An Analysis of Spillovers Between Islamic and Conventional Stock Bank Returns: Evidence from the GCC Countries

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This paper features an application of Diebold and Yilmaz's (2009) spillover index model to assess the impact of the global financial crisis on spillovers between the bank sectors in terms of both returns and volatility time series. The spillover investigation is performed on daily return data for Islamic and conventional banks in the Gulf Cooperation Council countries for the period 2005-2015. We use a dynamic conditional multivariate GARCH to directly model the time varying spillover effects among the studied time series. This study finds a strong bidirectional returns spillover between conventional banks and a very weak spillover from Islamic banks to conventional banks, so the transmission of shocks from Islamic banks to conventional banks is reduced. It also finds that the dependence between stock returns in an Islamic bank market structure is more strongly affected by the financial crisis than in a conventional bank market. Moreover, the volatility linkage is highly affected by the crisis in an Islamic context than that in a conventional bank system. Finally, using the DCC-GARCH model this study shows a high persistence in the time series of correlation among all GCC countries, except Bahrain, indicating that a long-run average of the correlation can be pushed away by shocks for a very long period. The empirical results are expected to have potentially important implications for improving the process of selection and allocation for domestic and international portfolios.

Keywords: financial crisis; islamic banks; spillover index; dependence; multivariate GARCH

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Acknowledgements: We greatly appreciate the financial support of the SABIC chair for Islamic Financial Market Studies at Al Imam Mohammad Ibn Saud Islamic University (IMSIU). We thank Professor Mohammad Al-Suhaibani for his consistent support during the course of this work.

(*Multinational Finance Journal*, 2017, vol. 21, no. 2, pp. 91–132)

Article history: Received: 1 August 2017, Received in final revised form: 3 November 2017, Accepted: 26 January 2018, Available online: 24 September 2018

I. Introduction

The recent global financial crisis has seriously affected the conventional banking system all over the world, inducing a series of bank failures and leading to increased interest in the Islamic banking system. This paper examines whether there is evidence of spillovers of return and volatility from one bank to another. The study focuses on three types of banks: conventional, Islamic and mixed banks. The paper features an application of Diebold and Yilmaz's (2009) spillover index model to assess the impact of the global financial crisis on spillovers to the Saudi bank sector in terms of both returns and volatility time series. The spillover investigation is performed on the overall time series, a subsample for the pre-crisis and a subsample for the post-crisis. This is followed by an application of a dynamic conditional multivariate GARCH to directly model the time varying spillover effects among the studied time series.

According to Hasan and Dridi (2010), Islamic banks fared better than conventional banks during 2008-2009. They find that on average, Islamic banks showed stronger resilience during the global financial crisis. This drew widespread attention to Islamic banking as the ideal banking model since it avoids both interest and interest-based assets. In addition, Islamic modes of financing are based on profit- and loss-sharing investments. Recently, Islamic banks have contributed to financial innovations since they actively contribute to the capital markets and securitization, thus restricting speculation (Hassan and Lewis, 2007). In contrast, Hasan and Dridi (2010) find that Islamic banks suffered larger losses than their conventional peers did when the crisis hit the real economy.

Using data on 22 countries from 1995-2009 that included 510 banks, 88 of which are Islamic banks, Beck, Demirg-Kunt and Merrouche (2013) show that Islamic banks are less cost-effective but have a higher intermediation ratio and higher asset quality, and they are both better capitalized and less likely to disintermediate during crisis periods. They also note the relatively better stock market performance of Islamic banks in 2008-2009. However, the performance of Islamic banks is not universally superior, as there is a significant size effect. Moazzam and

Sajjad (2015) use a dataset from Pakistan, where Islamic and conventional banks co-exist. They compare the behaviour of Islamic and conventional banks during a financial panic and show that Islamic bank branches (banks that have both Islamic and conventional operations) are less prone to withdrawals during financial panics. Islamic bank branches have a tendency to attract deposits during panics. They also find that Islamic bank branches allow more credit during financial crises and that their lending decisions are less sensitive to changes in deposits. Using data on 19 banking systems with a substantial presence of Islamic banking, Cihak and Hesse (2010) find that small Islamic banks tend to be financially stronger than both small commercial banks and large Islamic banks, which reflect the challenges of credit-risk management in large Islamic banks.

This can be shown by the substantial importance of banks' funding structure to their resilience to various types of shocks. Indeed, conventional banks that primarily depend on wholesale funding as money market funds, funding from other banks, and corporate treasuries have been seriously affected by the crisis. Conversely, banks that primarily depend on depository funding have been very resilient to the crisis. The resistance to the crisis is intimately related to liquidity risk. For this reason, banks relying on depository funding are more stable during the crisis since they are less exposed to liquidity risk. Furthermore, liquidity risk can be propagated in the financial sector through strong dependence between various financial institutions. Nevertheless, the liquidity risk creates market risk and provokes systemic risk, which may affect even sound banks.

Specifically, banks' resilience to crisis may be reflected by the behaviour of stock bank returns both during (short run) and after (long run) the crisis. Using marginal analysis, the resilience of banks has been extensively investigated in the theoretical and empirical literature.

Moreover, banks' exposure to liquidity shocks in the context of increasing dependence in the bank system has been discussed in financial market theory. Freixas et al. (2000) show that liquidity shock that affects a single bank may incite depositors to search for solvent banks because of the lack of liquidity in the banking system. Allen and Gale (2000) show that an unanticipated liquidity shock could bankrupt the entire banking system.

These theoretical models are verified for the conventional bank system; however, the coexistence of conventional and Islamic banks may lead to better resilience to shocks that affect the entire bank system. This new mixed bank market structure is well developed in the GCC countries (Saudi Arabia, the United Arab Emirates (UAE), Qatar, Kuwait, and Bahrain). In the GCC area, the coexistence of conventional and Islamic banks may lead to stability in the sector and better resilience to bad news and financial crisis. However, there has been relatively little empirical analysis of the role that the mixed bank market plays in financial stability. In this context, the central motivation of this empirical study is to fill the gap in the literature about bank sectors and financial stability. Moreover, the article will investigate the soundness of bank using dependence and spillover rather than a marginal study. More specifically, this study aims to investigate the impact of shocks or bad news on the dependence between banks by analysing the spillover between stock returns and volatilities both before and after a crisis.

This paper also attempts to supplement the empirical literature on Islamic banking. To our knowledge, it is the first paper to analyse the impact of crisis on the interdependence between various Islamic conventional and mixed bank market structures.

There are already numerous interesting papers investigating the transmission mechanism and spillovers among stock price innovation or mean spillovers through international stock markets (see, e.g., Eun and Shim, 1989; Koch and Koch, 1991, and Theodossiou et al., 1997). There are also motivating earlier studies on the volatility spillover across international stock markets (Schwert, 1989; Yasushi, Ronald, and Victor, 1990; Theodossiou, Panayiotis, and Unro Lee, 1993).

The empirical papers that focus on the dependence and spillover among financial markets or between assets are usually divided into two sets. To investigate the short-run interdependence between markets or assets, the more frequently used approach is the implementation of multivariate autoregressive conditional heteroscedasticity models (MGARCH), Longin and Solinik (1995), Bekiros (2014) and Chiang, Chen, and Lin (2013), Benlagha (2014). However, to explore the long-run interdependence between financial time series, the usual method is to employ cointegration tests. Onour (2010), Alagidede, Panagiotidis, and Zhang (2011) and Gil-Alana (2011).

The literature on interdependence shows that these two approaches, which are used to investigate the long- and the short-run interdependence between financial or economic time series, have some limits. The cointegration approach is suitable for exploring the long-run relationships and is inappropriate for describing the short-run relationship and the dynamic characteristics of possible dependence or spillover. In contrast, the multivariate GARCH approach can estimate the complicated dynamics of spillovers; however, a maximum of two or three time series can be employed with the MGARCH to accomplish a numerical conversion in the estimation.

Accordingly, this empirical paper focuses on the methodology proposed by Diebold and Yilmaz (2009), who first introduced the spillover measures that are founded on forecast error variance decompositions from the previously orthogonalized impulse response function. The approach can investigate a large number of time series simultaneously and enables the exploration of various dynamic features of spillovers.

We find that there is a strong bidirectional returns spillover between conventional banks and a very weak spillover from Islamic banks to conventional banks, so the transmission of shocks from Islamic banks to conventional banks is reduced.

We also find that the dependence between stock returns in an Islamic bank market structure is more strongly affected by the financial crisis than in a conventional bank market. Moreover, the volatility linkage is highly affected by the crisis in an Islamic context than that in a conventional bank system.

The outline of the remainder of this paper is as follows. Section II offers an extended presentation of the literature investigating the spillover effects. The subsequent section describes the methodology and tools used to investigate the spillover among bank sectors. Section III presents the data and some preliminary statistics. Section IV reports and discusses the main empirical findings. Section V concludes.

II. Literature Review

There are two motivations for this paper. The first motivation is empirical and has roots in the literature that has modelled and investigated spillover effects among markets and financial assets.

Many empirical works have analysed the spillover effect in a range of commodity, stock and international markets. Engle, Ito, and Lin (1990), Cheung and Ng (1996) and Hong (2001) use return-based volatility to develop tests for volatility spillover effects and apply those tests to various conventional stocks and exchange rates. More recently, Bekiros (2014) adopts vector autoregressions and various multivariate GARCH representations to examine dynamic linear and nonlinear causal linkages among the US, the EU and the BRIC markets using a sample that covers the after-Euro period and includes both the financial crisis and the Euro-zone debt crisis. The results show that the BRICs have become more internationally integrated after the US financial crisis, and contagion is further substantiated. Chiang, Chen, and Lin (2013) use an autoregressive conditional jump intensity model (ARJI) to investigate the spillover effects of returns and volatility in the US stock market on the stock markets of Brazil, Russia, India, China and Vietnam in a crisis context. Their results reveal that the greatest contagious effects of returns and volatility from the US market before the crisis were felt by Russia. Gilenko and Fedorova (2014) use daily data on developed stock markets and BRIC stock market indices to estimate a 4-dimensional BEKK-GARCH-in-mean model and investigate the external and internal spillovers of returns and volatilities. They found that the influence of the developed stock markets on the BRIC stock markets, though present, decays over time. All of these studies use multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to investigate the spillover effect. These empirical studies focused on return-based volatility.

The spillover index provides a measure of interdependence among variables with a higher index value, implying that a larger proportion of the shocks in all markets can be explained by cross-variable shocks rather than by own-variable shocks.

From a different viewpoint, Diebold and Yilmaz (2009, 2012) propose a new spillover index to analyse interdependence effects across major stock markets worldwide. A higher index value indicates that a larger proportion of the shocks in bank sectors (Islamic and conventional) can be observed by cross-variable shocks rather than by own-variable shocks. The proposed volatility spillover indices are based on the forecast-error variance decomposition framework of a VAR model. Numerous empirical studies have employed this new approach. Ehrmann, Fratzscher, and Rigobon (2011) examine the strength of the transmission mechanisms both among different asset markets within a country and across countries. Bubák, Kočenda, and Žikeš (2011) propose a dynamic adaptation of the Diebold-Yilmaz volatility spillover index and demonstrate that volatility spillovers tend to increase in periods characterized by market uncertainty. Diebold and Yilmaz (2012) investigate volatility spillovers among four key US asset classes: stocks, bonds, foreign exchange, and commodities. Awartani and Maghyereh (2013) examine the spillover effects of return and volatility among oil and equities in the Gulf Cooperation Council Countries. Results indicate that return and volatility transmissions are bi-directional, although asymmetric. In particular, the oil market gives other markets more than it receives in terms of both returns and volatilities. Zhou, Zhang, and

Zhang (2012) propose to study directional volatility spillovers between the Chinese and world equity markets. The results show that the US market had central volatility effects on other markets during the subprime mortgage crisis. The other studied markets were also very volatile and affected by bad news; their substantial volatilities were transmitted back to the US market. Antonakakis and Vergos (2013) analyse sovereign bond yield spread spillovers between Euro zone countries during a turbulent period encompassing both the global financial crisis and the Euro zone debt crisis. They mainly found that the between-effect of BYS spillovers suggests directional spillovers of greater magnitude from the periphery to the Euro zone core than vice versa. Duncan and Kabundi (2013) analyse various sources of volatility transmission for South African bonds, commodities, currencies, and equities. The results indicate that commodity and equity shocks are identified as the key sources of spillovers to other asset classes. Sugimoto, Matsuki, and Yoshida (2014) study the relative importance of the global and regional markets for financial markets in developing countries during the US financial crisis and the European sovereign debt crisis. They suggest that African markets are most severely affected by spillovers from global markets and only modestly affected by commodity and currency markets. Antonakakis, Chatziantoniou, and Filis (2014) examine the dynamic relationship between changes in oil prices and the economic policy uncertainty index. Their results in the studied sample show that economic policy uncertainty responds negatively to aggregate demand oil-price shocks. Moreover, total spillovers increase considerably, reaching record heights during the great recession. Zhang and Wang (2014) examine return and volatility spillovers between China and world oil markets. Results reveal that return and volatility spillovers between China and world oil markets are bi-directional and asymmetric.

Grobys (2015) studies volatility spillovers among the foreign exchange-rate markets related to three of the US's major trading partners and the US stock market. The results reveal that the level of total volatility spillover effects is high only when they pave the way to periods of economic instability. If the economy is quiet, volatility spillover effects are almost non-existent. Antonakakis and Kizys (2015) study the dynamic linkage among returns, the volatility of commodities and major currency markets. They mainly found that the information content of gold, silver, platinum, and the CHF/USD and GBP/USD exchange rates can help improve the forecast accuracy of returns and the volatilities of palladium, crude oil and the EUR/CHF and GBP/USD exchange rates.

Nevertheless, the studies employing the methodology suggested by Diebold and Yilmaz to investigate interdependence and spillover effects are mainly related to either commodities or financial asset markets. Numerous other financial or economic variables must be examined. From that perspective, this paper proposes to investigate the dynamic spillover among Islamic and conventional stock returns. This paper's motivation is to detect the behaviour of Islamic banks and conventional banks during liquidity crises and to determine how the coexistence of Islamic and conventional banking institutions in the same market can reduce risk through diversification. Empirical results are expected to have potentially important implications for improving the process of selection and allocation for domestic and international portfolios.

III. Methodology

In this study, we use two competing approaches to investigate the spillover effects between stock returns and stock volatilities related to Islamic and conventional banks in GCC. We first employ the method proposed by Diebold and Yilmaz (2009) to estimate and compare the spillover index among the considered banks. To analyse time varying conditional dependence, we estimate a multivariate DCC-GARCH model.

A. Spillover index

For the formal specification of the spillover, Diebold and Yilmaz (2009) considered the basic form of the *VAR* model of Engle, Ito, and Lin (1990), expressed as follows:

$$Y_t = \Pi + \Gamma_0 Y_t + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Γ_0 is a $(k \times k)$ matrix that assigns the coefficient to the contemporaneous variables with a diagonal of zeros. Γ_i are $(k \times k)$ matrices assigning coefficients to the i^{th} lag, y_{t-i}. ε_t is a $(k \times 1)$ vector of independent and Gaussian errors.

After removing the constant form in model (1), the standard model can be rewritten as follows

$$Y_t = \sum_{i=1}^{p} B_0 \Gamma_i Y_{t-i} + B_0 \varepsilon_t \tag{2}$$

where

$$B_0 = [I - \Gamma_0]^{-1} \tag{3}$$

With the contemporaneous variables subtracted from both sides of the equation, the remaining parameters in equation (2) can be identified and estimated using the Ordinary Least Square method.

To derive parameter estimates for the initial form in equation (1) from equation (2), we need to impose several restrictions on the values of the parameters, lest the initial form of the model be under-identified. The most common method of doing so is to impose Cholesky decomposition on the B_0 matrix, which allows us to derive unique estimates of the orthogonalised errors in equation (1).

Since we are mainly interested in forecast errors, we may rewrite equation (2) as an infinite order Moving Average process in which the lag operator, L_i, corresponds to the i^{th} lag of the respective variable:

$$\left(I - \sum_{i=1}^{p} B_0 \Gamma_i L^i \right) x_t = B_0 \varepsilon_t .$$

Then,

$$x_t = \left[I - \sum_{i=1}^{p} B_0 \Gamma_i L^i \right]^{-1} B_0 \varepsilon_t .$$

To simplify the expression, we define

$$A(L) = \left[I - \sum_{i=1}^{p} B_0 \Gamma_i L^i \right]^{-1} B_0 ,$$

such that $x_t = A(L)\varepsilon_t$ and the forecast error

$$e_{t+1,t} = x_{t+1} - E_t(x_{t+1}) = A(L)\varepsilon_{t+1} \tag{4}$$

where ε_t represents the orthogonalised errors with identity covariance matrix $E(\varepsilon\varepsilon') = I_k$. Hence, the error, $\varepsilon_{i,t}$, describes the shock that is purely attributable to variable i; and the degree to which this shock may spill over to variable j is described by the coefficients in the off-diagonal elements of the $A(L)$ matrix.

Consider a bivariate first-order model for two indices (Islamic and conventional), which has the vector of forecast errors ($e_{t+1};t$). After expanding equation (4), we could write

$$\begin{pmatrix} e_{1,t+1} \\ e_{2,t+1} \end{pmatrix} = \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{pmatrix} \tag{5}$$

Since $E(\varepsilon\varepsilon')=I_2$, this gives us the covariance matrix,

$$\begin{aligned} E\left(e_{t+1}e'_{t+1}\right) = A_0A'_0 &= \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix}' \\ &= \begin{pmatrix} a_{0,11}^2 + a_{0,12}^2 & a_{0,11}a_{0,21} + a_{0,12}a_{0,22} \\ a_{0,11}a_{0,21} + a_{0,12}a_{0,22} & a_{0,21}^2 + a_{0,22}^2 \end{pmatrix} \end{aligned} \tag{6}$$

Diebold and Yilmaz (2009) define "own variance" as the fraction of the forecast error variance from forecasting $x_{1,t}$ that is attributable to shocks relating to $x_{1,t}$ and the "cross variance" as the forecast error variance in $x_{1,t}$ that is attributed to shocks from the other variable, $x_{2,t}$. The cross variance is what is referred to as the spillover effect, where the total spillover is the sum of the spillover effects that relate to the two variables.

Hence,

$$\text{Total spillover} = a_{0,21}^2 + a_{0,12}^2 \tag{7}$$

One can then derive a spillover index, which reflects the proportion of the total forecast error variance (i.e., the sum of the forecast variance for all indices at all forecast horizons) that is explained by total spillovers (Diebold and Yilmaz, 2009),

$$\begin{aligned} S &= \frac{a_{0,21}^2 + a_{0,12}^2}{a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2} \times 100 \\ &= \frac{a_{0,21}^2 + a_{0,12}^2}{trace(A_0A'_0)} \times 100 \end{aligned} \tag{8}$$

For further details about the construction and statistical proprieties of this index spillover, see Kloessner and Wagner (2014).

B. Multivariate GARCH

The second approach used in this paper to investigate the degree of volatility dependence between stock returns is the parametric modelling of conditional variance. Engle, Ito, and Lin (1990), Hamao, Masulis, and Ng (1990) and Booth, Ainscow, and Dyson (1997) were among the first to investigate the volatility linkage between markets using univariate generalized autoregressive conditional heteroscedastic GARCH model in the tow stage. Subsequently, the multivariate GARCH model became the most commonly used parametric approach to investigate the volatility linkage. Various specifications are proposed; here, we present a DCC-GARCH construction that allows for the estimation of the dynamic conditional volatility linkage.

The Dynamic Conditional Correlation model was proposed by Engle and Sheppard (2001). The model was mainly employed to investigate the dynamic conditional correlation between financial assets, Nelson (1991), Hansson and Hordahl (1998) and more recently, Engle and Colacito (2006), Silvennoinen and Terasvirta (2008), Mills and Markellos (2008) and Benlagha (2014).

The DCC specification can be expressed as: $H_t \equiv D_t R_t D_t$ where H_t is the covariance matrix and R_t is an $n \times n$ matrix of conditional correlation of the asset returns. The diagonal matrix D_t of time-varying standard deviations from univariate GARCH is written as follows:

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \dots & 0 \\ 0 & \sqrt{h_{2t}} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ 0 & \dots & \dots & \sqrt{h_{nt}} \end{bmatrix} \tag{9}$$

Since H_t is a covariance matrix, it needs to be positive and definite. Moreover, R_t is symmetric by construction.

III. Data and summary statistics

To study volatility dependence and contagion between Islamic and

TABLE 1. Conventional banks' descriptive statistics

Bank Name	Mean	Min	Max	SD	Skewness	Kurtosis	JB	Q(10)	PP
ANB.SE	0.004	–11.12	9.44	2.05	–0.187	9.3	4589.21	138.9	–50.58***
RBS.SE	–0.004	–10.81	9.7	1.89	–0.228	11.28	7922.55	178.75	–50.58***
SFG.SE	–0.004	–10.54	9.51	1.93	0.13	8.95	4080.67	183.18	–50.56***
SBB.SE	0.011	–10.54	12.29	2.03	0.038	8.6	3606.6	194.74	–47.58***
ADCB.AD	0.026	–10.54	13.98	2.46	0.123	6.93	1785.83	136.58	–47.58***
ENBD.DU	–0.001	–27.76	20.95	2.52	–0.04	14.67	15695.39	159.39	–47.56***
FGB.AD	0.066	–10.39	10.61	2.38	–0.053	7.17	2007.39	169.48	–48.57***
NBAD.AD	0.036	–10.2	13.98	2.33	0.08	7.36	2193.99	178.38	–48.56***
COMB.QA	0.004	–11.67	9.75	2.2	–0.317	7.99	2908.36	120.25	–48.6***
DOBK.QA	0.001	–11.78	10.69	2.18	–0.238	8.03	2937.4	134.03	–49.05***
QNBK.QA	0.056	–12.3	12.94	1.95	0.129	8.83	3925.04	140.33	–49.05***
BURG.KW	0.025	–9.18	8.7	1.89	0.067	6.26	1228.05	148.88	–49.02***
CBKK.KW	0.004	–8.55	10.82	1.89	0.249	6.55	1483.25	143.87	–45.29***
NBKK.KW	0.019	–9.53	9.18	1.75	0.083	7.61	2447.27	166.51	–45.3***
BBKB.BH	–0.002	–14.76	15.42	2.02	0.007	14.93	16389.71	169.06	–45.29***
NATB.BH	0.008	–19.67	19.67	2.31	0.143	14.92	16373.87	177.69	–51.53***

Note: This table presents descriptive statistics for the daily return series of the 16 conventional bank stock prices series. Skewness and kurtosis refer to the series skewness and kurtosis coefficients. For the Jarque-Bera statistic test of normality of the series, we report the p-value of this statistic. For this statistic, the normality hypothesis is rejected if the p-value is lower than 5%. Q(10) is the Ljung-Box tests for 10th-order serial correlation in the returns. The PP refers to the Phillips and Perron (1988) unit root test after first difference of log prices.

TABLE 2. Islamic banks' descriptive statistics

Bank Name	Mean	Min	Max	SD	Skewness	Kurtosis	JB	Q_Stat	PP
Rajhi.SE	0.007	–10.54	9.84	2.1	–0.093	9.77	5283.27	201.16	–51.53***
ALJAZIRA.SE	0.027	–10.79	11.16	2.49	–0.027	7.28	2110.41	224.06	–51.54***
Albilad.SE	–0.031	–10.89	9.84	2.27	–0.049	9	4142.21	225.06	–45.2***
ADIB.AD	0.035	–10.54	13.73	2.33	0.047	8.14	3046.12	238.78	–45.21***
DISB.DU	0.022	–14.84	15.72	2.63	0.63	10.38	6458.95	77.59	–45.19***
SIB.AD	–0.019	–10.54	13.85	2.29	0.092	7.14	1978.34	90.2	–51.39***
QIIB.QA	0.034	–11.29	11.23	2.01	–0.102	10.02	5675.86	95.29	–51.39***
QISB.QA	0.028	–11.56	10.16	2.07	–0.113	7.91	2777.62	103.89	–51.4***
BKME.KW	0.03	–9.68	9.35	1.93	0.352	6.3	1312.99	218.46	–47.88***
KFIN.KW	0.02	–9.35	9.53	1.81	–0.02	6.94	1784.93	257.45	–47.88***
KIBK.KW	–0.013	–9.53	9.53	2.05	0.084	5.96	1013.52	266.76	–47.93***
BISB.BH	–0.029	–22.31	18.23	3.68	–0.229	8.33	3291.93	278.51	–49.13***
ITHMR.BH	–0.029	–17.19	17.19	3.25	0.095	7.65	2492.57	134.42	–49.13***

Note: This table presents descriptive statistics for the daily return series of the 16 conventional bank stock prices series. Skewness and kurtosis refer to the series skewness and kurtosis coefficients. For the Jarque-Bera statistic test of normality of the series, we report the p-value of this statistic. For this statistic, the normality hypothesis is rejected if the p-value is lower than 5%. Q(10) is the Ljung-Box tests for 10th-order serial correlation in the returns. The PP refers to the Phillips and Perron (1988) unit root test after the first difference of log prices.

conventional banks in GCC countries, we use daily return data for Islamic and conventional banks in those countries for the period covering 2005 and 2014. There are 24 Islamic banks and 20 conventional banks in the GCC financial markets, but only 29 banks (13 Islamic and 16 conventional) are considered in the sample because of the availability of 2005 data. The daily returns are calculated as: $y_{it} = \ln(p_{it}) - \ln(p_{it-1})$.

Tables 1 and 2 report basic properties of mean standard deviation and Jarque-Bera for conventional and Islamic banks, respectively. The daily mean returns for most of the banks were positive in the 2005-2014 periods. Over the available sample periods, we find that the Albilad Bank (listed in Saudi Arabia Stock Market) provides the lowest return, whereas Adib Bank (Listed in Abu Dhabi Stock market) provides the highest return. Both of these institutions are Islamic banks. The descriptive statistics indicate that the standard deviation of Islamic banks is relatively higher than that of conventional banks. The conventional National Bank of Kuwait (NBKK.KW) exhibits the lowest sample volatility, whereas the Bahrain Islamic Bank (BISB.BH) is the most volatile. The empirical distribution of the daily return diverges from the normal distribution. Banks show both a significant negative or positive skewness and a large kurtosis, signifying that the return distribution is a fat-tailed one. Skewness and kurtosis rates satisfy the Jarque-Bera test for normality, which is rejected. We use the Phillips-Perron (PP) test (Phillips and Perron, 1988) in a time series analysis to test the null hypothesis that a time series is integrated in order 1. This unit root test allows us to confirm that returns are stationary. The stationary of time series is very important since the Diebold-Yilmaz approach used in this study requires the stationary of all input variables.

IV. Empirical results

A. Full-sample analysis

We employ Diebold and Yilmaz (2009) to calculate the spillover index (SOI) on the returns and volatilities of various stocks in the GCC banking system. We consider a panel of Islamic and conventional banks to first measure the dependence between the returns of various types of banks. Next, we study the volatility spillover among the variances in bank stock returns.

Tables 3a to 3e correspond to spillover tables for the five GCC bank stock daily returns over the entire sample: January 2005 to December 2014. Each table presents the spillover index and the fraction of the forecast-error variance that one bank exports to all the other banks. Then, after determining the shift dates of the crisis relative to all GCC banks, as shown in table 4, in table 6, we report a summary of spillover effects for bank stock returns and volatility both before and after the crisis.

To analyse the dependence between stock returns and the volatility of conventional and Islamic banks, we investigate the decomposition of the spillover index called ij^{th} into all the forecast errors variance components for bank i coming from shocks to bank j, for all banks i and j.

The value of the total return spillover index in table 4a is 35.92%, signalling a great interdependence among banks in Saudi Arabia. The Arab National Bank (ANB) (conventional bank) reports the greatest spillover to (168.95%) and the lowest from (1.78%). The results in table 4a show that innovations of Islamic stock bank returns in Saudi Arabia market are responsible for 0.354 percent (0.11+0.058+0.186) of the error variance of the first conventional bank returns (ANB: Arab National Bank). The remaining error variance of this bank (1.423%) is attributable to the innovations of the other conventional banks. The innovations of the ANB's returns are responsible for 33.30% and 32.84% of the error of variance in forecasting the Riyadh Bank (RBS) and the Rajhi Bank (Rajhi), respectively, but only 19.86% of the error of variance in forecasting the Bank Albilad (Albilad) returns. The innovations of the Rajhi Bank returns (the greater market capitalization in Saudi bank sector) are responsible for 11.89% and 11.21% of the error of variance in forecasting Albilad and Aljazira, respectively, but conventional banks make no contribution to the error of variance in forecasting returns. Aljazira can be seen to impart great spillover from (44.7%) and very weak to (5.63%). Similar results are observed for Albilad, both to (0.81%) and from (46.31%). As shown in table a4 in the first column, the bank's market share plays an important role in the interaction between returns in the bank sector. There is a large bidirectional spillover between conventional banks and from conventional banks to Islamic banks, except for the Saudi British Bank SJSC (SBB). A spillover effect is observed from the Rajhi Bank to other Islamic banks, but a very weak spillover to conventional banks. These results show that the spillover index of the Saudi bank market is mainly

TABLE 3a. Spillover table for Saudi bank stock returns

	Conventional Banks				Islamic Banks			
	DANB. SE	DRBS. SE	DSFG. SE	DSBB. SE	DRajhi. SE	DALJAZIRA. SE	Dalbilad. SE	From Others
Conventional Banks								
DANB.SE (1.52%)	98.223	0.789	0.612	0.022	0.11	0.058	0.186	1.777
DRBS.SE (2.29%)	33.305	65.484	0.524	0.034	0.143	0.269	0.241	34.516
DSFG.SE (2.71%)	28.397	6.497	64.932	0.001	0.109	0.036	0.028	35.068
DSBB.SE (2.56%)	29.668	6.257	5.52	58.377	0.035	0.077	0.066	41.623
Islamic Banks								
Drajhi.SE (5.02%)	32.184	9.292	2.21	0.636	55.3	0.24	0.137	44.7
DALJAZIRA.SE (0.42%)	25.541	8.427	1.35	0.785	11.208	52.536	0.152	47.464
Dalbilad.SE (0.77%)	19.855	7.959	0.709	0.942	11.886	4.956	53.694	46.306
To others	168.95	39.222	10.926	2.42	23.49	5.636	0.811	251.454
Net (+: to; –: from)	167.17	4.706	–24.142	–39.203	–21.21	–41.828	–45.496	SOI= 35.922

(Continued)

TABLE 3a. (Continued)

Note: 1- This table shows robust spillover for the studied period. The columns show the fraction of forecast-error variance that the headline bank exports to all the remaining banks. The rows indicate the fraction of the forecast-error variance that the headline bank imports from all the remaining banks. The row Net displays the difference between To Others and From Others. The SOI corresponds to the average of all non-diagonal column sums (labelled contribution to others) or row sums (labelled contribution from others). 2- Values in parenthesis represent the size of the bank in the relative capital market.

TABLE 3b. Spillover table for UAE stock returns

	Conventional Banks				Islamic Banks			
	DADCB.AD	DENBD.DU	DFGB.AD	DNBAD.AD	DADIB.AD	DDISB.DU	DSIB.AD	From Others
Conventional Banks								
DADCB.AD (11.26%)	97.919	0.314	0.239	0.002	0.094	1.249	0.183	2.081
DENBD.DU (15.71%)	8.193	89.992	0.32	0.41	0.026	0.999	0.059	10.008
DFGB.AD (13.66%)	18.433	1.686	77.724	0.145	0.121	1.315	0.577	22.276
DNBAD.AD (9.91%)	19.21	1.476	6.148	72.314	0.047	0.647	0.158	27.686
Islamic Banks								
DADIB.AD (3.17%)	17.418	1.54	4.17	2.173	72.747	1.582	0.371	27.253
DDISB.DU (8.74%)	21.185	5.367	3.332	1.243	3.816	64.773	0.283	35.227
DSIB.AD (0.88%)	9.659	1.262	2.712	1.238	4.044	3.915	77.17	22.83
To others	94.099	11.646	16.921	5.211	8.149	9.706	1.63	147.362
Net (+: to; –: from)	92.018	1.638	–5.355	–22.475	–19.104	–25.521	–21.2	SOI=21.052

TABLE 3c. Spillover table for Qatar bank stock returns

	Conventional Banks			Islamic Banks		
	DCOMB. QA	DDOBK. QA	DQNBK. QA	DQIIB. QA	DQISB. QA	From Others
Conventional Banks						
DCOMB.QA (2.83%)	99.186	0.477	0.228	0.104	0.005	0.814
DDOBK.QA (2.12%)	41.507	58.231	0.149	0.052	0.061	41.769
DQNBK.QA (20.86%)	24.206	6.609	69.019	0.014	0.152	30.981
Islamic Banks						
DQIIB.QA (1.90%)	26.034	6.168	1.221	66.443	0.134	33.557
DQISB.QA (4.96%)	35.162	5.973	1.823	15.350	41.691	58.309
To others	126.909	19.227	3.420	15.521	0.353	165.43
Net (+: to; –: from)	126.095	–22.542	–27.560	–18.036	–57.956	SOI=33.086

TABLE 3d. Spillover table for Kuwait bank stock returns

	Conventional Banks			Islamic Banks			
	DBURG. KW	DCBKK. KW	DNBKK. KW	DBKME. KW	DKFIN. KW	DKIBK. KW	From Others
Conventional Banks							
DBURG.KW (3.74%)	97.778	0.284	0.436	0.333	0.739	0.43	2.222
DCBKK.KW (2.91%)	2.57	96.775	0.281	0.088	0.212	0.075	3.225
DNBKK.KW (17.22%)	11.906	1.578	85.068	0.14	1.000	0.309	14.932
Islamic Banks							
DBKME.KW (3.5%)	4.939	0.988	5.04	88.308	0.343	0.382	11.692
DKFIN.KW (11.38%)	12.053	2.219	15.155	1.256	68.786	0.531	31.214
DKIBK.KW (0.98%)	9.353	0.923	6.415	1.135	4.089	78.084	21.916
To others	40.821	5.991	27.327	2.953	6.383	1.726	85.201
Net (+: to; –: from)	38.600	2.766	12.395	–8.739	–24.831	–20.19	SOI=14.2

TABLE 3e. Spillover table for Bahrain bank stock returns

	Conventional Banks		Islamic Banks		
	DBBKB. BH	DNATB. BH	DBISB. BH	DITHMR. BH	From Others
Conventional Banks					
DBBKB.BH (2.26%)	99.56	0.028	0.144	0.269	0.44
DNATB.BH (3.81%)	0.112	99.819	0.060	0.009	0.181
Islamic Banks					
DBISB.BH (0.46%)	0.091	0.235	99.205	0.469	0.795
DITHMR.BH (0.83%)	0.184	0.063	0.483	99.27	0.73
To others	0.386	0.326	0.686	0.747	2.146
Net (+: to; -: from)	–0.054	0.145	–0.108	0.018	SOI=0.536

TABLE 4. Results of the Zivot and Andrews test on financial index series.

	TASI	QSI	ADI	KWSE	BAX.
Intercept	4.520e-01	2.595e-01	5.989e-02	1.547e-01	1.126e-02
	(8.518e-02) ***	(3.753e-02) ***	(2.573e-02) *	(3.009e-02) ***	1.249e-02
y.l1	9.577e-01	8.855e-01	9.712e-01	9.351e-01	9.907e-01 ***
	(7.280e-03) ***	(8.553e-03) ***	(4.547e-03) ***	(6.459e-03) ***	2.203e-03
trend	–3.124e-04	–4.148e-05	–3.911e-05	–1.691e-05	–1.049e-05
	(6.613e-05) ***	(3.531e-05) ***	(2.549e-05)	(2.418e-05)	1.403e-05
y.dl1	–9.495e-01	–4.133e-01	–4.406e-01	–3.824e-01	–2.874e-01
	(1.878e-02) ***	(1.431e-02) ***	(1.369e-02) ***	(1.403e-02) ***	1.398e-02***
y.dl2	1.441e-02	–1.967e-01	–2.007e-01	–2.205e-01	–4.281e-02**
	(1.807e-02) ***	(1.358e-02) ***	(1.374e-02) ***	(1.364e-02) ***	1.394e-02
Dt	4.696e-04	1.946e-04	9.012e-05	1.111e-04	2.802e-05*
	(9.510e-05) ***	(4.209e-05) ***	(3.182e-05) **	(3.083e-05) ***	1.682e-05
RSE	0.5466	0.6003	0.4622	0.5295	0.2258
F-statistic	1.821e+04	1.102e+04	3.702e+04	1.55e+04	1.516e+05
	(<2.2e-16) ***	(<2.2e-16) ***	(<2.2e-16) ***	(<2.2e-16) ***	(<2.2e-16) ***

Note: RSE: Residual standard error. Values between () correspond to the standard deviation for estimated parameters and the p-value for the F-statistic. Dt is a dummy variable in the model.

composed of the variance errors of conventional bank stock returns. This result is very important in the sense that it permits a possible successful diversification and reduced risk when we combine conventional and Islamic banks in a single portfolio.

A small part of the variance explained by the Islamic banks is also provided for all the conventional banks. However, the share of the error variance of the Islamic stock bank returns explained by the innovations to the conventional bank stock returns seems important. The analysis of the spillover table highlights a similar feature for the other GCC counties, principally for the (UAE), Qatar and Kuwait; moreover, there is no spillover in the Bahrain market, which has a spillover index of less than 1%. The values of the total return spillover index as indicated in tables 3b to 3d are very important and equal 21.05% for UAE, 33.09% for Qatar, and a less important spillover of 14.2% for Kuwait. For these markets, we note a strong bidirectional interaction between conventional banks and strong unidirectional effects from conventional to Islamic banks. The bidirectional spillovers between Islamic banks are less important than the bidirectional spillovers between conventional banks.

A similar analysis of the variance spillover table for the full sample indicates that the behaviour of the volatilities indexes follows the spillover for returns (see tables 8a to 8e). The total volatilities spillover indexes values are high for Saudi Arabia, the UAE and Qatar at 33.88%, 18.29% and 24.1%, respectively. However, the total volatility spillover index value is relatively small for Kuwait, at 16.11%. For Bahrain, the value of the volatility spillover index is less than 2%, indicating a very weak interdependence between banks. The directional "to" for conventional banks is higher than that for Islamic banks. The Arab National Bank (ANB) is very important in this Saudi stock market; the ANB's volatility imparts strong shocks estimated at 34.34% and 27.44% spillovers to the Riyadh Bank (RBS) and the Rajhi Bank, respectively, but it receives only a 4.2% spillover from the rest of the Saudi banks. The Rajhi Bank's volatility imparts shocks to other Islamic banks but has no impact on conventional banks.

For the UAE bank sector, the total volatility spillover is lower than in the Saudi bank sector. The Abu Dhabi Commercial Bank, which is conventional, seems to play the most important role in shock transmission: it imparts 73.61% to other banks but receives a very weak spillover from other banks. The Islamic banks impart less than a 1% volatility spillover to conventional banks, but there are some volatility spillovers between Islamic banks. Similar results are observed for the Qatar and Kuwait bank sectors. The spillover impact in Bahrain bank sectors is not significant.

This full-sample investigation provides interesting empirical and practical implications in terms of local and international diversification opportunities. First, since there are strong spillover effects among conventional stock bank returns, the inclusion of Islamic bank stocks in conventional portfolios may improve their opportunity set, thus encouraging conventional investors to consider Islamic bank stocks as a complement in their asset-allocation decisions. In addition, there is a residual local diversification opportunity that might be beneficial to both investors and risk managers. The second implication from our full-sample analysis is that there is also a presence of international diversification opportunities when bank stocks from different GCC countries are combined into a single portfolio.

In addition to this full-sample analysis, we investigate the soundness of various banks during the financial crisis. To do so, we first use Zivot and Andrews' (1992) test to detect the timing of the crisis in the studied bank markets. Next, we calculate the spillover indexes for returns and volatilities both before and after the crisis.

B. Timing of the crisis

Before estimating and analysing the soundness of conventional and Islamic banks, it is necessary to empirically detect the timing of the crisis in each studied GCC country. To achieve this goal, we perform a Zivot and Andrews (1992) test to endogenously search for a breakpoint and test for the presence of a unit root when the process has a broken constant or trend.

The results of the Zivot and Andrews (1992) test are detailed in table 4 and the timing of the breakpoint for each series is reported in table 5.

Our results show that the crisis does initially affect the Bahrain and UAE financial markets. This may reflect the fact that these financial markets are more strongly integrated into international markets than are the financial markets of Kuwait, the UAE or Saudi Arabia. We also can argue that ultimately, the Saudi and Qatari financial markets are more resilient than the other GCC markets. These shifting dates correlate precisely for the Saudi economy with those found by Benlagha and Mseddi (2016) when they investigated the macroeconomic and financial impacts of the European crisis on Saudi Arabia.

TABLE 5. Timing of the breakpoint for each series.

Series	Minimum *t*-stat	Shift dates
TASI (Saudi Arabia)	–5.8047***	08/12/2010
QSI (Qatar)	–13.385***	10/11/2010
ADI (UEA)	–6.3361***	09/8/2009
KWSE (Kuwait)	–10.0482***	23/03/2010
BAX (Bahrain)	–4.2326*	09/06/2009

Note: For each time series of the minimum t-statistics, three specifications are estimated (with constant, with trend and with both). The selected specification is based on the AIC and BIC information criteria. The minimum *t*-statistic reported is the minimum over all $T - 2$ regressions. The shift dates indicate the presence of a structural break in each studied series. The critical values for the *t*-statistic detecting a break are –4.93, –4.42, and –4.1 at the 0.01, 0.05 and 0.1 level, respectively.

C. Bank resilience

Because of the huge number of results, in table 5, we summarize the calculated spillover indexes applied to the returns and volatilities for different banks in the five GCC countries in different studied periods (before and after the crisis).

The results show that for most of the studied banks, the spillover index measures on returns and volatilities decrease after the financial crisis. The results also highlight that the variation of the index spillover is significantly higher in the Islamic bank sector than in a conventional bank system. However, when considering a mixed market composed of both conventional and Islamic banks, the variation of the spillover index is lower than the two previous structures. These results are highlighted for the five GCC countries.

In light of these results, we conclude that the dependence between stock returns in an Islamic bank market structure is more affected by the financial crisis than in a conventional bank market. Moreover, the volatility linkage is more strongly affected by the crisis in an Islamic context than in a conventional bank system. In other term, in an Islamic bank system, the volatility of one bank stock as the result of an exogenous event strongly affects the volatility of another bank stock return.

In a mixed system, the volatility linkage between bank stock returns is less affected by exogenous bad news than in a market composed only of Islamic or conventional banks.

These results reveal that the shock induced by the financial crisis rapidly impacts the relationship among Islamic banks.

TABLE 6. Returns and volatilities spillovers, before, after and all periods: full sample estimation.

	Returns			Volatilities		
	Islamic Banks	Conventional Banks	All Banks	Islamic Banks	Conventional Banks	All Banks
Saudi Arabia						
Before Crisis	31.564	32.674	34.036	26.560	25.734	34.425
After Crisis	22.451	25.913	32.417	19.458	25.807	32.468
All Period	28.963	27.897	35.922	25.885	27.109	33.881
Qatar						
Before Crisis	26.874	27.354	36.698	21.803	17.774	26.572
After Crisis	15.128	13.622	19.522	13.836	3.699	13.612
All Period	24.433	24.424	33.086	20.986	14.969	24.410
UAE						
Before Crisis	16.961	13.982	22.263	11.047	10.772	17.477
After Crisis	12.194	17.099	21.053	16.716	26.283	30.532
All Period	14.300	14.767	21.052	11.574	13.111	18.285
Kuwait						
Before Crisis	12.115	10.291	19.134	9.726	8.080	18.692
After Crisis	6.689	3.351	9.691	6.186	3.579	10.431
All Period	9.225	5.931	14.200	9.641	6.610	16.311
Bahrain						
Before Crisis	1.404	0.334	2.240	1.386	3.832	4.616
After Crisis	0.436	0.385	0.612	0.236	0.877	1.363
All Period	0.485	0.070	0.536	0.478	1.525	1.637

At this level of analysis, our results are somewhat different from those advocated by Hasan and Dridi (2010) in the IMF's report showing that Islamic banks fared better in all countries in the investigated sample, except for Bahrain, Qatar, and the UAE.

However, our results corroborate those obtained by Moazzam and Sajjad (2015) using data from Pakistan, where Islamic and conventional banks co-exist, suggesting that greater inclusion of faith-based groups may enhance the stability of the banking system.

The increase in spillover effects among Islamic banks in one region during the crisis also has important practical implications for investors. Hence, investors and risk managers must reallocate their portfolios by diversifying both locally (Islamic and conventional stocks) and internationally by investing in different GCC countries to reduce volatility spillover effects without affecting returns.

The spillover index measurement proposed by Diebold and Yilmaz (2009) is a useful method to investigate the static spillover effects between markets. However, it does not consider a dynamic spillover effect between markets. To test a possible dynamic spillover, we estimate a DCC-GARCH, which enables us to test the dynamic correlation between financial time series.

D. Dynamic correlation analysis

To test for possible dynamics in spillovers between stock bank returns, we employ a DCC-GARCH proposed by Engle and Sheppard (2001). Our methodology consists of a test for DCC-GARCH followed by an estimation of models for the studied GCC bank markets using a maximum likelihood method.

Nevertheless, the results for the DCC(1,1)-GARCH(1,1) model presented in table 7 show that for all cases, the χ^2 statistics are significant at the 0.05 level, confirming the presence of dynamic correlation among stock bank returns. The results also show that all estimated GARCH model parameters (ω_i, α_i, β_i) are highly significant. For example, we can deduce that the conditional variance of one Saudi stock bank return is influenced both by the past return innovations in another stock bank return in the pair (α_{12}, α_{21}) and by its lagged variances (β_{12}, β_{21}). Moreover, the significance of β_{12} and β_{21} reveals that volatility transmission is bi-directional between two stock bank returns.

The DCC parameters α and β are statistically significant, and we have $\beta > \alpha$ for all cases. This result is supported by the fact that the behaviour of current variances is more affected by the magnitude of past variances than by past return innovations.

TABLE 7. DCC-GARCH estimation results

	KSA	UEA	Qatar	Kuwait	Bahrain
ω_1	0.1252 (0.0019)	0.1359 (0.0095)	0.1927 (0.0006)	0.0786 (0.0009)	0.2088 (0.0104)
α_1	0.1191 (0.0006)	0.1278 (0.0021)	0.1621 (0.0097)	0.0889 (0.0003)	0.1142 (0.0012)
β_1	0.8506 (0.0010)	0.8531 (0.0036)	0.8048 (0.0139)	0.8884 (0.0006)	0.8251 (0.0033)
ω_2	0.0629 (0.0042)	0.5381 (0.0560)	0.0850 (0.0031)	0.1272 (0.0020)	0.1644 (0.0342)
α_2	0.1560 (0.0024)	0.1657 (0.0013)	0.0753 (0.0006)	0.1212 (0.0003)	0.2112 (0.0068)
β_2	0.8440 (0.0044)	0.7471 (0.0044)	0.9066 (0.0012)	0.8502 (0.0005)	0.7888 (0.0112)
ω_3	0.1165 (0.0056)	0.2617 (0.0061)	0.0000 ($1.08E^{-06}$)	0.0755 (0.0011)	0.1493 (0.0368)
α_3	0.1116 (0.0017)	0.2244 (0.0024)	0.0515 (0.0003)	0.1218 (0.0008)	0.0643 (0.0011)
β_3	0.8617 (0.0033)	0.7449 (0.0024)	0.9485 (0.0003)	0.8519 (0.0014)	0.9286 (0.0020)
ω_4	0.1563 (0.0026)	0.0827 (0.0031)	0.1614 (0.0073)	0.1793 (0.0140)	0.3300 (0.0342)
α_4	0.1417 (0.0009)	0.1077 (0.0013)	0.1715 (0.0022)	0.1122 (0.0021)	0.0903 (0.0007)
β_4	0.8231 (0.0013)	0.8829 (0.0017)	0.8030 (0.0033)	0.8377 (0.0058)	0.8803 (0.0014)
ω_5	0.0540 (0.0004)	0.1299 (0.0094)	0.0182 (0.0001)	0.0861 (0.0011)	-
α_5	0.1007 (0.0003)	0.1632 (0.0032)	0.0923 (0.0003)	0.1081 (0.0005)	-
β_5	0.8903 (0.0003)	0.8283 (0.0047)	0.9077 (0.0003)	0.8634 (0.0010)	-
ω_6	0.1528 (0.0027)	0.1663 (0.0339)	-	0.1785 (0.0037)	-
α_6	0.0996 (0.0004)	0.1211 (0.0043)	-	0.1087 (0.0004)	-
β_6	0.8769 (0.0005)	0.8603 (0.0080)	-	0.8472 (0.0011)	-
ω_7	0.1902 (0.0104)	0.6584 (0.0530)	-	-	-
α_7	0.1165 (0.0010)	0.2021 (0.0018)	-	-	-
β_7	0.8476 (0.0022)	0.6717 (0.0066)	-	-	-

(*Continued*)

TABLE 7. (Continued)

	KSA	UEA	Qatar	Kuwait	Bahrain
α	0.0157 (8.5E^{-06})	0.0158 (15E^{-06})	0.0297 (7.95E^{-06})	0.0135 (7.95E^{-06})	0.0392 (1.76 E^{-04})
β	0.9465 (0.0002)	0.9333 (0.0003)	0.9223 (0.0002)	0.9560 (0.0002)	0.2031 (0.0144)
Stat	29.6602	30.5944	40.5217	69.4348	39.0113
p-value	1.62E^{-06}	1.03E^{-06}	8.25E^{-09}	5.662E^{-15}	1.72E^{-08}
LL likelihood	–34560.4	–39660.5	–25146.9	–31095.2	–2484

Note: This table displays the estimated parameters of the DCC-GARCH for the studied bank stock prices series. Stat and p-value present the DCC-GARCH statistics and their corresponding p-values, respectively. For this statistic, the dynamic correlation is rejected if the p-value is greater than 5%. LL represents the values of the likelihood function. Rank reflects the ranking of each copula within the six estimated copulas in terms of LL.

TABLE 8a. Spillover table for Saudi bank stock volatilities

	Conventional Banks				Islamic Banks			
	DANB. SE	DRBS. SE	DSFG. SE	DSBB. SE	DRajhi. SE	DALJAZIRA. SE	Dalbilad SE	From Others
Conventional Banks								
DANB.SE (1.52%)	95.8006	0.8878	0.9836	1.5071	0.1196	0.5089	0.1928	4.1995
DRBS.SE (2.29%)	34.3362	61.1851	1.0339	1.025	0.8668	0.7419	0.8115	38.815
DSFG.SE (2.71%)	20.2277	4.1027	74.6178	0.6792	0.2346	0.0781	0.0602	25.3823
DSBB.SE (2.56%)	28.0185	8.7722	4.8008	56.8392	0.7918	0.397	0.3808	43.1609
Islamic Banks								
Drajhi.SE (5.02%)	27.4442	7.5142	1.9043	4.7892	56.6694	0.9847	0.6945	43.3307
DALJAZIRA.SE (0.42%)	21.3958	5.4787	1.6432	2.4012	11.2272	57.4816	0.3727	42.5185
DAlbilad .SE (0.77%)	17.1753	4.5851	0.4429	2.3679	9.1882	6.0024	60.2385	39.7616
To others	148.5974	31.3405	10.8084	12.7694	22.4279	8.7128	2.5121	237.1683
Net (+: to; –: from)	144.398	–7.4746	–14.574	–30.3916	–20.9028	–33.8058	–37.2496	SOI= 33.8812

TABLE 8b. Spillover table for UAE stock volatilities

	Conventional Banks				Islamic Banks			
	DADCB. AD	DENBD. DU	DFGB. AD	DNBAD. AD	DADIB. AD	DDISB. DU	DSIB. AD	From Others
Conventional Banks								
DADCB.AD (11.26%)	94.0573	0.48666	3.99686	0.40334	0.09417	0.7382	0.22348	5.94272
DENBD.DU (15.71%)	2.5496	96.4363	0.62935	0.02465	0.14553	0.15137	0.06319	3.56368
DFGB.AD (13.66%)	13.0824	1.25154	84.6432	0.02746	0.20116	0.36461	0.42956	15.3568
DNBAD.AD (9.91%)	21.3171	0.92232	7.24305	70.1774	0.07114	0.12469	0.14432	29.8226
Islamic Banks								
DADIB.AD (3.17%)	12.7995	0.51186	7.89442	2.46324	75.5831	0.21647	0.53142	24.4169
DDISB.DU (8.74%)	16.5228	2.27633	5.36488	1.4259	2.83019	70.7233	0.85655	29.2767
DSIB.AD (0.88%)	7.34295	0.4765	3.81202	1.11163	3.96435	2.91014	80.3824	19.6176
To others	73.6144	5.9252	28.9406	5.45622	7.30656	4.50548	2.24852	127.997
Net (+: to; –: from)	67.6717	2.36152	13.5838	–24.366	–17.11	–24.771	–17.369	SOI=18.285

TABLE 8c. Spillover table for Qatar bank stock volatilities

	Conventional Banks			Islamic Banks		
	DCOMB.QA	DDOBK.QA	DQNBK.QA	DQIIB.QA	DQISB.QA	From Others
Conventional Banks						
DCOMB.QA (2.83%)	95.3329	2.9297	0.3888	1.3042	0.0444	4.6671
DDOBK.QA (2.12%)	20.7142	77.116	0.7143	1.4201	0.0357	22.884
DQNBK.QA (20.86%)	11.5807	6.9942	80.813	0.5897	0.0223	19.187
Islamic Banks						
DQIIB.QA (1.90%)	16.0495	7.6213	1.8183	74.439	0.0719	25.561
DQISB.QA (4.96%)	21.5485	7.7077	2.8443	17.651	50.248	49.752
To others	69.8929	25.253	5.7658	20.965	0.1743	122.0508
Net (+: to; –: from)	65.2258	2.3684	–13.42	–4.5959	–49.577	SOI=24.410

TABLE 8d. Spillover table for Kuwait bank stock volatilities

	Conventional Banks				Islamic Banks		
	DBURG. KW	DCBKK. KW	DNBKK. KW	DBKME. KW	DKFIN. KW	DKIBK. KW	From Others
Conventional Banks							
DBURG.KW (3.74%)	92.0444	0.0617	4.8442	0.6219	1.8753	0.5525	7.95562
DCBKK.KW (2.91%)	0.81633	98.952	0.0157	0.1862	0.0204	0.0098	1.048445
DNBKK.KW (17.22%)	12.0301	0.1725	83.508	1.4971	2.3397	0.453	16.49236
Islamic Banks							
DBKME.KW (3.5%)	4.40591	0.5318	7.6401	86.051	0.5732	0.798	13.94895
DKFIN.KW (11.38%)	12.9947	0.1406	22.345	1.0316	63.24	0.2483	36.76008
DKIBK.KW (0.98%)	7.90425	0.1792	9.8695	1.9652	1.7441	78.338	21.6623
To others	38.1512	1.0857	44.714	5.302	6.5528	2.0616	97.8678
Net (+: to; –: from)	30.1956	0.0373	28.222	–8.6469	–30.207	–19.601	SOI= 16.311

TABLE 8e. Spillover table for Bahrain bank stock volatilities

	Conventional Banks		Islamic Banks		
	DBBKB. BH	DNATB. BH	DBISB. BH	DITHMR. BH	From Others
Conventional Banks					
DBBKB.BH (2.26%)	97.9103	1.3231	0.2076	0.5591	2.0897
DNATB.BH (3.81%)	1.72487	98.227	0.0074	0.0403	1.7726
Islamic Banks					
DBISB.BH (0.46%)	0.18593	0.5785	98.854	0.3813	1.1457
DITHMR.BH (0.83%)	0.67675	0.3411	0.524	98.458	1.5418
To others	2.58755	2.2426	0.7389	0.9807	6.5498
Net (+: to; –: from)	0.49782	0.47	–0.407	–0.5611	SOI=1.637

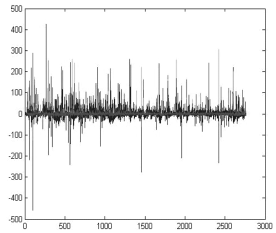
It is obvious that we cannot statistically compare multivariate GARCH results with those obtained in the spillover index approach proposed by Diebold and Yilmaz (2009). However, some differences must be mentioned.

The main advantage of a multivariate GARCH model compared to Diebold and Yilmaz's approach is that it informs us about the temporal persistence of correlations. For all GCC countries except Bahrain, our results show that β value is close to 1, revealing a high persistence in the time series of correlation. This high persistence indicates that a long-run average of the correlation can be pushed away by shocks for a very long period.

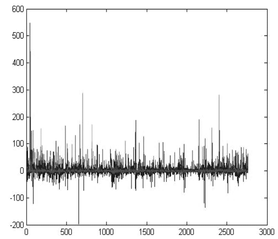
Moreover, the positive coefficients indicate that volatility was a double-sided phenomenon, produced mutually by idiosyncratic and systemic factors. From a financial viewpoint, the system is the aggregation of the individual components; volatility, as the result of individual and collective market participants, also captures the joint effects among individual entities, underpinning a potential transmission chain phenomenon. This important finding is in line with the concept of "shift-volatility" transmission in the East Asian equity markets proposed by Aloy et al. (2013), who explored volatility propagation from a low to a high level, and recently confirmed in the empirical study performed by Ben Amar, Ben Slimane and Bellalah (2017). The high persistence phenomenon is also highlighted in previous empirical studies.

That said, the results obtained using a DCC-GARCH model indicate that the dependence structure may vary with the sign and magnitude of returns. It becomes imperative to identify the best forecast method for the targeted part of the distribution. As indicated above, Diebold and Yilmaz's approach allows for a straightforward measure of the spillover index. Moreover, this enables a better understanding of the impact of one asset on another and a good measure of the fraction of the forecast-error variance that a headline asset (stock bank) exports to all the remaining studied assets.

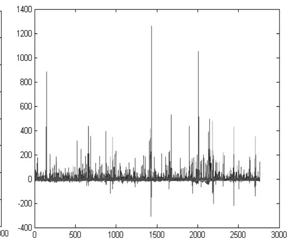
Figure 1 shows that the correlation between returns in one bank market is time varying. In particular, we observe the presence of a high correlation package for all the studied GCC countries just after the financial crisis. The graphic also indicates the presence of an extremal conditional correlation in bank markets. This extreme dependence could be related to financial and economic good or bad news. The number and the origins of these extremal events must be detected and analysed. Neither the Diebold and Yilmaz (2009) approach nor DCC-GARCH modelling provide useful information about this problem. From this perspective, we will discuss the presence of extremal co-movement or spillover in a future work.



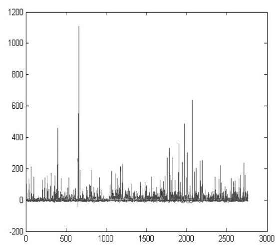
DCC conditional correlations for KSA



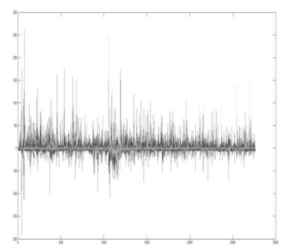
DCC conditional correlations for the UAE



DCC conditional correlations for Qatar



DCC conditional correlations for Bahrain



DCC conditional correlations for Kuwait

FIGURE 1.— DCC conditional correlations for the studied GCC bank markets

V. Conclusion

This paper investigated the spillover effects between the returns and volatilities of stocks related to Islamic and conventional banks in GCC countries using Diebold and Yilmaz's (2009) index measurement approach. We also employed DCC-GARCH, which provides useful information about the dynamic behaviour of correlation between such time series. The study sample contains 29 banks (13 Islamic and 16 conventional) listed in GCC financial markets during the period 2005-2014. The first part of the study attempts to measure and explain the returns and volatilities spillovers between conventional and Islamic banks for all the GCC countries except Oman because of a lack of available data since 2005. The main finding of our research is that there is a strong bidirectional returns spillover between conventional banks and a very weak spillover from Islamic banks to conventional banks. For that reason, the transmission of shocks from Islamic banks to conventional banks is reduced. This result has an important impact on portfolio diversification when combining conventional banks and Islamic banks in a single portfolio. The behaviour of the volatilities indexes follows spillover for returns. We find that the total volatilities spillover indexes values are lower than the return spillover indexes for Saudi Arabia, UAE and Qatar, but the results are reversed in Kuwait. The volatilities and returns spillovers are not interesting in Bahrain's bank sector. The second part of the study attempts to test bank resilience to shocks induced by the financial crisis. A Zivot and Andrews (1992) test is used to detect the timing of the crisis in each GCC studied country. We find that the dependence between stock returns in an Islamic bank market structure is more strongly affected by the financial crisis than in a conventional bank market. Moreover, the volatility linkage is more highly affected by the crisis in an Islamic context than that in a conventional bank system.

The third part of the study improves the results of Diebold and Yilmaz's (2009) approach by introducing dynamic spillover effects between markets using a DCC-GARCH model as proposed by Engle and Sheppard (2001). We find that the behaviour of current variances is more affected by the magnitude of past variances than during past return innovations. In addition, for all the GCC countries except Bahrain, a high persistence in the time series of correlation indicates that a long-run average of the correlation can be pushed away by shocks for a very long period.

Studying the relationship between stock returns and volatilities for Islamic and conventional banks using Diebold and Yilmaz (2009) is undoubtedly only one of several plausible spillover measurement alternatives. In particular, the method used is helpful for both investors and decision makers, since it provides a simple measure for the spillover between two time series. However, this approach does not allow for an examination of the structure of the correlation or relationship between financial or economic time series. A further extension of this work could investigate the dependence structure between stock returns and volatilities for Islamic and conventional banks using a copula approach, which has recently emerged as a useful tool to study both the tail and the entire structure of dependency among random variables.

Finally, a time varying extension for Diebold and Yilmaz's spillover index could be another important method enabling an investigation of the dynamic relationship between time series. From this perspective, we will apply a rolling-sample technique to estimate a time varying Diebold and Yilmaz spillover index.

Accepted by: *Prof. G. Koutmos*, *Guest Editor*, *January* 2018
Prof. P. Theodossiou, *Editor-in-Chief*, *January* 2018

Appendix A. Conventional and Islamic Banks in GCC Countries

Conventional Banks		Islamic Banks	
Saudi Arabia			
Arab National Bank	ANB.SE	Al Rajhi Banking and Investment Corp SJSC	Rajhi.SE
Riyad Bank SJSC	RBS.SE	Bank Aljazira JSC	ALJAZIRA.SE
Samba Financial Group SJSC	SFG.SE	Bank Albilad SJSC	Albilad.SE
Saudi British Bank SJSC	SBB.SE		
UAE			
Abu Dhabi Commercial Bank PJSC	ADCB.AD	Abu Dhabi Islamic Bank PJSC	ADIB.AD
Emirates NBD Bank PJSC	ENBD.DU	Dubai Islamic Bank PJSC	DISB.DU
First Gulf Bank PJSC	FGB.AD	Sharjah Islamic Bank PJSC	SIB.AD
National Bank of Abu Dhabi PJSC	NBAD.AD		
Qatar			
Commercial Bank of Qatar QSC	COMB.QA	Qatar International Islamic Bank QSC	QIIB.QA
Doha Bank QSC	DOBK.QA	Qatar Islamic Bank SAQ	QISB.QA
Qatar National Bank SAQ	QNBK.QA		
Kuwait			
Burgan Bank SAKP	BURG.KW	Ahli United Bank KSCP	BKME.KW
Commercial Bank of Kuwait KSC	CBKK.KW	Kuwait Finance House KSCP	KFIN.KW
National Bank of Kuwait SAK	NBKK.KW	Kuwait International Bank KSC	KIBK.KW
Bahrain			
BBK BSC	BBKB.BH	Bahrain Islamic Bank BSC	BISB.BH
National Bank of Bahrain BSC	NATB.BH	Ithmaar Bank BSC	ITHMR.BH

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