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Return and Volatility Linkages among G-7 and Selected Emerging Markets

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Abstract

In this research, using twelve year daily data on sixteen market indicies, we examine the return and volatility linkages among developed and selected emerging stock markets. All markets exhibit excess kurtosis and ARCH effect in addition to non-normality. Our results show the existence of non-normality, excess kurtosis and excess volatility (ARCH effect) in all markets. There is also a positive pair-wise correlation among these markets. Interesting observation is that the daily volatility of Indonesia, among all markets including G-7 markets, is observed to be the smallest and there is negative correlation between Hong Kong and China Markets during the sample period. We find that these markets are highly linked except for Italy. Further to our analysis, we observe that except for China, all these markets also exhibit leverage effects. We also observe the asymmetry in volatility in all markets, except for China. Volatility transmission among equity markets in the same continent have the most influence for the stock markets in that area, except for UK market that has links to the USA stock markets. Results also indicate portfolio mix for investors of any country is different from another country.

Keywords: volatility, GARCH, stochastic volatility, leverage effect, ARCH effect

1. Introduction

The interrelation among financial markets through information transmission and spillover effect has been the center of attention among academicians and practitioners since 1980s. As the internet era evolves since early 1990s, research in this field has evolved significantly as international markets have become more integrated, information generated in one country affect financial markets of other countries almost instantaneously as the world economy has become a virtual one economy. At first, the vast majority of the literature examines the return linkages. Later on, literature emerges towards understanding the volatility linkage as it is clearer to the academicians and practitioners that the prominence of the second moment is too important to ignore especially in portfolio decisions. Research on return and volatility linkages have been conducted considering combination of developed markets, developed and emerging markets, among selected emerging markets, and among all markets. Empirical research in the current literature finds the unidirectional linkages as well as bidirectional spillover between different international stock markets (e.g., Li, 2007; Choudhry, 2004). A large number of studies study volatility spillovers among the mature markets (e.g., Karolyi, 1995; Francis et al., 2006; Yang & Doong, 2004; Bhuyan et al., 2013). There also exists many volatility spillover studies on emerging markets in Asia and Latin America (e.g., Hashmi & Tai, 2007; Gebka & Serwa, 2007; Yang & Chang, 2008; Morales, 2008; Tai, 2007), Eastern Europe (e.g., Fedorova & Vaihekoski, 2009; Buttner & Hayo, 2008), and volatility spillovers from developed markets to emerging markets, (e.g., Syllignakis & Kouretas, 2006; Wang & Moore, 2009; Li & Majerowska, 2008; Engle, Gallo, & Velucchi, 2009; Beirne et al., 2008; Li & Majerowska, 2008 among others).

There are few prominent emerging markets that are getting attention from international investors for seeking positive alpha in their investments. These markets are Brazil, Argentina, China, India, Indonesia, Korea, Hong Kong, Taiwan, and Mexico. These countries are attractive to international investors as they experience high growth and offer superior returns to investors. These countries are frequently quoted by Wall Street pundits as key sources of investments for international diversification. The Main objective of this research is to investigate spillover effect among G-7 and these prominent countries to further contribute to this literature as it does not exist in the existing literature. Using twelve years of daily, we contribute to the literature by testing whether spillover is unidirectional from developed markets to these emerging markets or bidirectional. Our findings bring further to the literature the extent of relations among these markets, where, findings of the research should provide some insights in regards to global portfolio allocations and choices. We contend that as much as it is important to learn the transmission speed and spillover effect, it is also important to learn how information transmission can have impact on active asset allocation in optimal risk choice and hedging. The selected emerging markets that are poised for growth in the future as the developed markets have already matured, understanding the linkages of these markets should provide additional venue for potential investors in asset allocation that can enhance their investments beyond developed markets. From an econometric perspective, we use VAR (Vector Autoregression) and GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) family to conduct our research. The use of GARCH family should help eliminate the typical problem with conventional econometric time series models.

The rest of the paper is structured as follows: Section 2 briefly reviews current literature. Section 3 discusses the data and methodology followed in examining stock markets' returns and volatility dynamics. Section 4 analyzes evidences on returns and volatility linkages. It also discusses some implications of our findings in global portfolio diversification. Finally, Section 5 offers the conclusion of this research.

2. Literature Review

There is a vast research on returns and volatility linkages among countries around the world. Many different models and methodologies such as cross correlations, VAR models, cointegrations models, GARCH family, multivariate GARCH family, Regime switching models, and stochastic volatility models appear in the literature to investigate the extent of linkages. Engle et al. (1990a), Hamao et al. (1990), Koutmos and Booth (1995) or Booth et al. (1997), among others extend international monetary markets to international stock markets. It becomes apparent in the literature that some markets are more interdependent in volatility than in returns. Hong (2001) examines the presence of Granger causalities between U.S. dollar and Deutsche mark and Japanese Yen. He finds simultaneous interaction between the mean of two exchange rates. On the other hand, he finds simultaneous and one-way interactions in the variance. King and Wadhwani (1990) and Hong (2001) develop tests that are based on residual cross-correlation function to study the spillover effect. Van Dijk, Osborn, and Sensier (2005) continue their analysis to further account for the existence of structural breaks in volatility. Diebold and Yilmaz (2009) apply VAR model to in their research to calculate the level of spillovers. Engle, Gallo, and Velucchi (2009) examine daily volatility transmission to capture the dynamic relationships among volatilities in different markets. Finally, Wongswan (2006) observes the international return and volatility transmission from United States and Japan to Korea and Thailand. Engle and Ng (1988), Hamao, Masulis, and Ng (1990), Engle, Ito, and Lin (1990), King, Sentana, and Wadhwani (1994), Lin, Engle, and Ito (1994), Karolyi (1995), and Wongswan (2006) apply multivariate GARCH techniques to study the volatility spillovers among international markets and find the existence across international stock and foreign exchange currency markets. To further investigate on the spillover issue, Cheung and Ng (1996), Hong (2001), Pantelidis and Pittis (2004), Sensier and van Dijk (2004), and van Dijk, Osborne and Sensier (2005) apply simple tests of correlation in volatility based on the lead-lag of squared GARCH-standardized residuals. Gourieroux and Jasiak (2007) test spillover in volatility by approximating conditional log-Laplace transforms of compound AR processes. Diebold and Yilmaz (2008, 2009), on the other hand, examine volatility transmission using VAR on range-based volatility. Corradi, Distasso, and Fernandez (2009) examine the degree of transmission in volatility among world stock markets deriving several tests for conditional independence on daily volatility techniques. Their findings suggest that volatility transmission is stronger from China to Japan and US not the vice-versa. Beirne et al. (2008) investigate volatility transmission from developed markets to Emerging markets and test for their changes during crisis periods. Similar studies also jointly investigate transmission of volatility of Emerging markets to developed markets (Dungey et al., 2006, 2007; Kaminsky & Reinhart, 2003). Beirne et al. (2008) and Spagnolo (2009) look at the transmission mechanism during financial turbulence in developed countries, and review the conditional correlations of returns and find unidirectional volatility effects from developed markets to many emerging markets. Engle et al. (2009) in their research observe that volatility responds differently in quiet and turbulent periods except for East Asian countries. They also observe "build-up" in volatility transmission in case of major episode of the Asian crisis. As it is apparent from existing literature the interest and importance of transmission of return and volatilities among markets, this research extends the literature by investing the linkages among G-7 and prominent countries to bring more insights into the literature.

3. Data and Methodology

The main objective of this research is to investigate spillover effect among G-7 and these prominent countries to further contribute to this literature as it does not exist in the existing literature. We consider closing-to-closing data on stock market indices like Allen and McDonald (1995). In order to avoid stationary problem, we take natural logarithm of the raw data and continuously compounded return series are computed from market indices series as follows:

$$x_t = (\ln P_t - \ln P_{t-1}) \times 100 \tag{1}$$

Where x_t is current returns, P_t is the closing stock price index at time t, and P_{t-1} is the previous day closing stock market index. Our dataset comprises of daily closing indices (P_{it}) for the seventeen stock markets for the period December 30, 1995 to February 28, 2007. The beginning data is set based on the availability of data for all countries. The following indices are used for the respective stock markets: Merval, IBOVESPA, TSX Composite, IPC index, SSE Composite Index, Heng Seng Index, BSE Index, Jakarta Index, Seoul Composite, TSEC Index, DAX, Nikkei 225, CAC 40, MIBTEL, FTSE 100 and S&P 500. To understand the returns and volatility linkages, the Vector Auto Regressive has been considered for examining return and volatility linkages. The VAR model is expressed as follows:

$$X_t = C + \sum_{s=1}^{m} A_s X_{t-s} + \varepsilon_t \tag{2}$$

Where X_t is a 16 x 1 vector of return series for all markets, C is the constant, A_s are respectively, 16 x 1 and 16x 1 6 coefficient matrices, m is the number of lag length and e_t is the 16 xl stochastic error vector which is uncorrelated with all the past X_s. The block erogeneity test is applied to isolate the set of exogenous variables that have influence on endogenous variables. WE restrict all the lags of particular variables (X_ts) to zero and then test for the significance. This joint test is analogous to Granger causality. It is also applied to identify the most independent and dependent variables in returns and volatility linkages. We capture the sign, magnitude and persistence of responses of one market to another stock market. If the process used in this research is stochastic noise, the estimated VAR can be used in a moving average representation whose coefficients are forecast error impulse responses. The moving average representation takes the following form:

$$X_t = C + \sum_{s=0}^{k} B_s \varepsilon_{t-s} \tag{3}$$

Where, X_t denotes a linear combination of current and past one step ahead forecast error or innovation. The coefficient, B_s , is the response of one stock market returns to a one standard error shock of any of the markets "s" periods ago. The e_t's are serially uncorrelated although may be contemporaneously correlated. In this research, we use the Cholesky decomposition estimation criterion. We also use Variance decomposition to determine if a market is either dependent or independent. This can be guessed from the extent to which own-innovation can explain variations in first and second moments of the stocks market series.

To test for the volatility transmission among the markets, we first test the volatility of each market using the GARCH, EGARCH and GJR GARCH models. Conditional variance series are then generated using one of the most appropriate listed models that serve as a proxy for volatility for each markets and then is analyzed using the VAR together with impulse response and variance decomposition to examine the transmission among the selected markets. Like Takaendesa et al. (2006), this study also employs the following mean equation:

$$y_t = \mu + \varepsilon_t \tag{4}$$

Where y_t return for each markets and μ is a constant. If autocorrelation is observed, lagged values of the dependent variable would be added until serial correlation is eliminated. The equation is also tested for ARCH effect before proceeding to estimating volatility models. GARCH-M model of Engle et al. (1987) offers a very useful way of modeling risk and return. GARCH-M model is modeled here by extending the above mean equation as follows:

$$y_t = \mu + \delta h_{t-1} + \varepsilon_t, \ \varepsilon_t \approx N(0, \sigma_t^{\ 2}) \tag{5}$$

Where y_t denotes mean returns, h_{t-1} is a lagged conditional variance term and ε_t is the residual term. A conditional variance equation is derived and estimated. The δ in the equation is defined as risk premium. If it is positive and statistically significant, then increased risk leads to a rise in mean return. To test for the ARCH effect in the data we implement Lagrange Multiplier test. The GARCH model (Bolerslev, 1985), that applies MLE process is chosen in our research as it allows the conditional variance to be dependent on own lags. The conditional variance equation in GARCH (1,1) takes the following form:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \ \alpha + \beta < 1 \tag{6}$$

Where h_t represents conditional variance, ω is the constant, α is the coefficient of lagged squared residuals, ε_{t-1}^2 is the lagged squared residual from mean equation and β is the coefficient for the lagged GARCH component. Here, $a + \beta < 1$ is necessary for stationary of the GARCH model. We extend our analysis to capture the asymmetric effect. For this purpose, we apply EGARCH (Nelson, 1991) that is specified with the following conditional variance equation:

$$\log(h_t) = \omega + \beta\log(h_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \alpha\left[\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}} - \sqrt{2/\pi}}\right] \tag{7}$$

Here, $\delta + \beta < 1$, $\gamma \neq 0$ if there is asymmetry in impact and $\gamma < 0$ if there is leverage effect in the return series. If $\gamma \neq 0$ and significant, negative shocks imply a higher next period conditional variance than positive shocks of the same magnitude (i.e. asymmetric impacts). A leverage effect, which is a special case of asymmetric impacts, would exist if $\gamma < 0$. Finally, the GJR GARCH (proposed by Zakoian, 1990; Glosten et al., 1993) is also explored as this model also captures asymmetry with variation in specifications from EGARCH. This model is also a re-specification of the GARCH (1, 1) model with an added term representing asymmetry as follows:

$$h_t^2 = \alpha_0 + \alpha_1\varepsilon_t^2 + \beta h^2{}_{t-i} + \gamma\varepsilon^2{}_{t-i} I_{t-1}, \tag{8}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ or $=0$ if otherwise. Here, I represents asymmetry component and γ is the asymmetry coefficient. The presence of leverage effects is observed when the asymmetry coefficient is significantly positive (i.e. $\gamma > 0$). The intuition behind this is that good news ($\varepsilon_t > 0$) and bad news ($\varepsilon_t < 0$) have different impacts on conditional variance. The impact of good news is only α_1 and that of bad news is $\alpha_1 + \gamma$. Like Shikwambana (2007), we also analyze the trend of volatility overtime by regressing each of the conditional variance series against a constant and a time variable as follows:

$$\text{ht} = \beta_1 + \beta_2 T \text{ ft} \tag{9}$$

Here, h_t is conditional variance at time t for each market and T is the time in days. If β_1 is significantly positive, it implies that volatility increases over time. A significantly negative β_1 would implies that volatility should decrease over time.

4. The Results

Table 1. Descriptive statistics for return series

	Argentina	Brazil	Canada	Mexico	USA	China	HongKong	India	Indonesia	Japan	Korea	Taiwan	France	Germany	Italy	England
Mean	0.000616	0.0005	7.20E-0	0.0006	-7.79E-0	0.0001	6.89E-05	0.00055	0.000711	-0.0001	0.00031	-1.61E-0	-0.00018	-4.81E-0	-0.00024	-5.76E-0
Median	0.001143	0.0013	0.00044	0.0012	0.00060	0.0000	0.000214	0.00128	0.001242	0.0001	0.00136	0.00034	0.00018	0.00075	0.00023	0.00043
Maximum	0.161165	0.1367	0.09370	0.1044	0.10957	0.0940	0.134068	0.15990	0.076234	0.1323	0.11284	0.06524	0.10594	0.10797	0.10370	0.09384
Minimum	-0.129516	-0.1209	-0.09788	-0.0726	-0.09469	-0.0925	-0.135820	-0.11809	-0.109539	-0.1211	-0.12804	-0.09936	-0.09471	-0.07433	-0.08603	-0.09264
Std. Dev.	0.022407	0.0199	0.01269	0.0145	0.01388	0.0169	0.016678	0.01729	0.015355	0.0163	0.01772	0.01615	0.01576	0.01673	0.01314	0.01339
Skewness	-0.072102	-0.0875	-0.78124	0.0450	-0.10934	-0.1099	0.045350	-0.15733	-0.691249	-0.2712	-0.49610	-0.23377	0.04296	0.06400	-0.16691	-0.11511
Kurtosis	7.884198	6.7848	12.9870	7.3581	11.1230	7.1661	11.24070	9.56354	8.963763	9.2968	7.55999	5.38581	8.26164	7.33735	9.73863	9.43676
Jarque-Bera	2403.536	1445.1	10286.3	1912.8	6647.20	1752.1	6837.013	4346.69	3772.762	4021.1	2192.31	595.012	2787.68	1895.45	4582.41	4176.15
Probability	0.000000	0.0000	0.00000	0.0000	0.00000	0.0000	0.000000	0.00000	0.000000	0.0000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	1.488238	1.3774	0.17387	1.5742	-0.18828	0.3254	0.166350	1.33491	1.718016	-0.4257	0.76955	-0.03890	-0.45556	-0.11616	-0.57916	-0.13908
Sum Sq.Dev.	1.212549	0.9616	0.38936	0.5119	0.46585	0.6947	0.671736	0.72192	0.569389	0.6444	0.75888	0.63027	0.60007	0.67613	0.41750	0.43309
Observations	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416	2416

Table 1 provides descriptive statistics for return series of countries under consideration. The statistics show similar characteristics. For instance, there is non-normality in the form of fat tails. We observe some noticeable differences, especially between developed and emerging stock markets. First, returns are larger in emerging markets compared to those of developed markets. It is interesting to observe that the emerging markets exhibit the largest unconditional average daily return of 0.000181% with Indonesia being the highest with 0.000711% during the sample period. Of the developed stock markets Canada has the largest unconditional average return of 0.0000689%

and the lowest for the US of about -0.0000779%. Interesting to observe is also the smallest standard deviation for Indonesia which is well below some of the developed stock markets (Japan and Germany). All the markets show distributions with positive excess kurtosis and evidence of fat tails. A distribution with a kurtosis value of more than 3 is described as leptokurtic relative to normal which implies returns tend to contain extreme values. Finally, the Jarque-Bera (JB) statistic tests indicate that return series are non-normal for all return series which is also evident from the fatter tails of the kurtosis and negative and positive skewness.

Table 2 shows the pair wise correlation matrix among the return series. We find evidence of contemporaneous correlation among these markets during the sample period. Correlation dynamic is diverse indicating that there is no common trend or factor driving these markets in the same direction. This is supported for the possibility of international diversification in portfolio of asset allocations. The most interesting point is the correlation between Hong Kong and China's stock markets, because the number shows that both stock markets are negatively correlated. This information shows the benefit for investors who have interest in these two Chinese stock markets, can safely diversify their investment in both of them.

Table 2. Correlation matrix for return series

	Argentina	Brazil	Canada	Mexico	USA	China	HongKong	India	Indonesia	Japan	Korea	Taiwan	France	Germany	Italy	England
Argentina																
Brazil	0.08812															
Canada	0.03223	0.03626														
Mexico	0.00228	-0.0110	0.07846													
USA	-0.02366	-0.0022	-0.03958	0.06396												
China	-0.0075	0.02884	-0.0175	0.02868	0.05297											
HongKong	-0.01318	0.04793	0.03837	0.01149	0.07163	-0.0039										
India	0.02823	0.00831	-7.94E-	0.02714	-0.00388	0.07252	0.057081									
Indonesia	0.01942	-0.0436	0.04416	0.01513	0.06807	0.05302	0.038795	0.0431								
Japan	0.03484	0.02754	-0.03379	0.03659	-0.01561	0.00749	-0.060109	0.02591	0.09888							
Korea	-0.02219	0.01094	0.01172	0.00423	0.06724	0.02352	0.062126	0.02555	0.07833	-0.01941						
Taiwan	0.09398	0.09892	-0.00067	0.00908	-0.02165	0.00348	-0.019288	0.08671	0.02030	-0.01429	-0.01101					
France	-0.03137	-0.0325	0.02627	-0.0022	0.03560	0.04229	0.0157	-0.0086	-0.02032	0.07631	-0.01855	-0.0204				
Germany	-0.03327	-0.0063	0.03570	0.01854	0.02165	0.02843	-0.009867	0.01004	0.02671	0.05959	-0.00049	0.02149	0.23989			
Italy	-0.03881	-0.0184	0.04727	-0.0093	0.01497	0.00456	0.005996	0.02216	-0.00153	0.01167	0.02181	0.01792	-0.01934	-0.0305		
England	-0.04842	0.0109	0.0213	-0.0106	0.2049	-0.0126	0.099629	0.02601	0.012123	0.013186	0.080050	-0.0061	0.069623	0.033492	-0.12787	

When one look at the matrix, it is also observed that investors from one country can benefit from a mix of stocks of some countries that are different from investors of another country. For example, investors from Canada can benefit greatly by choosing USA, China, India, Japan, and Taiwan as portfolio holdings, whereas, investors from England can greatly benefit by investing in Argentina, Mexico, China, Taiwan, and Italy. Similarly, investors from USA can benefit by investing in Argentina, Brazil, Canada, India, Japan and Taiwan. So the country mixes are different for investors of different countries. Taiwan, interestingly, turns out to be a country of choice for most developed countries but not for the investors of developing countries. We conduct ADF and KPSS test with appropriate lag length of 30. Using SIC and the maximum lag length 30 it is expected that due to their information efficiency, the stock markets should react to new shocks or information within 30 days among countries from the origin of the information. The KPSS is estimated using the Bartlett Kernel estimation method and results of both tests are reported in the Table 3 and 4. Results from both the ADF and the KPSS show that, given the significance level of 1%, all the index series are non-stationary at level. However, all series becomes stationary at differenced once matching the results exist in the current literature as it is the case exist in the current literature.

Table 3. Unit root and stationarity test results (with intercept and trend)

SERIES	ADF		KPSS	
	Level	1st Difference	Level	1st Difference
Argentina	-1.731047	-46.97907	0.536800	0.097710
Brazil	-1.946775	-48.26284	0.444586	0.110090
Canada	-1.257814	-37.90337	0.557728	0.135056

Mexico	-1.577919	-35.49295	0.449272	0.131751
USA	-1.163480	-39.71579	0.574480	0.116217
China	-1.141275	-48.91090	0.485821	0.175725
Hong Kong	-1.474470	-50.60648	0.415993	0.121590
India	-1.835795	-35.29211	0.423481	0.143145
Indonesia	-1.887340	-43.12922	0.364662	0.126199
Japan	-1.133199	-51.01151	0.646266	0.145854
Korea	-1.926636	-48.30874	0.376282	0.083901
Taiwan	-1.045872	-46.76580	0.270087	0.092227
France	-0.847148	-24.32654	0.623244	0.140097
Germany	-0.729269	-51.11089	0.605014	0.137494
Italy	-1.646353	-22.61183	0.686728	0.169190
England	-1.252127	-23.73216	0.570642	0.105585

Note. The MacKinnon (1996) (i.e. for ADF test) 1% critical value = -3.961629 and the KPSS (1992) 1% critical value = 0.216, thus denotes the rejection of the hypothesis of a unit root/non-stationarity for both tests. The lag order for the series for the ADF was determined by the Schwarz information criterion and the spectral estimation method used for KPSS is Bartlett Kernel.

Table 4. Unit root and stationarity test for return series

Series	ADF at Level	KPSS at Level
Argentina	-46.96362*	n/a
Brazil	-48.23189*	n/a
Canada	-37.89748*	n/a
Mexico	-35.40573*	n/a
USA	-39.71512*	n/a
China	-48.91186*	n/a
Hong Kong	-50.60271*	n/a
India	-35.24046*	n/a
Indonesia	-43.04509*	n/a
Japan	-51.01980*	n/a
Korea	-48.30641*	n/a
Taiwan	-46.75839*	n/a
France	-24.30593*	n/a
Germany	-51.10413*	n/a
Italy	-22.59227*	n/a
England	-23.71138*	n/a

Note. The MacKinnon (1996) (i.e. for ADF test) 1 % critical value = -3.961629 and the KPSS (1992) 1% critical value = 0.216, thus * denotes the rejection of the hypothesis of a unit root/non-stationarity for both tests. The lag order for the series was determined by the Schwarz information criterion and the spectral estimation method is Bartlett Kernel for ADF and KPSS, respectively.

4.1 Return Linkage among Equity Markets

Using a VAR model, we test if the return series among the world equity markets are linked. We proceed with return series for our VAR analysis using a lag order of 1-10. Various methods are analyzed in choosing appropriate lags. We conduct our tests based on each of the four criteria shown in Table 5. Although results are very similar, we decide to follow the AIC in choosing lag to present our analysis consistent with existing literature. We present only the result of immediate lag that are significant in Table 6 in order to reduce the size of the paper. It is evident from the table that except for Italy, for all developed countries, own immediate lags have influence in return series and that is not the case for developing countries where lags further behind show significance. In case of Italy, lag 4 seems to be significant in own return influence. Argentina's one lag return has significant influence on Brazil and Taiwan at 5% level of significance, Brazil's lagged return has influence on Korea, Mexico has influence on Canada, Hong Kong influences France, and Japan influences Indonesia as an evidence of linkage. One of the implications of these return linkages for a trader/investor is to avoid including countries where one country has influence on another country and pool countries accordingly in portfolio selection which may help improve portfolio returns with justified risks.

Table 5. Lag length selection criteria

Criteria	Lag Length
LR	30
AIC	10
SC	0
HQ	1

Table 6. VAR results for return linkages

	ARG	BRA	CAN	MEX	USA	CHN	HKG	IDA	IDO	JAP	KOR	TWN	FRA	GER	ITA	BRI
ARG(-1)		0.0575**										0.0508**				
BRA(-1)											0.07063*					
CAN(-1)			-0.1114*		0.19423*											0.0749**
MEX(-1)			0.1378*	0.06**												0.050***
USA(-1)					-0.2058*											0.10859*
CHN(-1)									0.054**							
HKG(-1)							-0.09*						0.0577**			0.06471*
IDA(-1)			0.0480**					0.057***	0.0723*							
IDO(-1)									0.0991*	0.0687**						
JAP(-1)								0.074**	0.0932*							
KOR(-1)											-0.06***					
TWN(-4)												-0.07**				
FRA(-1)													-0.1260*			-0.054**
GER(-1)														-0.10078*		
ITA(-4)															0.0972*	
BRI(-1)					0.0612***		0.08**				-0.077***					-0.1570*

Note. *Significance at 1%, ** significance at 5% level, ***significance at 10% level.

4.2 Volatility Linkages among Equity Markets

In this section we present the results of volatility linkages among countries. We first generate volatility/conditional variance series of each market using univariate volatility model. We then analyze the volatility series using a VAR framework together with impulse response and variance decomposition. We test for the hypothesis that more risk implies more returns by including the GARCH-in mean component in each of the volatility models. The mean equation is estimated for each market and is then tested for ARCH effect to check whether volatility has been captured. Table 7 shows the DW statistics from the mean equations and ARCH LM F-statistics. Our findings indicate that there is no significant evidence of autocorrelation for the mean equations of each of the stock markets and all the markets show significant evidence of ARCH effect, implying that the mean equation does not adequately capture volatility. Once mean equations are determined, we determine the appropriate GARCH model and at the same time test for the hypothesis that high risk is associated with more returns. The univariate GARCH (1, 1), EGARCH (1, 1, 1) and GJR GARCH (1, 1, 1) models are estimated with a GARCH-M component to test the hypothesis that investors in a volatile market earn a premium. Our estimations are reported in Table 8. As observed, in case of Germany, we estimate the models with a residual component of order 2 i.e. GARCH (2, 1), EGARCH (2, 1, 1) and GJR GARCH (2, 1, 1) as the standard models could not adequately capture the volatility. The coefficient δ is the *Arch-in mean* coefficient and it measures the relationship between volatility and returns. For all the stock markets and in all models, this coefficient is statistically significant at 1% (except for China). This means that for all the stock markets, except for the China in some cases, there is significant risk premium in returns as expected. In GARCH (1, 1), EGARCH (1, 1, 1) and GJR GARCH (1, 1, 1) models, the coefficient ω represents the intercept, the coefficients $\alpha 1$ and β are the residual squared and variance squared coefficients, and $\alpha 2$ is the second residual squared coefficient. All three coefficients are significant at 1% for all three models. For all stock markets, the summation of the residual squared coefficient ($\alpha 1$) and the variance squared coefficient, β are very high (i.e. close to 1 or over) which means that volatility is persistent i.e. does not fade fast. Leverage/asymmetric coefficient γ, that tests the asymmetry hypothesis for volatility in the stock markets turns out to be significantly negative at 1% This indicates that bad news leads to less volatility than positive news of the same magnitude i.e. volatility is asymmetric and there is evidence of leverage effects in all the sixteen stock markets. The result from EGARCH model also finds the coefficient positive and significant for all the stock markets. To identify the most appropriate model, our selection criterion is based on summation of the residual and GARCH coefficients. For any GARCH model to be stationary, we must observe that $\alpha 1 + \beta < 1$. To capture ARCH effect is also considered in our model selection. We observe that in case of EGARCH model, $\alpha 1 + \beta > 1$ for all the stock markets and hence we drop the EGARCH model. However for the GJR GARCH, $\alpha 1 + \beta$ is also bigger than 1. Since the results show that volatility is asymmetric and leverage effects are present in all the stock markets, the standard GARCH better captures volatility in all stock markets and we now use this model to generate our conditional variance/volatility series for each of the stock markets.

Table 7. Autocorrelation test for the mean equation

STOCK MARKET	DW STATISTIC	ARCHLM
Argentina	2.102156	239.0545*
Brazil	2.098276	62.48754*
Canada	2.067353	280.3364*
Mexico	2.060807	50.02819*
USA	2.124900	103.7865*
China	2.016317	36.1468*
Hong Kong	2.192510	309.9013*
India	2.048753	81.54596*
Indonesia	2.076445	83.79729*
Japan	2.177597	133.1380*
Korea	2.048784	52.18535*
Taiwan	2.046328	47.22141*
France	2.066836	68.59643*
Germany	2.091393	80.50881*
Italy	2.085377	102.5436*
England	2.123219	146.9659*

Note. * implies significance at 1 % Level, **significance at 5% level and ***significance at 10% level.

To formally investigate the long-term behavior of volatility, the conditional variance series are regressed on time. The results for the estimation are reported in Table 9 in below. Table 9 shows that volatility in five stock markets (Argentina, Korea, Taiwan, France and the Germany) is increasing although not significantly in case of France. On the other hand, it is decreasing over time for the rest of the equity markets. Overall, volatility in all the stock markets is relatively stable overtime that implies these world stock markets have been relatively stable since 1995. This could be attributed to the fact that investors are becoming more confident in investing in equity markets and are not very responsive to crisis. This explanation is also confirmed by the fact that most of the markets under study, except China and Japan, do not respond very much to the Asian and Latin American crises. The volatility series for the various markets are examined for correlation using the pair-wise correlation matrix in multivariate framework and results are reported in Table 10.

Table 8. GARCH models for volatility analys

GARCH(1,1)

Parameter	Argentina	Brazil	Canada	Mexico	USA	China	HK	India	Indonesia	Japan	Korea	Taiwan	France	Germany	Italy	England
δ	-3.9295*	-10.696*	-8.5793*	-12.539*	-7.4243*	-4.728**	-6.2482*	-8.5487*	-16.045*	-8.5059*	-10.379*	-8.4942*	-9.0345*	-8.7838*	-12.759*	-9.7182*
ω	9.12E-06*	9.32E-06*	1.14E-06*	3.42E-06*	1.01E-06*	5.28E-06*	1.62E-06*	6.02E-06*	1.44E-05*	2.93E-06*	3.31E-06*	1.76E-06*	1.75E-06*	2.24E-06*	1.31E-06*	1.32E-06*
α1	0.113397*	0.082363*	0.102406*	0.09996*	0.08719*	0.08527*	0.07529*	0.16987*	0.15802*	0.09522*	0.08919*	0.06664*	0.08952*	0.10306*	0.10926*	0.11568*
β	0.869610*	0.892646*	0.894345*	0.88597*	0.90809*	0.89837*	0.91913*	0.82198*	0.78215*	0.89505*	0.90355*	0.92805*	0.90444*	0.89034*	0.88585*	0.87949*
α2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
α1+α2+β	0.983007	0.975009	0.996751	0.985937	0.995278	0.983643	0.99442	0.991855	0.940175	0.990269	0.992743	0.994684	0.993963	0.993398	0.995104	0.995179
γ	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
F-LM	1.877582	2.99117	1.408842	0.672353	5.549868	1.711190	2.827905	1.342150	3.252742	2.379162	1.928281	3.465396	6.393991	8.007481	0.120303	5.713819
SIC	-5.03010	-5.1328	-6.36896	-5.82886	-6.20185	-5.47704	-5.73748	-5.56637	-5.68094	-5.64367	-5.43778	-5.61285	-5.84699	-5.74846	-6.24914	-6.25226
AIC	-5.07564	-5.1784	-6.41449	-5.87439	-6.24738	-5.52257	-5.78304	-5.61190	-5.72647	-5.68918	-5.48328	-5.65838	-5.89252	-5.79399	-6.29467	-6.29779

GJR GARCH

Parameter	Argentina	Brazil	Canada	Mexico	USA	China	HK	India	Indonesia	Japan	Korea	Taiwan	France	Germany	Italy	England
δ	-2.5297**	-7.0096*	-5.2567*	-7.5375*	-3.6368*	-3.833**	-4.268**	-6.1477*	-13.387*	-5.4948*	-6.8106*	-5.5737*	-4.8463*	-5.4227*	-6.2398*	-5.3638*
ω	7.77E-06*	6.12E-06*	4.16E-07*	2.17E-06*	4.25E-07*	6.62E-06*	1.41E-06*	4.69E-06*	1.08E-05*	1.30E-06*	1.7E-6*	9.26E-07*	6.15E-07*	1.15E-06*	2.8E-7*	8.82E-07*
α1	0.17677*	0.156678*	0.148015*	0.15431*	0.13627*	0.16799*	0.11543*	0.24944*	0.22442*	0.15075*	0.1603*	0.11554*	0.13992*	0.17904*	0.1567*	0.18234*
β	0.87582*	0.91023*	0.92762*	0.91679*	0.94553*	0.87752*	0.92905*	0.84598*	0.81795*	0.91914*	0.9246*	0.94623*	0.94474*	0.92262*	0.9355*	0.91906*
α2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
α1+α2+β	1.052599	1.066915	1.075638	1.071106	1.081807	1.04551	1.044489	1.09543	1.042373	1.0699	1.08486	1.061781	1.084668	1.101671	1.09213	1.101415
γ	-0.12193*	-0.14926*	-0.13*	-0.1451*	-0.1514*	-0.1223*	-0.0943*	-0.1799*	-0.1563*	-0.1318*	-0.1533*	-0.1160*	-0.1572*	-0.1859*	-0.1575*	-0.1907*
F-LM	1.703888	2.402017	0.989394	0.314166	4.804885	1.618336	2.436685	1.071762	2.795527	2.025306	1.64211	2.832440	4.201942	7.000572	3.93634	4.618173
SIC	-5.040464	-5.15211	-6.38836	-5.85319	-6.23496	-5.4838	-5.74988	-5.58006	-5.69066	-5.65895	-5.46574	-5.63836	-5.88003	-5.78427	-6.29480	-6.28640
AIC	-5.088393	-5.20004	-6.43626	-5.90109	-6.28289	-5.53178	-5.79788	-5.62797	-5.73859	-5.70688	-5.51367	-5.68629	-5.92796	-5.83217	-6.34272	-6.33433

EGARCH

Parameter	Argentina	Brazil	Canada	Mexico	USA	China	HK	India	Indonesia	Japan	Korea	Taiwan	France	Germany	Italy	England
δ	-2.6263**	-11.041*	-9.1452*	-12.235*	-7.0764*	-2.92244	-5.9733*	-7.3966*	-14.1738*	-9.4034*	-8.9875*	-6.164*	-8.0329*	-8.1339*	-9.0519*	-9.6499*
ω	-0.3550*	-0.42075*	-0.25694*	-0.38241*	-0.21329*	-0.43129*	-0.22736*	-0.45071*	-0.84680*	-0.31642*	-0.34845*	-0.20003*	-0.22602*	-0.26219*	-0.22443*	-0.30887*
α1	0.22876*	0.17183*	0.17211*	0.18903*	0.1103*	0.20417*	0.14136*	0.27430*	0.30704*	0.16830*	0.1866*	0.13008*	0.11539*	0.12739*	0.15227*	0.14799*
β	0.97702*	0.96451*	0.98641*	0.97275*	0.98585*	0.96625*	0.9862*	0.97158*	0.92848*	0.97831*	0.97530*	0.98806*	0.98429*	0.98127*	0.98804*	0.97884*
α2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
α1+α2+β	1.205781	1.136324	1.158512	1.161771	1.096153	1.170414	1.127598	1.245887	1.235529	1.146612	1.161908	1.11815	1.09969	1.108668	1.140322	1.126841
γ	0.07669*	0.10568*	0.08776*	0.09449*	0.13606*	0.07507*	0.07150*	0.07457*	0.06886*	0.08542*	0.11006*	0.07667*	0.13642*	0.14395*	0.10864*	0.14832*
F-LM	0.933211	5.206292	3.286540	3.192479	7.829020	2.099898	4.930390	3.560254	7.154167	4.769311	4.614421	4.094531	7.542368	9.769449	3.145299	8.842191
SIC	-5.046320	-5.16251	-6.39015	-5.85722	-6.24752	-5.49107	-5.75329	-5.58777	-5.69941	-5.66838	-5.47446	-5.63153	-5.89081	-5.80334	-6.30266	-6.29306
AIC	-5.096645	-5.21283	-6.44048	-5.90754	-6.29784	-5.54140	-5.80361	-5.63809	-5.749745	-5.71871	-5.52479	-5.68186	-5.94119	-5.85366	-6.35298	-6.34339

Table 9. Volatility over time for all markets

Stock market	B1	P-value	B2	P-value
ARG	0.012506	0.0000	2.47E-06	0.0000
BRA	0.014890	0.0000	-1.91E-07	0.6282
CAN	0.010905	0.0000	-2.15E-06	0.0000
MEX	0.011621	0.0000	-1.04E-06	0.0005
USA	0.010200	0.0000	-7.80E-07	0.0098
CHN	0.016699	0.0000	-4.30E-06	0.0000
HKG	0.014566	0.0000	-2.75E-06	0.0000
IDA	0.014905	0.0000	-2.29E-06	0.0000
IDO	0.012035	0.0000	-1.00E-06	0.0016
JAP	0.012457	0.0000	-7.13E-07	0.0336
SKR	0.009649	0.0000	2.40E-06	0.0000
TWN	0.009070	0.0000	2.05E-06	0.0000
FRA	0.010405	0.0000	4.29E-07	0.1955
GER	0.009392	0.0000	1.87E-06	0.0000
ITA	0.009521	0.0000	-5.79E-07	0.0418
ENG	0.009881	0.0000	-6.25E-07	0.0288

Table 10. Correlation matrix on volatility

	VOLARG	VOLBRA	VOLCAN	VOLMEX	VOLUSA	VOLCHN	VOLKHG	VOLIDA	VOLIDO	VOLJAP	VOLKOR	VOLTWN	VOLFRA	VOLGER	VOLITA	VOLBRI
VOLARG																
VOLBRA	0.1753															
VOLCAN	0.1191	0.1819														
VOLMEX	0.1260	0.1771	0.2189													
VOLUSA	0.1716	0.1793	0.3341	0.1988												
VOLCHN	0.0151	0.0972	0.1416	0.0707	0.0955											
VOLHKG	0.1247	0.2233	0.2842	0.1981	0.3074	0.1292										
VOLIDA	0.0986	0.1257	0.1640	0.1565	0.1051	0.1260	0.1720									
VOLIDO	0.0842	0.1352	0.1250	0.0876	0.1539	0.0860	0.1409	0.1522								
VOLJAP	0.1904	0.2016	0.1615	0.1623	0.2226	0.0663	0.1643	0.2034	0.1928							
VOLKOR	0.0940	0.1428	0.1688	0.1370	0.2037	0.0154	0.1735	0.1022	0.0913	0.1120						
VOLTWN	0.1547	0.1501	0.1300	0.1509	0.1514	0.0112	0.1211	0.1207	0.0742	0.1181	0.1571					
VOLFRA	0.1202	0.1500	0.2408	0.1229	0.3346	0.0487	0.1844	0.0611	0.1189	0.1538	0.1207	0.1549				
VOLGER	0.1145	0.1341	0.2056	0.1074	0.2558	0.0285	0.1454	0.0592	0.0683	0.1683	0.1590	0.1365	0.4554			
VOLITA	0.0003	0.0104	0.0109	-0.0142	0.0571	-0.0355	0.0159	-0.0122	0.0110	0.0190	0.0270	0.0526	0.0473	0.0763		
VOLBRI	0.1328	0.1723	0.2601	0.2008	0.3301	0.0973	0.2814	0.0924	0.1070	0.1422	0.2337	0.1259	0.2787	0.2471	0.0371	

It is evident that, as in the case of returns, volatility for the stock markets is positively correlated. However, correlation in volatility seems to be more than that of returns. The US equity market volatility is highly correlated with the Canada, Hong Kong, Germany and Britain. Generally, volatility in the US is highly correlated with other markets, implying possibly that the US dominates volatility influence. This implies that potential gains from portfolio diversification are limited among these countries that are highly correlated. Additionally, it raises questions regarding the transmission of harmful contagion effects across the markets.

5. Conclusion

Return and volatility linkages among seven developed and nine prominent emerging stock markets are examined in this research taking twelve years of daily data. The results in descriptive statistics are in line with the properties of financial data, notably non-normality, excess kurtosis and excess volatility (ARCH effect). We also find positive, although low, pair wise correlation between the stock markets. Return linkages among the stock markets are examined using VAR. Our results indicate that world markets show significant returns linkages with the US followed by China. Next, volatility linkages are also analyzed. We find evidence of leverage effects and asymmetry in volatility in all markets, with an exception for the China. The evidence of risk premium in all stock markets is evident. Finally, we examine the volatility transmission among equity markets, and significant volatility interactions are observed. From our results, we also observe that stock markets in the same continent have the most influence in that area, except for UK market, which has links to the US stock market. An interesting extension of this research would be to experiment portfolio analysis based on the correlations among developed and emerging markets to see which combination provides positive alpha and better diversification. It would also be an interesting future research if we can find optimal portfolio allocation among these countries and compare the performance with large and small cap assets mixes of own country. This result should further validate that whether international diversification is superior to domestic investments only.

In terms of policy implications, given the volatility result, portfolio diversification between high/low volatile stocks should become an essential focus for most investors, particularly for emerging equity markets. This is quite crucial where volatilities of stocks returns are driven by changes in stocks' trading trend and volume that normally follow the flow of the new information and how such information are reflected and incorporated towards stock prices. Further, investors should consider other factors that affect their investment decision together with the risk (volatility) factor. Of such factors are the skewness and kurtosis of the stock's returns, stock's book to market value, the applied dividend's policy, dividend yields, interest rates, firm's earning and firm's size. For policy makers, markets with high volatility of stock returns may cause financial unsteadiness where capital normally seeks for more secure investment destinations. This is particularly true given the intra-integration between financial markets worldwide where less barriers to entry exist.

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