Are Islamic Indexes a Safe Haven for investors? An analysis of total, directional and net volatility spillovers between conventional and Islamic indexes.

*Abstract*: We examine the decoupling and contagion hypotheses on the safe haven status of Islamic indexes by investigating the total, directional and net volatility spillovers across nine regional Islamic stock indexes and their conventional counterparts, using the generalized vector autoregressive framework. We use daily data covering the period 1999 to 2014 which includes various financial crises such as those that took place in Asia, Russia, Argentina, Brazil and the United States. The results show that global financial crises strongly affect the cross-market volatility. Although the contagion hypothesis is evident for both Islamic and conventional indexes, the findings also suggest the presence of a decoupling of the Islamic indexes from their conventional counterparts during turbulent periods. The results provide several useful implications for policy makers and portfolio managers seeking to diversify their portfolios and to hedge the market risk, confirming that Islamic financial indexes are a safe haven for investors during financial crises. Furthermore, paper reports significant time-varying patterns in the volatility spillovers for all the Islamic and conventional stock indexes and point out the stress transmitters and receivers.

*JEL classification:*

*Keywords:* Islamic indexes, conventional indexes, volatility spillovers, vector autoregression, safe haven.

1. **Introduction**

During the last decade, global capital markets have witnessed the introduction and the expansion of Islamic assets, which are considered as ethics-filtered assets. These sharia-compliant assets have not only expanded in Islamic emerging markets but also in conventional capital markets. The Sharia-compliant stocks and Islamic bonds (sukuk) are viewed as innovations in the international financial system since they operate differently from their conventional counterparts. For example, Narayan and Bannigidadmath (2015) provide evidence that financial news predicts Islamic stock returns better than conventional stock returns. Taking the nine Islamic stock indexes and their corresponding non-Islamic indexes, these authors argue that investing in Islamic stocks is relatively more profitable than investing in conventional stocks. Alternative evidence is provided by Aloui et al. (2016) who apply a wavelet coherence and asymmetric causality methodology to the U.S. Islamic and conventional indexes. The Authors find that the Sharia rules have no influence on the connectedness between sentiment and Islamic equity returns. Their study shows that Islamic equity returns do not behave differently from their conventional counterparts.

The ambiguity of the empirical results regarding the behavior of the Islamic indexes has motivated us to reconsider the finance theory on information transmission mechanism across financial markets and to identify whether there are lead-lag relationships between Islamic indexes and their conventional counterparts that can explain the difference in behavior of these markets during and around crisis episodes. Particularly, in this paper, we test the contagion and decoupling hypotheses on the Islamic and conventional indexes.

To test these hypotheses, we conduct the analysis of daily volatility spillovers across Islamic and conventional indexes covering five regions, i.e. the United States, UK, Canada, Japan, Eurozone and Asia-Pacific using the generalized VAR methodology proposed by Diebold and Yilmaz (2012). The question of transmission of volatility across different asset classes is an important topic in the finance literature and has been widely analyzed in the studies that consider the contagion and decoupling hypotheses (e.g., Reboredo and Rivera-Castro, 2013; Barunik et al., 2015a, b; Martín-Barragán et al., 2015; Bekiros, 2014; Yarovaya et al. 2016; Yarovaya and Lau, 2016). The main theoretical argument is that a volatility shock originated in one market can cause a volatility shock in another market. Consequently, changes in prices of a contributor market can cause changes in prices of a recipient market. This effect can be especially pronounced during crisis episodes when diversification benefits are needed the most. In previous literature, the lead-leg relationships have been considered, for example, in the context of futures-spot price relationships, that is, whether spot prices lead futures prices or vice versa (e.g., Gannon & Choi, 1998; Zhong et al., 2004; Yang et al., 2011; and Antonakakis et al., 2015). However, to our best knowledge, this phenomenon has not been analyzed in the context of Islamic and non-Islamic stock indexes. Why is this important? There are two main reasons why volatility spillovers across Islamic and conventional stock indexes have attracted our attention in this study.

First, the Islamic financial markets have experienced high growth over the last decade. By the end of 2012, the total Islamic assets including the sharia-compliant stocks and sukuk, which are the main forces deriving the Islamic finance industry, reached US $1.27 trillion[[1]](#footnote-1) and are likely to sustain double-digit growth during the next three years. According to the Standard & Poor’s estimates, the global growth of the Islamic financial markets had continued unabated during 2014, fueled by the increase of uncertainty about the future of conventional financial markets in the world. In 2014, the assets under management of global Islamic funds grew 5.3% from the previous year and the number of funds increased by 11%[[2]](#footnote-2). Therefore, taking into account the increased role of the Islamic finance, from the theoretical perspective it is particularly interesting to investigate whether there are any differences in patterns of volatility transmission across the Islamic and conventional indexes around the financial crises to provide novel evidence of the contagion and decoupling phenomena. It is important to check whether the volatility patterns are affected by global risk factors induced by the occurrence of global financial crises. Understanding these issues is helpful for both managers and policy makers who deal with conventional and Sharia-compliant funds.

Second, these markets are of interest to investors and practitioners since the Islamic indexes can be viewed as “safe havens”. There is a strong need to enhance the understanding of the directions of information transmission across the conventional and Islamic indexes to help investors to create successful trading strategies and to maximize the benefits of diversification. It is worth mentioning that the Islamic finance industry is viewed as a new business model and an alternative source of financing in the world. As indicated in the above statistics, the last recent years have observed an impressive growth of the Islamic financial industry driven by sharia-compliant stock and sukuk issuances. Investors can select from either Islamic securities enclosed in the global Islamic indexes, which constitute the Islamic counterparts of conventional indexes or conventional securities. From a comparative point of view, investing in Islamic assets is different from investing in their conventional assets because the sharia-compliant stocks and sukuk have different risk-return characteristics. The Islamic sharia law permits investment in securities, provided that the firms do not engage in ‘Haram’ or prohibited activities Hammoudeh et al. (2015). In fact, Islamic fund managers often select some sharia-compliant stocks from the Islamic stock indexes or focus more on investing ethically in businesses complying with the sharia rules. Islamic scholars have made some concessions on the permissible firms that meet the financial screening, as most use debt to either address liquidity shortages or have excess cash to invest. Therefore, to fill the gap in knowledge regarding the ways how the Islamic and non-Islamic stocks markets interact is doubtfully an important task.

Given the Islamic finance particularities, it is interesting to deliver more thoughtful findings concerning the volatility spillovers and connectedness between Islamic capital markets and their conventional counterparts. Thus, our study distinguishes itself from most previous studies in at least three main aspects. First, we employ for the first time the Diebold and Yilmaz (2012) approach to estimate the total and directional volatility spillovers indexes that allow us to discern how the information is transmitted across conventional and Islamic indexes. Second, using the generalized VAR approach introduced by DY (2009, 2012), this paper provides a better understanding of the direction of the volatility between regional Islamic indexes and their conventional counterparts by determining which markets are stress transmitters/receivers.

The remainder of the paper is organized as follows. Section 2 reports a review of related literature. Section 3 specifies the gap in the literature. The data and methodology are reported in Section 4. The empirical findings, their discussions and some financial implications are provided in Section 5. In Section 6 two robustness checks are presented. The summary and concluding remarks are wrapped in Section 7.

**2. Literature review and theoretical background**

There are two main theoretical arguments that are widely discussed in the literature. The first suggests that the intensity of volatility spillovers across markets is increasing during crisis episodes limiting the benefits of portfolio diversification (i.e., this is the contagion hypothesis). The implication of this phenomenon is the fact that it is pointless for investor to try to achieve a portfolio risk reduction by investing in markets with low correlations, since markets tend to move together during financial turmoil periods. However, the second popular theoretical argument, i.e. the decoupling hypothesis, postulates that emerging markets were less affected by the crisis (Aggarwal et al., 1999). Indeed, the reverses the directions of spillovers from emerging to developed markets became the evident after the crisis indicates that diversification benefits are still achievable (e.g. Kenourgios et al., 2013; Bekiros, 2014; and Yarovaya and Lau, 2016). Although there are a plenty of studies investigated these hypotheses by measuring the intensity and direction of volatility spillovers around crisis periods across conventional indexes (e.g., Yarovaya et al. 2016), the contagion and decoupling hypotheses are left relatively uncommented in the context of the Islamic financial index. In this literature review, we provide examples of previous studies that investigated the dynamic linkages between Islamic stock markets and their conventional counterparts, using various econometric techniques.

Hakim and Rashidian (2002) employ the multivariate cointegration to examine the causality linkage between the Islamic and conventional markets represented by the Dow Jones Islamic Market Index (DJIM) and the U.S. Wilshire 5000 Index, respectively. The authors find no significant causality relationship between these markets. In a more recent paper, Dania and Malhorta (2013) uncover significant volatility spillovers between conventional index returns in the North American markets and their Islamic counterparts in the East and Pacific stock markets. Moreover, those authors provide evidence of asymmetry in the volatility spillovers between the two markets. Nazioglu et al. (2013) analyze volatility spillovers between the DJIM index and three conventional stock markets for the U.S., Europe and Asia during the sample periods, and the pre and post GFC sub-periods. Using the Hafner and Herwartz (2006) causality-in-variance test, the authors provide strong evidence of risk transfers between these apparently different stock markets, indicating a contagion between them. Furthermore, the authors also find evidence that the volatility structure is changing during the pre and post GFC sub-periods. When exploring the volatility impulse analysis between Islamic markets and other fundamental variables including the U.S. economic uncertainty and crude oil prices, Nazioglu and Herwartz (2006) report quite similar volatility patterns.

Using a heteroscedasticity-robust linear Granger causality and non-linear causality tests, Ajmi et al. (2014) investigate the relationship between conventional and Islamic global stock markets and also between Islamic markets and major global risk factors. The authors indicate the existence of both linear and non-linear linkages between Islamic and conventional markets. Moreover, they show that there is a strong causality running from Islamic markets to conventional markets, thereby supporting the main hypothesis that Islamic markets are not decoupled from their conventional counterparts. In other words, the sharia compliance rules do not constrain investments to make Islamic markets different from their counterparts in terms of coevolution.

Kassab (2013) employs a GARCH model to investigate the persistence of volatility of the DJIM and conventional (i.e., S&P 500 index) markets. The author reveals a strong volatility persistence of both markets, with the DJIM index being less volatile than the conventional index in the long-run and exhibiting less risk at crisis periods. Akhtar et al. (2013) investigate the volatility linkages between Islamic and conventional assets including equities, bonds and bills. The authors show that including at least one Islamic asset lowers the volatility spillovers by up to 7.17%. Those authors state that the particularities of Islamic finance assets lower the degree of the dynamic linkages between Islamic markets and their conventional counterparts. Using a multivariate-GARCH (M-GARCH) framework with dynamic conditional correlation (DCC) and constant conditional correlation (CCC), Majdoub and Mansour (2014) analyze the conditional correlation behavior across the US stock market and a sample of five Islamic emerging markets (Turkey, Qatar, Pakistan, Indonesia and Malaysia). The authors show that the Islamic and U.S. stock markets are weakly correlated through time. Accordingly, no complete evidence is found to support the spillovers among the selected Islamic emerging markets.

Dewandaru et al. (2014) investigate the co-movements between Islamic stock indexes and the major stock indexes across different regions during major global financial crises. Using the wavelet methods, the authors expose the multi-horizon nature of the co-movements and show that shocks are transmitted via excessive linkages during the recent GFC. However, it is found that the Islamic stock markets exhibit lower exposure to the recent crises. Using a quite similar approach based on the wavelet decomposition, Rizvi et al. (2015) examine the behavior through time and frequency of the co-movements between mainstream stock markets across the U.S. and the Asia Pacific basin. The obtained results support the main conviction that global shocks are conveyed from the U.S. to the Asia/Pacific basin and that the Islamic stock markets exhibit reduced risk exposure during the GFC, which may be due to their low leverage required by the financial ratio restrictions.

Using a copula approach, Hammoudeh et al. (2014) investigate the dependence structure between the global Islamic indexes represented the Dow Jones Islamic index and three major global conventional indexes. The authors show a strong time-varying dependence between the Islamic index and the three major conventional indexes. Accordingly, the Sharia compliance rules seem to be not restrictive enough to make the global Islamic index different from the conventional ones in terms of dependence structure. Furthermore, Hammoudeh et al. (2014) unveil that some global risk factors including the 10-year Eurobond index, the crude oil prices and stock market implied volatility are identified as common factors of risk contagion between the Islamic and conventional stock markets. The conclusions of this study are in line with those of Krasicka and Nowak (2012) who conducted a comparative analysis between the Malaysian Islamic and conventional stock prices regarding their reactions to macroeconomic risk factors. Their findings indicate that the Islamic and conventional bond and stock prices are derived by common risk factors, and therefore the gap between Islamic and conventional ﬁnancial practices is weakening.

1. **Literature Gap**

As can be seen from this review, there is undoubtedly an impressive growing interest in the literature examining the causality linkages and dynamic relationships between Islamic stock markets and their conventional counterparts. However, there is no definitive conclusion regarding the directional linkage between the markets. Indeed, there is no consensus in the literature on the directional relationship between Islamic stock markets and conventional markets, and thus and there is room for other methodologies to demystify the casualties and relationships. Albeit there is a compromise regarding the relevance of conventional and Islamic financial markets, the existing literature remains limited and particularly focused on the risk transmission between the two markets and the time-varying patterns of the volatility spillovers around financial crises. In this paper, we attempt to fill the gap in the existing literature and offer comprehensive findings regarding the assessment of the total and the direction of the volatility spillovers between Islamic stock indexes and their conventional counterparts across regions and during global financial crises.

Methodologically, a large range of empirical analytical frameworks are used to analyze volatility spillovers between Islamic stock markets and their conventional counterparts including: cointegration tests (Hakim and Rashidian, 2002), linear and non-linear causality tests (Naziouglu et al., 2013; Ajmi et al., 2014), SVAR models (Hammoudeh et al., 2015), multivariate GARCH models (Kassab, 2013; Majdoub and Mansour, 2014), wavelet decomposition (Rizvi et al., 2015; Dewandaru, 2014), stochastic volatility models (Akhtar et al., 2013), and copulas (Hammoudeh et al., 2014) to name a few. Our study adds to this literature by applying the recent methodology suggested by Diebold and Yilmaz (2012) (hereafter DY, 2012) to measure the volatility spillovers using a generalized vector autoregression framework where the forecast-error variance decompositions are invariant to variables’ ordering. We also extend this methodology by using the EGARCH model to generate the volatility series for the considered indexes to account for asymmetry in those indexes. As far as we know, in spite of the relevance of the research area, there are no empirical studies that use the DY (2012) approach to analyze the volatility spillovers between the Islamic stock markets and their conventional counterparts. Volatility spillovers allow for identifying the perceived markets and incorporate the arrival of new information. Furthermore, analyzing the volatility patterns between the Islamic and the conventional markets is of great interest, particularly during turbulent periods with notable irregularities (see, among others, Reinhart and Rogoff, 2008). In this vein, DY (2012) state that it is important to provide better understanding of volatility spillovers to provide an early warning system for a looming crisis and to track the progress of existing crises (DY, 2012, p. 57).

This study uses a sample of nine regional stock conventional indexes including the United States (large, mid and small caps), U.K, Canada, Japan, Europe, Asia-Pacific and the World, and their Islamic counterparts. The data are expressed in daily frequency and cover the period 1999-2014, mostly to include major financial crises that occurred during the last two decades. We assess both total and directional volatility spillovers between the conventional sector indexes, between the Islamic sector indexes, and between the Islamic and the conventional sector indexes across different regions testing the contagion and decoupling hypotheses.

1. **Methodology and data**

*4.1 Research hypotheses*

As mentioned earlier, this paper provides novel empirical evidence on the contagion and decoupling hypotheses, addressing the question whether the Islamic markets are safe haven for investors in the conventional markets. There are several reasons why we can expect differences in the patterns of volatility transmission across the conventional and Islamic indexes under consideration. For investors to be sharia- compliant, they must adhere to several sharia-based criteria. They should exclude firms that hold interest-bearing debt, receive interest, impure income or trade debts for more than their face values. They should also avoid firms whose debt-income ratio is equal to or exceeds 33%. They should shun companies with "impure plus non-operating interest income" revenue equal to or greater than 5% of total income. Finally, they should eschew firms whose accounts receivable-to-total assets is equal to or exceed 45% or more. For sukuk to be compliant with the sharia ethics, three main criteria must be met: (1) the certificates must represent ownership in tangible assets, usufruct or services of revenue-generating firms; (2) the payments to investors should come from after-tax profits; and (3) the value repaid at maturity should reflect the current market price of the underlying asset and not the original amount invested (see, Godlewski et al., 2013). All these restrictions can cause imbalances in the transmission of the information flows and consequently create the differences in dynamics and intensity of volatility spillovers across the Islamic indexes in comparison with their conventional counterparts. Thus, refereeing to the contagion phenomenon, we specify two research hypotheses.

H1: *There is an increase in the intensity of the volatility spillovers across the selected conventional indexes during a crisis period.*

H2: *There is an increase in intensity of the volatility spillovers across the selected Islamic indexes during a crisis period.*

Acceptance of H1 and H2 provides supporting evidence for the contagion phenomenon. Besides, regarding the decoupling hypothesis discussed above, we specify the third research hypothesis considered in this empirical study.

H3: *There is a decrease in the intensity of the directional volatility spillovers from the conventional indexes to their Islamic counterparts during the crisis period.*

Acceptance of H3 provides the supporting evidence for the decoupling hypothesis.

*4.2 Econometric framework*

As the first step of this research, in order to examine the time-varying nature and the co-movements of the indexes, we employ the exponential GARCH (EGARCH) model developed by Nelson (1991). We use the EGARCH conditional variance as a proxy of daily volatility of both conventional and Islamic markets. The main feature of the EGARCH model, in contrast to that of other GARCH models, is that it does not require any restrictions on the estimated parameters, since the positivity of variance is automatically satisfied as the equation is expressed on log variance instead of variance. Moreover, the EGARCH model captures major stylized facts of the financial time-series such as the leverage effect and volatility clustering (that is, a perceived shock at time  impacts the variance at time ). For a return time-series given as , where is the expected return and is a zero-mean white noise, the conditional variance specified by an EGARCH (1,1) model can de written as follows;

 (1)

In the second step of this research, we refer to the DY’ (2012) approach to describe how to measure volatility spillovers. The following sub-sections report the details of the corresponding total volatility index, directional spillovers and net volatility spillovers. The total volatility spillovers index is based on the variance decomposition illustrated in Koop, Pesaran, and Potter (1996), referred to as KPPS thereafter, and Pesaran and Shin (1998). DY (2012) consider two variance shares (own variance shares and cross variance shares). Initially, the assets’ own variance shares are defined as the fraction of the H-step-ahead error variances in forecasting variablethat is due to the same variable shocks, for  The cross variance, or more precisely the spillovers, is calculated as the H-step-ahead error variances in forecasting variablethat are due to another variable’s shocks , for  , where . For , the KPPS H-step-ahead forecast error decomposition is given as;

** (2)

where **is the variance matrix for the error vector .  refers to the standard deviation of the error term for the *jth*equation, and is the selection vector, with one as the *i*th element and zeros otherwise. Following Louzis (2013) and Baruník et al. (2015), in the generalized VAR framework, the shocks to each asset variable’ are not orthogonalized and, in consequence, the sum of each row of the variance decomposition matrix does not equal to one. Hence, each element of the decomposition matrix can be normalized by the row sum

** (3)

By construction, **and **

Based on the above contribution, the total volatility spillover index is given as follow;

** (4)

The main benefit of total spillover index is that it allows us to know how much of the shocks to volatility spills over across variables.

The directional spillover is computed using the normalized elements of the generalized variance decomposition matrix. The use of the directional spillover allows us to decompose the total spillovers to those pending from or coming to a particular asset. The directional spillovers received by index  from all indexes are proposed by the following equation:

** (5)

Similarly, the directional volatility spillover transmitted by index *i* to another index *j* are given by this equation:

** (6)

The net volatility spillover from index *i* to all other indexes *j* is given as the difference between the gross volatility shocks broadcast to and those received from all other indexes. The corresponding equation is written as follows

 (7)

Net spillovers can indicate how much each index contributes to the volatility of other indexes in net terms.

The net pairwise volatility spillover is inspired from the previous equation and is defined as the difference between the gross shocks transmitted from  index to index  and shocks broadcast from  to . Following DY (2012), the net pairwise volatility spillover from  index to index  is computed as follows:

 (8)

*4.3. Data and descriptive statistics*

We use daily Islamic and conventional indexes covering six countries/regions; namely the United States, UK, Canada, Japan, Eurozone and Asia-Pacific. These are DJI US, DJI UK, DJI Japan, DJI Canada, DJI Europe and DJI Asia-Pacific of the conventional and Islamic indexes. In addition, we include the World Islamic and conventional stock indexes. For the United States, we use three different sub-indexes, which are for DJI US large Cap., DJI US mid Cap., and DJI US small Cap. of the Islamic and conventional indexes. Thus, all the nine selected indexes and sub-indexes correspond to both the Dow Jones Islamic market (hereafter, DJIM) index and the conventional index (hereafter, DJI). The data are gathered from DataStream and cover the period April 1999 –June 2014. The daily returns are computed from the daily index data by taking the natural logarithm of the ratio of two successive prices. To examine the volatility spillover patterns between the conventional and Islamic indexes, we run a rolling window of 10-daily volatility observations.

Table 1 reports the descriptive statistics of the nine conventional and Islamic logarithmic index returns. Concerning the conventional returns, we perceive that the Dow Jones for Canada exhibits the highest kurtosis test value, followed by the DJI- large Cap for the United States-, and the DJI- United States for both the conventional and Islamic returns. This evidence indicates that that these indexes and sub-indexes are available with more frequency and some extreme observations. In terms of asymmetry, the daily logarithmic index returns of both the Islamic and conventional markets show negative skewness except for the Islamic DJIM-large Cap and the DJIM for the Eurozone region. Taken together, the logarithmic daily returns of all the nine conventional indexes and Islamic indexes fail the Jarque-Bera test that attests for normality.

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| **Table 1.** Descriptive statistics of conventional and Islamic daily returns | | | | | | | |
| ***Regional conventional index returns*** | Max | Min | Mean | S. Dev. | Kurtosis | Skewness | J-B |
| DJI Asia/Pacific | 0.0900 | - 0.0910 | 0.00020 | 0.0120 | 7.876 | -0.4254 | 254.57\*\*\* |
| DJI US large CAP | 0.1101 | -0.0947 | 0.00017 | 0.0127 | 10.92 | -0.1893 | 877.24\*\*\* |
| DJI US mid CAP | 0.0997 | -0.0109 | 0.00036 | 0.0138 | 9.640 | -0.4175 | 660.64\*\*\* |
| DJI US small CAP | 0.0965 | -0.1079 | 0.00029 | 0.0163 | 7.063 | -0.2930 | 949.98\*\*\* |
| DJI Europe | 0.1152 | -0.0991 | 0.00020 | 0.0141 | 9.381 | -0.0410 | 152.63\*\*\* |
| DJI Canada | 0.0997 | -0.1358 | 0.00033 | 0.0142 | 12.33 | -0.7213 | 404.57\*\*\* |
| DJI World | 0.0866 | -0.0716 | 0.00019 | 0.0103 | 10.07 | -0.3655 | 145.94\*\*\* |
| DJI Japan | 0.1124 | -0.0914 | 0.00010 | 0.0141 | 6.862 | -0.2028 | 117.41\*\*\* |
| DJI US | 0.1076 | -0.0963 | 0.00019 | 0.0128 | 10.53 | -0.2382 | 887.60\*\*\* |
| ***Regional Islamic index returns*** | | | | | | | |
| DJIM Asia/Pacific | 0.0969 | -0.0969 | 0.00021 | 0.01267 | 7.904 | -0.4399 | 294.21\*\*\* |
| DJIM US large CAP | 0.1199 | -0.0945 | 0.00012 | 0.01260 | 10.469 | 0.0253 | 344.34\*\*\* |
| DJIM US Mid CAP | 0.1121 | -0.1095 | 0.00035 | 0.01529 | 7.777 | -0.2554 | 672.80\*\*\* |
| DJIM US small CAP | 0.0905 | -0.1039 | 0.00038 | 0.01598 | 6.314 | -0.1978 | 610.91\*\*\* |
| DJIM Europe | 0.1358 | -0.1111 | 0.00018 | 0.01615 | 8.709 | 0.0301 | 154.92\*\*\* |
| DJIM Canada | 0.1191 | -0.1721 | 0.00023 | 0.01876 | 12.650 | -0.8079 | 222.36\*\*\* |
| DJIM World | 0.0978 | -0.0818 | 0.00018 | 0.01084 | 9.832 | -0.3060 | 117.60\*\*\* |
| DJIM Japan | 0.1066 | -0.0955 | 0.00010 | 0.01457 | 6.363 | -0.2014 | 388.65\*\*\* |
| DJIM US | 0.1174 | -0.0969 | 0.00017 | 0.01297 | 9.701 | -0.0518 | 526.69\*\*\* |
| Notes: \*\*\*designates significance at the 1% level. J-B is the Jarque-Bera normality test statistic. S. Dev. refers to the standard deviation of each stock return. | | | | | | | |

1. **Empirical results and discussion**
   1. *Time-movements of Islamic and conventional stock indexes*

In Figure 1, we plot the time movements of the nine Dow Jones (DJIM) indexes and their conventional counterparts during the whole sample period. From these plots, we note that the DJI conventional Eurozone index and the DJIM Eurozone index move closely together over the whole sample period. This feature is clearly evident around the recent GFC. Moreover, it can evidently be observed that a same sharp depreciation took place for all index pairs until the beginning of 2010. This notable drop is perceived in particular for both the DJI Canadian conventional index and the DJIM Canadian index.

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| **Figure 1.** Time-movements of the Dow Jones Islamic indexes and their conventional counterparts | | | |
| 1. Asia/Pacific | 1. Canada | | 1. Europe |
|  |  | |  |
| 1. Japan | | 1. US Large Cap. | 1. US Mid. Cap. |
|  | |  |  |
| 1. US small Cap. | | 1. US | 1. World |
|  | |  |  |

Notes: The green trajectories refer to the Islamic indexes, while the blue ones represent the conventional indexes.

*5.2. Conventional and Islamic index co-volatilities*

In this sub-section, we report the results of the time-varying measures of correlations obtained from the EGARCH model estimation. As noted earlier, to examine the volatility spillover patterns between the conventional and the Islamic indexes, we run a rolling window of 10-daily return volatility observations. Figure 2 conveys the evolution of the co-movements between the conditional return volatilities of both sets of indexes. As can be seen, the volatilities are time-varying through the whole sample period. For both the Islamic and conventional stock markets, the return volatilities are substantially higher at the beginning and the end of the sample period. A sizable peak of volatility is detected during the pre-GFC and the post-GFC periods.

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| --- | --- |
| **Figure 2**. The conditional return volatility co-evolution for each daily conventional index and its corresponding Islamic index | |
| **Fig (2.a).** Daily co-volatility for conventional DJI Asia/Pac index and its Islamic counterpart | **Fig (2.b).** Daily co-volatility for conventional DJI US large cap index and its Islamic counterpart |
| **Fig (2.c).** Daily co-volatility for conventional DJI US mid-cap index and its Islamic counterpart | **Fig (2.d).** Daily co-volatility for conventional DJI US small cap index and its Islamic counterpart |
| **Fig (2.e).** Daily co-volatility for conventional DJI Europe index and its Islamic counterpart | **Fig (2.f).** Daily co-volatility for conventional DJI Canadian index and its Islamic counterpart |
| **Fig (2.j).** Daily co-volatility for conventional DJI World index and its Islamic counterpart | **Fig (2.h).** Daily co-volatility for conventional DJI Japan index and its Islamic counterpart |
| **Fig (2.i).** Daily co-volatility for conventional DJI US index and its Islamic counterpart |  |
| Notes: The red trajectories represent the Islamic stock volatility, while the blue ones denote the conventional stock volatility. | |

*5.3. Volatility spillovers for conventional markets*

Table 2 displays the results of the degrees and directions of volatility spillovers within and across the all the nine conventional market indexes. The entry is the estimated spillover contribution to the forecast error variance of market  from shocks emanating from market. When the diagonal elements assess the own-market volatility spillovers, and when the off-diagonal elements measure the cross-market volatility spillovers within two markets. While each element of the “contribution to others” that corresponds to the sum of each of the off-diagonal columns refers to the total “to” volatility spillovers in each market, the sum of each of the off-diagonal rows (named “Contribution from others”) gives the “from” volatility spillovers of each market in our sample. Besides, it is worth indicating that the sum of the variances in a row is 100%[[3]](#footnote-3). The difference between “from” and “to” is labeled the net volatility spillovers from market index  to all other markets. The total volatility spillover is given as the average of the spillovers from all the other markets.

Several meaningful remarks can be made from the estimated results for the conventional markets. First, we identify large and varying cross-market volatility spillovers between all the nine conventional stock returns. Second, we perceive that the indexes distressing other indexes the most are the DJI Canada (99.24% of the total forecast error variance as the total contribution to other conventional markets), the DJI Euro-zone index (94.49%), the DJI US small Cap (93.61%), the DJI US mid Cap. (92.62%), the DJI US index (91.94%) and the DJI US large Cap (91.78%). High levels of the percentages of the total contribution to other stock markets’ volatility may be due to ‘pure contagion’ effects, which is explained by an excessive transmission of shocks from an economic or financial shock in an origin country to others beyond any idiosyncratic disturbances (see, among others, Forbes and Rigobon, 2002; Bae et al., 2003). However, the conventional indexes that distress others the least are the DJI Asia/Pacific index (53.48%) and Japan (67.27%).

These results suggest that there are substantial differences between two groups of the conventional markets, acting as sources of varying stress to each other. The first group, which includes the U.S., Canada and Eurozone, constitutes the source of strong stressors, while the second group that comprises DJI Asia/Pacific and DJI Japan acts as the weaker source of stressors. Interestingly, the US market indexes for all sizes are among the major stressors. These results support the high degree of volatility spillovers between the US, Canada and Eurozone, and highlight the presence of strong contagion effects between them but they are not the same for Asia, Pacific basin and Japan. Moreover, the row sum labeled “contribution from others” unveils that that the DJI World and the DJI Euro-zone are the most affected by the contribution of others, suggesting that the euro-zone conventional stock markets are largely affected by the volatility shocks occurring outside the euro area, which may also be due to strong contagion effects and investor herding behavior. Conversely, the gross directional volatility spillovers from others are the lowest for the DJI Asia Pacific and the DJI Japan. This means that stock return volatility shocks are moderately transmitted to other stock markets from those oriental markets. The values of gross volatility spillovers from others and to others support the hypothesis of the bidirectional volatility spillovers between the conventional stock markets, with the volatility shocks are mainly transmitted from Canada, the U.S. (all size markets) and Euro-zone.

Third, the total volatility spillover index which appears in the lower right corner of Table 2 filters the various directional volatility spillovers into a single index. Accordingly, across the whole sample, the value of the total volatility spillover across all the conventional indices on average is 88.89 %, indicating that on average 88.89 % of the volatility forecast error variance in all conventional markets comes from the spillovers. The high level of the volatility index clearly indicates strong volatility spillovers among the various conventional markets.

As for the net directional volatility spillovers (differences between the contributions to others minus the contributions from others, which are posted in the lower row of Table 2, the largest are from the US small cap market (17.48%) to others, the Canada stock market (7.83%) and the US large Cap. markets (2.72%). However, we note that the net directional volatility spillovers are negative for the Eurozone region, implying that the Eurozone stock markets are net receivers of volatility shocks occurring outside Europe. Similarly, the negative percentages of net volatility spillovers are obtained for Asia/Pacific and Japan.

In Figure 3, we plot the total volatility spillovers between the regional conventional stock markets. As noted earlier, the volatility spillovers are estimated using a 252-day rolling sample window and we assess the extent and the nature of the behavior of the volatility spillovers over the sample period. From this figure, we notice a substantial volatility spillover among these indexes. It can visibly be seen that there is an important variability in the total volatility spillover indexes over the whole sample period. Precisely, a notably increasing volatility spillover between the conventional indexes is observed between the ends of 2006 and 2012 (ranging between 6%-30%). This result is not surprising as the total volatility spillover indexes are a responsive to changes in global financial and economic risk factors and the occurrence of financial crises. For instance, during periods of financial distress such as the post-Asian financial crisis of 1997, the 2007-2008 GFC and the following 2010-2013 European debt crisis, there is a nearly increase in multi-lateral connectedness among the major conventional stock markets. Therefore based on these results we can accept the Hypothesis 1 of this study, i.e. there is an increase in the intensity of the volatility spillovers across the selected conventional indexes during a crisis period.

According to the results, there is no doubt that the volatility spillovers are not constant and their fluctuations are substantially high during the sample period. However, it is important to note that the time-movement of the total volatility spillovers among the regional conventional markets is noticeably impacted by the occurrence of the main recent financial crises, providing the supporting evidence for Hypothesis 1 Indeed, some extreme observations are easily identified in the total volatility plot. For instance, we identify a significant increase in the total volatility spillovers during the 2007-2008 GFC (specifically, the July-August 2007 and the January-March 2008 subperiods). Even after the collapse of the Lehman Brothers in mid-September 2008, the major stock markets have observed a substantial increase in their volatility spillovers, matching with the global liquidity crisis. Despite the prominence of the analysis of the time-movement of the total volatility spillover index, this index rejects directional information contained in the “contribution to others” and “contribution from others”(see, Antonakakis, 2012, and Antonakakis and Badinger, 2015). For this reason, we focus more attention on the directional volatility spillovers.

|  |  |  |
| --- | --- | --- |
| |  | | --- | | **Figure 3.** Total volatility spillovers for conventional markets, 252-day rolling windows | | Notes: The blue trajectory refers to the total volatility spillovers between the regional conventional stock markets. The volatility spillovers are estimated using a 252-day rolling sample window. | |

Fig.4 and Fig.5 report the directional volatility spillovers from each of the conventional markets indexes to others (Fig. 4) and from others to the conventional markets (Fig. 5), respectively. As can be seen, the directional volatility spillovers from each index are more pronounced than the directional volatility spillovers from others to each of the conventional indexes. For example, the directional volatility spillovers from the DJI Euro-zone, DJI Canada and DJI Japan indexes to others reach up to 30% each, while the directional volatility spillovers from others to these corresponding indexes do not exceed 10%. However, we perceive that the time movements of the directional volatility spillovers for the World and the U.S. indexes are quite similar, while for Canada and Japan they are different and display relatively high fluctuations over the whole sample period. Besides, it is worth noting that the overall directional volatility spillovers vary substantially through time. Particularly, the directional spillovers have strengthened during the recent GFC and the European sovereign debt crisis, which is also support Hypothesis 1 of this study

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| --- | --- | --- |
| **Figure 4.** Directional volatility spillovers *from* the following individual conventional markets to (all other conventional indexes (all other conventional markets) | | |
| 1. DJI Asia/Pac | 1. DJI US large Cap. | (c) DJI US mid Cap. |
|  |  |  |
|  |  |  |
| 1. DJI US small Cap. | (e) DJI Eurozone | (f) DJI Canada |
|  |  |  |
|  |  |  |
| (g) DJI World | (h) DJI Japan | 1. DJI US |

|  |  |  |
| --- | --- | --- |
| **Figure 5.** Directional volatility spillovers *from* all other conventional indexes (all other conventional markets) to the following individual conventional markets | | |
| 1. DJI Asia | 1. DJI US large Cap. | (c) DJI US mid Cap. |
|  |  |  |
| (d) DJI US small Cap. | (e) DJI Eurozone | (f) DJI Canada |
|  |  |  |
| 1. DJI World | (h) DJI Japan | 1. DJI U.S. |
|  |  |  |

Using 252-day rolling windows, we plot the net volatility spillovers in Fig. 6 (Figs. a to i) below. As stressed earlier, the net volatility spillovers provide an idea of how much each index contributes to the volatility in other indexes in net terms. In this graph, a positive value designates that the index is a net volatility transmitter, while a negative value indicates that the index is a net volatility receiver. Subsequently, we can classify the following graphs into two groups of net spillover transmitters/receivers. The DJI large Cap, the DJI mid Cap, the DJI small Cap, the DJI World and the DJI US are net volatility transmitters and are similar over the entire sample period, while the other indexes particularly the DJI Asia Pacific and DJI Japan are net volatility receivers. This finding underscores the importance of heeding crises originating from the U.S. such the 2007 subprime mortgage crisis and the financial meltdown that took place in summer 2008.

Fig. 6 also reveals that both the DJI Canada and the DJI-Europe indexes display the highest fluctuations in the volatility interactions over the sample period. It is interesting to note that during the recent GFC period, the DJI Canada becomes a net volatility receiver probably because Canada is a resource country and that commodities particularly oil were hit very hard during the global crisis. Canada is also the U.S. largest trading partner and the latter is the originator of the crisis. Furthermore, we notice that, among all the selected market indexes and over the sample period, the DJI US is the largest net volatility transmitter, with a visible increase during the post-GFC period (up to 18% in 2011).

As indicated, Figs. b, c, and d, show that the U.S mid Cap., small Cap. and large Cap. are net volatility transmitters and their net volatility paths are quite similar over the entire sample period. In addition,it can be seen thatover the sample period, the World and the U.S. markets are net volatility transmitters to all indexes, demonstrating that these markets are closed markets and are not considerably affected by the volatilities of the other markets.

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| **Figure 6.** Net volatility spillovers from all other conventional markets indexes to the following individual conventional markets | | |
| 1. DJI Asia | (b) DJI US large Cap. | (c) DJI US mid Cap. |
|  |  |  |
| (d) DJI US small Cap. | (e) DJI Eurozone | (f) DJI Canada |
|  |  |  |
| 1. DJI World | (h) DJI Japan | (i) DJI U.S. |
|  |  |  |
| Notes*:* In this Figure, a positive value designates that the index is a net volatility transmitter, while a negative value indicates that the index is a net volatility receiver. | | |

*5.4. Volatility spillovers for Islamic stock markets*

Table 3 reports the total volatility spillovers among the Islamic stock markets and a comparison with results for the conventional markets illustrated in sub-section 4.3. Generally, we perceive that the “contributions to other Islamic market” from each Islamic stock market are not much different from the corresponding results of their conventional counterparts discussed earlier (see Table 2). The Islamic indexes affecting other Islamic indexes the most are the DJIM US mid Cap, the DJIM Europe, the DJIM Canada, the DJIM World and the DJIM Japan, in this row. The estimated results for “contribution to others” show that more than 90% of the individual Islamic indexes’ own volatilities are transmitted to the other Islamic markets. The highest average is for the DJIM US mid-Cap index. (99.49%). The contribution of the DJIM US index to the volatility of other Islamic stock markets is only 66.56%, which is lower than its contribution (91.94%) to its counterparts in the conventional markets case (see, Table 2). The effect of the other Islamic markets on the DJIM US index is only 51.99%, which is the lowest gross directional volatility spillover from others Islamic stock markets to other Islamic markets, still pointing to the closeness of the Islamic U.S. market. According to the total volatility spillover, approximately 88.8% of the volatility of the forecast error variance in Islamic stock markets comes from volatility spillovers of the other Islamic markets. A quite similar result is reported for the conventional stock markets, which indicates that in terms of the measure of the total volatility spillovers, the Islamic stock markets seem to have the same behavior like their conventional counterparts.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3.** Volatility spillovers: The Islamic stock markets (%) | | | | | | | | | | | |
|  | Asia/Pac | US  Large | US Mid | US Small | Europe | Canada | World | Japan | US | Contribution from others | Contribution including own |
| DJIM Asia/Pacific | 1.53 | 1.47 | 1.,46 | 1.56 | 1.52 | 1.50 | 1.52 | 1.56 | 1.54 | 74.03 | 113.29 |
| DJIM US large CAP | 1.41 | 1.40 | 1.40 | 1.42 | 1.40 | 1.40 | 1.40 | 1.42 | 1.41 | 52.61 | 61.66 |
| DJIM US Mid CAP | 2.81 | 2.80 | 2.80 | 2.83 | 2.81 | 2.80 | 2.81 | 2.82 | 2.81 | 66.66 | 74.76 |
| DJIM US small CAP | 4.09 | 4.13 | 4.13 | 4.07 | 4.10 | 4.11 | 4.10 | 4.08 | 4.09 | 83.9 | 90.89 |
| DJIM Europe | 6.90 | 6.92 | 6.92 | 6.90 | 6.91 | 6.92 | 6.91 | 6.90 | 6.90 | 107.52 | 108.71 |
| DJIM Canada | 11.00 | 11.05 | 11.05 | 10.97 | 11.01 | 11.03 | 11.01 | 10.98 | 11.00 | 140.08 | 141.93 |
| DJIM World | 16.75 | 16.71 | 16.71 | 16.77 | 16.74 | 16.73 | 16.74 | 16.77 | 16.75 | 82.43 | 89.2 |
| DJIM Japan | 27.75 | 27.76 | 27.76 | 27.74 | 27.75 | 27.76 | 27.75 | 27.74 | 27.75 | 140.72 | 158.62 |
| DJIM US | 27.75 | 27.76 | 27.76 | 27.74 | 27.75 | 27.76 | 27.75 | 27.74 | 27.75 | 51.99 | 60.89 |
| **Contribution to others** | 60.75 | 94.57 | 99.49 | 78.06 | 97.33 | 97.15 | 95.54 | 97.21 | 66.56 |  | **Total Spillover**  799.94/900= 88.8% |
| **Net spillovers** | -13.28 | 41.96 | 32.83 | -5.84 | -10.19 | -42.93 | 13.11 | -43.5 | 14.57 |  |  |
| Notes: The spillover contributions come from the first row to the first column. Net spillover is the difference between the ‘contribution to others’ minus the ‘contribution from others’. | | | | | | | | | | | |

In the present sub-section, we examine graphically the spillover variations of the Islamic indexes over time using the 252-day rolling window sample. For this raison, Fig. 7 corresponds to the time-varying measure of volatility spillovers of the Islamic indexes. When we look at this plot, we can divide the sample period into the two sub-sample periods (1999-2006) and (2007-2014).

|  |
| --- |
| **Figure 7.** Total volatility spillovers, 252-day rolling windows  (all Islamic markets) |
| Notes: The blue trajectory refers to the total volatility spillovers between all of the regional Islamic stock markets. The volatility spillovers are estimated using a 252-day rolling sample window. |

From Fig. 7, we observe that there is a remarkable variability in the total volatility spillovers over the first sub-period (1999-2006). During this sub-period, the total volatility spillovers fluctuate between 5% and 22%. However, after 2006 the spillover index recorded a moderate upward movement (ranging from 8% to 21%). In the second sub-period (2007-2014), the total volatility spillovers exceeded the 28% level between 2007 and 2009 (i.e., the GFC years) and then moderated at the 24% level between 2011 and 2013 (the European crisis). Thus, the level of volatility spillover is much higher during the GFC and euro-debt crisis periods.

Fig. 8 and Fig. 9 report the directional volatility spillovers from each of the Islamic indices to all the other Islamic indexes as well as the directional volatility spillovers from the other Islamic indexes to each of the Islamic index, respectively. Fig. 8 shows that the spillovers from each index to other Islamic indexes are below 20% during the tranquil and crisis periods (with the exception of the Islamic Eurozone index, for which the spillover moves up to the 29% level between 2006 and 2007).

|  |  |  |
| --- | --- | --- |
| **Figure 8.** Directional volatility spillovers *from* the following individual Islamic indexes to all other Islamic indexes (all other Islamic markets) | | |
| 1. DJIM Asia | (b) DJIM US large Cap. | (c) DJIM US mid Cap. |
|  |  |  |
| (d) DJIM US small Cap. | (e) DJIM Eurozone | (f) DJIM Canada |
|  |  |  |
| (g) DJIM World | (h) DJIM Japan | 1. DJIM U.S. |
|  |  |  |

From Fig. 9 we can see that the directional volatility spillovers from the Islamic others to each of the individual Islamic indexes seem to be quite stable through time for all the individual Islamic indexes. Indeed, the volatility spillovers do not surpass the 10% level over the entire period. Their time path is quite similar except for Islamic Japan where the directional volatility is relatively unstable over the whole sample period. These results may be due to the fact that restrictive sharia principles are an important factor that contributes to the reduction of the directional volatility spillovers among Islamic stock markets. These findings suggest the rejection of the Hypothesis 2 of this study (i.e. there is an increase in intensity of the volatility spillovers across the selected Islamic indexes during a crisis period), because the increase in spillovers during the crises has not been identified by our empirical analysis.

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| **Figure 9.** Directional volatility spillovers *from* all other Islamic indexes (all other Islamic markets) to the following individual Islamic markets | | |
| 1. DJIM Asia | (b) DJIM large Cap | (c) DJIM mid Cap |
|  |  |  |
| (d)DJIM small Cap. | (e) DJIM Eurozone | (f) DJIM Canada |
|  |  |  |
| (g) DJIM World | (h) DJIM Japan | 1. DJIM U.S. |
|  |  |  |

The net volatility spillovers for the Islamic indexes are displayed in Fig. 10 (Fig. a- to Fig. i). From these plots, we can distinguish between two major phases of net volatility spillovers. While the first phase of volatility transmission begins from 1999 to 2005, the second one spreads from 2006 to 2014. During the first phase, which starts after the 1997 financial Asian crisis, the net volatility spillovers for the mainstream Islamic markets do not exceed 6%, indicating moderate levels of spillovers, which further provides the supporting evidence for the rejection of the Hypothesis 2Moreover, during this stage all Islamic market indexes, except the Islamic DJIM Canadian index, both the transmitting and receiving volatility have an equal magnitude. At the beginning of the second period, the DJIM Eurozone reaches 20% and is identified as a transmitter of volatility to the other Islamic stock markets. Compared to the conventional market indexes, the conventional World and the US markets are also transmitters of net volatility to all indexes. Similarly, the net volatility does not exceed the 5% level.

|  |  |  |
| --- | --- | --- |
| **Figure 10.** Net volatility spillovers from all the Islamic market indexes to the following Islamic markets | | |
| 1. DJIM Asia | (b) DJIM US large Cap | (c) DJIM US mid Cap |
|  |  |  |
| (d)DJIM US small Cap. | (e) DJIM Eurozone | (f) DJIM Canada |
|  |  |  |
| (g) DJIM World | (h) DJIM Japan | 1. DJIM U.S. |
|  |  |  |

*Notes:* In this graph, a positive value designates that the index is a net volatility transmitter, while a negative value indicates that the index is a net volatility receiver.

*5.5. Volatility spillovers between Islamic and conventional indexes*

Several important remarks can be made from Fig. 11 (Fig. a to Fig. i) that corresponds to thepairs for the conventional indexes and their counterpart Islamic indexes. A first view of all the figures shows that the Islamic indexes are recipients of volatility spillovers during the periods of the financial crises, which suggest the rejection of the Hypothesis 3. For instance, the DJIMs are net receivers of modest levels of volatility from the conventional DJI Asia-Pacific, DJI large Cap. and DJI Europe indexes. For these pairs, the spillovers do not exceed the 10% level during the GFC period. In addition, we perceive quite similar patterns of the volatility spillovers between the Islamic and conventional indexes for the US large and mid-Cap markets, suggesting that the volatility transmission seems to be not affected by firm sizes in the US market. The Canadian Islamic index is a receiver of volatility from his conventional counterpart over in the pre- crises period. However, as can be seen, there is a notable change in the volatility spillover relationship between these indexes, in terms of both direction and magnitude during the turbulent periods. For the pair of Canadian Islamic and conventional indexes, which has the volatility spillover reaches close to 40% at the beginning of the period, corresponding to the 9/11 terrorist attacks, the Canadian Islamic index is a recipient of moderate levels of volatility (10%) during the turmoil period. Towards the start of the global financial crisis, the DJI (conventional) World index transmits a volatility of 5% to the Islamic DJIM World index. These findings confirm the Hypothesis 3 tested in this study, i.e. there is a decrease in the intensity of the directional volatility spillovers from the conventional indexes to their Islamic counterparts during the crisis period (for example for Canadian pair of indexes the decrease was from 40% to 10% and to 5% during and post-crisis periods respectively).

|  |  |  |
| --- | --- | --- |
| **Figure 11.** Spillovers for the nine pairs of indexes: conventional and Islamic indexes | | |
| (a) Asia/Pac | (b) US large Cap. | (c ) U.S. mid Cap |
|  |  |  |
| (d) US small Cap. | (e ) Eurozone | (f) Canada |
|  |  |  |
| (g) World | (h) Japan | 1. U.S. |
|  |  |  |

*Notes:* Each plot depicts the spillovers for the pairs of DIJ and DJIM indexes of the different regions.

*5.6. The net volatility shifts behavior around the recent financial crises*

In light of the previous analysis, the net volatility spillovers between the Islamic and conventional stock indexes have shown to be persistently higher and exhibit significant increases around the regional and financial crises. In order to further examine the decoupling hypothesis (Hypothesis 3) in this section we present the analysis of the net-volatility shifts behavior around the recent financial crises. Apart from high theoretical significance, a deeper analysis of the behavior of the net volatility spillovers will bring further practical implications. It may have potential implications for portfolio managers and hedge funds active in the Islamic and conventional markets. Since it is well recognized that a higher level of correlations may reduce diversification benefits, and higher conditional correlations exhibit higher volatility levels, then portfolio managers will opt to employ the estimated correlations for portfolio asset allocations (see Chiang et al., 2007).

To do so, we construct a GARCH model to describe the net volatility spillover dynamics and also include dummy variables in both the mean and conditional variance equations to account for extreme events or crises. The changing sign of the dummy variable in the conditional mean or the conditional variance of the net volatility spillovers indicates that the selected events have an impact on the net volatility spillovers among the stock markets. Thus, using variables corresponding to major extreme events and turbulent periods allows us to capture volatility shifts during financial crisis periods. In concordance with some prior studies including Chiang et al. (2007), Aloui (2011), among others, we estimate the following mean equation:

 (9)

where  is the net volatility spillovers between the pairs of the Islamic indexes (i) and conventional counterparts (j). We use the AIC and SIC information criteria to specify the optimal lag length in the net volatility mean equation. For the dummy variables, we have subdivided the whole sample period into five sub-periods based on the dates of major financial crises. It should be stressed that our sample period is large and includes various financial crises such as those that took place in Asia, Russia, Argentina, Brazil, United States as well as some geopolitical events such as the September 11, 2001 terrorist attack and the 2003 Iraq invasion. In the present study, the focus is on some major domestic financial crises as well as the recent US subprime crisis.

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| --- | --- |
| **Table 4**. The sample subdivisions according to crises | |
| Selected subsamples | Pre and post financial crises |
| 1/14/1999- 01/06/2002 | Post Brazilian financial crisis and to Argentinean financial crisis |
| 01/07/2002 -10/13/2008 | Post Argentinean crisis and prior to US subprime crisis |
| 03/17/2008-09/12/2008 | The collapse of Lehman Brothers |
| 10/13/2008-09/15/2009 | Post-subprime crisis |
| 10/03/2009-02/08/2013 | European sovereign debt crisis |

The estimated results of the model are provided in Table 5. With reference to the LM-ARCH tests, all the net volatilities exhibit strong evidence of heteroscedasticity. Thus, as in Chiang et al. (2007), we estimate the GARCH (1,1) model that includes the dummy variables in order to test for the volatility shift behavior. Formally, the conditional variance equation is written as follows:

 (10)

According to this model, the found significance of the dummy variables’ coefficients in the mean or/and the conditional variance implies the presence of shifts in the net volatility behavior around the international or/and domestic financial crises. The estimates of GARCH (1,1), using the maximum-likelihood method, are displayed in Table 5. Panels A and B report the estimated results for the mean and the variance equations respectively, while the results of the diagnostic tests are shown in Panel C.

The coefficients of the dummy variables embedded in the mean and variance equations of the GARCH model allows to test if the occurrence of a financial crisis has an impact on the net volatility spillover between the conventional and Islamic pairs. The estimated coefficient of the first dummy variable corresponding to the post Asian financial crisis and prior to Brazilian financial crisis is positive and statistically significant for the DJI and DJIM Canada and World pairs, suggesting that this crisis has a “contagion effect” for these pairs between the conventional and Islamic markets. It also implies that this crisis has increased the magnitude of volatility spillover between these pairs. In addition, the estimated results reported in Panel B suggest that the post Brazilian financial crisis and prior to the Argentinean financial crisis has a negative and statistically significant impact on the volatility spillover between all the pairs. This impact continues during the post Argentinean crisis period. The estimates for the dummy variable corresponding to the Lehman Brother collapse also show negative coefficients except for the DJI and DJIM Eurozone pair, indicating that the European equities have higher sensitivity to the collapse of this large American bank. The estimated coefficients of the post U.S. subprime mortgage crisis and the European debt crisis dummies are significantly negative in both the conditional mean and the conditional variance of net volatility for the majority of pairs. Thus, these findings for the dummy variables suggest that the Islamic indexes move against conventional indexes during periods of crises that affect major countries and regions such as the United States and the Eurozone. This indicates that dichotomy hypothesis for the conventional and Islamic markets works during global crises, thereby implying that the Islamic indexes can be used as a hedge or a safe haven for the conventional indexes during extreme events. Overall, the estimated results show that the pair-wise net volatility spillovers between the Islamic and conventional markets reveal a weak magnitude of net volatility spillovers during periods of economic and financial turbulences. Therefore, we can robustly argue that Islamic financial indexes are decoupling from their conventional counterpart during the crises. Thus, based on the results above we confirm the Hypothesis 3.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5.** Estimates of GARCH(1,1) of the net volatility for pairs of matching Islamic and conventional markets around major global crises | | | | | | | | | |
|  | Asia-pacific | Large cap | Mid cap | Small cap | Europe | Canada | World | Japan | US |
| *Panel A. The mean equation* | | | | | | |  |  |  |
| Constant | 0.00027  (0.0107) | 6.639e-05  (0.0013) | 0.000229  (0.00654) | -0.00203  (-0.1509) | -0.0006  (-0.055) | -0.2143\*\*\*  (-59.376) | -0.0389\*\*\*  (-8.3833) | -0.0027\*\*\*  (-6.040) | -7.30e-05  (-0.8200) |
|  | 0.998\*\*\*  (32.94) | 0.999\*\*\*  (16.770) | 0.99361\*\*\*  (29.170) | 0.9897\*\*\*  (111.60) | 0.9885\*\*\*  (86.506) | -0.6818\*\*\*  (-34.005) | -0.9777\*\*\*  (-187.343) | 0.0034  (0.0452) | -0.0016  (-0.01249) |
|  | -0.00092  (-0.0028) | -0.0048  (-0.00702) | 0.00313  (0.00513) | -0.00414  -(0.0117) | 0.0103  (0.1320) | -0.3112\*\*\*  (-5.4122) | 0.1177\*\*\*  (25.239) | 0.2108\*\*\*  (29.303) | 0.153\*\*\*  (103.376) |
|  | -0.00077  (-0.004) | 0.000176  (0.00050) | -0.0040  (-0.0489) | 0.00386  (0.0254) | 0.0091  (0.7365) | -0.3000\*\*\*  (-9.2863) | 0.0335\*\*\*  (7.1993) | -0.0430\*\*\*  (-9.8268) | -0.081\*\*\*  (-94.1621) |
|  | 0.01296 (0.0495) | -0.01409  (-0.0259) | 0.0013  (0.0021) | -0.00011  -(0.00025) | -0.0802  (-1.1133) | -0.5532\*\*\*  (-8.5727) | -0.0264\*\*\*  (-5.6580) | -0.2344\*\*\*  (39.5482) | -0.137\*\*\*  (-85.2768) |
|  | 0.0079  (0.019) | -0.0045  (-0.0055) | 0.0028  (0.00526) | -0.00963  -(0.0257) | -0.0202  (-0.1841) | -0.0649  (-0.9488) | -0.0391\*\*\*  (-111.471) | -0.2343\*\*\*  (-46.901) | -0.1505\*\*\*  (-92.9403) |
|  | -0.01109  (-0.032) | 0.0176  (0.0295) | 0.00154  (0.00190) | 0.00563  (0.01160) | 0.0828  (0.7341) | 0.50832\*\*\*  (7.3259) | -0.00019  (-0.04218) | 0.4239\*\*\*  (57.009) | 0.2920\*\*\*  (157.839) |
| *Panel B. The variance equation* | | | | | | |  |  |  |
| Constant | 0.00024\*\*\*  (4.2236) | 0.000491\*\*\*  (5.0826) | 0.00046\*\*\*  (6.0223) | 0.00047\*\*\*  (4.792) | 0.00047\*\*\*  (7.1887) | 0.01589\*\*\*  (32.027) | -0.03898\*\*\*  (5.87101) | 0.00012\*\*\*  (21.1377) | 3.288\*\*\*  (7.7661) |
|  | 0.1489  (1.0146) | 0.141662  (1.3483) | 0.12914  (1.4848) | 0.1495  (1.374) | 0.2500\*  (1.7468) | 0.53598\*\*\*  (7.7875) | -0.97778\*\*\*  (17.730) | 0.4090\*\*\*  (17.827) | 0.1948\*\*\*  (40.1498) |
|  | 0.591\*\*\*  (6.053) | 0.59049  (7.229) | 0.5741\*\*\*  (8.2866) | 0.5852\*\*\*  (7.093) | 0.5752\*\*\*  (9.5802) | 0.23088\*\*\*  (6.2097) | 0.11772\*\*\*  (55.4357) | 0.6031\*\*\*  37.3130 | 0.8343\*\*\*  (243.080) |
|  | 0.00012  (0.5232) | 0.00023  (0.490) | -0.00027  (-0.57413) | 5.477e-05  (0.0775) | 0.00048  (0.9171) | 0.07570\*\*\*  (10.585) | 0.03351\*\*\*  -(5.86637) | -0.00024\*\*  (-2.8394) | 1.466e-08  (0.01184) |
|  | -0.00063\*\*  (-3.473) | -0.001072\*\*  (-3.699) | -7.540e-05  (-0.3297) | -0.00127\*\*  (-2.390) | 0.00026\*\*  (2.4194) | -0.0209\*\*  (-3.1476) | -0.02644\*\*\*  -(5.8581) | -0.00016\*\*\*  -(5.7522) | -5.335e-06\*\*\*  (-7.6943) |
|  | -1.82e-05  (-0.0485) | -2.99e-05  (-0.0333) | -0.00039  (-0.6851) | -2.914e-05  (-0.0273) | 0.00055  (0.63108) | -0.0207  (-1.4882) | -0.03919\*\*\*  -(5.8633) | -0.0011\*\*\*  (-14.006) | -3.743e-06\*\*  (-2.123) |
|  | -7.60e-05  (-0.2410) | -0.00013  (-0.229) | -0.00142\*\*  (-2.2336) | -0.000175  (-0.1589) | -0.00315\*\*\*  (4.992) | 0.1250\*\*\*  (16.0614) | -0.00019\*\*  (-3.1559) | 0.00202\*\*\*  (23.7036) | -1.958e-06  (-1.113) |
|  | -0.0006  (1.3788) | -0.00163  (-1.4971) | -0.0022\*\*  (-2.740) | -0.00113  (-1.006) | -0.0037\*\*\*  (3.4842) | -0.0784\*\*\*  (-13.9181) | -0.03898\*\*\*  (-5.8359) | -0.0011\*\*\*  (-13.825) | -6.867e-06\*\*  (-3.4872) |
| *Panel C. Diagnostic tests* | | | | | | |  |  |  |
| Q(5) | 1.83 | 1.43 | 1.42 | 1.42 | 1.43 | 1.37 | 1.44 | 1.43 | 1.37 |
| ARCH(5) | 445.39\*\*\* | 295.82\*\*\* | 172.57\*\*\* | 32.94\*\*\* | 177.56\*\*\* | 33.84\*\*\* | 72.63\*\*\* | 383.37\*\*\* | 75.68\*\*\* |
| Notes: The lag length is determined by the AIC criterion. Q(5) is the Ljung-Box Q-statistics up to five days, testing the serial correlation of the residuals. ARCH(5) is the ARCH LM test up to five days, testing the heteroscedasticity of the residuals. (\*\*\*), and (\*\*) denote the statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are the Z-statistics. | | | | | | | | | |

1. **Robustness checks**

I order to check the robustness of our empirical results we employed the alternative technique. Thus, in this section, we illustrate the maximum overlap discrete wavelet transform correlation (hereafter, MODWT) and the cross-correlation results about the assessment of the degree of dependence and the lead-lag relationship for the conventional vs. Islamic index pairs.

The Discrete wavelet transform (hereafter, DWT) of a time series is a suitable method that enables one to analyze the multi-scale features of this time series. This analysis decomposes a time series into a set of equally orthogonal wavelet basis functions. The MODWT is a slight variation of the DWT. This approach is defined as a linear filtering process that is able to transform a time series into coefficients which are linked to deviations over different scales. Unlike the DWT, the MODWT can over-sample the data and thus increase the resolution of signal at high scales, which allows us to acquire maximum information about the variability of the signal (see Gallegati, 2010). To provide the MODWT wavelet correlation and the MODWT cross correlation analysis formulas, we adopt the same annotations used by Gallegati (2008). The MODWT wavelet and scaling coefficient and are given as follows;

 and  (11)

where and denote the level wavelet and scaling filters. The MODWT wavelet and scaling filters (Eq.11) are directly generated from the DWT filter and are respectively given as;

 and  (12)

By considering a second-order stationary stochastic process with zero mean, the wavelet variance at scale is defined as the variance of the wavelet coefficients at the scale  (see, Percival, 1995) and given as;

 (13)

Given the wavelet covariance of (,) and the wavelet variance of the two stochastic processes and , the MODWT estimator of wavelet correlation is given as :

 (14)

According to Gençay et al. (2001) the covariance of two stochastic processes and at wavelet scale *j* is specified as . Using the MODWT, an unbiased estimator of wavelet covariance after removing all wavelet coefficients affected by periodic boundary conditions is obtained. Using MODWT, the estimator of wavelet covariance is given by the following equation;

 (15)

For scale  and lag , the MODWT estimator of wavelet cross-correlation coefficients is taken by using the wavelet cross-covariance given in Eq. (15) and the squared root of the two time series wavelet variances  and ;

 (16)

The wavelet cross-correlation coefficients given in Eq. (16) provide the lead/lag wavelet analysis between two time series on a scale-by-scale basis and are between 0 and 1.

* 1. *MODWT correlation*

Our main concern is to visualize whether conventional indexes are leading the Islamic indexes or not. Fig. 12 (Fig. 12a to Fig. 12i) diplays the wavelet correlation between the conventional and Islamic market indexes across daily time scale periods. From this figure, we can show three lines of three colors where the red color line illustrates the pair-wise correlation coefficients and the green and blue lines reveal the upper and lower band for the 95% confidence interval, respectively. A visual inspection for the plots demonstrates that the level of correlation is very close to unity, indicating a high level of correlation between the indexes in the long-run horizon and thus an interesting interconnection between the conventional and Islamic indexes in different scales. In addition, Fig. 12f reveals that, among all pairs, the Canadian conventional and Islamic indexes are least correlated pair, especially at levels 2, 3, 4 and 5.

|  |  |
| --- | --- |
| **Figure 12.** The wavelet correlation plots of nine pairs of indexes: conventional and Islamic indexes | |
| Fig. 12a. Asia/ Pacific | Fig. 12b. US Large Cap. |
| Fig. 12c. US Mid Cap. | Fig. 12d. US Small Cap**.** |
| Fig12e. Eurozone | Fig12f. Canada |
| Fig12g. Japan | Fig12h. World |
| Fig12i. U.S. |  |

* 1. *MODWT cross-correlation*

The wavelet cross-correlation adequately exhibits how the relationship between the two indexes changes with scale. Specifically, this tool enables us to analyze the lead/lag (spillover) relationship between conventional and Islamic indexes for different scales. Following Dajčman (2013), if one variable leads the other variable, then its realizations may be used to forecast the realizations of the lagging variable.

The following plots[[4]](#footnote-4) (Figs. 13a to Fig.13i) provide the MODWT-based wavelet cross-correlation between the aforesaid couple at all scales *(j=1,..,5).* The individual cross-correlation functions in wavelet scales are linked with changing of 2-4, 4-8, 8-16, 16-32 and 32-64 days[[5]](#footnote-5). The red lines bound refers to the 95% confidence interval for the wavelet cross-correlation. When the wavelet cross-correlation is skewed to the right (left) side of the graph, the second time series is leading (lagging) the first time series. If both the 95% confidence intervals are above (bellow) the horizontal axes, it means that there is a significant positive (negative) wavelet cross-correlation. The cross-correlation function is plotted for 100 unit of leads/lags (where

At shorter scales (i.e. levels 1 and 2), the condensed peaks shown at the right half of the figure reflect the instability of interactions between the two markets. Levels 3 and 4 are consistent with our previous finding which reveals significant positive correlation between the conventional and Islamic markets at medium scales. While the cross-wavelet curve becomes smoother at scale 5 meaning that the attractions powers are less impacted by unexpected changes after 32-64 days, the correlation is still closer to unity given that the cross-correlation gests stronger with higher frequencies.

Looking at each pair, we show that the Canadian conventional and Islamic indexes (Fig. 13c, Appendix A) exhibit a smallest cross-correlation where the Islamic index has the potential to lead the conventional index at all scales. Therefore these results provide the supportive evidence for decoupling hypothesis (Hypothesis 3) for this market pair.

The results of robustness tests confirm in part our earlier findings. Our results based on the wavelet correlation and the wavelet cross-correlation indicated that, except for Canadian case, the conventional and Islamic markets are highly integrated especially at low scales. This is consistent with the results of application of DY’ (2012) framework which show the high interactions between the chosen global and regional Islamic stock markets and their conventional counterparts. From a portfolio management point of view, the results show that there are more potential gains of diversification at low scales (high frequencies). From this, we can say that long-term investors have more portfolio diversification opportunities. However, the Canadian case suggest the confirmation of decoupling hypothesis since the Islamic index led its conventional counterpart at all scales.

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1. **Concluding remarks**

In this paper, we analyze the volatility spillovers between nine major Islamic and conventional regional stock indexes, namely the Unites States, the Eurozone, UK, Canada and Asia Pacific. We examine three groupings of those markets. The first group includes the conditional markets’ indexes only; the second contains the Islamic indexes while the third comprises all the conventional and Islamic indexes.

We use daily data for the period 1999-2014 mostly to cover major financial crises and turbulent periods that took place during the last two decades. For this purpose, we make use of the generalized vector autoregressive framework developed by DY’ (2012) to assess the total, directional and net volatility spillovers among the selected global Islamic stock indexes and their conventional counterparts. The DY (2012) analysis performed because the forecast-error variance decompositions are invariant to the variable ordering. In addition, we extend the DY (2012) approach by choosing the conditional variance of an EGARCH model as a proxy of the daily volatility primarily to account for asymmetry in the volatility spillover patterns between those selected regional stock indexes.

Our results based on the DY’ (2012) framework display rich interactions between the chosen global and regional Islamic stock markets and their conventional counterparts, implying that Islamic stock markets are not isolated from the global financial system shocks during normal periods. From the net volatility spillovers analysis among those global indexes, we uncover that Islamic indexes are recipients of volatility spillovers especially during the major global crises, which rejects the decoupling hypothesis. For instance, some Islamic indices are net receivers of volatility spillovers from the DJI Asia, the DJI U.S (large Cap) and the DJI Eurozone. In addition, the results show that the U.S. is the major volatility transmitter and contagion emitter because its markets are more closed to contagion than the other conventional markets. Our findings are in line with, some previous studies including Hammoudeh et al. (2014) and Akhtar et al. (2013) who examine more aggregated market indexes.

Based on the estimated results, we found that around the crises the Islamic stock markets and its conventional counterparts are highly interconnected. The results suggest that the Islamic equities do not differ much from their conventional counterparts in terms of volatility spillovers and their response to the main volatility shocks. Put it another way, the Islamic finance system does not offer a virtuous cushion against financial shocks that affect the conventional markets or large diversification benefits for hedge funds. However, the analysis of the behavior of the net volatility spillovers between the Islamic and conventional markets over time unveils that the Islamic indexes move against conventional indexes during turbulent periods that affect major countries and regions such as the United States and the Eurozone. These results provide the supporting evidence for decoupling hypothesis for Islamic markets during the periods of financial turbulence. Furthermore, the more recent major financial crises in emerging countries such as Argentina and Brazil and Asian countries have a significant effect on the strength of the net volatility spillovers for the Asia/Pacific, US (all size markets), Canada, and Japan since their corresponding dummy variables are negatively signed and significant in the conditional variance equation. This result further indicates that the decoupling effect for the conventional and Islamic markets works during global crises. From a portfolio management perspective, the findings show that Islamic indexes can be employed as a hedge or a safe haven for the conventional indexes during extreme events.

Therefore, the results unveil some useful findings for portfolio managers, international hedge funds and policy makers. They reveal significant differences in the extent and nature of the dynamic linkages between the Islamic indexes and their conventional counterparts for six major regions in the world. Whilst, the fundamentals and volatility transmission mechanisms are not explicitly considered in this investigation, an investigation of the main volatility spillover channels appears to be a potential avenue for future research.

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**Appendix A.**

|  |  |
| --- | --- |
| **Figure 13a.** The wavelet cross correlation: DJI Asia /Pacific vs. Asia/Pacific Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13b.** The wavelet cross correlation: DJI U.S. Large CAP vs. US Large Cap Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13c**. The wavelet cross correlation: DJI Canada vs. Canada Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days**)** |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13d.** The wavelet cross correlation : DJI Europe vs. Europe Islamic index | |
| Level 1(2-4 days**)** | Level 2(4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13e.** The wavelet cross correlation: DJI World vs. World Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13 f.** The wavelet cross correlation: DJI Japan vs. Japan Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13g.** The wavelet cross correlation: DJI Mid CAP vs. Mid CAP Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days**)** |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13 h.** The wavelet cross correlation: DJI Small CAP vs. Small CAP Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days) |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

|  |  |
| --- | --- |
| **Figure 13i.** The wavelet cross correlation: DJI U.S vs. U.S Islamic index | |
| Level 1 (2-4 days) | Level 2 (4-8 days**)** |
| Level 3 (8-16 days) | Level 4 (16-32 days) |
| Level 5 (32-64 days) |  |

1. See the Islamic Finance Outlook, 2014, p. 2. [↑](#footnote-ref-1)
2. Thomson Reuters Global Islamic Asset Management Outlook Report. According to this report, there were two very positive signs for the industry in 2014. First, the year saw the lowest number of liquidated funds since 2008 totaling US$127 million, compared to US$315 million in 2013. Second, the total size of the new funds launched increased to US$2.27 billion up from US$1.52 billion in 2013, representing a 49% increase. On 2014, assets in Mutual funds worth $53.17 billion, making up 88% of the total global Islamic funds. They are mostly driven by diversification and liquidity. The report is available on the link: http://www.twentyfoursevennews.com/headline/global-islamic-funds-witness-growth-of-5-3-in-2014/ [↑](#footnote-ref-2)
3. We calculate , which presents the basic spillover index, by the method of column normalization. This method makes the sum of the variances in every column equal to unity. For more details, see Diebold and Yilmaz (2011b) and Zhou et al. (2012). [↑](#footnote-ref-3)
4. These figures are reported in Appendix A. [↑](#footnote-ref-4)
5. A common wavelet filter length of 8 is used in the MODWT transformation of indices' return series to study the ~~l~~inkages between financial time series. The maximum level of MODWT is 6 () to achieve an optima balance between sample size and the length of filter. For example, scale 1 or scale (as measures the dynamic of returns over 2 to 4 days. In other words, the MODWT coefficients are linked with oscillations in the period of . For more details, see Gençay et al. (2002, 2003) and Dajčman (2013). [↑](#footnote-ref-5)