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By *Pejman Abedifar, Paolo Giudici and Shatha Hashem*

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Heterogeneous Market Structure and Systemic Risk: Evidence from Dual Banking Systems

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Abstract

This paper investigates how banking system stability is affected when we combine Islamic and conventional finance under the same roof. We compare systemic resilience of three types of banks in 6 GCC countries with dual banking systems: fully-fledged Islamic banks (IB), purely conventional banks (CB) and conventional banks with Islamic windows (CBw). We employ market-based systemic risk measures such as MES, SRISK and ΔCoVaR to identify which sector is more vulnerable to a systemic event, and use graphical network models to determine the banking sector that can more easily spread a systemic shock to the whole system. Using a sample of 2,608 observations on 79 publicly traded banks operating over the 2005-2014 period, we find that CBw is the least resilient sector to a systemic event and is more interconnected with other banks during crisis times.

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1 Introduction

The recent financial crisis asserted the inadequacy of micro-prudential regulations and highlighted the importance of macro-prudential policies in identifying emerging systemic events and containing them before they materialize (Ioannidou et al., 2015). Financial institutions of advanced economies are becoming more homogeneous, because of their inclination for holding market portfolio, which is recommended by modern portoflio theory (Markowitz, 1952). Wagner (2010) points out that the increasing homogeneity of financial institutions may increase stability of each individual financial institution but, from a macro prudential viewpoint, it makes them vulnerable to the same risks, as they become more similar to each other. He indicates that there is a trade-off between a lower probability of an idiosyncratic failure and a higher probability of a systemic adverse event. In a related work, Ibragimov et al. (2011) show that diversification for individual institutions might be suboptimal for a banking system.

In the Muslim world, we observe a different trend, wherein banking systems are becoming more heterogeneous as a result of introducing Islamic financial products. Since its inception in 1970s, Islamic banking has expanded very rapidly into many Muslim countries. According to the Islamic Financial Services Board report (IFSB, 2015), Islamic banking has experienced a double-digit growth in recent years, and the assets managed under this new technology have reached \$1.9 trillion in 2014. This trend has transformed the structure of the banking industry in several Muslim countries to a dual system, in which Islamic banks operate alongside their conventional counterparts and provide financial services that are compatible to the religious belief of devout individuals, and thereby facilitate access to finance for a wider population. The existing literature has shown differences between Islamic and conventional banks in terms of asset growth (Hasan and Dridi, 2011), bank-firm relationship (Ongena and Sendeniz-Yunc, 2011), business orientation (Shaban et al., 2014), corporate social responsibility (Mallin et al., 2014), credit risk (Abedifar et al., 2013; Baele et al., 2014), customer loyalty and interest rate risk (Abedifar et al., 2013), efficiency (Al-Jarrah and Molyneux, 2006; Abdul-Majid et al., 2011a,b,c), insolvency risk (Cihak and Hesse, 2010; Pappas et al., 2016) and market power (Weill, 2011). Such differences stimulate the overall performance of dual banking systems (Gheeraert, 2014; Gheeraert and Weill, 2015; Abedifar et al., 2016) but, on the other hand, may affect the stability and resilience of the banking system against systemic events.

Islamic financial products can be provided to the society through two main channels: a) Islamic branches/windows of conventional banks (CBw), and b) fully fledged Islamic banks (IB). The choice between these options will affect the stability of the banking system. In the former case, existing conventional banks (CB) can exploit economies of scope and scale by establishing Islamic branches and combining Islamic with conventional banking. The banking system will then consist of a pool of similarly diversified quasi-conglomerate banks with a portfolio of clients that have different religious consciousness. In the latter case, instead, banks will focus on either Islamic or conventional products, and religious diversity will be observed across banks. Under this scenario, a portfolio of different but less diversified individual banks will form the banking system.

In this paper, we attempt to address the consequence of alternative banking system configurations on financial stability, by comparing the systemic risk of CBw with that of IB and CB banks, using market based measures, including MES, SRISK and ΔCoVaR. Billio et al. (2012b) and Giglio et al. (2016) show that using a plurality of systemic risk measures, rather than a single one, provides higher prediction ability in explaining banks behavior under systemic events. We follow this literature, and consider several alternative measures of systemic risk. All our measures are based on the DCC-GARCH model introduced by Engle (2002). This enables us to address the distortion in correlation coefficients, caused by heteroskedasticity in periods of high volatility such as crisis times (see e.g. Forbes and Rigobon, 2002; Ronn et al., 2009). The DCC approach is robust to heteroskedasticity problems (see e.g Caporale et al., 2005; Cappiello et al., 2006). However, the detected cross-correlations between pairs of stock returns provide information about the similarity of their return change, without controlling for the impact of other assets in the market. We attempt to address this effect by extending the DCC approach with conditional correlation measures.

We also examine contagion and diffusion of risk in a dual banking system. We use a graphical network model, following Giudici and Spelta (2016), to investigate which sector is more strongly interconnected with other banking sectors. Our objective is to explore how a bad news about a banking sector can adversely affect other sectors.

For our study, we focus on banking sectors of a fairly homogeneous sample of countries, given substantial cross country variations in Muslim countries reported by the existing literature (see e.g. Beck et al., 2013). This allows us to establish robust results across our sample, and to control for country-specific factors that may influence systemic risk of our banking sectors. We study the countries in the Gulf Cooperation Council (GCC) region as they hold nearly 40% of the total global Islamic banking assets, with a significant market share of the Islamic banking sector (IFSB, 2016).

The GCC countries consist of Saudi Arabia (SA), Kuwait (KW), Qatar (QA), United Arab Emirates (AE), Bahrain (BH) and Oman (OM). These 6 countries have a similar Muslim share of population and a similar economic environment. In addition, the 6 countries have economies that are mostly oil dependent and are thus similarly vulnerable to the negative impact of the global crisis through oil price fluctuations. Oil revenue accounts for almost 48% of the GCC countries GDP (Sturm et al., 2008): this enables us to use the crude oil WTI returns as a unified volatility index in place of the equity market index and test the robustness of our results.

We use daily stock returns of 79 publicly traded banks and bank holding companies over the period 2005-2014. The results of our analysis indicate that the CBw banking sector is the least resilient banking sector and has the highest importance in destabilising the financial system of GCC countries. It also has the highest synchronicity with the market, whereas the IB sector is less aligned.

The graphical network model results indicate that the CBw sector, especially during crisis periods, is the most interconnected sector. On the other hand, the IB sector is negatively correlated to the CB sector, indicating a diversification benefit for a system that has both, but not a CBw sector. The results also suggest that systemic risk positively depends on bank size for both the CBw and IB sectors, consistently with Laeven et al. (2016). In line with the literature, oil return fluctuations are also quite influential in all GCC countries.

Our study contribute to the market structure and financial stability literature and has policy implications for regulators and supervisors, particularly in Muslim countries taking into account the fact that Islamic banking is increasing its size and importance, and more countries would seek introducing Islamic financial products into their conventional banking system. It is interesting to note that the Qatar Central Bank started showing extreme consciousness toward this issue in 2010 by restricting lending activities of CBw, and eventually in 2011 ordered conventional banks to close their Sharia-based operations by the end of 2011, which adversely affected 6 local as well as 2 foreign banks. Other beneficiaries of our results could be conventional banks, which can gain insight regarding the effect of diversifying their services with Islamic banking activities. Finally, asset managers and investors may also benefit from our research results in making portfolio allocation decisions.

The remainder of this paper is organized as follows. Section two outlines our measurement methodology and, in particular, the systemic risk measures, the interconnectdness measures, the DCC approach and the netted measures. Section three describes the data, and some summary statistics. Section four provides the results obtained with the application of the proposed measures to the data. The final Section provides summary conclusions and policy implications.

2 Methodology

Systemically Important Financial Institutions ($SIFI$) are defined by the Financial Stability Board (2011) as "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity". In a similar vein, our aim is to identify the Systemically Important Financial Sectors using systemic risk measures and interconnectedness analysis.

To achive this aim, we use stock market return data of banks, aggregated by their type to compute the systemic risk of each banking sector (IB, CB and CBw) in each country. We use aggregate data as our aim is to determine the systemic risk contribution of each banking sector. The aggregation process is based on the standard construction method for a market capitalization weighted index. We start by deriving the time series of daily stock prices, which we transform into daily returns. Formally, if p_t and p_{t-1} are the closing stock prices at times t and $t-1$, the return at time t is the variation represented by $r_{it} = ln(p_t/p_{t-1})$, where $p_{t-1} \neq 0$.

Then, for each country, we classify banking institutions into banking sectors, according to their bank type: IB, CB and CBw. To construct the aggregate return of each sector, let n_{sj} indicate the number of banks in the banking sector s of a country j. We define the aggregate return of the banking sector sj at time t to be a market capitalization weighted average as in the following:

$$r_{sjt} = \sum_{i=1}^{n_{sj}} w_i r_{it}$$

in which $w_i = MV_i / \sum_{i=1}^{n_{sj}} MV_i$ represents the weight of the i-th bank in the specified banking sector s of country j, given by its market capitalization MV_i relative to the sector aggregate capitalization $\sum_{i=1}^{n_{sj}} MV_i$.

2.1 Systemic risk measures

We use a plurality of systemic risk measures: the Marginal Expected Shortfall (MES) of Acharya et al. (2016) and the systemic risk measure (SRISK) of Acharya et al. (2012), extended by Brownlees and Engle (2012), to investigate the banking sectors resilience or vulnerability under a systemic stress event. In addition, we investigate the contribution of the banking sectors to the system risk using the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2016). These measures are extensions of the two standard risk measures, the Value at Risk (VaR) and the Expected Shortfall (ES), and are commonly used at individual banking unit level to identify Systemically Important Financial Institutions. Here we extend the application of these measures at the aggregate banking system level, to identify the vulnerability or the systemic importance of different banking sectors.

MES evaluates the sensitivity of a financial entity to a change in the system's Expected Shortfall. More precisely, it is the one day capital loss expected if the market returns are less than a given threshold C (such as $C = -2\%$). In our context, MES can be expressed as a weighted function of the tail expectations for a country specific market index standardized return ε_{jt} and of the tail expectations for the banking sector standardized idiosyncratic return ξ_{sjt}:

$$MES_{sjt}(C) = \sigma_{sjt}\, \rho_{sjt}\, \mathbb{E}_{t-1}(\varepsilon_{jt} | \varepsilon_{jt} < \frac{C}{\sigma_{jt}}) + \sigma_{sjt} \sqrt{1-\rho_{sjt}^2}\, \mathbb{E}_{t-1}(\xi_{sjt} | \varepsilon_{jt} < \frac{C}{\sigma_{jt}}),$$

where σ_{sjt} is the (time dependent) volatility of the aggregate returns of sector s in country j, σ_{jt} is the (time dependent) volatility of the market index returns of country j and, finally, ρ_{sjt} is the (time dependent) correlation between the aggregate returns of sector s in country j and the corresponding market index returns in country j. From an economic viewpoint, a higher MES indicates a higher vulnerability of a banking sector of a certain country to a systemic event that causes a crash in the reference market.

To assess vulnerability at the country level, we need to aggregate the MES of its different banking sectors. To achieve this aim, we follow Banulescu and Dumitrescu (2015), who propose the Component Expected Shortfall, for which the expected shortfall of a system can be measured by linearly aggregating the expected shortfalls of the individual components. In our context, we propose to measure the Global Expected Shortfall (GES) of a country banking system j as a linear aggregation of the expected shortfall of its banking system components:

$$GES_{jt} = \sum_{s=1}^{S} w_{sjt} MES_{sjt}$$

in which $w_{sjt} = MV_{sjt} / \sum_{s=1}^{S} MV_{sjt}$ represents the weight of the banking sector s in country j at time t, given by its market capitalization value MV_{sjt} relative to the aggregate capitalization of the country banking system $\sum_{s=1}^{S} MV_{sjt}$ and where S is the number of considered sectors (in our context, $S = 3$). Economically, a higher GES indicates a higher vulnerability of a country to a systemic event. We also aggregate the MES of each banking sector across different countries to identify the least resilient sectors in the GCC region.

The SRISK measure was introduced by Acharya et al. (2012), and extended by Brownlees and Engle (2012). SRISK extends MES to take into account idiosyncratic firm characteristics, as it explicitly accounts for a financial institution's leverage and size. It measures the expected capital shortage faced by a financial institution during a period of distress, when the market declines substantially. The measure combines high frequency market data (daily stock prices and market capitalizations) with low frequency balance sheet data (leverage) to provide a daily SRISK estimation. Following Acharya et al. (2012), the quantification of SRISK requires: the regulatory minimum capital ratio k (here we take $k = 8\%$), the book value of debt D (here we consider the total liabilities), the equity market capitalization value MV and the long-run marginal expected shortfall ($LRMES$), which represents the expected loss for the equity of a financial entity under a crisis, during which the aggregate market declines significantly in a six-month period. $LRMES$ is usually approximated with daily MES, such that $LRMES \simeq 1 - exp(-18 \times MES)$, fixing the threshold C at $C = -40\%$. The SRISK for institution i at time t is then defined by:

$$SRISK_{it} = max\Bigg[0; \bigg(\underbrace{k(D_{it} + (1 - LRMES_{it})MV_{it})}_{Required\ Capital} - \underbrace{(1 - LRMES_{it})MV_{it}}_{Available\ Capital} \bigg)\Bigg]$$

Note that if we define leverage as $L_{it} = (D_{it} + MV_{it})/MV_{it}$, SRISK can be rewritten as:

$$SRISK_{it} = max\big(0; \big[kL_{it} - 1 + (1 - k)LRMES_{it}\big] w_{it}\big),$$

which shows that higher leverage and higher market capitalization will increase SRISK. In our context, we aim to calculate SRISK of banking systems, rather than that of financial institutions. This can be easily done, as SRISK can be linearly aggregated (see Acharya et al., 2012). and, therefore, the SRISK of a banking sector is equal to the sum of the SRISK of its banks. From an economical viewpoint, the banking sector with the largest positive SRISK has the highest capital shortfall and, therefore, will be the greatest contributor to systemic risk. Note that, in our application of SRISK, we will not lower bound it at zero, as negative values can also be meaningful, in providing information on capital surplus.

The ΔCoVaR was introduced by Adrian and Brunnermeier (2016) as an upgrade of the Value at Risk concept. It is based on the calculation of the VaR of a market portfolio return, conditional on the observed return level of a financial entity i. More precisely, the ΔCoVaR of i reflects its contribution to systemic risk by assessing the difference between the VaR of the system, conditional on the returns of i at their VaR level, and the VaR of the system, conditional on the returns of i at the median level. Adrian and Brunnermeier (2016) set the VaR level at the 5% probability quantile and use quantile regression to derive the conditional VaRs of the system. To extend the measure at the banking system level, we can calculate the VaR of a country banking system j, conditional on its sectors' return levels, using aggregate banking system returns, and obtain $\Delta CoVaR_{jt}$ as:

$$\Delta CoVaR_{jt} = VaR(r_j|r_{sjt} = VaR(r_{sj})) - VaR(r_j|r_{sjt} = Median(r_{sj}))$$

From an economic viewpoint, a higher level of ΔCoVaR indicates a higher contribution from a banking sector to the systemic risk level of a country's financial system.

2.2 Interconnectedness measures

Besides calculating the vulnerability and the systemic importance of banking sectors, we aim to understand their interconnectedness, trying to detect the pattern of diffusion of systemic risk among them. To achieve this aim we proceed as in Billio et al. (2012a), and consider a cross-sectional analysis to produce a correlation network structure that can describe the mutual relationships between the banking sectors. More specifically, we follow Giudici and Spelta (2016) and employ a graphical network model based on conditional independence relationships described by partial correlations. We extend their analysis by considering, as graphical nodes, the banking sectors of the different countries and, as random variables associated to each node, the systemic risk measures previously described.

More formally, let $X = (X_1, ..., X_N) \in R^N$ be a $N-$ dimensional random vector of (standardised) systemic risk measures for the N considered banking sectors, where N is equal to $S \times J$, the number of sectors times the number of countries (6×3 in our context). We assume that X is distributed according to a multivariate normal distribution $\mathcal{N}_N(0, \Sigma)$, where Σ is the correlation matrix, which we assume not singular. A graphical network model can be represented by an undirected graph G, such that $G = (V, E)$, with a set of nodes $V = \{1, ..., N\}$, and an edge set $E = V \times V$ that describes the connections between the nodes. G can be represented by a binary adjacency matrix A, that has elements a_{ij}, which provides the information of whether pairs of vertices in G are (symmetrically) linked between each other ($a_{ij} = 1$), or not ($a_{ij} = 0$). If the nodes V of G are put in correspondence with the random variables $X_1, ..., X_N$, the edge set E induces conditional independences on X via the so-called Markov properties (see e.g. Lauritzen, 1996).

Let Σ^{-1} be the inverse of Σ, whose elements can be indicated as $\{\sigma^{ij}\}$. Whittaker (1990) proved that the following equivalence holds:

$$\rho_{ijV} = 0 \Longleftrightarrow X_i \perp X_j | X_{V \setminus \{i,j\}} \Longleftrightarrow e_{ij} = 0$$

where the symbol $\perp$ indicates conditional independence and $\rho_{ijV} = -\sigma^{ij}/\sqrt{\sigma^{ii}\sigma^{jj}}$ denotes the ij-th partial correlation, that is, the correlation between X_i and X_j, conditionally on the remaining variables $X_{V \setminus \{i,j\}}$. From an economical viewpoint, the previous equivalence implies that, if the partial correlation between two measures is not significant, the corresponding systemic risk measures are conditionally independent and, therefore, the corresponding banking systems do not contage (directly) each other. More generally, a contagion network model among all banking systems can be estimated using only the corresponding partial correlation coefficients, which can be calculated inverting the correlation matrix among the systemic risk measures.

After estimating a network model, we can summarize the systemic importance of its nodes using network centrality measures (see e.g. Giudici and Spelta, 2016). We can use: a) degree centrality, to measure the number of links that are present between a single node and all others; b) betweenness centrality, to measure the intemediation importance of a node based on the extent to which it lies on the shortest paths between other nodes; c) closeness centrality, to measure the average geodesic distance between a node and all other nodes; d) eigenvector centrality, to measure the relative influence of a node in the network, with the principle that connections to few high scoring nodes contribute more to the node score than equal connections to low scoring nodes. In our context, each node is a banking sector for a specific country and we have several networks, corresponding to the diffrent employed systemic risk measures. The most systemically important banking sector within the GCC region will be the one that occupies the largest number of high centrality ranks, among the different networks. To summarize ranks with a single measure, we use a Ranking Concentration ratio (RC), as the one employed by Hashem and Giudici (2016). The larger the RC value, the higher the systemic risk importance of a specified banking sector.

2.3 Dynamic Conditional Correlations

For each of the considered systemic risk measures, the Dynamic Conditional Correlation model (Engle, 2002) can be used to estimate time-varying correlations between each banking system and its reference market and, accordingly, smooth the observed returns. We follow Brownlees and Engle (2012) and base the DCC model on the GJR-GARCH of Glosten et al. (1993), to control for the heteroskedasticity effect in measuring correlations.

In our context, the model is updated, at any time point t, with r_t, an $SJ \times 2$ matrix, whose rows contain the aggregate banking system r_{sjt} and the corresponding reference market returns r_{jt}. We assume that:

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

where $\epsilon_t = (\varepsilon_{jt} \xi_{sjt})'$ is a random vector with mean $\mathbb{E}(\epsilon_t) = 0$ and identity covariance matrix $\mathbb{E}(\epsilon_t \epsilon_t') = I_2$, and

$$H_t = \begin{pmatrix} \sigma_{jt}^2 & \sigma_{jt}\, \sigma_{sjt}\, \rho_{sjt} \\ \sigma_{jt}\, \sigma_{sjt}\, \rho_{sjt} & \sigma_{sjt}^2 \end{pmatrix}$$

with σ_{jt} and σ_{sjt} represent a time varying conditional standard deviation for the market and for the banking sector, and ρ_{sjt} represents a time varying correlation.

Note that, in the DCC model, a key parameter is the correlation coefficient ρ_{sjt}, which is assumed to capture, at any given time point, the dependency between the returns of the banking sector and those of its reference market. We extend this assumption in the next seubsection.

2.4 Netted systemic risk measures

Systemic risk measures capture the vulnerability of a banking sector to a systemic event, or the contribution of a banking sector to the overall risk level of a system. However, they are computed on the basis of the correlations between the returns of a sector and those of the corresponding market, without considering the returns of other sectors in the same country. To correctly take this interconnectedness into account, we propose to replace correlations, that capture both direct and indirect relationships, with partial correlations, that are "netted" measures, which consider only direct relationships.

To estimate partial correlations note that, for any two variables X_i and X_j in a random vector X_V, the partial correlation coefficient ρ_{ijV} can also be defined by the correlation between 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 formula:

$$\rho_{ijV} = corr(\, e_{X_i|X_{V\setminus\{j\}}}, e_{X_j|X_{V\setminus\{i\}}}).$$

From an interpretational viewpoint, the partial correlation coefficient measures the additional contribution of variable X_j to the variability of X_i, that is not explained by the other variables.

In our context, consider two regressions, for each banking sector, along with the corresponding country market, with the dependent variable of the first regression being the banking sector return r_{sj}, and the dependent variable of the second regression being the market return r_j. Let $s = 1$, without loss of generality. Both dependent variables can be regressed on the remaining variables $r_{2j}, ..., r_{Sj}$ that represent the returns of the other banking sectors in country j, as in the following:

$$\begin{cases} r_{1jt} = a_1 + \beta_2 r_{2jt} + ... + \beta_S r_{Sjt} + e_{1jt} \\ r_{jt} = a'_1 + \beta_2' r_{2jt} + ... + \beta_S' r_{Sjt} + e_{jt} \end{cases}$$

where e_{1jt} and e_{jt} are the residual vectors of the banking sector i_1 and the market j. In our context, $S = 3$ and the above process is repeated for all $J = 6$ countries. We can then calculate the netted (partial) correlation between the returns of banking sector 1 and the returns of the country market, using the corresponding residual time series, as:

$$\rho_{1jV} = corr(\, e_{1j}, e_j).$$

In general, for a banking sector s, and in terms of the considered systemic risk measurems, we propose to replace the correlation ρ_{sj}, with the partial correlation ρ_{sjV}, using the residual return time series (e_{sjt}, e_{jt}) in place of the return series $(r_{sjt}\ , r_{jt})$ in the DCC model. Doing so, the estimated returns will correctly take into account the "net" correlation between a banking sector and its reference market, without the inclusion of indirect, spurios components.

3 Data and descriptive Statistics

We consider all GCC banking institutions included in Bureau Van Djik's Bankscope database, for the period from January 2005 to December 2014. We exclude those that are not publicly traded and those that have disappeared before December 2014, thus leading to 79 banks, from 6 GCC countries. From Bankscope, we gather quarterly data on the book value of total liabilities and total assets for each bank. We also employ Thomson Reuters Data-stream to obtain daily stock market closing prices with their corresponding market capitalization, leading to 2608 observations on the 79 selected institutions.

The 6 selected GCC countries are dual banking systems that hold nearly 40% of the global Islamic banking assets. IFSB (2016) reports that the Islamic banking market shares in these countries are: 49% in Saudi Arabia (SA), 38.9% in Kuwait (KW), 26.1% in Qatar (QA), 18.4% in the United Arab Emirates (AE), almost 15% in Bahrain (BH), and only 7% in Oman (OM). Table 1 describes the analysed data in terms of total assets, aggregated at the country banking system level, within the considered period.

From Table 1, note that the CBw sector has the largest asset size within each country. The IB sector is larger than the CB sector in SA, QA, KW and BH, whereas it is almost the same as the CB sector in AE, and the CB sector is larger in OM. Note that the asset size generally increases over time, but the magnitude of the increase differs across countries and banking sectors. Figure 1 helps to understand the time evolution of each banking sector, at the aggregate GCC level.

Figure 1 shows that the CB sector has a strong negative slope through the crisis period, but bounces back afterwards. The CBw sector reduces its size with the crisis, but in a much slower way. Differently, The IB sector experiences a positive trend of growth throughout.

Table 2 describes the analysed data in terms of market capitalisation, aggregated at the country banking system level. The table also provide the banking sectors' leverage, as defined within the context of the SRISK.

In Table 2, the CBw sector is the largest in terms of market capitalization, whereas the smallest sector is the CB one. In terms of leverage, Table 2 shows that the CBw sector group has the highest leverage, in all periods. The IB sector has the lowest leverage in the pre crisis period, whereas the CB sector has the highest leverage in the post crisis period.

Next, we provide in Table 3 some summary statistics for the country banking sector returns. We also present summaries for the stock market index returns and for the crude oil (WTI) index returns.

The descriptive statistics in Table 3 cover three subsequent biannual time periods, roughly equivalent to the pre-crisis period of 2005-2006, the crisis period of 2007-2008 and the post-crisis period of 2009-2014. Table 3 shows that all countries experience the highest volatility in their market indexes during the crisis period, except SA. The market index volatility declines for all countries in the post crisis period, and similarly for the crude oil index. In terms of the specific banking sectors, the volatility of the IB sector is the highest during the crisis period. Finally, all countries market indices and the crude oil index are negatively skewed during the crisis period, indicating more frequent negative daily returns.

4 Empirical findings

In the following, we present the estimated systemic risk measures MES, SRISK and $\Delta CoVaR$ for all country banking sectors using: a) the time varying correlations and the reference market indices, leading to "standard" systemic risk measures; b) the time varying partial correlations and the reference market indices, leading to "netted" systemic risk measures; c) the time varying correlations and the crude oil index in place of the market indices, leading to "oil index" systemic risk measures. We then show the estimated Global Expected Shortfall (GES) measure, at the country and at the GCC level. Finally, we analyze the channels of systemic risk diffusion, by means of a graphical netowrk model based on the netted systemic risk measures.

Table 4 provides the MES for each country banking sector.

The results show that the CBw sector has a higher MES, especially during the crisis and post-crisis periods, whereas the MES of the IB sector reflects a higher vulnerability in the pre-crisis period. Last, the CB sector has the lowest MES. Comparing banking sectors, the IB sector of SA has the highest systemic risk magnitude in the pre-crisis and crisis periods, whereas the CBw sector of KW has the highest risk in the post crisis period. Looking at the oil index measue, note that the CBw and IB sectors of countries with larger banking systems, that is, AE, SA, QA and KW, are less resilient to the volatility of the oil index. Finally, note that the netted MES measures are lower in magnitude than other estimates, due to the exclusion of indirect effects.

Table 5 provides the SRISK for each country banking sector.

From Table 5 notice that all banking sectors have positive capital buffers (indicated by a negative sign). Overall, the CBw sector has higher capital buffers than the IB sector and the CB sector has the lowest capital buffers. These results, apparently in conflict with those from the MES measure, can be explained recalling that SRISK, differently from MES, depends on the size and the leverage of a banking sector. Indeed, if we take the ratios between each banking sector's SRISK measure in Table 5 with the corresponding capitalisations in Table 2, the resulting measure becomes coherent with the MES. For instance, the Netted SRISK measure gives an aggregated SRISK ratio of -81% for CBw and -78% for IB in the pre-crisis period; an aggregated SRISK ratio of -63% for CBw and -73% for IB in the crisis period and, finally, an aggregated SRISK ratio of -50% for CBw and -62% for IB, in the post-crisis period. Similar results are obtained using the standard and the oil index measure. These results clearly indicate higher (relative) capital buffers for the IB with respect to the CBw, during the crisis and post-crisis periods.

Table 6 provides the $\Delta CoVaR$ for each country banking sector.

From Table 6 we find that the standard, the oil and the netted $\Delta CoVaR$ identify the CBw banking sector as the main contributor to market systemic risk, followed by the IB and CB sectors, which is consistent with the results from the MES systemic risk indicators. Note also that the IB sector of SA has the highest $\Delta CoVaR$ in the pre-crisis and crisis periods, and the CBw sector of KW has the highest risk in the post crisis period, again consistently with MES results. Similarly to what happens with the MES, the CBw and IB of larger banking systems are less resilient to oil volatility and the netted measures are lower in magnitude.

Consider now the Global Expected Shortfall measure (GES). For each of the six GCC country, the banking sectors MES and the aggregate GES measures, calculated with standard, netted and oil index measures, are provided in Figures 2 - 7.

From Figures 2 - 7 note that the GES of each country is generally driven by the CBw sector, except for SA and BH, where the main systemic risk driver is the IB sector. The CB sector appears to have the smallest effect. Looking at the time evolution of systemic risk, all graphs show a high risk synchronization during the crisis period of 2008, that reaches its maximum level in 2009. Only in that year, the behaviour of the IB sector approaches that of the CBw and CB banking sectors. In other words, the IB sector seem to be more resilient to the crisis, but only until the crisis itself does not affect the real economy. We remark that the observed synchronisation effect for GCC countries is similar to others found in the literature (see, for example, Hasan et al. 2014).

The results from the GES measure can be easily calculated, thanks to the aggregation property of the measure, for the GCC region as a whole. In Figure 8, we provide the time variation of the GES measure for the three main banking sectors at the aggregate GCC level.

From Figure 8 note that the time variation of the GES measure for the Gulf region strongly depends on the CBw sector, which has the highest systemic risk importance. Timewise, the banking sectors become more synchronized in 2009. Comparing the three measures, note that both the netted and the oil measures provide a clearer distinction between the three banking sectors. We can also observe that the oil index graph is almost similar to the standard one, a result in line with the finding that the stock market returns in the GCC region are mainly affected by oil price volatility (Maghyereh and Al-Kandari, 2007; Arouri et al., 2011, Mohanty et al., 2011).

We finally address the issue of how different banking sectors are interconnected with each other. For this purpose, we build a graphical network model, based on the netted MES measure, in Figure 9; one based on the netted SRISK, in Figure 10; and one based on the netted $\Delta CoVaR$, in Figure 11. Within each graph, the size of each node represents the magnitude of the systemic risk measure for the specified banking sector. The link between any two nodes represents the presence of a significant partial correlation coefficient between them: the thickness of the edge line indicates the link magnitude, and the color its sign. All networks are then summarized into four centrality measures that are used to rank banking sectors from the most to the least systemically important. In Table 7 the four centrality measures associated with the three networks are further summarised into an aggregate Rank Concentration (RC) score (see Hashem and Giudici, 2016). A higher RC score indicates a higher contagion capacity for the associated banking sector, across all considered countries.

From Figure 9 and the RC scores of the netted MES in Table 7, we find that CBw sector occupies the highest rank during the crisis period, whereas the IB sector dominates the post crisis higher ranks, with the CB sector always being the least systemically important.

From Figure 10 and the RC scores of the netted SRISK in Table 7, the IB sector has the highest importance, followed by CBw in the pre and acute crisis periods. Note that the SRISK of the IB sector lowers after the crisis, in terms of all considered centrality measures, indicating its stronger resilience. This effect can also be explained by the fact that, in the post-crisis graphical network model, the IB sector is typically negatively correlated with the CB sector, whereas the CBw sectors is typically positively correlated with both IB and CB. This indicates a diversification gain for the IB sector and, conversely, a concentration loss for the CBw sector.

Finally, the results of Figure 11 and of the RC of netted $\Delta CoVaR$ graphs are consistent with the netted MES results, and confirm that CBw sector is the one that has the highest contribution to systemic risk, especially during the crisis period. On the other hand, the CB sector is the least systemic, also because of its smaller market share.

5 Conclusions

The main objective of this study is to investigate the consequence for financial stability of the following options: 1) combining Islamic and conventional banking under the same roof; 2) providing Islamic and conventional banking through two separate institutions.

To explore this issue, we measure systemic risk of CBw, IB and CB in six GCC countries with a dual banking system, in particular during the financial crisis. We use market based systemic risk measures, such as MES, SRISK and $\Delta CoVaR$ and compute them in different methods: a) standard b) netted and c) oil index. Our analysis is based on a sample of 2608 observations on 79 banks and banks holding companies in the 2005-2014 time span.

The systemic risk measures of MES and $\Delta CoVaR$ show that the CBw sector is the most systemically vulnerable, and the one with the highest systemic importance. The SRISK shows that the CBw sector has the highest capital buffers but, if we normalise the buffers by the corresponding capitalisations, the results become coherent with those from MES and $\Delta CoVaR$.

Using the aggregate GES measure, at the country and GCC level, the findings are similar, with the CBw sector being the most systemically important, especially during the crisis period. In addition, the CBw sector has the highest synchronicity with the market, whereas the IB sector is less aligned, until 2009, when it also comoves with the market.

The interconnectedness analysis based on graphical network models shows that the CBw sector is the most interconnected sector during the crisis period, whereas the IB sector is more interconnected in the post crisis period. Moreover, we find that the IB sector is negatively correlated to the CB sector, indicating a diversication benefit for a system that has both, but not a CBw sector.

We believe that our findings have important policy implications. They underscore the importance of heterogeneity in banking system stability and the necessity of prudential regulation and supervision for the CBw sector, given its systemic importance and interconnectedness. The results also highlight that stock market returns in the GCC region are correlated with the crude oil index, and this indicates that swings in oil price can be informative to regulators and supervisors, in an early warning perspective.

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Appendix

Table 1: Total assets of the GCC country banking sectors

This Table provides the total assets distribution per country and banking system, on a yearly basis from 2005 to 2014. For each country, assets are classified according to banking sector type (CB,CBw and IB), and within each type are further classified based on ownership (as a count for the number of banks, and as a percentage for the aggregate total assets). The table is prepared based on authors' classification and calculations.

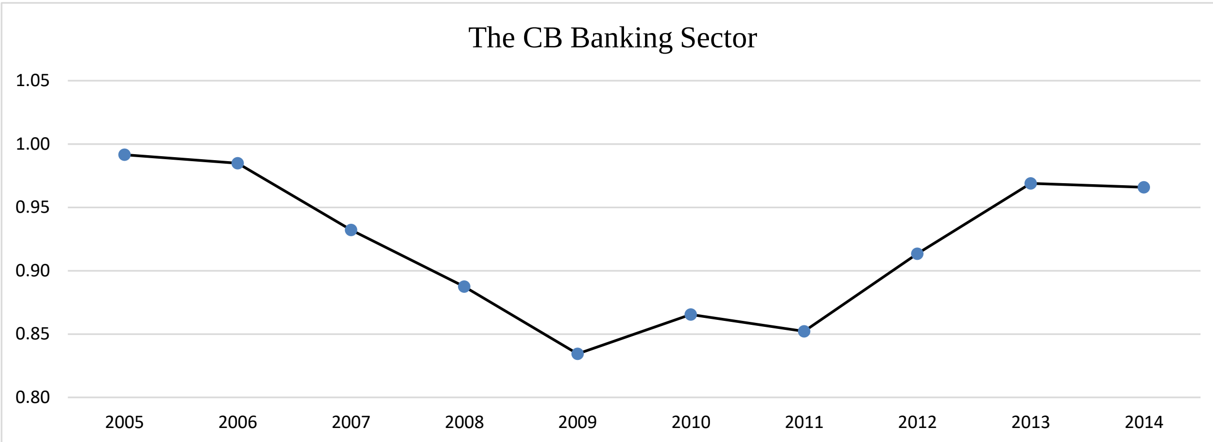
Country	*Bank Type*	*Ownership*	*Count*	*2014*	*2013*	*2012*	*2011*	*2010*	*2009*	*2008*	*2007*	*2006*	*2005*
OM	*CB*	*Public*	*5*	0.1218	0.1298	0.1382	0.1468	0.0986	0.117	0.1167	0.1127	0.1486	0.1689
		Private	*2*	0.0137	0.0146	0.0141	0.0139	0.0139	0.0143	0.0132	0.0137	0.0162	0.0219
	CB.win	*Public*	*5*	0.6285	0.6063	0.5927	0.5833	0.6106	0.5722	0.5797	0.6146	0.6131	0.5551
		Private	*2*	0.2261	0.2403	0.2465	0.2561	0.277	0.2965	0.2903	0.2591	0.2221	0.2541
	IB	*Public*	*1*	0.0068	0.0061	0.0051	0	0	0	0	0	0	0
		Private	*1*	0.0032	0.0031	0.0035	0	0	0	0	0	0	0
	Banking System	*Total Public*	*11*	0.757	0.7421	0.736	0.7301	0.7092	0.6892	0.6965	0.7272	0.7617	0.724
		Total Private	*5*	0.243	0.2579	0.264	0.2699	0.2908	0.3108	0.3035	0.2728	0.2383	0.276
		Total Assets	*16*	97,271,221	84,158,952	75,535,737	69,027,144	58,695,117	51,749,367	48,445,794	45,005,903	31,288,219	22,990,976
BH	*CB*	*Public*	*2*	0.0069	0.0065	0.0064	0.0085	0.0074	0.0084	0.0077	0.0065	0.0035	0.007
		Private	*6*	0.1521	0.1592	0.1551	0.1621	0.1623	0.1803	0.2397	0.2722	0.2882	0.3178
	CB.win	*Public*	*4*	0.4448	0.444	0.4613	0.5296	0.4972	0.5202	0.5034	0.5402	0.5484	0.5206
		Private	*2*	0.0641	0.0752	0.0492	0.0069	0.0285	0.0025	0	0	0	0
	IB	*Public*	*7*	0.2468	0.229	0.2308	0.1918	0.1895	0.1886	0.1642	0.129	0.1239	0.1264
		Private	*18*	0.0852	0.0861	0.0972	0.1011	0.1151	0.1001	0.085	0.052	0.0359	0.0282
	Banking System	*Total Public*	*13*	0.6985	0.6795	0.6984	0.7299	0.6941	0.7172	0.6754	0.6758	0.6759	0.6541
		Total Private	*26*	0.3015	0.3205	0.3016	0.2701	0.3059	0.2828	0.3246	0.3242	0.3241	0.3459
		Total Assets	*39*	178,491,905	169,144,233	151,157,555	126,739,419	134,850,310	117,718,680	125,617,066	122,948,061	95,114,734	75,734,958
KW	*CB*	*Public*	*1*	0.0496	0.0506	0.052	0.064	0.062	0.0678	0.0709	0.0752	0.0907	0
		Private	*0*	0	0	0	0	0	0	0	0	0	0
	CB.win	*Public*	*5*	0.6044	0.6005	0.5881	0.6012	0.59	0.6315	0.6402	0.6603	0.6286	0.6977
		Private	*0*	0	0	0	0	0	0	0	0	0	0
	IB	*Public*	*10*	0.3451	0.3477	0.3588	0.3341	0.3473	0.2997	0.2876	0.2637	0.2807	0.3023
		Private	*2*	0.001	0.0012	0.0011	0.0008	0.0007	0.001	0.0013	0.0008	0	0
	Banking System	*Total Public*	*16*	0.999	0.9988	0.9989	0.9992	0.9993	0.999	0.9987	0.9992	1	1
		Total Private	*2*	0.001	0.0012	0.0011	0.0008	0.0007	0.001	0.0013	0.0008	0	0
		Total Assets	*18*	241,159,890	223,893,976	203,261,985	164,345,351	178,280,457	152,446,532	155,141,579	144,222,669	92,453,820	62,648,797

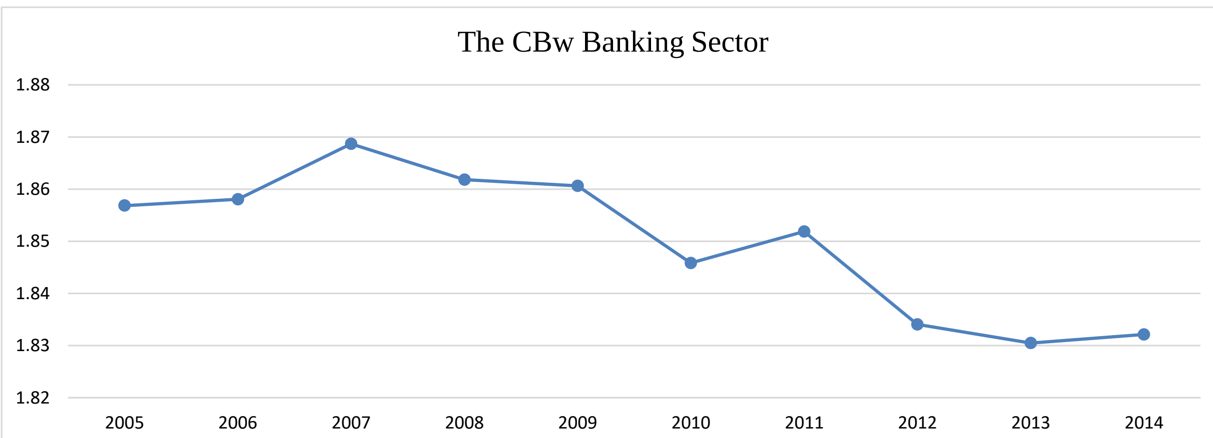
Table 2: Continued

Country	Bank Type	Ownership	Count	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
QA	CB	Public	0	0	0	0	0	0	0	0	0	0	0
		Private	2	0.0658	0.0667	0.0737	0.0629	0.0707	0.0589	0.0631	0.0435	0.0433	0.0432
	CB.win	Public	5	0.7239	0.7396	0.7139	0.7269	0.7172	0.7483	0.7951	0.8292	0.8606	0.8682
		Private	0	0	0	0	0	0	0	0	0	0	0
	IB	Public	4	0.2314	0.1905	0.1749	0.1121	0.1465	0.0856	0.0539	0.0337	0.0159	0.0102
		Private	1	0.0044	0.0033	0.0028	0.0044	0.0037	0.005	0	0	0	0
	Banking System	Total Public	9	0.9553	1.93	2.8887	3.839	4.8638	5.8339	6.8489	7.863	8.8765	9.8785
		Total Private	3	0.0702	1.07	2.0765	3.0672	4.0744	5.064	6.0631	7.0435	8.0433	9.0432
		Total Assets	12	288,484,210	256,675,999	214,122,728	139,776,935	180,516,442	116,976,862	97,501,681	68,046,844	42,543,931	29,633,161
SA	CB	Public	0	0	0	0	0	0	0	0	0	0	0
		Private	2	0.0196	0.0227	0.0165	0.0162	0.0165	0.0161	0.0153	0.0166	0.0158	0.0161
	CB.win	Public	8	0.7186	0.7183	0.7252	0.7656	0.7422	0.7788	0.7863	0.7979	0.794	0.7929
		Private	0	0	0	0	0	0	0	0	0	0	0
	IB	Public	4	0.225	0.22	0.2219	0.1827	0.2038	0.1688	0.1659	0.1489	0.1508	0.1499
		Private	1	0.0369	0.0389	0.0364	0.0356	0.0375	0.0363	0.0325	0.0366	0.0395	0.041
	Banking System	Total Public	12	0.9435	0.9383	0.9471	0.9482	0.946	0.9476	0.9522	0.9468	0.9448	0.9428
		Total Private	3	0.0565	0.0617	0.0529	0.0518	0.054	0.0524	0.0478	0.0532	0.0552	0.0572
		Total Assets	15	593,099,888	532,298,841	482,946,123	387,811,914	424,198,169	371,958,084	357,547,286	292,467,531	234,117,698	206,981,802
AE	CB	Public	4	0.1455	0.1383	0.1106	0.0741	0.0898	0.0682	0.0677	0.0714	0.0908	0.1311
		Private	6	0.0204	0.0207	0.0163	0.0091	0.0099	0.0085	0.011	0.0102	0.0115	0.015
	CB.win	Public	12	0.672	0.6614	0.6947	0.7308	0.7296	0.7479	0.7487	0.7621	0.7125	0.6718
		Private	0	0	0	0	0	0	0	0	0	0	0
	IB	Public	7	0.1492	0.1497	0.1506	0.1563	0.1422	0.1503	0.1507	0.1562	0.1852	0.1821
		Private	2	0.0128	0.0299	0.0278	0.0297	0.0285	0.025	0.0219	0	0	0
	Banking System	Total Public	23	0.9667	0.9495	0.9559	0.9612	0.9616	0.9664	0.9671	0.9898	0.9885	0.985
		Total Private	8	0.0333	0.0505	0.0441	0.0388	0.0384	0.0336	0.0329	0.0102	0.0115	0.015
		Total Assets	31	615,693,005	564,234,726	491,067,182	402,841,683	431,002,091	373,209,553	340,012,385	277,965,633	177,095,192	113,200,679

Figure 1: Asset growth of the GCC country banking sectors

This figure presents the annual percentage change, for the GCC banking sectors, using a log transformation for the ratio between the banking sector assets and the GCC total banking assets.





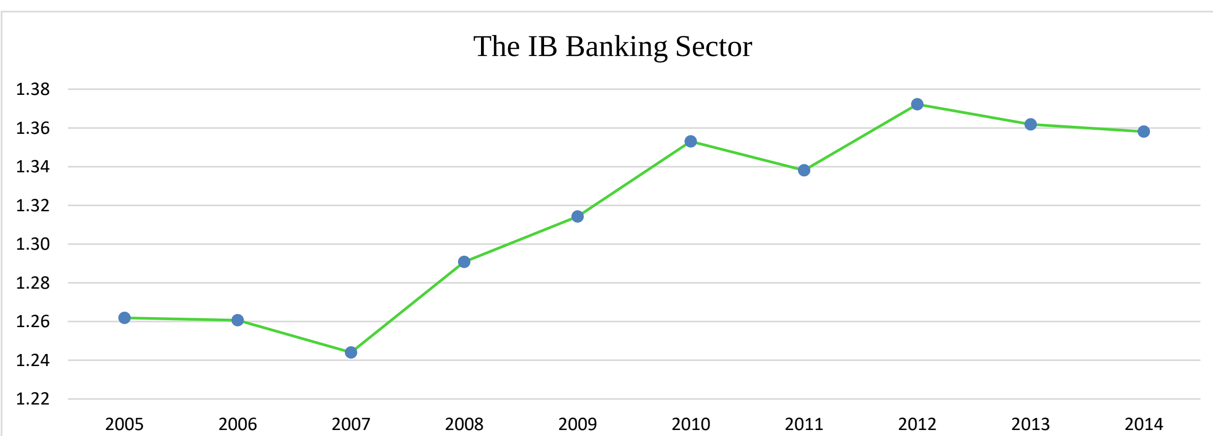


Table 2: Capitalisation of the GCC country banking sectors

The Table provides the market capitalization of each banking sector in each country (in million U.S. dollars). In addition, it provides the (quasi) leverage, the ratio of book value of debt divided by market share, plus one. The leverage is calculated for three sub-periods: the first is the pre-crisis period, from the beginning of January 2005 until the end of December 2006, the second is the crisis period, from the beginning of January 2007 until the end of December 2008, the third is the post crisis period, from the beginning of January 2009 until the end of December 2014.

Sector	Country	Market Capitalization			Leverage		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
CB	AE	1,738,686	1,911,293	1,734,313	2.31	3.21	5.17
	KW	2,366,259	3,815,578	2,800,840	4.17	3.60	4.44
	BH	224,252	267,469	226,714	2.62	2.35	2.42
	OM	1,207,104	1,397,523	1,524,171	3.53	3.88	5.17
	Total	5,536,301	7,391,863	6,286,037	3.16	3.26	4.30
CBw	AE	55,208,423	50,925,119	49,805,786	2.87	5.41	7.36
	SA	96,851,843	73,975,213	5,967,3371	2.64	4.44	6.06
	QA	21,529,509	22,041,625	38,137,765	2.24	3.45	4.11
	KW	12,139,935	15,956,478	10,062,579	3.52	3.98	5.58
	BH	6,644,680	8,683,116	7,467,486	6.58	7.90	9.18
	OM	4,155,795	6,745,862	6,397,893	3.22	4.01	5.55
	Total	196,530,184	178,327,413	171,544,880	3.51	4.86	6.31
IB	AE	15,555,298	11,407,684	9,753,137	2.65	6.23	8.14
	SA	68,496,296	45,031,798	37,807,771	1.43	1.95	3.01
	QA	12,844,002	10,772,994	13,351,518	1.59	2.03	3.27
	KW	19,533,126	22,659,197	18,364,591	2.18	2.94	4.56
	BH	5,772,538	5,153,380	2,695,177	3.47	4.86	11.95
	OM	397,405	397,404	383,108	1.01	1.01	1.06
	Total	122,598,665	95,422,457	82,355,302	2.06	3.17	5.33

Table 3: Returns for the GCC banking country sectors

This table presents descriptive statistics, for each country banking sectors returns (CB, CBw and IB) and for the corresponding market index returns and crude oil index returns. The sample consists of 2608 observations, for the period from January 2005 to December 2014. The descriptive statistics are calculated for three sub-periods: the first is the pre-crisis period which includes 520 observation from the beginning of January 2005 until the end of December 2006, the second is the crisis period which includes 523 observation from the beginning of January 2007 until the end of December 2008, the third is the post crisis period which includes 1565 observation from the beginning of January 2009 until the end of December 2014.

Banking	Std. Dev.			Skewness			Min			Max		
Sectors	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
AE_CB	2.02	1.81	1.58	1.61	5.11	16.64	-9.85	-7.14	-7.95	9.14	8.37	11.49
AE_CBw	1.39	1.07	1.06	7.93	33.28	10.73	-5.18	-4.02	-7.01	7.22	6.39	8.91
AE_IB	2.25	1.88	1.23	34.57	8.04	25.96	-10.77	-8.78	-7.39	13.09	8.72	10.68
AE_ind	2.07	2.27	1.78	-81.91	-176.83	34.58	-11.71	-17.26	-10.66	8.35	10.98	18.63
BH_CB	0.06	0.07	0.11	-44.75	254.36	43.80	-0.48	-0.47	-0.96	0.34	0.63	0.86
BH_CBw	0.97	1.20	1.01	63.07	-14.92	-185.95	-4.34	-5.97	-13.71	5.00	6.30	4.54
BH_IB	0.93	1.27	1.74	65.26	90.38	73.95	-3.80	-5.56	-27.71	5.34	10.07	30.41
BH_ind	1.00	1.46	1.31	368.70	-233.15	-393.70	-5.05	-11.60	-23.43	11.50	7.17	7.84
KW_CB	1.96	1.93	1.63	52.32	27.61	-15.70	-10.52	-9.45	-9.76	8.44	8.88	8.11
KW_CBw	2.55	2.67	3.06	62.28	8.25	-35.93	-8.79	-10.54	-25.39	11.27	12.23	14.26
KW_IB	1.04	1.63	1.37	38.39	-31.66	-12.17	-3.18	-6.47	-7.20	4.94	6.29	7.84
KW_ind	1.37	1.62	1.25	-267.97	-165.96	-56.19	-14.77	-11.57	-10.52	7.90	6.58	9.20
OM_CB	0.91	1.82	1.13	-21.99	-101.44	20.79	-4.27	-10.80	-6.91	4.14	7.54	6.61
OM_CBw	3.05	1.87	1.24	95.20	-70.69	-26.02	-46.58	-10.58	-9.30	48.74	8.74	8.98
OM_IB	0.01	0.01	0.86	-151.70	-145.79	-9.62	-0.03	-0.04	-11.47	-0.01	-0.01	10.53
OM_ind	0.92	1.68	0.89	38.76	-103.39	-63.45	-4.77	-8.70	-6.50	4.82	8.04	5.94
QA_CBw	1.96	2.04	1.42	22.13	-27.73	10.29	-6.11	-9.75	-8.23	8.35	9.25	8.36
QA_IB	1.88	2.60	1.35	-8.81	29.07	62.16	-8.91	-18.26	-9.08	8.03	20.49	9.10
QA_ind	1.95	2.02	1.23	371.42	-119.92	17.33	-8.06	-13.17	-8.55	24.68	9.18	11.26
SA_CBw	2.00	2.10	1.09	-31.95	-30.56	52.36	-10.46	-9.80	-7.07	10.54	8.48	8.06
SA_IB	3.76	2.28	1.23	-247.18	5.74	24.89	-43.11	-10.27	-7.52	30.24	9.55	9.15
SA_ind	2.46	2.11	1.14	-37.05	-73.36	-39.48	-11.68	-10.33	-7.55	16.40	9.09	9.04
Crude oil_ind	2.47	4.13	3.78	-7.28	-32.94	-14.87	-10.65	-20.56	-19.92	6.98	25.18	17.75

Table 4: MES for the GCC country banking sectors

This provides the MES measure for each country banking sector, the netted MES measure obtained using partial correlations, and the MES measure calulated using, as market index, the oil index. The MES is represented in million U.S. dollars.

Sector	Country	Standard-MES			Netted-MES			Oil-MES		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
CB	AE	0.898	0.925	0.774	0.081	0.133	0.116	0.206	0.195	0.170
	KW	0.461	0.449	0.419	-0.177	-0.129	-0.137	0.134	0.130	0.121
	BH	0.004	0.004	0.006	-0.184	-0.166	-0.182	-0.001	-0.001	-0.001
	OM	0.885	2.065	1.407	0.190	0.270	0.212	0.091	0.189	0.124
	Average	0.562	0.861	0.651	-0.023	0.027	0.002	0.107	0.128	0.103
CBw	AE	1.368	1.309	1.328	0.192	0.165	0.170	0.268	0.257	0.316
	SA	1.854	3.107	1.612	0.024	0.195	0.135	0.288	0.532	0.317
	QA	1.536	1.979	1.495	-0.054	0.118	0.136	0.369	0.349	0.248
	KW	1.526	3.010	3.420	0.140	0.190	0.355	0.580	0.565	0.663
	BH	0.219	0.263	0.220	0.091	0.111	0.093	0.071	0.083	0.071
	OM	0.383	2.274	2.277	-0.046	0.678	0.730	0.232	0.248	0.220
	Average	1.148	1.990	1.725	0.058	0.243	0.270	0.301	0.339	0.306
IB	AE	2.601	2.162	1.424	0.076	-0.012	0.102	0.651	0.525	0.346
	SA	3.219	3.723	2.549	0.865	0.748	0.436	0.275	0.192	0.564
	QA	1.700	2.150	1.377	0.203	0.015	0.227	0.383	0.488	0.250
	KW	0.837	1.122	1.130	0.081	0.103	0.103	0.288	0.377	0.337
	BH	0.837	1.122	1.130	-0.011	0.420	0.333	0.219	0.231	0.240
	OM	0.008	0.006	0.149	0.013	0.004	-0.009	-0.008	-0.006	-0.056
	Average	1.534	1.714	1.293	0.205	0.213	0.199	0.3012	0.301	0.280

Table 5: SRISK for the GCC country banking sectors

This table provides the SRISK measure for each country banking sector, the netted SRISK measure obtained using partial correlations, and the SRISK measure calulated using, as market index, the oil index. The SRISK is represented in million U.S. dollars. The negative signs represent capital buffers.

Sector	Country	Standard-SRISK			Netted-SRISK			Oil-SRISK		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
CB	AE	-1,182,264	-1,154,628	-822,752	-1,395,242	-1,378,757	-998,080	-1,359,500	-1,359,618	-982,394
	KW	-1,407,381	-2,499,602	-1,651,925	-1,659,053	-2,854,090	-1,904,645	-8,467,785	-10,641,076	-5,416,677
	BH	-177,803	-217,408	-183,160	-184,981	-225,195	-190,215	-177,986	-217,638	-183,430
	OM	-717,726	-632,432	-590,781	-831,122	-919,684	-834,147	-850,295	-938,832	-855,628
	Total	-348,5174	-4,504,070	-3,248,618	-4,070,398	-5,377,727	-3,927,086	-10,855,566	-13,157,164	-7,438,130
CBw	AE	-32,061,502	-21,857,706	-13,009,710	-41,109,483	-29,740,662	-21,182,159	-40,381,008	-29,151,314	-20,206,275
	SA	-58,101,930	-26,728,430	-18,715,270	-76,996,210	-49,393,736	-30,517,307	-72,564,308	-45,813,337	-28,837,021
	QA	-13,355,596	-10,481,205	-18,109,431	-18,102,985	-15,637,098	-24,641,180	-16,500,317	-14,833,170	-24,216,696
	KW	-6,102,061	-5,440,674	-1,564,671	-8,459,675	-10,501,937	-5,045,384	-1,365,381	-2,441,896	-1,551,511
	BH	-2,895,363	-3,047,329	-1,852,825	-3,031,552	-3,257,886	-2,002,202	-3,053,992	-3,298,737	-2,028,379
	OM	-2,970,937	-3,006,192	-1,611,437	-11,825,437	-4,134,223	-2,839,847	-2,934,529	-4,583,674	-3,325,390
	Total	-115,487,388	-70,561,537	-54,863,344	-159,525,340	-112,665,541	-86,228,079	-136,799,534	-100,122,128	-80,165,273
IB	AE	-7,161,829	-3,864,856	-1,759,827	-12,126,528	-6,891,319	-3,619,224	-10,735,163	-6,032,126	-3,237,214
	SA	-40,935,488	-19,768,305	-16,197,828	-51,974,588	-33,504,901	-26,114,495	-57,420,471	-37,675,220	-25,417,642
	QA	-8,246,349	-6,181,937	-7,253,894	-10,795,230	-9,022,004	-9,246,876	-10,455,230	-8,287,985	-9,275,252
	KW	-14,518,054	-13,239,277	-8,371,496	-15,860,229	-17,315,503	-11,364,365	-15,215,612	-16,420,691	-10,722,131
	BH	-3,425,861	-2,376,908	-209,111	-4,183,122	-2,920,585	-93,438	-3,962,863	-3,027,573	-142,795
	OM	-364,865	-364,963	-343,187	-364,509	-365,131	-351,694	-365,894	-365,770	-354,353
	Total	-74,652,446	-45,796,246	-33,717,120	-95,304,206	-70,019,442	-50,790,091	-98,155,233	-71,809,366	-49,149,387

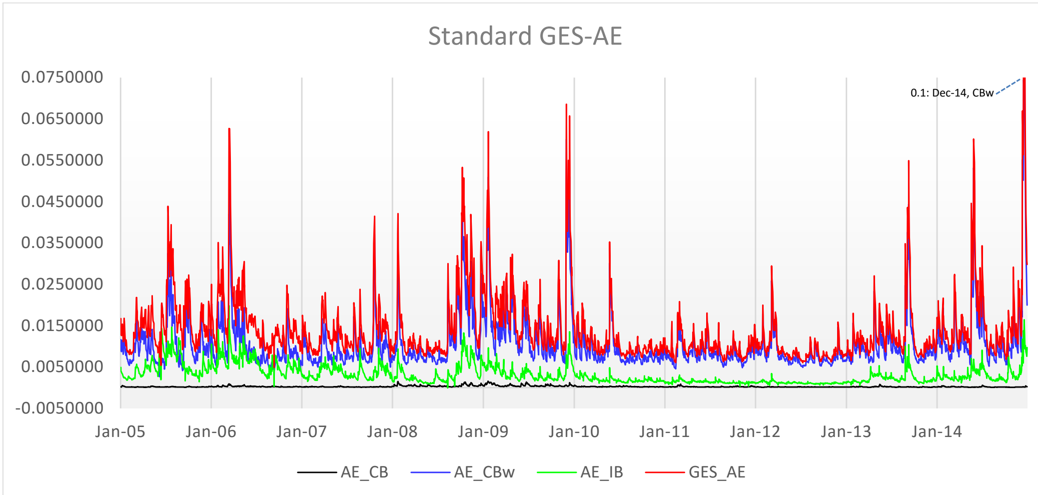
Table 6: ΔCoVaR for the GCC country banking sectors

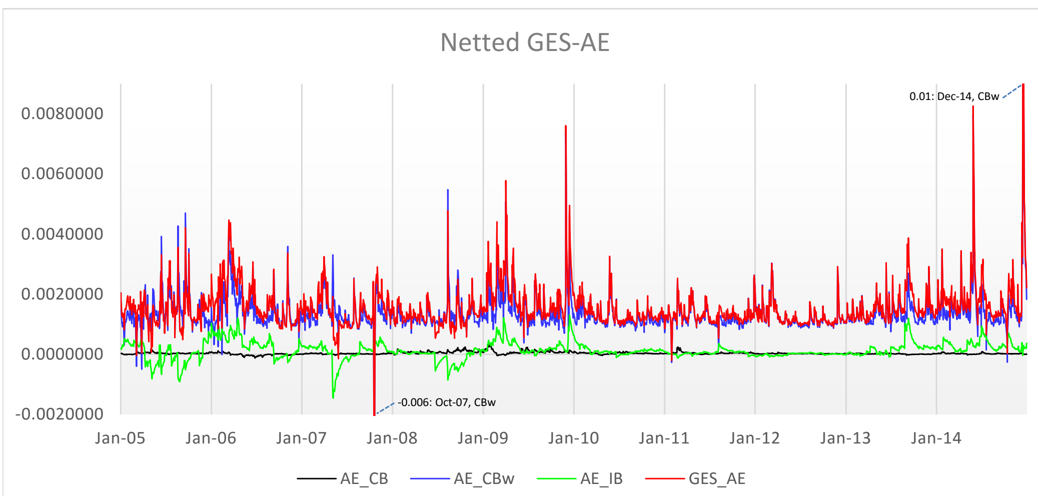
This table provides the ΔCoVaR measure for each country banking sector, the netted ΔCoVaR measure obtained using partial correlations, and ΔCoVaR measure obtained replacing the market index with the oil index.

Sector	Country	Standard-ΔCoVaR			Netted-ΔCoVaR			Oil-ΔCoVaR		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
CB	AE	0.395	0.499	0.359	0.004	0.045	0.025	0.150	0.191	0.190
	KW	0.243	0.259	0.229	-0.007	0.019	-0.004	0.143	0.182	0.181
	BH	0.005	0.007	0.006	-0.003	-0.003	-0.003	-0.014	-0.018	-0.018
	OM	0.500	1.195	0.735	0.157	0.162	0.088	0.154	0.207	0.206
	Average	0.286	0.490	0.332	0.038	0.056	0.026	0.108	0.141	0.140
CBw	AE	1.354	1.704	1.460	0.091	0.089	0.086	0.192	0.389	0.571
	SA	1.643	2.146	1.132	-0.017	0.198	0.171	0.164	0.485	0.549
	QA	0.958	1.331	1.104	0.168	0.317	0.208	0.357	0.454	0.447
	KW	0.464	1.106	0.950	0.059	0.120	0.242	0.288	0.358	0.373
	BH	0.136	0.171	0.160	0.031	0.034	0.034	-0.057	-0.076	-0.071
	OM	0.171	0.897	0.576	0.041	0.234	0.158	0.270	0.344	0.342
	Average	0.788	1.226	0.897	0.062	0.165	0.150	0.202	0.326	0.368
IB	AE	1.382	1.458	1.206	0.093	-0.070	0.122	0.280	0.361	0.357
	SA	1.536	2.007	1.045	0.580	0.453	0.315	0.062	0.078	0.677
	QA	1.024	1.159	1.013	0.147	-0.073	0.211	0.286	0.375	0.365
	KW	0.004	0.012	0.010	0.145	0.156	0.140	0.280	0.357	0.355
	BH	0.257	0.478	0.415	-0.110	0.138	0.075	0.125	0.159	0.158
	OM	0.057	0.063	0.036	0.140	0.060	0.027	0.049	0.063	0.057
	Average	0.710	0.863	0.621	0.166	0.111	0.148	0.180	0.232	0.328

Figure 2: MES and GES for AE Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for United Arab Emirates (AE) using the standard, netted and oil systemic risk measurement variations. The MES of the AE-CB sector is denoted in black, the MES of AE-CBw in blue, the MES of AE-IB in green and the GES of AE banking system portfolio GES-AE is denoted in red. The systemic risk driver of AE, based on banking sectors vulnerability, is the CBw sector.





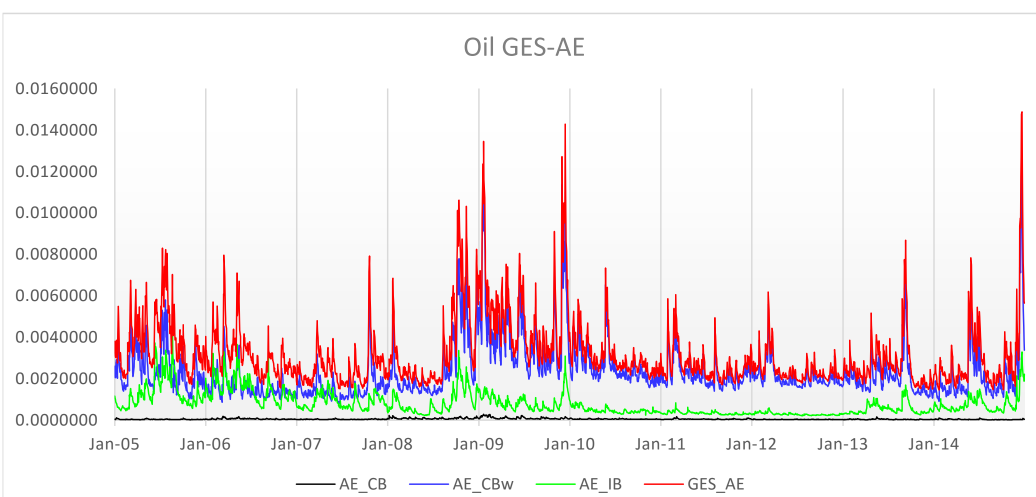


Figure 3: MES and GES for BH Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for Bahrain (BH) using the standard, netted and oil systemic risk measurement variations. The MES of the BH-CB sector is denoted in black, the MES of BH-CBw in blue, the MES of BH-IB in green and the GES of BH banking system portfolio GES-BH is denoted in red. The systemic risk driver of BH, based on banking sectors vulnerability, is the IB sector.

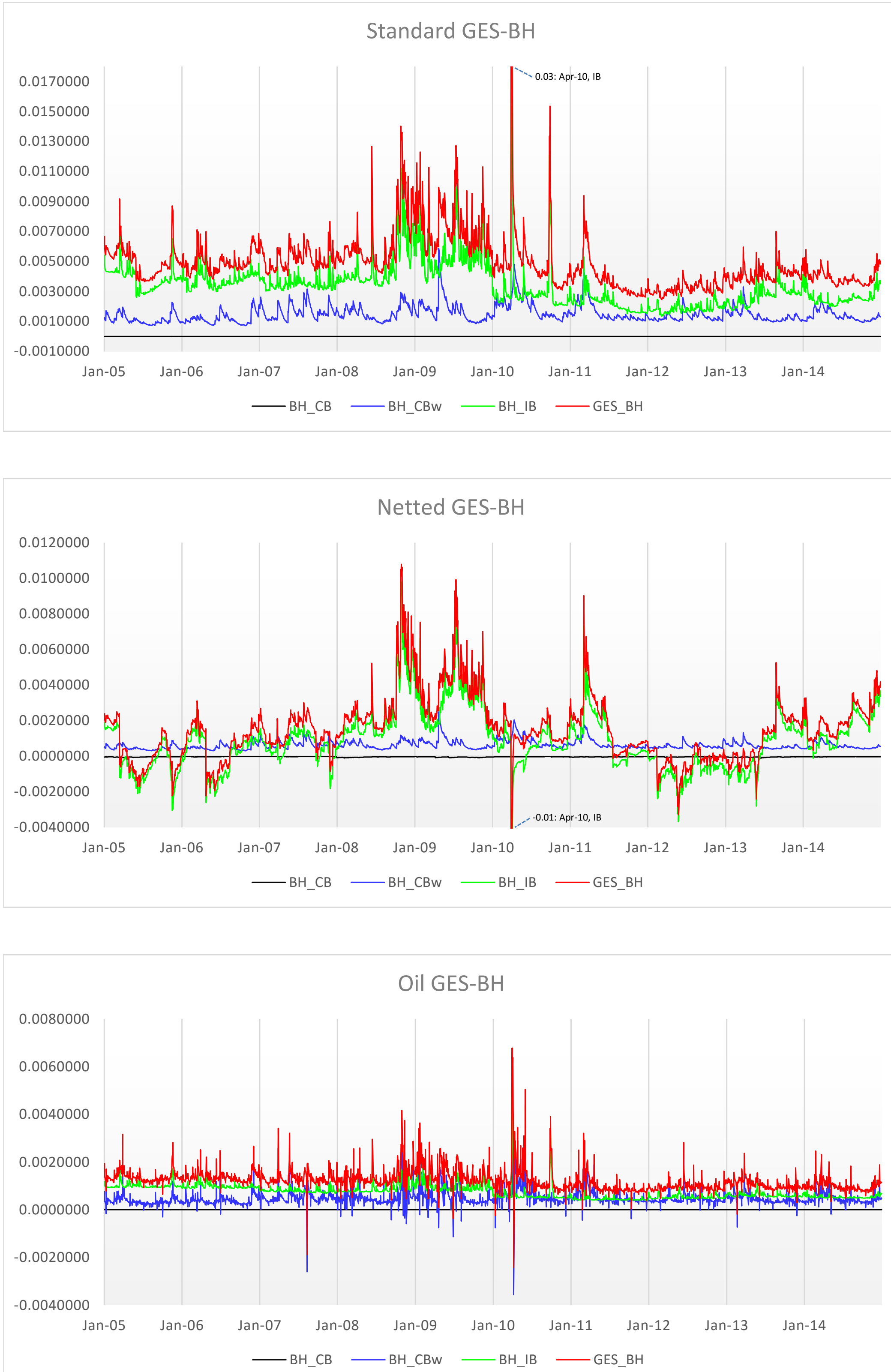
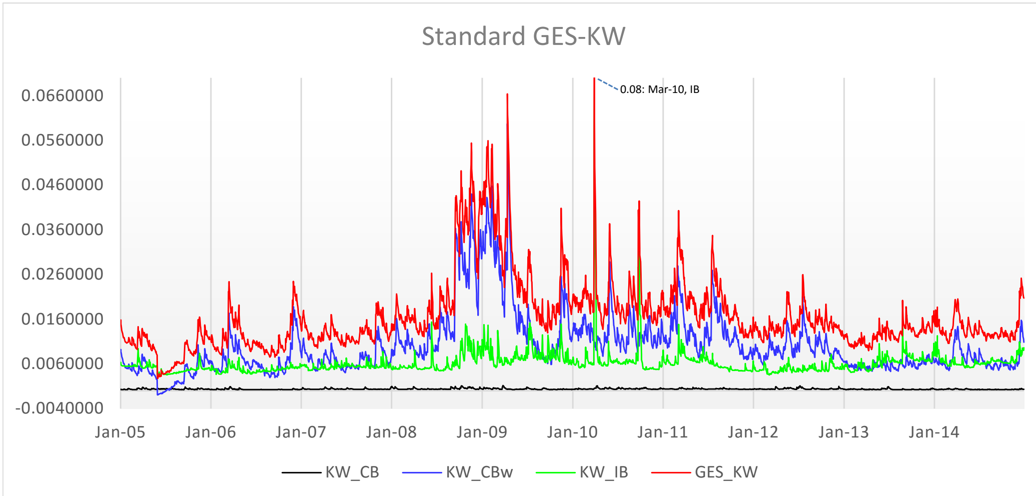
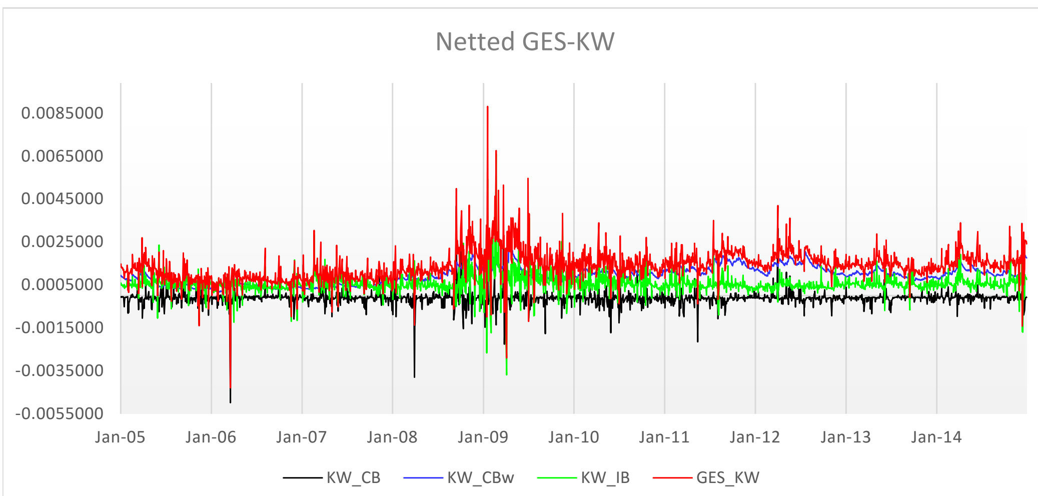


Figure 4: MES and GES for KW Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for Kuwait (KW) using the standard, netted and oil systemic risk measurement variations. The MES of the KW-CB sector is denoted in black, the MES of KW-CBw in blue, the MES of KW-IB in green and the GES of KW banking system portfolio GES-KW is denoted in red. The systemic risk driver of KW, based on banking sectors vulnerability, is the CBw sector.





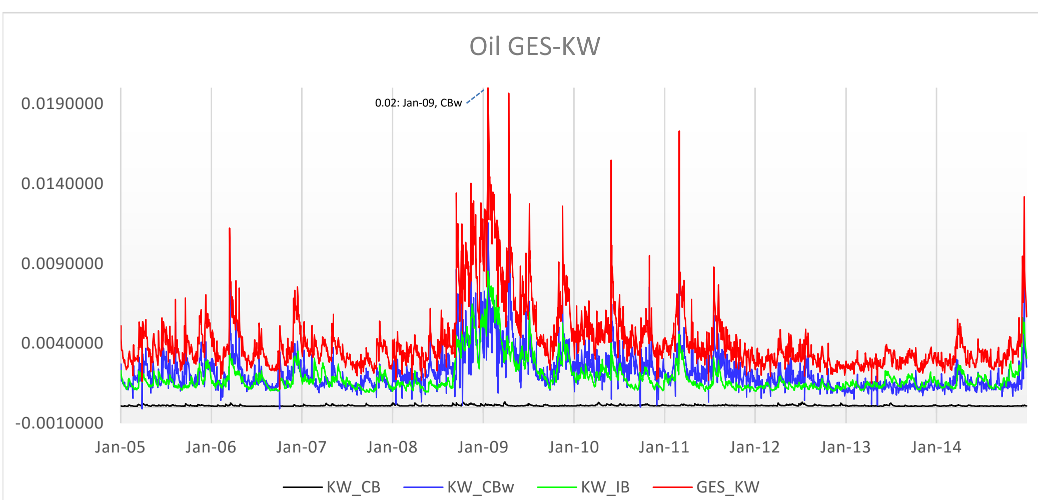


Figure 5: MES and GES for OM Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for Oman (OM) using the standard, netted and oil systemic risk measurement variations. The MES of the OM-CB sector is denoted in black, the MES of OM-CBw in blue, the MES of OM-IB in green and the GES of OM banking system portfolio GES-OM is denoted in red. The systemic risk driver of OM, based on banking sectors vulnerability, is the CBw sector.

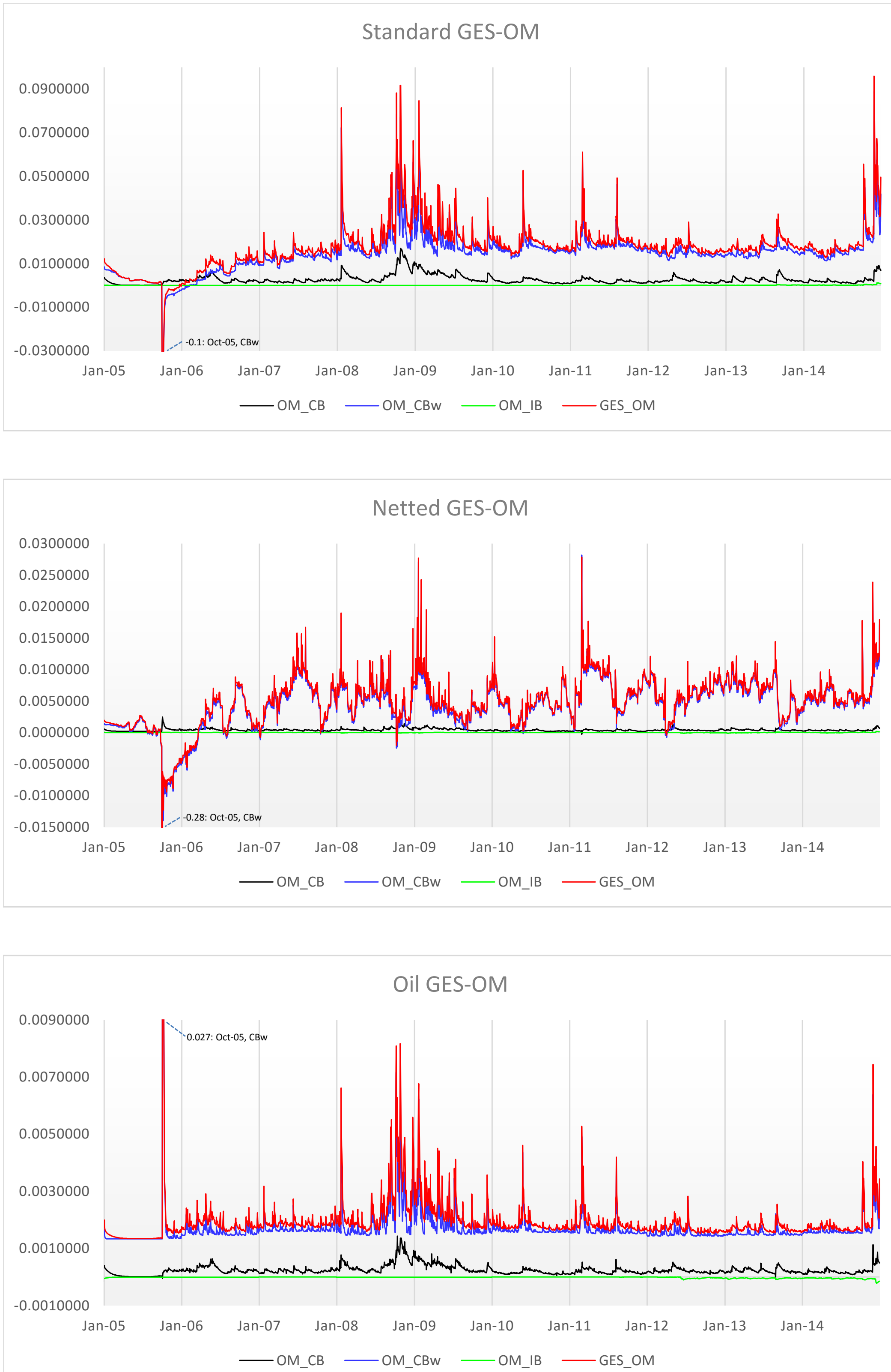
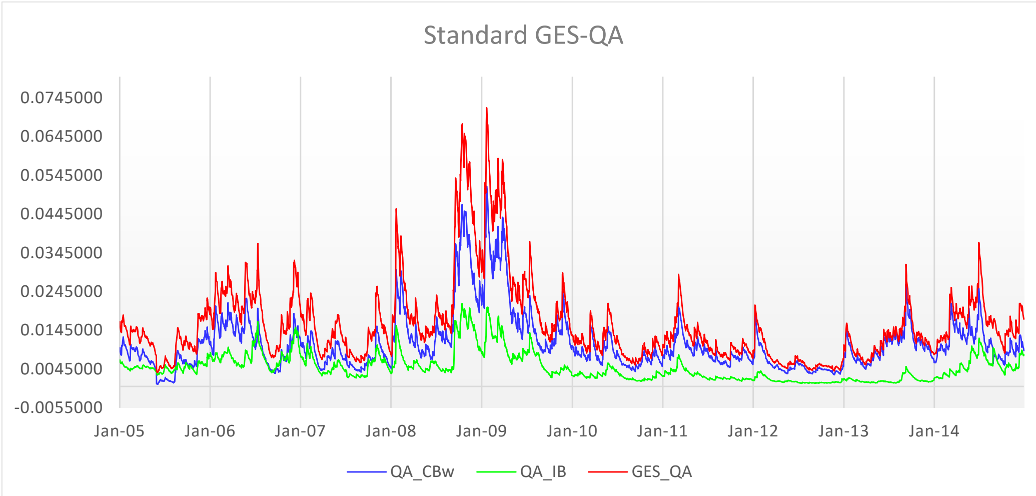
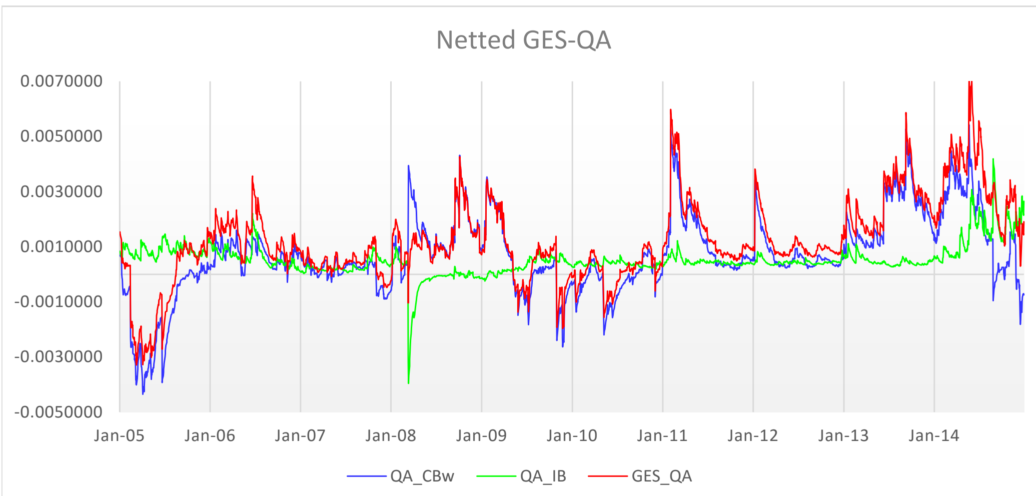


Figure 6: MES and GES for QA Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for Qatar (QA) using the standard, netted and oil systemic risk measurement variations. The MES of the QA-CB sector is denoted in black, the MES of QA-CBw in blue, the MES of QA-IB in green and the GES of QA banking system portfolio GES-QA is denoted in red. The systemic risk driver of QA, based on banking sectors vulnerability, is the CBw sector.





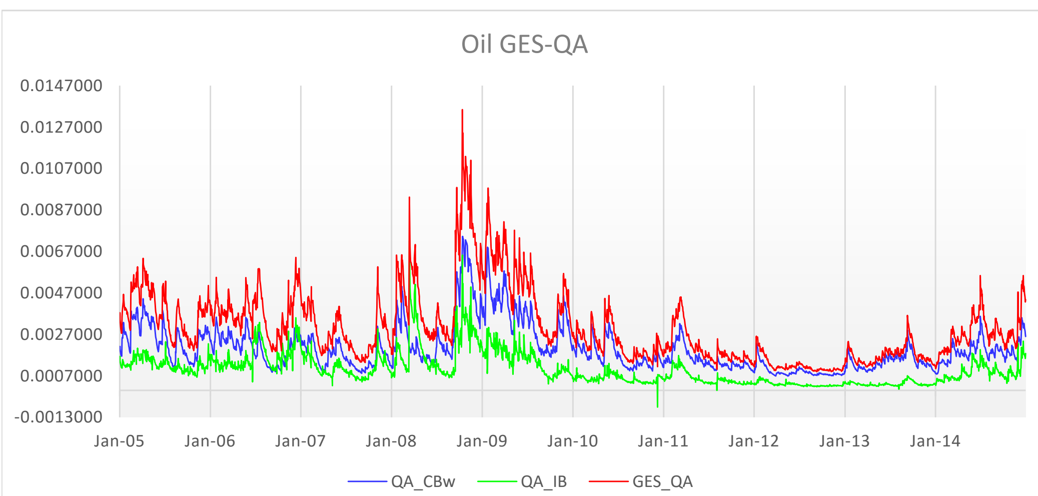
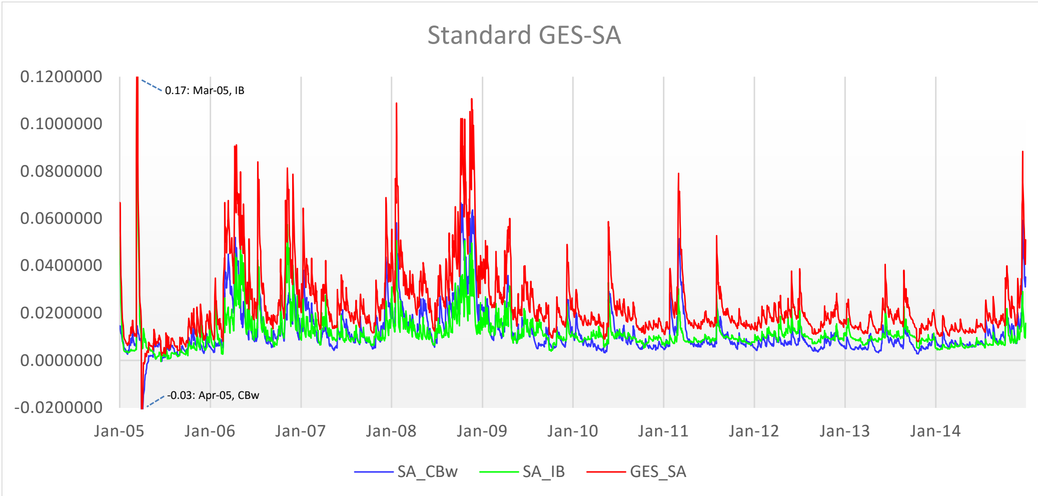
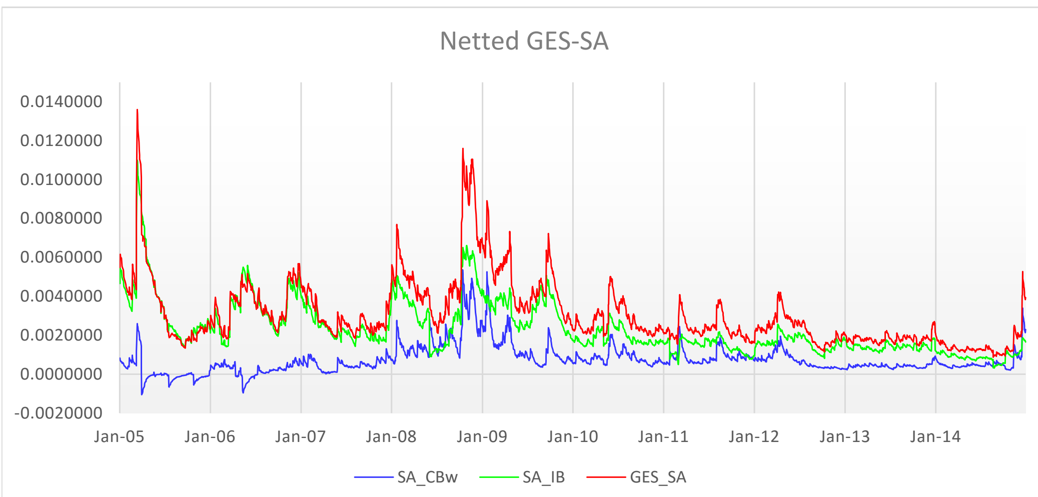


Figure 7: MES and GES for SA Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of MES per banking sector type, and GES of the banking system portfolio for Saudi Arabia (SA) using the standard, netted and oil systemic risk measurement variations. The MES of the SA-CB sector is denoted in black, the MES of SA-CBw in blue, the MES of SA-IB in green and the GES of SA banking system portfolio GES-SA is denoted in red. The systemic risk driver of SA, based on banking sectors vulnerability, is the IB sector.





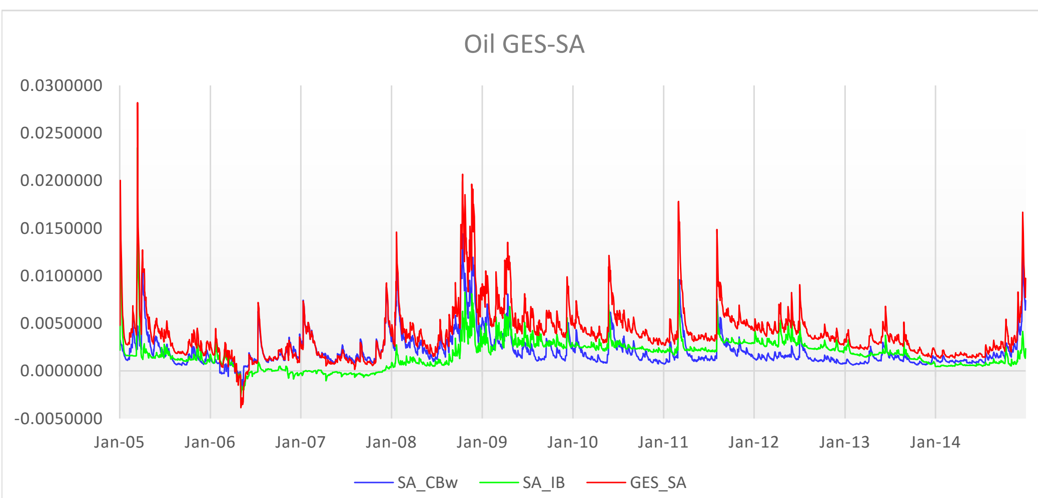


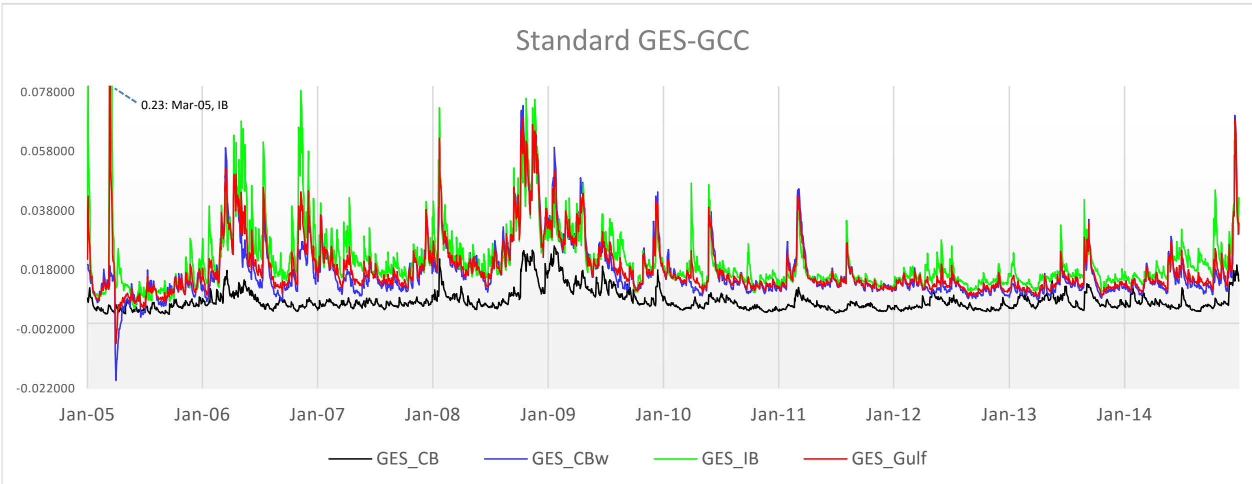
Table 7: Rank Concentration Ratio of the Banking Sectors

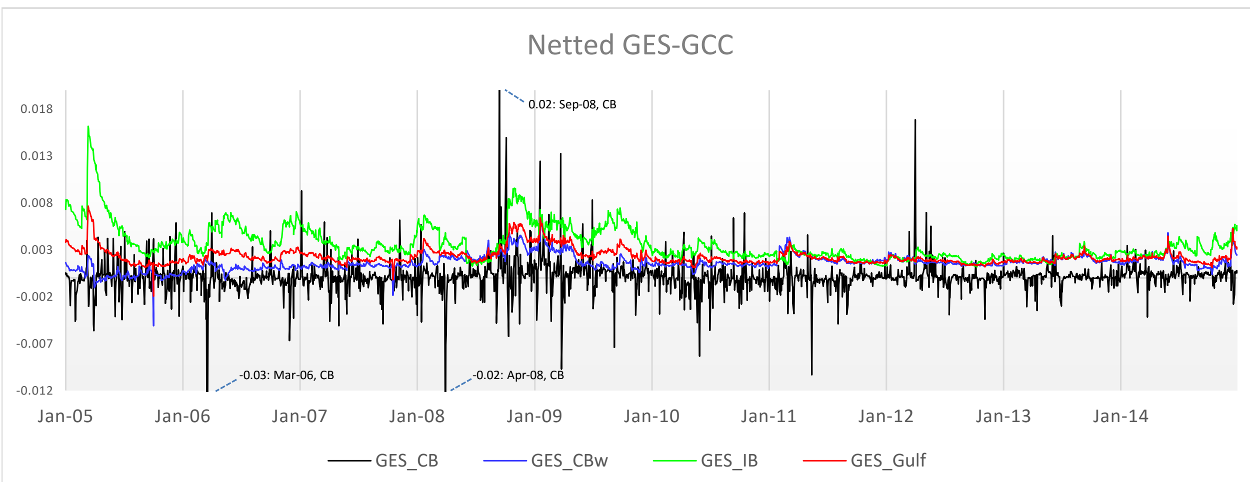
This table provides the Rank Concentration Ratio, which summarizes centrality measures, based on the aggregate score of the ranks that each banking sector occupies within a specific centrality measure. A higher Ranking *RC* indicates a higher systemic importance for the specified banking sector type.

Banking Sector	***Betweenness***			***Closeness***			***Node Degree***			***Eigen Vector Centrality***		
	pre-crisis	***during-crisis***	***post-crisis***	***pre-crisis***	***during-crisis***	***post-crisis***	***pre-crisis***	***during-crisis***	***post-crisis***	***pre-crisis***	***during-crisis***	***post-crisis***
	RC% of Netted MES											
CB	0.35	0.15	0.19	0.33	0.21	0.23	0.29	0.21	0.23	0.21	0.21	0.21
CBw	0.29	0.54	0.35	0.30	0.43	0.29	0.31	0.43	0.29	0.32	0.38	0.30
IB	0.35	0.31	0.46	0.37	0.37	0.49	0.40	0.37	0.49	0.47	0.42	0.49
	RC% of Netted SRISK											
CB	0.31	0.29	0.31	0.34	0.29	0.32	0.34	0.29	0.32	0.31	0.26	0.29
CBw	0.32	0.27	0.45	0.31	0.32	0.44	0.32	0.32	0.44	0.29	0.32	0.46
IB	0.38	0.44	0.24	0.35	0.39	0.24	0.34	0.39	0.24	0.40	0.41	0.26
	RC% of Netted DeltaCoVaR											
CB	0.28	0.16	0.27	0.32	0.17	0.27	0.32	0.17	0.24	0.35	0.13	0.20
CBw	0.24	0.43	0.32	0.29	0.46	0.35	0.29	0.46	0.32	0.27	0.49	0.32
IB	0.48	0.41	0.40	0.38	0.37	0.39	0.38	0.37	0.44	0.38	0.38	0.49

Figure 8: GES of the Gulf Region Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, of the GES per banking sector type, and GES for the overall banking system portfolio of the Gulf Cooperation Region (GCC), using the standard, netted and oil systemic risk measurement variations. The GES of the CB sector, GES-CB, is denoted in black, the GES of the CBw sector, GES-CBw, is in blue, the GES of the IB sector, GES-IB, is in green and the GES of GCC overall banking system portfolio, GES-Gulf, is denoted in red. The systemic risk driver of the GES-Gulf, based on banking sectors vulnerability, is mostly related to the CBw sector.





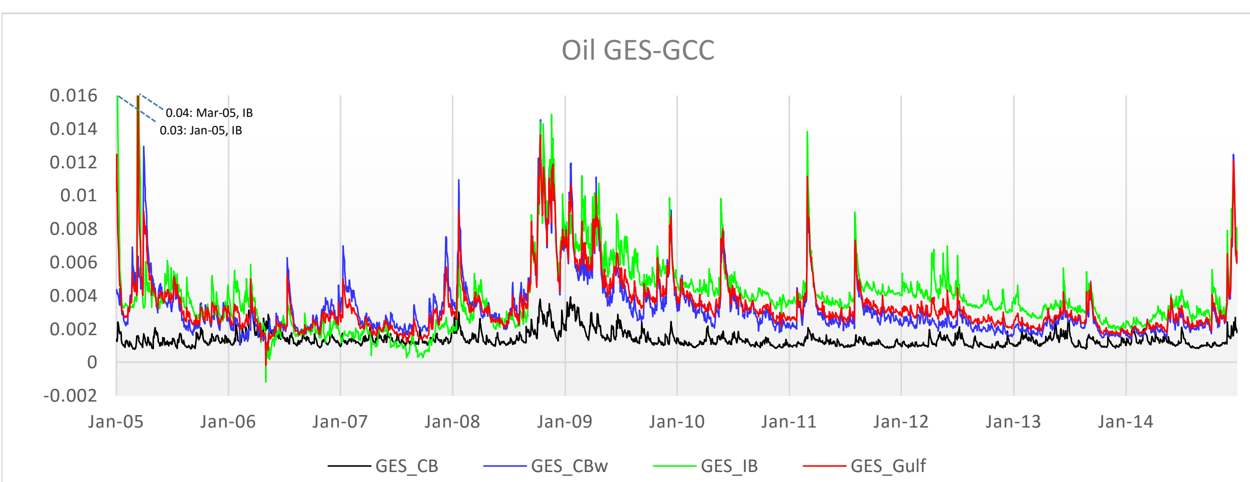
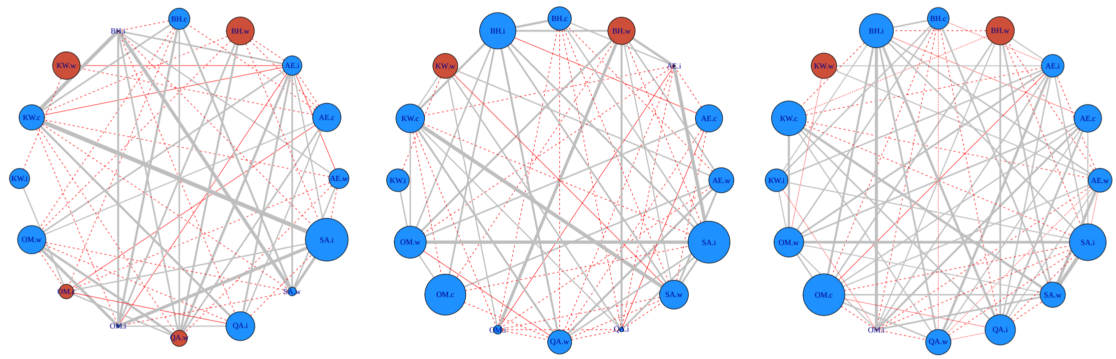


Figure 9: Netted MES Network

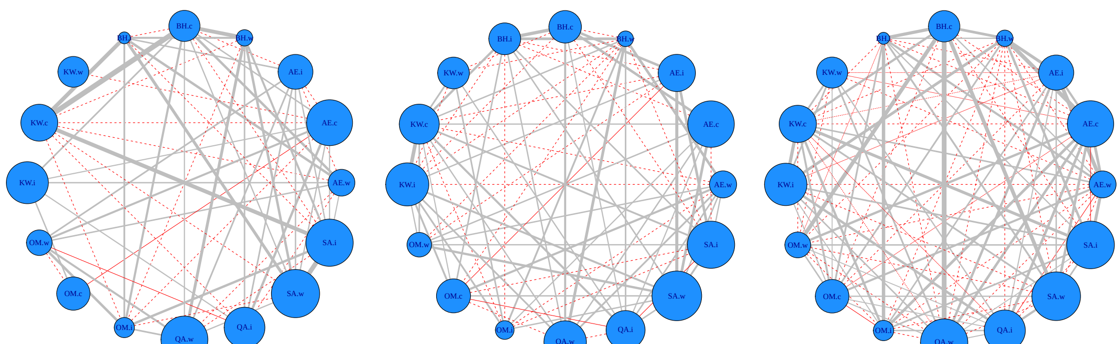
In this figure, we present the netted MES partial correlation network for the three sub-periods of a) pre-crisis, b) during-crisis and c) post-crisis. The blue node color indicate a positive risk value, whereas the red indicates a negative one. The gray link color indicates a positive partial correlation, whereas the red indicates a negative one. The larger size of a node indicate higher risk magnitude, and the thickness of the link indicate the strength of the partial correlation.



(a) Pre-Crisis *(b) During-Crisis* *(c) Post-Crisis*

Figure 10: Netted SRISK Network

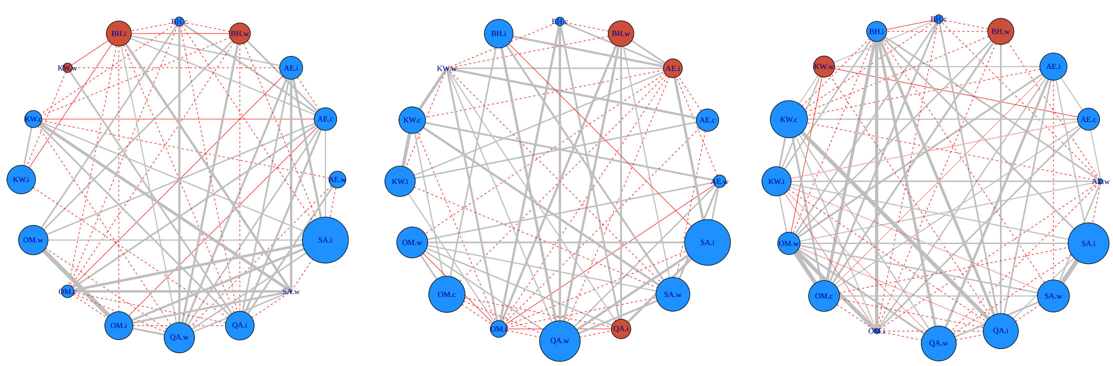
In this figure, we present the netted SRISK partial correlation network for the three sub-periods of a) pre-crisis, b) during-crisis and c) post-crisis. The blue node color indicate a capital buffer, whereas the red indicates a capital shortfall. The gray link color indicates a positive partial correlation, whereas the red indicates a negative one. The larger node size indicates a higher capital buffer, and the thickness of the link indicate the strength of the partial correlation.



(a) Pre-Crisis *(b) During-Crisis* *(c) Post-Crisis*

Figure 11: Netted ΔCoVaR Network

In this figure, we present the netted ΔCoVaR partial correlation network for the three sub-periods of a) pre-crisis, b) during-crisis and c) post-crisis. The blue node color indicate a positive risk value, whereas the red indicates a negative one. The gray link color indicates a positive partial correlation, whereas the red indicates a negative one. The larger size of a node indicate higher risk magnitude, and the thickness of the link indicate the strength of the partial correlation.



(a) Pre-Crisis *(b) During-Crisis* *(c) Post-Crisis*

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