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 six GCC member 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 CoVaR to identify which sector is more vulnerable to a systemic event. We also compute weighted average GES to determine which sector is most synchronised with the market. Moreover, we use graphical network models to determine the most interconnected banking sector that can more easily spread a systemic shock to the whole system. Using a sample of 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, it has the highest synchronicity with the market, and it is the most interconnected banking sector during crisis times.

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1. Introduction

Since its inception in 1970s, Islamic banking has expanded very rapidly into many Muslim countries[1]. This trend has transformed the structure of 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.

Alongside the rapid growth of Islamic banking, researchers have extensively examined various aspect of this innovation. In particular, its standalone risks such as credit, insolvency, market, liquidity and interest rate risks have been investigated in the literature (Abedifar et al., 2013; Čihák and Hesse, 2010; Erge and Arslan, 2013; Fakhfekh et al., 2016; Hasan and Dridi, 2011; Pappas et al., 2017). Surprisingly, however, the impact of introducing Islamic banking on resilience of financial system has attracted little attention from academia, whereas 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).

This paper seeks to fill the void and explores the systemic importance of Islamic banking and the stability of dual banking systems. This is worthwhile to explore given that the rapid transformation of financial systems in several Muslim countries has already attracted the attention of policy makers and market participants towards the consequence for systemic risk and financial stability of having dual banking systems. For instance, Qatari regulators were the first to react to this phenomenon. In 2010, they restricted activities of commercial banks that offer both Islamic and conventional banking, and in 2011, they ultimately banned conventional banks from providing Islamic financial products[2].

There are two channels for provision of Islamic banking services to the society: a) Islamic branches or windows of conventional banks (CBw), and b) fully fledged Islamic

[1] 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.

[2] https://www.ft.com/content/0ab164e0-3858-11e0-8257-00144feabdc0

banks (IB). The choice between these two options can affect the banking system stability. 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 address the consequence of these alternative banking system configurations on financial stability. The link between financial systems architecture and systemic risk is an ongoing debate among regulators and researchers even in advanced economies. The extant literature underscores the importance of the structure of financial systems in forming systemic events (Acemoglu et al., 2015; Gofman, 2017; Roukny et al., 2016, among others), and highlights that financial institutions have become more homogeneous and intertwined[3]. 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. Paul Volcker, the former Fed chairman, said "the risk of failure of large, interconnected firms must be reduced, whether by reducing their size, curtailing their interconnections, or limiting their activities" (Volcker, 2012). Richard Fisher, the CEO of Fed Dallas argued that "I favour an international accord that would break up these institutions into more manageable size" (Fisher, 2011). As a result, we observe that post-crisis regulatory reforms in Europe and the US (such as Dodd Frank Act, 2011; Erkki Liikanen Report, 2012) recommend restricting activities or structure of large financial institutions to mitigate their complexity and interconnectedness.

[3]This is because of the inclination for holding market portfolio, which is recommended by modern portfolio theory (Markowitz, 1952), and the de-regulations in Europe and the US following the Second Banking Directive of 1989 and the Gramm-Leach-Bliley Act (1999).

In this paper, we study the banking systems of the Gulf Cooperation Council (GCC) member countries: Bahrain (BH), Kuwait (KW), Oman (OM), Qatar (QA), Saudi Arabia (SA), and the United Arab Emirates (AE). These countries hold nearly 40% of the total global Islamic banking assets, and a significant market share of the Islamic banking sector (IFSB, 2016). Moreover, they are a homogeneous sample of countries, whereas recent studies show significant cross-country variations in the performance of Islamic banks across Muslim countries due to different institutional environments (see eg. Bitar et al., 2017). These six countries have a similar Muslim share in population and a similar economic environment. In addition, the six 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). Furthermore, it is found that the oil index volatility has a spillover effect on the stock market return in the GCC region (see e.g. Arouri and Rault, 2012; Arouri et al., 2011; Fayyad and Daly, 2011; Maghyereh and Al-Kandari, 2007; Mohanty et al., 2011; Zarour, 2006), which enables us to use the crude oil (WTI) index as a unified volatility index for all countries and test the robustness of our results.

We use a rigorous and robust methodology in our analysis. We employ “Standard” market based measures that include MES, SRISK and ΔCoVaR to gauge systemic risk of IB, CB and CBw sectors. All measures are based on the DCC-GARCH model introduced by Engle (2002). This helps 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; Caporale et al., 2005; Cappiello et al., 2006; Ronn et al., 2009). Moreover, we extend the DCC approach by using partial correlation coefficients to exclude the impact of other assets in the market on computing the co-movements between two assets. We also use the crude oil WTI returns as a unified volatility index for all countries. We examine banking sectors’ synchronicity with the market by applying the Component Expected Shortfall technique introduced by Banulescu and Dumitrescu (2015). Finally, we employ a novel application of the graphical network models, described in Giudici and Spelta (2016), to identify the most interconnected banking sector.

The results of our analysis, based on daily stock returns of 79 publicly traded banks and bank holding companies over the period 2005-2014, indicate that the CBw sector is the least resilient sector, has the highest synchronicity with the market and the greatest importance in destabilising the financial system of the GCC countries.

In addition, the graphical network model well describes the interconnections among banking systems of different countries. It shows that the CBw sector, especially during crisis periods, is the most interconnected sector, whereas the IB depicts a negative correlation with the CB sector, indicating diversification benefits of having both in a system.

This paper contributes to the Islamic banking literature. It provides significant evidence on the relative importance of Islamic banking in the configuration of financial systems, and thereby mitigation or resonance of systemic risk. 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 lkay endeniz Ync, 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; Aysan et al., 2014), efficiency (Abdul-Majid et al., 2011a,b, 2009; Al-Jarrah and Molyneux, 2006; Johnes et al., 2015), insolvency risk (Čihák and Hesse, 2010; Pappas et al., 2017) and market power (Weill, 2011). Such differences stimulate the overall performance of dual banking systems (Abedifar et al., 2016; Gheeraert and Weill, 2015; Gheeraert, 2014). In view of the existing literature, our work unravel that the mechanism of introducing Islamic banking can affect stability and resilience of dual banking systems against systemic events.

The remainder of this paper is organized as follows. Section two outlines our hypotheses, methodology and statistical Specifications. Section three describes the data and summary statistics. Section four discuss our empirical findings. The final Section provides summary and concluding remarks.

2. Hypotheses, Methodology and Statistical Specifications

Systemically Important Financial Institutions ($SIFI$) are defined by Finanacial 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 by testing the following three hypotheses:

Hypothesis 1: CBw has the highest systemic risk.
Hypothesis 2: CBw has the highest synchronicity with the market.
Hypothesis 3: CBw is the most interconnected sector.

To empirically test the first hypothesis, we compute systemic risk measures for each banking sector. We use Component Expected Shortfall approach to gauge synchronicity of banking sectors and the market index. Finally, we employ graphical network models to examine the third hypothesis.

Existing theories have conflicting predictions on these hypotheses. Earlier studies (see e.g. Allen and Gale, 2000; Freixas et al., 2000) suggest that financial resilience increases in a more interconnected system, because the loss of a failure is distributed among more creditors. However, recent studies have a different prediction. Blume et al. (2013) argue that in a highly interconnected financial system, the likelihood of emerging a systemic event increases. Gai et al. (2011) claim that financial stability declines with an increase in the complexity of the financial network. Castiglionesi et al. (2017) show that greater financial integration is associated with a more stable interbank interest rate in normal times, but it leads to larger interest rate spikes in crisis times.

2.1. Systemic Risk Measures

We employ several commonly used systemic risk measures for our analysis. We use the Marginal Expected Shortfall (MES) of Acharya et al. (2010), and the systemic risk measure (SRISK) of Acharya et al. (2012), extended by Brownlees and Engle (2017), 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 often used to identify the 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.

2.1.1. Marginal Expected Shortfall

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 function of the tail expectations for a country market index standardized return ε_{jt} and of the tail expectations for the banking sector standardized idiosyncratic return ξ_{sjt}:

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

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.

2.1.2. SRISK

The SRISK measure was introduced by Acharya et al. (2012), and extended by Brownlees and Engle (2017). 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 approximated with daily MES, such that $LRMES \simeq 1 - exp(-18 \times MES)$, using the threshold C fixed at $C = -40\%$. SRISK for institution i at time t is then defined by:

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

Note that using leverage definition $L_{it} = (D_{it} + MV_{it})/MV_{it}$, 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. SRISK of a banking sector is equal to the sum of SRISK of its related banks as SRISK can be linearly aggregated (see Acharya et al., 2012). 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. On the other hand, negative values of SRISK indicate capital surpluses.

2.1.3. ΔCoVaR

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, 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.

2.1.4. Component Expected Shortfall

To assess the vulnerability at the country level, we follow Banulescu and Dumitrescu (2015), who propose the Component Expected Shortfall measure, from which the expected shortfall of a system is measured by linearly aggregating the expected shortfalls of the individual components. In a similar fashion, we compute the Global Expected Shortfall (GES) of a country j as a linear aggregation of the expected shortfall of its banking sectors:

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

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 $\sum_{s=1}^{S} MV_{sjt}$; whereas S is the number of considered sectors (in our context, $S = 3$). Economically, a higher GES indicates a higher vulnerability of a (country-specific) market to a systemic event. Note that the GES is the sum of each banking sector's contribution and, therefore, it helps understanding the synchronicity of each sector to the whole market: the larger weight of a component in the sum indicates its higher synchronicity.

2.2. Graphical Network Models

Besides calculating systemic importance and synchronicity of banking sectors, we examine their interconnectedness, in order to detect the pattern of diffusion of systemic risk among them. To achieve this objective we follow Billio et al. (2012), 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 the banking sectors of the different countries as graphical nodes, and the systemic risk measures previously described as random variables associated to each node.

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 (3×6 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 is not significant, the corresponding systemic risk measures are conditionally independent and, therefore, the corresponding banking systems do not contage (directly) each other. Hence, to understand whether contagion between any two pairs of banking systems is significant, it is sufficient to calculate the corresponding partial correlation. All partial correlations can be simultaneously obtained 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 other nodes; b) betweenness centrality, to measure the intermediation 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 different 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 the banking sectors centrality ranks, we use the Ranking Concentration ratio (RC) as introduced by Hashem and Giudici (2016), which allows to express the importance of all the ranks that a sector occupies as a percentage. The larger the RC percentage value, the higher the systemic risk importance of a specified banking sector.

2.3. Statistical Specifications

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. 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 banks into three sectors, according to their bank type: IB, CB and CBw sectors. 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 weighted average return of the banking sector sj at time t according to the following formula:

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

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 $\sum_{i=1}^{n_{sj}} MV_i$.

2.3.1. Dynamic Conditional Correlations

For all systemic risk measures, we use the Dynamic Conditional Correlation model of Engle (2002) to estimate time-varying correlations between each banking system and the market. We follow Brownlees and Engle (2017) and base the DCC model on the GJR-GARCH of Glosten et al. (1993), to control for the heteroskedasticity effect in measuring correlations.

In this paper, the model is estimated, at each time point t with data coming from a $SJ \times 2$ matrix, whose rows contain the aggregate banking system returns r_{sjt} and the corresponding reference market returns r_{jt}. We assume that:

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

where $r_t = (r_{jt} r_{sjt})$ denotes the vector of market and banking sector returns, $\epsilon_t = (\varepsilon_{jt}\ \xi_{sjt})'$ 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 subsection.

2.3.2. Partial correlations

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 market. 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, and consider only direct relationships.

The partial correlation coefficient ρ_{ijV}, for any two variables X_i and X_j in a random vector X_V, can be defined by the correlation between the residuals from the regression of X_i on all other variables (excluding X_j) and the residuals from the regression of X_j on all other variables (excluding X_i):

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

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

In our study, the dependent variable of the first regression is the banking sector return r_{sj}, and the dependent variable of the second regression is the market return r_j. 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 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, 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 spurious components.

We finally remark that an alternative way of "netting" systemic risk measures is to explain them with a common factor which explains the volatility of all banking sectors. In the GCC region, such common factor is provided by the crude oil index (WTI). Indeed, the economies of the GCC countries are generally oil dependent, with oil constituting 48% of the GCC region GDP (Sturm et al., 2008).

3. Data and Descriptive Statistics

We select six GCC countries with dual banking systems: Saudi Arabia (SA), Kuwait (KW), Qatar (QA), United Arab Emirates (AE), Bahrain (BH) and Oman (OM).

IFSB (2016) reports that the Islamic banking market shares in these countries are: 49% in SA, 38.9% in KW, 26.1% QA, 18.4% in AE, 15% in BH, and 7% in OM. Altogether, these countries hold nearly 40% of the global Islamic banking assets.

For those countries, 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, which results in having 79 banks in our sample. From Bankscope, we gather annual data on the book value of total liabilities and total assets for each bank. We also employ Thomson Reuters Datastream to obtain daily stock market closing prices with their corresponding market capitalizations, leading to 2608 observations for the banking sector return series.

Table .1 describes the analysed data, in terms of total assets, aggregated at the country banking system level, within the considered period. The table provides 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 they are further classified based on whether they are publicly traded or privately held.

Table .1 shows that the CBw sector has the largest asset size within each country. The IB sector comes second in most countries. The asset size generally increases over time, but the magnitude of the increase differs across countries and banking sectors. Note also that publicly traded banks, the main subject of our analysis, are largely representative, with their assets being nearly 70% of the total. A closer inspection of the table reveals that, in 2012, CBw banks disappeared in QA, following Qatar's Central bank decision to ban CBw operations.

Figure .1 helps to better understand the evolution of each banking sector over time. It plots the ratio between the assets of each banking sector and the total assets, at the aggregate GCC level, on the logarithmic scale to make it more visible.

Figure (.1a) shows that the CB sector has a strong decrease in its assets during the crisis period, but bounces back afterwards. Precisely, its share of assets goes from 9.81% down to 6.83% and then back to 9.25%. Figure (.1b) shows that the CBw sector reduces its size after 2007. Its share of assets goes from 71.92% down to 67.94%. Conversely, Figure (.1c) shows that the IB sector experiences an increasing trend of growth after 2007. Its share of assets start at 18.27% and ends at 22.81%.

A different view on the data is provided by Table .2, which provides the market capitalization and the leverage of each banking sector in each country. Both market capitalisation and leverage are calculated for three sub-periods: the first is the *pre-crisis* period, defined from the beginning of January 2005 until the end of December 2006, the second is the *crisis* period, defined from the beginning of January 2007 until the end of December 2008, the third is the *post-crisis* period, defined from the beginning of January 2009 until the end of December 2014.

Table .2 shows that both the IB and the CBw sector decreased their capitalisation during crisis times and beyond, as it occurred to all banks worldwide. Conversely, CB banks seem to increase their capitalisation during crisis. Combining the evolution of capitalisation with that of the total assets, the leverage of the CB sector remains substantially unchanged through the crisis, whereas both the IB and the CBw sectors increase their leverage. Overall, these results seem to indicate that, during crisis times, Islamic banks (and CBw banks) maintain credit supply to the economy, at the expense of a higher leverage, which may bring a higher systemic risk level.

To complete the description of our data, Figures .2 and .3 report the time evolution of the main macroeconomic variables of the GCC countries: the oil price and the GDP growth of each country. Figure .2 reports the time evolution of the crude oil price, in dollars per barrel (crude oil WTI index)[4]. It shows that the crude oil price is quite volatile, with the largest peaks in 2008, at the burst of the financial crisis. Figure .3 presents the time evolution of the annual GDP growth of the six considered countries. From this Figure, note that most economies are synchronised with the oil price. This is the case especially for the Arab Emirates, Kuwait, Saudi Arabia and, on a higher GDP level, Qatar.

[4]WTI Crude Oil index can be downloaded from two sources:
http://www.gulfbase.com/tools/indexcommodity/6?pageid=64
http://finance.yahoo.com

4. Empirical Findings

4.1. Banking Sector Systemic Risk

In this subsection, we apply the proposed systemic risk measures in order to test our first hypothesis, that is, to establish whether the CBw sector has the highest systemic risk.

Table .3 summarises the results from the application of the MES measures. We compute the measures in three methods: first, the “Standard” measure, following Acharya et al. (2010); second, our proposed netted MES measure obtained using partial correlations; third, the MES measure calculated using, instead of the market index, the crude oil index as a unified index. All MES measures are calculated as averages over three sub-periods: the pre-crisis, the crisis, and the post crisis periods.

Columns (1) to (3) report the results using the standard MES measure for the pre-crisis, the crisis and the post-crisis periods respectively. The figures show that the CBw sector experienced the highest increase during the crisis period (column 2), in most countries. For example, the MES of the CBw sector of Saudi Arabia increases by 126 basis points against a 50 basis points increase of the IB sector. Columns (4) to (6) display the estimation when we use netted MES for our analysis. The results are in line with our findings for the first three columns, although on a smaller scale, due to the exclusion of indirect and spurious effects. Columns (7) to (9) report the MES measures when the crude oil index is used as a unified index for the whole region. Our findings persist in this specification and confirm that the CBw sector is the most vulnerable sector to systemic risks.

Table .4 summarises the results obtained from the application of the SRISK measure. The table provides three SRISK measures for each banking sector, with negative signs representing capital buffers. First the “Standard” measure, calculated as in Acharya et al. (2012); second, the “Netted” SRISK measure obtained using partial correlations; third, the SRISK measure calculated using the “Crude oil” index as a unified index for the whole region. All SRISK measures are calculated as averages over three sub-periods: the pre-crisis, the crisis, and the post crisis periods.

The results show that, overall, the CBw sector has higher capital buffers than the IB sector, and that 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 both the size and the leverage of a banking sector. Indeed, if we take the ratios between each banking sector's SRISK measure in Table .4 with the corresponding market capitalisations in Table .2, the resulting measure becomes more coherent with 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. Note that the CB sector has, relative to its small capitalisation, high buffers.

Table .5 provides the $\Delta CoVaR$ for each banking sector. The table provides three ΔCoVaR measures for each banking sector. First the "Standard" measure, calculated following Adrian and Brunnermeier (2016); second, the "Netted" ΔCoVaR measure obtained using partial correlations; third, the ΔCoVaR measure calculated using the "Crude oil" index. All ΔCoVaR are calculated as averages over three sub-periods: the pre-crisis, the crisis, and the post crisis periods. From Table .5 we observe that the "Standard", the "Netted", and the "Crude oil" $\Delta CoVaR$ 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 and SRISK systemic risk indicators.

Overall, all measures confirm our first hypothesis: the CBw banking sector has the highest systemic risk.[5]

4.2. Banking Sectors Synchronicity

In this subsection, we apply the GES measure to test our second hypothesis, that is, to establish whether the CBw sector has the highest synchronicity with the market. The Tables presented so far compare banking sectors of different countries in absolute terms. However, we would like to compare the banking sectors in terms of their relative contribution to the performance of their market. To this aim, we

[5] We remark that as a robustness check, we have applied the proposed measures to four Asian countries with dual banking systems: Bangladesh, Indonesia, Malaysia and Pakistan. The results, not reported here but available upon request, show that CBw is the most vulnerable banking sector.

employ the proposed GES measure as an aggregate for the weighted MES of the different banking sectors. In addition, we compare the GES with the overall MES of a country, which we obtain without classifying banks into three banking sectors[6].

Figures .8-.13 in the appendix illustrate the full time evolution of the GES measure per country, along with its components: $GMES_{CB}$, $GMES_{CBw}$, $GMES_{IB}$, and the country MES. The measures are calculated with three different methods: the "Standard", the "Netted", and the "Crude oil" index. By looking at the GES and at its components, we are able to individuate which banking sector is most synchronised with the overall market in terms of systemic risk. From an econometric viewpoint, figures .8-.13 show that the GES well approximates the country MES and can thus be taken as an appropriate representative. From an economic viewpoint, all figures show a high risk synchronization during the crisis period of 2008, that reaches its maximum level in 2009. This is consistent with the macroeconomic behaviour of all countries, whose GDP growth declined or even became negative in 2009.

The figures are summarised in Table .6, which shows the GES, and the percentage contribution of each banking sector to the GES, as an average over the three subperiods. From the table we note that the GES of AE, KW, OM and QA is driven by the CBw sector, which has the largest percentage in all periods. Whereas, in SA, the GES is driven by both CBw and IB, with the former prevailing during crisis times. Last, in BH the main systemic risk driver is the IB sector. As for the CB sector, it appears to have the smallest effect, which is consistent with its relatively lower size. Table .6 also shows that the distribution of the GES into its components is very stable under the standard MES and less so when we use the netted MES, which takes multidimensionality into account. The distribution of the GES under the oil-based measure is also less stable, reflecting the response of the markets to the high volatility of the crude oil price.

The analysis of synchronicity can be carried out, thanks to the aggregation property of the GES measure, at the GCC region level as a whole. In Figure .4 we provide the time variation of the GES measure, along with its components, for the three

[6]GES is a coherent risk measure, in which the sum of its weighted components (sum of banking sectors GMES) is equal to the country GES, hence, the effect of each component can be traced back to the aggregate country level. Whereas MES is not a coherent risk measure, but it is effective in tracing the ability of GES to represent the country risk level.

main banking sectors, at the aggregate GCC level. We also calculate the overall MES of the GCC countries, without classifying the banks into three sectors[7]. At the GCC level, we observe that figure .4a shows a strong dependence of the "Standard" GES on the CBw sector, illustrating that this sector has the highest synchronicity at this aggregation level. The figure also shows that all banking sectors become more synchronized in 2009, coincident with the decline in the GDP growth. The "Netted" GES shown in figure .4b illustrates that the CBw sector has the highest synchronisation during crisis period. The "Crude oil" index GES shown in figure .4c illustrates a similar behaviour along most of the time period, in line with the finding that the stock market returns in the GCC region are mainly affected by oil price volatility (see e.g. Arouri et al., 2011). Indeed, from Figure .2 we note that the crude oil price peaks steadily during crisis times, exactly when the GES does, and other smaller or shorter peaks of the GES can also be correlated with variations of the oil price. Exceptions to this trend are BH and OM, whose GDP is in fact less synchronised with the oil price.

The results from the GES measure thus lead to the conclusion that Hypothesis 2 is confirmed: the CBW sector is the one that is most synchronised with the market[8].

4.3. Banking Sector Interconnectdness

In this subsection, we apply graphical netowrk models to examine our third hypothesis, that is, whether the CBw sector is the most interconnected sector. Figures .5-.7 illustrate the graphical network models using MES, SRISK, and ΔCoVaR respectively. In all figures, we use the "Netted" method, which takes interdependences into account, and build a separate model for each of the pre-crisis, crisis, and post-crisis periods. Within each graph, the size of a 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 shows its sign.

[7]Note that we cannot calculate the Netted MES of the GCC as we do not have a correlation structure at the aggregate level.

[8]We remark that, as a robustness check, we have applied the GES measure to four Asian countries with dual banking systems: Bangladesh, Indonesia, Malaysia and Pakistan. The results, not reported here but available upon request, show that CBw is the banking sector most synhcronised to the market.

To better illustrate the results in Figures .5-.7 we summarise the obtained graphical network models using centrality measures to rank the banking sectors from the most to the least systemically important. The four centrality measures (ie. Betweeness, closeness, Node Degree, and Eigenvector Centrality) are further summarised into an aggregate Rank Concentration (RC) score that is provided in table .7 (for more details see Hashem and Giudici, 2016). A higher RC score indicates a higher contagion capacity and a greater potential for diffusing risk in the system.

Figure .5, and the RC scores of the netted MES in Table .7, indicate that the 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.

Figure .6, and the RC scores of the netted SRISK in Table .7, indicate that the IB sector has the highest importance in terms of its capital buffer (capital surplus), followed by CBw in the pre-crisis and crisis periods, implying that the CBw sector is riskier than the IB one under crisis events[9]. Note that the netted SRISK of the IB sector lowers after the crisis for all centrality measures. This effect can 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 sectors. This points out a diversification gain for the IB sector.

Finally, Figure .7, and the RC scores of the netted ΔCoVaR in Table .7, are consistent with the netted MES and SRISK results, and further confirm that the CBw sector is the most interconnected, especially during the crisis period. On the other hand, the CB sector is the least connected sector. We can thus conclude that the Hypothesis 3 holds: CBw is the most interconnected sector.

[9] The CB sector has the lowest capital buffer, but because of its low market share and its lower level of interconnectedness, its ability to diffuse its risk at the system level is limited in comparison with the two larger size CBw and IB sectors.

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 the systemic risk of CBw, IB and CB in six GCC member countries with dual banking systems, in particular during the financial crisis. We use market based systemic risk measures, such as MES, SRISK and ΔCoVaR and compute them with different methods: a) the standard b) the netted (using partial correlations) and c) the crude oil index models. Our analysis is based on a sample of 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 GES measure, at the country and at the GCC level, we can evaluate which banking sector is highly synchronised with the market. The results show that the CBw sector has the highest synchronicity with the market, especially in the crisis period, whereas the IB sector is less aligned until 2009, when it also comoves with the market.

The interconnectedness analysis based on graphical network models reveals that the CBw sector is the most interconnected sector during the crisis, 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 diversification benefit for a system that has both.

Our results show that financial stability of dual banking systems depends amongst other factors on how Islamic banking is introduced to the system, which has important policy implications. The findings underscore the necessity of prudential regulation and supervision for the CBw sector, given its systemic importance and interconnectedness.

The results also highlight the presence of similarities between the stock market returns in the GCC region and the crude oil index, which needs to be further investigated to determine if they can be used by the regulators as an early warning sign for equity market swings in this region.

We finally remark that the results in the paper and, in particular, the netted measures, are based on a specific correlation network model. This may lead to instable results, especially with highly volatile time series. Future research should address the issue of taking model uncertainty into account, possibly by means of a Bayesian approach.

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Appendix

Table .1: Banking Sectors Total Assets For Each GCC Country

This Table provides 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 they are further classified based on ownership (as a count for the number of banks, and as a percentage from the country total assets). The table is prepared based on authors' classification and elaborations.

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		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		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		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

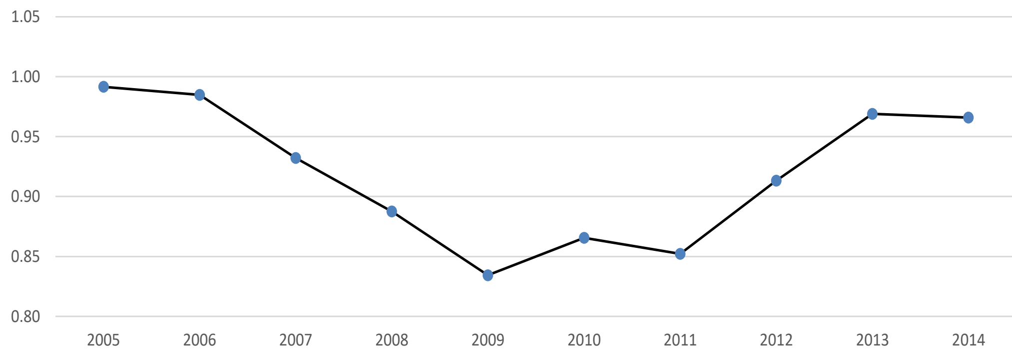
Table 1: Continued

Country	*Bank Type*	*Ownership*	*Count*	*2014*	*2013*	*2012*	*2011*	*2010*	*2009*	*2008*	*2007*	*2006*	*2005*
QA	*CB*	*Public*	*0*	0.7239	0.7396	0.7139	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	0	0	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		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		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		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

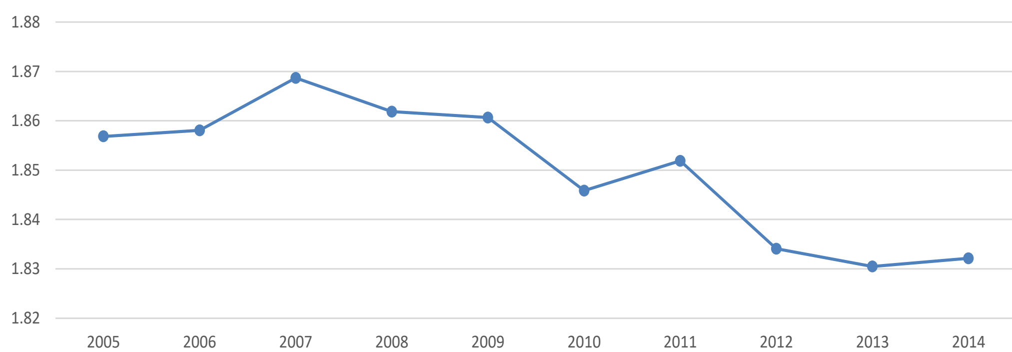
Figure .1: Asset Growth of the GCC Country Banking Sectors

This figure plots the time variation for the ratio of each banking sector total assets to the GCC total assets, on annual basis, for the period from Jan.2005 to Dec.2014. The figure includes total assets annual percentage change of (a) the CB banking sector, (b) the CBw banking sector and (c) the IB banking sector.

(a) The CB Banking Sector



(b) The CBw Banking Sector



(c) The IB Banking Sector

Table .2: Capitalisation of the GCC country banking sectors

This Table provides the market capitalisation of each banking sector in each country (in million U.S. dollars). In addition, it provides the leverage, calculated as the ratio of the book value of debt divided by the market share, plus one. The leverage is calculated for three sub-periods: the first is the pre-crisis period, defined from the beginning of January 2005 until the end of December 2006, the second is the crisis period, defined from the beginning of January 2007 until the end of December 2008, the third is the post crisis period, defined 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
CBw	AE	55,208,423	50,925,119	49,805,786	2.87	5.41	7.36
	SA	96,851,843	73,975,213	59,673,371	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
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

Figure .2: Time Evolution of WTI Crude Oil Price

This figure plots the WTI crude oil closing price through time.

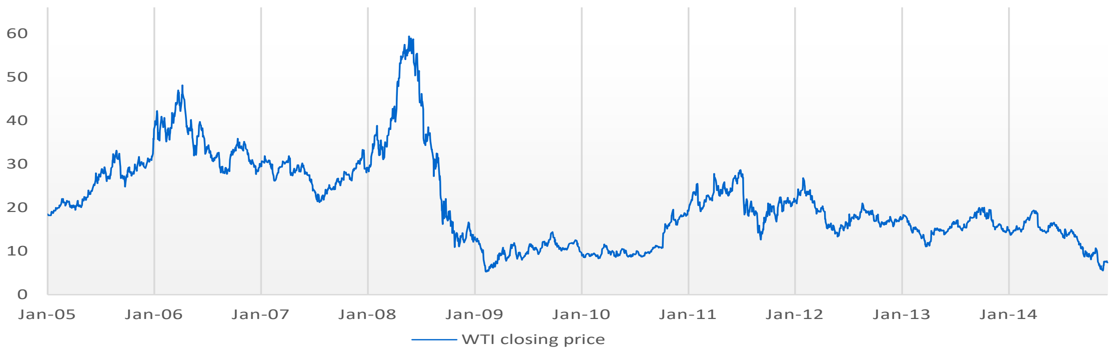


Figure .3: Time Evolution of GDP Growth per GCC country

This figure plots the GDP growth through time for each GCC country.

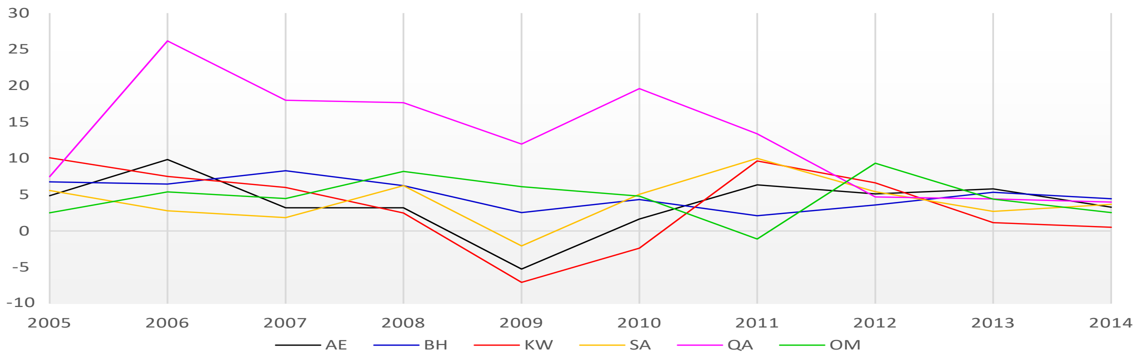


Table .3: MES for the GCC country banking sectors

This Table provides three MES measures for each country banking sector, expressed in million U.S. dollars. First the "Standard" measure, calculated as in Acharya et al. (2012); second, the netted MES measure obtained using partial correlations; third, the MES measure calculated using instead of the market index, the crude oil index. All MES are calculated as averages over three sub-periods: the first is the pre-crisis period, defined from the beginning of January 2005 until the end of December 2006, the second is the crisis period, defined from the beginning of January 2007 until the end of December 2008, the third is the post crisis period, defined from the beginning of January 2009 until the end of December 2014. The table also reports the MES calculated at the country level, referred to as MES.system.

Country	*Sector*	Standard-MES			Netted-MES			Oil-MES		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
AE	*CB*	0.898	0.925	0.774	0.081	0.133	0.116	0.206	0.195	0.170
	CBw	1.368	1.309	1.328	0.192	0.165	0.170	0.268	0.257	0.316
	IB	2.601	2.162	1.424	0.076	-0.012	0.102	0.651	0.525	0.346
BH	*CB*	0.004	0.004	0.006	-0.184	-0.166	-0.182	-0.001	-0.001	-0.001
	CBw	0.219	0.263	0.220	0.091	0.111	0.093	0.071	0.083	0.071
	IB	0.837	1.122	1.130	-0.011	0.420	0.333	0.219	0.231	0.240
KW	*CB*	0.461	0.449	0.419	-0.177	-0.129	-0.137	0.134	0.130	0.121
	CBw	1.526	3.010	3.420	0.140	0.190	0.355	0.580	0.565	0.663
	IB	0.837	1.122	1.130	0.081	0.103	0.103	0.288	0.377	0.337
OM	*CB*	0.885	2.065	1.407	0.190	0.270	0.212	0.091	0.189	0.124
	CBw	0.383	2.274	2.277	-0.046	0.678	0.730	0.232	0.248	0.220
	IB	0.008	0.006	0.149	0.013	0.004	-0.009	-0.008	-0.006	-0.056
QA	*CBw*	1.536	1.979	1.495	-0.054	0.118	0.136	0.369	0.349	0.248
	IB	1.700	2.150	1.377	0.203	0.015	0.227	0.383	0.488	0.250
SA	*CBw*	1.854	3.107	1.612	0.024	0.195	0.135	0.288	0.532	0.317
	IB	3.219	3.723	2.549	0.865	0.748	0.436	0.275	0.192	0.564
Total	*CB*	2.249	3.443	2.605	-0.09	0.107	0.008	0.43	0.513	0.414
	CBw	6.887	11.942	10.353	0.348	1.457	1.618	1.807	2.035	1.835
	IB	9.203	10.286	7.76	1.228	1.278	1.191	1.807	1.806	1.681

Table .4: SRISK for the GCC country banking sectors

This Table provides three SRISK measures for each country banking sector, expressed in million U.S. dollars, with negative signs representing capital buffers. First the "Standard" measure, calculated as in Acharya et al. (2016); second, the netted SRISK measure obtained using partial correlations; third, the SRISK measure calculated using instead of the market index, the crude oil index. All SRISK are calculated as averages over three sub-periods: the first is the pre-crisis period, defined from the beginning of January 2005 until the end of December 2006, the second is the crisis period, defined from the beginning of January 2007 until the end of December 2008, the third is the post crisis period, defined from the beginning of January 2009 until the end of December 2014. Besides country banking sectors, the table also reports aggregate figures corresponding to the GES (weighted average of the sector MES).

Country	Sector	Standard-SRISK			Netted-SRISK			Oil-SRISK		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
AE	*CB*	-1,182,264	-1,154,628	-822,752	-1,395,385	-1,378,795	-998,150	-1,182,264	-1,154,628	-822,752
	CBw	-32,061,502	-21,857,706	-13,009,710	-41,109,038	-29,741,874	-21,182,696	-32,061,502	-21,857,706	-13,009,710
	IB	-7,161,829	-3,864,856	-1,759,827	-12,127,923	-6,891,950	-3,619,373	-7,161,829	-3,864,856	-1,759,827
BH	*CB*	-177,803	-217,408	-183,160	-184,992	-225,226	-190,204	-177,803	-217,408	-183,160
	CBw	-2,895,363	-3,047,329	-1,852,825	-3,031,577	-3,258,011	-2,002,216	-2,895,363	-3,047,329	-1,852,825
	IB	-3,425,861	-2,376,908	209,111	-4,183,269	-2,920,501	-93,460	-3,425,861	-2,376,908	209,111
KW	*CB*	-1,407,381	-2,499,602	-1,651,925	-1,659,000	-2,853,939	-1,904,658	-1,407,381	-2,499,602	-1,651,925
	CBw	-6,102,061	-5,440,674	-1,564,671	-8,459,692	-10,502,524	-5,045,450	-6,102,061	-5,440,674	-1,564,671
	IB	-14,518,054	-13,239,277	-8,371,496	-15,860,000	-17,314,149	-11,364,364	-3,425,861	-2,376,908	209,111
OM	*CB*	-717,726	-632,432	-590,781	-831,127	-919,734	-834,120	-717,726	-632,432	-590,781
	CBw	-2,970,937	-3,006,192	-1,611,437	-11,831,212	-4,134,231	-2,839,934	-2,970,937	-3,006,192	-1,611,437
	IB	-364,865	-364,963	-343,187	-364,410	-365,153	-351,697	-364,865	-364,963	-343,187
QA	*CBw*	-13,355,596	-10,481,205	-18,109,431	-18,100,962	-15,636,902	-24,641,022	-13,355,596	-10,481,205	-18,109,431
	IB	-8,246,349	-6,181,937	-7,253,894	-10,795,173	-9,021,969	-9,247,387	-8,246,349	-6,181,937	-7,253,894
SA	*CBw*	-58,101,930	-26,728,430	-18,715,270	-77,021,923	-49,393,690	-30,516,869	-58,101,930	-26,728,430	-18,715,270
	IB	-40,935,488	-19,768,305	-16,197,828	-51,975,385	-33,504,589	-26,114,633	-40,935,488	-19,768,305	-16,197,828
Total	*CB*	-3,485,174	-4,504,070	-3,248,618	-4,070,504	-5,377,694	-3,927,131	-3,485,174	-4,504,070	-3,248,618
	CBw	-115,487,388	-70,561,537	-54,863,344	-159,554,404	-112,667,233	-86,228,188	-115,487,388	-70,561,537	-54,863,344
	IB	-63,560,253	-34,933,877	-25,136,513	-95,306,160	-70,018,312	-50,790,914	-63,560,253	-34,933,877	-25,136,513

Table .5: ΔCoVaR for the GCC country banking sectors

This Table provides three ΔCoVaR measures for each country banking sector, expressed in million U.S. dollars. First the "Standard" measure, calculated as in Adrian and Brunnermeier (2016); second, the netted ΔCoVaR measure obtained using partial correlations; third, the ΔCoVaR measure calculated using instead of the market index, the crude oil index. All ΔCoVaR are calculated as averages over three sub-periods: the first is the pre-crisis period, defined from the beginning of January 2005 until the end of December 2006, the second is the crisis period, defined from the beginning of January 2007 until the end of December 2008, the third is the post crisis period, defined from the beginning of January 2009 until the end of December 2014.

Country	Sector	Standard-ΔCoVaR			Netted-ΔCoVaR			Oil-ΔCoVaR		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
AE	*CB*	0.395	0.499	0.359	0.004	0.045	0.025	0.150	0.191	0.190
	CBw	1.354	1.704	1.460	0.091	0.089	0.086	0.192	0.389	0.571
	IB	1.382	1.458	1.206	0.093	-0.070	0.122	0.280	0.361	0.357
BH	*CB*	0.005	0.007	0.006	-0.003	-0.003	-0.003	-0.014	-0.018	-0.018
	CBw	0.136	0.171	0.160	0.031	0.034	0.034	-0.057	-0.076	-0.071
	IB	0.257	0.478	0.415	-0.110	0.138	0.075	0.125	0.159	0.158
KW	*CB*	0.243	0.259	0.229	-0.007	0.019	-0.004	0.143	0.182	0.181
	CBw	0.464	1.106	0.950	0.059	0.120	0.242	0.288	0.358	0.373
	IB	0.257	0.478	0.415	0.145	0.156	0.140	0.280	0.357	0.355
OM	*CB*	0.500	1.195	0.735	0.157	0.162	0.088	0.154	0.207	0.206
	CBw	0.171	0.897	0.576	0.041	0.234	0.158	0.270	0.344	0.342
	IB	0.057	0.063	0.036	0.050	0.304	0.208	0.049	0.063	0.057
QA	*CBw*	0.958	1.331	1.104	0.168	0.317	0.208	0.357	0.454	0.447
	IB	1.024	1.159	1.013	0.147	-0.073	0.211	0.286	0.375	0.365
SA	*CBw*	1.643	2.146	1.132	-0.017	0.198	0.171	0.164	0.485	0.549
	IB	1.536	2.007	1.045	0.580	0.453	0.315	0.062	0.078	0.677
Total	*CB*	2.215	3.164	1.997	0.069	0.797	0.594	0.618	1.064	1.119
	CBw	7.963	12.147	8.495	1.269	1.944	1.506	1.93	2.876	3.721
	IB	7.315	10.763	7.998	1.304	1.412	1.789	2.358	3.033	3.606

Table .6: GES and its components for each GCC country banking system

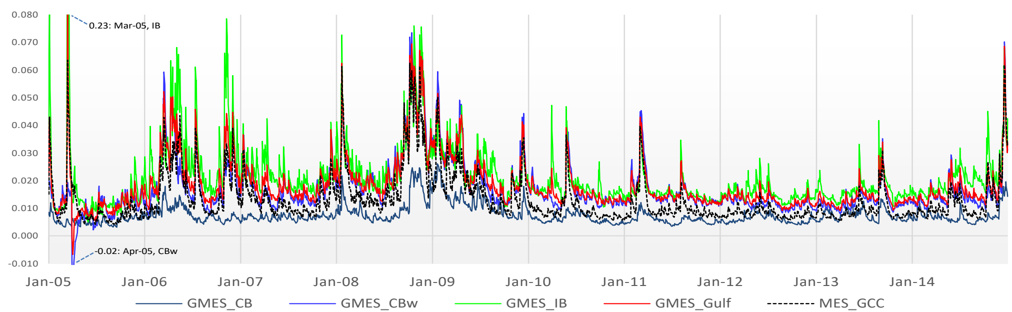
This Table provides the GES measure, and the percentage contribution to it, from each country banking sector component, for the considered time periods. Note that, at the bottom of the table, the "Total" is the sum of the percentages across all countries.

Component Type		Standard-MES			Netted-MES			Oil-MES		
Country	Sector	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
AE	GES_AE	1.62	1.43	1.33	0.17	0.14	0.16	0.35	0.30	0.32
	% GMES_CB	0.01	0.02	0.02	0.01	0.03	0.02	0.01	0.02	0.02
	% GMES_CBw	0.64	0.73	0.81	0.89	0.96	0.87	0.58	0.69	0.81
	% GMES_IB	0.35	0.25	0.17	0.10	0.01	0.11	0.41	0.29	0.17
BH	GES_BH	0.50	0.57	0.46	0.04	0.22	0.16	0.14	0.14	0.11
	% GMES_CB	0.00	0.00	0.00	0.06	0.02	0.02	0.00	0.00	0.00
	% GMES_CBw	0.23	0.28	0.34	0.85	0.30	0.39	0.27	0.38	0.44
	% GMES_IB	0.77	0.72	0.66	0.09	0.68	0.59	0.73	0.62	0.56
KW	GES_KW	1.06	1.81	1.83	0.08	0.12	0.16	0.38	0.43	0.43
	% GMES_CB	0.03	0.03	0.02	0.12	0.08	0.07	0.02	0.03	0.03
	% GMES_CBw	0.52	0.65	0.62	0.45	0.53	0.62	0.54	0.51	0.52
	% GMES_IB	0.45	0.32	0.36	0.43	0.39	0.31	0.44	0.46	0.45
OM	GES_OM	0.46	2.11	2.02	0.02	0.58	0.60	0.18	0.23	0.19
	% GMES_CB	0.38	0.17	0.13	0.60	0.08	0.06	0.11	0.15	0.12
	% GMES_CBw	0.62	0.83	0.87	0.38	0.92	0.94	0.89	0.85	0.87
	% GMES_IB	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01
QA	GES_QA	1.60	2.04	1.46	0.04	0.09	0.16	0.38	0.39	0.25
	% GMES_CBw	0.60	0.66	0.74	0.32	0.93	0.63	0.62	0.60	0.72
	% GMES_IB	0.40	0.34	0.26	0.68	0.07	0.37	0.38	0.40	0.28
SA	GES_SA	2.41	3.34	1.98	0.37	0.41	0.26	0.29	0.40	0.42
	% GMES_CBw	0.46	0.57	0.49	0.04	0.29	0.31	0.59	0.81	0.45
	% GMES_IB	0.54	0.43	0.51	0.96	0.71	0.69	0.41	0.19	0.55
Total	% GMES_CB	0.42	0.22	0.17	0.79	0.21	0.17	0.14	0.2	0.17
	% GMES_CBw	3.07	3.72	3.87	2.93	3.93	3.76	3.49	3.84	3.81
	% GMES_IB	2.51	2.06	1.96	2.28	1.86	2.07	2.37	1.96	2.02

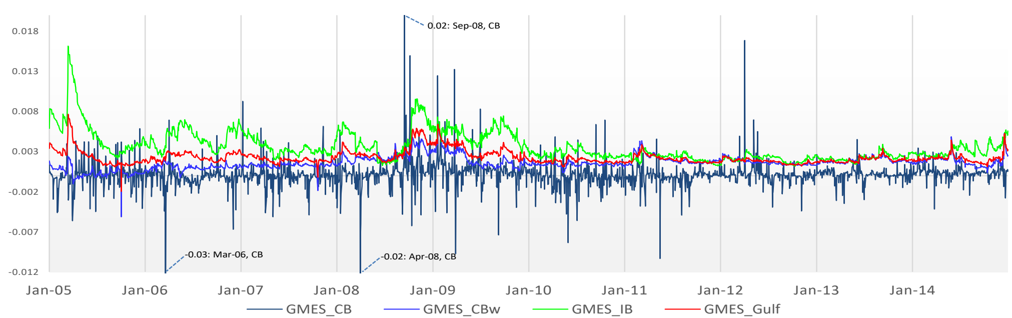
Figure .4: GES for the GCC Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for GCC marginal expected shortfall (MES) per banking sector type, we also represent the complete GCC banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-GCC) is denoted in red, and the MES of GCC banking system portfolio (MES-GCC) is denoted with a black dashed line.

(a) Standard GES-GCC



(b) Netted GES-GCC



(c) Oil GES-GCC

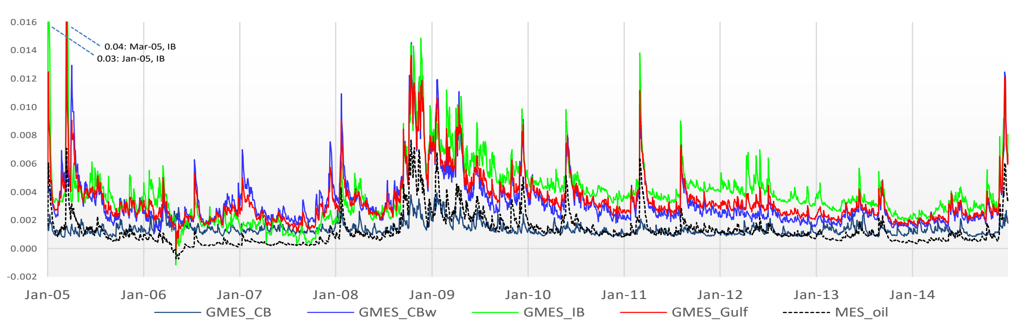
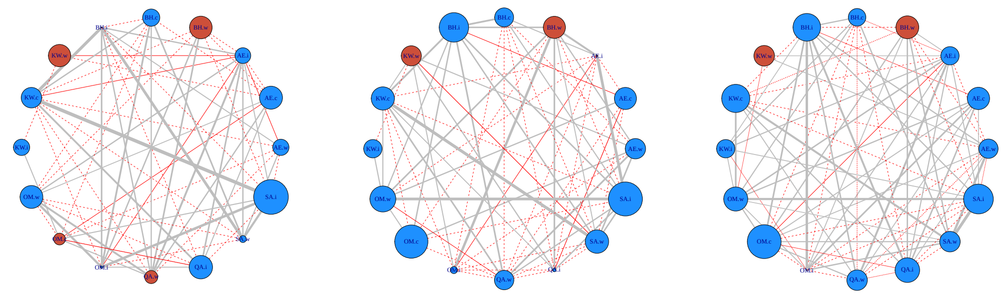


Figure .5: Netted MES Network

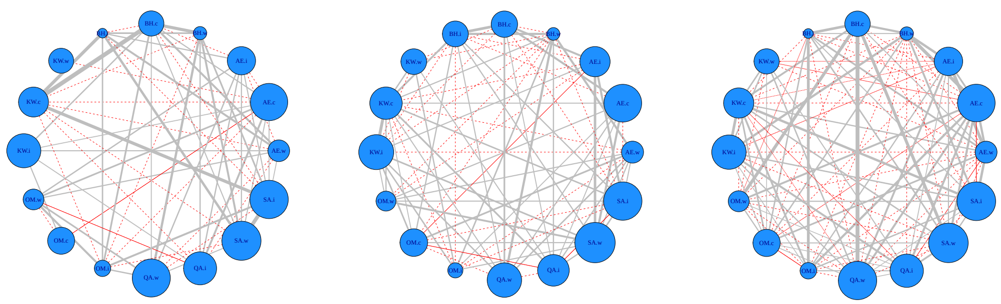
In this figure, we present the netted MES partial correlation network for the three sub-periods of a) pre-crisis, b) during-crisis and c) post-crisis. The blue node color indicate a positive risk value, whereas the red indicates a negative one. The gray link color indicates a positive partial correlation, 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 .6: Netted SRISK Network

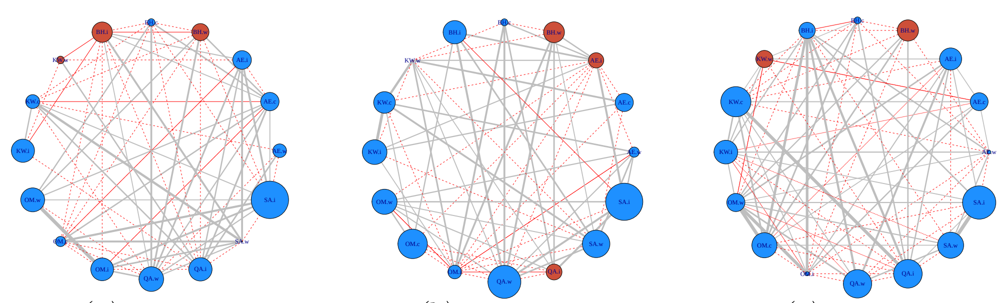
In this figure, we present the netted SRISK partial correlation network for the three sub-periods of a) pre-crisis, b) during-crisis and c) post-crisis. The blue node color indicate a capital buffer, whereas the red indicates a capital shortfall. The gray link color indicates a positive partial correlation, 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 .7: 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*

Table .7: Rank Concentration Ratio of the Banking Sectors

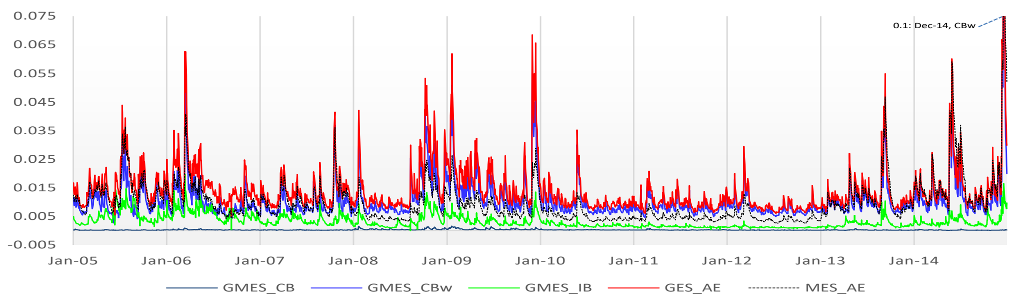
This table provides the Rank Concentration Ratio, which summarizes centrality measures, based on the aggregate score of the ranks that each banking sector occupies within a specific centrality measure. THe ratio is normalised and expressed in percentage terms. A higher Ranking *RC* indicates a higher 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

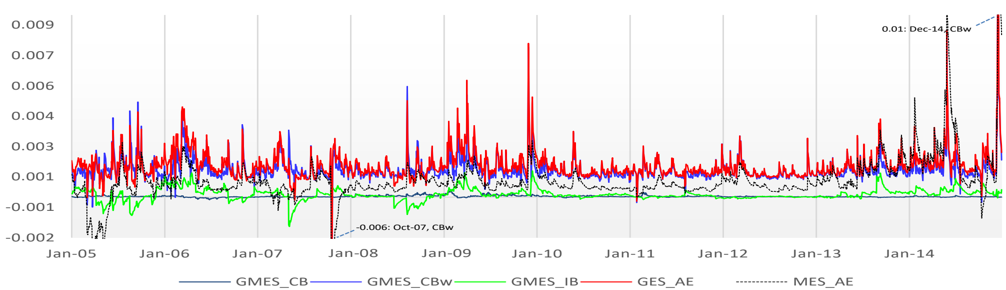
Figure .8: MES and GES for AE Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for United Arab Emirates (AE) marginal expected shortfall (MES) per banking sector type, we also represent the complete AE banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-AE) is denoted in red, and the MES of AE banking system portfolio (MES-AE) is denoted with a black dashed line.

(a) Standard GES-AE



(b) Netted GES-AE



(c) Oil GES-AE

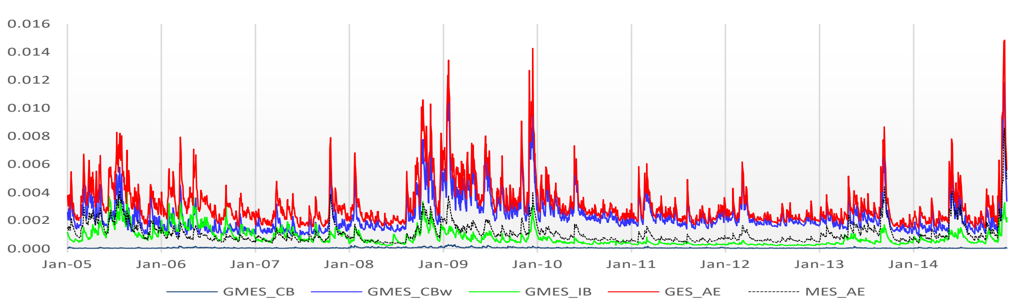
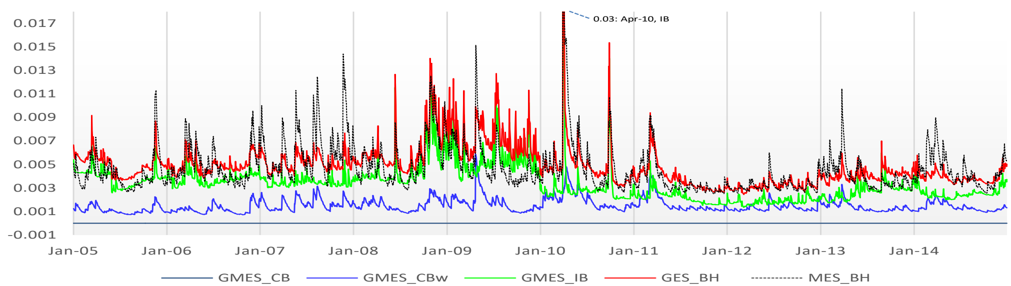


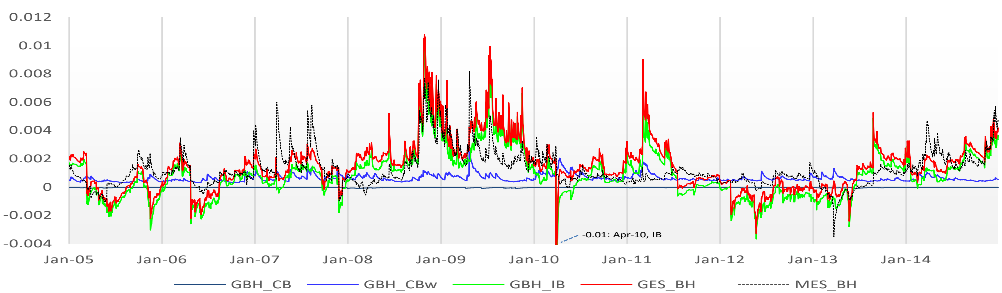
Figure .9: MES and GES for BH Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for Bahrain (BH) marginal expected shortfall (MES) per banking sector type, we also represent the complete BH banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-BH) is denoted in red, and the MES of BH banking system portfolio (MES-BH) is denoted with a black dashed line.

(a) Standard GES-BH



(b) Netted GES-BH



(c) Oil GES-BH

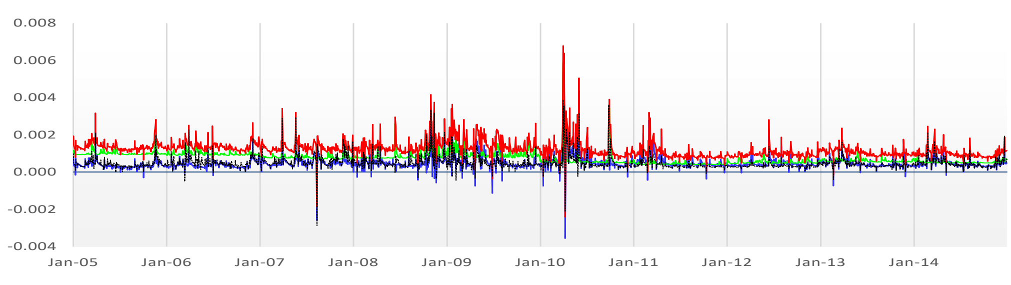
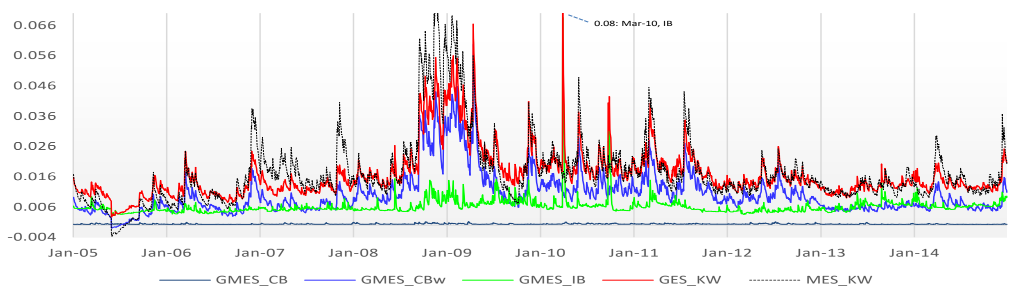


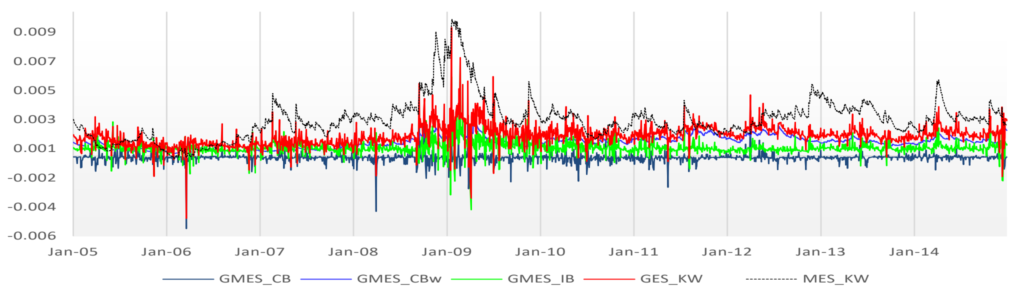
Figure .10: MES and GES for KW Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for Kuwait (KW) marginal expected shortfall (MES) per banking sector type, we also represent the complete KW banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-KW) is denoted in red, and the MES of KW banking system portfolio (MES-KW) is denoted with a black dashed line.

(a) Standard GES-KW



(b) Netted GES-KW



(c) Oil GES-KW

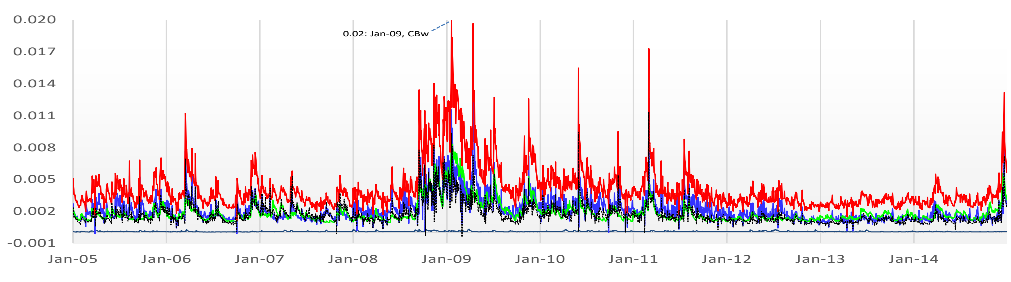
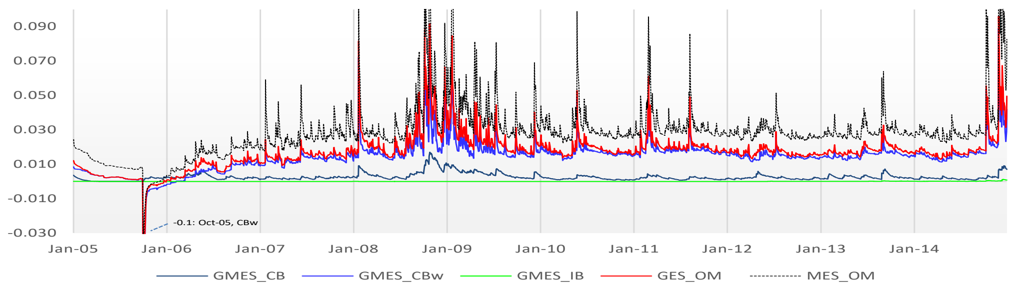


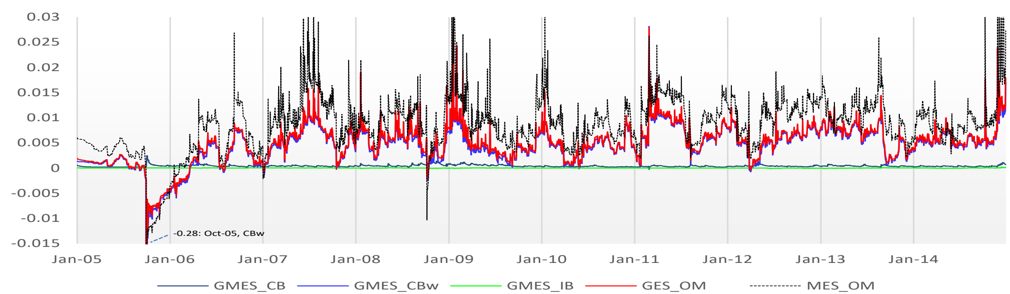
Figure .11: MES and GES for OM Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for Oman (OM) marginal expected shortfall (MES) per banking sector type, we also represent the complete OM banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-OM) is denoted in red, and the MES of OM banking system portfolio (MES-OM) is denoted with a black dashed line.

(a) Standard GES-OM



(b) Netted GES-OM



(c) Oil GES-OM

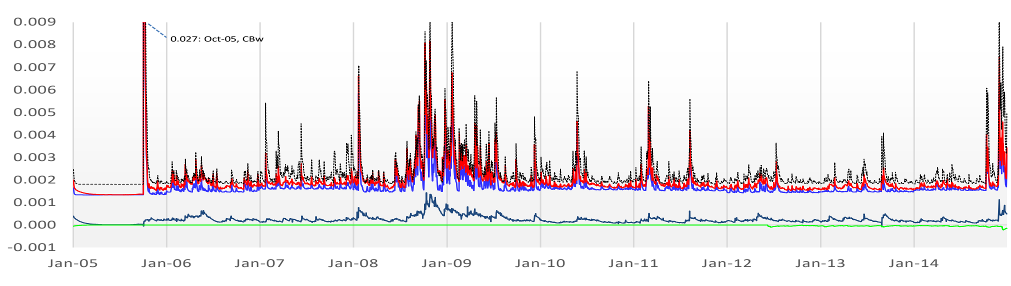
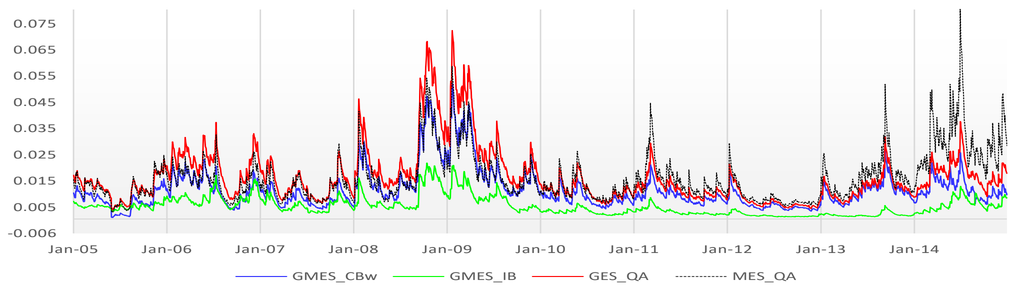


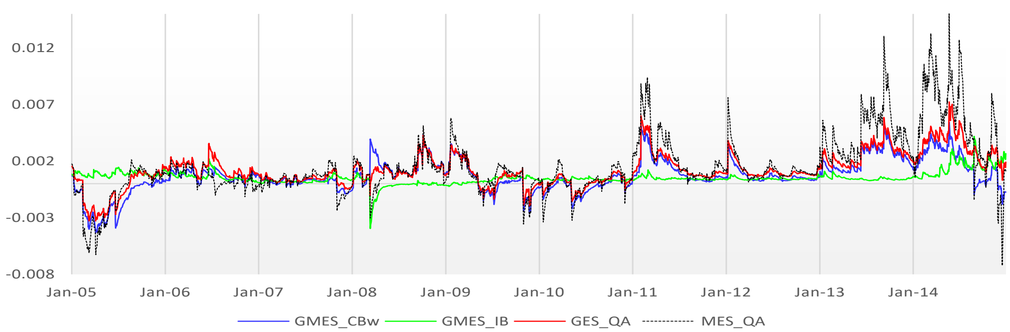
Figure .12: MES and GES for QA Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for Qatar (QA) marginal expected shortfall (MES) per banking sector type, we also represent the complete QA banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-QA) is denoted in red, and the MES of QA banking system portfolio (MES-QA) is denoted with a black dashed line.

(a) Standard GES-QA



(b) Netted GES-QA



(c) Oil GES-QA

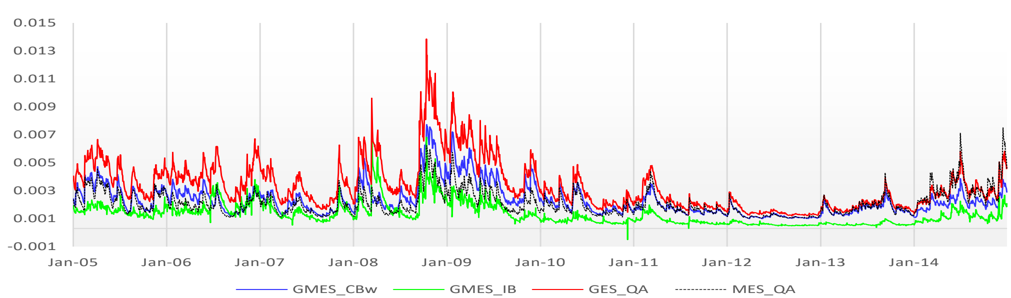
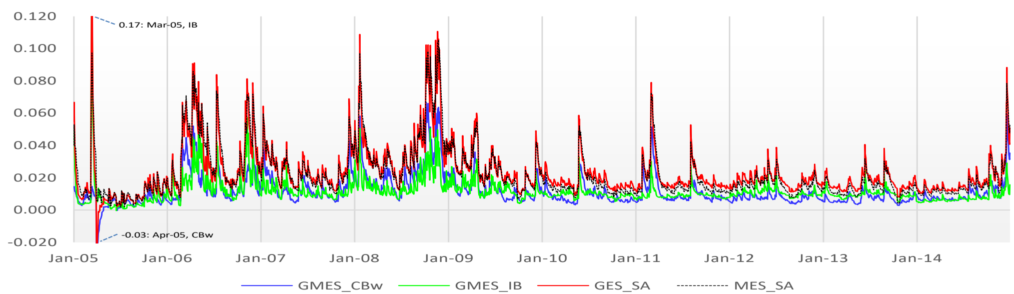


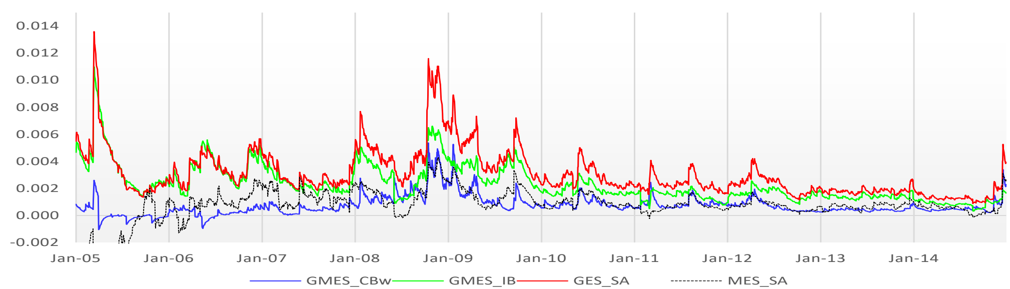
Figure .13: MES and GES for SA Banking System Portfolio

In this figure, we present the time evolution plot, from Jan.2005 to Dec.2014, for Saudi Arabia (SA) marginal expected shortfall (MES) per banking sector type, we also represent the complete SA banking system portfolio using both GES and MES. The figure is provided using the (a) standard, (b) netted and (c) oil systemic risk measurement variations. In this figure, MES of the conventional banking sector (MES-CB) is denoted in black, MES of the conventional banking sector with an Islamic window (MES-CBw) is denoted in blue, MES of the Islamic banking sector (MES-IB) is denoted in green. The GES of the complete banking system portfolio (GES-SA) is denoted in red, and the MES of SA banking system portfolio (MES-SA) is denoted with a black dashed line.

(a) Standard GES-SA



(b) Netted GES-SA



(c) Oil GES-SA