Stock Market Volatility Spillover from Developed Markets to Regional Markets

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ABSTRACT

This paper builds on the work of Kim and Langrin (1996) to investigate the co-movement in stock markets between the developing countries of the Caribbean as well as from developed markets. Multivariate Generalised Autoregressive Conditional Heteroscedasticty (GARCH) is employed to examine the volatility spillover between the three regional exchanges namely that of Jamaica, Trinidad and Barbados, and from the New York Stock Exchange (NYSE). The study utilises daily data on the composite index of each stock market to assess the extent to which volatility spillovers exist. Results suggest that significant spillovers indeed exist between each of the regional exchanges, as well as from the NYSE.

Keywords: Caribbean, Stock Exchange, GARCH, Volatility Spillover

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1. Introduction

The last two to three decades have witnessed increasing levels of financial integration among the World economies, as restrictions on capital mobility across countries have gradually weakened. The consequential increase in cross-border financial flows, along with the increasing regionalisation of economic activity, has resulted in greater interdependence of major financial markets all over the world. Caribbean countries are no exception here, being part of a regional grouping, many of these countries have instituted a continuing policy of financial market liberalisation, which should have resulted in increasing internationalisation of their financial markets. In addition, these countries have strong economic ties with USA through international trade. As such, one would expect some degree of information spillover between the individual markets and also with that of the USA, which could be in terms of actual returns, the volatility of returns or both[1].

Most of the research has been focused on the more developed markets of the US and Europe, with a focus on examining the extent of financial integration (See Eun and Shim 1989, Hamao et al. 1990, Lucey and Voronkova 2006, Chelley-Steeley 2005, among others). However, there has also been some recent work on emerging markets, for instance, Harrison and Moore (2009). The authors investigate the comovement of stock markets between the emerging economies of Central and Eastern Europe and the developed Markets of Western Europe using time-varying realised correlation ratios, time-varying cointegration statistics, and a Generalized Autoregressive Conditional Hetroscedasticity (GARCH) model. The results suggest an absence of significant comovement between the stock exchanges and show that the developed equity markets are more integrated than emerging markets.

While there has been less attention in literature regarding the comovement of stock markets in the Caribbean, a few studies have investigated other areas of volatility concerning these regional markets. For instance, Hamilton (1996) investigates the GARCH effect in the returns of three

[1] Much of the earlier research concentrated exclusively on spillover of the first moment, that is, co-movement among the returns. However, more recent research have demonstrated that that much of the information would be revealed in the volatility of stock prices, which is in the conditional second moments of the price, rather than in the price itself.

companies listed on the Jamaica Stock Exchange (JSE). The study tested the hypothesis found by Lamorex and Lastrapes (1990) that the unobservable cause of volatility is the time varying rates of informational arrival, and that once volume is introduced the GARCH effect is significantly reduced, implying that volume might be a good proxy of the informational arrival. The author concludes that GARCH does not always model return volatility on the JSE well, and that volume traded does not necessarily manifest the time varying volatility in stock returns.

In estimating the responsiveness of sectoral sub index returns to changes in the domestic market portfolio on the Trinidad and Tobago Stock Exchange, Leon et al. (2000) compares predictions of non-systematic risk, using GARCH and EGARCH specifications of the error variance. The results suggest that returns for the portfolios of Commercial Banks and Conglomerates respond more than proportionately to changes in the market portfolio, and that nonsystematic volatility appears to have been greater during periods of macroeconomic instability and political unrest.

Of more relevance for our purposes is the study by Hurditt (2004). The study applies the GARCH-BEKK procedure to the returns from the Jamaican bond, foreign exchange and stock markets in order to estimate the magnitude of the common market and cross-market volatility transmission. The results of the model indicate that there are generally high levels of common market volatility transmission relative to the cross market volatility transmission. The authors note that the strong common market transmission in the foreign market and the stock market relative to the bond market reflects the uncertainty momentum that often characterizes these risky markets. The strongest cross market effects occur from the bond market to the foreign exchange and stock markets.

Kim and Langrin (1996) note that as controls on capital movements, including repatriation of the investment proceeds, is relaxed, it becomes easier for foreign and domestic investors to move assets into and out of these small emerging markets. The authors use GARCH models to examine the question of whether there is increased volatility spillover from developed markets to the stock markets of Trinidad and Tobago and Jamaica as a result of the liberalisation of their foreign exchange markets. The results suggest that volatility spillovers increased following the liberalization of the exchange market in Jamaica, but not for Trinidad. The reason for this was argued to be that the barriers to entry to the stock market in Jamaica were more binding that in Trinidad.

In this study, we build on the work of Kim and Langrin (1996) to examine the extent volaility spillover from a US stock exchange to that of the regional markets, using the most recent data. In addition, we analyse the degree of comovement between the regional markets, an area which was not investigated in the aforementioned study. We also introduce the stock market of Barbados in the analysis, since to the authors' knowledge there are no previous studies on the volatility of the stock maket in Barbados. Moreover, since then, there has been some expansion and improvement as it relates to multivariate GARCH models.

Examining the comovement between stock markets is considered to be important for several reasons. International portfolio diversification is beneficial only if returns from international stock markets are not significantly correlated (Harrison and Moore 2009). Bekaert (1995) found that the emerging market returns are higher, and more predictable, with higher volatility that developed markets and correlations with developed markets were low, thus representing attractive hedging opportunities for investors in developed markets. Stock market comovement also gives a measure of the level of market integration between the countries (Kim and Langrin 1996). Policy makers are also interested in whether stock markets exhibit comovement because in a world of increasingly liberalised capital flows, the degree of stock market comovement can impact on the stability of the international monetary system (Harrison and Moore 2009). Finally, analysing price volatility can give market participants an assessment of the risk associated with various financial products and thus facilitate their valuation along with the development of different hedging techniques (Ng, 2000).

Hence, the fundamental aim of the paper is to conduct an up-to-date review on the extent of co-movement of volatility between stock markets within the Caribbean, as well as between these regional markets and more developed markets. The study employs daily returns of each of the stock market indices and utilises both univariate and multivariate GARCH models. The remainder of the paper is structured as follows: section 2 provides a brief background on the regional stock markets; section 3 describes the data and outlines the methodology; section 4 presents and analyses the results; and section 5 summarises and concludes.

2. Background on Regional Stock Markets

The stock exchanges of Barbados, Trinidad and Tobago and Jamaica are the only stock markets within the Caribbean Region. In 1991, the three exchanges entered into an agreement for cross border trading in equity, to form the Regional Stock Exchange. The Regional Stock Exchange is not a physical entity but an agreement of cooperation to facilitate the purchase and sale of shares cross border.

2.1 Barbados

The Barbados Stock Exchange (BSE), formerly the Securities Exchange of Barbados, was established in 1987, under the Securities Exchange Act, Cap 318A, of 1982, in order to create a market to promote trading in financial securities and encourage investment by the public in business enterprises. The BSE was reincorporated in 2001 simultaneously with the enactment of the Securities Act 2001-13, which repealed and replaced the original Act of 1982. It is a privately owned (by its Members), non-profit organization. Also in 2001, the BSE switched from the manual, open auction outcry method of trading to electronic trading using the Order routing method.

The Regular market is the main market of the BSE, while the Junior market caters to smaller and newer public companies, which may not meet the requirements necessary for listing on the Regular market. The BSE is the smallest of the regional exchanges and there are approximately 24 companies and 26 securities currently listed on the exchange, with a market capitalization for the composite index close to 5.5 billion (US dollars). The main indices on the BSE are the Local Share Index, the Cross Listed Index and the Composite Index.

2.2 *Jamaica*

The Jamaica Stock Exchange (JSE) was incorporated as a private limited company in August 1968. Stock-trading on the JSE is restricted to Broker-members who trade both as agents and as principals. For the first time in Jamaica's history, a US dollar share was listed on the JSE in July 1996. The Jamaica Central Securities Depository was established in 1998, and since then the back office operations has been automated. Since January 2000, the Jamaican Stock Exchange had a fully automated trading platform.

2.3 *Trinidad and Tobago*

The Securities Market Trinidad and Tobago existed informally for about twenty (20) years before the official opening of the Trinidad and Tobago Stock Exchange. In the early 1970's, the Government decided as a matter of policy to localise the foreign-owned commercial banking and manufacturing sectors of the economy, a policy which was to allow such companies to divest and sell a majority of their shares to nationals. The establishment of the stock exchange in 1981 under the provisions on the Securities Industry Act 1981 was a natural extension of the policy to formalise the Securities market in Trinidad and Tobago. It was subsequently replaced with the Securities Industry Act of 1995, to deal with the inefficiencies of the former, which brought into operation the establishment of a Securities and Exchange Commission.

The Trinidad and Tobago Stock Exchange (TTSE) implemented the Horizon Electronic Trading System on March 18th 2005 replacing the manual open outcry system which was used since its inception. As at April 1st 2008, the trading days for the Exchange are every business day, Monday to Friday and there are presently thirty-nine (39) companies listed on the exchange, with 41 securities being traded. The composite index registers current a market capitalization of approximately 12 billion (US dollars).

3. Data and Methodology

3.1 Data

The study employs daily data on composite indices on the Barbados Stock Exchange (BSE), the Jamaica Stock Exchange (JSE), the Trinidad Stock Exchange (TTSE) and the New York Stock Exchange (NYSE), from the period 2005 to 2010. This data was obtained from the respective online databases of the Stock Exchanges. Table 1 provides summary statistics of the daily returns for the sample period. Daily returns are calculated as $R_{t,d}^{i} = \ln\,(p_{t,d}^{i}/p_{t,d-1}^{i}) * 100$, where $p_{t,d}^{i}$ is the index of the i^{th} country, in year *t* on trading day *d*. Figures 1 and 2 plot the index for each stock market and the daily returns respectively.

Table 1:
Summary Statistics of Daily Returns of the Regional Exchanges

	Mean	Median	Max	Min	Std.Dev.	Skew	Kurt	Jarque-Bera	p-value
TTSE	-0.026	0.000	1.701	-3.470	0.336	-0.790	16.103	9616.841	0.000
JSE	-0.018	0.000	7.958	-6.319	0.807	0.279	18.938	14040.360	0.000
BSE	-0.021	0.000	3.873	-4.172	0.372	-4.260	66.830	228942.500	0.000
NYSE	0.003	0.057	11.526	-10.232	1.572	-0.372	12.817	5351.517	0.000

Mean returns were negative throughout the period for the TTSE, JSE and BSE, the lowest being in Trinidad (-0.026 percent), while the average for the more developed NYSE was recorded at 0.003 percent. In addition to having the largest daily returns, the NYSE is also significantly more volatile than the other markets as indicated by the higher standard deviation. Of the regional markets, average volatility is higher on the JSE (0.807) as compared to 0.372 for the BSE and 0.336 for the TTSE.

With the exception of the stock market in Jamaica, the other markets are negatively skewed, and significantly so for the BSE. Additionally, the kurtosis of the returns from each exchange are considerably higher than 3 suggesting a non-normal distribution of returns. This observation is confirmed by the significance of the Jarque-Bera statistic in each case.

Figure 1
Composite Indices of the Regional Exchanges

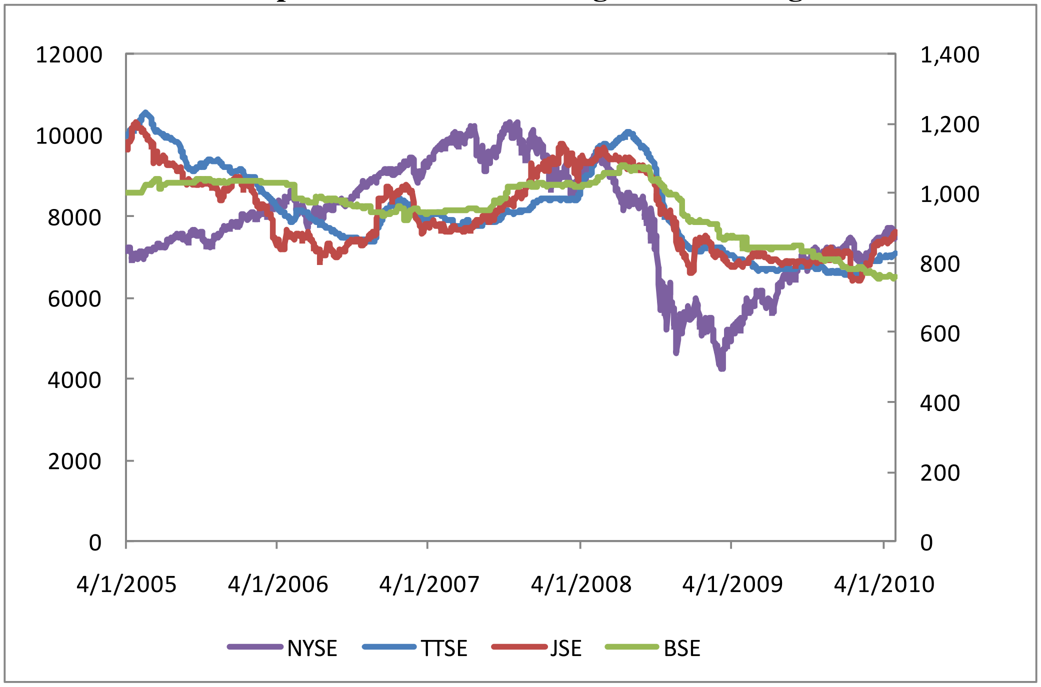

Figure 2
Daily Returns to the Regional Exchanges

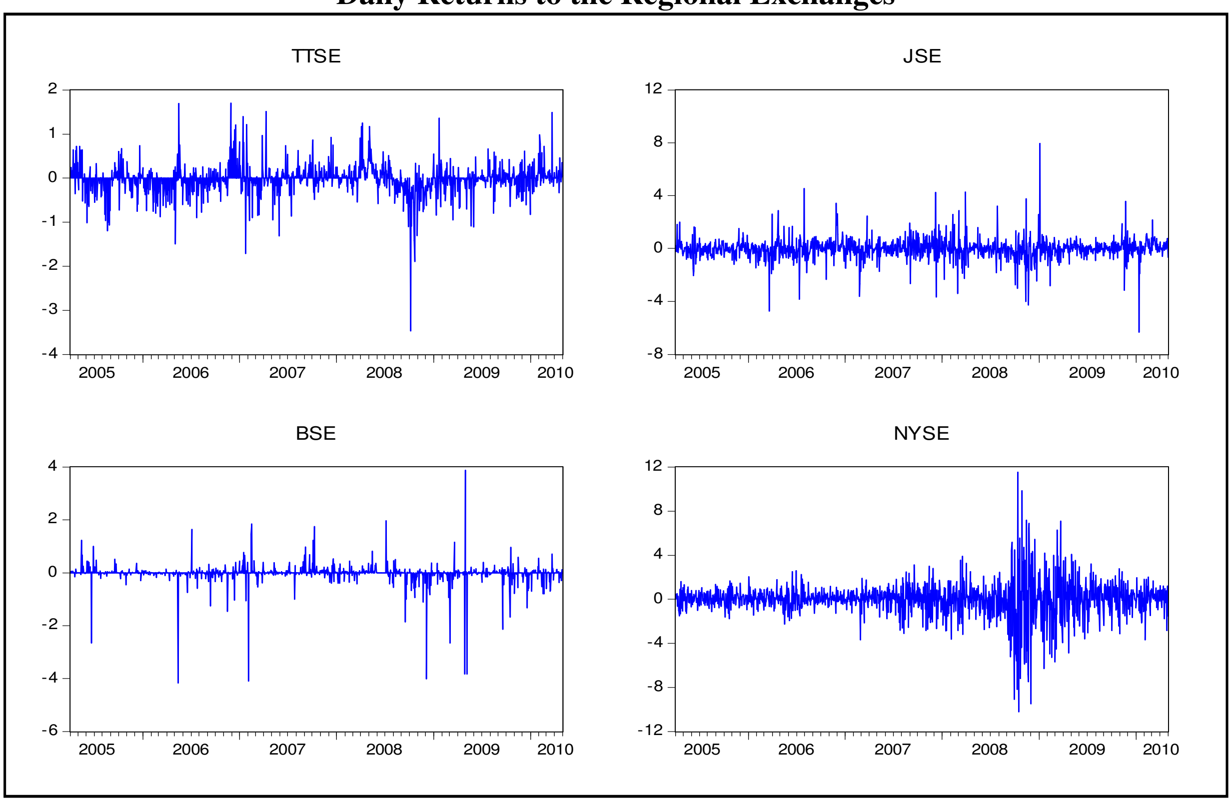

Table 2 presents the contemporaneous and lagged cross-correlation coefficients of returns between the exchanges and indicates that the cross correlations between each of the returns are relatively low. A similar result was also found by Kim and Langrin (1996) who examined the cross correlations in both pre- and post-liberalisation periods of the TTSE, the JSE and the Standard and Poors 500 (S&P) index. However, the coefficients appear to be somewhat higher for some pairs of returns than that found by the authors, even in the post-liberalisation period. For instance, cross correlation coefficents between the JSE and NYSE ranging between 0.013 and 0.064 were found in Kim and Langrin (1996), compared to 0.036 to 0.114. In addition the highest correlations were found between the JSE and the TTSE, a result which was also observed in the above-mentioned study.

Table 2:
Cross-correlations Between JSE, TTSE, BSE and NYSE Returns

	Lags on NYSE	**JSE**	**TTSE**	**BSE**
NYSE	0	0.036491	0.030109	-0.00807
	1	0.113501	-0.02482	0.031918
	2	0.040735	0.006049	-0.01275
JSE	0		0.157219	0.019314
	1		0.157208	0.019303
	2		0.157403	0.019314
TTSE	0			0.076986
	1			0.076974
	2			0.076974

Another obsevation is that the cross correlations between the regional exchanges remains at the same level up to a lag length of two, whereas correlation with the NYSE is more short-term as it becomes smaller after the first lag.

3.2 Methodology

Although there are several approaches to assessing the extent of the spillover of information among the national markets, ARCH family of models is prehaps the most popular as it pertains to financial time series. As such, this paper utilises multivariate GARCH to examine the volatility spill over effects amongst the regional stock markets , as well as the spill over from the more developed NYSE to these markets to determine the extent of co-movement.

ARCH models were introduced by Engle (1982), and generalized as GARCH (Generalised ARCH) by Bollerslev (1986) and Taylor (1986). The GARCH model states that the error variance of any series *y* at time *t* depends on the squared error terms from previous periods as well as past variances, where the ARCH effect (the coefficient on the past squared error terms) captures the short-run persistence of innovations (an indication of the strength of the shocks in the short run) and the GARCH effect (the coefficient on the past variances) measures the contribution of these innovations to long run persistence.

3.2.1 Univariate Conditional Volatility Models

Consider the simple GARCH (1, 1) specification for daily returns:

$$Y_t = X_t'\theta + \varepsilon_t \tag{1}$$

$$\begin{aligned} \varepsilon_t &= \eta_t \sqrt{\sigma_t^2}, \qquad \eta \sim iid(0,1) \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned} \tag{2}$$

where equation (1) is the mean equation given as a function of exogenous variables and an error term, and ω >0, α >0 and β >0 are sufficient conditions to ensure that the conditional variance σ_t^2 >0. The parameter α represents the ARCH effect, while β represents the GARCH effect.

Maximum Likelihood estimation (MLE) is used to obtain the parameters of the model with a joint normal distribution of η. Weiss (1986) and Bollerslev and Wooldridge (1992) show that the quasi-maximum likelihood estimator (QMLE) is consistent if the conditional mean and conditional variance are correctly specified. However, the QMLE is inefficient, with the degrees of inefficiency increasing with the degree of departure from normality (Engle and Gonzalez-Rivera 1991). As a result, other distributions, namely the Student and GED distributions, are available which would capture the higher observed kurtosis, and thus perform better. The Skewed Student distribution could also be used to account for skewness, since the above-mentioned distributions assume symmetry.

The necessary and sufficient condition for the existence of stationarity for the GARCH (1,1) model is $\alpha + \beta < 1$, which is also sufficient for the consistency of QMLE. Nelson (1991) derived the weaker log-moment condition which is also sufficient for QMLE given as:

$$E[\log(\alpha\eta_t^2 + \beta)] < 0 \qquad (3)$$

However, the QMLE is inefficient, with the degrees of inefficiency increasing with the degree of departure from normality (Engle and Gonzalez-Rivera 1991). The observed excess kurtosis in each of the series suggest fatter tails than for a normal distribution

Equation (2) assumes that the effects of positive shocks on the conditional variance of daily returns are the same as negative shocks, i.e. a symmetric GARCH model. In order to capture possible asymmetry in the data, Glosten et al. (1993) put forward the asymmetric (or threshold) GARCH, or GJR model, given by:

$$\sigma_t^2 = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (4)$$

where

$$I(\eta_t) = \begin{cases} 1, \eta_t < 0 \\ 0, \eta_t \geq 0 \end{cases} \qquad (5)$$

is an indicator variable which differentiates between positive and negative shocks such that asymmetric effects are captured by γ, and ω >0, $\alpha + \lambda$ >0 and β >0, are sufficient conditions to ensure the positivity of the conditional variance. The short run persistence of a positive shock to daily stock returns is given by α, whereas the persistence of a negative shock is given by $(\alpha + \gamma)$. However, given that the conditional shocks follow a symmetric distribution, the average short run persistence of shocks is $\alpha + \gamma / 2$, while the contribution of shocks to average long run persistence is $\alpha + \lambda / 2 + \beta$. The necessary and sufficient condition for the existence of a second moment of the GJR (1,1) model is given as $\alpha + \beta + \gamma / 2 < 1$. McAleer (2003) gives the weaker log moment condition for the GJR (1,1) as:

$$E[(\log((\alpha+\gamma I(\eta_t))\eta_t^2+\beta)]<0 \tag{6}$$

This study explores the GARCH (1,1), AR(1)-GARCH (1,1), and ARMA(1,1)-GARCH(1,1) univariate specifications to determine which models fit the data best. The ARMA parameters are included in the mean equations to account for possible serial correlation in stock returns, which could be as a result of infrequent or non-synchronous trading. The respective GJR models are also included to capture likely asymmetry in the data as it is expected that a negative shock to stock returns would result in greater volatility. To determine the appropriateness of applying the GARCH methodology, the ARCH test is used to test for the presence of conditional heteroscedasticity in each of the mean equations. The results suggest that ARCH effects indeed exist in the mean equations of each of the four (4) series.

3.2.2 Multivariate Conditional Volatility Models

This section utilises the multivariate GARCH (MGARCH) process to assess the extent of co-volatility among the daily returns of the BSE, TTSE and JSE, and co-volatility between returns on the NYSE and each of the regional exchanges. Consider the following specification for daily returns:

$$\begin{aligned} y_t &= E(y_t \mid I_{t-1}) + \varepsilon_t \\ \varepsilon_t &\sim N(0, H) \end{aligned} \tag{7}$$

where y_t is a $mx1$ vector of daily returns for each exchange, and I_t is an mxm matrix of historical information available at time t. ε_t is a $mx1$ vector, which is independently and identically distributed (iid) with mean 0 and variance H_t. Similar to the univariate model, the variance may be specified as

$$H_t = \omega + \alpha * \varepsilon^2{}_{t-1} + \beta * H_{t-1} \tag{8}$$

where ω represents a mxm matrix of constants, α is a mxm matrix of coefficients measuring ARCH effects, while β is a mxm matrix capturing GARCH effects. Hence, the volatility of, and co-volatility among, the varying stock markets can be modeled using equation (8).

The most common approaches to multivariate GARCH are the VECH model of Bollerslev, Engle, and Wooldridge (1988) and the BEKK model of Baba et. al (1990). The problem with the general MGARCH models outlined above is that the size of the variance-covariance matrix H_t increases exponentially as we increase the number of variables in the model, making the general model extremely difficult to estimate. To reduce the computational burden of GARCH modeling, one can impose a diagonal VECH (DVEC) model or a diagonal BEKK (DBEKK) model, or alternatively use a Constant Conditional Correlation (CCC) model (Bollerslev 1990). The CCC model imposes a constant correlation over time, while the diagonal BEKK model does not capture spillover. Hence, given the objective of this paper, the DVEC approach is utilised.

The DVEC transformation requires that H_t depends on the squares and cross products of innovations, ε_t and lagged volatility H_{t-1}.

$$H_t = C + A * \varepsilon_{t-1}\varepsilon_{t-1} + B * H_{t-1} \tag{9}$$

VEC is the operator that stacks the lower triangle of the variance-covariance matrix. A is a *mxm* matrix of ARCH terms and B is a *mxm* matrix of GARCH terms measuring own volatility and cross volatility spill over. As with the univariate specification, the parameters are subjected to the positivity conditions imposed on the MGARCH process and co-variance stationarity is required. In this paper, equation 9 is estimated in the Eviews programme version 7.0 using both the BHHH and Marquandt algorithms, depending on which is able to achieve convergence.

4. Analysis of Results

4.1 Univariate Conditional Volatility Models

The results of the univariate GARCH and GJR models for daily returns of the stock indices are presented in Tables 3 and 4 respectively. The conditional mean estimates suggest that on average the ARMA (1,1)-GARCH (1,1) estimates are preferred for each of the stock markets, on the basis of the significance of estimates, the Akaike Information Criterion and the Schwartz Information Criterion. Additionally, the Log-likelihood is improved in the ARMA (1,1) specification relative to the others. The results of the misspecification tests, including the Box-Pierce statistics, suggest that generally the models are well specified. The sufficient conditions, $\omega>0$, $\alpha>0$ and $\beta>0$ to ensure positivity are met for each of the series, as well as the second moment conditions. Hence, the coefficients of the conditional variance for these models are consistent and asymptotically normal and inference on these estimates can be used for policy analysis. The coefficients of the variance equations are statistically significant both in the short- and the long-run for each stock market, indicating the presence of important ARCH effects.

Based on the results obtained from the ARMA (1, 1) specification, the ARCH coefficients range between 0.054 and 0.166. These results indicate that the degree of own volatility spillover is highest for the JSE and lowest for BSE. Volatility persistence (the GARCH effect), which can be interpreted as the markets sustain the past volatility changes of stock returns to the volatility in the future periods, is highest for the NYSE (0.913) compared to 0.855, 0.747 and 0.726 for the TTSE, BSE and JSE respectively.

Table 3 reports the asymmetric GARCH models, namely the GJR (1,1), AR (1)-GJR (1,1) and ARMA(1,1)-GJR(1,1) models. The coefficients of the mean equations bare similar statistical significance to the GARCH models. The necessary condition has been met to ensure positivity, as well as the second moment condition. The asymmetric effect is significant, for each of the stock returns (and positive) suggesting that the effect of negative shocks on conditional volatility is greater than positive shocks. This result is not surprising since it is expected that an anticipated fall in prices on the stock market would create greater uncertainty, than an unanticipated increase. Therefore, a past negative shock in the mean stock returns to each of the respective markets would have a greater impact on today's volatility, when compared to a past positive shock. This effect is largest for the NYSE, relative to the other markets, which may be attributed to more efficient transmission of information, and which would allow companies to respond to news more quickly.

Table 3:

Univariate GARCH (1,1), AR(1)-GARCH(1,1) and ARMA(1,1)-GARCH(1,1) Estimates

Country	Mean Equation			Variance Equation			AIC	SIC	Log Likelihood
	C	AR(1)	MA(1)	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$			
BSE	0.023*			0.027**	0.055**	0.749**	0.751	0.767	-493.5504
	-0.023*	0.008		0.027**	0.055**	0.748**	0.753	0.773	-493.7703
	-0.043	0.993**	-0.984**	0.027**	0.054**	0.747**	0.748	0.772	-489.3405
JSE	-0.008			0.011**	0.062**	0.928**	2.294	2.310	-1515.753
	-0.009	0.021		0.011**	0.063**	0.928**	2.296	2.315	-1514.781
	-0.022	0.923**	-0.876**	0.087**	0.166**	0.726**	2.295	2.319	-1513.600
TTSE	-0.021**			0.008**	0.085**	0.851**	0.543	0.559	-355.8078
	-0.020*	0.142**		0.007**	0.078**	0.859**	0.533	0.553	-348.0053
	-0.029	0.960**	-0.856**	0.008**	0.070**	0.855**	0.456	0.479	-295.7924
NYSE	0.051*			0.014**	0.081**	0.911**	3.011	3.027	-1991.082
	0.051**	-0.079**		0.013**	0.079**	0.914**	3.009	3.029	-1986.920
	0.054**	0.709**	-0.774**	0.013**	0.080**	0.913**	3.009	3.032	-1985.418

Note: ** and * indicates significance at the 5 and 10 percent levels of testing.

Table 4:

Univariate GJR (1,1), AR(1)-GJR(1,1) and ARMA(1,1)-GJR(1,1) Estimates

Country	Mean Equation			Variance Equation				AIC	SIC	Log Likelihood
	C	AR(1)	MA(1)	$\hat{\omega}$	$\hat{\alpha}$	γ	$\hat{\beta}$			
BSE	-0.020			0.025**	-0.027**	0.139**	0.770**	0.751	0.771	-492.7038
	-0.023	0.011		0.025**	0.026**	0.044**	0.760**	0.754	0.778	-493.2608
	-0.039	0.992**	-0.983**	0.025**	0.029**	0.037**	0.760**	0.749	0.777	-489.0189
JSE	-0.017			0.012**	0.032**	0.051**	0.930**	2.286	2.305	-1509.396
	-0.018	0.014		0.012**	0.032**	0.052**	0.929**	2.288	2.311	-1508.442
	-0.032	0.915**	-0.879	0.011**	0.032**	0.055**	0.930**	2.281	2.308	-1502.708
TTSE	-0.020*			0.008**	0.072**	0.022**	0.851**	0.534	0.563	-354.8604
	-0.019*	0.147**		0.007**	0.063**	0.027**	0.859**	0.533	0.556	-346.5289
	-0.034	0.958**	-0.854**	0.008**	0.050**	0.034**	0.858**	0.455	0.483	-294.3224
NYSE	0.007			0.013**	-0.026**	0.144**	0.941**	2.978	2.997	-1967.815
	0.013	-0.064		0.013**	-0.022*	0.135**	0.941**	2.977	3.000	-1964.897
	0.016	0.400	-0.463	0.013**	-0.019**	0.131**	0.939**	2.978	3.005	-1964.459

Note: ** and * indicates significance at the 5 and 10 percent levels of testing.

4.2 Multivariate Conditional Volatiliy Models

Given that the ARMA(1,1) specification appears to fit the data best, we utilise the VARMA (1,1)-GARCH(1,1) approach to capture co-movement in the volatility of mean returns to each of the stock markets. The estimates for the conditional mean equation of the model are provided in Table 5.

Table 5:
VARMA(1,1)-GARCH(1,1) Conditional Mean Estimates

	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
	BSE (i=1)		JSE (i=2)	
ω	-0.037	0.001**	-0.032	0.001**
α_{i1}	-0.733	0.035**	0.011	0.018
α_{i2}	0.006	0.030	-0.736	0.019**
α_{i3}	-0.016	0.004**	-0.011	0.003**
α_{i4}	0.001	0.002	0.007	0.002**
	TTSE (i=3)		NYSE (i=4)	
ω	0.000	0.001	-0.004	0.005**
α_{i1}	-0.010	0.033	-0.013	0.130
α_{i2}	0.061	0.038*	0.007	0.149
α_{i3}	0.960	0.009**	0.017	0.029
α_{i4}	0.009	0.004**	0.337	0.028**

Note: ** and * indicates significance at the 5 and 10 percent levels of testing.

The results suggest that there are mean spillover effects between the regional markets, as well as from the NYSE. In Barbados, lagged returns on the TTSE influence current returns, while the JSE had an insignificant impact on returns in this country. Lagged returns on the TTSE have a significant effect on the JSE, and vice versa. However, evidence suggests negative mean spillover from the TTSE to the JSE, while the JSE appears to have a positive impact on the TTSE. The NYSE has a mean positive spillover on the three regional exchanges, however, the intra-regional mean effects are larger than those originating from the NYSE, perhaps because of the direct link between the regional exchanges due to the number of cross listings.

The estimated conditional variance-covariance equations are presented in Table 6. The results suggest that there is evidence of significant own-volatility spillover for each series of returns as previously indicated by the univariate results. With regards to the cross volatility spillover, there is evidence of transmission between each pair of regional markets, as well as between the regional markets and that of the NYSE.

Table 6:
VARMA(1,1)-GARCH(1,1) Conditional Variance Estimates

Parameter	BSE (*i=1*)	JSE (*i=2*)	TTSE (*i=3*)	NYSE(*i=4*)
	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**
ω_{i1}	0.000**			
ω_{i2}	0.000	0.000**		
ω_{i3}	0.000	0.000	0.000**	
ω_{i4}	0.000	0.000	0.000	0.000**
α_{i1}	0.050**			
α_{i2}	0.072**	0.104**		
α_{i3}	0.047**	0.067**	0.043**	
α_{i4}	0.056**	0.081**	0.052**	0.063**
β_{i1}	0.745**			
β_{i2}	0.768**	0.792**		
β_{i3}	0.806**	0.831**	0.872**	
β_{i4}	0.833**	0.859**	0.901**	0.931**
$\alpha_{ii}+\beta_{ii}$	0.795	0.896	0.915	0.994

Note: ** and * indicates significance at the 5 and 10 percent levels of testing.

As it relates to persistence in this conditional volatility transmission, the GARCH effects are also significant between the four stock exchanges. Own-volatility persistence bears similar results to that suggested by the univariate specification. The coefficients for cross-volatility persistence range between 0.768 (between the BSE and JSE) and 0.901(between the NYSE and TTSE). The highest level of intra-regional cross volatility persistence occurs between the JSE and TTSE (0.831), while the highest level of cross volatility persistence from the NYSE is evident in the TTSE.

5. Conclusion

The purpose of this paper is to examine the volatility spillover between the stock markets of the Caribbean, namely the JSE, the TTSE and the BSE, and to determine the extent of spillover from the developed NYSE to these regional markets. Using univariate and multivariate GARCH techniques, the study employs daily data from 2005 to 2008 on the composite stock market indices to evaluate the extent of co-movement of volatility of returns.

The univariate results suggest that there are indeed ARCH and GARCH effects in each of the series, and that the ARMA specification appears to be superior. Own-volatility spillover was found to be highest for the JSE and own-volatility persistence being highest in the NYSE. Asymmetric effects were found to be significant in each of the series indicating that a negative shock to the volatility of returns today would have a greater impact on volatility tomorrow than a positive shock.

The findings also suggest that there are significant mean spillover effects among the three Caribbean countries and also between the NYSE and the exchanges in these countries. In particular, the evidence suggests significant bi-directional mean spillover between the TTSE and the JSE, while the BSE had no significant impact on either of the two regional exchanges. Lagged returns on the NYSE influences current returns on each of the regional markets, but to a much lesser degree than the intra-regional spillover.

As far as volatility transmission is concerned, there are significant cross spillover effects between each of the series. The GARCH effects suggest that the highest level of intra-regional cross volatility persistence occurs between the JSE and the TTSE, while the highest level evident from the NYSE is evident in the TTSE. The BSE has the lowest level of transmission from the NYSE when compared to the other regional markets, which is not surprising since it is the smallest of the three markets. Additionally, Trinidad and Tobago and Jamaica have engaged in more foreign exchange market liberalisation procedures, relative to Barbados, which would suggest a greater level of financial integration.

These findings suggest that the regional markets are sufficiently integrated so that each market responds to both current and historical news generated in the other markets of the Caribbean, an to a lesser extent developed markets. Collectively the findings imply that investment and fund managers with access to news on other regional markets may react to changes faster than those who do not. In addition, the results also imply that investors should not only rely current regional news to guide their investment decisions but also take into consideration historical regional and international news.

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