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Research Paper

NetMES: a network based marginal expected shortfall measure

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ABSTRACT

This paper aims to build novel measures of systemic risk that take the multivariate nature of the problem into account by means of network models. To account for model uncertainty, we also employ a Bayesian approach, which allows model averaging over different network classes. The resulting systemic risk measure, which we call NetMES, is applied to the evaluation of the financial stability of the banking system in the Gulf Cooperation Council countries. Banks are classified as fully-fledged Islamic banks, conventional banks or hybrids: conventional banks with an Islamic window. The empirical findings indicate the presence of a difference between the two banking systems in terms of systemic risk, which can be explained by different levels of capitalization and leverage.

Keywords: correlation networks; dynamic conditional covariances; graphical Gaussian models; partial correlations; systemic risk measures; Islamic banks.

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1 INTRODUCTION

The recent 2007–8 global financial crisis placed the financial system under distress, leading it to the edge of failure. The burden that this crisis placed on the financial system has emphasized the importance of systemic risk identification, measurement and management.

Systemic risk is typically measured in a financial system comprised of a network of connected institutions, with linkages that allow the transfer and magnification of financial distress during times of financial crisis (Billio *et al* 2012b). Some definitions of systemic risk point out the correlation and direct causation that endogenously exist within a network of financial institutions (see, for example, Bank for International Settlements 1994; Kaufman 1994; Crockett 1997; George 1998; Board of Governors of the Federal Reserve System 2001). Others point out an exogenous microeconomic event that diffuses with a spillover effect from specific business units to others (see, for example, Kaminsky and Schmukler 1999; Aharony and Swary 1996; Kaminsky and Reinhart 2000; Kaufman 1994), or a macroeconomic event that adversely affects market participants through causing simultaneous severe losses that diffuse through the system (Benoit *et al* 2015).

Our proposed methodology follows the approach of Billio *et al* (2012a), who introduces several econometric measures of connectedness based on principal component analysis and Granger causality networks. In a related paper, Diebold and Yılmaz (2014) propose vector autoregressive models; these are augmented with a least absolute shrinkage and selection operator (LASSO)-type estimation procedure, aimed at selecting the significant links in a network model. Similarly, Hautsch *et al* (2014) and Peltonen *et al* (2015) propose tail dependence network models aimed at overcoming the bivariate nature of the available systemic risk measures. The previous models are based on the assumption of full connectedness among all institutions, which makes their estimation and interpretation quite difficult, especially when a large number of them are being considered. To tackle this issue, Ahelegbey *et al* (2015) and Giudici and Spelta (2016) have recently introduced correlation network models, which can fully account for partial connectedness, expressed in terms of conditional independence constraints. A similar line of research has been followed by Barigozzi and Brownlees (2014), who have introduced multivariate Brownian processes with a correlation structure determined by a conditional independence graph. Our contribution follows this latter perspective.

The main aim of this work is to evaluate and compare different banking systems in terms of their systemic risk contribution. For this purpose, we use the stock market return data of financial institutions, aggregated by banking sector type, for each considered country. We then derive a correlation network between the different banking sectors to investigate how risks spread. The recently introduced correlation network models (Giudici and Spelta 2016) can account for partial connectedness, expressed in terms of conditional independence constraints. They are based on graphical Gaussian models, which gives them a stochastic background, as well as on Bayesian model averaging, which improves their robustness.

Once a network is estimated, a natural request is to summarize it as a systemic risk measure. This can be done, in financial network models, using network centrality measures. Below, we review the most important ones. In the next section, we propose an alternative measure of risk, which combines the well-known marginal expected shortfall (MES) with a correlation network approach. Note that, in this paper, nodes in a network represent banking sectors of a country, the main object of our analysis.

We start the network centrality measures' review with node degree centrality, as it is considered the simplest network summary. Node degree centrality measures the significant links that are present in the selected model, between a single node and all others. For a node i in a network model with nodes $j = 1, \dots, n$, let e_{ij} represent a binary variable that indicates whether a link between i and j is present (1) or not (0). The degree of a node i is then

$$D_i = \sum_{j=1}^{n} e_{ij}.$$

Another important measure is betweenness centrality, which measures the intermediation importance of a node based on the extent to which it lies on paths between other nodes. It is defined as

$$B_i = \sum_{j_t, j_k} \frac{n_{j_t, j_k}(i)}{m_{j_t, j_k}},$$

where $n_{j_t, j_k}(i)$ is the number of shortest geodesic paths between nodes j_t and j_k passing through node i, and m_{j_t, j_k} is the total number of shortest geodesic paths between j_t and j_k, given that $i \neq j_t \neq j_k$ for all nodes in the network.

A third measure is closeness centrality, which for each node measures the average geodesic distance to all other nodes. For a node i, it is defined as

$$C_i = \frac{1}{\sum_{j=1}^{n} d(i, j)},$$

in which $d(i, j)$ is the minimum geodesic path distance between nodes i and j.

A further measure that is considered pivotal in financial network models is the eigenvector centrality (see, for example, Furfine 2003; Billio *et al* 2012a). It measures the importance of a node in a network by assigning relative scores to all nodes in that network, based on the principle that connections to few high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes.

More formally, for the ith node, the eigenvector centrality is proportional to the sum of the scores of all nodes which are connected to it, as in the following equation:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} a_{i,j} x_j,$$

where x_j is the score of a node j, $a_{i,j}$ is the (i, j) element of the adjacency matrix of the network, λ is a constant and N is the number of nodes of the network. The previous equation can be rewritten for all nodes, more compactly, as

$$Ax = \lambda x,$$

where A is the adjacency matrix, λ is the eigenvalue of the matrix A and x is the associated eigenvector for an N-vector of scores (one for each node). Generally, there will be many different eigenvalues λ for which a solution to the previous equation exists. However, the additional requirement that all the elements of the eigenvectors be positive (a natural request in our context) implies (by the Perron–Frobenius theorem) that only the eigenvector corresponding to the largest eigenvalue provides the desired centrality measures. Therefore, once an estimate of A is provided, network centrality scores can be obtained from the previous equation as elements of the eigenvector associated with the largest eigenvalue.

All the previously introduced measures are based on the adjacency matrix of a correlation network and depend, therefore, only on the presence or absence of a link between two nodes, and not on the actual dependence between them. To introduce such dependence, we can extend the node degree into a partial correlation degree. This employs partial correlation between pairs of nodes as weights, as follows:

$$s_i = \sum_j e_{ij} \rho_{ijV}.$$

Once calculated, centrality measures must be interpreted. In general, for each centrality measure, the most important node will be the one with the highest score rank. As, in this paper, nodes are banking sectors of a country, the most systemic banking sector will be the one with the highest rank.

Note, however, that for policy purposes it may be important to compare banking systems across all countries, somewhat aggregating the corresponding ranks. To this end, we can calculate a ranking concentration (RC) ratio, as follows.

Consider a vector of ranks k_i, where $i = \{1, \dots, n\}$ is the rank number such that 1 is the highest and n is the lowest. Then, let w_i indicate the weight of each rank, defined by

$$w_i = n - (k_i) - 1.$$

Let $i_s = \{1, \dots, n_s\}$ indicate the set of all indexes that correspond to a specific banking sector s, such that $i_s \subset i$. The RC ratio of a banking sector s is the percentage of the aggregate weight, for each banking sector type $\sum_{i_s=1}^{n_s} w_{i_s}$, from the total weight of all ranks' numbers $\sum_{i=1}^{n} w_i$. Then, the RC ratio can be defined as

$$\mathrm{RC}_s = \frac{\sum_{i_s=1}^{n_s} w_{i_s}}{\sum_{i=1}^{n} w_i}.$$

The RC ratio RC_s describes the risk of a banking sector, based on the ranks it has, in the different countries that have that banking sector. A higher RC ratio indicates higher systemic risk for the specified banking sector type.

The introduction of the RC ratio will improve the achievement of the main applied aim of this paper: the comparison of the stability, in terms of systemic risk contribution, of different banking sectors.

In pursuing this aim, we will focus on a relatively homogeneous set of countries: those belonging to the Gulf Cooperation Council (GCC). Our data analysis will include publicly traded banks (deposit-taking institutions) within the GCC region for the period 2005–14. The banks will be classified as one of three types: the fully-fledged Islamic banks (IB), the conventional banks (CB) and the conventional banks with Islamic services window (CBwin).

Our application to the GCC countries contributes to the ongoing debate regarding the ability of the Islamic banking system to support the financial system stability of the country or region in which it is based. This debate gained momentum as Islamic Banks maintained stronger asset growth compared with conventional banks during the later stages of the 2007–8 financial crisis (Hasan and Dridi 2011). The attention of policy makers and researchers was thus directed toward them. According to our current knowledge, there is no direct research comparison between Islamic and conventional banks from a systemic risk point of view.

For completeness, we recall the main peculiarities of the Islamic banking business model. An Islamic bank is a financial institution that is engaged in all the banking activities of a conventional bank, but at a zero interest rate, in accordance with Islamic Shariah rules (see, for example, Shafique *et al* 2012). The Islamic bank accounts are based on profit and loss sharing (PLS) rather than on having an interest obligation, as is the case in a conventional bank. In addition, all its transactions are equity based or asset based; in other words, each transaction is backed by real assets or equity. Other rules that an Islamic bank must satisfy include not being allowed to take excessive uncertainty (called "gharar"), as in short-selling transactions, or excessive risk-taking (called "maysir"), as in gambling. Finally, Islamic banks are not allowed to finance any activity that is not halal, such as alcohol production or distribution (all ethically accepted actions under Islamic Shariah principles are referred to as halal).

This paper is organized into four main sections. Section 2 is the methodology that will introduce our proposal. Section 3 includes the description of the data and our results. Section 4 ends the paper with a summary conclusion from the obtained results.

2 METHODOLOGY

2.1 Correlation networks

Following Billio *et al* (2012a), we consider a cross-sectional perspective to understand systemic risk transmission mechanisms, fitting to the data a network structure that can describe the mutual relationships between the different economical agents involved.

Correlation network models, introduced in Giudici and Spelta (2016), are suitable to stochastically infer a network structure, employing pairwise correlations among a set of N observed, agent-specific time series.

If we associate different time series with different nodes of a network, each pair of nodes can be thought to be connected by an edge, with a weight that can be related to the correlation coefficient between the two corresponding time series. Thus, a network of N nodes can be described by its associated matrix of weights, named the adjacency matrix: this is an $N \times N$ matrix, say A, with elements $a_{i,j}$. Alternatively, if the aim of the research is to focus more on the structure of the interconnections, and less on their magnitude, the adjacency matrix can be made binary by setting $a_{i,j} = 1$ when two nodes are correlated, and $a_{i,j} = 0$ when they are not correlated.

It is well known that pairwise correlations measure both the direct and the indirect effects of one variable on another. If the aim is to measure only the direct effect between two variables, without the mediation of others, pairwise partial correlations, rather than marginal ones, should be calculated. From a statistical viewpoint, correlations can be estimated, on the basis of N observed time series of data, assuming that observations follow a multivariate Gaussian model, with an unknown variance–covariance matrix Σ; meanwhile, partial correlations can be estimated assuming that the same observations follow a graphical Gaussian model, in which the variance–covariance matrix Σ is constrained by the conditional independence described by a graph (see, for example, Whittaker (1990) and Lauritzen (1996), or, from an econometric viewpoint, Corander and Villani (2006) and Carvalho and West (2007)).

More formally, let $x = (x_1, \dots, x_N) \in R^N$ be an N-dimensional random vector distributed according to a multivariate normal distribution $\mathcal{N}_N(\mu, \Sigma)$. We will assume throughout that the covariance matrix Σ is not singular. For an undirected graph, let $G = (V, E)$, with vertex set $V = \{1, \dots, N\}$ and edge set $E = V \times V$; this is a binary matrix, with elements e_{ij} that describe whether pairs of vertexes are (symmetrically) linked to each other ($e_{ij} = 1$) or not ($e_{ij} = 0$). If the vertexes V of a graph are put in correspondence with the random variables $X_1, \dots, X_N$, the edge set E induces conditional independence on X via the so-called Markov properties (see, for example, Lauritzen 1996). More precisely, the pairwise Markov property determined by G states that, for all $1 \leqslant i < j \leqslant N$,

$$e_{ij} = 0 \iff X_i \perp X_j \mid X_{V \setminus \{i,j\}};$$

this indicates that the absence of an edge between vertexes i and j is equivalent to independence between the random variables X_i and X_j conditionally on all other variables $x_{V \setminus \{i,j\}}$.

In our context, all random variables are continuous and it is assumed that $X \sim \mathcal{N}_N(0, \Sigma)$. Let the elements of Σ^{-1}, the inverse of the variance–covariance matrix, be indicated as $\{\sigma^{ij}\}$. Whittaker (1990) proved that the following equivalence also holds:

$$X_i \perp X_j \mid X_{V \setminus \{i,j\}} \iff \rho_{ijV} = 0,$$

where

$$\rho_{ijV} = \frac{-\sigma^{ij}}{\sqrt{\sigma^{ii}\sigma^{jj}}}$$

denotes the ijth partial correlation, that is, the correlation between X_i and X_j conditionally on the remaining variables $X_{V \setminus \{i,j\}}$. It can also be shown that the partial correlation coefficient ρ_{ijV} is equal to the correlation of the residuals from the regression of X_i on all other variables (excluding X_j) with the residuals from the regression of X_j on all other variables (excluding X_i), as in the following:

$$\rho_{ijV} = (\varepsilon_{X_i \mid X_{V \setminus \{j\}}}, \varepsilon_{X_j \mid X_{V \setminus \{i\}}}).$$

In other words, the partial correlation coefficient measures the additional contribution of variable X_j to the variability of X_i not already explained by the others, and vice versa.

A graphical Gaussian model is a Gaussian distribution constrained by a set of partial correlations equal to zero, which corresponds to variables whose additional contribution is not statistically significant.

Mathematically, by means of the pairwise Markov property, and given an undirected graph $G = (V, E)$, a graphical Gaussian model can be defined as the family of all N-variate normal distributions $\mathcal{N}_N(0, \Sigma)$ that satisfy the constraints induced by the graph on the partial correlations for all $1 \leqslant i < j \leqslant N$, as follows:

$$e_{ij} = 0 \iff \rho_{ijV} = 0.$$

In practice, the available data will be used to test which partial correlations are different from zero at the chosen significance level threshold α. This leads to the selection of a graphical model on which all inferences are conditioned and, in particular, summary network measures, such as those seen in Section 1, are determined.

A drawback of all the previous measures is that they are conditional on a fixed graphical structure. To overcome this problem and robustify the results, we assume an open model perspective and employ a Bayesian model averaging approach, in which the measure estimates are the averages of those coming from different graphs, each with a weight that corresponds to the Bayesian posterior probability of the corresponding graph.

To achieve the above aim, the first task is to derive the likelihood of a graphical network and specify an appropriate probability distribution over all graphical networks, as follows.

For a given graph G, consider a sample X of size n from a Gaussian probability distribution $P = \mathcal{N}_N(0, \Sigma)$, and let S be the observed variance–covariance matrix that estimates Σ.

For a subset of vertexes $A \subset N$, let Σ_A denote the variance–covariance matrix of the variables in X_A, and denote by S_A the corresponding observed variance–covariance submatrix. When the graph G is decomposable, the likelihood of the data, under the graphical Gaussian model specified by P, nicely decomposes as follows (see, for example, Giudici and Spelta 2016):

$$p(x \mid \Sigma, G) = \frac{\prod_{c \in \mathcal{C}} p(x_C \mid \Sigma_C)}{\prod_{s \in \mathcal{S}} p(x_S \mid \Sigma_S)},$$

where C and S, respectively, denote the set of cliques and separators of the graph G, and

$$P(x_C \mid \Sigma_C) = (2\pi)^{-n*|C|/2} |\Sigma_C|^{-n/2} \exp[-1/2tr(S_C(\Sigma_C)^{-1})],$$

and similarly for $P(x_S \mid \Sigma_S)$. A convenient prior for the parameters of the above likelihood is the hyper-inverse Wishart distribution. This can be obtained from a collection of clique-specific marginal inverse Wisharts, as follows:

$$l(\Sigma) = \frac{\prod_{c \in \mathcal{C}} l(\Sigma_C)}{\prod_{s \in \mathcal{S}} l(\Sigma_S)},$$

where $l(\Sigma_C)$ is the density of an inverse Wishart distribution, with hyperparameters T_C and α, and similarly for $l(\Sigma_S)$. For the definition of the hyperparameters, we follow Giudici and Spelta (2016) and let T_C and T_S be the submatrixes of a larger matrix T_0 of dimension $N \times N$, obtained in correspondence of the two complete sets of vertexes C and S. Assume also that $\alpha > N$. To complete the prior specification, for $P(G)$, we assume a uniform prior over all possible graphical structures.

Dawid and Lauritzen (1993) show that, under the previous assumptions, the posterior distribution of the variance–covariance matrix Σ is a hyper Wishart distribution, with $\alpha + N$ degrees of freedom and a scale matrix given by

$$T_n = T_0 + S_n,$$

where S_n is the sample variance–covariance matrix. This result can be used for quantitative learning on the unknown parameters for a given graphical structure. In addition, Dawid and Lauritzen (1993) show that the proposed prior distribution can be used to integrate the likelihood with respect to the unknown random parameters, obtaining the so-called marginal likelihood of a graph, which will be the main metric for structural learning. Such marginal likelihood is equal to

$$P(x \mid G) = \frac{\prod_{c \in \mathcal{C}} p(x_C)}{\prod_{s \in \mathcal{S}} p(x_S)},$$

in which

$$p(x_C) = (2\pi)^{-n*|C|/2} \frac{k(|C|, \alpha + n)}{k(|C|, \alpha)} \frac{\det(T_0)^{\alpha/2}}{\det(T_n)^{(\alpha+n)/2}};$$

here, $k(\cdot)$ is the multivariate gamma function, given by

$$k_p(a) = \pi^{p(p-1)/4} \prod_{j=1}^{p} \Gamma\left(a + \frac{1-j}{2}\right).$$

Assume that we have several possible graphs, say $|G|$, and that they are equally likely a priori, so that the probability of $|G|$ is

$$P(G) = \frac{1}{|G|}.$$

By Bayes's rule, the posterior probability of a graph is given by

$$P(G \mid x) \propto P(x \mid G) P(G);$$

therefore, since we assume a uniform prior over the graph structures, maximizing the posterior probability is equivalent to maximizing the marginal likelihood. For graphical model selection purposes, we shall thus search in the space of all possible graphs for the structure, such that

$$G^* = \arg\max_G P(G \mid x) \propto \arg\max_G P(x \mid G).$$

A Bayesian model averaging approach does not force conditioning inferences on the (best) model chosen. If we assume that the network structure G is random and assign a prior distribution to it, we can derive any inference on unknown parameters as model averages with respect to all possible graphical structures, with weights that correspond to the posterior probabilities of each network. This derives from the application of Bayes's theorem, as follows:

$$P(\Sigma \mid X) = P(\Sigma \mid x, G) P(G \mid x).$$

Note that, in many real problems, the number of possible graphical structures could be very large, and we may need to restrict the number of models to be averaged. This can be done efficiently, for example, following a simulation-based procedure for model search, such as Markov chain Monte Carlo (MCMC) sampling. In our context, given an initial graph, the algorithm samples a new graph using a proposal distribution. To guarantee irreducibility of the Markov chain, we follow Giudici and Spelta (2016) to test whether the proposed graph is decomposable. The newly sampled graph is then compared with the old graph, calculating the ratio between the two marginal likelihoods: if the ratio is greater than a predetermined threshold (acceptance probability), the proposal is accepted; otherwise, it is rejected. The algorithm continues until practical convergence is reached.

2.2 A network-based marginal expected shortfall

The measures of systemic risk that are most employed in the academic and regulatory worlds include the MES, proposed by Acharya *et al* (2010); the systemically risk important financial institution measure (SRISK), proposed by Acharya *et al* (2012) and Brownlees and Engle (2012); and the Delta conditional value-at-risk (ΔCoVaR), introduced by Adrian and Brunnermeier (2011).

It is known that the MES is in favor of a too-interconnected-to-fail (TIF) logic rather than of a too-big-to-fail (TBTF) one. This makes it appropriate as a systemic risk measure based on network models.

In our implementation of MES, we will use a dynamic conditional correlation approach to take into account the increase in volatility during crisis times. To this end, we will follow Brownlees and Engle (2012) and Engle (2012), who employ a bivariate GARCH model for the demeaned returns process, which is based on a capital asset pricing model (CAPM). We now briefly review their assumptions.

Consider a bivariate vector $r_t = (r_{it}, r_{mt})'$ that contains, at each time point, the returns of a sector and those of its reference market. Let H be its variance–covariance matrix; Brownlees and Engle (2012) and Engle (2012) propose that

$$r_t = H_t^{1/2} \epsilon_t,$$

where $\epsilon_t = (\epsilon_{mt}, \eta_{it})$ represents a vector of independent and identically distributed (iid) zero mean innovations, and

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\,\sigma_{it}\,\rho_{it} \\ \sigma_{mt}\,\sigma_{it}\,\rho_{it} & \sigma_{it}^2 \end{pmatrix}, \tag{2.1}$$

where σ_{mt} is the standard deviation of the reference market returns, σ_{it} is the standard deviation of the sector returns, and ρ_{it} is the correlation between the sector and the reference market returns.

To estimate H_t, we use the dynamic conditional correlation model of Engle (2002) and Engle and Sheppard (2001). Once H_t is estimated, we can proceed with the estimation of the MES measure, which is a function of H_t.

The MES measures the vulnerability of a banking sector i to the systemic risk originating from a financial market m. MES provides the one-day loss expected if market returns are less than a given threshold C (in practice, it is assumed that $C = -2\%$). More precisely, MES is defined as a weighted function of tail expectations for the market residual, and tail expectations for the banking sector residual, both calculated at time $t-1$, as follows:

$$\begin{aligned} \mathrm{MES}_{it}(C) = {} & \sigma_{mt}\rho_{it}\mathbb{E}_{t-1}\left(\varepsilon_{mt} \,\middle|\, \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\ & + \sigma_{it}\sqrt{1-\rho_{it}^2}\,\mathbb{E}_{t-1}\left(\eta_{it} \,\middle|\, \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right). \end{aligned}$$

From an interpretational viewpoint, the higher a banking sector MES, the higher its contribution to the risk of the financial system.

We propose to modify the MES measure by building the bivariate GARCH model on an extension of the CAPM model that takes correlations into account with more precision.

As previously described, the Engle (2012) model expresses returns as a function of the correlation between the market and the sector under consideration. In highly correlated markets, such as financial ones, it could very well be the case that the correlation between the market and one sector's returns contains other effects, for example, the correlation of the considered sector with another sector, or the correlation of the market with another sector's returns.

To remove "spurious" effects, which may bias the correlation between the sector and the market returns, we replace correlations with partial correlations: the correlations between the residuals from the regression of the sector returns on all other sectors, and the residuals from the regression of the market returns on all other sectors. In this way, we obtain a "netted" estimate of H, which is not biased by spurious effects, and, consequently, a "netted" estimate of the MES.

Partial correlations can be easily calculated, conditionally on a graphical structure, within the quantitative learning framework of graphical Gaussian models described in Section 2.1.

They can then be inserted in the H_t formula (2.1) in place of the corresponding correlations, giving rise to a different estimate of H and, consequently, MES. We will call the latter NetMES, emphasizing both the fact that the new measure is "netted" from spurious correlations and also that it is conditional on a graphical network model.

To improve the stability and the robustness of the results, we can average the NetMES result from the different graphical networks, in a Bayesian model averaging perspective, according to the paradigm introduced in Section 2.1, as follows:

$$E(\text{MES} \mid x) = \sum_{g} E(\text{MES} \mid x, g) P(g \mid x),$$

where x represents the observed data evidence and g is a specific network model. We refer to $E(\text{MES} \mid X)$ as a Bayesian network-based MES measure (Bayesian NetMES).

3 APPLICATION

3.1 Data description

In this subsection, we focus on data extraction. We work with the GCC countries, as they hold 38.19% of the total global Islamic banking assets (Islamic Financial Services Board 2014). To construct our sample, we extract the GCC deposit-taking institutions present in Bureau Van Djik's Bankscope, and we gather quarterly data on liabilities, equity and total assets from the beginning of 2005: this provides us with 130 institutions. We exclude those that are not publicly traded, as our network models and systemic risk measure are based on equity returns: this reduces the number of institutions to eighty-three. We also exclude those that disappeared before the end of our sample period in December 2014, leading to seventy-nine publicly traded, deposit-taking institutions, from six GCC countries. These are Bahrain (BH), with thirteen institutions; Kuwait (KW), with fifteen; Qatar (QA), with nine; United Arab Emirates (AE), with twenty-three; Saudi Arabia (SA), with twelve; and, finally, Oman (OM), with eleven.

For the seventy-nine chosen institutions, we extract daily stock market closing prices and corresponding market capitalization from Thomson Reuters Datastream, for a total of 2608 observations, over a study period from January 2005 to December 2014.

We construct stock market return time series under the stationary assumption that the mean $\mu = 0$. To achieve stationarity, we transform the daily stock market closing price into returns that are expressed, as usual, in time variation. Formally, if V_{it} and V_{it-1} are the closing stock prices of bank i at times t and $t-1$, the return is the variation represented by $r_{it} = (V_{it} - V_{it-1})/V_{it-1}$, where $V_{it-1} \neq 0$ and is prepared using log returns.

Then, for each country, we classify institutions into sectors, according to their bank type, and construct aggregate sectorial returns. We define the aggregate sectorial return r_{st} as the value-weighted average of the returns of all banks that belong to a country specific sector s: $i = 1, \dots, n_s$, as in the following:

$$r_{st} = \sum_{i=1}^{n_s} w_{it} r_{it},$$

in which $w_{it} = \text{mv}_{it}/\sum_{i=1}^{n_s}\text{mv}_{it,s}$ represents the weight of the ith bank in the specified banking sector s at time t, given by its market capitalization mv_{it} relative to the sector aggregate capitalization $\sum_{i=1}^{n_s}\text{mv}_{it,s}$.

The list of countries, along with the corresponding percentage of banking sector assets, is described in Table 1.

From Table 1, we note that the country with the largest banking assets is AE, followed by SA, QA, KW, BH and OM, in descending order. Note also that the CBwin sector is usually the largest one for all GCC countries. Further, the CB sector is larger than the IB sector in both OM and AE, but IB is larger than CB in SA, QA, KW and BH.

We also report the banking sectors, ranked in terms of their leverage (defined as the ratio between the book value of equity and the book value of assets) in Table 2, market value (defined as the number of shares outstanding multiplied by share price) in Table 3, and quasi-leverage (defined as the ratio between the market value of assets and the market capitalization) in Table 4. In Table 5, we report the RC ratio, RC%, which summarizes the importance of each banking sector type (CBwin, IB and CB). The first part of Table 5 shows the RC% for leverage, the second part shows the RC% for market capitalization and the third part shows the RC% for quasi-leverage.

Table 2 lists the CBwin sector in the highest leverage ranks for all periods. However, the RC% for leverage shows that the CBwin sector has its highest leverage level in the crisis period but decreased after, while the IB sector increased its leverage in the post-crisis period; the CB sector seems to have a stable low leverage ranking level across the three periods.

Table 3 also lists the CBwin sector in the highest market capitalization ranks for all periods. The RC% for market capitalization shows that the CBwin sector increased its capitalization in the crisis period, while the IB sector has the opposite behavior. As for the CB sector, it shows a stable low market capitalization level in all periods.

Table 4 shows results that are consistent with those in Table 2, with the addition of aspects related to Table 3. This is expected, as quasi-leverage takes both leverage and capitalization into account.

3.2 Correlation network models

In this subsection, we address the issue of how different banking sectors are interconnected with each other. For this purpose, we build a graphical Gaussian model, on the basis of partial correlations between the aggregate returns of the banking sectors, for the pre-crisis (2005–6), during crisis (2007–8) and post-crisis (2009–14) periods. The best model is selected using a backward selection procedure that starts from a fully connected model and subsequently tests for edge removal at the selected significance

TABLE 1 Asset distribution of the GCC banking sectors. [Table continues on next three pages.]

Country	Type	Ownership	Count	2014	2013	2012	2011	2010
OM	CB	Public	5	0.1218	0.1298	0.1382	0.1468	0.0986
		Private	2	0.0137	0.0146	0.0141	0.0139	0.0139
	CB.win	Public	5	0.6285	0.6063	0.5927	0.5833	0.6106
		Private	2	0.2261	0.2403	0.2465	0.2561	0.277
	IB	Public	1	0.0068	0.0061	0.0051	0	0
		Private	1	0.0032	0.0031	0.0035	0	0
	Banking sector	Total public	11	0.757	0.7421	0.736	0.7301	0.7092
		Total private	5	0.243	0.2579	0.264	0.2699	0.2908
		Total assets	16	97 271 221	84 158 952	75 535 737	69 027 144	58 695 117
BH	CB	Public	2	0.0069	0.0065	0.0064	0.0085	0.0074
		Private	6	0.1521	0.1592	0.1551	0.1621	0.1623
	CB.win	Public	4	0.4448	0.444	0.4613	0.5296	0.4972
		Private	2	0.0641	0.0752	0.0492	0.0069	0.0285
	IB	Public	7	0.2468	0.229	0.2308	0.1918	0.1895
		Private	18	0.0852	0.0861	0.0972	0.1011	0.1151
	Banking sector	Total public	13	0.6985	0.6795	0.6984	0.7299	0.6941
		Total private	26	0.3015	0.3205	0.3016	0.2701	0.3059
		Total assets	39	178 491 905	169 144 233	151 157 555	126 739 419	134 850 310
KW	CB	Public	1	0.0496	0.0506	0.052	0.064	0.062
		Private	0	0	0	0	0	0
	CB.win	Public	5	0.6044	0.6005	0.5881	0.6012	0.59
		Private	0	0	0	0	0	0
	IB	Public	10	0.3451	0.3477	0.3588	0.3341	0.3473
		Private	2	0.001	0.0012	0.0011	0.0008	0.0007
	Banking sector	Total public	16	0.999	0.9988	0.9989	0.9992	0.9993
		Total private	2	0.001	0.0012	0.0011	0.0008	0.0007
		Total assets	18	241 159 890	223 893 976	203 261 985	164 345 351	178 280 457

TABLE 1 Continued.

Country	Type	Ownership	Count	2009	2008	2007	2006	2005
OM	CB	Public	5	0.117	0.1167	0.1127	0.1486	0.1689
		Private	2	0.0143	0.0132	0.0137	0.0162	0.0219
	CB.win	Public	5	0.5722	0.5797	0.6146	0.6131	0.5551
		Private	2	0.2965	0.2903	0.2591	0.2221	0.2541
	IB	Public	1	0	0	0	0	0
		Private	1	0	0	0	0	0
	Banking sector	Total public	11	0.6892	0.6965	0.7272	0.7617	0.724
		Total private	5	0.3108	0.3035	0.2728	0.2383	0.276
		Total assets	16	51 749 367	48 445 794	45 005 903	31 288 219	22 990 976
BH	CB	Public	2	0.0084	0.0077	0.0065	0.0035	0.007
		Private	6	0.1803	0.2397	0.2722	0.2882	0.3178
	CB.win	Public	4	0.5202	0.5034	0.5402	0.5484	0.5206
		Private	2	0.0025	0	0	0	0
	IB	Public	7	0.1886	0.1642	0.129	0.1239	0.1264
		Private	18	0.1001	0.085	0.052	0.0359	0.0282
	Banking sector	Total public	13	0.7172	0.6754	0.6758	0.6759	0.6541
		Total private	26	0.2828	0.3246	0.3242	0.3241	0.3459
		Total assets	39	117 718 680	125 617 066	122 948 061	95 114 734	75 734 958
KW	CB	Public	1	0.0678	0.0709	0.0752	0.0907	0
		Private	0	0	0	0	0	0
	CB.win	Public	5	0.6315	0.6402	0.6603	0.6286	0.6977
		Private	0	0	0	0	0	0
	IB	Public	10	0.2997	0.2876	0.2637	0.2807	0.3023
		Private	2	0.001	0.0013	0.0008	0	0
	Banking sector	Total public	16	0.999	0.9987	0.9992	1	1
		Total private	2	0.001	0.0013	0.0008	0	0
		Total assets	18	152 446 532	155 141 579	144 222 669	92 453 820	62 648 797

TABLE 1 Continued.

Country	Type	Ownership	Count	2014	2013	2012	2011	2010
QA	CB	Public	0	0	0	0	0 0	
		Private	2	0.0658	0.0667	0.0737	0.0629	0.0707
	CB.win	Public	5	0.7239	0.7396	0.7139	0.7269	0.7172
		Private	0	0	0	0	0	0
	IB	Public	4	0.2314	0.1905	0.1749	0.1121	0.1465
		Private	1	0.0044	0.0033	0.0028	0.0044	0.0037
	Banking sector	Total public	9	0.9553	1.93	2.8887	3.839	4.8638
		Total private	3	0.0702	1.07	2.0765	3.0672	4.0744
		Total assets	12	288 484 210	256 675 999	214 122 728	139 776 935	180 516 442
SA	CB	Public	0	0	0	0	0	0
		Private	2	0.0196	0.0227	0.0165	0.0162	0.0165
	CB.win	Public	8	0.7186	0.7183	0.7252	0.7656	0.7422
		Private	0	0	0	0	0	0
IB		Public	4	0.225	0.22	0.2219	0.1827	0.2038
		Private	1	0.0369	0.0389	0.0364	0.0356	0.0375
	Banking sector	Total public	12	0.9435	0.9383	0.9471	0.9482	0.946
		Total private	3	0.0565	0.0617	0.0529	0.0518	0.054
		Total assets	15	593 099 888	532 298 841	482 946 123	387 811 914	424 198 169
AE	CB	Public	4	0.1455	0.1383	0.1106	0.0741	0.0898
		Private	6	0.0204	0.0207	0.0163	0.0091	0.0099
CB.win		Public	12	0.672	0.6614	0.6947	0.7308	0.7296
		Private	0	0	0	0	0	0
IB		Public	7	0.1492	0.1497	0.1506	0.1563	0.1422
		Private	2	0.0128	0.0299	0.0278	0.0297	0.0285
	Banking sector	Total public	23	0.9667	0.9495	0.9559	0.9612	0.9616
		Total private	8	0.0333	0.0505	0.0441	0.0388	0.0384
		Total assets	31	615 693 005	564 234 726	491 067 182	402 841 683	431 002 091

TABLE 1 Continued.

Country	Type	Ownership	Count	2014	2013	2012	2011	2010
QA	CB	Public	0	0	0	0	0	0
		Private	2	0.0589	0.0631	0.0435	0.0433	0.0432
	CB.win	Public	5	0.7483	0.7951	0.8292	0.8606	0.8682
		Private	0	0	0	0	0	0
	IB	Public	4	0.0856	0.0539	0.0337	0.0159	0.0102
		Private	1	0.005	0	0	0	0
	Banking sector	Total public	9	5.8339	6.8489	7.863	8.8765	9.8785
		Total private	3	5.064	6.0631	7.0435	8.0433	9.0432
		Total assets	12	116 976 862	97 501 681	68 046 844	42 543 931	29 633 161
SA	CB	Public	0	0	0	0	0	0
		Private	2	0.0161	0.0153	0.0166	0.0158	0.0161
	CB.win	Public	8	0.7788	0.7863	0.7979	0.794	0.7929
		Private	0	0	0	0	0	0
IB		Public	4	0.1688	0.1659	0.1489	0.1508	0.1499
		Private	1	0.0363	0.0325	0.0366	0.0395	0.041
	Banking sector	Total public	12	0.9476	0.9522	0.9468	0.9448	0.9428
		Total private	3	0.0524	0.0478	0.0532	0.0552	0.0572
		Total assets	15	371 958 084	357 547 286	292 467 531	234 117 698	206 981 802
AE	CB	Public	4	0.0682	0.0677	0.0714	0.0908	0.1311
		Private	6	0.0085	0.011	0.0102	0.0115	0.015
CB.win		Public	12	0.7479	0.7487	0.7621	0.7125	0.6718
		Private	0	0	0	0	0	0
IB		Public	7	0.1503	0.1507	0.1562	0.1852	0.1821
		Private	2	0.025	0.0219	0	0	0
	Banking sector	Total public	23	0.9664	0.9671	0.9898	0.9885	0.985
		Total private	8	0.0336	0.0329	0.0102	0.0115	0.015
		Total assets	31	373 209 553	340 012 385	277 965 633	177 095 192	113 200 679

Based on authors' calculations.

TABLE 2 Leverage.

Pre-crisis	Crisis	Post-crisis
SA.CBwin	SA.CBwin	AE.CBwin
AE.CBwin	AE.CBwin	SA.CBwin
BH.CBwin	BH.CBwin	QA.CBwin
KW.CBwin	QA.CBwin	SA.IB
SA.IB	KW.CBwin	KW.IB
QA.CBwin	AE.IB	AE.IB
AE.IB	KW.IB	BH.CBwin
KW.IB	SA.IB	KW.CBwin
BH.IB	BH.IB	QA.IB
OM.CBwin	OM.CBwin	OM.CBwin
KW.CB	QA.IB	BH.IB
QA.IB	KW.CB	KW.CB
OM.CB	OM.CB	OM.CB
AE.CB	AE.CB	AE.CB
BH.CB	BH.CB	BH.CB
OM.IB	OM.IB	OM.IB

TABLE 3 Market capitalization.

Pre-crisis	Crisis	Post-crisis
SA.CBwin	SA.CBwin	SA.CBwin
SA.IB	AE.CBwin	AE.CBwin
AE.CBwin	SA.IB	QA.CBwin
QA.CBwin	KW.IB	SA.IB
KW.IB	QA.CBwin	KW.IB
AE.IB	KW.CBwin	QA.IB
QA.IB	AE.IB	KW.CBwin
KW.CBwin	QA.IB	AE.IB
BH.CBwin	BH.CBwin	BH.CBwin
BH.IB	OM.CBwin	OM.CBwin
OM.CBwin	BH.IB	KW.CB
KW.CB	KW.CB	BH.IB
AE.CB	AE.CB	AE.CB
OM.CB	OM.CB	OM.CB
OM.IB	OM.IB	OM.IB
BH.CB	BH.CB	BH.CB

TABLE 4 Quasi-leverage.

Pre-crisis	Crisis	Post-crisis
BH.CBwin	BH.CBwin	BH.IB
KW.CB	AE.IB	BH.CBwin
OM.CB	AE.CBwin	AE.IB
KW.CBwin	BH.IB	AE.CBwin
BH.IB	SA.CBwin	SA.CBwin
OM.CBwin	OM.CBwin	KW.CBwin
AE.CBwin	KW.CBwin	OM.CBwin
AE.IB	OM.CB	AE.CB
SA.CBwin	KW.CB	OM.CB
BH.CB	QA.CBwin	KW.IB
AE.CB	AE.CB	KW.CB
QA.CBwin	KW.IB	QA.CBwin
KW.IB	BH.CB	QA.IB
QA.IB	QA.IB	SA.IB
SA.IB	SA.IB	BH.CB
OM.IB	OM.IB	OM.IB

level of $\alpha = 0.05$. The selected graphical model for the pre-crisis period is described in Figure 1; the crisis period model is described in Figure 2; and the post-crisis period model is described in Figure 3.

In Figures 1–3, we can read the capacity of the corresponding banking sectors as agents of systematic risk through the indication of their contagion channels. The graphs that correspond to the above figures can be employed to derive the centrality measures introduced in Section 1, in order to rank sectors from the most to the least contagious.

Table 6 for the pre-crisis period, Table 7 for the crisis period and Table 8 for the post-crisis period show the centrality measure rankings that are calculated on the basis of the graphical models in Figures 1, 2 and 3, respectively. In addition, Table 9 shows the RC ratio, RC%, for each of the centrality measure tables.

Tables 6–8 display the change in network centrality ranks before, during and after the crisis. If we focus on the sector that appears in the top rank within the different centrality measures, we find that both the CB and CBwin sectors have higher risks in the pre-crisis period. The CBwin sector dominates the crisis period except when the node partial correlation measure is considered, which selects the IB sector instead. As for the post-crisis period, we note that all three banking sectors appear in the top ranks: both of the CBwin and IB sectors have two top ranks, while the CB sector has one top rank, in terms of closeness centrality.

TABLE 5 RC% for leverage, market capitalization and quasi-leverage.

(a) RC% for leverage

	Pre-crisis	Crisis	Post-crisis
CBwin	0.56	0.57	0.52
IB	0.33	0.33	0.38
CB	0.11	0.10	0.10

(b) RC% for market capitalization

	Pre-crisis	Crisis	Post-crisis
CBwin	0.49	0.51	0.51
IB	0.42	0.40	0.38
CB	0.10	0.10	0.10

(c) RC% for quasi-leverage

	Pre-crisis	Crisis	Post-crisis
CBwin	0.46	0.51	0.49
IB	0.23	0.29	0.33
CB	0.31	0.20	0.18

In summary, the RC% table shows that the CBwin sector almost always has the highest systemic risk concentration in the pre-crisis period, and that it fully dominates the crisis period. The IB sector increases its systemic importance in the post-crisis period, in which its systemic importance becomes equivalent to that of the CBwin sector.

To improve the robustness of our conclusions with respect to model selection, we have repeated the analysis with different significance thresholds (in particular, at $\alpha = 0.01$). The results described above did not substantially change.

To further check our conclusions' robustness, we have considered model averaging for all the results, using a Bayesian approach, and have thus provided inferences that fully take model uncertainty into account. In order to match the time periods with those of the correlation network models, all centrality measures have been calculated on a two-year time window. Tables 10–14 provide the resulting Bayesian model centrality measure rankings. In addition, Table 15 shows the RC% for the centrality measures of the Bayesian averaging model in the subsequent time periods.

From the previous tables, note that the rankings of the centrality measures obtained via Bayesian model averaging are mostly consistent with those conditional on the

FIGURE 1 Pre-crisis network.

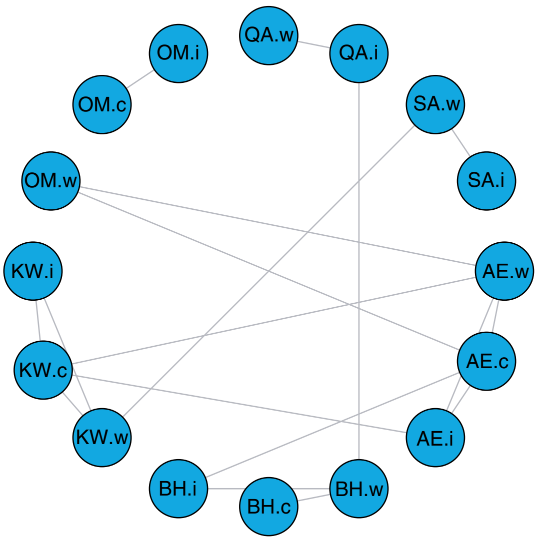


FIGURE 2 During-crisis network.

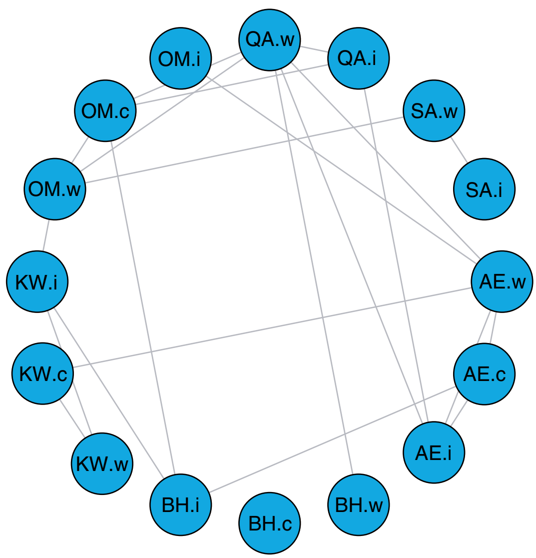


FIGURE 3 Post-crisis network.

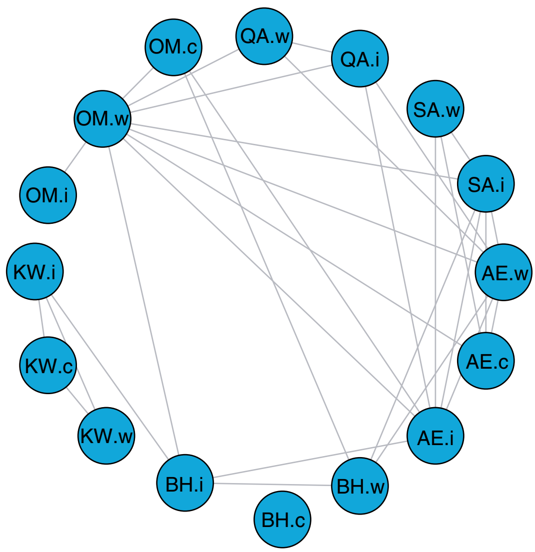


TABLE 6 Correlation model centrality rankings: pre-crisis (2005–6).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
AE.CB	AE.CB	AE.CBwin	AE.CBwin	AE.CBwin
AE.CBwin	KW.CB	AE.CB	KW.IB	AE.CB
KW.CB	BH.IB	AE.IB	QA.IB	AE.IB
AE.IB	BH.CBwin	KW.CB	KW.CBwin	KW.CB
BH.CBwin	KW.CBwin	BH.IB	QA.CBwin	OM.CBwin
KW.CBwin	AE.CBwin	OM.CBwin	AE.IB	KW.CBwin
BH.IB	AE.IB	BH.CBwin	BH.IB	KW.IB
KW.IB	SA.CBwin	KW.CBwin	OM.CB	BH.IB
OM.CBwin	QA.IB	KW.IB	SA.IB	SA.CBwin
QA.IB	OM.CB	QA.IB	SA.CBwin	BH.CBwin
SA.CBwin	OM.IB	SA.CBwin	BH.CBwin	SA.IB
BH.CB	KW.IB	BH.CB	OM.IB	QA.IB
OM.CB	SA.IB	QA.CBwin	AE.CB	BH.CB
OM.IB	BH.CB	SA.IB	KW.CB	QA.CBwin
QA.CBwin	QA.CBwin	OM.CB	BH.CB	OM.CB
SA.IB	OM.CBwin	OM.IB	OM.CBwin	OM.IB

TABLE 7 Correlation model centrality rankings: crisis (2007–8).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
QA.CBwin	QA.CBwin	QA.CBwin	KW.IB	QA.CBwin
AE.CBwin	OM.CBwin	AE.CBwin	AE.IB	AE.IB
AE.IB	AE.CBwin	OM.CBwin	AE.CBwin	AE.CBwin
OM.CBwin	SA.CBwin	OM.CB	QA.CBwin	OM.CB
OM.CB	KW.IB	AE.IB	OM.CB	QA.IB
AE.CB	OM.CB	BH.IB	OM.CBwin	OM.CBwin
BH.IB	BH.IB	KW.IB	SA.CBwin	AE.CB
KW.IB	KW.CB	AE.CB	SA.IB	BH.IB
QA.IB	AE.CB	QA.IB	KW.CBwin	KW.IB
KW.CBwin	AE.IB	KW.CB	QA.IB	BH.CBwin
KW.CB	KW.CBwin	BH.CBwin	BH.IB	KW.CB
SA.CBwin	QA.IB	KW.CBwin	KW.CB	OM.IB
BH.CBwin	SA.IB	SA.CBwin	BH.CBwin	SA.CBwin
OM.IB	OM.IB	OM.IB	AE.CB	KW.CBwin
SA.IB	BH.CBwin	SA.IB	BH.CB	SA.IB
BH.CB	BH.CB	BH.CB	OM.IB	BH.CB

TABLE 8 Correlation model centrality rankings: post-crisis (2009–14).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
OM.CBwin	BH.IB	BH.CB	AE.IB	OM.CBwin
AE.CBwin	OM.CBwin	OM.CBwin	OM.CBwin	AE.CBwin
AE.IB	KW.IB	AE.IB	AE.CBwin	AE.IB
SA.IB	AE.IB	BH.IB	KW.IB	SA.IB
AE.CB	AE.CBwin	AE.CBwin	QA.IB	QA.IB
BH.CBwin	BH.CBwin	BH.CBwin	SA.IB	AE.CB
BH.IB	SA.IB	SA.IB	QA.CBwin	BH.CBwin
QA.IB	AE.CB	AE.CB	SA.CBwin	QA.CBwin
KW.IB	OM.CB	QA.IB	KW.CBwin	BH.IB
OM.CB	QA.IB	OM.CB	OM.CB	OM.CB
QA.CBwin	SA.CBwin	QA.CBwin	OM.IB	SA.CBwin
SA.CBwin	QA.CBwin	SA.CBwin	AE.CB	OM.IB
KW.CBwin	KW.CBwin	KW.IB	BH.IB	KW.IB
KW.CB	KW.CB	OM.IB	BH.CBwin	KW.CBwin
OM.IB	OM.IB	KW.CBwin	KW.CB	KW.CB
BH.CB	BH.CB	KW.CB	BH.CB	BH.CB

TABLE 9 RC% for correlation network model.

(a) Pre-crisis (2005–6)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.40	0.35	0.41	0.40	0.42
IB	0.32	0.35	0.33	0.46	0.33
CB	0.29	0.30	0.26	0.13	0.25

(b) During crisis (2007–8)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.44	0.49	0.44	0.44	0.40
IB	0.34	0.30	0.34	0.40	0.38
CB	0.22	0.21	0.22	0.16	0.22

(c) Post-crisis (2009–14)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.42	0.39	0.38	0.43	0.43
IB	0.41	0.46	0.38	0.46	0.41
CB	0.17	0.15	0.24	0.11	0.15

selected models, commented on beforehand, thus emphasizing the robustness of the results.

In more detail, the pre-crisis and crisis periods list the CBwin banking sector in the top rank across all centrality measures. For interpretational purposes, the post-crisis period of this model does not extend over the whole 2009–14 period; instead, it is split into three parts. The first post-crisis period of 2009–10 lists the CB sector in the top rank, except for node partial correlation, in which the IB sector has higher risk. The second post-crisis period of 2011–12 lists only the CBwin banking sector in the top rank, while the third post-crisis period is also in favor of the CBwin sector, except for node partial correlation, which is repeatedly in favor of the IB sector.

The RC% table gives a summary perspective for the higher systemic risk sectors. The pre-crisis period indicates that the CBwin sector has the highest systemic risk. The crisis period shows that the systemic risk of the IB sector increases at the expense of the CBwin sector, and this increase continues in the first post-crisis period, with

TABLE 10 Bayesian model centrality rankings: pre-crisis (2005–6).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
OM.CBwin	OM.CBwin	OM.CBwin	AE.CBwin	OM.CBwin
AE.CBwin	AE.CBwin	AE.CBwin	QA.IB	SA.CBwin
AE.CB	AE.CB	AE.CB	AE.IB	AE.CBwin
AE.IB	AE.IB	AE.IB	QA.CBwin	BH.CBwin
BH.CBwin	BH.CBwin	BH.CBwin	BH.IB	BH.CB
BH.CB	BH.CB	BH.CB	SA.CBwin	BH.IB
BH.IB	BH.IB	BH.IB	SA.IB	KW.CBwin
KW.CBwin	KW.CBwin	KW.CBwin	OM.CB	KW.CB
KW.CB	KW.CB	KW.CB	OM.IB	OM.CB
OM.CB	KW.IB	OM.CB	BH.CBwin	OM.IB
OM.IB	OM.CB	OM.IB	KW.CBwin	QA.CBwin
QA.CBwin	OM.IB	QA.CBwin	AE.CB	QA.IB
QA.IB	QA.CBwin	QA.IB	BH.CB	SA.IB
SA.CBwin	QA.IB	SA.CBwin	KW.IB	AE.CB
SA.IB	SA.CBwin	SA.IB	OM.CBwin	AE.IB
KW.IB	SA.IB	KW.IB	KW.CB	KW.IB

TABLE 11 Bayesian model centrality rankings: crisis (2007–8).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
OM.CBwin	OM.CBwin	OM.CBwin	OM.CBwin	OM.CBwin
QA.IB	QA.IB	QA.IB	SA.CBwin	BH.CBwin
SA.IB	SA.CBwin	SA.IB	SA.IB	BH.CB
BH.CBwin	OM.IB	OM.IB	QA.CBwin	BH.IB
BH.CB	SA.IB	SA.CBwin	OM.CB	KW.CBwin
BH.IB	KW.IB	BH.CBwin	QA.IB	OM.CB
KW.CBwin	QA.CBwin	BH.CB	KW.IB	SA.IB
OM.CB	OM.CB	BH.IB	BH.IB	QA.IB
OM.IB	BH.CBwin	KW.CBwin	AE.CBwin	OM.IB
SA.CBwin	BH.CB	KW.IB	AE.IB	SA.CBwin
KW.IB	BH.IB	QA.CBwin	AE.CB	KW.IB
QA.CBwin	KW.CBwin	OM.CB	BH.CBwin	QA.CBwin
AE.CBwin	AE.CBwin	AE.CBwin	KW.CB	AE.CBwin
AE.CB	AE.CB	AE.CB	KW.CBwin	AE.CB
AE.IB	AE.IB	AE.IB	BH.CB	AE.IB
KW.CB	KW.CB	KW.CB	OM.IB	KW.CB

TABLE 12 Bayesian model centrality rankings: post-crisis, part 1 (2009–10).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
KW.CB	KW.CB	KW.CB	KW.IB	OM.CB
OM.CB	OM.CB	OM.CB	QA.IB	SA.CBwin
KW.IB	QA.IB	KW.IB	AE.IB	KW.IB
QA.IB	KW.IB	QA.IB	OM.CBwin	KW.CB
SA.CBwin	SA.CBwin	SA.CBwin	QA.CBwin	SA.IB
OM.CBwin	OM.CBwin	OM.CBwin	SA.IB	OM.CBwin
OM.IB	OM.IB	OM.IB	KW.CBwin	OM.IB
SA.IB	SA.IB	SA.IB	AE.CBwin	QA.IB
AE.CB	KW.CBwin	AE.CB	SA.CBwin	AE.CB
BH.CBwin	AE.CB	BH.CBwin	OM.CB	BH.CBwin
QA.CBwin	BH.CBwin	QA.CBwin	KW.CB	QA.CBwin
KW.CBwin	QA.CBwin	KW.CBwin	BH.IB	KW.CBwin
AE.CBwin	BH.CB	AE.CBwin	AE.CB	AE.CBwin
AE.IB	AE.CBwin	AE.IB	BH.CB	AE.IB
BH.CB	AE.IB	BH.CB	BH.CBwin	BH.IB
BH.IB	BH.IB	BH.IB	OM.IB	BH.CB

TABLE 13 Bayesian model centrality rankings: post-crisis, part 2 (2011–12).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
SA.CBwin	SA.CBwin	SA.CBwin	SA.CBwin	SA.CBwin
KW.CBwin	KW.CBwin	KW.CBwin	KW.IB	KW.CB
KW.CB	KW.CB	KW.CB	KW.CBwin	QA.CBwin
QA.CBwin	KW.IB	QA.CBwin	QA.CBwin	KW.CBwin
BH.IB	OM.CB	BH.IB	SA.IB	OM.IB
KW.IB	QA.CBwin	KW.IB	OM.CBwin	BH.IB
OM.CB	SA.IB	OM.CB	AE.CBwin	SA.IB
OM.IB	BH.IB	OM.IB	QA.IB	OM.CB
SA.IB	QA.IB	SA.IB	AE.IB	AE.IB
AE.IB	OM.IB	AE.IB	OM.CB	OM.CBwin
BH.CBwin	BH.CBwin	BH.CBwin	AE.CB	BH.CB
BH.CB	BH.CB	BH.CB	BH.IB	BH.CBwin
OM.CBwin	AE.IB	OM.CBwin	BH.CBwin	KW.IB
QA.IB	OM.CBwin	QA.IB	OM.IB	QA.IB
AE.CBwin	AE.CBwin	AE.CBwin	BH.CB	AE.CB
AE.CB	AE.CB	AE.CB	KW.CB	AE.CBwin

TABLE 14 Bayesian model centrality rankings: post-crisis, part 3 (2013–14).

Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
OM.CBwin	OM.CBwin	OM.CBwin	AE.IB	OM.CBwin
SA.CBwin	SA.CBwin	SA.CBwin	OM.CBwin	SA.IB
SA.IB	SA.IB	SA.IB	SA.IB	BH.IB
BH.IB	BH.IB	BH.IB	AE.CBwin	KW.CBwin
KW.CBwin	KW.CBwin	KW.CBwin	SA.CBwin	AE.CBwin
AE.CBwin	OM.IB	AE.CBwin	KW.IB	AE.IB
AE.IB	AE.CBwin	AE.IB	QA.IB	BH.CBwin
BH.CBwin	AE.CB	BH.CBwin	QA.CBwin	BH.CB
BH.CB	AE.IB	BH.CB	OM.CB	KW.CB
KW.CB	BH.CBwin	KW.CB	KW.CBwin	KW.IB
KW.IB	BH.CB	KW.IB	OM.IB	QA.CBwin
OM.CB	KW.CB	OM.CB	BH.IB	QA.IB
QA.CBwin	KW.IB	QA.CBwin	BH.CBwin	SA.CBwin
QA.IB	OM.CB	QA.IB	KW.CB	OM.CB
OM.IB	QA.CBwin	OM.IB	AE.CB	OM.IB
AE.CB	QA.IB	AE.CB	BH.CB	AE.CB

the IB sector becoming the highest systemic risk sector. More specifically, the first post-crisis period shows that the differences between the three sectors' RC% become very small. In the second post-crisis period, the CBwin sector retrieves its highest systemic risk level. Finally, in the third post-crisis period, the IB sector again starts to increase its risk level, but to a lesser magnitude.

Overall, Bayesian model averaging confirms the presence of a difference in the systemic risk level of the three banking sectors. The CBwin sector has the highest rank and highest RC% in most time periods and is indeed the main driver of contagion in GCC countries. However, the systemic risk originating in the IB sector gains importance in the crisis period, and in the first part of the post-crisis period.

We finally remark that the ranks obtained with correlation networks, in both the conditional and model-averaged versions, closely resemble those obtained with the quasi-leverage measure, which means that they capture a mixed effect from both leverage and market capitalization.

3.3 NetMES and Bayesian NetMES

In this section, we compare the systemic risk contribution of the three banking sectors in the GCC countries using the standard MES, the proposed NetMES measure and the Bayesian NetMES measure. Table 16 describes the banking sectors' systemic

TABLE 15 RC% for Bayesian model averaging.

(a) Pre-crisis (2005–6)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.44	0.43	0.44	0.40	0.54
IB	0.26	0.29	0.26	0.46	0.22
CB	0.29	0.29	0.29	0.14	0.24

(b) Crisis (2007–8)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.40	0.42	0.42	0.44	0.43
IB	0.41	0.43	0.44	0.38	0.35
CB	0.18	0.15	0.14	0.18	0.21

(c) Post-crisis, part 1 (2009–10)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.33	0.33	0.33	0.40	0.35
IB	0.37	0.36	0.37	0.46	0.37
CB	0.30	0.31	0.30	0.15	0.28

(d) Post-crisis, part 2 (2011–12)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.41	0.39	0.41	0.50	0.41
IB	0.37	0.38	0.37	0.38	0.35
CB	0.22	0.24	0.22	0.12	0.24

(e) Post-crisis, part 3 (2013–14)

	Node degree	Betweenness	Closeness	Node partial corr. degree	Eigenvector centrality
CBwin	0.49	0.46	0.49	0.44	0.45
IB	0.35	0.38	0.35	0.46	0.40
CB	0.15	0.17	0.15	0.10	0.15

TABLE 16 MES rankings.

Pre-crisis	Crisis	Post-crisis
SA.IB	SA.IB	KW.CBwin
AE.IB	SA.CBwin	SA.IB
SA.CBwin	KW.CBwin	OM.CBwin
QA.IB	OM.CBwin	SA.CBwin
QA.CBwin	AE.IB	QA.CBwin
KW.CBwin	QA.IB	AE.IB
AE.CBwin	OM.CB	OM.CB
AE.CB	QA.CBwin	QA.IB
OM.CB	AE.CBwin	AE.CBwin
BH.IB	BH.IB	BH.IB
KW.IB	KW.IB	KW.IB
KW.CB	AE.CB	AE.CB
OM.CBwin	KW.CB	KW.CB
BH.CBwin	BH.CBwin	BH.CBwin
OM.IB	OM.IB	OM.IB
BH.CB	BH.CB	BH.CB

risk rankings using the standard MES. Table 17 describes the same rankings using the proposed NetMES, in which we consider a multivariate perspective, as we replace the correlations in MES estimation with partial correlations. Table 18 describes the rankings using the proposed Bayesian NetMES measure, which averages the previously estimated NetMES; finally, Table 19 shows the RC% for the risk measures rankings.

Table 16 for MES and Table 17 for NetMES both show that the IB banking sector dominates the top rank in the pre-crisis and crisis periods, while the CBwin sector dominates the top ranks in the post-crisis period. In other words, within the GCC banking systems case, it seems that MES ranks capture the size effect, represented by market capitalization, which is also captured by node partial correlation degree, but not by the other centrality measures that seem to be more dependent on leverage.

In terms of the RC% for the systemic risk measures, the first part of Table 19 indicates for the MES measure a higher risk for the IB sector in the pre-crisis period, followed by the dominance of the CBwin sector in both the crisis and post-crisis periods. The same risk hierarchy applies to the NetMES measure. The Bayesian NetMES RC% instead indicates that CBwin is the higher risk sector throughout all periods.

To better understand the difference between the MES, NetMES and Bayesian NetMES measures, we further examine their evolution in a time dynamic manner. For this purpose, we follow the component expected shortfall (CES) measure prin-

TABLE 17 NetMES rankings.

Pre-crisis	Crisis	Post-crisis
SA.IB	SA.IB	OM.CBwin
QA.IB	OM.CBwin	SA.IB
AE.CBwin	BH.IB	KW.CBwin
OM.CB	OM.CB	BH.IB
KW.CBwin	SA.CBwin	QA.IB
BH.CBwin	KW.CBwin	OM.CB
KW.IB	AE.CBwin	AE.CBwin
AE.CB	AE.CB	QA.CBwin
AE.IB	QA.CBwin	SA.CBwin
SA.CBwin	BH.CBwin	AE.CB
OM.IB	KW.IB	KW.IB
BH.IB	QA.IB	AE.IB
OM.CBwin	OM.IB	BH.CBwin
QA.CBwin	AE.IB	OM.IB
KW.CB	KW.CB	KW.CB
BH.CB	BH.CB	BH.CB

TABLE 18 Bayesian NetMES rankings.

Pre-crisis	Crisis	Post-crisis
SA.IB	SA.IB	KW.CBwin
KW.CBwin	SA.CBwin	SA.IB
SA.CBwin	KW.CBwin	OM.CBwin
AE.IB	QA.IB	KW.IB
QA.CBwin	OM.CBwin	SA.CBwin
OM.CBwin	OM.CB	QA.CBwin
QA.IB	AE.IB	OM.CB
KW.IB	QA.CBwin	AE.IB
AE.CBwin	KW.IB	QA.IB
BH.IB	AE.CBwin	AE.CBwin
OM.CB	BH.IB	BH.IB
AE.CB	AE.CB	AE.CB
KW.CB	KW.CB	KW.CB
BH.CBwin	BH.CBwin	BH.CBwin
OM.IB	OM.IB	OM.IB
BH.CB	BH.CB	BH.CB

TABLE 19 RC% for MES, NetMES and Bayesian NetMES.

(a) RC% for MES

	Pre-crisis	Crisis	Post-crisis
CBwin	0.40	0.46	0.49
IB	0.43	0.40	0.37
CB	0.17	0.15	0.15

(b) RC% for NetMES

	Pre-crisis	Crisis	Post-crisis
CBwin	0.38	0.46	0.45
IB	0.44	0.35	0.40
CB	0.18	0.18	0.15

(c) RC% for Bayesian NetMES

	Pre-crisis	Crisis	Post-crisis
CBwin	0.46	0.44	0.46
IB	0.42	0.40	0.39
CB	0.12	0.15	0.15

ciple that is provided by Banulescu and Dumitrescu (2015). We prepare a weighted aggregate for MES, NetMES and Bayesian NetMES, per banking sector type and at the overall GCC region level, using market capitalization as a weighting scheme.

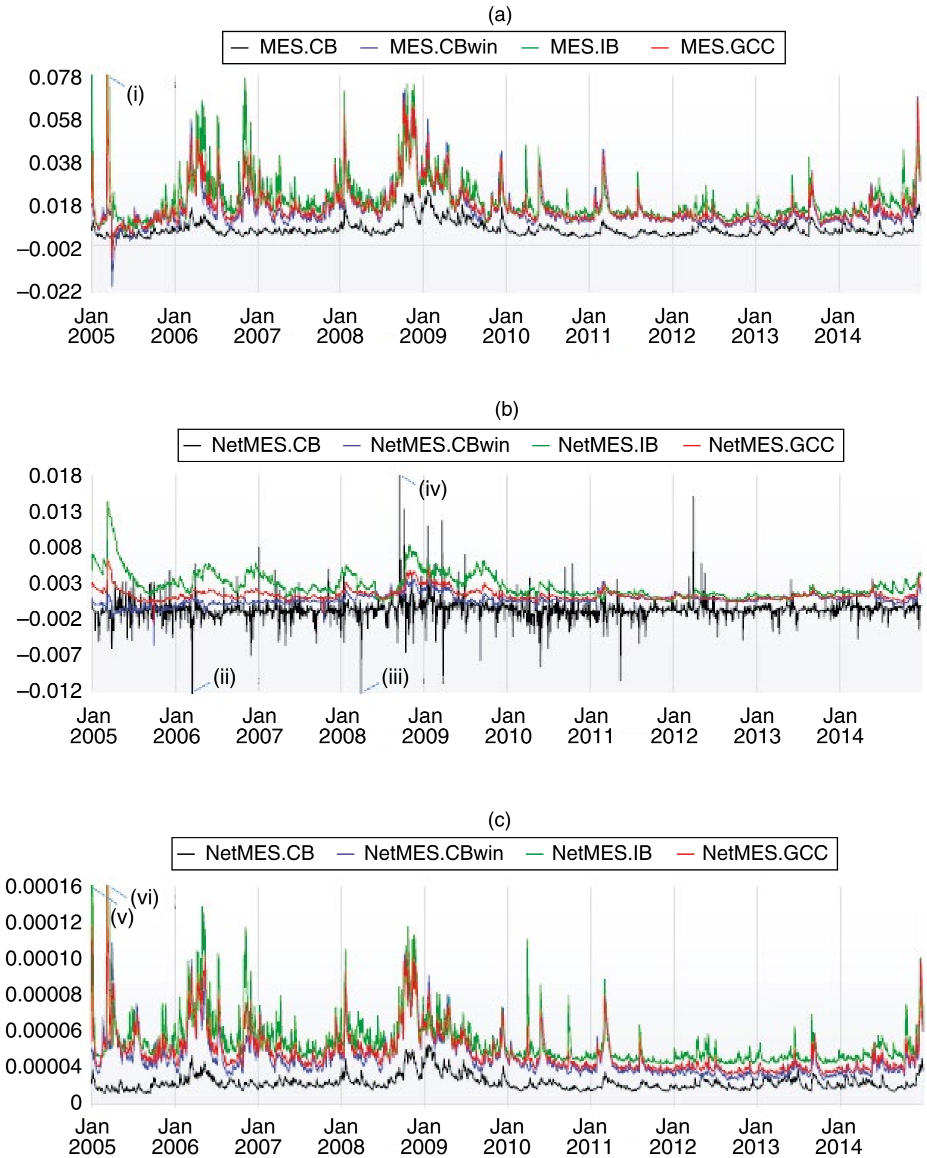
More formally, the timely aggregate systemic risk measure $\mathrm{RM}_{s,t}$ for each banking sector type is

$$\mathrm{RM}_{s,t} = \sum_{j=1}^{n_j} w_{js,t}\,\mathrm{rm}_{js,t},$$

where $\mathrm{rm}_{js,t}$ is the risk measure for the specific banking sector type s in country j at each time point t, and $w_{js,t} = \mathrm{mv}_{js,t}/\sum_{j=1}^{n_j}\mathrm{mv}_{js,t}$ represents the weight of the banking sector s in country j at time t, given by its market capitalization $\mathrm{mv}_{js,t}$, relative to the aggregate capitalization of that sector $\sum_{j=1}^{n_j}\mathrm{mv}_{js,t}$ across all countries in the GCC region that have that banking sector, $j = \{1,\dots,n_j\}$. We repeat a similar weighting scheme process on the resulting $\mathrm{RM}_{s,t}$ in order to have the aggregate GCC level measure, $\mathrm{RM}_{\mathrm{GCC},t}$.

Figure 4 describes the resulting aggregated GCC measure, using the weighted MES, the weighted NetMES and, finally, the weighted Bayesian NetMES.

FIGURE 4 MES, NetMES and Bayesian NetMES at the GCC banking sectors' level.



(a) MES weighted by market capitalization per sector; (i) 0.23: March 2005, IB. (b) NetMES weighted by market capitalization per sector; (ii) −0.03: March 2006, CB; (iii) −0.02: April 2008, CB; (iv) 0.02: September 2008, CB. (c) Bayesian NetMES weighted by market capitalization per sector; (v) 0.028%: January 2005, IB; (vi) 0.055%: March 2005, IB.

From Figure 4, note that the CB sector has a lower magnitude than the CBwin and IB sectors: this is due to its lower market capitalization weight in the GCC countries. We also note that all graphs depict the presence of high volatility during 2005, and that the effect of the global crisis started prior to 2007 and increased in 2009, with the alignment of crisis effect on three sectors' aggregates.

Comparing the graphs of MES and NetMES, we note that the latter takes less account of the size effect, resulting in a lower magnitude scale. This is expected, as NetMES is based on partial rather than marginal correlations. The Bayesian NetMES is, as expected, more consistent in terms of its results than the previous two measures. Even though the changes in the sectors' aggregates have similarities with the MES graph, they have a lower magnitude, as in NetMES. Moreover, the Bayesian NetMES clearly can better distinguish the differences between the banking sectors compared with MES, but in a more smooth manner than NetMES.

We can conclude that, in spite of the high systemic risk effect that the IB sector had on the region before 2007, the main systemic risk driver in the GCC countries, during both the crisis period and going forward, is the CBwin sector. In addition, the CB banking sector shows high volatility, especially in terms of the weighted NetMES measure; however, this volatility does not much affect the system, as its market size is much lower than that of the other two sectors.

4 CONCLUSIONS

The aim of this research was twofold: to develop a novel measure of systemic risk, which takes its multivariate nature into account, and to determine if there are differences between the Islamic and the conventional banking sectors in terms of systemic risk, especially in the wake of the recent financial crisis.

The results indicate that the proposed NetMES and Bayesian NetMES measures are, indeed, valid systemic risk measures that can detect crisis signals and differences between different banking systems. The Bayesian NetMES is more robust than NetMES, as it takes model uncertainty into account.

From an applied viewpoint, our findings confirm a difference in the systemic risk measurement of the different banking sectors. Interconnectedness, measured by network centrality measures, mostly depends on leverage. In this sense, the CBwin sector is the most systemic, followed by the IB sector in the post-crisis period. Loss impact, measured by the MES, mostly depends on market capitalization. In this sense, the CBwin sector is gaining more and more relevance as its relative market size grows. Finally, conventional banks exhibit a high level of volatility that is not, however, carried onto the system due to their small market size.

From a policy-making viewpoint, the most systemic sectors are found to be those with a large asset size and a relatively high leverage, such as SA.CBwin, SA.IB and AE.CBwin.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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