Emerging Equity Markets Connectedness, Portfolio Hedging Strategies and Effectiveness

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Abstract

In this paper, we investigate the volatility spillovers between equity market indexes for Islamic and non-Islamic emerging countries. To do so, we implement a combination of a vector autoregressive (VAR) and a multivariate GARCH models under BEKK specification (VAR-BEKK-MGARCH) models with constant conditional correlation (CCC) and dynamic conditional correlations (DCC) for daily equity returns of six markets, namely Turkey, Indonesia, Egypt, Mexico, China and Brazil. Our findings disclose strong volatility spillovers among the Islamic and the non-Islamic country' market returns. The volatility spillovers are time varying and are affected by the occurrence of recent financial crises. Furthermore, we extent the volatility spillovers analysis by providing some financial implications in terms of optimal portfolio' allocations and hedging effectiveness. Specifically, we estimate the optimal weights for a minimum risk multi-country portfolios, we compute the hedge ratio and we assess the hedging strategies' effectiveness. Our findings provide prominent implications for policy makers and portfolio managers in terms of the stability of the financial systems, asset allocation decisions and designing portfolio hedging strategies.

Keywords: volatility spillovers, multivariate GARCH, emerging markets, hedging strategies, hedging effectiveness

1. Introduction

Equity markets co-movement is a key parameter that to be estimated when allocating assets and designing portfolios' hedging strategies (Elton and Gruber 1973, Chan et al. 1998, Gibson and Boyer 1998, and Aggarwal et al. 1999). Empirically, the analysis of the co-movement and the volatility spillovers among equity returns allows for the risk quantification and the analysis of volatility shock transmission between two or several equity markets. The related empirical literature shows that most prior studies were concerned with conventional equity markets between developed equity markets and emerging equity markets or between emerging markets located on the same region.

Specifically, in this paper, we ask the following two research questions. First, how strong is the connectedness between emerging equity markets? Do stock markets in Islamic countries behave differently from those in operating in non-Islamic countries? How dynamic correlations between equity returns evolving through time? Are they affected by the extreme events such as global financial crisis? How can we exploit the correlation behavior to provide more insights to portfolio managers in relation to asset allocation decision and portfolio risk hedging?

Based on the aforementioned research questions, this study has two main objectives. The first is to investigate the return and volatility spillovers among emerging equity markets. Specifically, we ask whether there are differences in terms of causality linkages and volatility spillovers between equity markets operating in Islamic countries and those operating in non-Islamic countries. The second objective is check whether it is possible to extract the time varying correlations between these markets to find the optimal weights, to design hedging strategies and to assess these

In the present paper, we extend the literature on the return and volatility spillovers between emerging equity markets by providing new evidence from six emerging equity markets; namely, Egypt, Turkey, Indonesia, China, Mexico, and Brazil for the period (April, 2005-November, 2011). Specifically, we perform a multivariate Generalized Autoregressive Conditional Heteroscedasticity (hereafter, M-GARCH) model in order to investigate the existence and the direction of volatility spillovers between emerging equity markets from different regions. In addition, we extend our multivariate analysis to offer conspicuous managerial implications in terms of portfolio asset allocation,

and assessment of hedging effectiveness. More precisely, we use the dynamic conditional correlations (hereafter, DCCs) to estimate the optimal weights for a multi-country equity portfolio, to design hedging strategies and to test their effectiveness in terms of risk reduction.

Briefly, our findings mainly confirm the conclusions from other studies on volatility spillovers across regions. Specifically, our multivariate analysis unveils the existence of strong volatility shocks transmissions between the selected equity markets. Moreover, we perceive that the occurrence of extreme events such as the recent global financial crisis is affecting the time varying co-movement between equity markets. The obtained results are very useful for portfolio managers, hedge funds operating in those countries as well as policy makers. In fact, we extended our multivariate analysis to provide more prominent implications in terms of optimal equity portfolios and hedging strategies.

The reminder of the paper is structured as follows. Section 2 relates the literature review. Section 3 exposes the VAR-multivariate GARCH-DCC model. Section 4 describes the used datasets and relates the main empirical results while managerial financial implications are wrapped in section 5. Section 6 concludes.

2. Review of Previous Studies

Understanding volatility spillovers is important for portfolio asset allocation and designing hedging strategies. Now, it is well documented in the literature that greater integration of equity markets and correlated stock price volatility reduces the opportunities for international portfolio diversification (see, among others, Bekaert, Harvey and Ng, 2005, Bekaert and Harvey, 2002, 2003). On the other hand, analyzing the transmission of volatility between emerging equity markets may also shed light on the nature of information flows between international markets. In this vein, King and Wadhwani (1990) explain the volatility spillovers by the rational attempts of agents to use imperfect information about the events relevant to equity prices. Lin et al. (1994) revealed that foreign exchange returns can significantly affect the domestic equity returns for Japan and US. Using a quite similar approach, Ng (2000) assessed the strength and the time varying pattern of the volatility spillovers between Japan and the US equity markets and showed that regional and global factors including cultural, and religion factor are important variables that affect the time varying patterns of the market volatility. In his paper, Calvo et al. (2000) claimed that developed equity markets can act as a conduit for volatility across emerging markets in different regions. Furthermore, Dungey and Martin (2007) provide empirical evidence for the role of developed equity markets in the volatility transmission across regions.

During the last two decades, an abundant empirical studies were concerned with the volatility spillovers between emerging equity markets. The earlier studies were provided by Bekaert et al. (1995, 1997, and 2000) and Harvey and Ng (2005). Caporaleet al. (2006) investigated the volatility spillovers of some East Asian emerging markets during the 1997 financial crisis using a bivariate GARCH model. They found evidence of causality linkages. Ledoit et al. (2003) employed a general diagonal-Vech formulation of a MGARCH to estimate the volatility spillovers between seven major international equity markets. The authors unveiled that this model is more suitable to capture volatility spillovers. Quite similar approach was used by Lucey and Voronkova (2007) for the Russian market. Performing a MGARCH with constant conditional correlation (hereafter, CCC) model, Worthington and Higgs (2004) analyzed the return and the volatility spillovers between some developed and emerging Asian stock markets. Their results point out high degree of co-movement and volatility spillovers. Arouri et al. (2008) were concerned with the dynamic linkage between the main LA stock markets. They implemented a MGARCH-DCC and showed an increase in the short and the long term linkages between Latin American and the world market. Similarly, Li and Majerowska (2008) used a MGARCH-DCC to investigate the time varying correlations between two emerging markets (Warsaw and Budapest) and the German and the US stock markets. They showed that the two selected emerging markets are weakly linked to those in developed countries. Also, Frank and Hesse (2009) estimated a DCC-MGARCH-DCC model for some emerging stock markets and provided strong evidence of a sharp increase in the DCC behavior during the financial crisis period. In his study, Billio and Caporin (2005) investigated the behavior over time of the DCC'sMGARCH model using a two state Markov switching (MS) regime and uncovered some discontinuities in the volatility spillovers behavior through time. Diamantis' (2009) was focused on Latin American equity markets and showed that their interdependence to the US market has been strengthened during the Asian financial crisis. Beirne et al. (2010) analyzed the volatility spillovers between global and regional emerging stock markets. The authors used a trivariate VAR-GARCH model for 41 emerging stock markets and revealed a strong evidence of volatility spillovers between them.

Bala and Premaratne (2010) analyzed the volatility spillovers between Singapore stock market and some major international markets using different multivariate GARCH-class models. The authors provided evidence of a high degree of volatility co-movements between the selected markets. Using a bivariate GARCH specification, Shamiri and Isa (2009) examined the volatility spillovers between US and the South East Asian stock markets during the financial crisis period. They provided strong evidence of volatility spillovers running from the US market to all of the South East Asian stock markets. Moreover, Chiang et al. (2007) checked the existence of eventual shifts in the MGARCHDCC's behavior for nine Asian stock markets. The authors identified shifts in variance for the DCC's patterns during the crisis period. Concerned with the Eastern European countries, Savva and Aslanidis (2009) analyzed the degree of equity markets integration using MGARCH specification with smooth transition conditional correlation version. Silvennoinen and Teräsvirta (2007) used a MGARCH model with atime-varying conditional correlation structure and they provided evidence supporting growing degree of integration among equity markets.

Using a MGARCH model, Gebka and Serwa (2007) found mixed results on the volatility spillovers between emerging equity markets in Eastern Europe, East Asia and Latin America. Using a multivariate GARCH framework, Li (2012) investigates the influence of China's stock market reforms on the stock market interrelationships between China, the U.S., Korea, and Japan. The obtained results show that the Chinese stock market is connected with these overseas markets and the reforms tend to accentuate the spillovers from China to these markets. Malik and Ewing (2009), and Arouri et al. (2011) analyzed the equity markets integration using a MGARCH model. They uncovered strong evidence of return and volatility spillovers. In a more recent study, Balli et al. (2015) analyze the return and volatility spillovers models, the authors point out significant effects of volatility spillovers. Furthermore, the authors show that bilateral factors such as trade volume, portfolio investment and distance are significant in explaining the spillover effects.

Our study distinguishes itself from the aforementioned studies on two main aspects. First, we perform a VAR-MGARCH model under both CCC and DCC to analyze the volatility spillovers and shocks transmission between Islamic and non-Islamic equity markets. In fact, considering both the CCC and the DCC specifications is important to provide better comprehensive results to the time-varying correlations between equity returns and volatilities and to evaluate the degree of equity markets integration. Second, we extend our volatility spillovers analysis to offer prominent implications in terms of portfolio asset allocations and hedging strategies. Specifically, we refer to Kroner and Ng' (1998) framework in order to find optimal weights for a minimum risk portfolio combining both Islamic and non-Islamic countries. Such approach is very important for portfolio managers, hedge funds and other financial institutions operating in these countries since it allows them to find their optimal weights when the correlations between equity markets are varying through time. More importantly, we perform the Ku et al. (2007) approach in order to compute the hedge effectiveness index. The hedge strategies allow portfolio managers having long and short trading positions in the equity markets protection against price volatilities. Furthermore, show hedge strategies constructed by means of methodologies applied in the variance modelling of equity returns and the dynamic correlations extracted from the multivariate VAR-MGARCH framework.

3. Research Methodology

As noted earlier, we use a multivariate generalized autoregressive conditional heteroscedasticity (hereafter, MGARCH) model to capture the dynamic interactive linkage between Islamic country equity markets and other emerging markets. To do so, we first employ the BEKK model of Engle and Kroner (1995). Specifically, we estimate the multivariate GARCH with constant conditional correlation (hereafter, MGARCH-CCC) of Bollerslev (1990) and the multivariate GARCH model with the DCC suggested by Engle (2002) (hereafter, MGARCH-DCC).

3.1 The VAR (1) -MGARCH (1, 1) Model

We implement the vector autoregression (VAR) framework with one lag to assess the dynamic connectedness between Islamic country markets and other non-Islamic emerging markets equity returns. Formally, the model is written as follows:

$$R_t = \alpha + \beta R_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_{t} = D_{t}\mu_{t}/I_{t-1_{t}} \sim N(0, H_{t})$$

Where R_t is a (6×1) vector of stock markets returns, α is a (6×1) vector of constant terms, β is a(6× 6)diagonal matrix of autoregressive parameters. \mathcal{E}_t is a (6×1) vector of random errors representing the innovation at time (t) with a (6×6) conditional variance-covariance matrix H_t . I_{t-1} refers to the market information at time (t-1). The multivariate GARCH-BEKK parameterization suggested by Engle and Kroner (1995) guarantees positive semi-definiteness of the conditional variance-covariance matrix H_t . The specification shows that the variance-covariance matrix depends on the squares and cross products of residual terms ε_t and volatility. The conditional variance-covariance matrix takes the following form:

$$H_{t} = C'C + A'\varepsilon_{t-1}\dot{\varepsilon}_{t-1}A + G'H_{t-1}G$$
(2)

Where C is a (6×6) lower triangular matrix of constants, A and G are (6×6) matrices whose the diagonal parameters measure the effect of own past shocks and past volatility of market (i) on its conditional volatility. The off-diagonal elements these matrices assess the cross-market effects of shock spillover and the cross effect of volatility spillover. The parameters of the BEKK model can be obtained by means of the maximum likelihood estimation assuming normally distribution errors.

3.2 The Conditional Correlation: CCC and DCC Models

Bollerslev (1990) introduced a class of MGARCH-CCC in which the conditional correlations are time-invariant and therefore the conditional variances are proportional to produce of the corresponding conditional standard deviations. This restriction greatly reduces the number of unknown parameters and thus simplifies the estimation. The conditional covariance matrix can be written as follows:

$$H_{t} = D_{t}RD_{t} = \left(\rho_{ij}\sqrt{h_{ii,t}h_{jj,t}}\right)$$
(3)

Where $R = (\rho_{ij} = E(\eta_i \eta_i))$ is a symmetric $k \times k$ definite positive matrix containing the conditional

correlation $P_{ij}(\rho_{ij}=1 \quad \forall i)$, $\varepsilon_t = D_t \eta_t$, η_t is a *i.i.d.* random vectors and $D_t = diag(h_{11t}^{1/2}, \dots, h_{kkt}^{1/2})$. This

model assumes that the conditional variance h_{iiit} follows a univariateGARCH model.

$$h_{iit} = w_i + \sum_{j=1}^{q} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{p} \beta_{ij} h_{ii,t-j}, \quad i = 1, \dots, k$$
(4)

However, the assumption that the random shocks have a time-invariant conditional correlation may not be supported in many empirical studies. To make the conditional correlation matrix time-variant, Tse and Tsui (2002), Engle (2002) and Engle and Sheppard (2001) suggested a generalization of the CCC model. Tse and Tsui (2002) introduced a varying correlation GARCH model that the conditional correlations are function of the conditional correlations of the previous period. The DCC of Tse and Tsui (2002) has the following form:

$$H_t = D_t R D_t \tag{5}$$

$$R_{t} = (1 - \theta_{1} - \theta_{2})R + \theta_{1}\psi_{t-1} + \theta_{2}R_{t-1}$$
(6)

Where D_t is defined as in Eq. (3), R is a symmetric $k \times k$ positive definite parameter matrix with unit diagonal elements, Ψ_{t-1} is the $k \times k$ correlation matrix of the past P standardized residual $(\hat{\varepsilon}_{t-1}...\hat{\varepsilon}_{t-p})$, A necessary condition to ensure the positivity of Ψ_{t-1} is $P \ge k$, θ_1 and θ_2 are non-negative scalar parameters satisfying $\theta_1 + \theta_2 < 1$. Furthermore, Engle (2002) suggests various DCC models. The DCC model of Engle (1982), the covariance matrix is decomposed as follows:

$$H_{t} = D_{t}R_{t}D_{t}$$

$$R_{t} = diag(q_{11t}^{1/2}.....q_{kkt}^{1/2})Q_{t}diag(q_{11t}^{1/2}.....q_{kkt}^{1/2})$$
(7)

Where Q_t is a symmetric $k \times k$ positive definite matrix containing the conditional covariance of standardized residuals given by:

$$Q_{t} = (1 - \theta_{1} - \theta_{2})Q_{0} + \theta_{1}\eta_{t-1} + \theta_{2}Q_{t-1}$$
(8)

Where Q_0 is the unconditional covariance matrix of η_t , η_t is defined as in eq. 4, θ_1 and θ_2 are non-negative scalar parameters satisfying $\theta_1 + \theta_2 < 1$, θ_1 represents the impact of last shocks on a current conditional correlation and θ_2 captures the impact of the past correlation. If θ_1 and θ_2 are statistically significant, the conditional correlations are not constant. Engle (2002) shows that the likelihood function can be written as:

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^{T} \left(\log 2\pi + 2\log |D_t| + \log |R_t| \eta_t R_t^{-1} \eta_t \right)$$
(9)

The DCC model can be estimated consistently in two stages. First, Q_t used to calculate the dynamic conditional correlation:

$$\rho_{ij,t} = q_{ij} (q_{ii,t} q_{jj,t})^{1/2}$$
(10)

Second, $\rho_{ij,t}$ is used to estimate conditional covariance:

$$h_{ij,t} = \rho_{ij} (h_{ii,t} h_{jj,t})^{1/2}$$
(11)

Where $h_{ii,t}(h_{jj,t})$ and $h_{ij,t}$ are the conditional variance and conditional covariance generated by using univariate GARCH models.

4. Empirical Results and Financial Implications

4.1 Data

We use daily equity indexes for six emerging markets, namely Turkey (XU100 Index), Indonesia (JKSE Index), Egypt (EGX30 index), Mexico (IPC index), China (Shang Comp index) and Brazil (Bovespa Index). The dataset is covering the period January, 4, 2005 - November, 2011 and yielding 1,280 observations. The data were gathered from DataStream and are expressed in the US dollar. The equity returns are computed as the first difference of the natural logarithm.In Table 1, we report the descriptive statistics for the return time series.

From the descriptive statistics, we perceive that the highest daily returns are observed in the Indonesian and the Brazilian equity markets (0.07%) and the Egyptian equity markets (0.06%) while the highest volatility, as measured by the standard deviation, is observed for in Turkish (2.1%) and Brazilian equity market (2.2%). All the equity return series are skewed to the left. In addition, all the selected returns, except Turkey exhibit significant excess kurtosis indicating the existence of asymmetry. The Jarque-Bera statistics reject the null hypothesis of the normal distribution. Using the Ljung-Box LB statistic of order 10, we can also reject the null hypothesis of white noise and attest that all series are serial correlated. All of the equity return series are stationary since we can strongly reject the null hypothesis of the ADF test at the 1% significant level. Therefore, The Augmented Dickey Fuller (ADF) unit root test give us a consistent conclusion that equity returns are stationary. In addition, The ARCH-LM test reveals that all returns exhibit conditional heteroscedasticity. This initial assessment provides some empirical support for employing multivariate GARCH-type models to capture the volatility spillovers between the emerging equity markets. Figure 1 displays the daily returns series. All series are characterized by volatility clustering where large (small) changes tend to be followed by large (small) changes. This indicates the presence of ARCH effect. These insights may suggest also potential volatility interactions among the selected equity markets.

Table 1. Descriptive statistics of daily returns

	Turkey	Indonesia	Egypt	Mexico	China	Brazil
Mean	0.0003	0.0007	0.0006	0.0003	0.0002	0.0007
Std.Dev	0.021	0.019	0.019	0.016	0.016	0.022
Skewness	-0.033	-0.279	-0.831	-0.557	-0.162	-0.027
Kurtosis	2.543	4.780	7.799	6.872	7.637	5.851
JB	344.856^{*}	1234.261*	3388.938^{*}	2582.462^{*}	3113.441*	1824.401*
LBQ	15.741	32.477	46.532	29.108	6.672	12.350
ARCH-LM	18.402	40.851	8.962	27.041	96.459	98.332
ADF	-20.580^{*}	-19.856*	-17.658*	-20.632*	-20.922*	- 21.190 [*]

Notes: (*) denotes the significance at the1% level. Std. Dev. refers to the standard deviation. JB is the Jarque-Bera statistic test for normality test. *LBQ* (Ljung-Box) is the statistics test for serial correlation of order 10. ARCH-LM is the statistics test for conditional heteroskedasticity of order 2. ADF refers to the statistics test for unit root test. The total number of usable observations is 1,280.



Figure 1. Time movement of equity returns

4.2 Equity Return and Volatility Spillover Effects

To investigate the shock and volatility transmission between the selected emerging equity markets, we estimate the conditional variance and covariance matrix H_t . The estimated parameters of the off-diagonal parameters of $A(a_{ij})$ and $G(g_{ij})$ allow us to identify the interrelationships between the two equity returns. The ARCH parameters a_{ij} and GARHC parameters g_{ij} in the conditional volatility of each markets respectively measure the effect of the own and cross past shock and past conditional volatility of the other markets. The estimation results of the VAR(1)-GARCH(1,1) model (Note 1) are displayed in Table 2.

From the estimation results, we note that all the autoregressive parameters are statistically significant at the conventional levels implying that that all the equity market returns are sensitive to their past own values. Specifically, the current values of conditional volatility of the emerging stock markets are positively sensitive to their past own shocks since the corresponding diagonal parameters a_{ii} are statistically significant at conventional levels, except Mexico where the current conditional volatility is negatively affected by its past shocks. Moreover, the estimation results unveil that the all diagonal parameters g_{ii} are statistically significant at conventional levels. These results indicate that all equity markets are positively affected by their own past volatility, except Turkey stock market which is negatively influenced by its past volatility.

For the shock and volatility spillover effects among the emerging markets, the reported results indicate the existence of bidirectional shock and volatility transmissions between all of them, except Egypt and Indonesia since these two

markets are not influenced by the past shocks of Egyptian stock market. In addition, we perceive that there are strong bidirectional relationships between the Chinese and the Brazilian equity markets and unidirectional shock linkage running from the Mexican to the Brazilian equity market. Moreover, we uncover that there is bidirectional positive volatility spillover between all the selected markets except Brazil and China. For these two markets, the shock linkage from Brazil to China is negative and from China to Brazil is positive.

Parameters	Turkey (i=1)	Indonisia (i=2)	Egypt (i=3)	Mexico (i=4)	China (i=5)	Brazil (i=6)
α	0.0010^{**}	0.0013*	0.0014^{*}	0.0005	0.0004^{**}	0.0011^{*}
	(4.997E-04)	(4.351E-04)	(5.257E-04)	(4.193E-04)	(1.777E-04)	(2.176E-04)
β	-0.058**	0.038***	0.101^{*}	0.087^{**}	0.024	0.057^{*}
	(0.025)	(0.022)	(0.029)	(0.040)	(0.017)	(0.015)
a _{i1}	0.051**	0.057^{**}	0.072^*	0.121^{*}	-0.052	0.081^{**}
	(0.023)	(0.025)	(0.025)	(0.025)	(0.046)	(0.031)
a _{i2}	0.073^{*}	0.160*	-0.001	-0.060**	-0.242*	0.152^{*}
	(0.019)	(0.017)	(0.016)	(0.020)	(0.028)	(0.022)
a _{i3}	0.127^{*}	0.093*	0.202^*	-0.044**	-0.087*	0.037
	(0.020)	(0.021)	(0.019)	(0.022)	(0.034)	(0.025)
a_{i4}	0.206^{*}	0.179^{*}	0.017	-0.270^{*}	-0.017	0.247^{*}
	(0.019)	(0.020)	(0.023)	(0.027)	(0.032)	(0.026)
a _{i5}	0.015	0.038^{*}	0.027^{*}	-0.003	0.107^*	0.128^{*}
	(0.012)	(0.011)	(0.009)	(0.013)	(0.021)	(0.015)
a _{i6}	0.042^{**}	0.046^{*}	0.026^{**}	0.005	-0.075**	0.274^{*}
	(0.017)	(0.016)	(0.013)	(0.019)	(0.030)	(0.019)
g _{i1}	- 0.701 [*]	0.241^{*}	-0.765*	-0.03	0.367^{*}	0.134**
	(0.021)	(0.049)	(0.035)	(0.042)	(0.054)	(0.047)
g_{i2}	-0.277*	0.967^{*}	-0.135*	-0.061**	0.667^{*}	-0.302*
	(0.023)	(0.012)	(0.019)	(0.029)	(0.041)	(0.025)
g _{i3}	-0.722*	0.113*	0.623^{*}	-0.257*	0.314^{*}	0.005
	(0.022)	(0.019)	(0.025)	(0.027)	(0.036)	(0.027)
g_{i4}	-0.152*	0.136*	-0.163*	0.244^{*}	0.281^{*}	-0.084*
	(0.021)	(0.018)	(0.020)	(0.036)	(0.041)	(0.024)
g _{i5}	-0.213*	-0.049*	-0.118*	0.042^{**}	1.434*	-0.358*
	(0.015)	(0.015)	(0.011)	(0.019)	(0.012)	(0.012)
g _{i6}	-0.321*	-0.031	-0.182*	-0.064**	0.906^{*}	0.486^{*}
	(0.020)	(0.021)	(0.016)	(0.026)	(0.020)	(0.016)
JB	93.036*	349.758^{*}	3257.104*	472.019^{*}	535.807^{*}	430.894^{*}
LB	22.598**	16.083***	16.432***	5.900	6.602	11.070
ARCH	1.975	4.947	0.871	2.050	24.658^{*}	20.724**
LB^2	18.599**	77.781*	10.449	16.567**	473.792*	436.028**

Table 2. Estimation results of VAR(1)-MGARCH model

Notes: a_{ij} and g_{ij} captures shock and volatility effects respectively for market i to j; JB is the Jarque-Bera test for normality of the standardized residuals; LB is the Ljung-Box test for autocorrelation of order 10 of the standardized residuals; LB^2 is the Ljung-Box test for autocorrelation of order 10 of the squared standardized residuals; and ARCH refers to the test for conditional heteroscedasticity of order 10 of the standardized residuals; *, ** and **** indicate rejection of the null hypothesis of the associated tests at 1%, 5% and 10% levels, respectively. The values in parentheses are the standard errors.

Now we turn to analyze the causality linkage between emerging equity markets. The reported results (see Table 2) reveal bidirectional shock linkage between Turkey/Mexico, Egypt/China and Indonesia and all emerging market. Furthermore, we identify a unidirectional shock spillover effect running from Egypt to Mexico and from Brazil to Egypt. Concerning the volatility spillover effect, we find evidence of bidirectional volatility links between all equity markets except Indonesia/Brazil, Egypt/brazil and Turkey/Mexico pairwise. The results show the existence of a negative volatility spillover effects running from the Brazilian to the Indonesian and the Egyptian equity markets and

from the Mexican to the Turkish markets. We note that the current equity markets' volatilities are responding negatively to the past volatilities, except for Indonesia/Turkey country' pairwise. Another noticeable feature is that the cross-market ARCH parameters for Mexico, Brazil and China are higher than the cross-market GARCH parameters of the conditional volatility for Egypt, Turkey and Indonesia. This finding suggest that the sensitivity of current conditional volatility to cross-market past news is more significant than the sensitivity to past volatility for Egypt, Turkey and Indonesia. Overall, our results point out that there is strong evidence of conditional independence between the selected emerging equity markets. Such findings are very important in terms of portfolio asset allocation decision and designing appropriate hedging strategies.

4.3 Constant and Dynamic Conditional Correlation

In Table 3, we report the estimation results of the VAR-MGARCH specification. Panel A displays the estimation results for CCC specification while Panel b conveys the corresponding results for a DCC specification. The analysis of the volatility between the selected markets using the CCC-VAR(1)-MGARCH(1.1)model indicates that all estimated correlations parameters (Panel B) are significant at the conventional levels. This results support the existence of stable correlations between the six emerging markets. More precisely, we perceive that the Indonesian equity market exhibit the highest level of correlation with the remaining markets followed by Turkey and Egypt. Therefore, the stability of the conditional correlation may be due to the transmission of the shocks and the bilateral trade between these Islamic countries.

Panel A. The CCC specification					
R_{21}^{*}	0.337	R_{62}^{*}	0.549		
R_{31}^{*}	0.184	R_{43}^{*}	0.231		
R_{41}^{*}	0.25	R_{53}^{*}	*0.25		
R_{51}^{*}	0.392	R_{63}^{*}	0.255		
R_{61}^{*}	0.399	R_{54}^{*}	0.368		
R_{32}^{*}	0.233	R_{64}^{*}	0.384		
R_{42}^{*}	0.347	R_{65}^{*}	0.862		
R_{52}^{*}	0.526				
Panel B. The DCC specification					
θ_1^*	0.007	${\theta_2}^*$	0.958		

Table 3. The CCC and the DCCs among emerging equity markets

Notes: R_{ij} refers to the CCCs between market *i* and market *j*; θ_1 and θ_2 refer to the DCC parameters. (*) indicates the rejection of null hypothesis at the 1% significance level.

For the DCC' behavior over time, the reported results (see, Panel B) show that both parameters of the condition correlation equation θ_1 and θ_2 in Eq. (8) are statistically significant. Additionally, we note that $\hat{\theta}_1$ estimated parameteris close to zero, while $\hat{\theta}_2$ parameters close to the unity indicating that Q_t in is close to Q_{t-1} . These findings show that the current conditional correlations are strongly sensitive to their past values than past shocks. On another side, the time-varying DCCs plotted in Figure 2 show significant fluctuations over time. A closer inspection of this figure indicates that the DCCs have substantially decreased during the recent global financial crisis 2007-08.



Figure 2. The DCCs behavior over time

5. Portfolio Designs and Risk Management

The aforementioned findings show significant causality connections between the six emerging equity markets. In this sub-section, we extend our previous analysis to provide more prominent financial implications in terms of portfolio designing strategies and hedging effectiveness. To do so, the estimated conditional volatilities of equity return generated by the BEKK-GARCH specification are employed for estimating optimal weights for a multi-country equity portfolio. In the present study, we construct portfolios combining one Islamic countries (Egypt, Turkey, and Indonesia) with the other non-Islamic countries (Mexico, China and Brazil). Methodologically, we follow Kroner and Ng (1998) approach in order to find optimal weights for a minimum risk portfolio. Accordingly, the optimal weights of the two equities (Islamic/non Islamic) is given by:

$$w_{ie,t} = \frac{h_{ee,t} - h_{ie,t}}{h_{ii,t} - 2h_{ie,t} + h_{ee,t}}$$
(12)

and $w_{ie,t} = \begin{cases} 0, & if \quad w_{ie,t} < 0 \\ w_{ie,t}, & if \quad 0 \le w_{ie,t} \le 1 \\ 1, & if \quad w_{ie,t} > 1 \end{cases}$

Where $h_{ii,t}$ and $h_{ee,t}$ are the conditional variance of the selected emerging equity returns respectively. $h_{ie,t}$ refers to the conditional covariance between the two equities. The corresponding weights of the emerging equity in a one-dollar portfolio of the two assets are given by $W_{ie,t}$ and $(1 - W_{ie,t})$, respectively.

Table 4 reports the optimal weights for each Islamic/non-Islamic country pairwise portfolio. The results show that the optimal weights are varying from 27.8% for the Turkey/Mexico to 78.8% for the Indonesia/Brazil. It is found that the Egypt/ Brazil, Indonesia/Brazil and Turkey/Brazil portfolios have the highest optimal weights, while the lowest optimal weights are found for the Egypt/Mexico, Turkey/Mexico and Indonesia/Mexico portfolios. Furthermore, we perceive that the optimal weight of Turkey stock market holding in a one-dollar Turkey/Mexico' portfolio should be

around 27.8% and it is around 83.2% invested in the Mexico equity market. These optimal weights correspond respectively to 61.3% and 38.7% for the Brazilian equity market. Put it another way, these findings suggest that, for example, Turkish investors should hold more Mexico (Turkey) equities market than Turkey (Brazilian) in order to minimize the risk without reducing the expected return. Quite similar implications are found for the Indonesian and the Egyptian equity markets.

Furthermore, we extend our results of the conditional volatility to compute the optimal hedge ratio for Islamic/non-Islamic multi-country portfolio. Doing so, we follow the Kroner and Sultan' (1993) approach where, the optimal portfolio hedge ratio is obtained using the following expression:

$$\beta_{ie,t} = \frac{h_{ie,t}}{h_{ee,t}} \tag{13}$$

The measure of portfolio hedge ratio indicates that to minimize the risk of a portfolio an investor should short β_{ie} of the non-Islamic country and 1 long in the Islamic country.

The hedge effectiveness index can be assessed by quantifying the degree of risk reduction. According to Ku et al. (2007), the hedge effectiveness (HE) index is defined as the percentage reduction in variance of the hedge portfolio to the unhedged portfolio.

$$HE = \frac{V_u - V_h}{V_u} \tag{14}$$

Where the V_u and V_h refer to the variance of the returns on the unhedged and the hedged portfolios respectively. Ku et al. (2007) claimed that a higher hedge effectiveness index reflects a larger risk reduction and indicates that the adopted portfolio management strategies can be considered as the better hedging strategy. It is worthily noting that in order to compute the hedge effectiveness index (HE), we first construct the hedged portfolios $R_{i,t} - \beta_{ie,t}R_{e,t}$ then we use the variance of the return on the unhedged and hedged portfolios to obtain HE index. The $\beta_{ie,t}$ is the optimal hedge ratios obtained from Equation (14). R_i and Re are the Islamic and non-Islamic countries' equity returns respectively.

Portfolio	W _{ie}	eta_{ie}	HE
Turkey/Mexico	0.278	0.468	0.075
Indonesia/Mexico	0.333	0.508	0.158
Egypt/Mexico	0.34	0.38	0.069
Turkey/China	0.284	0.637	0.123
Indonesia/China	0.358	0.686	0.302
Egypt/China	0.387	0.416	0.086
Turkey/Brazil	0.613	0.459	0.159
Indonesia/Brazil	0.788	0.501	0.341
Egypt/Brazil	0.627	0.297	0.098

Table 4. Optimal portfolio' weights, hedge ratios and hedging effectiveness

Notes: HE refers to the hedging ratio.

Table 4 reports the average values of the optimal portfolio hedge ratio. Some interesting comments emerge. Firstly, we perceive that the Egypt/Brazil portfolio has the lowest hedge ratio (29.7%), while the highest is observed for Indonesia/China portfolio (68.6%). Moreover, we note that that Islamic country /China portfolio exhibit the highest optimal hedge ratio, while the lowest optimal hedge ratios are observed for the Islamic country/Mexico portfolio. For the China, the results show that \$1000 long in Egypt should be shorted by \$416 of the Chinese equity market. However, \$1000 long in the Indonesian equity market must be shorted by \$866 of the Chinese equity market. For

Mexico, the results show that \$1000 long in the Turkish equities must be shorted by \$416 in the Mexican equities. Similarly, \$1000 long in Egyptian equities must be shorted by \$866 in the Mexican equities.

The results of the hedging effectiveness ratios reported in table 4 show that the Islamic country/Brazil portfolio have the highest HE index followed by Islamic country/China and Islamic country/Mexico portfolio. For instance, the Islamic country /Brazil portfolio, the risk reduction as measured by the variance ranges from 34.1% (Indonesia) to 15.9% (Turkey) and from 15.8% (Indonesia) to 7.5% (Turkey) for the Islamic country/Mexico portfolio. It is worthily noting that the selected hedging strategies reduce significantly the portfolio risk implying that for a diversified portfolio, the risk substantially decreases when emerging stock market are included into portfolios. Overall, our results establish clear evidence of sensitivity of the optimal weights, hedge ratios and hedge effectiveness to equity markets connectedness in terms of volatility and return spillovers.

6. Conclusion

The main purpose of this paper is to provide more insights into the return volatility spillovers between six emerging equity markets from Islamic (Egypt, Indonesia, and Turkey) and non-Islamic countries (China, Brazil, and Mexico). To do so, we implement a VAR-multivariate GARCH model with DCCs and CCCs to examine the strength and the direction of the return causality linkage and the volatility shocks transmission between these markets.

There are some results that stem from our study. First of all, we uncover a strong evidence of return and bidirectional volatility spillovers among the selected emerging countries. The volatility spillover seems to be more accurate between the Islamic countries. Secondly, the obtained results confirm the time varying of the conditional correlations and their significant increase during the recent global financial crises. Thirdly, the multivariate analysis allows us to offer more useful and practical implications in terms of portfolio management and hedging strategies. Specifically, we extend our analysis of the time varying co-movement between equity markets to estimate the optimal weights for minimum risk portfolios, to estimate the hedge ratios and to assess the hedging effectiveness of the proposed asset allocation strategies.

Overall, we believe that our findings provide a stab to a comprehensive analysis of the volatility spillovers between Islamic and non-Islamic equity markets within a multivariate framework. More interestingly, we offer some prominent implications for portfolio managers, and hedge funds operating in these markets in terms, asset allocation decisions, designing hedging strategies and assessing hedging effectiveness.

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Note

Note 1. The VAR(1)-GARCH(1,1) model is the most appropriate model we have obtained based on the AIC and BIC criteria.