volatility changes assuming that both the magnitude and sign of volatility was important in determining spillover volatility.
The indices are basically designed to reflect the largest firms. The S&P500 is a value weighted index representing approximately 75 percent of total market capitalization. The DAX-30 is a price-weighted index of the 30 most heavily traded stocks in German market, while CAC-40 calculated on the basis of 40 best French titles listed on Paris bourse while the FTSE-100 is the principal index in the UK and consists of the largest 100 UK companies by full market value.

The US market is included because it's the largest economy in the world and many of worlds largest companies are based in the US. The European stock markets include the four top stock markets out of the first ten in the world, as expressed by total market capital and value traded. It includes the UK, as the third stock market of the world after the US and Japan, Germany stock market as the fourth market, France stock market as the fifth market.

In addition the international flow of fund reveal that the European stock markets are now the most important destinations of international equity capital, dominating the leadership that the US and Japans markets experienced in previous periods Antoniou (2003), Christos et. al. (2005), Christiansen (2005) and Melle, (2003). Also the introduction of the common Euro currency in 1999 represents the most dramatic event in European economic integration, so the impact of this event on European financial markets has become a specific focus of recent research.

The study used daily data span for all markets from 1992 to April 2010, as observed in standard textbooks (e.g., Ingersoll (1985) and (Campel, Lo, and MacKinlay (1997)), higher sampling frequency is associated with more accurate (contemporaneous) correlation and volatility estimates. This is due to the fact that, unlike mean return estimation for which the sampling frequency is unimportant, lower frequency data smoothes variation between adjacent observations resulting in smoothed estimates of correlation and volatility that discard important information.

In addition many international events occur during the sample period such as September eleven, Iraq war, Eurozone in January 1999, Asian financial crises 1997-1998.

Furthermore as Merton (1980), Nelson (1992), Campbell et al. (2001), and Xu and Malkiel (2001) demonstrate, data frequency is likely to be a more important issue than the design of estimator for the estimation of volatility.

However, the benefits of more frequent sampling must be balanced against other problems, commonly called microstructure issues, which arise particularly in the case of intraday data. To over come these difficulties I follow Cappiello, L.et.al.(2003) Christos.,et al. (2005), Eun and Shim (1989) and Andersen and Bollerslev, (1997) use daily indices data recorded at 16:00 London time of DAX-30 (German ),S&P500(USA), CAC-40 (French). FTSE-100 (UK). I use 16:00 London time in order to avoid the problems of non-synchronous data (see Martens and Poon 2001). The period of data are chosen to include financial crises events. Since the data come from different countries, different holidays apply for each market. I side-step this problem by taking the holiday price as being the same as the previous day. Hence the sample for each country contains all days of the week except weekends. The source of the data is DataStream. This is an international organization which publishes stock market data for most if not all major stock markets in the world.

The rest of the paper is organized as follows. Section II is devoted to present the review of related literature, Section III present econometric methodology; Section IV contains descriptive statistics, Section V present Cointegration, Section VI present Volatility Spillover, and Section VII. Conclusions.

II. Review of the Related Literature
Numerous studies have been conducted to examine the spillover effect between stock markets in developed and emerging markets, for instance Good Hart (1997) conclude that uni-directional volatility spillover exists from US equity markets to other equity markets. (Tse 1998) show that after the 87 crash in USA markets there is evidence of bi-directional spillover from US markets to other markets and from other markets to US markets.Noor and Aisyah,et.al.(2011) examined the spill-over effect of US sub-prime crisis on ASEAN-5 stock market returns. They
estimated the impact of stock returns in response to the US financial conditions using pooled, fixed effect, random effect and instrumental variable techniques. They found that increasing volatility of US stock returns reduces ASEAN-5 stock market return. Wei et al. (2011) investigated the existence of spillover effect in Malaysian market. They found that return transmission mechanisms between large and small stocks in Bursa Malaysia are reciprocal, where both types of stocks have significant spillover effects on each other; particularly during and after Asian financial crisis. Huyghebaert and Wang (2010) examined the integration and causality of interdependencies among seven major East Asian stock exchanges including the Greater China stock markets, he found that shocks in Hong Kong market did not affect the returns of Mainland China market after the Asian financial crisis. Kim and Cyn-Hyen (2010) investigated the influence of China's stock market on the Korean stock market after the global financial crisis. They found strong evidence of uni-directional volatility spillover effect from the Chinese stock market to the Korean stock market. Kumar and Pandey (2010). Beirne et al. (2010) examined volatility spillovers running from mature to emerging stock markets. They concluded that spillovers from mature markets do influence the dynamics of conditional variances of returns in many local and regional emerging stock markets. Naoui, Liouane and Brahim (2010) examined contagion phenomenon as induced by the subprime crisis that started in 2007 in the American risk-based mortgage market and which spread worldwide. The result showed that by the end of the crisis correlations considerably increased to exceed 80% for all developed countries. Wang and Wang (2010) investigated price and volatility spillover effects between Greater China, US and Japan stock markets using multivariate GARCH model. They found weak evidence of volatility interdependence from developed markets to Greater China market. Thus it would be a good exercise to see if intensified economic relations with USA and European Union have manifested it self in interdependence among stock markets. For these reasons I will examine the spillover effect among USA and major European stock markets.

III. Econometric Methodology

It now accepted that there’s spillover effect among markets. This study therefore examines spillover effect among USA (S&P 500) markets, German (DAX-30) markets, French (CAC-40) markets and UK (FTSE-100) for this purpose, class of multi-variate GARCH models of Engle (2002) and EGARCH models of Nelson (1991) will be used To see how the DCC model is implemented, consider:

\[ r_t \sim N(0, H_t) \]

\[ H_t = D_t R_t D_t \]

Where \( r_t \) is the \( k \times 1 \) vector of zero mean return conditional on the information set available at time \( t \). \( R_t \) is the time-varying correlation matrix. \( D_t \) is \( k \times k \) diagonal matrix with time-varying standard deviations estimated by univariate GARCH model applied to each single time series.

The elements on its main diagonal are the conditional standard deviations of the returns on each stock, the diagonal parameter matrices imposed to make the model tractable for applied purposes this class of models lends to relatively easy theoretical derivations of stationary and conditions and unconditional moments, He and Teasvirta (2002).

The correlation matrix containing the conditional correlations as can be seen from rewriting this equation \( H_t = D_t R_t D_t \) as

\[ r_t = D_t^{-1} E_{t-1} \]

The estimation procedure of the simple DCC model is described in (Engle 2002) as follows. In the first step the univariate GARCH volatility models will be estimated for each of the \( k \) assets and in the second step transformed residuals from the first step are used to obtain conditional correlation estimator.

The time-varying volatility is estimated by the univariate GARCH(p,q) model represented by the following equation:
\[ h_t = \omega + \sum \alpha_i r_{t,i}^2 + \sum \beta_j h_{t,j} \] ..........................(1)

This univariate GARCH process needs to be stationary i.e. \((1 - \alpha - \beta) \neq 0\), for the unconditional covariance matrix of the standardized residuals to be existing. It means that the conditional variance of each data series, evaluated at time \(t\), is proportional to the square shocks on the price level of each asset \((r_{2t-i})\) and to the past values of variance \((h_{t-j})\). Having normalized these series, in the second step we can estimate the correlations among the standardized returns \(\varepsilon_t\) of the several assets.

One the univariate volatility models are estimated the standardized residuals for each market is used to estimate the dynamics of the correlations. The DCC model of (Engle 2002) specifies the dynamics of correlation structure for returns as follows:

\[ Q_t = \left(1 - a - b\right) Q + a \varepsilon_{t-1} \varepsilon_{t-1}' + b Q_{t-1} \] .......................... (2)
\[ R_t = Q_t^* \quad Q_{t-1}^* \] .......................... (3)

Where \(a\) and \(b\) are scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations.

The DCC model proposed by (Engle, 2002) does not take account for spillovers, so we use DCC form of multivariate EGARCH model by Nelson (1991), to investigate spillovers among stock markets in different countries. Following Antonioa, et, al. (2003), we model the conditional variance according to EGARCH model as:

\[ \sigma^2_{i,t} = \exp \left[ \alpha_{i,0} + \alpha_{ij} f_j(z_{j,t-1}) + \delta_i \ln(\sigma^2_{i,t-1}) \right] \] .......................... (4)
\[ F_j (z_{j,t-1}) = (|z_{j,t-1}| - E|z_{j,t-1}|) + \gamma_j z_{j,t-1} \] .......................... (5)

So spillovers are measure by the coefficients \(\alpha_{ij} (i \neq j)\), so significant positive \(\alpha_{ij}\) implies there is volatility spillover between the two markets, negative \(\delta\) I implies bad news has different impact than good news.

**IV. Descriptive Statistics**

The first phase of our analysis is based on descriptive statistics of the returns Table (1) provides summary statistics; all the series seem to display "stylized" facts common to many financial assets such as nonnormality in the form of fat tails. As indicated by skewness statistics, DAX30, CAC40 and FTSE100 returns seem to be positively skewed which indicates along right tail in empirical distributions, while S&P500 returns are negatively skewed which indicates along left tail and supports the idea that these series have asymmetric distributions, while the kurtosis of DAX, FTS, CAC and S&P500 is lower than normal distribution, which has kurtosis of three.

Also, the Jarque-Bera test which combines the skewness and kurtosis result, indicate that the hypothesis of normality is rejected decisively for all return series at 5% level. The analyzed series present a slight right asymmetry, therefore, the frequency distributions of returns are no Gaussians but leptokurtic and slightly asymmetric therefore in this case the univariate specification GARCH (1, 1) is very significant to estimate the time-varying conditional volatility of observation time series. The Jarque-Bera test strengthens this condition, rejecting the null hypothesis of normality at 5% level for all series.
The second phase of our analysis is based on estimating the unconditional Correlation for our sample. Correlation coefficient between the indices provides a useful measure on the long-run relationship between indices, and cornerstones for asset allocations. Table (2) shows that Major European stock markets are highly correlated with each other and with S&P500, with the highest correlation between German and French stock markets and this may due by fixing of the exchange rates between Germany and French in 1999, and the monetary union has strengthened real integration among its members Frank and Ross (1997), which is consistent with increase economic and financial integration between these countries. This confirms the results reported by cappiello,et,al.(2003), and it is consistent with the increase in the intensity of volatility spillover effects within EMU countries noticed by Bale, (2002). Furthermore Taylor and Bartram, (2005), confirmed the above results but only for large equity Europeans markets.

**Table (2) Unconditional Correlation Coefficient for our Sample**

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P500</th>
<th>FTSE</th>
<th>DAX</th>
<th>CAC</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500</td>
<td>0.93372360600</td>
<td>0.90885971070</td>
<td>0.972154116291</td>
<td>1</td>
<td>CAC</td>
</tr>
<tr>
<td>0.94378106065</td>
<td>0.96309941764</td>
<td>1</td>
<td>0.97215411629</td>
<td>DAX</td>
<td></td>
</tr>
<tr>
<td>0.94978523364</td>
<td>1</td>
<td>0.96309941764</td>
<td>0.90885971070</td>
<td>FTS</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.94978523364</td>
<td>0.94378106065</td>
<td>0.93372360600</td>
<td>S&amp;P500</td>
<td></td>
</tr>
</tbody>
</table>

Source researcher calculations.
IV.1. Test for Stationary

Since the study dealing with time series data and interested in possible long-run relationships between the stock market indices included in this study, it appears to be necessary to check whether the individual stock index series are stationary in levels or are difference stationary. Because there is a critical problem associated with non-stationary variables that are the spurious correlation. The non-stationary variables could produce a weak result. To avoid the spurious regression problem, it is essential to test for unit root of each index employed in the study. The Augmented Dickey-Fuller (ADF) test is proposed in this study to examine the stationarity (unit root) of the stock market indices (S&P500, DAX30, FTSE100, and CAC40,).

Tables (3) providing ADF test for stock market indices. The results of this exercise, strongly confirm at the standard 5% significance level that the stock index series are not stationary in levels, but are stationary in first differences. Or integrated of order one I (1).

<table>
<thead>
<tr>
<th>Index</th>
<th>ADF at level</th>
<th>ADF at first difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500</td>
<td>-0.653051</td>
<td>-31.88659 ***</td>
</tr>
<tr>
<td>DAX(30)</td>
<td>-1.466</td>
<td>-47.841 ***</td>
</tr>
<tr>
<td>FTSE(100)</td>
<td>-1.566</td>
<td>-32.3591 ***</td>
</tr>
<tr>
<td>CAC(40)</td>
<td>-1.398</td>
<td>-31.7861 ***</td>
</tr>
</tbody>
</table>

Source researcher calculations.
Note: (*** ) denotes significant at1%, 5% and 10% significant level.

IV.2. Univariate GARCH

It may be useful, before carrying out the estimation of the multivariate GARCH specification, estimate a univariate GARCH model, from which we can extract the estimated volatility of the individual stock markets. The univariate GARCH models, used to estimate the conditional volatility of each single data series. Researcher examining high-frequency financial data has suggested that volatility dynamics may be confounded by the existence of both a periodic pattern and long-memory volatility.

Thus, we derived By far the most successful volatility forecasting model is the GARCH (1, 1) Bollerslev(1986), whose variance \( \sigma^2 \), is represented by:

\[
\sigma^2 \epsilon_t = \kappa + \alpha \epsilon_{t-1}^2 + \beta \sigma^2 \epsilon_{t-1}^2
\]

Where \( \epsilon_t \sim N(0, \sigma^2) \)

\( \alpha, \beta \geq 0, \alpha + \beta < 1 \)

Subject to \( \kappa > 0 \),

Coefficient \( \alpha \) and \( \beta \) determine the short run dynamics of the resulting volatility time series. A large \( \beta \)
indicates that shocks to conditional variance take along time to dissipate, that is, volatility is said to persistent. A large $\alpha$ indicates that volatility reacts intensely to market movements. Table (4) shows the results of univariate GARCH (1, 1) estimation. All parameters are significant at 5% level. All series exhibit significant volatility persistence as indicated by large GARCH parameter estimates ($\beta$ parameter in the last column in table 4) which indicates that shocks to conditional variance take along time to dissipate. Although the GARCH model captures thick tailed returns and volatility clustering phenomenon that are evident in financial returns, it is unable to account for any asymmetric response of volatility to positive and negative shocks, since the conditional variance is function of the magnitude of the lagged residuals not their signs.

Table (4) univariate GARCH (1, 1) estimation results.

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>$\alpha$</th>
<th>$\kappa$</th>
<th>$\mu$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500</td>
<td>.9658(.0046)</td>
<td>.0545(.0044)</td>
<td>.0058(.0011)</td>
<td>.05541(.0142)</td>
</tr>
<tr>
<td>DAX30</td>
<td>.9240(.0079)</td>
<td>.0728(.0063)</td>
<td>.0376(.0051)</td>
<td>.0524(.0215)</td>
</tr>
<tr>
<td>CAC40</td>
<td>.9370(.0098)</td>
<td>.0622(.0070)</td>
<td>.4456(.0065)</td>
<td>.0411(1.7466)</td>
</tr>
<tr>
<td>FTSE100</td>
<td>.9325(.0085)</td>
<td>.06984(.0072)</td>
<td>.0132(.0025)</td>
<td>.0410(.0154)</td>
</tr>
</tbody>
</table>

$+ \beta \sigma_t^2$, Standard errors Source: researcher calculations. Notes: the model is $r_t = \mu + \epsilon_t, \sigma_t^2 = \kappa + \alpha \epsilon_{t-1}^2$ are in parentheses.

V. Co-integration test

Engle and Granger (1987) suggested that two non-stationary variables might converge to a common equilibrium in the long run. Then a stationary combination of the two non-stationary variables should exist. Such variables are then called cointegrated and the vector that transforms the two non-stationary variables into a stationary one is called cointegration vector. Test for cointegration, suggested by Engle and Granger (1987) was extended by Johansen to a multivariate case. Both tests rely on the assumption that stability of cointegration vector is stable over time. However, it is highly likely that during longer periods a fundamental or nonfundamental shock may disrupt the equilibrium, which would result in a change in the parameters of cointegration vector. The researcher use cointegration techniques Johansen maximum likelihood estimator to test and determine the number of cointegrating relationships in US, Major European, markets. The purpose is to model the long and short run interactions among stock indices. If the series are cointegrated then a vector error correction model will be estimated. Otherwise, an unrestricted vector auto regression would be appropriate. The results of Johansen cointegration test summarized in table (5) shown both the trace and the maximum-eigenvalue test indicate that the hypothesis of at most one cointegrating relationship among series cannot be rejected at 5 percent level.
However, at 1% significance level test result point to no cointegration for the series. Our findings with respect to presence of multivariate cointegration suggest somewhat limited diversification benefits available to US investors investing in major European countries. However, this result does not provide any evidence regarding the temporal stability of the parameters of the relationship. This is consistent with Kasa (1992) who examines the major equity markets over the 1974-1990 period, using cointegration test and finds a single cointegration vector indicating low levels of convergence. However, the analysis performed in Kasa (1992) is subject to criticism by Richards (1995) due to potential small sample bias. Similar results for major world markets are found by Arshanapalli and Doukas (1995). In contrast, Chou et al. (1994) find no evidence of cointegration for the G7 countries.

Table (5) Johansen Test for Multiple Co-integration test of indices Sample(adjusted): 1/10/1992 2/08/2010

| Included observations: 4451 |
| Excluded observations: 6 after adjusting endpoints |
| Trend assumption: Linear deterministic trend (restricted) |
| Series: CAC DAX FTS SP |
| Lags interval (in first differences): 1 to 4 |

Unrestricted Cointegration Rank Test

<table>
<thead>
<tr>
<th>Critical Value</th>
<th>Critical Value</th>
<th>Trace Statistic</th>
<th>Eigenvalue</th>
<th>No. of CE(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>70.05</td>
<td>62.99</td>
<td>64.42704</td>
<td>0.007081</td>
<td>None *</td>
</tr>
<tr>
<td>48.45</td>
<td>42.44</td>
<td>32.79700</td>
<td>0.003528</td>
<td>At most 1</td>
</tr>
<tr>
<td>30.45</td>
<td>25.32</td>
<td>17.06451</td>
<td>0.002571</td>
<td>At most 2</td>
</tr>
<tr>
<td>16.26</td>
<td>12.25</td>
<td>5.606145</td>
<td>0.001259</td>
<td>At most 3</td>
</tr>
</tbody>
</table>

*(***) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates 1 cointegrating equation(s) at the 5% level
Trace test indicates no cointegration at the 1% level

<table>
<thead>
<tr>
<th>Critical Value</th>
<th>Critical Value</th>
<th>Max-Eigen Statistic</th>
<th>Eigenvalue</th>
<th>No. of CE(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>36.65</td>
<td>31.46</td>
<td>31.63003</td>
<td>0.007081</td>
<td>None *</td>
</tr>
<tr>
<td>30.34</td>
<td>25.54</td>
<td>15.73249</td>
<td>0.003528</td>
<td>At most 1</td>
</tr>
<tr>
<td>23.65</td>
<td>18.96</td>
<td>11.45837</td>
<td>0.002571</td>
<td>At most 2</td>
</tr>
<tr>
<td>16.26</td>
<td>12.25</td>
<td>5.606145</td>
<td>0.001259</td>
<td>At most 3</td>
</tr>
</tbody>
</table>

*(***) denotes rejection of the hypothesis at the 5%(1%) level Max-eigenvalue test indicates 1 cointegrating equation(s) at the 5% level
Max-eigenvalue test indicates no cointegration at the 1% level

Source: researcher calculations.
VI. Volatility spillovers

The Maximum likelihood estimates of the bivariate EGARCH model for standard returns are reported in table (6). Volatility spillover in our model is measured by $\alpha_{ij}$ for $i,j = 1,2,3,4$. A significant $\alpha_{ij}$ implies volatility spillovers. The values of $\alpha_{1,2}$ $\alpha_{3,2}$ $\alpha_{4,2}$ indicates that London market plays central role, being significant at less than 1 percent for all other markets, including New York. There are no significant volatility spillovers from New York to any other market ($\alpha_{2,1}$ $\alpha_{3,1}$ $\alpha_{4,1}$).

This consistent with Engle and Susmel (1994) finding who examined the relationship between the New York and London stock markets using current hourly returns. They did not report any significant evidence of volatility spillovers between both markets. Contradicts (Jeong, 1999) who employed overlapping high-frequency data (5-minute returns) to explore the transmission pattern of intraday volatility among the USA and UK markets. His results showed that there existed strong inter-market dependence, implying that the information produced in any market is affecting other cross-border markets. Good and Ohara (1997) conclude that uni-directional volatility spillover exists from US equity markets to other equity markets. (Tse, 1998) show that after the 87 crash in USA markets there is evidence of bi-directional spillover from US markets to other markets and from other markets to US markets.

Within the Europe there is unidirectional volatility spillover effect from Frankfurt to Paris ($\alpha_{4,3}$) and from Paris to London ($\alpha_{4,2}$). Which is consistent with (1996 Koutmos) finding; he documented significant volatility transmissions across major European markets. This may be due to high degree of interdependence. There are several plausible explanation mentioned in financial literature for the volatility between markets. However, the volatility results may due partly to the different times within the trading day .Andersen and Bollerslev,(1997) show that the volatility in US stock market is higher during opening and closing periods. Another possible explanation for the volatility between markets is the degree of interdependence between markets, trade integration and equity market developments. Furthermore Table (6) shows that volatility is asymmetric for the four markets. Therefore, a statistically significant positive $\alpha_{ij}$ coupled with a negative $\gamma$ implies that negative innovations in market $j$ have a greater impact on the volatility of market $i$ than positive (negative) innovations. That is, the coefficient measuring asymmetry, namely $\gamma_j$ is significant for three markets ($\gamma_{1}$, $\gamma_{2}$, $\gamma_{3}$, $\gamma_{4}$) which means that bad news increase volatility more than good news. Consistent with Cappiello, et.al. (2004) finding, they found strong evidence of asymmetries in conditional covariance of equity and bond returns. And the general finding of Koutmos, and Both. (1995), Koutmos (1996), Veigan and Mcaleer, (2003), Christos, s, et.al. (2005), that asymmetric volatility exist between major stock markets and USA market , so that volatility increase induced by bad news are transmitted more strongly than volatility declines. The degree of asymmetry, on the basis of the estimated $\delta_j$ coefficients, is similar for four markets.
Table (6) Estimated volatility and asymmetric DCC model

<table>
<thead>
<tr>
<th></th>
<th>Paris</th>
<th>Frank Furt</th>
<th>London</th>
<th>New York</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{4,0}$</td>
<td>0.0098***</td>
<td>$\alpha_{3,0}$</td>
<td>0.0092***</td>
<td>$\alpha_{2,0}$ = -0.0031**</td>
</tr>
<tr>
<td>$\alpha_{4,1}$</td>
<td>-0.0043</td>
<td>$\alpha_{3,1}$</td>
<td>0.00070</td>
<td>$\alpha_{2,1}$ = 0.00450</td>
</tr>
<tr>
<td>$\alpha_{4,2}$</td>
<td>0.0190***</td>
<td>$\alpha_{3,2}$</td>
<td>0.02420***</td>
<td>$\alpha_{2,2}$ = 0.0621***</td>
</tr>
<tr>
<td>$\alpha_{4,3}$</td>
<td>0.02001**</td>
<td>$\alpha_{3,3}$</td>
<td>0.00590***</td>
<td>$\alpha_{2,3}$ = 0.0019</td>
</tr>
<tr>
<td>$\alpha_{4,4}$</td>
<td>0.04950**</td>
<td>$\alpha_{3,4}$</td>
<td>0.0081</td>
<td>$\alpha_{2,4}$ = 0.03900***</td>
</tr>
<tr>
<td>$\gamma_{4}$</td>
<td>- 0.5510***</td>
<td>$\gamma_{3}$</td>
<td>-0.2910***</td>
<td>$\gamma_{2}$ = -0.5210**</td>
</tr>
<tr>
<td>$\delta_{4}$</td>
<td>0.9842***</td>
<td>$\delta_{3}$</td>
<td>0.9856***</td>
<td>$\delta_{2}$ = 0.9840***</td>
</tr>
</tbody>
</table>

* Denotes significance at 10% level ** denotes significance at 5% level
*** Denotes significance at 1% level
VII. Conclusion

This study is aimed mainly to examine spillover effect between USA and major European stock market, using the EGARCH model, the results showed that there is spillover effect from London market to New York, Pairs and Frankfurt stock markets, so London market plays central role, being significant at less than 1 percent for all other markets, including New York, consistence with Christos,et.al..(2005). Furthermore our findings support the work of Didier et al. (2010), suggesting that financial contagion is still applicable in the current situation. Rose and Spiegel (2009), in their recent study for a cross-section of 85 countries, consider aspillover effect between stock markets.

There are no significant volatility spillovers from New York to any other market. Further more Within the Europe there is unidirectional volatility spillover effect from Frankfurt to Paris and from Paris to London. Volatility increases induced by bad news are transmitted more strongly than volatility declines. On the other hand volatility is asymmetric for all markets. Which means that bad news increases volatility more than good news. Which consistent with Cappiello, et.al. (2004) finding, they found strong evidence of asymmetries in conditional covariance of equity and bond returns.
References


