Article

Examining mean-volatility spillovers across national stock markets

Vinodh Kesavaraj Natarajan\textsuperscript{a,}\textsuperscript{*}, Azariah Robert Raja Singh\textsuperscript{b}, Nagarajan Chidham Priya\textsuperscript{c}

\textsuperscript{a} Department of Management Studies, Narayanaguru College of Engineering, Anna University Chennai, Tamilnadu, India
\textsuperscript{b} Department of Management Studies, Narayanaguru College of Engineering, Anna University Chennai, Tamilnadu, India
\textsuperscript{c} Scott Christian College (Autonomous), Manonmaniam Sundaranar University, Tamilnadu, India

\textbf{ARTICLE INFO}

\textit{Article history:}
Received 18 July 2013
Accepted 28 January 2014

\textbf{JEL classification:}
G10
G14
G17
C22
E44

\textbf{Keywords:}
Stock market index
Volatility
Spillovers
GARCH-M model

\textbf{ABSTRACT}

The study of the stock market in a country and the understanding of the influence of stock market crashes within and across the markets has been the subject matter of many researches, academicians and analysts during recent times. In this study we investigate the mean-volatility spillover effects that happen across international stock markets. The study, by taking into consideration the stock market returns based on various indices, investigates the mean-volatility spillover effects using the GARCH in Mean model for the period January 2002 to December 2011. The GARCH-M model seeks to provide useful insights into how information is transmitted and disseminated across stock markets. In particular, the model examines the precise and separate measures of return spillovers and volatility spillovers. The analysis provides the evidence of strong mean and volatility spillover across some stock exchanges.

\section*{1. Introduction}

On October 19th, 1987 the Dow Jones Industrial Average (DJIA) stood at 1738 points. It fell 508.32 points, which constituted 22.6% of the value of the entire stock exchange. Over 600 million shares had been traded and the value of the stocks on the New York Stock Exchange had fallen by over $750 million. This event triggered stock
High and low of major index between October 2007 and March 2009.

Table 1

<table>
<thead>
<tr>
<th>Indices</th>
<th>Highest points during 2007</th>
<th>Date</th>
<th>Lowest points during 2009</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSE Sensex</td>
<td>20,238.16</td>
<td>30-Oct-2007</td>
<td>8047.17</td>
<td>6-Mar-2009</td>
</tr>
<tr>
<td>FTSE 100</td>
<td>6754.10</td>
<td>13-Jul-2007</td>
<td>3460.714</td>
<td>9-Mar-2009</td>
</tr>
<tr>
<td>NIKKIE</td>
<td>18,300.40</td>
<td>26-Feb-2007</td>
<td>7021.284</td>
<td>10-Mar-2009</td>
</tr>
<tr>
<td>BOVESPA</td>
<td>64,609.00</td>
<td>12-Nov-2007</td>
<td>37,105.00</td>
<td>2-Mar-2009</td>
</tr>
</tbody>
</table>

They examined the transmission mechanism of the conditional first
dependence of prices and price volatility across three major
markets.

They used the ARCH family of statistical models in their analysis.

The objective of this paper is to study the inter-market volatility
and whether there is an association between volatility in one mar-
ket and volatility in another market. In other words the study aims
to show the extent to which security price changes in one mar-
ket influence the opening prices in the next market to trade; and
whether changes in price volatility in one market are positively
related to changes in price volatility in the next market to trade.
Also the influences of volatility surprises in one-market over the
volatility returns in other markets are examined. This is because
spillovers of returns across markets have important implications
for portfolio choice and risk management.

This study assumes much significance due to the fact that, mar-
kets tend to move together at exactly at those times when investors
do not want them to (i.e., when volatility is high) thus reducing
the benefits of international portfolio diversification. Thus analyz-
ing volatility spillover among markets would help investors to seek
appropriate strategy to make limit his risk from international diver-
sification portfolio.

2. Previous research

One of the important issues in stock market investments
have been the all-inclusive concept of inter-market information
spillovers. A collection of important empirical studies related to the
interdependence among national stock markets has been brought
out.

Agmon (1972) studied the lead lag relationship between four
major stock markets. He stated that the one market hypothesis
implies that all potential gains international as well as internal,
diversification are already reflected in the current prices of capital
assets traded on the world market. His findings proved that there
was substantial amount of relationship among the stock markets
of UK, US, Germany and Japan.

Panton, Lessig, and Joy (1976) investigated the structure of
twelve of the major international equity markets co-movements.
Their analysis stated that markets that are well-developed and open
to international capital flows have high degree of similarity than
other markets.

Hilliard (1979) focused on the degree of interdependence and
causality among national stock markets. His study was mainly
related in examining the structure of international equity market
indices during a world-wide crisis. His findings stated that intra-
continental prices move simultaneously, even in the context of
hourly fluctuations, with respect to inter-continental prices, most
do not seem to be closely related and he therefore dismissed the
question of lead and lags.

Eun and Shim (1989) investigated the international transmis-
sion mechanism of stock market movements by estimating a
nine-market vector auto regression (VAR) system. His emphasis
was on understanding the mechanism by which innovations in
one stock market are transmitted to other markets over time. His
evidence indicated that a substantial amount of interdependence
exists among national stock markets. Moreover, the US stock mar-
ket was found to be the most influential in terms of its capability
of accounting for the error variances of other markets. His analysis
supported the view of informational efficient international stock
markets.

Hamao, Masulis, and Ng (1990) studied the short-run inter-
dependence of prices and price volatility across three major
international stock markets, i.e., New York, Tokyo, and London.
They used the ARCH family of statistical models in their analysis.
They examined the transmission mechanism of the conditional first
and second moment’s in common stock prices across international
stock markets and allowed for changing conditional variance as
well as conditional mean returns. They found that spillover effects
from foreign markets on the conditional means of the close-to-open
return (which reflect effects on the opening prices in the domestic
market) are predicted by international asset pricing models, while
spillover effects on conditional means of the open-to-close return
(which reflect effects on prices in the domestic market after the
opening of trading) are predicted not to occur. Their evidence stated
that price volatility spillovers from New York to Tokyo, London to
Tokyo, and New York to London was observed.

King and Wadhwani (1990) article provides an excellent un-
derstanding of the subject of price volatility. Their study investigated
why, in October 1987, almost all stock markets fell together
despite widely differing economic circumstances. They constructed
a model in which “contagion” between markets occurred as a result
of attempts by rational agents to infer information from price
changes in other markets. This provides a channel through which a
“mistake” in one market can be transmitted to other markets.
Their conclusion was based on the following principle, which is “A
world in which investors infer information from price changes in
other countries is also one in which a ‘mistake’ in one market can
be transmitted to other markets”. Moreover, they suggested that
an increase in volatility lead in turn to an increase in the size of the
contagion effects which was depicted by the rise in the correlation
between markets just after the crash. Basing on their evidence, they
categorically stated that it would have the important implication
that volatility can, in part, be self-sustaining.

Liu and Pan (1997) studied the mean return and volatility
spillover effects from the US and Japan to four Asian stock mar-
kets, including Hong Kong, Singapore, Taiwan, and Thailand. They
used a GARCH model in their study. Their conclusions indicated that
there was instability in the international mean return and volatility
transmissions, and the spillover effects increase substantially after
the October 1987 stock market crash.

Engle and Patton (2001) harped on the theme that a volatility
model must be able to forecast volatility, which this is the central
requirement in almost all-financial applications. Their conclusion
was that pronounced persistence and mean-reversion, asymmetry
such that the sign of an innovation also affects volatility and the
possibility of exogenous or pre-determined variables influencing
between Hong Kong and US financial markets, using band spectrum
regression techniques to examine the dynamic properties of the
interactions between capital markets. They found that before the
Asian financial crisis there is a feedback relationship between the
two markets which is driven by long cycles (with low frequencies),
while post-911 periods, there is a one-way causality from the US
market to the Hong Kong market.

Li (2007) examines the linkages between the two emerging
stock exchanges in mainland China and the established markets
in Hong Kong and in the US by a multivariate GARCH approach.
The results indicated no evidence of a direct linkage between the
stock exchanges in mainland China and the US market, but
found evidence of uni-directional volatility spillovers from the
stock exchange in Hong Kong to those in Shanghai and Shenzhen.
The implication of the weak integration is that by investing in Chi-
inese market overseas investors will benefit from the reduction of
diversifiable risk.

Several empirical regularities can be spotted from the research
undertaken in this field. It can be said that the volatility of stock
price is time varying and when volatility is high, the price changes
in major markets tend to become highly correlated. Moreover cor-
relation in volatility and prices appear to be causal from the United
States to other countries; and lagged spillovers of price changes and
price volatility are found between major markets.
It is with setting, this paper proceeds to examine the direction and extend of mean spillovers and volatility spillovers across five stock markets. The rest of the paper is organized as follows: Section 3 explains the research method and describes the data used in the study, Section 4 describes the model and discusses the results, and Section 5 concludes.

3. Research method and data description

In this study, we adopt one model GARCH-M to analyze a financial time series data to see for volatility spillover effects. This paper aims at investigating the issue of volatility spillovers across national stock markets for the period 2001 to 2011. This study is mainly based on secondary data that have been collected from the database on Indian economy maintained by Reserve Bank of India. To test for the presence of volatility spillovers a return series is required which can be sampled. The study undertaken uses the Weighted Average Stock Price Index as a measure of stock market return. Consequently the return series for each market is chosen on the basis of the market index which provides an historical daily time-series.

Five globally-traded stock market indices were selected to test the versatility and robustness of the approach for mean and volatility spillover. The S&P ASX 200 for Australia, S&P 500 composite for the US, BOVESPA for Brazil, DAX 30 performance for Germany and HANG SENG for Hong Kong are examined in our empirical experiment. The stock indices data used in this paper are daily and are obtained from DataStream respectively. The methodology requires matched observations between all the markets. Consequently, the sample period commences from January 1st, 2002 to December 30th, 2011. For brevity, the original data are not listed in the paper, and detailed data can be obtained from the sources. For the sake of facilitating forecast and portfolio optimization, we choose the daily excess returns of these indices and exchange rates as forecast variables.

In any time series data the volatility or changes in some periods may be due to some event. To neutralize the impact of this event on the time series we include dummy variables. A dummy variable can take the value of either 0 or 1. The transformation of indices to change in logarithms has the advantage that it eliminates most first-order serial correlation and produces series that are of greater theoretical interest. Also the data are transformed into elasticity, which are better suited in analyzing and interpretations.

The volatility of returns in stock market has a significant influence on the volatility of returns in other stock markets and there exists a causal relationship. This is because volatility in one market induces volatility in another market, through a lead-lag relationship. This happens as the trading hours between the markets are not common when measured in Greenwich Mean Time (GMT). When measured in GMT the various markets open and close at different times on a 24 hour time horizon.

When measured in GMT, the US market is 5 and ½ hours ahead of the Hong Kong market, 7 and ½ hours ahead of Australia and the other time lag between markets can be seen from the figure above. The problem between measuring volatility spillovers between different time zones as well as use of the closing price of the indices any common influence from the one market will first reveal itself in the next opening market and then in the next succeeding market. However this effect can happen through an association between concurrent day volatility between the two markets when they open at the same time. Therefore a common stock market factor will induce an association between current day markets of two stock exchanges. Therefore it is advisable to use intra-day data sampled at the open and close of each market. This would help in accurately distinguishing between effects. But as these data were not available for the study we did not use them. The advantage of using closing data as stated earlier is that spillover effects may be the strongest at the opening prices. As closing prices incorporate noise generated during the trading period, the use of closing prices provides a stronger test for spillover effects.

4. Model description and empirical results

4.1. Model description

The empirical results found while running the GARCH (1,1) M-model for estimating the volatility spillovers from the stock markets are presented below. First a preliminary statistics of the data are analyzed. Secondly, a detailed analysis of the results obtained in the model is undertaken. Finally we see whether the concluded tests present any serious evidence against the estimated GARCH (1,1) M-model.

All indices are based on local currencies and do not include dividends. The returns for each market are calculated by the following formula.

\[ \text{Return}_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \]

where LN = natural log to the base e.

The summary statistics for the daily returns of the five national stock markets are reported in Table 2. The means of returns are positive and range between 0.0002 (Hong Kong) and 0.0029 (Brazil). The standard deviation of returns ranges between 0.0083 for (Australia) and 0.0291 for (Brazil). This indicates that the Brazilian stock market is the most volatile and the Australian market is the least volatile. The high excess kurtosis in these markets suggests that their daily return series have a fat-tailed distribution. The Ljung–Box (LB) Q statistic for the returns are highly significant at the five percent level for all markets except Australian, which indicates the presence of serial correlations and suggesting the presence of time-varying volatility. Thus the preliminary analysis of the data suggests the use of a GARCH model in capturing the fat-tails and time-varying volatility found in these stock return series. The correlations of returns range from a high of 0.4745 between Hong Kong and Australia, to a low of 0.0872 between the USA and Australia. Since all values are less than 0.8 the problem of multicollinearity will not be encountered (Tables 3 and 4).

### Table 2

<table>
<thead>
<tr>
<th>Country</th>
<th>Trading hours (Eastern standard time)</th>
<th>Major index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>09:15 a.m. to 16:12 p.m.</td>
<td>S&amp;P/ASX 200</td>
</tr>
<tr>
<td>Brazil</td>
<td>10:00 a.m. to 17:00 p.m.</td>
<td>BOVESPA</td>
</tr>
<tr>
<td>Germany</td>
<td>09:00 a.m. to 17:30 p.m.</td>
<td>DAX</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>09:20 a.m. to 16:00 p.m.</td>
<td>HANG SENG</td>
</tr>
<tr>
<td>US</td>
<td>09:30 a.m. to 16:00 p.m.</td>
<td>S&amp;P 500</td>
</tr>
</tbody>
</table>

Source: Author (compiled from websites of various national stock exchanges).

### Table 3

Preliminary statistics on the stock market returns.

<table>
<thead>
<tr>
<th>Variable(s)</th>
<th>AUS</th>
<th>BRZ</th>
<th>GER</th>
<th>HKG</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>0.0572</td>
<td>0.2882</td>
<td>0.0755</td>
<td>0.1725</td>
<td>0.0557</td>
</tr>
<tr>
<td>Minimum</td>
<td>−0.0703</td>
<td>−0.1723</td>
<td>−0.0888</td>
<td>−0.1474</td>
<td>−0.0711</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0003</td>
<td>0.0029</td>
<td>3.3910</td>
<td>0.0002</td>
<td>0.0003</td>
</tr>
<tr>
<td>Std. deviation</td>
<td>0.0083</td>
<td>0.0291</td>
<td>0.0138</td>
<td>0.0181</td>
<td>0.0104</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.4633</td>
<td>0.5425</td>
<td>−0.4216</td>
<td>0.0795</td>
<td>−0.1907</td>
</tr>
<tr>
<td>Kurtosis − 3</td>
<td>4.7458</td>
<td>7.8959</td>
<td>3.4862</td>
<td>8.7144</td>
<td>4.5518</td>
</tr>
<tr>
<td>Coeff. of variation</td>
<td>30.5624</td>
<td>10.0069</td>
<td>40.6836</td>
<td>73.7598</td>
<td>36.8671</td>
</tr>
<tr>
<td>LB (12)</td>
<td>19.4121</td>
<td>82.5342</td>
<td>23.6756</td>
<td>38.0246</td>
<td>24.0166</td>
</tr>
<tr>
<td>LB (24)</td>
<td>26.6232</td>
<td>141.2074</td>
<td>51.3284</td>
<td>47.9043</td>
<td>40.3609</td>
</tr>
</tbody>
</table>

Source: Computed data.

* Means not statistically significant at 5% level.
** Means statistically significant at 5% level.
In the next step the stationarity of the data has been tested by the unit root test. The augmented Dickey–Fuller statistic was used to test for a unit root in the five stock market return series. Here we assume:

\[ H_0 = \text{non-stationary}, \]
\[ H_1 = \text{stationary}. \]

The ADF test result for the variables using a maximum lag of 4 was used. The results are shown below.

Tables 5 and 6 show the unit root tests. The tests indicate the existence of two logged indexed stationary series and three first differences logaramatic values of S&P 500 composite price.

The ARCH effects for the three stock markets were estimated. The ARCH effect test from order 1 to 4 for each of the three variables which are found to be of the order 1 (1).

Probability values of both statistic tests, i.e., LM version and F version are less than 0.05 using the 95% confidence level of significance test is reported in Table 7. This implies that we can reject the null hypothesis of no ARCH effects, i.e., \( \alpha = 0 \) for all orders from 1 to 4 for all the three variables and hence accept the existence of ARCH effects.

After having tested for multicollinearity, stationarity and for ARCH effects the study uses the GARCH \((p,q)\) process, which allows lagged conditional variances to enter the equation above as opposed to the ARCH \((q)\) process where the conditional variance is specified as a linear function of past sample variances only. In the GARCH–Mean model the conditional variance of \( U_t \) is used as one of the regressor explaining the conditional mean of the return of the variable. Below a basic model based on the data is specified.

\[
R_t = \text{Constant} + \beta_1X_{t-1} + \gamma h^2 + U_t
\]
\[
DA_t = C + b_1DA_{t-1} + \gamma h^2_t + U_t
\]
\[
DG_t = C + b_1DG_{t-1} + \gamma h^2_t + U_t
\]
\[
DU_t = C + b_1DU_{t-1} + \gamma h^2_t + U_t
\]
\[
h^2_t = \alpha_0 + \alpha_1U^2_{t-1} + \phi h^2_{t-1} = V(U_t / \Omega_{t-1})
\]

where \( X_{t-1} \) can be taken as the vector of ex ante dated variables and is assumed to include \( DA_{t-1}, DG_{t-1} \) and \( DU_{t-1} \). \( DA = \) the difference logaramatic values of S&P ASX 200 price index; \( DG = \) the difference logaramatic values of DAX 30 performance price index; \( DU = \) the difference logaramatic values of S&P 500 composite price.

The \( U^2 \) past squared innovations \((i.e., \ e_{t-1}^2 = (R_{t-1} - \mu_{t-1})^2) \) which are used as proxies for past volatility shocks during day \( t = 1 \); are taken as the residuals from running the regression of a variable on its one period lagged variable \((e.g., DA = \text{constant} + DA(-1) + U_t)\). The actual model employed in the study is stated in the equation below which analyses the mean spillovers.

\[
\mu_{t,t} = m_1 + \beta_{USA,R_{USA,t-1}} + \beta_{GER,R_{GER,t-1}} + \beta_{AUS,R_{AUS,t-1}} + \delta_1\sigma_{t,t} = m_1 + R_{t-1}\beta_1 + \delta_1\sigma_{t,t}
\]

Table 5
Unit root tests for variables.

<table>
<thead>
<tr>
<th>Countries</th>
<th>Test statistic: SBC (Schwarz Bayesian criterion)</th>
<th>95% Critical value for the augmented Dickey–Fuller statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>−1.9821 [ADF(1)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>Brazil</td>
<td>−8.8300 [ADF(1)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>Germany</td>
<td>−1.8057 [ADF(1)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>−2.8842 [ADF(3)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>USA</td>
<td>−1.5732 [ADF(1)]</td>
<td>−2.8632</td>
</tr>
</tbody>
</table>

Source: Computed data.

Table 6
Unit root tests for variables after first order difference.

<table>
<thead>
<tr>
<th>Countries</th>
<th>Test statistic: SBC (Schwarz Bayesian criterion)</th>
<th>95% Critical value for the augmented Dickey–Fuller statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>−37.1496 [ADF(4)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>Germany</td>
<td>−37.3953 [ADF(4)]</td>
<td>−2.8632</td>
</tr>
<tr>
<td>USA</td>
<td>−38.2591 [ADF(4)]</td>
<td>−2.8632</td>
</tr>
</tbody>
</table>

Source: Computed data.
The empirical model was run based on the equations above along with the lagged variable of the other variables, choosing an order of 1;1 GARCH M-model. The distribution used was the student's t distribution for each of the conditional mean equations. The conditional variance of returns in market $i$ is specified as a linear function of its own past conditional variance and past volatility shocks from all five markets.

4.2. Results of mean spillovers and volatility spillovers testing

The above equation helps in analyzing the volatility spillovers. The empirical model was run based on the equations above along with the lagged variable of the other variables, choosing an order of 1;1 GARCH M-model. The distribution used was the student T distribution. The initial estimates for $\gamma_i$, $\alpha_i$, and $\phi_i$ (“in Mean”) was 0.3, 0.1 (MA lag 1), and 0.3 (AR lag 1) respectively (a dumping factor of (0.010) was used) (Table 8).

4.2.1. Mean spillovers

The results for the conditional mean equations show statistically significant positive mean spillovers from the markets of the USA to Australia, Germany to Australia and negative mean spillovers from Australia to Germany. The cross mean spillovers from the markets of USA to the Australia and Germany is 0.25081 (.000), .37431 (.000) respectively. Past USA returns have a greater effect on current returns in Germany relative to Australia. The coefficients $0.64330(26.6101), 0.89746(35.5274), 0.87970(23.66)$ for the volatility components of all conditional mean equations are statistically significant and very large, since the ($t$-ratios) are >1.96. This indicates high relation between conditional market volatility and expected returns.

To assess the extent to which the mean spillovers relations can predict future stock market returns, we can use a univariate $R_2$ measure for each of the conditional mean equations. The $R_2$ equals 1 − [variance of error/variance of returns] which measures the percentage of variation in the returns of market $i$ explained by the conditional mean equation. If the conditional mean equations could be used by investors to predict the future course of prices, the weak form of efficient market hypothesis would be violated.

4.2.2. Volatility spillovers

The coefficients for the one lag conditional variances ($\gamma_i$) for the markets of Australia and Germany are .79071 (35.08), .88796 (4.3277), respectively. The coefficient for the Australian market as compared to the German market is quite large and highly significant at 5% level, indicating the presence of structure in the data. Here by structure we mean high volatility persistence. Since both $t$-ratio are greater than 1.96 we conclude the presence of volatility in these markets. Persistence of stock market volatility is higher in Australia than Germany. Negative own-spillovers are present in all the stock markets. Since own-spillovers coefficients $-0.65148 (.000), -0.75323 (.000), -0.13966 (.000)$ are very high and are statistically significant, we can say that past market volatility shocks in all these markets have a great effect on future volatility in these markets. If the own-spillovers coefficients are statistically insignificant we can conclude that conditional volatility in these markets are imported only from abroad.

Past-market volatility shocks in the USA influence current volatility in both, the Australian and German market, with varying degrees of intensity. That is, the USA volatility coefficients to Australia and Germany are .27555 (.000), .43946 (.000) respectively. Therefore majority of the volatility spillovers on the German stocks is from the USA markets. This may be due to the fact that the Australian market opens only after the German market and US markets have opened. According to the results, the volatility spillover from Germany to Australia is not present as the coefficient (.014631 (659)) is insignificant. Since the coefficient (.27555 (.000)) of volatility spillover from USA to Australia is significant, we can tell that majority of the volatility spillovers on the Australian stocks is from USA stock market. The presence of cross volatility spillover is seen between the Australian and German market. Since the volatility spillover coefficient ($-0.058683 (.000)$) of Australia market to German market is less than the volatility spillover coefficient (.43946 (.000)) of German market to Australian market, the Australian market is influenced more by the German market. This may be due to the fact that the Australian market is the last to open its market according to the time horizon. Therefore, the Australian market may be exposed

<table>
<thead>
<tr>
<th>Table 8</th>
<th>GARCH (1,1)-M: Mean model estimates.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional mean parameters</td>
<td>Countries</td>
</tr>
<tr>
<td>Constant</td>
<td>.0001515(.723)</td>
</tr>
<tr>
<td>BDA</td>
<td>- .42817(.000)</td>
</tr>
<tr>
<td>BDG</td>
<td>.065719(.000)</td>
</tr>
<tr>
<td>BDU</td>
<td>.25081(.000)</td>
</tr>
<tr>
<td>H-squared</td>
<td>-.22416(.717)</td>
</tr>
<tr>
<td>E–SQ(–1)</td>
<td>.165176(6.1586)</td>
</tr>
<tr>
<td>δ(H–SQ(–1))</td>
<td>.64330(26.6101)</td>
</tr>
<tr>
<td>Source: Computed data.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 9</th>
<th>GARCH (1,1) M-variance estimation results.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional mean parameters</td>
<td>Countries</td>
</tr>
<tr>
<td>Constant</td>
<td>-.0001414(.761)</td>
</tr>
<tr>
<td>BEDA</td>
<td>-.65148(.000)</td>
</tr>
<tr>
<td>BEDG</td>
<td>.058683(.000)</td>
</tr>
<tr>
<td>BDU</td>
<td>.27555(.000)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>.79071(35.08)</td>
</tr>
<tr>
<td>Source: Computed data.</td>
<td></td>
</tr>
</tbody>
</table>
The study shows that regulations and rules enacted and put forward to control the effects are not working or more need to be done to curb this inter market negative effects. But this may not be possible as with each day the world markets are becoming more and more correlated. Secondly, there may be other variables apart from these that affect stock return volatility. However, despite many regulatory measures, volatility in stock prices exists. In general, an increase in price volatility may be due to an increase in the variability of economic information that affects stock market prices or failure to observe an increase in price volatility may be due to a decrease in the variability of economic information, making any increase in price volatility. Finally, we can conclude that the test has given some results which prove that the financial markets are integrated in these countries. Any news arising in one country has an impact on the other country to some extent. Also, previous news of a country influences the future price of another country. Although we found the presence high relation between conditional market volatility and expected returns, our results are not conclusive enough as we must control for other factors that affect stock price mean and volatility spillovers, before inferring a direct casual effect obtained from the above study.

Future research in this field can be undertaken for the most stock markets and for longer time period, and the results can be compared for different sample periods as well. It is further advisable to use intra-day (open and close) of each market (as it helps to accurately distinguish between results) or to decompose daily price changes (returns and volatility) into daytime (open to close) and overnight (close to open) returns, where the daytime segment in one market is a subset of the overnight segment of the other market. This decomposition of daily price changes is essential for clean tests of how information is transmitted from one market to the other.

**Appendix A. Supplementary data**

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jefas.2014.01.001.

**References**


