Financial Stability of Islamic Banks: A Systemic Risk Perspective

By

Shatha Qamhieh Hashem

shatha.hashem01@universitadipavia.it

Matricola:424242

Dissertation submitted in partial fulfillment of

(DREAMT Doctor of Philosophy Program)

Offered by

Department of Economics and Management Science

Pavia University

And by

Department of Engineering management, information and production

University of Bergamo.

Date: 01/01/2017

Supervisor:

Prof.Paolo Giudici

paolo.giudici@unipv.it

External Committee Member#1

External Committee Member#2

External Committee Member#3

Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy of DREAMT Program from the Department of Economics and Management Science, Pavia University, and the Department of Engineering Management, Information and Production, Bergamo University, 2017

Thesis: Declaration of Authorship

I, Shatha Qamhieh Hashem, declare that this PhD thesis titled *"Financial Stability of Islamic Banks: A Systemic Risk Perspective",* and the work presented in it are my own and has been generated by me as the result of my own original research under the supervision of Professor Paolo Giudici, and with the collaboration of dr. Pejman Abedifar within paper no.2 *"titled Systemic Risk in Dual Banking Systems"*.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:

   Paper no.1:Thesis pages (33-51)
   Hashem, S.Q. and Giudici, P. (2016) "Systemic Risk of Conventional and Islamic Banks: Comparison with Graphical Network Models". *Applied Mathematics*, **7**, 2079-2096.
   http://dx.doi.org/10.4236/am.2016.717166

   Paper no.3:Thesis pages(95-130)
   Hashem, S.Q. and Giudici, P. (2016) "NetMES: a network based marginal expected shortfall measure". *Journal of Network Theory in Finance* **2**(3), 1–36.
   http://dx.doi.org/10.21314/JNTF.2016.020

Signed: …………Shatha Qamhieh Hashem………………………..

Date: ……………………01/01/2017…………………………………..

Acknowledgments

I start by thanking the merciful and almighty God for the countless gifts that he always grants to me through all my life, and for the energy to undertake this PhD study.

Next, it is a great pleasure to express my sincere gratitude to my supervisor, Prof. Paolo Giudici, the full professor of statistics within the department of economics and management sciences at Pavia University, for his continuous guidance and support during my PhD study and related research, for his patience, motivation, and immense knowledge.

My sincere thanks also goes to Prof. Giorgio Rampa, the full professor of economics; the Director of the DREAMT PhD program and Dean of the Department of Economics and management at Pavia University, for his continuous support, his generosity and kindness towards me and all the program participants. Furthermore, many thanks to all the wonderful professors from Pavia and Bergamo universities that are involved in DREAMT PhD program, and to all the other working staff that supported me during this thesis. Also, I thank Dr. Pejman Abedifar, from the Center for Responsible Banking & Finance of the School of Management at the University of St Andrews in the UK, for the data and the collaboration in the second paper of this thesis.

I also gratefully acknowledge the PhD scholarship award that is coordinated by the University of Pavia (Italy) and co-coordinator by An-Najah National University (Palestine), offered within the DUNIA BEAM project that is funded by the European Union through the Erasmus Mundus Program, with many thanks to all the scholarship team from both universities. In addition, I acknowledge the financial support from the PRIN project MISURA: multivariate models for risk assessment, and of the PhD program in Economics and management of technology (DREAMT) at the University of Pavia.

Besides, I would like to thank my thesis external reviewers: Prof. Massimiliano Caporin from the University of Padova, and Prof. Monica Billio from the University of Venice; for their insightful comments that incented me to widen my research from various perspectives. Moreover, I'm thankful to all the professors that provided me with insightful comments in the workshops and conferences during this thesis.

Last but not the least, I would like to thank my family: my parents, my husband and his family, my suns, my siblings, relatives, friends and beloved ones, for supporting me spiritually, and for their continuous encouragement throughout this thesis and throughout my life in general.

Abstract

The late global financial crisis reveled the fragility of the conventional banking system under an adverse systemic event, but highlighted Islamic banks resilience in comparison with their conventional counterparts. The aim of this thesis is to empirically assess the claim regarding Islamic banks strength to support the financial system stability, based on measuring their systemic risk contribution to the overall financial system. The work is applied is applied first to the MENA region from 2007 to 2014, and is applied next to the GCC region from 2005 to 2014. We use stock market returns of publicly traded banks, which we classify into fully-fledged Islamic banks (IB), conventional banks (CB), and conventional banks with Islamic services window (CBwin), from which we construct stock market banking indices (banking sectors), and measure the systemic risk taking into consideration the interconnectedness of the banking sectors within the financial system. We measure the systemic risk of the banking sectors using correlation network models, augmented by equity based market measures of MES, SRISK, ΔCoVaR, and CES, and we extend those measures by developing netted systemic risk ones that employ partial correlation instead of the marginal one, to take the multivariate nature of systemic risk into account. We test our novel NetMES measure using the Bayesian averaging analysis. The results confirm the lower contribution of Islamic banks to systemic risk, and thus their strength to support the financial stability, under the limitation of the crisis materialization within the real economic side, upon which the IB banking sector stability and strength deteriorates.

Keywords: Islamic banks, conventional banks, systemic risk, financial stability, correlation networks, NetMES.

Contents

1 Introduction

Healthy financial systems augment the economic development and prosperity of any country. To ensure the continuation of the economic prosper, regulatory bodies oversee and organize financial institutions and practices, and particularly banking institutions, due to their crucial intermediary role in the financial system. However, in spite of those regulating efforts, financial crisis do occur, as in the case of the 2007-2008 global financial crisis, which eventually left a stressful negative effect on the economic system of many countries.

This recent global financial crisis clearly revealed the fragility and weaknesses of the conventional financial system in front of systemic events. The resulting global economic recession and the failure of main banking institutions highlighted the importance of sound risk management and mitigation practices, and stressed the importance of systemic risk identification and assessment in the process of macro prudential policies improvement. The crisis also directed the attention towards the difference in the crisis effect between Islamic and conventional banks. From a theoretical point of view, an Islamic bank is a financial institution that is engaged in all banking activities at a zero-interest rate according to Islamic Shariah rules (see e.g. Shafique et al., 2012), and instead of the interest rate, the Islamic bank receives a fee or a rate of return according to the transaction performed, in addition, the Islamic bank accounts are based on profit and loss sharing (PLS), its transactions are equity-based or asset-based, with the transaction being backed by real assets, and the bank is not allowed to take excessive uncertainty (ex. Derivatives and gambling are not allowed), or to finance any activity that is not halal such as alcohol production or distribution (all ethically accepted actions under Islamic Shariah principles are referred to as halal).

However, in spite the Islamic banking business model restrictions, still in the late crisis period they were found to be in a better position in terms of the crisis resilience in comparison with conventional banks, in addition to a time shift (time lag) in the crisis effect for Islamic banks (Khediri et al., 2015). In a speech for the governor of the Malaysian central bank (Aziz, 2008), he pointed out that Islamic banks resilience is a result of being protected from high exposure to excessive leverage and risk taking, and as a result of its business model feature, and specifically being equity-asset based with a risk sharing ability. However, knowing that Islamic banks are rooted in the real economic side because of their transactions being backed by real assets, their resilience to a systemic event is challenged from another perspective. Islamic banks were found to be affected by the crisis in its second round as it reached the economic side, specifically when real estate tumbled down Kammer et al. (2015). Betz et al. (2014) pointed out that the presence of a strong connection to the real economy will increase the system exposure to contagion effects. Thus, the stability and resilience of Islamic banks are challenged in a novel way. Nevertheless, the recorded variation in the crisis impact on Islamic banks, caused a debate regarding the influence that this model exerted on stabilizing the financial system. In this thesis, the main aim is to empirically assess Islamic banks strength to support the stability of the financial system from a systemic risk point of view.

1.1 The stability of the Islamic banking model

To understand the stability and resilience prospects that the Islamic banking model may imply, we start by considering the difference between Islamic and conventional banks assets growth rate, Islamic banking assets grow rapidly in size and importance within Islamic, and is starting to move towards the non-Islamic countries (see e.g. Thomson Reuters, 2015), including Europe (Cattelan, 2013; Lewis and Algaoud, 2001; Khan and Porzio, 2010; di Mauro et al., 2013) and America (Tacy, 2006; di Mauro et al., 2013). The Islamic banking system is rapidly diffusing not only through the increasing establishment of fully fledged Islamic banks (banks that are fully dedicated to offer Islamic banking services), but also through the integration of Islamic banking services within conventional banks, through an Islamic banking window. Islamic banking started in Egypt in the year 1963 (Kumru and Sarntisart, 2016), to service the Islamic population demand for Shariah banking services. Since then, Islamic banking continued to grow and expand worldwide and especially in Muslim countries. Imam and Kpodar (2013) investigated the expansion pattern of Islamic banking, they found that the share of the Muslims in the population and the income per capita along with the level of economic integration with Middle East countries are factors that support this expansion.

In general, Islamic banks have maintained stronger asset growth compared to conventional banks during the crisis (Hasan and Dridi, 2011). Islamic finance assets maintained a double-digit annual growth rate since 2007, and expanded to $1,086 bn in 2011 (Financial Times, 2011), to reach an overall total value of USD 1.88 trillion by 2015 IFSB (2016), from which Islamic banking assets account for nearly 80% of Islamic finance assets (TheCityUK, 2015; IFSB, 2016). The Islamic banking assets continued growing through the following years to reach more than USD $881 b in 2014 (Ernst & Young, 2014), and is approximated around $1.6 trillion by the end of 2015 (IFSB, 2016). The annual growth rate of the Islamic banking assets, during the 2007-2008 financial crisis and during 2009, was reported to be approximately 20% (IFSB, 2014). Nevertheless, the compound annual growth rate slowed down to a recorded 16% between 2010-2014 (Ernst & Young, 2015). However, in spite of the impressive growth record that this industry is recording, its share from the global banking assets is small at approximately 1% (Pinner and LinYan, 2013; Kammer et al., 2015).

Imam and Kpodar (2016) found that despite the relatively small size of Islamic banking activities within the overall financial system, yet Islamic banking activities have a positive effect on economic growth. From a theoretical point of view, the Islamic banking model was argued to be similar to many countries reform proposals for the banking system, and especially USA, and that it may be better able to absorb shocks that disturb the payment mechanism and thus showing a higher ability in maintaining the financial system stability (Khan, 1986, 1987). Djennas (2016) points out that "countries that adopt the principles of Islamic finance are strongly positioned to avoid various situations of crisis and economic downturns." The debate whether this model will be better able to withstand a negative systemic event chock intensified in terms of the model performance and risks, especially after the late crisis. However, the differences between the Islamic and the conventional banking systems has been actively investigated by scholars even prior to the late crisis, with two underlying main viewpoints, the first claims that Islamic banking practices are similar to the conventional ones (see e.g. Kuran, 2004; Nomani, 2006; Chong and Liu, 2009; Khan, 2010), while the other claims the presence of differences in both practices and business models (see e.g. Sundararajan and Errico, 2002; Iqbal and Llewellyn, 2002; Solé, 2008; Ariffin et al., 2009).

Nevertheless, considering the crisis period itself, and starting from the noticeable performance differences, Islamic banks were found to have a higher performance level during the crisis period with higher profits, better capitalization and higher asset quality (see e.g. Olson and Zoubi, 2008; Hasan and Dridi, 2011; Abedifar et al., 2013; Beck et al., 2013; Bourkhis and Nabi, 2013; Al-Hares et al., 2013; Wijnbergen and Zaheer, 2013; Khediri et al., 2015), and lower disintermediation ratio (Beck et al., 2013). However, the two models differences were found to be more apparent for small size banks rather than large size ones (Beck et al., 2013; Abedifar et al., 2013), the negative effect of increased size on the stability and performance of Islamic banks is contributed to the weakness and limitations of the risk management practices in Islamic banks (Beck et al., 2013; Čihák and Hesse, 2010).

Furthermore, comparing the two models equity market data, Islamic banks were found to have a limited crisis effect in comparison with conventional banks in terms of their equity markets (Kenourgios et al., 2016), with a better stock market performance (see e.g. Beck et al., 2013; Ashraf and Mohammad, 2014; Narayan and Bannigidadmath, 2015; Ho et al., 2014), and a slower drop down in stock prices during crisis times (Alexakis et al., 2016). However, Islamic stocks profitability is foreseen as a risk compensation rather than mispricing (Narayan et al., 2016). Moreover, publicly traded Islamic banks were found to have lower deposit insurance premiums without an increase in this cost during the crisis period (Grira et al., 2016).

The previous performance findings casted doubts on the current functionality of the conventional banking system, and pointed out the Islamic banks potential in supporting the stability of the financial system in front of systemic risk events. None the less, if we consider the systemic risk positive relation to bank size and inverse relation to bank capital during crisis times (Laeven et al., 2016), this can contribute to the explanation of these differences, but this does not convey the whole spectrum that Islamic banking features has in terms of systemic risk contribution. Grais and Kulathunga (2007) argue that Islamic banks business model and regulatory framework may have imposed capital requirements that supported stability and confined contagion risk.

Furthermore, we continue with the performance differences between the two business models based on efficiency. Bader et al. (2008) compared Islamic and conventional banks efficiency, within the Organization of Islamic Conference (OIC) countries, using a stochastic frontier approach, but found no difference in terms of efficiency between Islamic and conventional banks. Within the same countries, Abdul-Majid et al. (2010) found Islamic banks to be less technically efficient using a distance function, but Bader et al. (2008) found no difference between Islamic and conventional banks efficiency based on data envelopment analysis. In addition, Ghannouci et al. (2012) did not find a difference in technology or cost efficiency between the two models. Another comparison was provided by Beck et al. (2013), in which Islamic banks were found to be relatively more efficient than conventional banks, but this does not hold true as they confine the analysis to dual banking systems, where the two models compete within the same market, in which Islamic banks were found to have higher overhead costs along with a small higher value for the cost to income ratio (less cost effective).

On the other hand and beyond performance analysis, several empirical studies infer the stability of Islamic banks through risk analysis. We start with the work of Pappas et al. (2016), in which the researchers used survival models and found that Islamic banks have a significant lower failure risk than conventional ones, with the risk being based on both banks specific and macroeconomic variables. Baele et al. (2014) indicated that in Pakistan; loans default rates of conventional banks are almost twice those of Islamic ones. Using z-score indicator for insolvency risk and stability, Shahid and Abbas (2012) also found that small Islamic banks in Pakistan are more stable than both small conventional and large Islamic banks, while large conventional banks being more stable than large Islamic ones. Another case for Pakistan is the work of Wijnbergen and Zaheer (2013), in which they found that Islamic banks are more stable than conventional banks, and also, for the conventional banks that have both Islamic and conventional branches, Islamic branches are more stable unless their size is small.

Gamaginta and Rokhim (2015) found that in Indonesia, there is no significant difference in the level of stability between the small banks of the two banking models during the crisis period, however, the stability of conventional banks with an Islamic banking window is higher than that of the fully fledged Islamic banks. Čihák and Hesse (2010) applied multiple variations of z-score indicator and found that bank size affects its risk level, in which small Islamic banks are financially stronger than small conventional ones, whereas large size conventional banks are stronger than Islamic ones. Masood et al. (2011) found that small Islamic banks are more stable than large ones despite the higher income diversity of the later. In spite of the higher credit risk level that Islamic banks have, they are still more stable than the conventional banks, with a lower overall risk level (Ali 2012). Abedifar et al. (2013) pointed out that Islamic banks are more stable than conventional ones, but the significance of the difference vanishes for large banks. Beck et al. (2013) found a lower distance to insolvency for Islamic banks and confirmed the size effect, but highlighted large cross country differences of the considered banks.

In the same context, Daly et al. (2013) measured the resilience of bank performances and found that small size Islamic banks are financially stronger and more resilient but large size conventional ones are stronger. Rajhi and Hassairi (2013) found that Islamic banks are in general more stable than conventional ones but this is not held for small Islamic ones, with the main insolvency cause being both credit risk and income diversity. Altaee et al. (2013) pointed out that no difference is found in terms of the stability of Islamic and conventional banks within the Gulf Cooperation Council (GCC) countries. Belouafi et al. (2015) commented on the results of the empirical research using z-score, in which they pointed out that z-score indicator does not take into account the specificity of Islamic banks, in terms of being asset-based, in addition to their profit and loss sharing ability with their investment account holders.

In relation to market risk, Boumediene and Caby (2009) applied EGARCH and GARCH asymmetric models, they found that conventional banks show high volatility in their returns during the crisis period, while Islamic banks started from a low level of volatility, but had a substantial increase during the crisis as a result of their link to the real economy. Al-ali and Yousfi (2015) also applied GARCH, EGARCH GJR-GARCH models to banks in Jordan, they found that Islamic banks were more stable than conventional banks. Fakhfekh et al. (2016) used an FIEGARCH model for the two banking models within the GCC countries and found that conventional banks volatility is more responsive to bad news, with their volatility being more persistence after a shock, in addition, Islamic banks are more resilient but at a degrees that is sample dependent, with Saudi Arabia Islamic banks being the most resilient ones.

Furthermore, Hasan and Dridi (2011)found that Islamic banks better credit and asset growth allowed them to receive a more favorable risk assessment from external rating agencies. A related study concluded that profit sharing within Islamic banking can reduce market risk, however, Islamic banks need to develop risk mitigation techniques to be effectively stable in front of future financial crisis (Karim et al., 2012). Imam and Kpodar (2013) suggested that Islamic banks can complement, rather than substitute, conventional banks, allowing for the diversification of the banking sector, which may be helpful to the overall financial stability. Nevertheless, the same authors also indicated that interest rates have a negative influence on Islamic banks as they implicitly use them as a benchmark in paying returns to their depositors. The same was confirmed by the Malaysian banks case that was investigated by Chong and Liu (2009), in which they found that Islamic banks deposits have a return that follows the interest rate on the conventional banks deposits.

However, Abedifar et al. (2013) found that Islamic banks are less sensitive to the changes of the domestic interest rates. Bourkhis and Nabi (2013) pointed out that Islamic banks practices have deviated from the original Islamic finance model towards the conventional one, which puts their resilience under the pressure of the financial crisis. Weill (2011), found that Islamic banks have lower price markups than conventional banks in 17 OIC member countries. In terms of credit risk, Abedifar et al. (2013) indicted that Islamic banks generally have lower credit risk in comparison to conventional banks, and the effect is prominently apparent for small banks, for the ones based in Muslim population dominated countries, and for leveraged ones. Beck et al. (2013) indicated a negative relationship between Islamic bank size and credit risk, and suggested that it is possibly related to the lack of benefits from diversification and scale economies. In Pakistan, Wijnbergen and

Zaheer (2013) argue that the Islamic banks response to monetary contraction is similar to large banks, in which they maintain their lending level disregarding their actual liquidity positions, thus the monetary policy credit channels may be less strong as the Islamic banking system increase its size and importance, also Khan and Khanna (2012) found that Islamic banks deposits have higher growth rate than conventional ones even during the recent financial crisis, in spite that those Islamic banks have lower credit scores.

1.2 Unique features and risks of the Islamic banking system

The previous risk comparisons highlighted that Islamic banks are exposed to the generic risks that are similar to conventional banks, but are at the same time exposed to unique risks which are specific to the features of the Islamic banking business model. Unique Islamic banking risks include rate of return risk, displaced commercial risk, equity investment risk and Shariah noncompliance risk. In order to understand those unique risks, it is essential to comprehend the main principles upon which Islamic banking resides, along with the main contracts used within its transactions, and the risks that those instruments imply. The Islamic financial system is based on principles that emerge from the Islamic transaction rules known as Fiqh Al-Muamalah, that are part of the Islamic Shariah rules. In the following we discuss Islamic finance principles with more details in connection to the main Islamic banking instruments and their implied risks within Islamic banking:

1.2.1 The prohibition of interest, usury or unjust enrichment (Riba):

Interest or Riba is defined as any payment or receipt of interest which is forbidden by the Islamic Shareah rules (Obaidullah, 2005; Greuning and Iqbal, 2007; Tiby, 2011). In other words, it is not allowed to use interest or any guaranteed positive fixed predetermined rate or amount that is paid regardless of the realized performance of the transaction, based on the maturity and the amount of the transaction principal (Iqbal, 1997). The debt contracts that are conducted on this basis are referred to as Qard al Hassan, which is a debt of goodwill and benevolence, to be repaid at the original amount according to the predetermined contract conditions without interest, however an extra amount over the principal may be voluntarily given by the debtor to the lender, not because any written agreement or any predetermined provision or term. (Visser, 2009). Current deposits in Islamic banks are an example of Qard Al-Hasan or Amana.

From a theoretical point of view, the prohibition of interest is expected to expose Islamic banks to both operational and liquidity risk. Operational risk stems from any transaction that does not fully adhere to interest prohibition, which is perceived by the Shariah Supervisory Board (SSB), that monitors the bank Islamic operations, as a fiduciary risk in general, and as a shareah non-compliance risk in specific. This type of risk arise from conducting transactions that do not adhere to, or are not based on, Islamic finance principles. As for liquidity risk, it emerges from Islamic banks limitation in terms of the availability of their interbank market and money market. However, Islamic scholars are already working within the financial engineering field to develop high-quality short-term liquid assets, to be traded as money market instruments, that are compliant to Islamic shareah rules.

1.2.2 Islamic financial arrangements: profit and loss sharing vs. mark-up transactions.

This rules promote social justice between market participants as they pursue their aim to maximize their welfare and wealth. Under the Islamic shareah restrictions, Islamic banks are allowed to conduct their business transactions with their clients using a partnership relation, a trade relation, a trustee relation or a mix of those relations. Partnership relation comes from the Profit and loss sharing (PLS) rule, where borrowers and lenders share the realized profit or loss of the transaction (Khan and Ahmed, 2001). PLS arrangements can be referred to as an equity-based financing mode (Mudaruba: trustee partnership, Musharuka: partnership). As for the trade relation, it is based on selling or leasing an asset at a clearly declared mark-up rate (Murabaha: cost-plus trade), following the rules of fairness and transparency between traders. Mark-up arrangements can be referred to as non-PLS arrangements with the return calculated as a cost-plus rate, they include two subtypes; selling-based, and debt-based financing modes. Those arrangements are classified as debt-based if the bank sells assets to the client with a markup, and are classified as lease-based if the bank rents assets to the client. In either case, the bank must have in his position the ownership of the assets included in the transaction, otherwise, the bank needs to acquire them either through purchasing or manufacturing the assets. As for the trustee relation, it is similar to the case of the conventional banking system but with the shareah restrictions.

PLS arrangements are a unique specificity of Islamic banks, they reduce the mismatch between the assets of liabilities side that is commonly found in conventional banks, but at the same time they imply a unique risk and return source. With the partnership feature, the Islamic bank encounters equity investment risk and rate of return risk, and if losses are achieved then the Islamic bank is set under clients withdrawal risk, which leads the bank into displaced commercial risk. To further understand the risks that this feature imply, we need to discuss the Islamic bank balance sheet from the liability side. In theory, PLS investment accounts holders (depositors) are more alike equity holders, thus they provide protection to Islamic banks in disturbance times when the profit rates decline, in contrast to conventional banks obligation to compensate their depositors regardless of their actual outcome.

PLS arrangements in the liabilities side are recorded as deposits account, but they do not include current deposits (Amanah/Qard Hassan), or savings deposits in the form of (wadiah), rather they include savings deposit in the form of (Mudarabah), and include Investment deposits as in the case of term-deposits or time-deposits in the conventional system (Mudarabah/Musharukah, for a fixed-term or for an unlimited term), with two subtypes; restricted and unrestricted.

Current deposits principal is guaranteed to be repaid on demand and the depositor does not gain any share of the profit or any other return in any form with the bank acting as a trustee. The current deposits are either considered a trust account (Amanah), and such the bank does not use them without prior authorization from the depositor, or are considered as interest-free loan (Qard Hasan), and thus the bank uses the funds at its own risk without authorization from the depositors.

As for savings deposits, they generally have relaxed conditions on minimum balance and withdrawal without a prior notice. The bank takes a permission to use the funds at its own risk, and may voluntarily provide a low return to the account holders as a gift (for Wadiah), with the deposit principal being fully guaranteed and the bank acting as a trustee. Otherwise, the bank is authorized to invest the funds, which are usually invested in short-term low risk investments, at a low share of profit (loss), offered in an agreed manner, on the minimum maintained balance for the time period (for Mudarabah) with the principal and return not being guaranteed and the bank acting as a trustee partner responsible for managing the funds. The losses is absorbed by the fund provider or the client, in addition, the depositors will have a withdrawal cost as they do not receive the share of profits for the period in which the withdrawal is made.

In terms of Investment deposits, the investors also have a share of profit (or loss) in a given proportion with the bank, the share is usually higher than the one of savings accounts with the principal and return also not being guaranteed. In general, the investment time period is usually longer than the savings account, during which withdrawals are not allowed without prior notice, with the investment account holders having to endure a withdrawal cost as explained previously. The bank can utilize the investment deposits within a pooled investment portfolio that is applied to different operations and projects (for unrestricted investments), but the bank is formally authorized to invest only in specific projects (for restricted or special investments). In case of a realized loss, they are absorbed by the fund provider, which is only the account holder (Mudarabah) unless it is proved that the loss occurred as a result of the bank misconduct. However, if the funds are provided by the client and the bank in a partnership manner (Musharukah), and thus the loss is absorbed by both; the account holder and the bank, in accordance to the proportion that each of them have in the contributed capital (Iqbal et al., 1998; Obaidullah, 2005).

From the previous discussion we note that the PLS arrangements may help the Islamic banks to be more flexible during downturn times, but at the same time they imply additional risks. PLS deposit holders are commonly a source of funds for Islamic banks, and are directly related to withdrawal risk, which impacts the bank lending strategy and credit risk level. The withdrawal risk which arise from the PLS holders is claimed to be related to their religiously level. Several researches claim the presence of a relationship between religious beliefs and risk aversion level of the individual (Miller and Hoffmann, 1995; Osobo, 2003; Hilary and Hui, 2009).

Islamic banks may foresee this relationship from two perspectives; if the bank perceives the depositors as risk averse, this will increase the probability of withdrawal risk, and thus the

Islamic bank will be disciplined to have lower risk taking and lending appetite (Khan and Ahmed, 2001). On the other hand, if the bank perceives them as loyal to endure losses, this will decrease the probability of withdrawal risk, and the Islamic bank will have a more aggressive lending strategy, which will transfer credit risk to the investment deposit holders (Sundararajan and Errico, 2002).

Islamic banks try to mitigate withdrawal risk, which leads them to not fully commit to the PLS rule of shareah. They smooth the return that they provide to investment account holders to control for the withdrawal risk, by matching market competitive rates regardless of realized performance (Obaidullah, 2005), and this practice creates the displaced commercial risk, which is unique to the Islamic banking model. The logic that Islamic banks follow is that poor returns to investment account holders may simulate withdrawals that will cause a liquidity shortage and even a solvency crisis.

Displaced commercial risk is defined as the risk that Equity holders will be deprived part of their returns for the sake of investment depositors, to control for withdrawal risk, as a result for Islamic banks practice of smoothing the returns of the investment account holders (AAOIFI, 1999). In other words, this means that Islamic banks distribute profits to their investment account holders using the positive competitive market rate as a benchmark, even if they have realized losses, through using part of the profits that are entitled to equity holders and are kept in a special reserves account called profit equalization reserves (PER). Thus, the displaced commercial risk is also linked to benchmark yield risk, interest-rate risk and rate-of-return risk. However, even with the presence of this unique risk source, the arguments continue regarding Islamic banks higher ability to endure losses under crisis as they can share those losses with the investment account holders, even if they try to avoid doing so (Ahmed, 2002; Čihák and Hesse, 2010; Khan, 1987; Ali, 2007).

On the other hand, PLS arrangements on the assets side have the same previously explained sharing mechanism, in which the bank will be the provider of funds. The PLS financing transactions of (Mudarabah, Musharukah) are perceived by Islamic banks to bear high risk to the degree that Islamic banks are found to avoid the PLS modes in extending credit to their clients, and instead they rely more on the use of mark-up financing modes (Murabaha), which are mainly mark-up trade-based transactions, and are not a PLS based financing mode (eg. Salam: forward selling contract, Ijara: lease contract). The equity investment risk of PLS financing are especially related to the rate of return risk, displaced commercial risk and credit risk.

The balance sheet composition of Islamic banks reflect that they have approximately 20% of their total assets in PLS investments, which leaves nearly 80% of total assets in non-PLS ones (Bourkhis and Nabi, 2013), this practice is meant to avoid the complexity of PLS arrangements structuring and management (Errico and Farahbaksh, 1998; Mills and Presley, 1999; Aggarwal and Yousef, 2000; Dar and Presley, 2000; Sundararajan and Errico, 2002; Siddiqi, 2006; Chong and Liu, 2009; Baele et al., 2014), especially that Islamic banks cannot reduce the credit risk by requesting a collateral (Errico and Farahbaksh, 1998). However, it is also claimed that this behaviour of Islamic banks does not reduce the withdrawal risk in comparison with conventional banks (Khan and Ahmed, 2001; Sundararajan and Errico, 2002).

1.2.3 Prohibition of Money for Money transactions: transactions are backed by real assets.

Islamic shareah requires that all conducted transactions should be backed by tangible real assets, this is referred to as asset-backed financing which leads to the integration of the Islamic banking activities with the real economy. This is a main difference from the conventional banking system that requires its banking institutions to own and invest in debt based financial assets, money and monetary papers only, which means that they cannot position or own goods for trade as in the case of Islamic banks.

Moreover, Islamic finance recognizes money as a medium of exchange for a real asset, and thus, the profit is achieved based on the difference between the monetary value of different assets, in addition to the change of the money value of the same asset through time. This indicates that Islamic shareah rules take into consideration what the conventional system refer to as the time value of money, but confines this concept to become an asset-time value expressed in monetary units, instead of the money for money as in the use of interest rate on the money principal. Therefore, the Islamic shareah allows the same real asset to be sold on spot at a current value that is different from the value of the same asset if sold on differed payments (Usmani, 2002; Obaidullah, 2005). This Islamic finance rule restricts the Islamic banks from making money trade profits, as in the case of the conventional currency exchange rates and trade papers that are based on them. As a result, the Islamic banks transactions are dependent on illiquid assets (real assets and inventories) in comparison with conventional banks.

As a consequence for this restriction, the bank is under the risk of the change in the value of the used asset, especially that the shareah rules require the bank to have the assets in his position when a trade financing arrangement is initiated and until the contract maturity date. This increases the exposure of the Islamic bank to market risk, which arises from the unfavorable changes of the assets market value, such as price risk from the commodity prices, which affects the financial value of the used asset over the life of the contract. It is essential for Islamic banks to manage the volatility of their transaction arrangements from the current time frame and through the future time, to control for the market risk and its components, including mark-up risk, price risk, leased assets value risk, currency risk, securities price risk, rate of return risk, equity investment risk, benchmark risk, hedging risk and business environment risk (Greuning and Iqbal, 2007).

1.2.4 Prohibition of excessive uncertainty (Gharar) and speculative behaviour (Maysir).

Gharar refers to excessive or deceptive uncertainty in the transaction contract and Maysir refers to the high levels of uncertainty and risk taking as in gambling. Islamic shareah rules prohibits excessive uncertainty and gambling so as not to allow one of the contract participants to acquire profits, while the other is denied to have any, which does not provide fairness and equity for the transaction parties. The Islamic contracts are considered to be sacred duties and must have clear certainty in their clauses, which means that the contract parties should be protected from being deceived through ignorance or the presence of unclear essential elements of the transaction. This rule does not allow the bank to sell goods or assets that are not in his position to deliver, which implies uncertainty in the quality and the ability to deliver and the fair price of transaction. This also indicates the prohibition of gains based on a game of chance, as in the case of derivatives and options, which are foreseen as pure speculative transactions.

From a logical point of view, every business decision will include some level of speculation or uncertainty, but the rationality of Islam accepts this as long as the decisions are taken using all relevant valuable information, to reduce the risk of not having symmetric information and reduce moral hazards. Maysir and Gharar are often two inter-related actions, in which the presence of one dictates the presence of the other. Based on this rule, it is forbidden to invest a small amount of money for the hope of winning or earning a large undeserved sum, if the investor does not achieve this sum, then he will lose the total value of his investment, on the other hand, if the investor achieves the high earnings, the other party of the contract will be in a deficit position that is proportional to the difference between the small initial investment and the investor earnings, such as in the case of gambling and also the life insurance contract (Obaidullah, 2005).

Since derivatives are constrained under this rule, the Islamic banks appear to have a conservative risk taking ability. If we add up to this the asset-based or equity-based rules that connect them to real economy, then the stability of the Islamic bank is expected to be higher than the conventional bank, due to the constraints on their leverage level and exposure to speculative behaviour (Bourkhis and Nabi, 2013). Nevertheless, prohibition of gharar and maysir limits the Islamic bank in terms of short and long term investment opportunities, in terms of liquidity access and wholesale funding.

Greuning and Iqbal (2007) pointed out that Islamic banks are subject to two types of Liquidity risk; lack of access to funding sources and lack of available liquidity in the market, which makes liquidity risk management a critical task for Islamic banks. They also denoted several factors that contribute to Islamic banks higher exposure to liquidity risk, including limited money market instruments that are shareah based, limited interbank and secondary market trading ability, in addition to the characteristics of the Islamic banking instruments. As a result, the Islamic bank may maintain a high level of cash to meet the current deposits withdrawals and will be reluctant to engage in long term investments to avoid the high illiquidity of the included assets. The Islamic banking regulating bodies with the help of the Islamic scholars have supplemented the Islamic instruments with debt vehicles that are called sukuk and Islamic notes as equivalent instruments to conventional bonds and notes respectively, in order to reduce the liquidity and funding limitations, in addition to the continuous efforts to resolve the interbank market activation.

1.2.5 Prohibition of Shariah unapproved activities: Non-Halal transactions (Haram).

This rule refers to the prohibition of all transactions that are not accepted according to Islamic shareah ethical standards and are classified as non halal or haram. Interest based activities are an example of the prohibited transactions, other haram items include pork and alcohol production and selling, financing casinos...etc. In addition, Islamic banks are monitored through the Shariah Supervisory Board (SSB), in addition to central banks and regulating bodies, and in case the bank violates any of the Islamic finance rules then the bank will expose itself to the shareah non-compliance risk, which may cause the bank to be denied from having or providing certain Islamic finance instruments or may even cause the withdrawal of its Islamic activities license by the Islamic banking regulating bodies.

1.3 Review of Systemic Risk definitions and measurement

Up until now, there is no consensus on a single definition regarding systemic risk. Benoit et al. (2016) referred to systemic risk as a macroeconomic event that causes simultaneous severe losses for market participants that diffuses through the system. From another point of view, Billio et al. (2012a) considered the systemic risk of a financial system that is comprised of a network of connected institutions, with business linkages that allow the transfer and magnification of liquidity, insolvency and loss problems during times of financial crisis.

Kaufman and Scot (2003) provided a literature review for the definitions of systemic risk. The available concepts are categorized into three main definition clusters, the first cluster has pointed out the systemic risk as a likelihood of a large unexpected major macroeconomic level shock that has an adverse effect on the business system and the economy as a whole, with funds being misallocated rather than directed to the most productive institutions. The second and third definition clusters have identified systemic risk as microeconomic level events and have taken into consideration the propagation and diffusion of the adverse shock along with the spillover effect from the individual institution unit to other business units.

In the case of the first cluster; such as the ones provided by Bartholomew and Whalen (1995), and by Mishkin (1995), the definitions do not specify the process by which the shock effects are spreading to individual business institutions, or the sequence of its movement between the different types of institutions, neither do they specify the ones that will be mostly affected. In regards to the second definition cluster; such as in the case of Bank for International Settlement (1994), Kaufman (1994), Crockett (1997), George (1998), and the Board of Governors of the Federal Reserve System (2001). Those definitions have characterized systemic risk as the probability of having a cumulative loss event that takes a chain reaction diffusion pattern from one business institution to other participants within a network of institutional system. In this case, these definitions pointed out the correlation and direct causation that exists within a network of financial institutions and financial markets in identifying systemic risk.

As for the third cluster of definitions, it is concerned about the spillover of an external adverse shock and the correlation effect without stressing the direct causation within the network; rather its focus is on indirect linkages. These definitions underline the resemblance between network units and their risk exposure from third-party. Thus, one unit failure will undermine the value of other units that are subject to the same drastic event, with a probability of loss that is positively correlated to the degree of units similarities, creating a wave of uncertainty between investors in this system and thus will lead to a common shock accompanied by intensified sharp liquidity problems. This cluster also distinguishes between direct and indirect causes of systemic risk, in addition to random systemic risk caused by irrational investors behavior that lack an information base, and their opposite information based ones; such as in the case of the definitions provided by Kaminsky and Schmukler (1999), Aharony and Swary (1996), Kaminsky and Reinhart (2000), and Kaufman (1994).

The systemic importance guidance report of IMF/BIS/FSB (2009) asserted that the late 2008 financial crisis pointed out the need to develop instruments that can inspect the existence of systemic risk at its startup, in an early stage, in order to enable the regulating bodies to take the actions that help them in containing its expansion, in other words, supervising conditional correlations. Billio et al. (2012b) pointed out that during market failure, the correlations increase. Thus, to estimate systemic risk, two stages for the financial crisis should be taken into account, the first is the run-up phase, in which the crisis builds up, the second is the crisis-phase in which it erupts, the two stages are important and none of them should be neglected when measuring systemic risk (Brunnermeier and Oehmke, 2013). In addition, the financial system itself is represented as a connected network of financial institutions that includes firms with spillovers which are capable of undermining the system as a whole in case of their default.

The Finanacial Stability Board (2011) identified systemically Important Financial Institutions SIFIs 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." Benoit et al. (2013) classified the practice of risk management into two approaches to determine the contribution of each firm to the system risk. The approaches differ in the source of data that is used in the analysis. The first one exploits the data provided by the financial institution to the regulator, the second one exploits publicly available market data. The first is referred to as the supervisory approach, variables regarding the firm size, liquidity, leverage, complexity, interconnectedness and substitutability are used in this approach (see e.g. IMF/BIS/FSB, 2009; FSOC, 2012; Gouriéroux et al., 2012; Basel Committee on Banking Supervision, 2013; Greenwood et al., 2015).

The second is based on the assumption that publicly available data reflect the information about the publicly traded firm, and thus, it utilizes variables as stock returns and CDS spreads in its measures. Systemic risk measures included in this approach are Value-at-Risk measure (VaR), delta conditional value at risk (ΔCoVaR), expected shortfall (ES), marginal expected shortfall (MES), systemic risk (SRISK) and component expected shortfall (CES). At the firm level, VaR is the most common measure in this category that is used to measure the risk of each financial unit in isolation from the system. q-VaR measures maximum loss in monetary units within a q-confidence interval (Kupiec, 2002; Jorion, 2007). Using VaR includes limitations as it is not considered a coherent risk measure, it ignores the measurement of the 1% worst case loss, it fails to detect portfolio concentration risk, and does not differentiate between the diverse outcomes in the q-tail (Artzner et al., 1999).

An upgrade to VaR is the ΔCoVaR measure that was introduced by Adrian and Brunnermeier (2011) and which accounts for the losses that exceed the VaR measure. CoVaR is a measure of systemic risk that allows to override the idiosyncratic risk and determine the risk spillovers between financial institutions or financial systems. CoVaR can be used to specify the VaR of the financial system return conditional on a tail event observed for a financial firm as it becomes under financial distress and its stock returns deteriorate to become at its bottom 5% probability level. ΔCoVaR reflects the contribution of a financial unit to the risk level of a second financial unit or to the financial system, it represents the difference between the VaR of the financial system (or institution) conditional on a financial institution being under financial distress, and the VaR of the financial system (or institution) conditional on the financial institution being in its median state.

Another extension for VaR is the expected shortfall ES, which takes into account the loss distribution in the q-tail; it represents the expected loss conditional on being in the q-tail. This measure outperforms VaR as it gets along in the tail with the coherent risk measure of average value at risk (Fllmer and Schied, 2011). However, its shortcoming is that it is difficult to estimate the loss distribution in the 1% tail without having theoretical distributions in the form of parametric assumptions regarding the tail distribution. This means that, in case of extreme risk situations, it lacks a reality-based defined reliable measures for tail events probabilities. These assumptions turn the expected shortfall measure to a stable multiple of VaR instead of being a precise indicator for potential tail risk, another down turn is that expected shortfall cannot be used in back testing such as in the case of VaR (Rowe, 2012).

A modified version of ES is MES, which refers to the expected loss or decline in equity values when the market drops under a specified threshold within a determined time horizon. MES was proposed by Acharya et al. (2010) and was extended by Brownlees and Engle (2012) to a conditional one. MES extends the concept of Expected Shortfall (ES) to account for the marginal contribution of the financial institution to the financial market systemic risk, and is considered an extension of the concept of marginal VaR proposed to the ES by Jorion (2007). MES allows to assess the sensitivity of the financial system risk to a unit change in the financial firm ES, in other words, it is the one day loss expected if market returns are less than a given threshold (originally -2%). However, MES does not account for the idiosyncratic characteristics of the firm such as size and leverage, which means that it does not account for the too big to fail logic (TBTF). As a small firm may be assessed to be more systemically risky than a big one, MES is in favor of too interconnected to fail logic (TIF). Higher MES indicates higher vulnerability to market risk and imply a higher contribution ability to market fall (Acharya et al., 2010).

Another systemic risk measure is SRISK which was introduced by Brownlees and Engle (2012) and Acharya et al. (2012). SRISK is an estimate of the amount of the expected capital shortfall that the financial institution needs to avoid in order to survive during a financial crisis. SRISK is used to determine the most systemically risky institutions; which are the ones with higher expected capital shortfall during a financial crisis (Acharya et al., 2012; Brownlees and Engle, 2012). SRISK further extends MES as it uses the average of the future expected loss of the system due to a crisis over the next six month, which is referred to as the long-run marginal expected shortfall ($LRMES$). SRISK takes into account the idiosyncratic characteristics as it considers leverage and size of the financial institution in its calculation, which can be seen as a compromise between the TITF and the TBTF paradigms. The measure combines high frequency market data (daily stock prices and market capitalization) and low frequency balance sheet data (leverage) to provide a daily forecast SRISK index, but this means that it assumes the liabilities of the firm to be constant at least on quarterly basis for the crisis period.

The previously mentioned systemic risk measures are not enough to describe the systemic risk level of a specified system. Brunnermeier and Oehmke (2013) stated the need to have a systemic risk measure at the overall system level that can be allocated to individual firms according to each firm total contribution to overall systemic risk. The risk allocation methods available include Proportional Allocation (Urban et al., 2003), With-andWithout Allocation (Merton and Perold, 1993; Matten, 1996), Euler or Gradient allocation (Patrik et al., 1999; Tasche, 2000), and Shapley Value Allocation (Tsanakas, 2009; Tarashev et al., 2009).

An appropriate allocation will equate between the overall systemic risk and the sum of individual firms risks, it will also motivates the individual firms to select the appropriate marginal amount of systemic risk, however, this is challenged by the nonlinear relationship between the two goals and the notion that one firm selection of marginal contribution is affected by other institutions risk level within the financial network (Brunnermeier and Cheridito, 2014). Keeping this in mind, the systemic risk measure should distinguish the individually large interconnected important financial institutions (SIFIs) that have negative risk spillovers on other institutions, along with the cluster of smaller institutions that are correlated in a way that will threaten the system; which is known as the clone property (Brunnermeier et al., 2009).

Those issues are partially addressed through the recently introduced CES measure that was provided by Banulescu and Dumitrescu (2015). CES measures the absolute contribution of the financial firm to the ES of the financial system. CES extends MES as it takes into account the firm size, but at the same time, relies in its calculation on market data only, which allows it to avoid the data frequency differences that are used in the calculation of SRISK, and at the same time combines between the two paradigms of TBTF and TITF.

The firm size in the calculation of CES is represented by the market capitalization weight of the financial institution relative to the financial system. CES is the multiplication of the financial institution market capitalization weight by its MES. The ES of the financial system is the sum of the CES of each institution included in the system at the specified time point. This characteristic allows to decompose ES risk of the financial system into its institutional components and allows to provide a percentage for each institution from the financial system ES, which facilitates monitoring those institutions by the regulating authorities.

Another aspect of systemic risk measurement is the interconnectedness between the financial institutions within the financial system. Billio et al. (2012b) introduced several econometric measures of connectedness based on principal component analysis and Granger-causality networks. In a related paper, Diebold and Yılmaz (2014) proposed Vector Autoregressive models, augmented with a LASSO type estimation procedure, aimed at selecting the significant links in a network model. Similarly, Hautsch et al. (2014) and Peltonen et al. (2015) proposed tail dependence network models aimed at overcoming the bivariate nature of the available systemic risk measures. The previous models are based on the assumption of full connectedness among all institutions, which make their estimation and interpretation quite difficult, especially when a large number of institutions is being considered. To seize this issue, Ahelegbey et al. (2015) and Giudici and Spelta (2016) have recently introduced correlation network models, which can fully account for partial connectedness, expressed in terms of conditional independence constraints. A similar line of research has been followed by Barigozzi and Brownlees (2014) who introduced multivariate Brownian processes with a correlation structure determined by a conditional independence graph.

1.4 Thesis contribution and experimental settings

From the previous literature discussion on the differences between Islamic and conventional banks, as provided in subsections 1.1 and 1.2, we recognize several points that have not been directly addressed. The first notice is the absence of a direct evaluation of the stability of Islamic banks, and its effect on stabilizing the financial system itself, from a systemic risk point of view, in terms of both, their exposure and contribution to the financial system systemic risk. Second, we notice that many studies oversee evaluating the difference in the financial system overall risk, between systems that include either Islamic, or conventional banks, and those that operate a hybrid of Islamic, conventional and conventional banks with an Islamic window (services), all together working within the same banking system.

Furthermore, the literature lacks modelling Islamic banks interconnectedness within the financial system, whether for the stand alone entities or for the hybrids. Finally, we notice that the literature, and especially regarding the inference of the stability of Islamic banks and their importance in supporting the general stability of the banking system, usually depends on individual unit level rather than the system level, despite that the financial system is comprised of a network of financial institutions. However, to just limit the analysis to firm level is not enough since it does not fully represent the overall systemic risk for two main reasons; first, the aggregation of individual risks of the different institutions does not necessarily represent the overall system risk of the financial system, second, if two or more institutions have the same level of risk, this does not mean that they have the same contribution to the overall system risk, as one of them may have a higher risk spillover during financial crises.

On the other hand, from the discussion on systemic risk definitions and measurement, as provided in subsection 1.3, we notice an issue that still needs further consideration in the current spectrum of systemic risk measures, MES, SRISK and ΔCoVaR. Those measures are estimated from a bivariate approach point of view, in which the systemic risk of a financial institution is conditioned on the market index, or on another institution, without taking into consideration the effect that arise from the presence of other institutions on the time varying conditional correlation that result from the bivariate analysis process. Despite the conditional time varying nature of this correlation, it is still considered a marginal one, that captures both direct and indirect associations between two entities, without controlling for the other entities in the financial network, which does not cope with the multivariate nature of systemic risk.

In this thesis, we address the previously stated literature gabs in a series of three successive empirical papers. The main aim of our work is to assess the stability of the Islamic banking model, by evaluating its systemic risk, and its strength to support the stability of a fragile financial system under a systemic event. We achieve this objective with comparative systemic risk studies that evaluate the systemic risk of the Islamic banking model (IB) against its counterparts, the conventional one (CB), and the hybrid between the previous two, which is the conventional banking system that offers Islamic banking services via an Islamic window (CBwin).

In the first paper, we investigate the presence of a systemic risk difference at the overall banking system level, for countries that operate either Islamic, or conventional, or the previous two with a hybrid banking model. In other words, we examine whether including Islamic banking activities within a country's banking system supports the financial stability at the country level. To achieve this purpose, we compare the banking systems in terms of their systemic risk implications based on graphical Gaussian models (see e.g. Lauritzen, 1996), to materialize the complex connectedness relationship between the banking systems of the countries. We use partial correlation in building our statistical model, as it allows to have a parsimonious correlation structure that avoids the complications of a fully connected network model, especially in terms of results interpretation (see e.g. Giudici and Spelta, 2016; Ahelegbey et al., 2015). We summarize the systemic risk of the included banking systems form the estimated network using network centrality measures (see e.g. Furfine, 2003; Billio et al., 2012b). The use of country level graphical models allows us to avoid the heterogeneity of the results at the individual bank level, that we perceived in the Islamic banking stability literature section 1.1, especially that the individual unit level captures the idiosyncratic effect but misses the systemic interconnectedness component, and overlooks the systemic risk as a macroeconomic event that causes simultaneous severe losses for market participants as it diffuse through the system (Benoit et al., 2016). Thus, the advantage of using graphical models is to provide a measurement for systemic risk that, differently from the classical risk comparisons and the z-score measure, takes into account the multivariate dependencies between the banking systems. In our model we use equity market data, as it captures the differences between thee stated banking models (see e.g. Kenourgios et al., 2016), and apply the study on the publicly traded banks located within the countries of the Middle East and North Africa (MENA) region, as it is found to hold approximately 78.57% of the total global Islamic banking assets, with the countries of the gulf cooperation (GCC) region holding approximately 40% of this total (IFSB, 2016).

Our first paper findings pointed out a difference between the conventional and the Islamic banking systems impact on systemic risk, not only in magnitude but also in timing, as there is a one year time lag for the crisis effect on Islamic banks. In addition, a hybrid system within a strong economy may in general support a lower systemic risk, which may be consistent with a diversification effect on the country's systemic level portfolio. From a technical point of view, we note that the eigenvector centrality dispersion measure can serve as an early warning indicator of a crisis. In summary, our first paper findings support the ability of the Islamic banking model to strengthen the financial stability, but also we remark the presence of a strong cross-country variability which is also pointed out by Beck et al. (2013). These results confirm the findings provided by the Islamic banking literature.

Following, we further work in paper 2 on our main aim of evaluating Islamic banks stability and impact on the financial system from a systemic risk point of view. However, in paper 2, we limit our country sample to the GCC region in order to avoid the large cross country variations that we remarked in the first paper, to benefit from the availability of developed financial markets, and form the relatively similar regulatory, financial and economic environment. Furthermore, the economies of the GCC countries are oil dependent (Sturm et al., 2008), and are integrated with the global market, thus are open to receive the negative impact of the global crisis (see e.g. Zarour, 2006; Maghyereh and Al-Kandari, 2007; Arouri et al., 2011; Mohanty et al., 2011; Fayyad and Daly, 2011; Arouri and Rault, 2012), however, their interaction is not necessarily equal to this volatility index, but still it will be more consistent in comparison with the larger MENA region. Another aspect that the GCC countries provide us with is that they represent Muslim population dominated countries, which reduces the variation that may result from different religious beliefs and share of Muslim population on the banking system risk level, as those factors were found to affect the risk and performance of the Islamic banking system, its development and the economic growth (see e.g. Imam and Kpodar, 2013; Baele et al., 2014; Gheeraert and Weill, 2015; Abedifar et al., 2016).

Furthermore, we progress in paper 2 with the methodological point of view, in which we evaluate the vulnerability and contribution of each IB, CB, and CBwin banking sector using the bivariate version of the systemic risk measures of MES, SRISK and ΔCoVaR, we also use CES at the aggregate systems level to which we refer as GES. Furthermore, we take into consideration the dependency between market returns and their higher volatility during crisis times by using the dynamic conditional correlation model (DCC) of Engle (2002), to control for the heteroskedasticity problem in the stock market returns. Nevertheless, as we noted before, those bivariate measures do not consider the financial system as a network of connected institutions, thus we extend their estimation using partial correlation to capture the unique variance between two financial entities, while eliminating the variance that stems from others, which allows to focus on the direct correlation, rather than the indirect one. In other words, partial correlation allows us to target the direct dependence between the market returns of two participants conditioned on the other market participants. We estimate partial correlations conditionally on a graphical structure, within the quantitative learning framework of graphical Gaussian models, and thus we obtain a netted variance covariance matrix, which results in netted systemic risk measures that take into account the multivariate nature of systemic risk. In addition, we extend the variables of the GCC region to include leverage of the banking sectors, and size in terms of both total assets, and of course, market share. In this paper, we aggregate the returns per banking sector type using the market capitalization weighing standard method (see e.g. Banulescu and Dumitrescu, 2015), rather than log returns, this is mainly to avoid the impact on MES from having a large approximation error during crisis times upon using log returns as provided in the work of Caporin and de Magistris (2012).

In our application, we use country specific stock market return index for each of the GCC counties and we repeat the systemic risk measures estimation using three variations, in which, we first estimate the standard bivariate systemic risk measures, next we estimate the netted systemic risk measures, and then we use the crude oil index, to check our results under a unified volatility index represented by the oil price for all the GCC countries, to control for the index heterogeneity that we have from using a local stock market index for each country. We also evaluate systemic risk at the overall banking system level of the GCC region. We finally model the banking sectors interconnectedness by building a static partial connectedness graphical Gaussian model as described in the work of Giudici and Spelta (2016). We employ an undirected graphical model for each netted systemic risk measure, in which the nodes represent the values of the risk measure, while the links represent the significant partial correlations between them, the main purpose is to evaluate the contagion and diffusion ability of the different banking sectors, and how the systemic risk level of one banking sector is expected to affect the level of other sectors.

The results of the analysis in paper 2 confirm that the Islamic banking system contributed to lowering the financial system systemic risk level at the beginning of the crisis, as long as the IB banking sector is well capitalized with a low leverage level, but this mitigation ability drops down when the financial crisis spills over the real economy, which clearly indicates the time shift in the crisis impact on the Islamic banking sector in comparison to the CBwin and CB banking sectors, thus our findings are in line with the work of Khediri et al. (2015), and with Hasan and Dridi (2011). In addition, we found that the CBwin banking sector has the highest systemic risk contribution, and based on its size and connection to both the IB and CB banking sectors, it could destabilize the financial system. Furthermore, the

CB sector is noticed to have higher volatility in its response to the systemic risk events which maybe related to its leverage, but this higher volatility is neutralized by its small market share size. Moreover, the three measures reflect a relation to size for the CBwin and IB sectors, but a stronger relation to leverage for the smaller CB sector. Also, we find that the netted systemic risk measures of MES and ΔCoVaR, have a lower magnitude than the standard and the oil volatility index. Nevertheless, the netted SRISK has the highest SRISK magnitude in comparison with the other two estimation variations. In other words, netted SRISK has higher levels of capital shortfall expectations, which indicates that the standard systemic risk measures underestimate the expected capital shortfall, and especially under crisis times. Another related findings is that the returns on the stock markets of the GCC region, including the three banking sectors, are affected by the changes in the crude oil index, this notion indicates that banking regulators should keep a close attention to the effect of the changes in the oil price on the capital shortfall of the banking system. As for the interconnectedness analysis, both Netted MES and ΔCoVaR reflected higher importance for CBw during crisis periods but higher IB importance afterwards, whereas netted SRISK indicated the opposite in regards to the banking sectors capital buffers. We explain the ranks exchange between CBw and IB sectors using partial correlation magnitude and direction, in which we find that the IB sector is on average negatively correlated to CB but positively to CBw, whereas CB and CBw sectors are mainly positively correlated. This indicates the IB diversification effect on the system portfolio, and the CBw magnification effect on the system risk. In addition, since the IB sector has lower leverage in comparison to CBw, the capital buffer of the IB sector can be seen as a safety net rather than a risk one.
We conclude the thesis work in paper 3, were we focus more on developing the novelty of the netted MES systemic risk measure, to further consider the systemic risk multivariate nature into account. We use, from the previous paper, the GCC stock market return data to derive a correlation network between IB, CB and CBwin banking sectors and investigate how risks spread. We use the correlation network models by Giudici and Spelta (2016) as they account for the partial connectedness, expressed in terms of conditional independence constraints, that are based on graphical Gaussian models, which gives them a stochastic background, and we apply Bayesian model averaging on the correlation network, in order to improve the robustness of our results. We use the banking sectors returns rather than the systemic risk vectors in the estimation of the graphical model. We apply the centrality measures to determine the system risk rankings of the banking sectors and we also introduce a Ranking concentration ratio to improve the inference ability of the resulting rankings of the sectors. In regards to the estimation of NetMES, we use the DCC model as in paper 2, to calculate MES per banking sector, and we replace the conditional correlation with conditional partial correlation for the calculation of NetMES. We also insert the DCC outputs of MES in the network algorithm, and set the model to replace the conditional correlation with the partial one that is extracted from the correlation network in a Bayesian averaging manner, in order to obtain the Bayesian version of NetMES.

In summary we confirm that the IB banking sector is found to strengthen the stability of the GCC financial system in the crisis period, but as before, this ability decreases afterwards. We also confirm that the main systemic risk driver in the GCC region, for the crisis period is the CBwin sector. In addition, our findings are robust for both, the correlation network and our NetMES, but we notice a small difference in the selection between them. Interconnectedness, measured by network centrality measures, depends on leverage and, in this sense, the CBwin sector is the most systemic, followed by the IB one in the post-crisis period. Loss impact, measured by the marginal expected shortfall, depends on market capitalization and, in this sense, the CBwin sector is gaining more and more relevance, as its relative market size grows. Last, conventional banks exhibit a high level of volatility which, however, is not carried onto the system due to their small market size. Furthermore, the results indicate that the proposed NetMES and Bayesian NetMES measures are valid systemic risk measures, that can detect crisis signals and differentiate between different banking systems. The Bayesian NetMES is, in our opinion, more robust than NetMES, as it takes model uncertainty into account.

We believe that the implications of our research results can be beneficial to regulators and central banks in terms of Islamic banking activities effect on the countries financial and economic stability during a crisis period, especially with the argument that the monetary policy credit channels and contraction policies may become less strong as the Islamic banking system increase its size and importance (Wijnbergen and Zaheer, 2013). On the other hand, the exclusion of Islamic banks from the financial system will deprive the positive benefit that this system is argued to have on economic growth. Gheeraert and Weill (2015) pointed out that the development of Islamic banking is in favor of macroeconomic efficiency. Also, the conventional banks can gain insight regarding the effect of diversifying their services with Islamic banking activities on the bank risk profile, especially that in the last years more conventional banks are being involved in Islamic banking activities. In addition, the islamic banks themselves can benefit from this work in the identification and management of their systemic risk, and thus in improving their stability. Finally, fund providers and investors may also benefit from the research results in making portfolio allocation decisions.

The remainder of this thesis is organized as follows; section two provides paper 1 titled; Systemic Risk of Conventional and Islamic Banks: Comparison with Graphical Network Models. Section three provides paper 2 titled; Systemic Risk in Dual Banking Systems. Finally, section four provides paper 3 titled; NetMES: a network based marginal expected shortfall measure

References

AAOIFI (1999). *Accounting, Auditing and Governance Standards for Islamic Financial Institutions*. Accounting and Auditing Organization for the Islamic Financial Institutions. Bahrain.

Abdul-Majid, M., Saal, D. S., and Battisti, G. (2010). Efficiency in islamic and conventional banking: an international comparison. *Journal of Productivity Analysis*, 34(1):25–43.

Abedifar, P., Hasan, I., and Tarazi, A. (2016). Finance-growth nexus and dual-banking systems: Relative importance of islamic banks. *Journal of Economic Behavior & Organization*, pages –.

Abedifar, P., Molyneux, P., and Tarazi, A. (2013). Risk in islamic banking. *Review of Finance*, 17(6):2035–2096.

Acharya, V., Engle, R., and Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, 102(3):59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. P. (2010). Measuring systemic risk. Working Paper, NYU.

Adrian, T. and Brunnermeier, M. (2011). CoVaR. NBER Working Paper 17454, National Bureau of Economic Research.

Aggarwal, R. K. and Yousef, T. (2000). Islamic banks and investment financing. *Journal of Money, Credit and Banking*, 32(1):93.

Aharony, J. and Swary, I. (1996). Additional evidence on the information-based contagion effects of bank failures. *Journal of Banking & Finance*, 20(1):57–69.

Ahelegbey, D. F., Billio, M., and Casarin, R. (2015). Sparse graphical vector autoregression: A bayesian approach. *SSRN Electronic Journal*.

Ahmed, H. (2002). A microeconomic model of an islamic bank. Research paper No. 59. Islamic Research And Training Institute, Islamic Development Bank, Jeddah, Saudi Arabia.

Al-ali, A. H. O. and Yousfi, I. (2015). Investigation of jordanian islamic and conventional banks stability: Evidence from the recent financial crisis. *European Journal of Economics, Finance and Administrative Sciences*, (82):5–25.

Al-Hares, O. M., AbuGhazaleh, N. M., and El-Galfy, A. M. (2013). Financial performance and compliance with basel III capital standards: Conventional vs. islamic banks. *JABR*, 29(4):1031.

Alexakis, C., Pappas, V., and Tsikouras, A. (2016). Hidden cointegration reveals hidden values in islamic investments. *Journal of International Financial Markets, Institutions and Money*.

Ali, A. S. (2012). Islamic banking structure: Implications for risk and financial stability. *Islamic Economic Studies*, 20(2):141–147.

Ali, S. S. (2007). Financial distress and bank failure: Lessons from closure of ihlas finans in turkey. *Islamic Economic Studies*, 14(1):1–52.

Altaee, H. H. A., Talo, I. M. A., and Adam, M. H. M. (2013). Testing the financial stability of banks in gcc countries: Pre and post financial crisis. *International Journal of Business and Social Research IJBSR*, 3(4):93–105.

Ariffin, N. M., Archer, S., and Karim, R. A. A. (2009). Risks in islamic banks: Evidence from empirical research. *Journal of Banking Regulation*, 10(2):153–163.

Arouri, M. E. H., Lahiani, A., and Nguyen, D. K. (2011). Return and volatility transmission between world oil prices and stock markets of the {GCC} countries. *Economic Modelling*, 28(4):1815 – 1825.

Arouri, M. E. H. and Rault, C. (2012). Oil prices and stock markets in gcc countries: Empirical evidence from panel analysis. *International Journal of Finance & Economics*, 17(3):242–253.

Artzner, P., Delbaen, F., Eber, J.-M., and Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, 9(3):203–228.

Ashraf, D. and Mohammad, N. (2014). Matching perception with the reality—performance of islamic equity investments. *Pacific-Basin Finance Journal*, 28:175–189.

Aziz, Z. A. (2008). Enhancing the resilience and stability of the islamic financial system. In *BIS Review*, number 145, pages 1–5. Bank for International Settlement, Islamic Financial Services Board and Institute of International Finance Conference, Kuala Lumpur.

Bader, M. K. I., Mohamad, S., Ariff, M., and Hassan, T. (2008). Cost, revenue, and profit efficiency of islamic versus conventional banks: International evidence using data envelopment analysis. *Islamic Economic Studies*, 15(2):23–76.

Baele, L., Farooq, M., and Ongena, S. (2014). Of religion and redemption: Evidence from default on islamic loans. *Journal of Banking & Finance*, 44:141–159.

Bank for International Settlement (1994). 64th annual report. Switzerland: BIS.

Banulescu, G.-D. and Dumitrescu, E.-I. (2015). Which are the SIFIs? a component expected shortfall approach to systemic risk. *Journal of Banking & Finance*, 50:575–588.

Barigozzi, M. and Brownlees, C. T. (2014). NETS: Network estimation for time series. *SSRN Electronic Journal*.

Bartholomew, P. F. and Whalen, G. W. (1995). *Fundamentals of Systemic Risk*, volume 7 of *In Research in Financial Services: Banking, Financial Markets, and Systemic Risk*. Greenwich, Conn.: JAI.

Basel Committee on Banking Supervision (2013). Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement. Technical report, Bank for International Settlements.

Beck, T., Demirgç-Kunt, A., and Merrouche, O. (2013). Islamic vs. conventional banking: Business model, efficiency and stability. *Journal of Banking & Finance*, 37(2):433–447.

Belouafi, A., Bourakba, C., and Saci, K. (2015). Islamic finance and financial stability: A review of the literature. In El-Karanshawy, H. A., Omar, A., Khan, T., Ali, S. S., Izhar, H., Tariq, W., Ginena, K., and Quradaghi, B. A., editors, *Financial stability and risk management in Islamic financial institutions*, Financial stability and risk management in Islamic financial institutions, chapter 5, pages 21–42. Bloomsbury Qatar Foundation, Doha, Qatar.

Benoit, S., Colletaz, G., Hurlin, C., and Pérignon, C. (2013). A theoretical and empirical comparison of systemic risk measures.

Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2016). Where the risks lie: A survey on systemic risk. *Review of Finance*, page rfw026.

Betz, F., Opriçă, S., Peltonen, T. A., and Sarlin, P. (2014). Predicting distress in european banks. *Journal of Banking & Finance*, 45:225–241.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012a). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.

Billio, M., Getmansky, M., and Pelizzon, L. (2012b). Dynamic risk exposures in hedge funds. *Computational Statistics & Data Analysis*, 56(11):3517–3532.

Board of Governors of the Federal Reserve System (2001). Policy statement on payments system risk. Docket No. R-1107, 113. Washington, D.C., May 30.

Boumediene, A. and Caby, J. (2009). The stability of islamic banks during the subprime crisis. Social Science Research Network SSRN.

Bourkhis, K. and Nabi, M. S. (2013). Islamic and conventional banks' soundness during the 2007–2008 financial crisis. *Review of Financial Economics*, 22(2):68–77.

Brownlees, C. T. and Engle, R. F. (2012). Volatility, correlation and tails for systemic risk measurement. Working Paper, NYU.

Brunnermeier, M., Crockett, A., Goodhart, C., Persaud, A. D., and Shin, H. (2009). The fundamental principles of financial regulation. Centre for Economic Policy Research (CEPR).

Brunnermeier, M. K. and Cheridito, P. (2014). Measuring and allocating systemic risk.

Brunnermeier, M. K. and Oehmke, M. (2013). Bubbles, financial crises, and systemic risk. In *Handbook of the Economics of Finance*, pages 1221–1288. Elsevier BV.

Caporin, M. and de Magistris, P. S. (2012). On the evaluation of marginal expected shortfall. *Applied Economics Letters*, 19(2):175–179.

Cattelan, V., editor (2013). *Islamic Finance in Europe Towards a Plural Financial System*. Edward Elgar Publishing, Inc., Cheltenham, UK.

Chong, B. S. and Liu, M.-H. (2009). Islamic banking: Interest-free or interest-based? *Pacific-Basin Finance Journal*, 17(1):125–144.

Čihák, M. and Hesse, H. (2010). Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research*, 38(2-3):95–113.

Crockett, A. (1997). Why is financial stability a goal of public policy? Economic Policy Symposium, pages 7–36, Jackson Hole - Federal Reserve Bank of Kansas City.

Daly, S., GhorbelZouari, S., and Frikha, M. (2013). Islamic financial stability during the us sub-prime crisis: Using from data panel. *Journal of Behavioural Economics Finance Entrepreneurship Accounting and Transport*, 1(1):1–12.

Dar, H. A. and Presley, J. R. (2000). Lack of profit loss sharing in islamic banking: Management and control imbalances. *International Journal of Islamic Financial Services*, 2(2):1–16.

di Mauro, F., Caristi, P., Couderc, S., Maria, A. D., Ho, L., Grewal, B. K., Masciantonio, S., Ongena, S., and Zaher, S. (2013). Islamic finance in europe. Technical Report 146, European Central Bank, Frankfurt am Main, Germany.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Djennas, M. (2016). Business cycle volatility, growth and financial openness: Does islamic finance make any difference? *Borsa Istanbul Review*, 16(3):121 – 145.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Ernst & Young (2014). World islamic banking competitiveness report 201415, participation banking 2.0. EY World IslamicBanking CompetitivenessReport 2016 .

Ernst & Young (2015). World islamic banking competitiveness report 2016, new realities, new opportunities. EY World IslamicBanking CompetitivenessReport 2016.

Errico, L. and Farahbaksh, M. (1998). Islamic banking: Issues in prudential regulations and supervision. *IMF Working Papers*, 98(30):1.

Fakhfekh, M., Hachicha, N., Jawadi, F., Selmi, N., and Cheffou, A. I. (2016). Measuring volatility persistence for conventional and islamic banks: An fi-egarch approach. *Emerging Markets Review*, 27:84 – 99.

Fayyad, A. and Daly, K. (2011). The impact of oil price shocks on stock market returns: Comparing {GCC} countries with the {UK} and {USA}. *Emerging Markets Review*, 12(1):61 – 78.

Finanacial Stability Board (2011). Policy measures to address systemically important financial institutions. FSB, November 4.

Financial Times (2011). Islamic finance. Technical report. Special Report.

Fllmer, H. and Schied, A. (2011). *Stochastic Finance*. Walter de Gruyter GmbH.

FSOC, F. S. O. C. (2012). Authority to require supervision and regulation of certain nonbank financial companies. Technical Report 77, Federal Register. pp. 21637.

Furfine, C. (2003). Interbank exposures: Quantifying the risk of contagion. *Journal of Money, Credit, and Banking*, 35(1):111–128.

Gamaginta and Rokhim, R. (2015). The stability comparison between islamic banks and conventional banks: Evidence in indonesia. In et al. (Eds.), H. A. E.-K., editor, *Financial stability and risk management in Islamic financial institutions.*, pages 101–120. Bloomsbury Qatar Foundation, Doha, Qatar.

George, E. A. J. (1998). The new lady of threadneedle street. Governors Speech, Bank of England, London, February 24.

Ghannouci, W., Fiordelisi, F., Molyneux, P., and Radic, N. (2012). Do islamic and conventional banks have the same technology? Centre for EMEA Banking, Finance and Economics. Working Paper Series, (34) .pp. 1-24.

Gheeraert, L. and Weill, L. (2015). Does islamic banking development favor macroeconomic efficiency? evidence on the islamic finance-growth nexus. *Economic Modelling*, 47:32–39.

Giudici, P. and Spelta, A. (2016). Graphical network models for international financial flows. *Journal of Business & Economic Statistics*, 34(1):128–138.

Gouriéroux, C., Héam, J.-C., and Monfort, A. (2012). Bilateral exposures and systemic solvency risk. *Canadian Journal of Economics/Revue canadienne d'économique*, 45(4):1273–1309.

Grais, W. and Kulathunga, A. (2007). *Capital Structure and Risk in Islamic Financial Services*, chapter 4, pages 69–93. John Wiley & Sons (Asia) Pte Ltd.

Greenwood, R., Landier, A., and Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, 115(3):471–485.

Greuning, H. V. and Iqbal, Z. (2007). *Risk Analysis for Islamic Banks*. World Bank.

Grira, J., Hassan, M. K., and Soumar, I. (2016). Pricing beliefs: Empirical evidence from the implied cost of deposit insurance for islamic banks. *Economic Modelling*, 55:152 – 168.

Hasan, M. and Dridi, J. (2011). The effects of the global crisis on islamic and conventional banks: a comparative study. *Journal of International Commerce, Economics and Policy*, 02(02):163–200.

Hautsch, N., Schaumburg, J., and Schienle, M. (2014). Forecasting systemic impact in financial networks. *International Journal of Forecasting*, 30(3):781–794.

Hilary, G. and Hui, K. W. (2009). Does religion matter in corporate decision making in america? *Journal of Financial Economics*, 93(3):455–473.

Ho, C. F., Rahman, N. A., Yusuf, N. M., and Zamzamin, Z. (2014). Performance of global islamic versus conventional share indices: International evidence. *Pacific-Basin Finance Journal*, 28:110–121.

IFSB (2014). Islamic financial services industry stability report 2014. Technical report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur, Malaysia.

IFSB (2016). Islamic financial services industry stability report 2016. Technical report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur, Malaysia.

Imam, P. and Kpodar, K. (2013). Islamic banking: How has it expanded? *Emerging Markets Finance and Trade*, 49(6):112–137.

Imam, P. and Kpodar, K. (2016). Islamic banking: Good for growth? *Economic Modelling*, 59:387 – 401.

IMF/BIS/FSB (2009). Guidance to assess the systemic importance of financial institutions, markets and instruments: Initial considerations. Report to the G-20 Finance Ministers and Central Bank Governors.

Iqbal, M., Ahmad, A., and Khan, T. (1998). Challenges facing islamic banking. Occasional Paper 1, Islamic Research And Training Institute, Islamic Development Bank, Jeddah, Saudi Arabia.

Iqbal, M. and Llewellyn, D. T., editors (2002). *Islamic Banking and Finance: New Perspectives on Profit Sharing and Risk*. Edward Elgar Publishing, Inc., Cheltenham, UK.

Iqbal, Z. (1997). Islamic financial systems. *Finance and development, International Monetary Fund (IMF)*, 34(2):1–4.

Jorion, P. (2007). *Value at Risk – The New Benchmark for Managing Financial Risk*. McGraw–Hill, 3rd edition.

Kaminsky, G. L. and Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of International Economics*, 51(1):145–168.

Kaminsky, G. L. and Schmukler, S. L. (1999). What triggers market jitters? *Journal of International Money and Finance*, 18(4):537–560.

Kammer, A., Norat, M., Pin, M., Prasad, A., Towe, C., Zeidane, Z., and an IMF Staff Team (2015). Islamic finance: Opportunities, challenges, and policy options. *International Monetary Fund*, pages 1–38. IMF Staff Discussion Note, SDN/15/05.

Karim, B. A., Lee, W. S., Karim, Z. A., and Jais, M. (2012). The impact of subprime mortgage crisis on islamic banking and islamic stock market. *Procedia - Social and Behavioral Sciences*, 65:668–673.

Kaufman, G. G. (1994). Bank contagion: A review of the theory and evidence. *Journal of Financial Services Research*, 8(2):123–150.

Kaufman, G. G. and Scot, K. E. (2003). What is systemic risk, and do bank regulators retard or contribute to it? *Independent Review*, 7(3):371–391.

Kenourgios, D., Naifar, N., and Dimitriou, D. (2016). Islamic financial markets and global crises: Contagion or decoupling? *Economic Modelling*, 57:36–46.

Khan, A. and Khanna, T. (2012). *Building Bridges across Financial Communities: The Global Financial Crisis, Social Responsibility, and Faith-Based Finance*. Harvard Law School, Cambridge, MA.

Khan, F. (2010). How 'islamic' is islamic banking? *Journal of Economic Behavior & Organization*, 76(3):805–820.

Khan, M. F. and Porzio, M., editors (2010). *Islamic Banking and Finance in the European Union, A Challenge*. Studies in Islamic Finance, Accounting and Governance. Edward Elgar Publishing Limited, Cheltenham, UK.

Khan, M. S. (1986). Islamic interest-free banking: A theoretical analysis. *Staff Papers (International Monetary Fund)*, 33(1):1–27.

Khan, M. S. (1987). *Theoretical studies in Islamic banking and finance*, chapter Islamic interest-free banking: A theoretical analysis., pages 15–36. Houston, Tex. : Institute for Research and Islamic Studies.

Khan, T. and Ahmed, H. (2001). Risk management: An analysis of issues in islamic financial industry. Occasional Papers 5, The Islamic Research and Teaching Institute (IRTI).

Khediri, K. B., Charfeddine, L., and Youssef, S. B. (2015). Islamic versus conventional banks in the GCC countries: A comparative study using classification techniques. *Research in International Business and Finance*, 33:75–98.

Kumru, C. S. and Sarntisart, S. (2016). Banking for those unwilling to bank: Implications of islamic banking systems. *Economic Modelling*, 54:1 – 12.

Kupiec, P. H. (2002). What exactly does credit VaR measure? *The Journal of Derivatives*, 9(3):46–59.

Kuran, T. (2004). *Islam and Mammon*. Princeton University Press, Princeton, New Jersey, United States.

Laeven, L., Ratnovski, L., and Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance*, 69:S25–S34.

Lauritzen, S. L. (1996). *Graphical Models*. Oxford Statistical Science Series. Clarendon Press, United Kingdom.

Lewis, M. K. and Algaoud, L. M. (2001). *Islamic Banking in Mixed Systems*, chapter 6, pages 119–158. Edward Elgar Publishing, Inc., Cheltenham, UK.

Maghyereh, A. and Al-Kandari, A. (2007). Oil prices and stock markets in gcc countries: New evidence from nonlinear cointegration analysis. *Managerial Finance*, 33(7):449–460.

Masood, O., Niazi, G. S. K., and Ahmad, N. (2011). An analysis of the growth and rise of smaller islamic banks in the last decade. *Qualitative Research in Financial Markets*, 3(2):105–116.

Matten, C. (1996). *Managing bank capital: capital allocation and performance measurement*. John Wiley & Sons Pte Ltd.

Merton, R. C. and Perold, A. (1993). THEORY OF RISK CAPITAL IN FINANCIAL FIRMS. *Journal of Applied Corporate Finance*, 6(3):16–32.

Miller, A. S. and Hoffmann, J. P. (1995). Risk and religion: An explanation of gender differences in religiosity. *Journal for the Scientific Study of Religion*, 34(1):63–75.

Mills, P. S. and Presley, J. R. (1999). *Islamic Finance: Theory and Practice*. Springer Nature.

Mishkin, F. (1995). *Comment on Systemic Risk*, volume 7 of *in Research in Financial Services: Banking, Financial Markets, and Systemic Risk*. Greenwich, CT: JAI Press.

Mohanty, S. K., Nandha, M., Turkistani, A. Q., and Alaitani, M. Y. (2011). Oil price movements and stock market returns: Evidence from gulf cooperation council (gcc) countries. *Global Finance Journal*, 22(1):42 – 55.

Narayan, P. K. and Bannigidadmath, D. (2015). Does financial news predict stock returns? new evidence from islamic and non-islamic stocks. *Pacific-Basin Finance Journal*.

Narayan, P. K., Phan, D. H. B., Sharma, S. S., and Westerlund, J. (2016). Are islamic stock returns predictable? a global perspective. *Pacific-Basin Finance Journal*, pages –.

Nomani, F. (2006). *The dilemma of riba-free banking in Islamic public policy*, chapter 8, pages 193–223. Routledge Taylor & Francis Group.

Obaidullah, M. (2005). *Islamic Financial Services*. Islamic Economics Research Center, King Abdulaziz University, Jeddah, Saudi Arabia.

Olson, D. and Zoubi, T. A. (2008). Using accounting ratios to distinguish between islamic and conventional banks in the GCC region. *The International Journal of Accounting*, 43(1):45–65.

Osobo, B. J. (2003). Risk preferences and the practice of religion: evidence from panel data. Working paper, West Virginia University.

Pappas, V., Ongena, S., Izzeldin, M., and Fuertes, A.-M. (2016). A survival analysis of islamic and conventional banks. *Journal of Financial Services Research*, pages 1–36.

Patrik, G., Bernegger, S., and Regg, M. B. (1999). The use of risk adjusted capital to support business decision making. *Casualty Actuarial Society Electronic Forum*, (9):243–334.

Peltonen, T. A., Piloiu, A., and Sarlin, P. (2015). Network linkages to predict bank distress. *SSRN Electronic Journal*.

Pinner, H. Q. and LinYan (2013). Islamic finance: foreign policy opportunities.

Rajhi, W. and Hassairi, S. A. (2013). Islamic banks and financial stability: A comparative empirical analysis between mena and southeast asian countries. *Region et Developpement*, 37:149–177.

Rowe, D. (2012). The false promise of expected shortfall. *Risk Journal*.

Shafique, A., Faheem, M. A., and Abdullah, I. (2012). Impact of global financial crises on the islamic banking system: Analysis of islamic financial system during financial crunch 2008. *Oman Chapter of Arabian Journal of Business and Management Review AJBMR*, 1(9):124–134.

Shahid, M. A. and Abbas, Z. (2012). Financial stability of islamic banking in pakistan: An empirical study. *African Journal of Business Management*, 6(10):3706–3714.

Siddiqi, M. N. (2006). Islamic banking and finance in theory and practice: A survey of state of the art. *Islamic Economic Studies*, 13(2):1–48.

Solé, J. (2008). Introducing islamic banks into conventional banking systems. *Journal of Islamic Economics, Banking and Finance*, 4(2):9–34.

Sturm, M., Strasky, J., Adolf, P., and Peschel, D. (2008). The gulf cooperation council countries economic structure, recent developments and role in the global economy. Technical Report 92, European Central Bank, Frankfurt am Main, Germany.

Sundararajan, V. and Errico, L. (2002). Islamic financial institutions and products in the global financial system: Key issues in risk management and challenges ahead. *IMF Working Paper*, 02(192):1–27.

Tacy, K. J. (2006). Islamic finance: A growing industry in the united states. *North Carolina Banking Institue*, 10(1):355—-378.

Tarashev, N., Borio, C., and Tsatsaronis, K. (2009). The systemic importance of financial institutions. *BIS Quarterly Review*, pages 75–87.

Tasche, D. (2000). Risk contributions and performance measurement. Technical report, Research paper, Zentrum Mathematik (SCA).

TheCityUK (2015). Islamic finance report. London Stock Exchange Group. Technical Report.

Thomson Reuters (2015). Icd thomson reuters islamic finance development report 2015: Global transformation.

Tiby, A. M. E. (2011). *Islamic Banking: How to Manage Risk and Improve Profitability*. John Wiley & Sons, Inc.

Tsanakas, A. (2009). To split or not to split: Capital allocation with convex risk measures. *Insurance: Mathematics and Economics*, 44(2):268–277.

Urban, M., Dittrich, J., Klppelberg, C., and Stlting, R. (2003). Allocation of risk capital to insurance portfolios. *Bltter der DGVFM*, 26(2):389–406.

Usmani, M. T. (2002). *An Introduction to Islamic Finance*. Kluwer Law International, 1 edition.

Visser, H. (2009). *Islamic Finance Principles and Practice*. Edward Elgar Publishing Limited, 2 nd edition.

Weill, L. (2011). Do islamic banks have greater market power? *Comp Econ Stud*, 53(2):291–306.

Wijnbergen, S. V. and Zaheer, S. (2013). *Capital structure, risk shifting and stability: conventional and Islamic banking*, page 6388. Financial intermediation and monetary transmission through conventional and Islamic channels. Rozenberg Publishing Services, Amsterdam.

Zarour, B. A. (2006). Wild oil prices, but brave stock markets! the case of gcc stock markets. *Operational Research*, 6(2):145–162.

Applied Mathematics, 2016, 7, 2079-2096
http://www.scirp.org/journal/am
ISSN Online: 2152-7393
ISSN Print: 2152-7385

Systemic Risk of Conventional and Islamic Banks: Comparison with Graphical Network Models

Shatha Qamhieh Hashem, Paolo Giudici

Department of Economics and Management Science, University of Pavia, Pavia, Italy
Email: shatha.hashem01@universitadipavia.it, paolo.giudici@unipv.it

How to cite this paper: Hashem, S.Q. and Giudici, P. (2016) Systemic Risk of Conventional and Islamic Banks: Comparison with Graphical Network Models. *Applied Mathematics*, **7**, 2079-2096.
http://dx.doi.org/10.4236/am.2016.717166

Received: August 11, 2016
Accepted: November 11, 2016
Published: November 14, 2016

Abstract

The main aim of this paper is to compare the stability, in terms of systemic risk, of conventional and Islamic banking systems. To this aim, we propose correlation network models for stock market returns based on graphical Gaussian distributions, which allows us to capture the contagion effects that move along countries. We also consider Bayesian graphical models, to account for model uncertainty in the measurement of financial systems interconnectedness. Our proposed model is applied to the Middle East and North Africa (MENA) region banking sector, characterized by the presence of both conventional and Islamic banks, for the period from 2007 to the beginning of 2014. Our empirical findings show that there are differences in the systemic risk and stability of the two banking systems during crisis times. In addition, the differences are subject to country specific effects that are amplified during crisis period.

Keywords

Financial Stability, Centrality Measures, Graphical Gaussian Models, Islamic Banks, Conventional Banks, Systemic Risk

1. Introduction

The late 2007-2008 global financial crisis has assured the importance of financial systems' stability and soundness under a systemic risk event. The crisis also highlighted the difference between Islamic and conventional banks in terms of their stability. Even though Islamic banks faced the challenges encountered by their conventional peers during the financial crisis, they managed to achieve an average growth rate of 20% after 2009 ([1]). The high growth rate and the resilience abilities of the Islamic banking model attracted the conventional financial sector participants to consider the use of Islamic finance characteristics as a means of financial stability. This has stimulated research, aimed at comparing Islamic and conventional banks in terms of risks and performances. An Islamic bank is a financial institution that is engaged in all banking activities at a zero-interest rate according to Islamic Shariah rules (see e.g. [2]). In addition, it is allowed to share profit and loss (PLS) between the provider and the user of funds, but all its transactions should be backed by real tangible assets, with restrictions on taking excessive uncertainty (gharar) as in the use of derivatives, or excessive risk taking (maysar) as in gambling, or financing any business activity that is not ethically accepted (only halal activities are allowed). The governor of the Malaysian central bank ([3]), asserted in a speech the protection from risk that an Islamic bank has as a result of its business model features. However, [4] found that a strong connection to the real economy will increase the system exposure to contagion effects, which challenges the stability of Islamic banks in a novel way due to its strong connection to the real economy.

Usually, Islamic banks stability is inferred through comparative risk analysis with conventional banks. [5] indicated that in Pakistan, loans default rates of conventional banks are almost twice those of Islamic ones. [6] found a size affect on the bank risk level, with a favorable stability effect for the small Islamic banks, whereas the stability of large banks are in favor of the conventional ones. In a similar study, the z-score indicator has shown that Islamic banks are more stable than conventional ones, but the significance of the difference vanishes for large banks ([7]). Finally, [8] found a lower distance to insolvency for Islamic banks and confirmed the size effect, but highlighted the presence of large cross country differences.

In addition to the previous stability inference based on the z-score measure, Islamic banks stability is also assessed based on market risk. [9] found that Islamic banks have better credit and asset growth, which contributed to the financial system stability during the crisis time, and allowed them to receive a more favorable risk assessment from external rating agencies. A related study concluded that the PLS feature of Islamic banks can reduce the market risk, but this is subject to the risk mitigation techniques used by them ([10]). [11] suggested that Islamic banks can complement, rather than substitute, conventional banks, which may be helpful to the overall financial stability through diversification. [12] showed that in general, the two banking models have no significant difference in spite Islamic banks higher return on assets, they also pointed out that Islamic banks have deviated from their model towards the conventional one, which puts their resilience under the pressure of the financial crisis.

From the previous discussion, we note that the literature does not directly consider the measurement of Islamic banks systemic risk. In addition, and to our knowledge, the issue of evaluating Islamic banks systemic risk, through modelling their interconnectedness within the financial system, has not yet been addressed, and has overlooked the process of systemic risk assessment that considers the financial system as a network of institutions with linkages, which allows the systemic risk and the financial distress to be transfered and magnified during crisis times, as applied by [13]. Furthermore, the literature does not directly assess the systemic risk implication that Islamic banks have on the countries which include both conventional and Islamic banking activities. We aim to fill this gap through studying Islamic banks' systemic risk impact on the financial system of the countries where they operate. This is in line with [8] findings, as our objective is to take into account the presence of cross country differences.

Our contribution tries to take into consideration the two prevailing research viewpoints present in the literature of Islamic banking stability. The first questions if there is a real difference between the Islamic and conventional banking systems (see e.g. [14] [15]); we address this point by including countries with a full Islamic or a full conventional banking system, if no difference is found between the two pure systems, then the Islamic and conventional banking systems are alike. The second suggests that the two models are different and may be complementary once the relative strengths and weaknesses are understood ([16] [17] [18] [19]); we address this point by measuring the systemic risk for countries that operate both Islamic and conventional banking systems, and compare them to the two pure system.

The main aim of this paper is to investigate whether including Islamic banking activities within a country's banking system supports the financial performance and stability at the country level. To achieve this purpose, we compare countries that operate either conventional or Islamic banking systems with those that operate both. We apply this study on the publicly trade banks located within the countries of the Middle East and North Africa (MENA) region, as the majority of the Islamic banking activities are settled there. The MENA region is found to hold 78.57% of the total global Islamic banking assets, with the GCC countries holding 38.19% of this total ([1]).

The methodological contribution of this paper is aimed at providing a statistical model that allows to compare banking systems in terms of their systemic implications using financial networks, based on graphical Gaussian models. Graphical Gaussian models were introduced in multivariate statistics to model complex relationships between many variables (see e.g. [20]). Recently, they have been found as powerful alternatives to measure systemic risk, with respect to fully connected network models, see for instance, the papers by [21], and [22].

Country level Graphical models allow us to avoid the heterogeneity of the results at the individual banks level, especially that the available literature assess Islamic banks' stability based on the individual bank level, whether using z-score or other risk indicators, which captures the idiosyncratic effects, but misses the systemic interconnectedness component, and overlooks the definition of systemic risk as a macroeconomic event that causes simultaneous severe losses for market participants as it diffuse through the system ([23]). Thus, the advantage of using graphical models is to provide a measurement for systemic risk that, differently from the classical risk comparisons and the z-score measure, takes into account the multivariate dependencies between the agents involved (banking systems).

We believe that the implications of our research results can be beneficial to regulators and central banks in terms of Islamic banking activities effect on the countries' financial and economic stability during a crisis period. Conventional banks can gain insight regarding the effect of diversifying their services with Islamic banking activities on the bank's risk profile, especially that in the last years several conventional banks from Europe, UK and the USA are being involved in Islamic banking activities. Finally, fund providers and investors may benefit from the research in making portfolio allocation decisions.

The paper is organized in five sections. The second section provides the proposed methodology, based on graphical Gaussian models and the centrality measures obtained from them. The third section describes the data and the application of the proposed models. And the final section provides the research conclusions.

2. Graphical Gaussian Network Models

The research field of systemic risk has emerged after the recent financial crisis. Several empirical studies have been carried out to determine the degree of contagion between conventional banks and the related financial systems.

Specific measures of systemic risk have been proposed by [24] [25] [26] [27] and [28]. All of these approaches are built on financial market price information, in which they lead to assessing the financial institution's appropriate quantiles of the estimated loss probability distribution, conditional on a crash event in the financial market. They however do not address the issue of how risks are transmitted between different institutions.

Trying to address this aspect of systemic risk, researchers have recently introduced financial network models. In particular, [29] propose several econometric measures of connectedness based on principal component analysis and Granger-causality networks. [30] propose Vector Autoregressive models, augmented with a LASSO type estimation procedure, aimed at selecting the significant links in a network model. [31] and [32] propose tail dependence network models aimed at overcoming the bivariate nature of the available systemic risk measures.

Network models, albeit elegant and visually attractive, are based on the assumption of full connectedness among all institutions, which makes their estimation and interpretation quite difficult, especially when a large number of them is being considered. To tackle the previous limitation, [22] and [21] have recently introduced graphical correlation models, which can account for partial connectedness, expressed in terms of conditional independence constraints. A similar line of research has been followed by [33], who have introduced multivariate Brownian processes with a correlation structure that is determined by a conditional independence graph.

Our contribution follows the latter perspective, and employs graphical network models to understand and compare the different banking systems in terms of systemic risk and its transmission mechanisms. To achieve this aim we use the closing price for the corresponding banks' shares, and we measure how such prices correlate. The data is assumed to be generated by a stationary process, with the mean $\mu = 0$. To achieve stationarity, we transform stock prices into stock returns that are expressed, as usual, in time variation.

Formally, if V_t and V_{t-1} are the closing stock prices at times t and $t-1$, the variation represents the returns denoted by $w(t)$, such that: $w(t) = V_t - V_{t-1}/V_{t-1}$, where $V_{t-1} \neq 0$.

In our framework, we consider a cross-sectional perspective to understand the change in systemic risk transmission mechanism in relation to the presence and absence of the financial crisis, in which the systemic risk can be depicted by a network that describes the mutual relationships between the different banking systems involved. Correlation based networks are suitable to visualize the structure of pairwise marginal correlations among a set of nodes N that corresponds to the investigated banking systems. Each banking system represents a node in the network, and each pair of nodes can be connected by an edge, which has a weight related to the correlation coefficient between the two nodes. Furthermore, the banking systems that comprise a network of N nodes can be described by an associated $N \times N$ matrix of weights, named adjacency matrix A, with each element in the matrix referenced as $a_{i,j}$. However, since the aim of the research is to focus on the structure of the interconnections, and less on the interconnectedness magnitude, the adjacency matrix A can be made binary (0,1), by setting $a_{i,j} = 1$ when two nodes are correlated, and $a_{i,j} = 0$ when they are not correlated.

Another issue that relates to correlation networks initialization is the specification of the correlation itself, as being marginal against being partial. It is known that the use of pairwise marginal correlations will measure both the direct and the indirect effect of one network node on another. On the other hand, the use of pairwise partial correlations will measure only the direct effect between the two network nodes, excluding the mediation of others, which better servers our purpose of modelling the systemic risk of each node, or in other words, the systemic risk of each banking system.

From a statistical viewpoint, marginal correlations can be estimated on the basis of the observed N time series, in which each time series contains the return data of a specific banking system, under the assumption that the observations follow a multivariate Gaussian model, with unknown variance-covariance matrix Σ. As for partial correlations, they can be estimated assuming that the same observations follow a graphical Gaussian model, in which the variance-covariance matrix Σ is constrained by the conditional independence described by a graph (see e.g. [20] [34]; or from an econometric viewpoint, [35] [36]).

More formally, let $x = (x_1, \cdots, x_N) \in R^N$ be a N-dimensional random vector (a returns vector), distributed according to a multivariate normal distribution $\mathcal{N}_N(\mu, \Sigma)$, where μ is the mean, and Σ is the covariance matrix which we assume throughout the work that it is not singular.

The network model is represented by an undirected graph G, such that $G = (V, E)$, with $V = \{1, \cdots, N\}$ being the vertex set (nodes), and $E = V \times V$ being the edge set. G is described with a binary adjacency matrix A, that has elements e_{ij}, which provides the information of whether pairs of vertices in G are (symmetrically) linked between each other ($e_{ij} = 1$), or not ($e_{ij} = 0$). If the vertices V of this graph are put in correspondence with the random variables $X_1, \cdots, X_N$, in which each X refers to the time series of a specific banking system stock returns, the edge set E induces conditional independence on X via the so-called Markov properties (see e.g. [20]). More precisely, the pairwise Markov property determined by G states that, for all $1 \le i < j \le N$:

$$e_{ij} = 0 \Leftrightarrow X_i \perp X_j \mid X_{V \setminus \{i,j\}} \tag{1}$$

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

In our context, all random variables are continuous and are assumed to be normally distributed, with each $X \sim \mathcal{N}_N(0, \Sigma)$, and with the elements of the inverse of the variance-covariance matrix Σ^{-1} being indicated as $\{\sigma^{ij}\}$. [34] proved that the following equivalence also holds:

$$X_i \perp X_j \mid X_{V \setminus \{i,j\}} \Leftrightarrow \rho_{ijV} = 0 \tag{2}$$

where

$$\rho_{ijV} = \frac{-\sigma^{ij}}{\sqrt{\sigma^{ii}\sigma^{jj}}} \tag{3}$$

ρ_{ijV} denotes the ij-th partial correlation, that is, the correlation between X_i and X_j conditionally on the remaining variables $X_{V \setminus \{i,j\}}$. Therefore, by means of the pairwise Markov property, and given an undirected graph $G = (V, E)$, a graphical Gaussian model can be defined as the family of all N-variate normal distributions $\mathcal{N}_N(0, \Sigma)$ that satisfy the constraints induced by the graph on the partial correlations for all $1 \le i < j \le N$, as follows:

$$e_{ij} = 0 \Leftrightarrow \rho_{ijV} = 0 \tag{4}$$

In practice, the available data will be used to test which partial correlations are different from zero at the chosen significance level threshold α. This leads to the selection of a graphical model on which all inferences are conditioned and from which the systemic risk is determined.

To summarize the systemic risk form the network that we estimated on the basis of the graphical Gaussian model, network centrality measures are used. The most important summary measure that has been proposed in financial network modeling, to explain the capacity of an agent to cause systemic risk, as a large contagion loss on other agents, is eigenvector centrality (see e.g. [29] [37]). Eigenvector centrality measures the systemic risk of a node based on the importance of that node in the network. This is done by assigning relative scores to all nodes in that network, using the principle that connections to few high scoring nodes contribute more to the score of the node in question than an equal number of connections to low scoring nodes.

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

$$Eg_i = \frac{1}{\lambda}\sum_{j=1}^{N} a_{i,j} Eg_j \tag{5}$$

where Eg_j is the eigenvector centrality score of the *j*-th node, λ is a constant, $a_{i,j}$ is the (i, j) element in the adjacency matrix *A* of the network, and *N* is the number of nodes in the network. The previous equation can be rewritten in terms of all nodes, more compactly, as:

$$AEg = \lambda Eg \tag{6}$$

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

A different, and simpler to interpret, measure of systemic risk is node degree, which is a measure of the number of links that are significantly present in the selected model, between a node and all others. For a node i in a graphical model with nodes $j = 1, \cdots, n$, let e_{ij} represent a binary variable that indicates whether a link between i and j is present (1) or not (0), then node degree is:

$$d_i = \sum_{j=1}^{N} e_{ij} \tag{7}$$

Both the previously introduced measures are based on the adjacency matrix of a correlation network and depend, therefore, only on the presence or absence of a link between two nodes, and not on the actual (direct) dependence between them. To introduce such dependence we can extend the node degree measure d_i into a partial correlation node degree ρd_i, that employs partial correlations as weights, the measure formula is:

$$\rho d_i = \sum_{j=1}^{N} e_{ij} \left|\rho_{ijV}\right| \tag{8}$$

In the application section, we compare node degree, partial correlation degree and eigenvector centrality measures. Before moving to the application, we remark that the measures are conditioned on the chosen graph and, therefore, may be quite unstable, depending on the results of the selection procedure.

To check the robustness of our results, a Bayesian approach can be followed so that the centrality measures can be estimated without being conditioned on the chosen graph, as in the classical approach, but rather as a model average between different graphs, each with a weight that corresponds to its posterior probability, and is repeated on a yearly base rolling window.

To achieve this aim, the first task is to recall the expression of the marginal likelihood of a graphical Gaussian model, and specify prior distributions over the parameter Σ as well as on the graphical structures G. For a given graph G, consider a sample X of size n from $P = \mathcal{N}_N(0,\Sigma)$, and let S_n be the corresponding observed variance-covariance matrix. For a subset of vertices $A \subset N$, let Σ_A denote the variance-covariance matrix of the variables in X_A, and define with S_A the corresponding observed variance-covariance submatrix.

When the graph G is decomposable, the likelihood of the data, under the graphical Gaussian model specified by P, nicely decomposes as follows (see e.g. [21]):

$$p(x \mid \Sigma, G) = \frac{\prod_{c \in \mathcal{C}} p(x_C \mid \Sigma_C)}{\prod_{s \in \mathcal{S}} p(x_S \mid \Sigma_S)} \tag{9}$$

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

$$P(x_C \mid \Sigma_C) = (2\pi)^{-\frac{n*|C|}{2}} |\Sigma_C|^{-n/2} \exp\left[-1/2\, tr\left(S_C (\Sigma_C)^{-1}\right)\right] \tag{10}$$

the same representation holds for $P(x_S \mid \Sigma_S)$.

A convenient prior for the parameters of the above likelihood is the hyper inverse Wishart distribution. It can be obtained from a collection of clique specific marginal inverse Wisharts as follows:

$$l(\Sigma) = \frac{\prod_{C \in \mathcal{C}} l(\Sigma_C)}{\prod_{S \in \mathcal{S}} l(\Sigma_S)} \tag{11}$$

where $l(\Sigma_C)$ is the density of an inverse Wishart distribution, with hyperparameters T_C and α, and similarly for $l(\Sigma_S)$. For the definition of the hyperparameters here we follow [21] and let T_C and T_S be the submatrices of a larger matrix T_0 of dimension $N \times N$, and choose $\alpha > N$. To complete the prior specification, for $P(G)$, we assume a uniform prior over all possible graphical structures.

It can be shown that, under the previous assumptions, the posterior distribution of the variance-covariance matrix Σ is a hyper Wishart distribution with $\alpha + N$ degrees of freedom and a scale matrix given by:

$$T_n = T_0 + S_n \tag{12}$$

where S_n is the sample variance-covariance matrix. This result can be used for quantitative learning on the unknown parameters, for a given graphical structure.

In addition, the proposed prior distribution can be used to integrate the likelihood with respect to the unknown random parameters, obtaining the so-called marginal likelihood of a graph, which will be the main metric for structural learning, that involves choosing the most likely graphical structures. Such marginal likelihood is equal to:

$$P(x \mid G) = \frac{\prod_{C \in \mathcal{C}} p(x_C)}{\prod_{S \in \mathcal{S}} p(x_S)} \tag{13}$$

in which

$$p(x_C) = (2\pi)^{-\frac{n*|C|}{2}} \frac{k(|C|, \alpha + n)}{k(|C|, \alpha)} \frac{\det(T_0)^{\alpha/2}}{\det(T_n)^{(\alpha+n)/2}} \tag{14}$$

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

$$k_p(a) = \pi^{\frac{p(p-1)}{4}} \prod_{j=1}^{p} \Gamma\left(a + \frac{1-j}{2}\right) \tag{15}$$

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

$$P(G \mid x) \propto P(x \mid G) P(G) \tag{16}$$

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

$$G^* = \arg\max_G P(G \mid x) \propto \arg\max_G P(x \mid G) \tag{17}$$

The Bayesian approach does not force conditioning inferences on the (best) model chosen. The assumption of G being random, with a prior distribution on it, allows any inference on quantitative parameters to be model averaged with respect to all possible graphical structures, with weights that correspond to the posterior probabilities of each graph. This is due to Bayes' Theorem:

$$P(\Sigma \mid X) = P(\Sigma \mid x, G) P(G \mid x) \tag{18}$$

However, in many real problems, the number of possible graphical structures could be very large and we may need to restrict the number of models to be averaged. This can be done efficiently, for example, following a simulation-based procedure for model search, such as Markov Chain Monte Carlo (MCMC) sampling.

In our context, given an initial graph, the algorithm samples a new graph using a proposal distribution. To guarantee irreducibility of the Markov chain, we follow [21] to test whether the proposed graph is decomposable. The newly sampled graph is then compared with the old graph, calculating the ratio between the two marginal likelihoods, if the ratio is greater than a predetermined threshold (acceptance probability), the proposal is accepted, otherwise it is rejected. The algorithm continues until practical convergence is reached.

3. Empirical Application

3.1. Data Description

We have selected all the publicly traded banks in the MENA region from Bureau Van Dijk's Bankscope database. The banks that have data availability limitations where discarded which resulted in a total sample size of 81 listed banks that belong to 14 different countries. The country list along with the corresponding percentage of banking assets for each bank type from MENA region total assets is described per year in Table 1.

Table 1. MENA countries banking assets distribution between bank types per year.

Country	Bank Type	2008	2009	2010	2011	2012	2013
AE	CB	0.11	0.1	0.13	0.16	0.15	0.15
	CB.win	1.3	1.22	0.96	0.87	0.67	0.69
	CB.sub	7.54	7.86	7.91	7.68	7.77	7.47
	IB	1.6	1.63	1.66	1.57	1.59	1.66
SA	CB.win	5.74	6.03	5.71	5.32	5.4	5.21
	CB.sub	0.96	1.01	1	0.98	1.06	1.02
	IB	1.67	1.85	2	2.26	2.56	2.6
IL	CB	8.65	8.76	9.03	8.81	8.36	8.15
KW	CB	0.84	0.77	0.9	0.86	0.88	0.89
	CB.win	1.41	1.46	1.32	1.27	1.28	1.25
	CB.sub	1.49	1.4	1.38	1.35	1.42	1.49
	IB	1.81	1.83	1.82	1.99	1.94	1.79
QA	CB.win	0.89	0.75	0.81	0.81	0.88	0.99
	CB.sub	1.66	1.77	1.96	2.37	2.8	3.06
	IB	0.86	0.75	0.8	0.94	1.09	1.07
IR	IB	1.44	1.89	1.97	2.17	2.34	2.85
BH	CB.win	0.5	0.36	0.34	0.37	0.38	0.36
	CB.sub	1.72	1.7	1.56	1.51	1.42	1.32
	IB	0.69	0.72	0.74	0.72	0.65	0.63
MA	CB	1.03	1.09	1.06	1.08	1.02	0.82
	CB.win	0.41	0.39	0.43	0.48	0.26	0.4
	CB.sub	1.08	1.14	1.1	1.12	0.72	0.92
LB	CB	0.17	0.17	0.2	0.25	0.27	0.27
	CB.sub	2.03	2.1	2.05	1.93	1.83	1.79
JO	CB	0.19	0.17	0.24	0.26	0.25	0.23
	CB.sub	1.08	0.93	0.87	0.88	0.85	0.79
OM	CB	0.21	0.09	0.08	0.08	0.14	0.15
	CB.win	1.04	0.72	0.76	0.75	0.82	0.82
EG	CB.win	0.4	0.36	0.37	0.38	0.39	0.36
	IB	0.24	0.14	0.14	0.15	0.15	0.15
MT	CB	0.42	0.31	0.19	0.23	0.23	0.23
	CB.win	0.34	0.24	0.22	0.14	0.17	0.18
TN	CB	0.48	0.31	0.28	0.28	0.27	0.25

Table 1 indicates that the highest proportions of bank assets in our sample can be attributed to Arab Emirates, Saudi Arabia, Israel, Kuwait and Qatar.

The banks in the sample are also classified according to four banking types: CBs group, which includes conventional banks that do not provide any type of Islamic financial services; CB-Win group, which includes conventional banks that provide Islamic financial services within their operations but do not operate a fully Islamic banking subsidiary; CB-Sub group, which includes conventional banks that provide Islamic financial services and operate an Islamic banking subsidiary; and IBs group, which includes fully fledged Islamic banks in all its services and subsidiaries. The 81 banks in the sample are distributed between the different banking groups to 19 CBs, 24 CB-win, 17 CB-sub, 21 IBs, a more detailed distribution by country is shown in Table 2.

Table 2 indicates that IL represents a full CBs system, while IR represents a full IBs one. In terms of total assets, at the overall MENA level, the CB group represent 23.42% of them, the CB-win group 21.41%, the CB-sub group 35.67% and the IBs group 19.49%.

We use a dataset that represents market data on equities that extends over 89 months from January 2007 to May 2014. The data set is split into two main parts, the first is

Table 2. Distribution of bank type per country.

Country	Country code	Gulf countries	CBs	CB-Win	CB-Sub	IBs
Kuwait	KW	Yes	2	3	1	4
United Arab Emirates	AE	Yes	1	4	6	4
Oman	OM	Yes	1	3	-	-
Qatar	QA	Yes	-	3	2	3
Saudi Arabia	SA	Yes	-	6	1	4
Bahrain	BH	Yes	-	2	2	2
Iran	IR	Yes	-	-	-	3
Total Number of Banks = 57			4	21	12	20
Israel	IL	No	6	-	-	-
Morocco	MA	No	3	1	1	-
Lebanon	LB	No	1	-	2	-
Jordan	JO	No	1	-	2	-
Malta	MT	No	2	1	-	-
Tunisia	TN	No	2	-	-	-
Egypt	EG	No	-	1	-	1
Total Number of Banks = 24			15	3	5	1
Total Number of Banks = 81			19	24	17	21

during the crisis period, which extends from January 2007 to December 2009, and the second is after the crisis period, from January 2010 to May 2014. Table 3 provides the descriptive statistics of the the stock market return data for MENA countries.

3.2. Contagion Network between Countries

Before studying systemic risks, we describe the systematic effects of countries on bank performances.

Figure 1 shows the time evolution of the aggregated bank returns on a per country basis for the period from 2007 to 2014.

Figure 1 indicates the presence of high volatility for some countries' returns, which seems to be centered around the trend of Israel. Overall, countries with a high portion of Islamic banks, such as Saudi Arabia and Iran, are more volatile than countries with a

Table 3. MENA countries return descriptive statistics.

	Returns per Country													
	IL	KW	MA	MT	TN	AE	OM	LB	JO	SA	QA	BH	EG	IR
Mean	0.539	0.187	1.530	0.378	1.154	0.046	−0.107	0.675	0.966	0.713	0.963	−0.236	0.527	−0.482
Standard Deviation	0.103	0.294	0.040	0.108	0.091	0.121	0.122	0.054	0.074	0.086	0.092	0.249	0.115	0.570
Kurtosis	2.084	10.100	−0.874	21.714	−1.208	−0.917	−0.072	−0.441	1.975	−0.336	0.704	0.711	−0.042	−1.247
Skewness	−1.559	−3.135	0.241	−3.106	−0.443	0.773	0.908	−0.199	1.530	0.732	−0.925	1.363	−0.424	0.375
Minimum	0.210	−0.960	1.450	−0.340	0.980	−0.100	−0.280	0.560	0.870	0.550	0.680	−0.590	0.240	−1.380
Maximum	0.670	0.480	1.620	0.550	1.320	0.280	0.220	0.780	1.200	0.930	1.150	0.400	0.740	0.480
Count	89	89	89	89	89	89	89	89	89	89	89	89	89	89

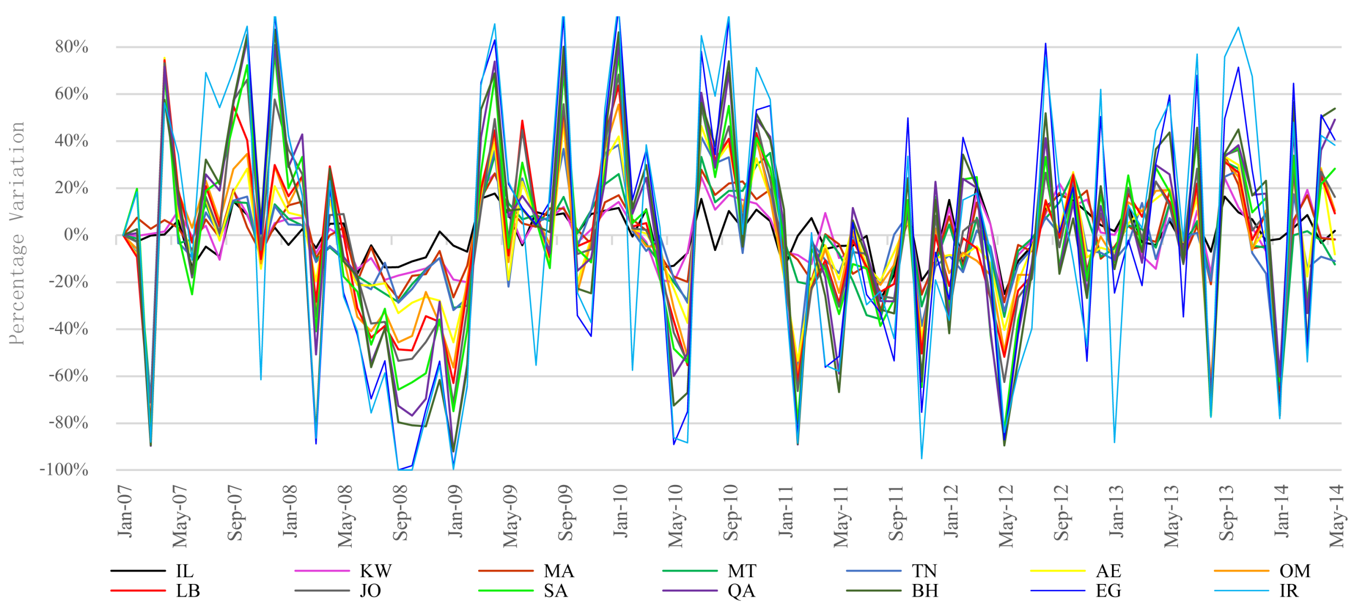


Figure 1. MENA countries stock-market return variation over the period 2007-2014.

high portion of conventional banks, such as Tunisia. Having seen the systematic effects of countries, we examine if this volatility is transmitted by assessing the impact in terms of systemic risk, the main focus of our paper.

To achieve this aim we present the graphical Gaussian model obtained on the basis of the partial correlations between aggregate country returns, separately for the crisis period (2007-2009) and the post-crisis period (2010-2014). We have chosen the best model by means of a backward selection procedure that, starting from the fully connected model, progressively tests for edge removal using a significance level of $\alpha = 0.05$. Figure 2 describes the selected graphical models during the crisis period and post crisis period.

In the above figure for the crisis and post crisis periods, the nodes with the highest number of edges are the most interrelated, we can determine the capacity of the corresponding countries as agents for systematic risk using centrality measures, and rank countries from the most to the least contagious.

Table 4 shows the centrality measures, introduced in Section 2, that are calculated on the basis of the graphical models in Figure 2.

The centrality measures in Table 4 show that the fully conventional banking system, represented by IL, has the highest rank for almost all the centrality measures of the selected models, whereas the fully Islamic banking system, represented by IR, ranks lowest during the crisis, but has a moderate increase in its contagion rank in the post-crisis period. This finding may suggest that the two systems are different in terms of systemic risk, with full Islamic banks being less contagious.

As for the dual banking systems, weak economies such as JO and LB are in relatively high ranks during and after the crisis, with the other weak economies moving upward in the ranks for the post crisis period. On the other hand, strong economies are relatively stable, as they have a moderate change in their ranks, except for KW, which seems to follow the behavior of the full conventional system in both its rank and its returns variability through time. These findings suggest that the impact of the dual hybrid systems strongly depends on the country in which they are based.

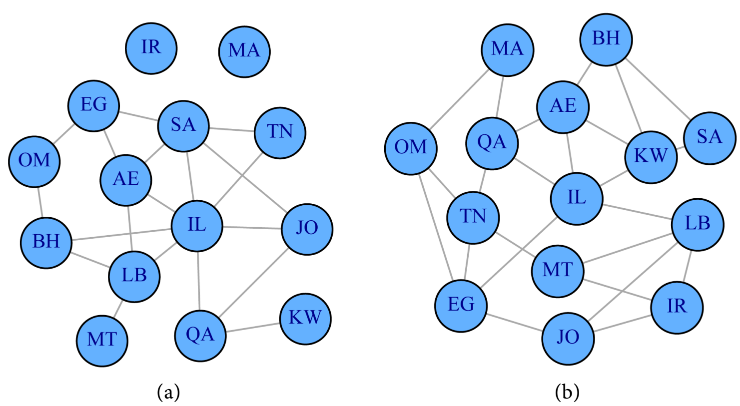


Figure 2. Contagion network between countries. (a) During-crisis network, (b) post-crisis network.

Table 4. Centrality measures.

	Node Degree		Node Partial Correlation Degree		Eigenvector Centrality	
Country	During-Crisis	Post-Crisis	During-Crisis	Post-Crisis	During-Crisis	Post-Crisis
IL	7	5	3.69	2.22	0.52	0.43
KW	1	4	0.43	2.23	0.06	0.31
MA	0	2	0	0.78	0	0.14
MT	1	3	0.43	1.19	0.08	0.2
TN	2	4	0.86	1.52	0.24	0.28
AE	4	4	1.95	1.94	0.37	0.35
OM	2	3	1.17	1.27	0.12	0.2
LB	4	4	2.13	1.64	0.3	0.28
JO	3	3	1.75	1.31	0.29	0.21
SA	5	2	2.43	0.92	0.42	0.14
QA	3	4	1.38	1.43	0.22	0.33
BH	3	3	1.62	1.7	0.24	0.22
EG	3	4	1.55	1.64	0.23	0.3
IR	0	3	0	1.42	0	0.19

We now consider the full time evolution of the eigenvector centrality measure by means of the Bayesian approach, which provides a stable averaged model inference on yearly basis as shown in Table 5.

The Bayesian model eigenvector centrality measure in Table 5 shows that the fully conventional banking system combined with a strong economy, as in the case of IL, has a high systemic risk rank during and after the crisis (except for the year 2011). Whereas the fully Islamic banking system, represented by IR, starts from a low contagion rank during the crisis, and moves upward in the rank in the post-crisis period. This finding confirms the previous model results regarding the difference between the two systems in terms of systemic risk, with the full Islamic banks being less contagious during crisis period.

In terms of the dual banking systems, weak economies such as MA, MT, TN, JO and LB are in relatively high ranks during the crisis and remain there after the crisis (except for JO). On the other hand, strong economies with a high concentration of Islamic banks, as in the case of SA, start in low ranks during the crisis, move to higher ranks upon its materialization in 2009, and progress towards lowering their ranks after. Similarly, the Bayesian model shows that KW starts from a high contagion rank and progresses towards a lower one after the crisis.

The dispersion in the eigenvector centrality measure estimated from the Bayesian model around its yearly average, from 2007 to 2013, is provided in Figure 3.

Figure 3 reflects the high dispersion of the eigenvector centrality measure during the 2007-2008 crisis period around its yearly average, which is mainly led by countries of

Table 5. Eigenvector centrality of the bayesian model.

	Eigenvector Centrality per Year						
Country	2007	2008	2009	2010	2011	2012	2013
IL	0.35	0.399	0.269	0.313	0.021	0.279	0.331
KW	0.001	0.399	0.269	0.313	0.021	0.193	0.144
MA	0.35	0.399	0.269	0.313	0.356	0.279	0.331
MT	0.35	0.418	0.269	0.313	0.356	0.279	0.331
TN	0.35	0.022	0.269	0.036	0.356	0.223	0.135
AE	0.06	0.001	0.269	0.313	0.356	0.279	0.331
OM	0.001	0.023	0.269	0.313	0.098	0.245	0.115
LB	0.35	0.399	0.271	0.008	0.098	0.353	0.372
JO	0.35	0.022	0.001	0.313	0.058	0.204	0.103
SA	0.009	0.024	0.269	0.313	0.374	0.231	0.135
QA	0.06	0.114	0.027	0.324	0.098	0.368	0.307
BH	0.365	0.399	0.006	0.324	0.133	0.076	0.139
EG	0.35	0.005	0.058	0.072	0.364	0.279	0.331
IR	0.062	0.11	0.586	0.036	0.414	0.322	0.343
Yearly Average	0.215	0.195	0.221	0.236	0.222	0.258	0.246

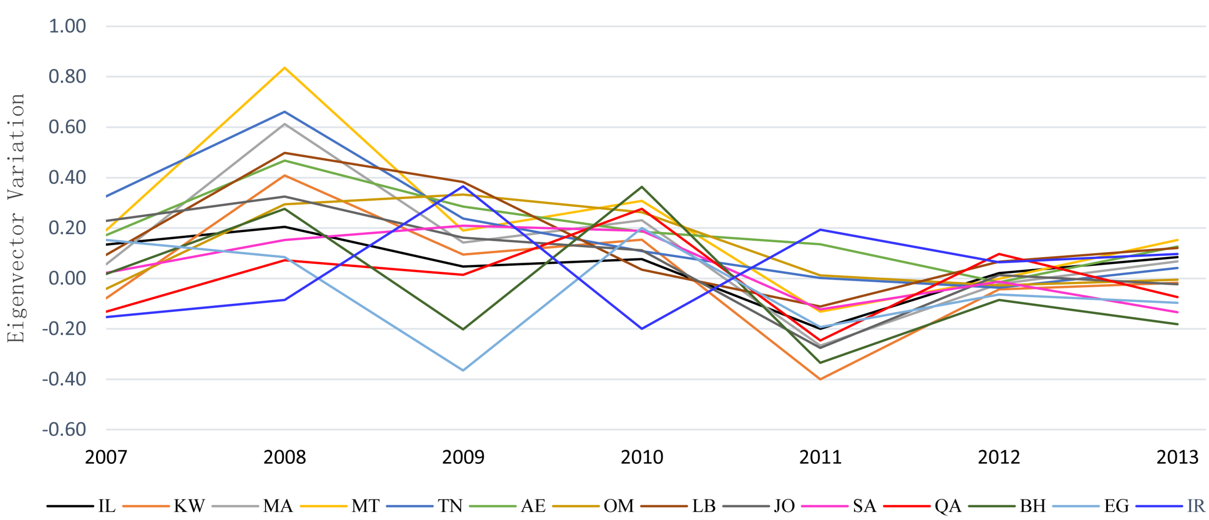


Figure 3. Countries eigenvector centrality variation around its yearly average.

higher conventional banking concentration, and reflects a lower extent of high dispersion during 2009 that is led by countries of higher Islamic banking concentration. For both systems, the dispersion around the mean is reduced in the following years. Overall, Figure 3 suggests that the countries have high differences in their contagion levels during the crisis, but have smaller differences after the crisis.

To summarize, our findings suggest that there is a difference between the conventional and the Islamic banking systems impact on systemic risk, not only in magnitude but also in timing as there is a one year time lag for the crisis effect on Islamic banks. In addition, a hybrid system within a strong economy may in general support a lower systemic risk which may be consistent with a diversification effect on the country's systemic level portfolio. Finally, we remark that the eigenvector centrality dispersion measure in **Figure 3** may be beneficial as an early warning indicator of a crisis.

4. Conclusions

The main aim of this paper is to investigate whether and how Islamic financial services support financial stability, based on how they affect the country level systematic risk. To achieve this aim, we have proposed a correlation network approach based on graphical Gaussian models, both classical and Bayesian, with a set of related centrality measures, which may describe the systemic risk of each country.

Our results support the ability of the Islamic banking model to enhance financial and economic stability, but also the presence of a strong cross-country variability. These results confirm the findings provided by the literature. Our findings also clearly describe the different impact of the recent financial crisis on the systemic risk levels of each country.

Suggestions for future research involve further studying systemic risk in dual systems combining graphical models with standard bivariate measures such as MES, SRISK and ΔCoVaR. Furthermore, it would be important to let systemic risk to depend on variables such as the leverage and the size of the banking sectors and the market share of different banking types.

Acknowledgements

The authors acknowledge the financial support from the PRIN project MISURA: multivariate models for risk assessment, and of the PhD programme in Economics and management of technology at the University of Pavia. The paper has been written by Shatha Hashem, with the supervision of Professor Paolo Giudici.

References

[1] Islamic Financial Services Board (2014) Islamic Financial Services Industry Stability Report 2014. Technical Report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur.

[2] Shafique, A., Faheem, M.A. and Abdullah, I. (2012) Impact of Global Financial Crises on the Islamic Banking System: Analysis of Islamic Financial System during Financial Crunch 2008. *Oman Chapter of Arabian Journal of Business and Management Review AJBMR*, **1**, 124-134. http://dx.doi.org/10.12816/0002166

[3] Aziz, Z.A. (2008) Enhancing the Resilience and Stability of the Islamic Financial System. BIS Review. 145, Bank for International Settlement: Islamic Financial Services Board and Institute of International Finance Conference, Kuala Lumpur, 1-5. http://www.bis.org/review/r081126c.pdf

[4] Betz, F., Oprică, S., Peltonen, T.A. and Sarlin, P. (2014) Predicting Distress in European Banks. *Journal of Banking & Finance*, **45**, 225-241. http://dx.doi.org/10.1016/j.jbankfin.2013.11.041

[5] Baele L., Farooq M. and Ongena S. (2014) Of Religion and Redemption: Evidence from Default on Islamic Loans. *Journal of Banking & Finance*, **44**, 141-159. http://dx.doi.org/10.1016/j.jbankfin.2014.03.005

[6] Čihák, M. and Hesse, H. (2010) Islamic Banks and Financial Stability: An Empirical Analysis. *Journal of Financial Services Research*, **38**, 95-113. http://dx.doi.org/10.1007/s10693-010-0089-0

[7] Abedifar, P., Molyneux, P. and Tarazi, A. (2013) Risk in Islamic Banking. *Review of Finance*, **17**, 2035-2096. http://dx.doi.org/10.1093/rof/rfs041

[8] Beck, T., Demirgç-Kunt, A. and Merrouche, O. (2013) Islamic vs. Conventional Banking: Business Model, Efficiency and Stability. *Journal of Banking & Finance*, **37**, 433-447. http://dx.doi.org/10.1016/j.jbankfin.2012.09.016

[9] Hasan, M. and Dridi, J. (2011) The Effects of the Global Crisis on Islamic and Conventional Banks: A Comparative Study. *Journal of International Commerce, Economics and Policy*, **2**, 163-200. http://dx.doi.org/10.1142/S1793993311000270

[10] Karim, B.A., Lee, W.S., Karim, Z.A. and Jais, M. (2012) The Impact of Subprime Mortgage Crisis on Islamic Banking and Islamic Stock Market. *Procedia—Social and Behavioral Sciences*, **65**, 668-673. http://dx.doi.org/10.1016/j.sbspro.2012.11.182

[11] Imam, P. and Kpodar, K. (2013) Islamic Banking: How Has It Expanded? *Emerging Markets Finance and Trade*, **49**, 112-137. http://dx.doi.org/10.2753/REE1540-496X490607

[12] Bourkhis, K. and Nabi, M.S. (2013) Islamic and Conventional Banks' Soundness during the 2007-2008 Financial Crisis. *Review of Financial Economics*, **22**, 68-77. http://dx.doi.org/10.1016/j.rfe.2013.01.001

[13] Billio, M., Getmansky, M., Lo, A.W. and Pelizzon, L. (2012) Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors. *Journal of Financial Economics*, **104**, 535-559. http://dx.doi.org/10.1016/j.jfineco.2011.12.010

[14] Chong, B.S. and Liu, M.H. (2009) Islamic Banking: Interest-Free or Interest-Based? *Pacific-Basin Finance Journal*, **17**, 125-144. http://dx.doi.org/10.1016/j.pacfin.2007.12.003

[15] Khan, F. (2010) How "Islamic" Is Islamic Banking? *Journal of Economic Behavior & Organization*, **76**, 805-820. http://dx.doi.org/10.1016/j.jebo.2010.09.015

[16] Sundararajan, V. and Errico, L. (2002) Islamic Financial Institutions and Products in the Global Financial System: Key Issues in Risk Management and Challenges Ahead. *IMF Working Paper*, **2**, 1-27. https://www.imf.org/external/pubs/cat/longres.aspx?sk=16109.0 http://dx.doi.org/10.5089/9781451859775.001

[17] Iqbal, M. and Llewellyn, D.T. (2002) Islamic Banking and Finance: New Perspectives on Profit Sharing and Risk. Edward Elgar Publishing, Inc., Cheltenham. http://www.elgaronline.com/view/1840647876.xml http://dx.doi.org/10.4337/9781843765318

[18] Solé, J. (2008) Introducing Islamic Banks into Conventional Banking Systems. *Journal of Islamic Economics, Banking and Finance*, **4**, 9-34. http://ibtra.com/pdf/journal/v4_n2_article1.pdf

[19] Ariffin, N., Archer, S. and Karim, R. (2009) Risks in Islamic Banks: Evidence from Empirical Research. *Journal of Banking Regulation*, **10**, 153-163. http://dx.doi.org/10.1057/jbr.2008.27

[20] Lauritzen, S.L. (1996) Graphical Models. Oxford Statistical Science Series. Clarendon Press,

Oxford.
https://global.oup.com/academic/product/graphical-models-9780198522195?cc=it&lang=en&#

[21] Giudici, P. and Spelta, A. (2016) Graphical Network Models for International Financial Flows. *Journal of Business & Economic Statistics*, **34**, 128-138. http://dx.doi.org/10.1080/07350015.2015.1017643

[22] Cerchiello, P. and Giudici, P. (2016) Conditional Graphical Models for Systemic Risk Estimation. *Expert Systems with Applications*, **43**, 165-174. http://dx.doi.org/10.1016/j.eswa.2015.08.047

[23] Benoit, S., Colliard, J.-E., Hurlin, C. and Perignon, C. (2015) Where the Risks Lie: A Survey on Systemic Risk. Working Paper. https://halshs.archives-ouvertes.fr/halshs-01142014/document

[24] Segoviano, M.A. and Goodhart, C. (2009) Banking Stability Measures. IMF Working Paper No. 09, 1-54. https://www.imf.org/external/pubs/ft/wp/2009/wp0904.pdf

[25] Acharya, V.V., Pedersen, L.H., Philippon, T. and Richardson, M.P. (2010) Measuring Systemic Risk.

[26] Adrian, T. and Brunnermeier, M. (2011) CoVaR. Working Paper 17454, National Bureau of Economic Research.

[27] Huang, X., Zhou, H. and Zhu, H. (2011) Systemic Risk Contributions. *Journal of Financial Services Research*, **42**, 55-83. http://dx.doi.org/10.1007/s10693-011-0117-8

[28] Brownlees, C.T. and Engle, R.F. (2015) Srisk: A Conditional Capital Shortfall Measure of Systemic Risk.

[29] Billio, M., Getmansky, M. and Pelizzon, L. (2012) Dynamic Risk Exposures in Hedge Funds. *Computational Statistics & Data Analysis*, **56**, 3517-3532. http://dx.doi.org/10.1016/j.csda.2010.08.015

[30] Diebold, F.X. and Ylmaz, K. (2014) On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms. *Journal of Econometrics*, **182**, 119-134. http://dx.doi.org/10.1016/j.jeconom.2014.04.012

[31] Hautsch, N., Schaumburg, J. and Schienle, M. (2014) Forecasting Systemic Impact in Financial Networks. *International Journal of Forecasting*, **30**, 781-794. http://dx.doi.org/10.1016/j.ijforecast.2013.09.004

[32] Peltonen, T.A., Piloiu, A. and Sarlin, P. (2015) Network Linkages to Predict Bank Distress.

[33] Barigozzi, M. and Brownlees, C.T. (2014) NETS: Network Estimation for Time Series.

[34] Whittaker, J. (1990) Graphical Models in Applied Multivariate Statistics. Wiley Series in Probability and Mathematical Statistics, John Wiley and Sons, Chichester. http://eu.wiley.com/WileyCDA/WileyTitle/productCd-0471917508.html

[35] Corander, J. and Villani, M. (2006) A Bayesian Approach to Modelling Graphical Vector Autoregressions. *Journal of Time Series Analysis*, **27**, 141-156. http://dx.doi.org/10.1111/j.1467-9892.2005.00460.x

[36] Carvalho, C.M. and West, M. (2007) Dynamic Matrix-Variate Graphical Models. *Bayesian Analysis*, **2**, 69-97. http://dx.doi.org/10.1214/07-BA204

[37] Furfine, C. (2003) Interbank Exposures: Quantifying the Risk of Contagion. *Journal of Money, Credit, and Banking*, **35**, 111-128. http://dx.doi.org/10.1353/mcb.2003.0004

Systemic Risk in Dual Banking Systems

Shatha Hashem
Department of Economics and Management Sciences,
University of Pavia, Italy
DREAMT PhD Program
shatha.hashem01@universitadipavia.it

Paolo Giudici
Department of Economics and Management Sciences,
University of Pavia, Italy
paolo.giudici@unipv.it

Pejman Abedifar
Center for Responsible Banking & Finance,
School of Management, University of St Andrews, UK
soulpa31@st-andrews.ac.uk

December 22, 2016

Abstract

In this paper, we measure the systemic risk of three types of banks in 6 GCC countries with dual banking systems, namely fully fledged Islamic banks (IB), purely conventional banks (CB), and hybrids that are conventional banks with Islamic window (CBw). We employ market-based systemic measures of MES, CES, SRISK and ΔCoVaR, which we extend through the use of partial correlation to obtain netted risk measures. We use 2,608 observations on 79 publicly traded banks and bank holding companies operating over 2005-2014 period. Next, we use graphical Gaussian models to explore the level of interconnectedness based on the netted risk measures for the three types of banks, which is particularly important during crises times. The results show that on average the CBw sector is less resilient to a systemic event, and is more interconnected during crisis times, indicating its higher effect on the financial stability of the whole system under stressful systemic events.

JEL classification: G21.

Keywords: Islamic and conventional banks, Systemic risk measures, Netted risk measures, Graphical gaussian models, Interconnectedness.

1 Introduction

The recent financial crisis asserted the inadequacy of micro-prudential regulations and highlighted the importance of macro-prudential policies to identify emerging systemic events and contain them before they materialize (Ioannidou et al., 2015). Financial systems might become more vulnerable to financial crises when financial institutions are more homogeneous (Wagner, 2008). Wagner (2010) shows that diversification increases stability of each individual financial institution; however, 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 idiosyncratic risk at the individual level and a higher probability of a systemic event. Ibragimov et al. (2011) develop a model showing that an optimal diversification for individual institutions might be suboptimal for society.

However, in the Muslim world, we observe a different trend, wherein banking systems are becoming more heterogeneous. 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 novel financial engineering have reached to \$1.9 trillion in 2014. This trend has transformed the structure of banking industry in several Muslim countries to a dual system. In such countries, Islamic banks operate alongside their conventional counterparts. They play a complementary role to conventional financial institutions by providing financial services that are compatible to religious belief of devout individuals, and thereby facilitate access to finance for a wider population (Frankfurt School of Finance and Management , 2006; C.G.A.P., 2008). The extant literature underscores the heterogeneity of Islamic vis-a-vis conventional banks in various aspects[1]. Such dissimilarities stimulate the overall performance of dual banking systems (Gheeraert, 2014; Gheeraert and Weill, 2015; Abedifar et al., 2016) and may even have influence on the stability and resilience of the banking system against systemic events depending on how Islamic banking is introduced to the system.

Islamic financial products can be provided to the society through two channels: a) Islamic branches/window of conventional banks (CBw), or b) fully fledged Islamic banks (IB), i.e. separate financial institutions. The choice between these two options will affect the architecture and thereby stability of the banking systems. In the former scenario, existing conventional banks can exploit economies of scope and scale by stablishing Islamic branches and combining Islamic and conventional banking. The banking system will then consist of a pool of similar diversified *quasi-conglomerate* banks with a portfolio of clients with different religious consciousness. In the latter case, however, banks will focus on either Islamic or conventional products and religious diversity will be observed across banks. In

[1] 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), clients loyalty and interest rate risk (Abedifar et al., 2013; Aysan et al., 2014), efficiency (Al-Jarrah and Molyneux, 2006; Abdul-Majid et al., 2011a,b,c; Johnes et al., 2015), insolvency risk (Čihák and Hesse, 2010; Pappas et al., 2016) and market power (Weill, 2011).

this case, a portfolio of different but less diversified and perhaps smaller banks will form the banking system.

In this paper, we attempt to address the consequence for financial stability of these two alternatives, by measuring systemic risk of CBw, IB and purely conventional banks (CB) using market based measures such as MES, CES, SISRISK and ΔCoVaR. In addition, we use the dynamic conditional correlation model (DCC) of Engle (2002b), to address the heteroskedasticity problem during crisis times. Furthermore, we take into account having simultaneous multiple interconnections by the use of partial correlation in the systemic risk measures calculation. We estimate the partial correlations conditionally on a graphical structure, within the quantitative learning framework of graphical Gaussian models to obtain the netted systemic risk measures, then we use a graphical presentation to analyze the interconnectedness between the netted measures, in order to detect the systemic risk diffusion channels between the banking sectors.

Our study is based on 2,608 observations on 79 publicly traded banks and bank holding companies operating in 6 countries in the Gulf Cooperation Council (GCC) region over 2005-2014 period. These are Saudi Arabia (SA), Kuwait (KW), Qatar (QA), United Arab Emirates (AE), Bahrain (BH) and Oman (OM). The importance of the GCC countries is that they hold nearly 40% of the total global Islamic banking assets with a systemically important average market share per country for the Islamic banking sector (IFSB, 2016). The relative similarity between the countries of the GCC region in terms of the economic environment allows us to control for the cross countries variations reported in the Islamic banking empirical research (see e.g. Beck et al. 2013). In addition, the GCC region economies are oil dependent (Sturm et al., 2008), and thus are open to receiving the negative impact of the global crisis. Furthermore, the GCC countries are dominated by a Muslim population at approximately equivalent shares, which allows to control for its effect on the banking system risk level, as religious beliefs are found to affect the risk and performance of the banking system, its development and its economic growth (see e.g. Imam and Kpodar, 2013; Baele et al., 2014; Gheeraert and Weill, 2015; Abedifar et al., 2016).

The results of the analysis indicate that the CBw banking sector has the highest systemic risk contribution, and could destabilize the financial system. Furthermore, the CB sector is noticed to have higher volatility in its response to the systemic risk events as a relation of its leverage, but this higher volatility is neutralized by its small market share size in the GCC region. Also, the standard, the netted and the oil estimated risk measures along with the partial correlation graphical model, reflect a relation to size within the higher risk ranks for both the CBw and IB sectors, and a relation to leverage for the smaller CB sector. Moreover, we find that the netted systemic risk measures of MES and ΔCoVaR, have a lower magnitude than the standard and the oil volatility index. Nevertheless, the netted SRISK measure has the highest SRISK magnitude in comparison with the other two estimation variations. In other words, netted SRISK has higher levels of capital shortfall expectations during crisis times. The CBw sector is also found to have higher interconnectedness during crisis periods based on the graphical model of the netted systemic risk measures. Another related findings is that the returns on the stock markets of the GCC region, including the three banking sectors, are affected by the changes in the crude oil index, this notion indicates that banking regulators should keep a close attention to the effect of the changes in the oil price on the capital shortfall of the banking system.

We believe that the implications of our research results can be beneficial to regulators and central banks in terms of Islamic banking activities effect on the countries' financial and economic stability during a crisis period, taking into account the fact that the Islamic banking system increases its size and importance (Wijnbergen and Zaheer, 2013). Furthermore, the conventional banks can gain insight regarding the effect of diversifying their services with Islamic banking activities on the bank's risk profile, especially that in the last years several conventional banks from Europe, UK and the USA are being involved in Islamic banking activities. Finally, fund providers and investors may also benefit from the research results in making portfolio allocation decisions.

The remainder of this paper is organized as follows; section two outlines our methodology of the banking sectors standard and netted systemic risk measures and their interconnectedness, section three describes the data and summary statistics, section four provides results discussion, and the final section provides our research conclusions.

2 Methodology

2.1 Systemic Risk Measures

We use the common metrics of systemic risk to investigate the resilience of the three banking sectors to a systemic risk event, which are the Marginal Expected Shortfall (MES), proposed by Acharya et al. (2010), the component expected shortfall (CES) systemic risk measure proposed by Banulescu and Dumitrescu (2015), the SRISK measure proposed by Acharya et al. (2012), and Brownlees and Engle (2012). In addition, we use Delta Conditional Value-at-Risk ΔCoVaR, that is introduced by Adrian and Brunnermeier (2011), to investigate the banking sector type that has higher contribution to the system risk. Those measures are extensions of the two standard risk measures, the Value at Risk (VaR) and the Expected Shortfall (ES). Those measures are commonly used at the individual banking unit level to identify the Systemically Important Financial Institutions $SIFIs$, which are defined by the Finanacial Stability Board (2011) as the "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 banking sectors in 6 dual banking systems.

2.1.1 Marginal, Component and Global Expected Shortfall: MES, CES and GES

The original MES measure was proposed by Acharya et al. (2010) and was extended by Brownlees and Engle (2012) to a conditional one. MES extends the concept of Expected Shortfall (ES) to account for the marginal vulnerability of the financial entity i to the financial system systemic risk, and is considered an extension of the concept of the marginal VaR proposed by Jorion (2007). MES evaluates the sensitivity of the financial entity risk level to a unit change in the system ES, in other words, it is the one day capital loss expected if market returns are less than a given threshold C (originally $C = -2\%$). However, MES does not account for the the idiosyncratic characteristics of the financial entity such as size and leverage.

MES can be expressed as a weighted function of tail expectations for the market index standardized residual, and the tail expectations for the financial entity standardized idiosyncratic residual:

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

In our context, the financial entity is represented by the banking sector. Higher MES indicates a higher vulnerability to the financial system risk, and if the banking sector has a systemically important market share or is highly leveraged, then a higher MES indicates a higher contribution by this banking sector to the systemic risk of the financial system.

To compare the three banking sectors systemic risk contribution to the financial system at the country and the GCC level, we follow an extension of MES which is the component expected shortfall (CES) systemic risk measure provided by Banulescu and Dumitrescu (2015). CES represents a market capitalization weighted MES for each financial institution. The main feature of the CES risk measure is that the expected loss of the financial system at any time can be measured by linearly aggregating the component losses, in other words, CES is a coherent systemic risk measure.

In our context, the financial system expected shortfall at the country level is the sum of the weighted average of MES for each banking sector included in that country j. For each country, we evaluate the financial system expected shortfall, and refer to it as a global expected shortfall GES_{jt} as follows:

$$GES_{jt} = \sum_{s_j=1}^{n_{s_j}} w_{s_jt} MES_{s_jt} \tag{2}$$

in which $w_{s_jt} = mv_{s_jt}/\sum_{s_j=1}^{n_{s_j}} mv_{s_jt}$ represents the weight of the banking sector s in country j at time t, given by its market capitalization mv_{s_jt} relative to the aggregate banking capitalization of the country banking system $\sum_{s_j=1}^{n_{s_j}} mv_{s_jt}$. We repeat the same construction of the global expected shortfall (GES) at the GCC regional level, to determine which of the banking sectors has higher systemic risk contribution to the GCC region aggregate banking system level, in other words, determine the GCC systemic risk driver. We check the robustness of the GES results by also estimating the system wise MES, SRISK and ΔCoVaR.

2.1.2 Systemic Risk: SRISK

SRISK was introduced by Brownlees and Engle (2012) and Acharya et al. (2012). SRISK further extends MES in order to take into account idiosyncratic firm characteristics, as it accounts for the financial institution leverage and size. SRISK can be seen as a compromise between the TITF and the TBTF paradigms. SRISK index 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 capitalization) with low frequency balance sheet data (leverage) to provide a daily forecast SRISK index.

We follow Acharya et al. (2012) in SRISK quantification, but we do not restrict SRISK to zero. Negative values of SRISK are meaningful to us, as they provide information on the relative capital surplus instead of shortfall. SRISK quantification for a financial entity incorporates the regulatory minimum capital ratio $k = 8\%$, the book value of debt (total liabilities) D_{it} , the equity market value w_{it} , the long-run marginal expected shortfall ($LRMES$), which represents the expected fractional loss for the equity of the financial entity under a crisis during which the aggregate market declines significantly in a six-month period, $LRMES$ is approximated using the daily MES as $LRMES \simeq 1 - exp(-18 \times MES_{it})$, where the given threshold C is set to -40%. We define SRISK as:

$$SRISK_{it} = max\left(\underbrace{k(D_{it} + (1 - LRMES_{it})W_{it})}_{Required\ Capital} - \underbrace{(1 - LRMES_{it})W_{it}}_{Available\ Capital} \right) \tag{3}$$

we define leverage as $L_{it} = (D_{it} + W_{it})/W_{it}$ (leverage estimation by market capitalization is referred to as quasi leverage), and we rewrite SRISK as:

$$SRISK_{it} = max\big(\big[kL_{it} - 1 + (1 - k)LRMES_{it}\big]W_{it}\big) \tag{4}$$

SRISK by definition is a coherent risk measure, thus can be linearly aggregated to estimate the total expected shortfall for the banking system, in other words, the overall financial system SRISK is equal to the sum of the financial entities SRISK (Acharya et al., 2012). From the previous expression, we note that higher leverage and market capitalization will increase SRISK. The financial entity with the largest positive SRISK, and hence capital shortfall, is assumed to be the greatest contributor to systemic risk especially during crisis periods, and is considered as the most systemically risky. In our context, the financial entity is represented by a banking sector.

2.1.3 Delta Conditional Value at Risk: ΔCoVaR

ΔCoVaR was introduced by Adrian and Brunnermeier (2011). The Conditional Value at Risk term CoVaR is an upgrade to the VaR concept as it allows to override the idiosyncratic risk and determine risk spillovers between financial entities. CoVaR is used to specify the VaR of the market portfolio return conditional on a tail event $C(r_{it})$ observed for the financial entity i as it becomes under financial distress and its stock return deteriorates to become at its bottom 5% probability level. CoVar is found to be a coherent risk measure where the system wise CoVaR is the linear aggregation of its individual components (Rockafellar and Uryasev, 2002). ΔCoVaR of the financial entity i reflects its contribution to systemic risk by assessing the difference between the VaR of the financial system conditional on entity i being under financial distress, and the VaR of the system conditional on entity i being in its median state. Adrian and Brunnermeier (2011) use the quantile regression method in which they consider the financial distress $C(r_{it})$ or entity i loss to be equal to its VaR. They define the $\Delta CoVaR_{it}(\alpha)$ as:

$$\Delta CoVaR_{it}(\alpha) = CoVaR_t^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_t^{m|r_{it}=Median(r_{it})} \tag{5}$$

A higher level of ΔCoVaR indicate a higher marginal contribution from the financial entity, or the banking sector, to the systemic risk level of the financial system.

2.2 Estimation Method

2.2.1 The Banking Indices

We use the 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 rather than individual unit one as our aim is to determine the systemic risk contribution of each banking sector from a portfolio point of view, and how each portfolio will contribute to the systemic risk of the country level financial system. Our analysis can be looked at from an investor point of view as an asset allocation decision with three risky assets; the CB sector, the IB sector and the CBw sector. The aggregation process is based on the standard construction method for a market capitalization weighted index, which we start by deriving the time series of the stock market return under the stationary assumption such that the mean is $\mu = 0$. To achieve stationarity, we transform daily stock market closing prices into log returns that are expressed, as usually, in time variation. Formally, if p_t and p_{t-1} are the closing stock prices at times t and $t-1$, the continuously compounded return 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 the banking institutions into banking sectors, according to their bank type, IB, CB and CBw. To construct the aggregate return time series of each sector, we let $i_{sj} = (1, \ldots, n_{sj})$ indicates a list of banks for the banking sector S within a specific country j, and we define the aggregate return time series of the banking sector r_{sj} to be a market capitalization-weighted average as in the following:

$$r_{sj} = \sum_{i_{sj}=1}^{n_{sj}} w_{i_{sj}} r_{i_{sj}} \tag{6}$$

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

2.2.2 Netted systemic Risk Measures using Partial Correlation

The bivariate risk measures capture the vulnerability of a financial entity to a systemic risk event, or the contribution of a financial entity to the overall risk level of a system. However, this is computed on the basis of a pairwise evaluation without directly considering other entities in the financial network. We use partial correlation to take the network aspect into account, in which we replace the marginal correlation that captures both direct and indirect associations between two entities with the partial correlation that takes the direct association after controlling for other entities in the financial network.

We take the direct dependence and variance between the market and the banking sector equity returns conditioned on other banking sectors. To achieve this, we estimate partial correlations conditionally on a graphical structure within the quantitative learning framework of Graphical Gaussian models (see.g. Lauritzen, 1996; Højsgaard et al., 2012; Giudici and Spelta, 2016), with the objective of obtaining a netted conditional variance covariance matrix.

We use the connection between the graphical models and the residuals of the multiple regression, in which the partial correlation coefficient $\rho_{ij.V}$ is equal to 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:

$$\rho_{ij.V} = (\ \varepsilon_{X_i|X_{V\setminus\{j\}}}, \varepsilon_{X_j|X_{V\setminus\{i\}}}) \tag{7}$$

The partial correlation coefficient allows to measure the additional contribution of variable X_j to the variability of X_i that is not already explained by the other variables, and vice versa.

More specifically, we define two multiple regression equations for each market and banking sector return series, with the dependent variable of the first being the market return series r_{mt} and the dependent variable of the second being the specified banking sector return series r_{i_1t}, both dependent variables are regressed on a set of independent variables of $r_{i_2t}, ..., r_{i_nt}$ that represent the other banking sectors in the financial system, as in the following:

$$\begin{cases} r_{mt} = a_1 + \beta_2 r_{i_2t} + ... + \beta_n r_{i_nt} + \epsilon_{i_1t} \\ r_{i_1t} = a_1 + \beta_2 r_{i_2t} + ... + \beta_n r_{i_nt} + \epsilon_{mt} \end{cases} \tag{8}$$

where ϵ_{i_1t} and ϵ_{mt} are the residual vectors of the banking sector i_1 and the market m. We repeat this extraction process for each pair of market and banking sector returns time series $(r_{mt}\ , r_{it})$. The residual vectors are checked for autocorrelation with the Durbin-Watson test, and for heteroskedasticity with Breush-Pagan test, and to take into account both issues, partial correlation is extracted using the GARCH-DCC model. Thus, each pair of residual vectors $(\epsilon_{it}, \epsilon_{mt})$ is used to replace the corresponding return series $(r_{mt}\,, r_{it})$ in the DCC model to obtain a time varying conditional partial correlation matrix that is used to estimate the netted systemic risk measures of MES, SRISK and ΔCoVaR.

2.2.3 Dynamic Conditional Correlation Model: DCC

The dynamic conditional correlation (DCC) model (Engle and Sheppard, 2001; Engle, 2002a) allows for the estimation of time-varying conditional correlations of each market and firm pairs. Brownlees and Engle (2012) allow for linear time varying dependences with a multivariate GARCH-DCC model to estimate MES conditional on the market returns being below a specified threshold. In this study, we use the GJR GARCH-DCC to control for the heteroskedasticity effect in measuring correlations. Glosten et al. (1993) GJR GARCH(1,1) modeling for the standardized residuals and conditional variances allows to account for asymmetry and captures the leverage effect by distinguishing the positive and negative shocks in the return conditional variance. In addition, we use Quasi Maximum Likelihood (QML) to estimate the parameters as it allows for consistent and asymptotically normal ones without distributional assumptions for the framework innovations. To initialize the GJR GARCH-DCC model we define r_t as a bivariate return vector, that contains the market r_{mt} and the financial entity r_{it} returns, such that:

$$r_t = (r_{mt}\,, r_{it})' \,|I_{t-1} \sim N(0, H_t) \tag{9}$$

where the pairwise demeaned return vector r_t has a conditional expectation of zero mean $\mathbb{E}_{t-1}(r_t) = 0$, and a two-by-two identity covariance matrix I_{t-1}. The variance-covariance matrix H_t is decomposable into a diagonal matrix for the time varying conditional variance obtained from the univariate GJR GARCH processes, along with a time varying conditional correlation matrix. By the bivariate GJR GARCH structure, the vector of demeaned returns can then be expressed as:

$$r_t = H_t^{1/2}\epsilon_t \tag{10}$$

where $\epsilon_t = (\varepsilon_{mt}\ \xi_{it})'$ is a vector of *i.i.d.* standardized innovations that are assumed to be unknown with no assumptions regarding the bivariate distributions. ϵ_t has a mean $\mathbb{E}(\epsilon_t) = 0$ and an identity covariance matrix of $\mathbb{E}(\epsilon_t\epsilon_t') = I_2$. The time varying conditional covariance matrix H_t is defined as:

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\,\sigma_{it}\,\rho_{it} \\ \sigma_{mt}\,\sigma_{it}\,\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{11}$$

where σ_{mt} and σ_{it} represent the conditional standard deviation for the market and the financial entity respectively. ρ_{it} represents the time varying conditional correlation.

For the calculation of the systemic risk measures, ρ_{it} is assumed to capture the full linear dependency between the returns of the market and the returns of the financial entity, which represents a banking sector in our context, and the non-linear dependencies are captured by the conditional expectation $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < \frac{C}{\sigma_{mt}})$.

2.2.4 Banking Sectors Interconnectedness

We analyze the interconnectedness of the banking sectors to detect the diffusion connections of systemic risk between them. As in Billio et al. (2012), we consider a cross-sectional aspect to understand systemic risk transmission mechanisms, in which we produce a network structure that can describe the mutual relationships between the different economical agents involved. We follow Giudici and Spelta (2016) in using a graphical model that accounts for the conditional independence concept using partial correlations. More precisely, we use a conditional graphical structure, employing partial correlations among a set of N observed time series for the specified economic agents.

We construct a separate graphical network model for each netted systemic risk measure using an undirected graph. The nodes of the graph represent the specified netted risk measure for the banking sectors. The availability of a link between each pair of nodes is based on the presence of a significant partial correlation coefficient between the two nodes. The network of N nodes corresponds to an adjacency matrix with each link being weighted based on the value of its significant partial correlation, and each node is weighted based on the corresponding average value of the specific netted risk measure.

Once the network is estimated, we summarize the systemic importance of its nodes using network centrality measures, while keeping in mind that each node in the network represents the estimated netted systemic risk measure for a specific banking sector in a particular country. We use the node centrality measures of betweenness, closeness, node degree and eigen vector centrality that are described in Giudici and Spelta (2016), in addition to the rank concentration ratio (RC %) that is described by Hashem and Giudici (2016).

3 Data and Descriptive Statistics

Our sample consists of 2608 observations, of stock market closing prices with the corresponding market capitalization, on 79 publicly traded banks and bank holding companies located in the GCC region countries, for the period from January 2005 to December 2014, taken from Thomson Reuters Data-stream. Moreover, as SRISK measure estimation requires balance sheet entries, we also use Bureau Van Djik's Bankscope database to gather quarterly data on the book value of liabilities and total assets for each banking system, including both publicly and privately owned banking institutions in order to check the systemic importance per banking sector based on the 15% share size criteria used by the Islamic financial standard board report (see e.g. IFSB, 2016).

The main advantage of the GCC countries banking systems is that they are considered dual systems that hold nearly 40% of the total global Islamic banking assets, and are reported to have a systemically important Islamic banking market share, in which Saudi Arabia (SA) has 49%, Kuwait (KW) has 38.9%, Qatar (QA) has 26.1% and United Arab Emirates (AE) has 18.4%, as for Bahrain (BH), its Islamic banking sector is almost systemically important with approximately 14% market share, but Oman (OM) does not fulfill this criteria with almost 7% (IFSB, 2016). Another advantage for those countries is that they have relative similarities in their regulatory, financial and economic environment. In addition, the economies of the GCC countries are oil dependent in which the oil constitutes almost 48% of the GCC GDP (Sturm et al., 2008). The GCC region oil dependency integrates the GCC countries local markets with the global ones, and thus makes them open to receiving the negative impact of the global crisis. Another aspect that the GCC countries provide us with is that they are dominated by a Muslim population at approximately equivalent levels, which reduces the variation in the banking system risk level that may result from having different Muslim population share level, especially that this factor is argued to affect the risk and performance of the Islamic banking system, its development and the economic growth (see e.g. Imam and Kpodar, 2013; Baele et al., 2014; Gheeraert and Weill, 2015; Abedifar et al., 2016).

We use a specific stock market return index (whole market index) for each of the GCC counties for the calculation of the systemic risk measures. In addition, to take into consideration the GCC countries oil dependent economies, and since oil is an energy commodity traded worldwide, the oil index is found to capture the global crisis impact, and that its volatility is spilled over the stock markets return in the GCC region (see e.g. Zarour, 2006; Maghyereh and Al-Kandari, 2007; Arouri et al., 2011; Mohanty et al., 2011; Fayyad and Daly, 2011; Arouri and Rault, 2012), thus we repeat the measures estimation using crude oil return index (WTI) as an approximation for a unified volatility index. From a technical point of view, the crude oil index servers as a unified volatility index for all the GCC countries, in other words, it facilitates the calculation of the systemic risk measures, for all countries banking sectors, using the same conditional standard deviation from the index (market) side, allowing to control for the index heterogeneity that we have from using six different stock market indexes.

The aggregation of the banking sectors returns for the six GCC countries results in 16 return time series. Table 1 provides the descriptive statistics of the banking sectors returns, and the stock market index return for each country.

Table 1 about here.

The descriptive statistics in Table 1 cover three successive time periods, the pre-crisis period of 2005-2006, the crisis period of 2007-2008 and the post-crisis period of 2009-2014. From Table 1 we first notice that all countries experienced the highest volatility in their market indexes during the crisis period, except for SA, and that the market volatility declined for all countries in the post crisis period. In terms of the specific banking sector type, the volatility of the IB sector was in general higher than other sectors during the crisis period. Another note is that the standard deviation of most banking sectors returns, within each country, was not aligned in its variation with the standard deviation of the country market index, except for QA, rather it was specific to the banking sector type within most countries. Finally, all countries market indexes were negatively skewed during the crisis period, indicating more frequent negative daily returns, as for the banking sectors returns, the CBw sector is the one that is in general negatively skewed during the crisis period within most countries.

Next, we describe our sample in terms of total assets distribution based on the balance sheet entries per country. Our Bankscope sample consists of 131 banks, from which 79 are publicly traded banks. The list of countries and banking sector types according to our classification, (CB, CBw and IB), with further details on the type of ownership and relative assets size are described in Table 2, on annual basis within the study time line.

Table 2 about here.

From table 2, we note that all our countries meet the 15% islamic banking assets share criteria to be considered systemically important, except for OM, which indicates that our sample is representative in terms of the Islamic banking sector systemic risk importance as reported by IFSB (2016). In addition, we arrange the countries in the table in an ascending order, from the smallest to the largest, in terms of total banking assets size (including listed and unlisted banks), from which OM and AE have the smallest and largest banking systems respectively. If we consider the overall change in total banking assets for all countries on a yearly basis, we notice that the total assets size of both CB and CBw sectors mostly decreased during the crisis time in contrast to the assets of the IB sector. In addition, we note that the CBw sector has the largest total banking assets size at the GCC region level and within each country. Furthermore, the IB sector is larger than the CB one in SA, QA, KW and BH, whereas in OM and AE, the CB sector is larger. Moreover, the per country aggregate banking system assets size generally increased over time for all countries, but the magnitude of the increase differed across them, with the least increase being achieved by BH, whereas QA achieved the highest increase.

In Figure 1, we present the annual percentage change, for each GCC banking sector type, using the log transformation for the banking sector assets percentage from the GCC total banking assets.

Figure 1 about here.

From Figure 1 we note that the CB sector assets percentage has a large variation in its direction, as it has a strong negative slope through the crisis period, but started the recovery to almost its previous level since 2009. On the other hand, the CBw sector variation reflects that this sector captured the crisis effect but the decrease was less steep and was gradual, however the assets percentage did not come back to its previous level. As for the IB sector assets percentage, the variation is positive in general, reflecting an increase even during the crisis time, but the growth in the percentage of the IB banking assets is reflecting a slow down starting from the end of 2009, where we also note that the assets percentage had a decrease by the end of this year, but managed to start a positive recovery in 2011.

We continue our data description in Table 3, in which we provide the size of market capitalization (henceforth we refer to it as the market share), per banking sector and country. Within each banking sector group, we list the countries from the largest to the smallest based on Table 1 for the ease of comparison between the two successive tables. In general, we can classify the banking sectors of the countries into two main groups, the large and the small asset size, in which the large includes the sectors of AE, SA, QA and KW, whereas the small includes BH and OM. Within the same table, we also provide the banking sectors quasi leverage as defined for the estimation of SRISK in equation 4. Several studies show that an increase in the banking institution size and leverage will increase its systemic risk level and thus decrease its banking stability (see e.g. Laeven et al., 2016; Kuzuba et al., 2016), and that larger size may induce more risk taking by the financial institution (Bhagat et al., 2015).

Table 3 about here.

In Table 3, the CBw sector remains the largest in terms of market capitalization as in the previous table findings, whereas the smallest sector is the CB one. In terms of quasi leverage, henceforth leverage, Table 3 shows that the CBw sector group has the highest leverage, in mean, in the three successive periods, in comparison with other sectors. In addition, the IB sector has the lowest leverage mean in the pre crisis period, whereas the CB sector has the lowest mean in the post crisis one.

We conclude our data description by pointing out that the CBw sector is the largest and has the highest leverage ratio, followed by IB and CB sectors respectively. In addition, we note that the IB sector increased its systemic importance in the post crisis period.

4 Empirical findings

In this section, we gauge the systemic risk of the three banking sectors (IB, CB and CBw) using market based systemic risk measures. We consider different aspects of systemic risk, in which we use MES and SRISK to evaluate the resilience of the banking sectors to a systemic shock. Moreover, we assess the systemic importance of each banking sector using ΔCoVaR and GES. We also take into consideration that the financial system is comprised of a network of connected institutions by extending the bivariate systemic risk measures using partial correlations.

In the following subsections, we first discuss the results of all banking sectors systemic risk level, grouped per banking sector and country. We estimate the systemic risk measures for the banking sectors using a) the conditional time varying variance covariance matrix from the DCC model, to which we refer as the standard bivariate systemic risk measures, b) the conditional time varying partial correlations to estimate the netted systemic risk measures, and c) crude oil index as a unified volatility index, which we refer to as the oil index measures. Furthermore, we use the Global Expected Shortfall (GES) systemic risk measure, as defined in equation 2, to determine the banking sector that has the highest systemic risk contribution to the banking system portfolio within each of the GCC countries, and for the aggregated GCC banking system level. Finally, we provide the netted systemic risk measures in a graphical model representation that reflects the interconnectedness between the different banking sectors based on partial correlation[2].

4.1 Resilience of Different Banking Sectors to Systemic Events

Table 4 provides the standard MES measure per banking sector and country, the netted MES measure obtained using conditional time varying partial correlation, and the unified volatility index measure represented by the oil index.

Table 4 about here.

From Table 4, we note that the CBw sector group generally has a higher MES level across the three estimations compared to other banking sectors, during both the crisis and post crisis periods, whereas the mean of the IB banking sector group reflects higher vulnerability in the pre crisis period. In addition, across all banking sectors, the IB sector of SA has the highest systemic risk magnitude for the pre crisis and the crisis periods, whereas the CBw sector of KW has higher risk in the post crisis one. We also note that the CBw and IB sectors, of larger asset size countries (AE, SA, QA and KW from table 2), are more vulnerable, and thus less resilient to the volatility of the oil index as estimated by MES, and thus are more subject to the negative contagion effect from the global financial system during crisis times. Finally, netted MES measures are lower in magnitude than other estimates, due to the exclusion of the spurious effect from other entities within the financial network. Netted MES also reflect a higher systemic risk importance for small size countries banking sectors, specifically for the CB and CBw sectors of OM during the crisis and post crisis periods, and for the IB and CBw sectors of BH in the crisis and post crisis periods respectively.

We now move to discuss the systemic risk evaluation based on the three SRISK measure variations, as presented in Table 5. From the table we notice that all banking sectors have capital buffers (indicated by the negative sign), except for the IB sector of BH in the post crisis period of the standard SRISK measure, in which it appears to have a capital shortfall, which is in line with Hasan and Dridi (2011) findings.

Table 5 about here.

In addition, the results of the SRISK measure are consistent across the three estimations, with minor changes in the magnitude. In general, the CB sector group is the one that has the lowest expected capital buffer across the successive periods, whereas the CBw sector has a higher expected capital buffer than the IB one. Across the three sectors, the CBw

[2]However, we denote that for the ease of results interpretation, the measures have been converted in their signs within the calculation process. In other words, the banking sector that has the highest positive magnitude for the systemic risk measure, is the one that has highest systemic risk importance level.

sector of SA has the highest expected capital buffer for all estimation variations and all periods, with the IB sector of the same country having the highest buffer for the IB group. Moreover, netted SRISK consistently selected the highest leverage sector as the lowest capital buffer one within each banking group.

4.2 Systemic Importance of Different Banking Sectors

The systemic risk contribution of the different banking sectors to the overall system risk is evaluated with ΔCoVaR estimations. Table 6 provides the three estimation variations of ΔCoVaR systemic measure, grouped per banking sector and country.

Table 6 about here.

From the above table we find that the standard, the oil and the netted ΔCoVaR identified the CBw banking sector as the main contributor to market systemic risk as a group mean, followed by the IB and CB sectors, which is consistent with the MES and SRISK systemic risk indicators. Across the different sectors, the CBw and IB sectors of SA are the ones mostly selected. In addition, within the CBw sector, SA CBw has the highest risk contribution, whereas the IB sector of SA is the highest contributor within its group and across other banking groups, which can be related to its size effect.

In summary, MES, SRISK and ΔCoVaR findings have similarities in terms of the sector that has the highest systemic risk level, in which the three mostly indicated the CBw sector as the most systemically vulnerable and the one with the highest systemic importance in comparison with the IB and CB sectors. The three measures higher systemic risk ranks are mainly related the assets size effect of the CBw and IB sectors, but are also related to a leverage effect for the CB sector that has a small size in our sample. In addition, netted MES and ΔCoVaR show a lower magnitude than the standard and the oil volatility index. Nevertheless, netted SRISK shows a higher capital shortfall magnitude, which indicates that the standard systemic risk measures underestimate the expected capital shortfall during crisis times.

4.3 Global Expected Shortfall of Gulf Region Banking System

We first apply the global expected shortfall (GES) within the banking system of each GCC country to determine the banking sector that, based on its MES and market share size, drives the systemic risk of the financial system portfolio within the specified country. Figures 2, 3, 4, 5, 6 and 7, describe the banking sectors MES and the GES of the banking system portfolio for AE, BH, KW, OM, QA and SA respectively.

Figures 2, 3, 4, 5, 6 and 7 about here.

From the previous figures, we note that the GES of each Gulf region country is generally driven by the CBw sector, except for SA and BH banking systems, where the main systemic risk driver is the IB one. In addition, keeping in mind that the GES measure is by construction affected by the market share size of the system components, we note that the CBw sector has the largest MES effect, whereas the CB sector appears to have the smallest effect, on the GES of the banking system portfolio.

On the other hand, the netted estimation of the risk measures shows higher vulnerability for the CB sector in response to the systemic risk events despite its smaller size compared to other sectors. In addition, netted GES reflects a diversification benefit from the IB sector on the GES of the banking system portfolio for most countries.

Furthermore, tracking the time evolution of systemic risk, all the graphs show a high risk synchronization during the crisis period of 2008, with an even higher risk level in 2009 as the IB sector risk becomes aligned with the CBw and CB banking sectors. In other words, the IB increase the strength of the financial system portfolio in a manner that is limited to the point where the crisis materialize within the real economy, with which the IB banking sector has strong connections due to its business model features.

Next, we use the global expected shortfall (GES) to aggregate one portfolio for each banking sector type, then we use the resulting three banking sectors GES to estimate the systemic risk level of the regional banking system portfolio. Our aim is to determine the banking sector that drives the systemic risk level of the GCC banking system portfolio. In Figure 8 and Table **??**, we provide the time variation of the GES systemic risk measure for the three main banking sectors and the regional GCC banking system, using the standard, the netted and the oil index estimations.

Figure 8 about here.

From the previous figure, we note that the findings at the regional level are consistent with our results for the systemic risk level of the individual banking sectors and the country level GES, in which the time variation of the GES measure, for the Gulf region overall banking system portfolio, follows the CBw sector that still has the highest systemic risk importance followed by the IB and CB sectors. We also note that the standard measure GES plot does not clearly distinguish the risk driver at the overall portfolio, whereas both the netted and oil measures provide higher distinction between the three banking sectors risk levels.

Furthermore, we note that the GCC region has its own local crisis during 2005-2006, in addition to being affected by the global crisis starting from 2007, with the global crisis effect having a higher magnitude in 2009, as seen from the GES time plot. In addition, the graphs reflect that the difference in the GES magnitude between the banking sectors started to decline after 2009. We also note that the oil index graph is almost similar to the standard method one, which is in line with the finding that the return of the stock markets within the GCC region countries are mainly affected by the oil price volatility (Maghyereh and Al-Kandari, 2007; Arouri et al., 2011), and that the stock markets of the GCC countries are significantly and positively exposed to crude oil price shocks (Mohanty et al., 2011).

4.4 Interconnectedness Analysis of The Banking Sectors

In this subsection we address the issue of how different banking sectors are interconnected with each other. For this purpose we build a graphical Gaussian model, on the basis of partial correlations between the netted systemic risk measures of the banking sectors for the pre, during and post crisis periods. The best model is selected using a backward selection procedure that starts from a fully connected model and subsequently tests for edge removal at the selected significance level of $\alpha = (.05)$. The selected graphical model of netted MES is described in Figure 9, the model of netted SRISK is described in Figure 10, and the model of ΔCoVaR is described in Figure 11. The graphs are then summarized into centrality measures that are used to rank the banking sectors from the most to the least systemically important in terms of contagion. Within each graph, the size of each node represents the magnitude of the systemic risk measure for the specified banking sector[3]. The link between any two nodes, represents the presence of a significant partial correlation coefficient between them, the thickness of the link line indicates the link magnitude[4]. The centrality measures of Figure 9, Figure 10 and Figure 11 are presented in Tables 7, 8 and 9 respectively. In addition Table 10 further summaries the centrality measures by providing a percentage for the systemic risk level of each banking sector type, based on the importance of the ranks that the specified sector type occupies within each centrality measure. A higher Ranking Concentration percentage indicates a higher contagion capacity for the specified banking sector type.

Figure 9, Figure 10 and Figure 11 about here.
Tables 7, 8 and 9 about here.
Table 10 about here.

From Figure 9, Table 7 and the RC% of netted MES in Table 10, we find that the CBwin sector has higher systemic ranks during the crisis period, whereas the IB sector dominates the post crisis one, with the CB sector being the least contagious. From Figure 10, Table 8 and the RC% of netted SRISK[5], the IB sector has higher contagion importance in terms of its capital buffers, followed by the CBwin, for both the pre and during crisis periods, but the capital buffer of the IB sector shrinks in the after crisis period. The results of the SRISK graphical model seem to not be in line with the systemic risk measures that gave higher systemic risk importance to CBw. Nevertheless, we inspect this change in ranks using the magnitude and direction of the partial correlation that this sector has with others, we find that the IB sector is on average negatively correlated with the CB

[3]The color of the node indicates a positive value for the systemic risk measure when it is blue, and a negative one when it is red.

[4]The more thick the line, the larger is the value of the significant partial correlation and the stronger the link is, also the color of the link indicates whether the partial correlation has a negative value represented by a red color, or a positive indicated by gray color.

[5]The sector that is represented by a blue color node in this particular graph has a capital buffer rather than capital shortfall as a result of the reversed signs in the measures calculation.

sector, and positively correlated with the CBw sector, whereas the CB and CBw sectors are mainly positively correlated, which indicates that the IB and CB sectors diversify the system portfolio, whereas CBw magnify the risk of both CB and IB systems, with the magnitude of increasing the vulnerability effect on IB being greater than that on the CB one in relation to the larger magnitude of the correlations between the larger asset size sectors. In addition, keeping in mind that the IB sector has lower leverage in comparison to CBw,the capital buffer of the IB sector can be seen as a safety net rather than a risk one. Finally, the results of Figure 11, Table 9 and the RC% of netted ΔCoVaR graphs are consistent with netted MES results.
Based on the simple node degree centrality measure, netted MES and SRISK show that the CBwin sector has the highest interconnectedness during the crisis period for the three netted measures, as for the post crisis period, the IB sector has the highest interconnectedness, indicating an increase in its systemic risk importance level. Finally, DCoVaR confirms that the CBwin sector is the one that has higher contribution to the system risk during the crisis period. The other centrality measures reflect approximately the same importance for the different banking sectors. Furthermore, all centrality measures show low importance for the CB sector, which may be interpreted in terms of its smaller market share.

5 Conclusions

The main applied aim of this study is to determine the Islamic banking sector strength in supporting the stability of the financial system, on the basis of its systemic risk level, especially under the presence of a financial crisis. To achieve this objective from the methodological point of view, we use the market based systemic risk measures in different variations based on the DCC model, with the aim of taking into account the different perspectives of systemic risk. In other words, the main methodological aim is to take the multivariate nature of systemic risk into account, by considering the financial system as a connected network, which we achieve by extending the bivariate systemic risk measures using partial correlation to create what we refer to as netted systemic risk measures.

From our data description we find that the higher systemic risk level sector, based on total assets size, market share and leverage is the CBw sector, followed by IB and CB sectors respectively. In addition, we note that the higher systemic risk level sector, based on size and leverage specifically during the crisis period is also the CBw sector, whereas the IB sector increased its systemic risk importance in the post crisis period.

In addition, using MES, SRISK and ΔCoVaR, the findings are consistent in terms of the sector that has the highest systemic risk level, as the three indicated the CBw sector as the most systemically vulnerable, and the one with the highest systemic risk contribution in comparison with the IB and CB sectors. Furthermore, the three measures reflect a relation to size for the CBw and IB sectors, but a stronger relation to leverage for the smaller CB sector. Moreover, MES and ΔCoVaR netted estimation has a lower magnitude than the standard and the oil volatility index. Nevertheless, the netted SRISK has the highest

SRISK magnitude in comparison with the other two estimation variations. In other words, netted SRISK has higher levels of capital shortfall expectations, which indicates that the standard systemic risk measures underestimate the expected capital shortfall, and especially under crisis times.

Accordingly, our findings confirm that the Islamic banking system contributed to lowering the financial system systemic risk level at the beginning of the crisis, as long as the IB banking sector is well capitalized with a low leverage level. On the other hand, we also found that the IB banking sector has a lower mitigation ability when the financial crisis spills over the real economy, in this context, it is noticed that it contributes to the systemic risk level of the financial system upon the crisis materialization within the real economy by 2009, which clearly indicates the time shift in the crisis impact on the Islamic banking sector in comparison to the CBw and IB banking sectors, thus, our findings are in line with the work of Khediri et al. (2015), in addition to Hasan and Dridi (2011).

At the country level and at the GCC level, the findings are consistent, with the CBw sector being the most systemically important, especially during the crisis period. We also note that the CBw sector systemic risk level is close in magnitude to the IB one, and both are higher in magnitude than the CB sector, as the later has lower market capitalization than the previous two. This difference is emphasized by the SRISK measure that indicated higher risk with lower capital buffers for the CB sector.

The interconnectedness analysis of the three banking sectors confirm that the CBwin sector has higher connectedness and higher systemic importance during the crisis period based on the netted risk measures graphical analysis of MES and ΔCoVaR. In addition, the analysis indicate the importance of the IB sector in strengthening and stabilizing the financial system during crisis times.

In summary, the IB banking sector is found to strengthen the stability of the GCC financial system, based on its evaluation using the equity based systemic risk measures with different estimation variations combined with interconnectedness analysis using graphical models. However, the IB is found to support the financial system stability as long as the crisis does not reach, in its impact, the real economic side, after which it will contribute to increasing the systemic risk of the financial system. In addition, we found that the CBw banking sector generally has the highest systemic risk contribution, and based on its size and connection to both the IB and CB banking sectors, it could destabilize the financial system. Furthermore, the CB sector is noticed to have higher volatility in its response to the systemic risk events as a relation of its leverage, but this higher volatility is neutralized by its small market share size. Another related findings is that the returns on the stock markets for the GCC region, including the three banking sectors, are affected by the changes in the crude oil index, this notion indicates that banking regulators should keep a close attention to the effect of the changes in the oil price on the capital shortfall of the banking system.

References

Abdul-Majid, Mariani, David S. Saal, and Giuliana Battisti (2011a) 'Efficiency and total factor productivity change of malaysian commercial banks.' *The Service Industries Journal* 31(13), 2117–2143

_ (2011b) 'Efficiency in islamic and conventional banking: An international comparison.' *Journal of Productivity Analysis* 34(1), 25–43

_ (2011c) 'The impact of islamic banking on the cost efficiency and productivity change of malaysian commercial banks.' *Applied Economics* 43(16), 2033–2054

Abedifar, P., P. Molyneux, and A. Tarazi (2013) 'Risk in islamic banking.' *Review of Finance* 17(6), 2035–2096

Abedifar, Pejman, Iftekhar Hasan, and Amine Tarazi (2016) 'Finance-growth nexus and dual-banking systems: Relative importance of islamic banks.' *Journal of Economic Behavior & Organization* pp. –

Acharya, Viral, Robert Engle, and Matthew Richardson (2012) 'Capital shortfall: A new approach to ranking and regulating systemic risks.' *American Economic Review* 102(3), 59–64

Acharya, Viral V., Lasse Heje Pedersen, Thomas Philippon, and Matthew P. Richardson (2010) 'Measuring systemic risk.' Working Paper, NYU

Adrian, Tobias, and Markus Brunnermeier (2011) 'CoVaR.' NBER Working Paper 17454, National Bureau of Economic Research

Al-Jarrah, Idries, and Philip Molyneux (2006) 'Cost efficiency, scale elasticity and scale economies in arab banking.' *Banks and Bank Systems* 1(3), 60–89

Arouri, Mohamed El Hedi, Amine Lahiani, and Duc Khuong Nguyen (2011) 'Return and volatility transmission between world oil prices and stock markets of the {GCC} countries.' *Economic Modelling* 28(4), 1815 – 1825

Arouri, Mohamed El Hedi, and Christophe Rault (2012) 'Oil prices and stock markets in gcc countries: Empirical evidence from panel analysis.' *International Journal of Finance & Economics* 17(3), 242–253

Aysan, Ahmet F., Mustafa, and Huseyin Oztruk (2014) 'The impact of religious commitment on islamic bank depositors: Does size matter?' Paper presented at a seminar on Finance and Development in Muslim Economies, sponsored by Islamic Research Training Institute (IRTI), Islamic Development Bank and the Journal of Financial Services Research, 15 September, Bangor University, UK

Baele, Lieven, Moazzam Farooq, and Steven Ongena (2014) 'Of religion and redemption: Evidence from default on islamic loans.' *Journal of Banking & Finance* 44, 141–159

Banulescu, Georgiana-Denisa, and Elena-Ivona Dumitrescu (2015) 'Which are the SIFIs? a component expected shortfall approach to systemic risk.' *Journal of Banking & Finance* 50, 575–588

Beck, Thorsten, Asli Demirgç-Kunt, and Ouarda Merrouche (2013) 'Islamic vs. conventional banking: Business model, efficiency and stability.' *Journal of Banking & Finance* 37(2), 433–447

Bhagat, Sanjai, Brian Bolton, and Jun Lu (2015) 'Size, leverage, and risk-taking of financial institutions.' *Journal of Banking & Finance* 59, 520 – 537

Billio, Monica, Mila Getmansky, and Loriana Pelizzon (2012) 'Dynamic risk exposures in hedge funds.' *Computational Statistics & Data Analysis* 56(11), 3517–3532

Brownlees, Christian T., and Robert F. Engle (2012) 'Volatility, correlation and tails for systemic risk measurement.' (Working Paper, NYU)

C.G.A.P. (2008) Technical Report 49, Islamic microfinance: An emerging market niche, August

Čihák, Martin, and Heiko Hesse (2010) 'Islamic banks and financial stability: An empirical analysis.' *Journal of Financial Services Research* 38(2-3), 95–113

Engle, Robert (2002a) 'Dynamic conditional correlation.' *Journal of Business & Economic Statistics* 20(3), 339–350

_ (2002b) 'Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models.' *Journal of Business & Economic Statistics* 20(3), 339–350

Engle, Robert, and Kevin Sheppard (2001) 'Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH.' Technical Report

Fayyad, Abdallah, and Kevin Daly (2011) 'The impact of oil price shocks on stock market returns: Comparing {GCC} countries with the {UK} and {USA}.' *Emerging Markets Review* 12(1), 61 – 78

Finanacial Stability Board (2011) 'Policy measures to address systemically important financial institutions.' FSB, November 4

Frankfurt School of Finance and Management (2006) 'Access to finance study in algeria, final report.' Technical Report, (Bankakademie International). Frankfurt: Frankfurt School of Finance and Management, July.

Gheeraert, Laurent (2014) 'Does islamic finance spur banking sector development?' *Journal of Economic Behavior & Organization* 103, S4–S20

Gheeraert, Laurent, and Laurent Weill (2015) 'Does islamic banking development favor macroeconomic efficiency? evidence on the islamic finance-growth nexus.' *Economic Modelling* 47, 32–39

Giudici, P., and A. Spelta (2016) 'Graphical network models for international financial flows.' *Journal of Business & Economic Statistics* 34(1), 128–138

Glosten, Lawrence R., Ravi Jagannathan, and Davide E. Runkle (1993) 'On the relation between the expected value and the volatility of the nominal excess return on stocks.' *The Journal of Finance* 48(5), 1779–1801

Hasan, Maher, and Jemma Dridi (2011) 'The effects of the global crisis on islamic and conventional banks: a comparative study.' *Journal of International Commerce, Economics and Policy* 02(02), 163–200

Hashem, Shatha Qamhieh, and Paolo Giudici (2016) 'NetMES: a network based marginal expected shortfall measure.' *The Journal of Network Theory in Finance* 2(3), 1–36

Højsgaard, Søren, David Edwards, and Steffen L. Lauritzen (2012) *Graphical Models with R.* (New York, USA.: Springer)

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden (2011) 'Diversification disasters.' *Journal of Financial Economics* 99(2), 333 – 348

IFSB (2015) 'Islamic financial services industry stability report 2015.' Technical Report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur, Malaysia.

_ (2016) 'Islamic financial services industry stability report 2016.' Technical Report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur, Malaysia.

Imam, Patrick, and Kangni Kpodar (2013) 'Islamic banking: How has it expanded?' *Emerging Markets Finance and Trade* 49(6), 112–137

Ioannidou, Vasso, Steven Ongena, and Jos-Luis Peydro (2015) 'Monetary policy, risk-taking and pricing: Evidence from a quasi-natural experiment.' *Review of Finance* 19(1), 95–144

Johnes, Jill, Marwan Izzeldin, and Vasileios Pappas (2015) 'Efficiency and productivity change in banks in the gulf cooperation council countries'

Jorion, Philippe (2007) *Value at Risk – The New Benchmark for Managing Financial Risk,* 3rd ed. (McGraw–Hill)

Khediri, Karim Ben, Lanouar Charfeddine, and Slah Ben Youssef (2015) 'Islamic versus conventional banks in the GCC countries: A comparative study using classification techniques.' *Research in International Business and Finance* 33, 75–98

Kuzuba, Tolga Umut, Burak Saltolu, and Can Sever (2016) 'Systemic risk and heterogeneous leverage in banking networks.' *Physica A: Statistical Mechanics and its Applications* 462, 358 – 375

Laeven, Luc, Lev Ratnovski, and Hui Tong (2016) 'Bank size, capital, and systemic risk: Some international evidence.' *Journal of Banking & Finance* 69, S25–S34

Lauritzen, Steffen L. (1996) *Graphical Models* Oxford Statistical Science Series (United Kingdom: Clarendon Press)

Maghyereh, Aktham, and Ahmad Al-Kandari (2007) 'Oil prices and stock markets in gcc countries: New evidence from nonlinear cointegration analysis.' *Managerial Finance* 33(7), 449–460

Mallin, Christine, Hisham Farag, and Kean Ow-Yong (2014) 'Corporate social responsibility and financial performance in islamic banks.' *Journal of Economic Behavior & Organization* 103, Supplement, S21 – S38. Special issue on Islamic Finance

Mohanty, Sunil K., Mohan Nandha, Abdullah Q. Turkistani, and Muhammed Y. Alaitani (2011) 'Oil price movements and stock market returns: Evidence from gulf cooperation council (gcc) countries.' *Global Finance Journal* 22(1), 42 – 55

Ongena, Steven, and lkay endeniz Ync (2011) 'Which firms engage small, foreign, or state banks? and who goes islamic? evidence from turkey.' *Journal of Banking & Finance* 35(12), 3213 – 3224

Pappas, Vasileios, Steven Ongena, Marwan Izzeldin, and Ana-Maria Fuertes (2016) 'A survival analysis of islamic and conventional banks.' *Journal of Financial Services Research* pp. 1–36

Rockafellar, R.Tyrrell, and Stanislav Uryasev (2002) 'Conditional value-at-risk for general loss distributions.' *Journal of Banking & Finance* 26(7), 1443 – 1471

Shaban, Mohamed, Meryem Duygun, Mokhamad Anwar, and Bahrullah Akbar (2014) 'Diversification and banks willingness to lend to small businesses: Evidence from islamic and conventional banks in indonesia.' *Journal of Economic Behavior & Organization* 103, Supplement, S39 – S55. Special issue on Islamic Finance

Sturm, Michael, Jan Strasky, Petra Adolf, and Dominik Peschel (2008) 'The gulf cooperation council countries economic structure, recent developments and role in the global economy.' Technical Report 92, European Central Bank, Frankfurt am Main, Germany, July

Wagner, Wolf (2008) 'The homogenization of the financial system and financial crises.' *Journal of Financial Intermediation* 17(3), 330 – 356

_ (2010) 'Diversification at financial institutions and systemic crises.' *Journal of Financial Intermediation* 19(3), 373 – 386. Risk Transfer Mechanisms and Financial Stability

Weill, Laurent (2011) 'Do islamic banks have greater market power?' *Comp Econ Stud* 53(2), 291–306

Wijnbergen, Sweder Van, and Sajjad Zaheer (2013) *Capital structure, risk shifting and stability: conventional and Islamic banking* Financial intermediation and monetary transmission through conventional and Islamic channels.

Zarour, Bashar Abu (2006) 'Wild oil prices, but brave stock markets! the case of gcc stock markets.' *Operational Research* 6(2), 145–162

Appendix

Table 1: Descriptive Statistics of Banking Sectors' Returns and Return Indexes

Our sample consists of 2608 observations, for the period from January 2005 to December 2014. The descriptive statistics is prepared for three sub-periods: the first is the pre-crisis period which includes 520 observation from the beginning of January 2005 till December 2006, the second is the crisis period which includes 523 observation from the beginning of January 2007 till December 2008, the third is the post crisis period which includes 1565 observation from the beginning of January 2009 till December 2014. The mean for the three periods of the stationary time series is approximately zero and thus isn't included in the table columns.

Banking	Std. Dev.			Skew.			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

Table 2: Assets Distribution of the GCC Banking Sectors Per Country

Table 3 provides the banking system total assets distribution per country on 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 count for no. of banks, and as a percentage from the aggregate total assets). In addition, the table provides the country aggregate banking system ownership percentages that are estimated from the total banking assets of the country (given in billion U.S. dollars). 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: Gulf Region Total Banking Assets Growth Per Banking Sector

In this figure, we present the annual percentage change, for the GCC banking sectors, CB, CBw and IB respectively, using the log transformation for the ratio of the banking sector assets to the GCC total banking assets. From the figure we note the steep decrease for the CB sector during crisis times, and the gradual recovery in the post crisis one, whereas the CBw sector had a gradual decrease during this period without retrieving its initial level afterwards, in contrast to the IB sector gradual increase through and after the crisis period.

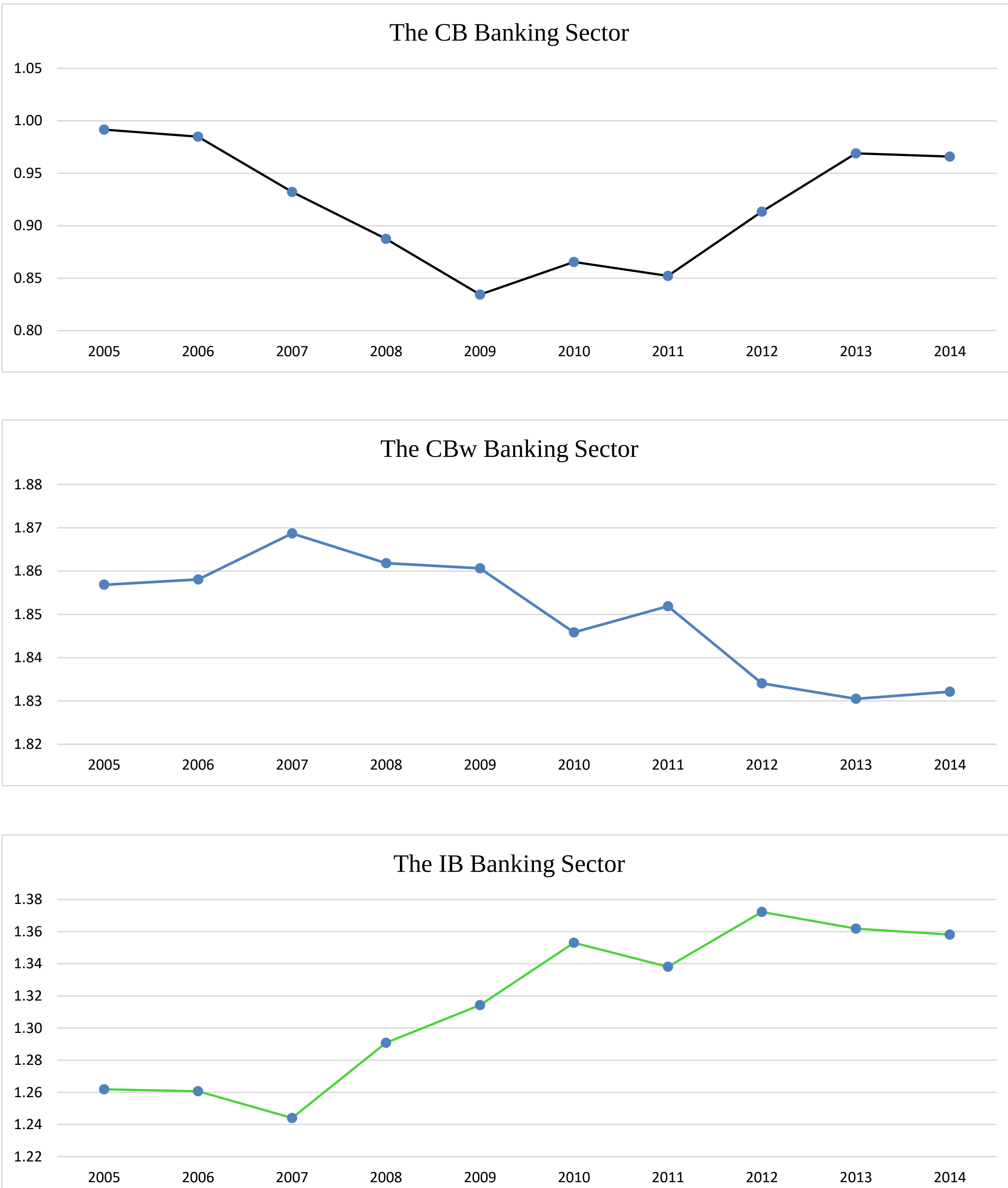


Table 3: Market Capitalization and Quasi Leverage Per Banking Sector

Table 3 provides the size of the market capitalization per banking sector and per country (given in billion U.S. dollars). In addition, we provide the quasi leverage ratio, which is the ratio of book value of debt divided by market share, plus one.

Sector	Country	Market Capitalization			Quasi 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 4: MES Per Banking Sector and Country

Table 4 provides the standard MES measure per banking sector and country, the netted MES measure obtained using conditional time varying partial correlation, and the MES measure in response to the volatility of the oil index. It also provides the average of each bank type for each risk measure estimation.

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 Per Banking Sector and Country

Table 5 provides the standard SRISK measure per banking sector and country, the netted SRISK measure obtained using conditional time varying partial correlation, and SRISK measure in response to the volatility of the oil index. It also provides the average of each bank type for each risk measure estimation. SRISK is given in billion U.S. dollars. The negative signs represent capital buffers, as a result of the sign convergence in the estimation process.

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 Per Banking Sector and Country

Table 6 provides the standard ΔCoVaR measure per banking sector and country, the netted ΔCoVaR measure obtained using conditional time varying partial correlation, and ΔCoVaR measure in response to the volatility of the oil index. It also provides the average of each bank type for each risk measure estimation.

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: The Global Systemic Risk of AE Banking System Portfolio

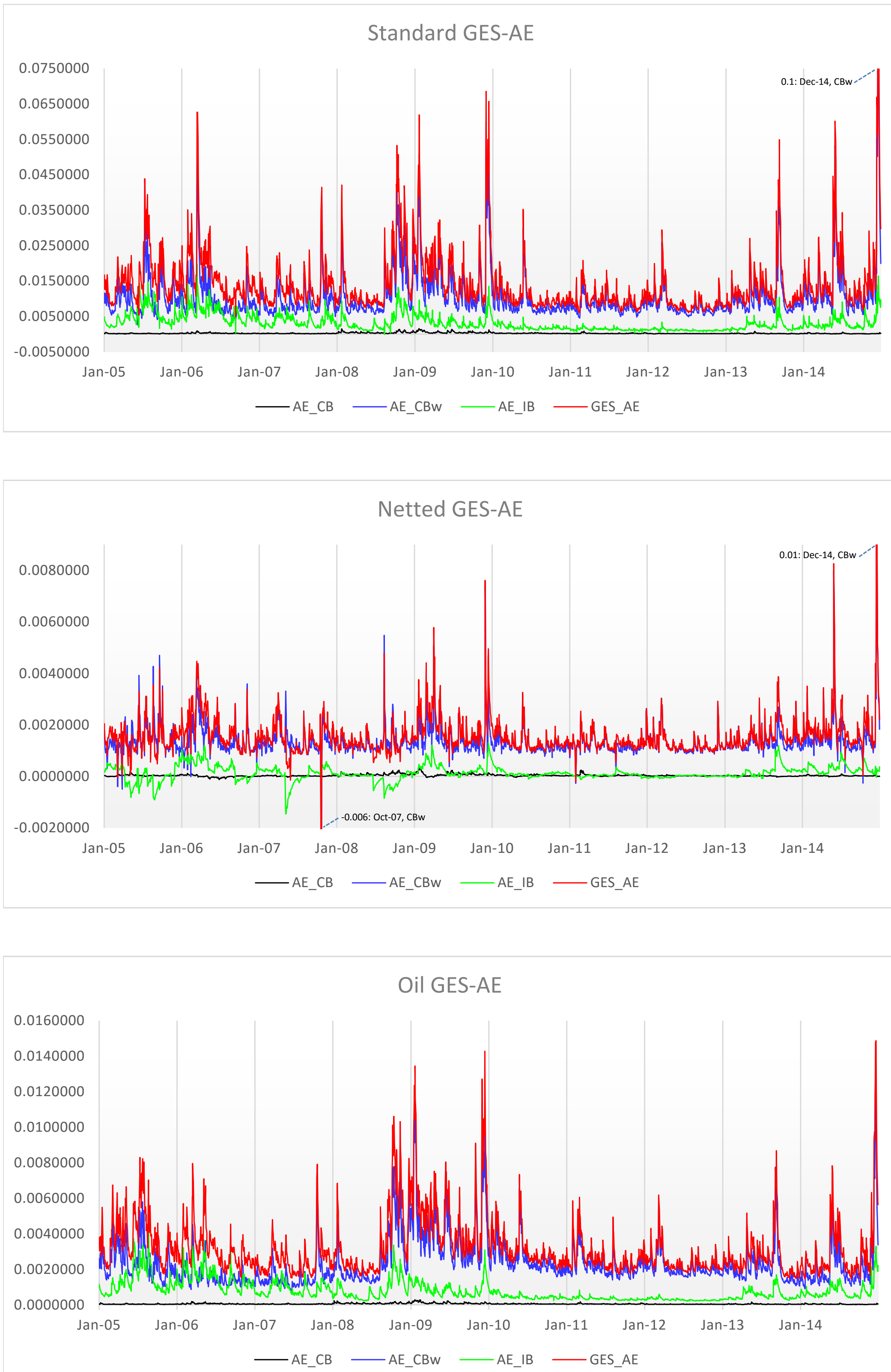


Figure 3: The Global Systemic Risk of BH Banking System Portfolio

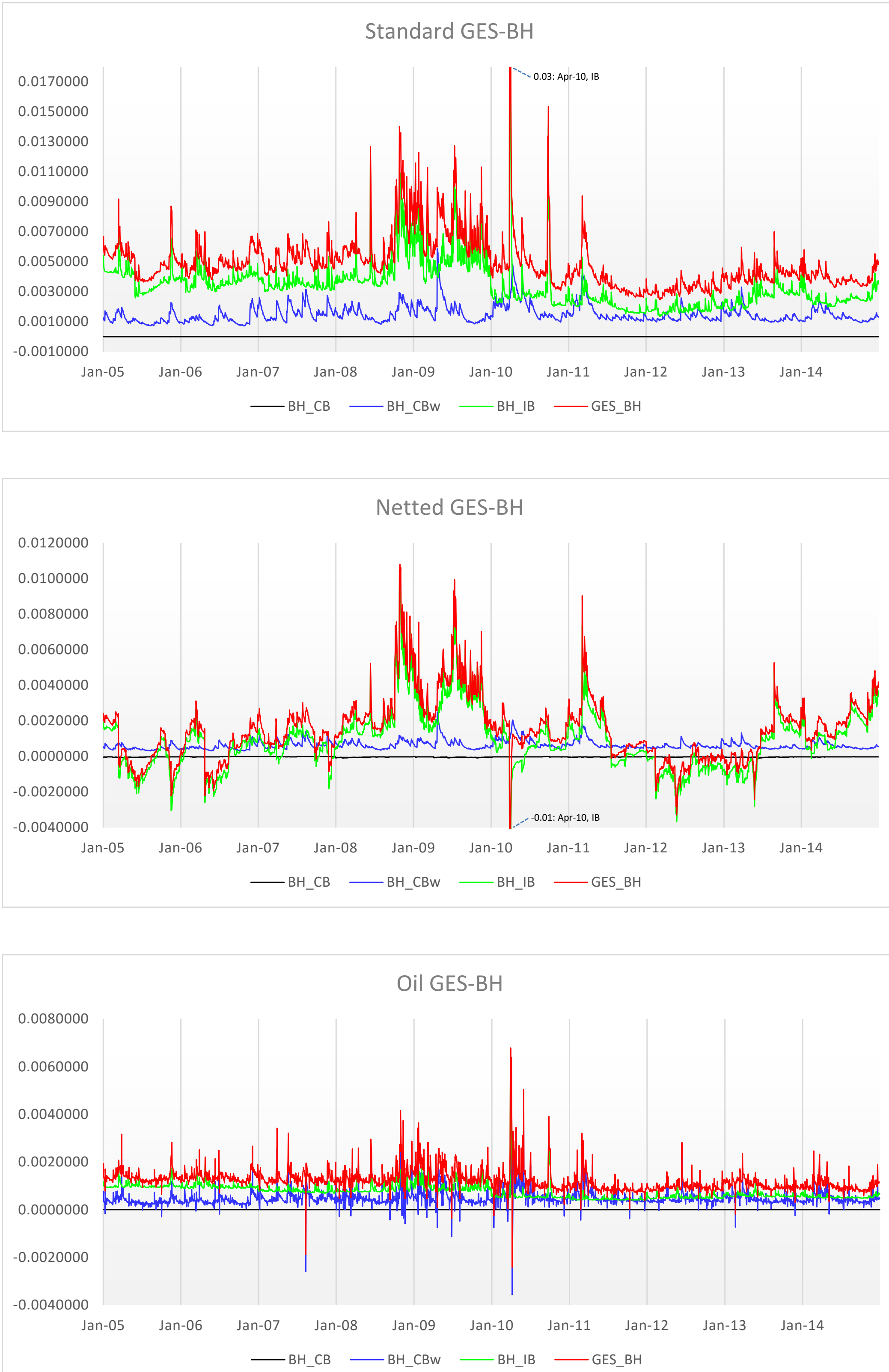
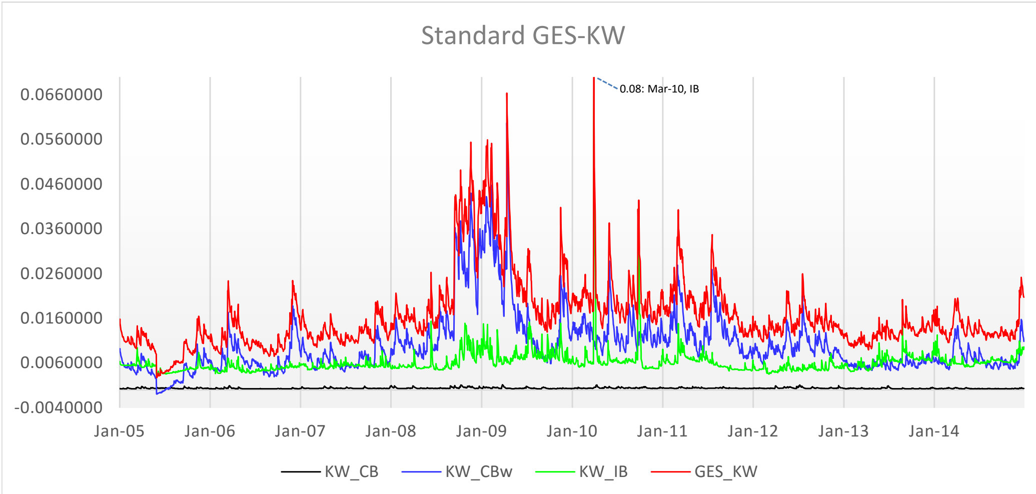
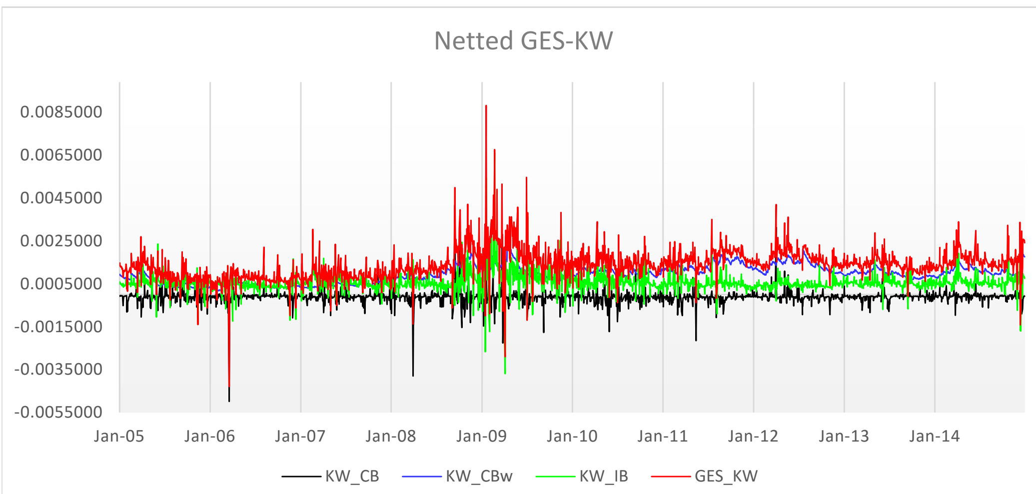


Figure 4: The Global Systemic Risk of KW Banking System Portfolio





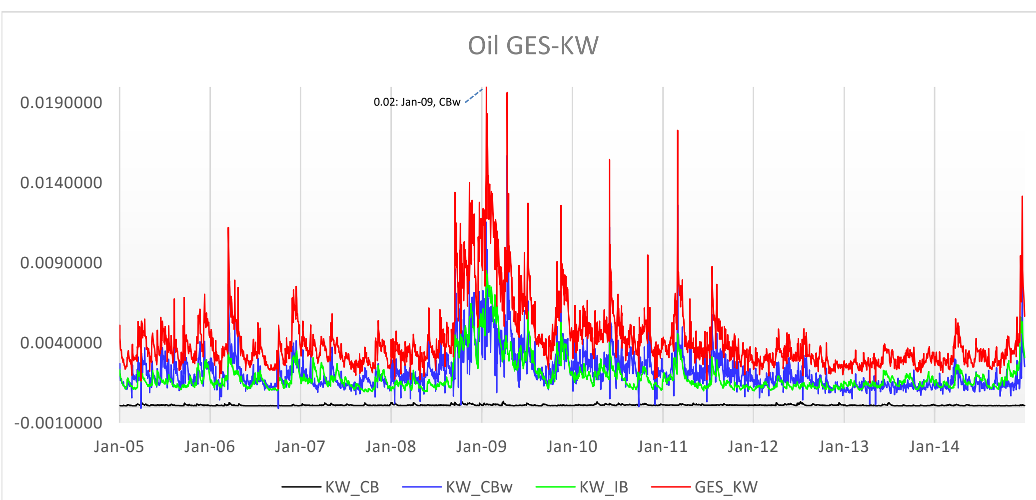


Figure 5: The Global Systemic Risk of OM Banking System Portfolio

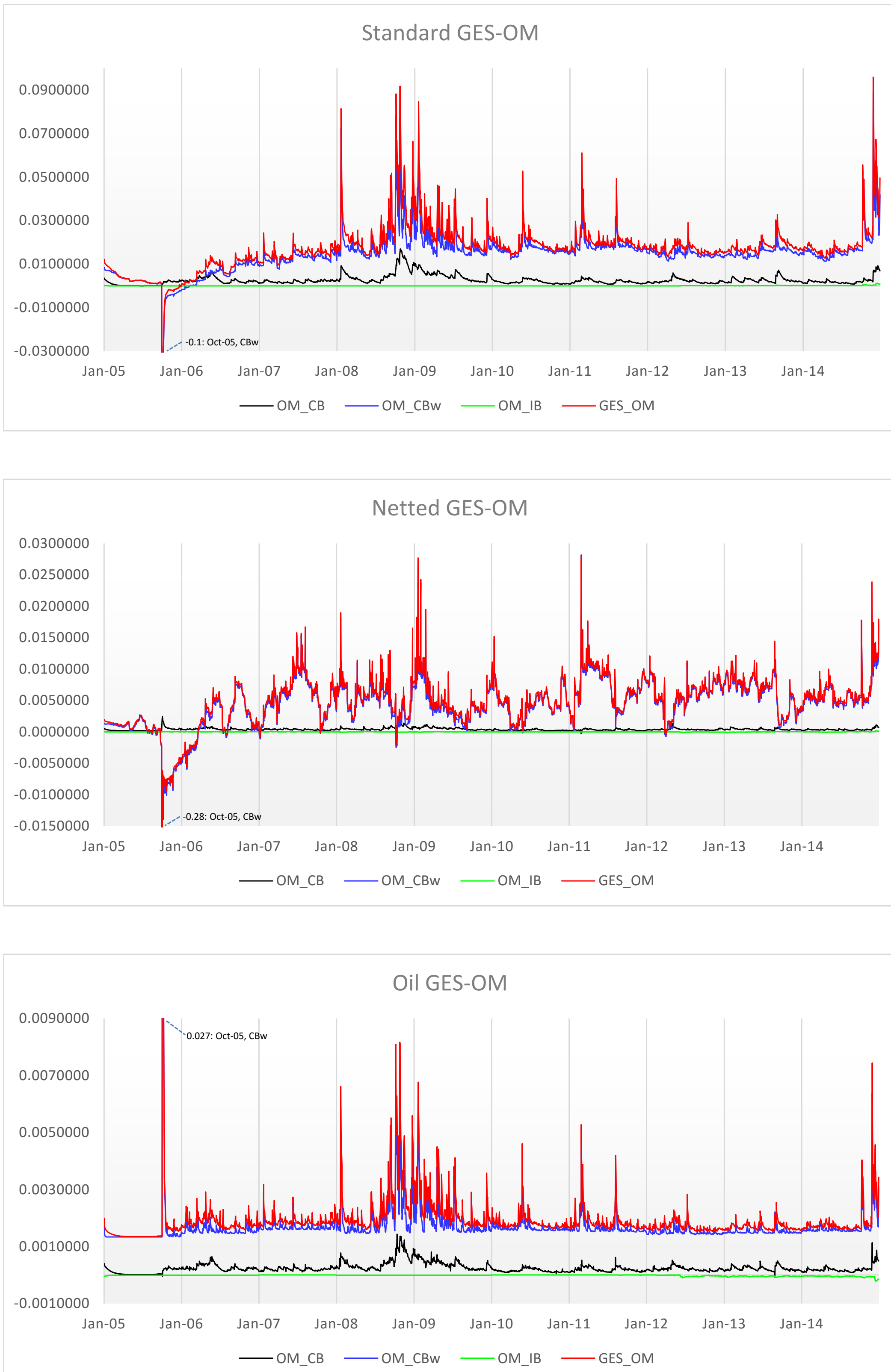


Figure 6: The Global Systemic Risk of QA Banking System Portfolio

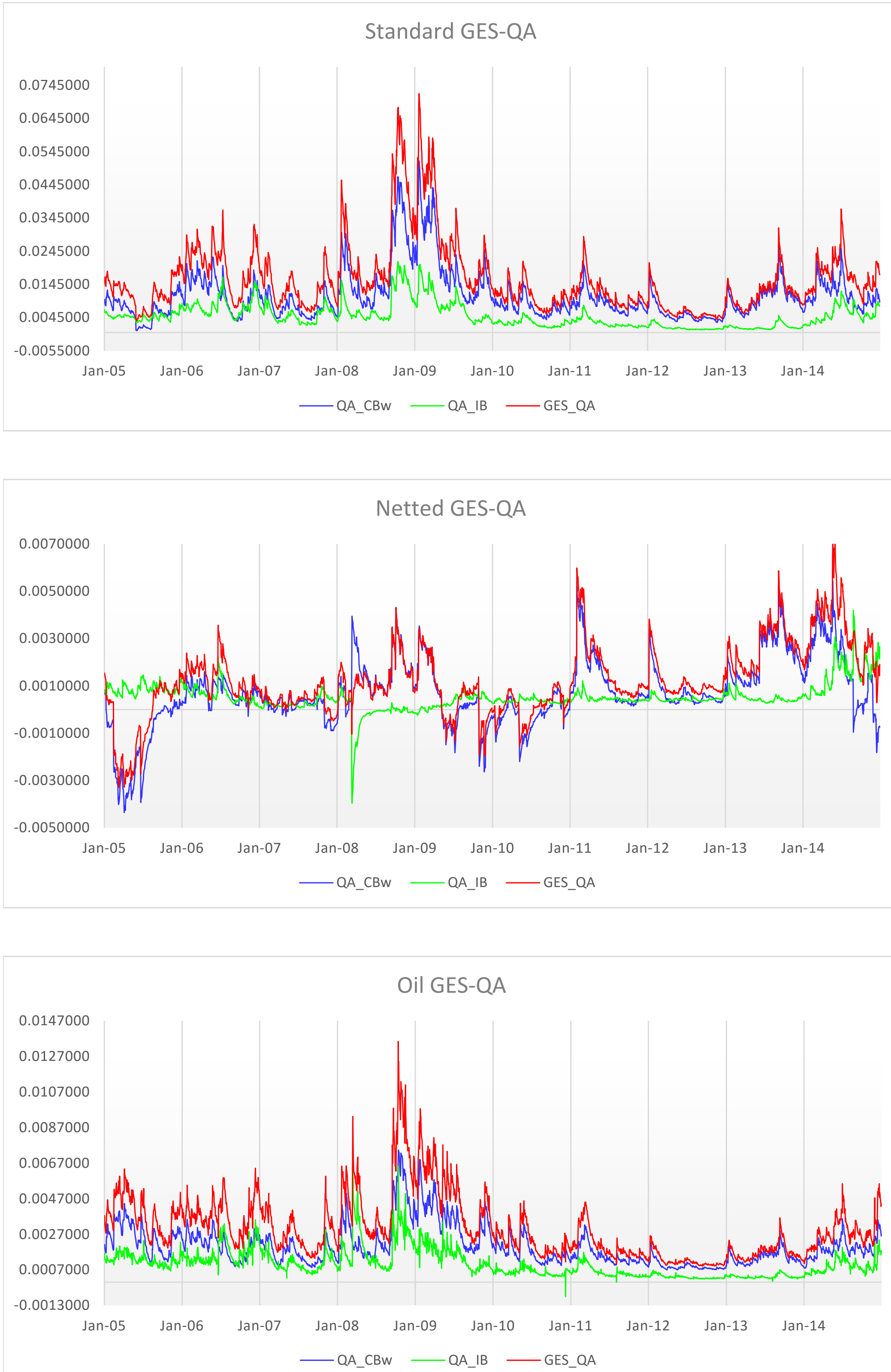


Figure 7: The Global Systemic Risk of SA Banking System Portfolio

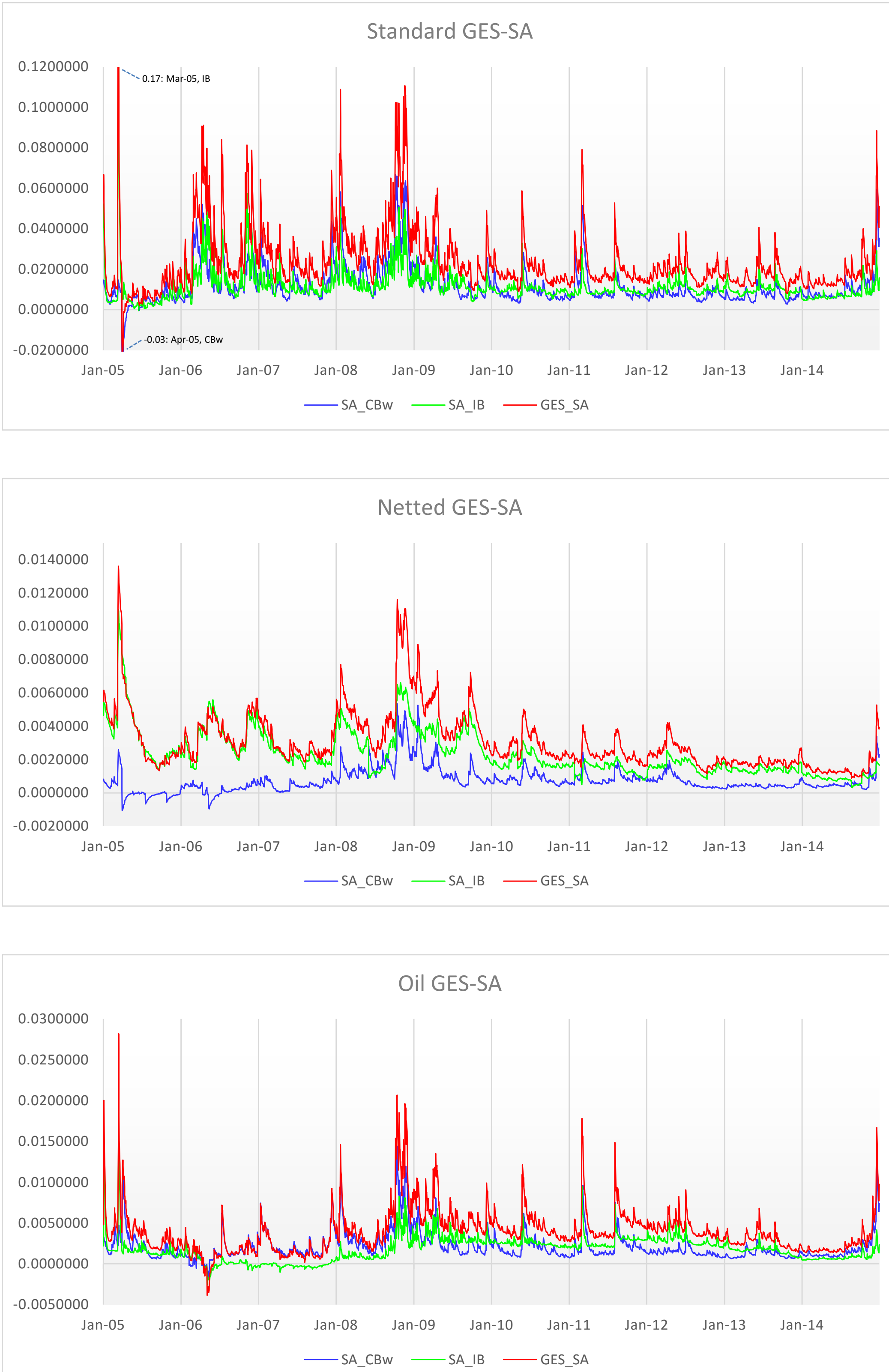
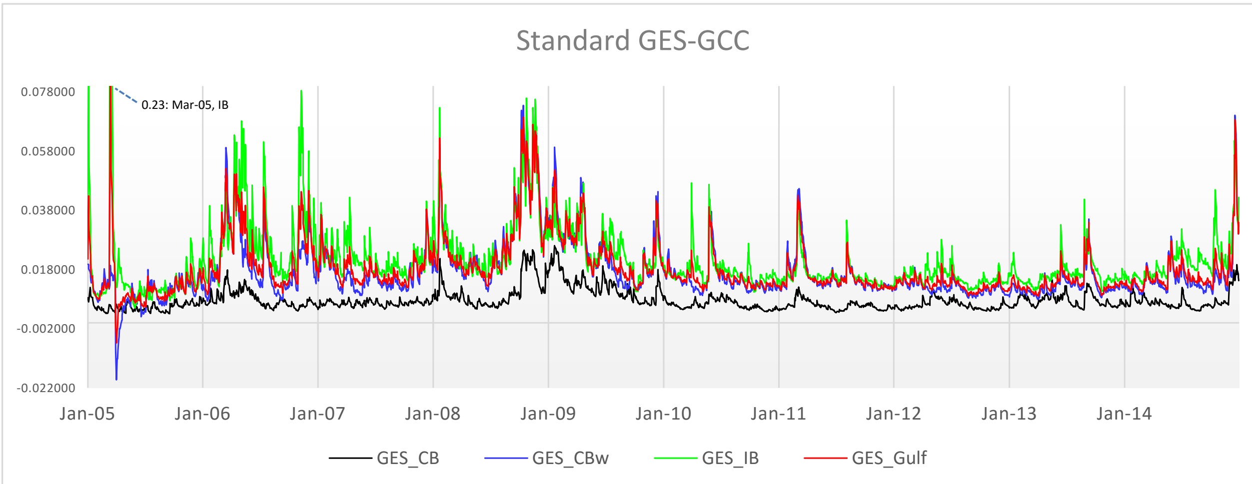
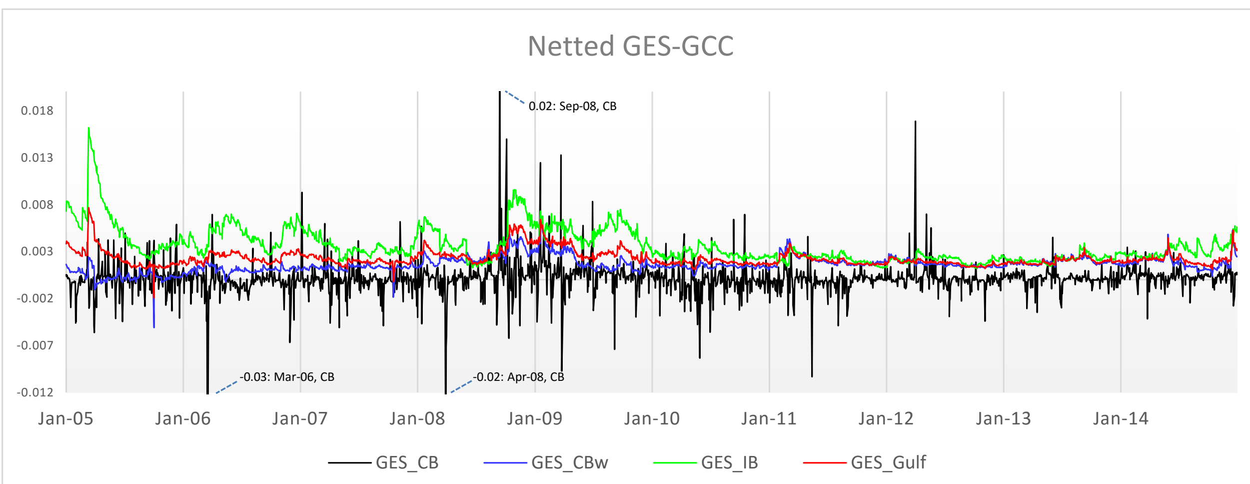


Figure 8: The Global Systemic Risk of the Gulf Region Banking System Portfolio





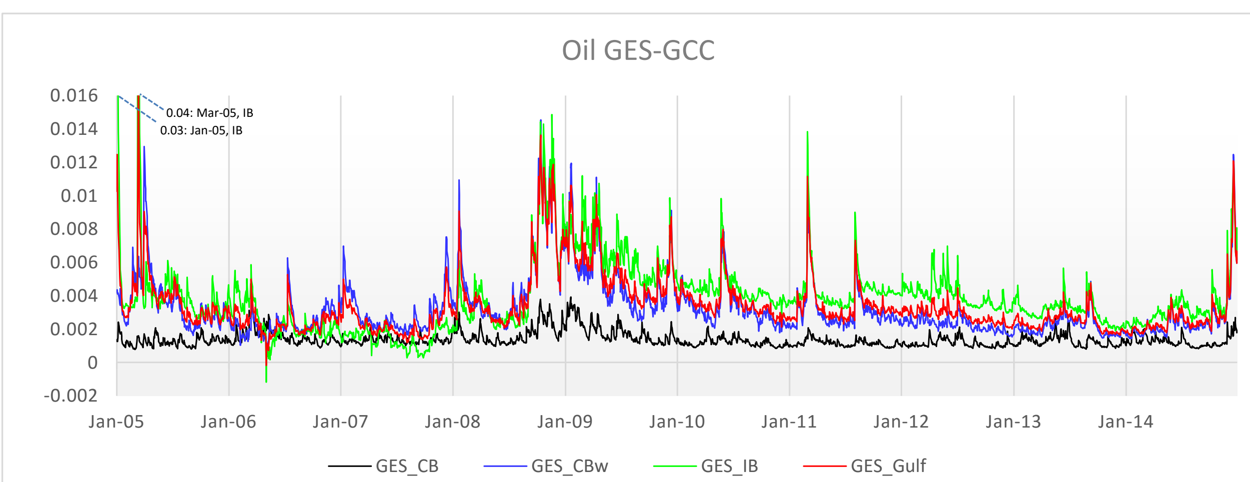
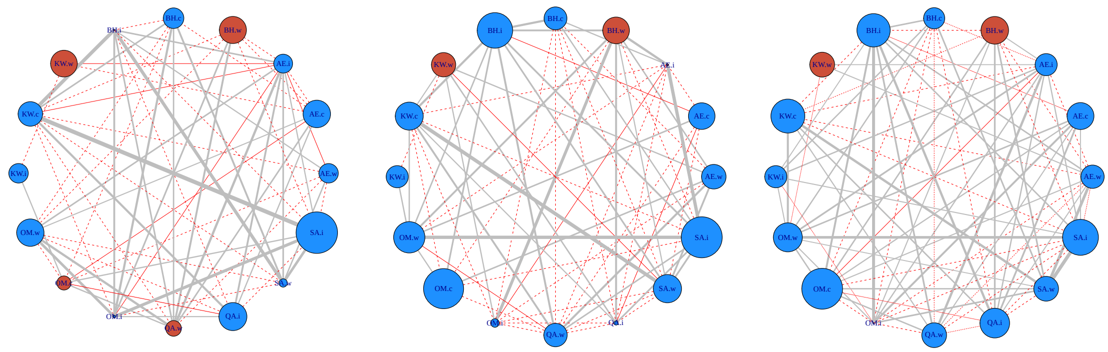
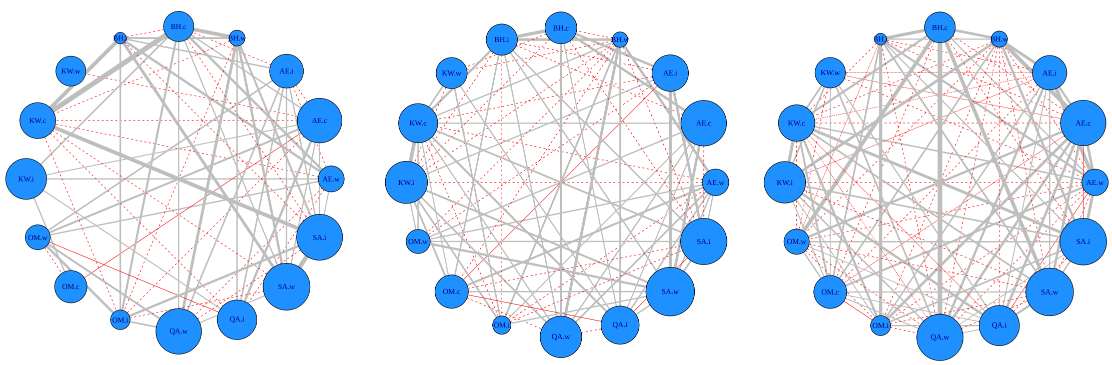


Figure 9: Netted MES Network



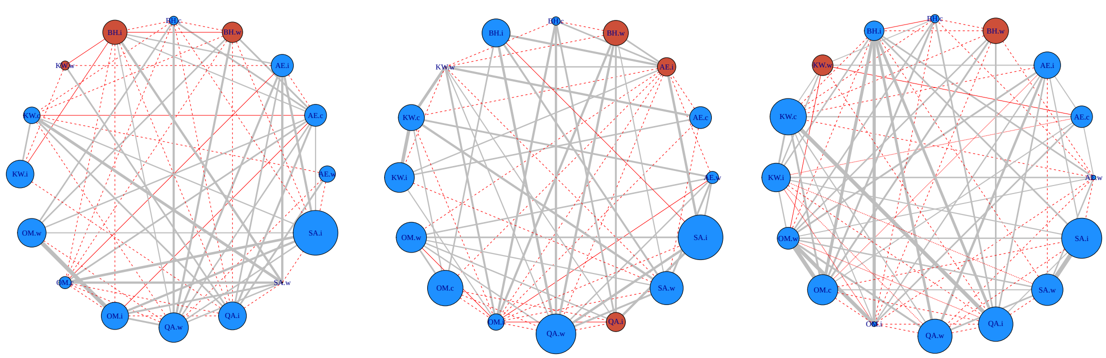
(a) Pre-Crisis *(b) During-Crisis* *(c) Post-Crisis*

Figure 10: Netted SRISK Network



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

Figure 11: Netted ΔCoVaR Network



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

Table 7: MES Centrality Measures Per Period

Banking Sector	*Betweenness*			*Closeness*			*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*
AE.c	5.09	0.74	0.53	0.05	0.04	0.04	8	6	7	0.22	0.19	0.19
BH.c	3.26	1.57	1.87	0.05	0.04	0.05	8	8	9	0.25	0.25	0.23
KW.c	2.96	4.57	1.34	0.05	0.05	0.05	10	10	9	0.31	0.29	0.23
OM.c	12.53	1.17	2.76	0.05	0.04	0.06	8	7	12	0.21	0.21	0.30
AE.w	1.68	2.25	5.27	0.04	0.04	0.05	7	7	11	0.23	0.20	0.27
BH.w	1.29	3.35	0.67	0.04	0.05	0.05	7	9	9	0.23	0.26	0.24
KW.w	2.57	5.37	0.14	0.04	0.04	0.04	3	6	3	0.07	0.15	0.08
OM.w	3.56	9.45	6.11	0.05	0.05	0.05	9	9	10	0.27	0.24	0.23
QA.w	3.65	5.94	1.56	0.05	0.06	0.05	9	12	10	0.27	0.34	0.26
SA.w	1.47	5.42	1.38	0.04	0.05	0.05	8	11	9	0.26	0.31	0.24
AE.i	13.24	2.44	6.84	0.06	0.05	0.06	12	9	12	0.34	0.27	0.28
BH.i	1.94	2.55	3.40	0.05	0.05	0.05	9	9	11	0.29	0.26	0.27
KW.i	0.50	0.50	0.35	0.03	0.03	0.04	2	2	6	0.03	0.04	0.16
OM.i	1.92	2.42	3.89	0.05	0.05	0.06	9	9	12	0.29	0.26	0.29
QA.i	2.73	3.76	2.40	0.05	0.05	0.05	8	10	11	0.26	0.29	0.28
SA.i	3.60	2.51	4.48	0.05	0.05	0.06	9	10	13	0.28	0.30	0.32

Table 8: SRISK Centrality Measures Per Period

Banking Sector	*Betweenness*			*Closeness*			*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*
AE.c	24.06	2.12	1.49	0.05	0.05	0.06	11	9	14	0.28	0.22	0.27
BH.c	6.24	2.64	0.08	0.05	0.05	0.05	11	9	10	0.34	0.22	0.20
KW.c	2.75	5.47	1.93	0.05	0.06	0.07	9	13	15	0.29	0.31	0.28
OM.c	0.25	1.70	1.61	0.03	0.05	0.06	3	10	14	0.07	0.26	0.27
AE.w	4.57	1.85	1.93	0.05	0.05	0.07	9	10	15	0.26	0.26	0.28
BH.w	1.68	4.05	1.15	0.04	0.06	0.06	8	12	14	0.26	0.29	0.27
KW.w	0.00	0.55	0.28	0.03	0.04	0.05	1	6	9	0.03	0.16	0.18
OM.w	4.81	1.21	1.17	0.04	0.05	0.06	7	8	13	0.19	0.21	0.25
QA.w	1.88	1.41	1.93	0.04	0.05	0.07	8	9	15	0.26	0.23	0.28
SA.w	1.94	2.54	1.15	0.05	0.05	0.06	9	10	14	0.30	0.25	0.27
AE.i	3.54	1.11	0.77	0.05	0.05	0.06	9	8	12	0.28	0.21	0.23
BH.i	0.95	2.66	0.50	0.04	0.05	0.06	8	11	12	0.27	0.28	0.24
KW.i	2.15	5.00	0.66	0.04	0.06	0.05	5	12	11	0.13	0.29	0.21
OM.i	3.24	2.04	0.67	0.05	0.05	0.06	9	9	13	0.29	0.23	0.26
QA.i	3.20	3.01	0.94	0.04	0.05	0.06	7	10	13	0.19	0.25	0.25
SA.i	2.73	3.65	0.75	0.05	0.06	0.06	10	12	12	0.32	0.29	0.23

Table 9: ΔCoVaR Centrality Measures Per Period

Banking Sector	*Betweenness*			*Closeness*			*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*
AE.c	3.40	0.10	1.00	0.05	0.04	0.04	11	5	7	0.32	0.16	0.16
BH.c	1.82	0.13	1.26	0.05	0.04	0.05	9	6	9	0.27	0.20	0.22
KW.c	5.36	1.48	4.03	0.05	0.04	0.06	9	7	12	0.24	0.21	0.28
OM.c	1.56	1.89	3.40	0.05	0.04	0.05	10	7	11	0.30	0.21	0.26
AE.w	0.21	1.00	3.59	0.04	0.04	0.05	4	7	11	0.12	0.22	0.26
BH.w	1.82	0.68	0.30	0.05	0.04	0.05	9	7	8	0.27	0.23	0.21
KW.w	0.33	4.63	1.04	0.04	0.05	0.04	4	10	7	0.10	0.28	0.17
OM.w	0.29	1.44	4.56	0.04	0.05	0.06	6	8	13	0.19	0.25	0.30
QA.w	6.57	6.73	1.11	0.06	0.06	0.05	12	12	10	0.32	0.33	0.25
SA.w	1.16	6.57	0.84	0.05	0.05	0.05	8	10	9	0.24	0.27	0.23
AE.i	3.21	12.63	2.79	0.05	0.06	0.05	8	13	10	0.23	0.34	0.23
BH.i	8.26	0.67	2.53	0.05	0.04	0.06	11	5	12	0.29	0.15	0.29
KW.i	0.64	0.30	3.20	0.04	0.04	0.05	4	6	11	0.10	0.18	0.26
OM.i	1.72	12.14	3.12	0.05	0.06	0.06	8	14	12	0.24	0.38	0.29
QA.i	12.19	2.27	4.38	0.06	0.05	0.06	12	8	13	0.29	0.23	0.30
SA.i	5.45	1.36	0.84	0.05	0.04	0.05	11	7	9	0.30	0.21	0.23

Table 10: Rank Concentration Ratio of the Banking Sectors

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

Journal of Network Theory in Finance **2**(3), 1–36
DOI: 10.21314/JNTF.2016.020

Research Paper

NetMES: a network based marginal expected shortfall measure

Shatha Qamhieh Hashem and Paolo Giudici

Department of Economics and Management Sciences, University of Pavia,
Via San Felice Al Monastero, 5, 27100 Pavia, PV, Italy;
emails: shatha.hashem01@universitadipavia.it, paolo.giudici@unipv.it

(Received July 5, 2016; revised September 5, 2016; accepted September 13, 2016)

ABSTRACT

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

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

Corresponding author: S. Q. Hashem
Print ISSN 2055-7795 | Online ISSN 2055-7809

1 INTRODUCTION

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$Ax = \lambda x,$$

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

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

$$s_i = \sum_{j}^{n} e_{ij} \rho_{ijV}.$$

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

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

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

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

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

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

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

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

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

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

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

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

2 METHODOLOGY

2.1 Correlation networks

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

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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$T_n = T_0 + S_n,$$

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

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

in which

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

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

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

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

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

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

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

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

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

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

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

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

2.2 A network-based marginal expected shortfall

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3 APPLICATION

3.1 Data description

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

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

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

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

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

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

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

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

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

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

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

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

3.2 Correlation network models

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

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

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

TABLE 1 Continued.

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

TABLE 1 Continued.

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

TABLE 1 Continued.

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

Based on authors' calculations.

TABLE 2 Leverage.

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

TABLE 3 Market capitalization.

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

TABLE 4 Quasi-leverage.

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

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

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

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

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

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

(a) RC% for leverage

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

(b) RC% for market capitalization

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

(c) RC% for quasi-leverage

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

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

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

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

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

FIGURE 1 Pre-crisis network.

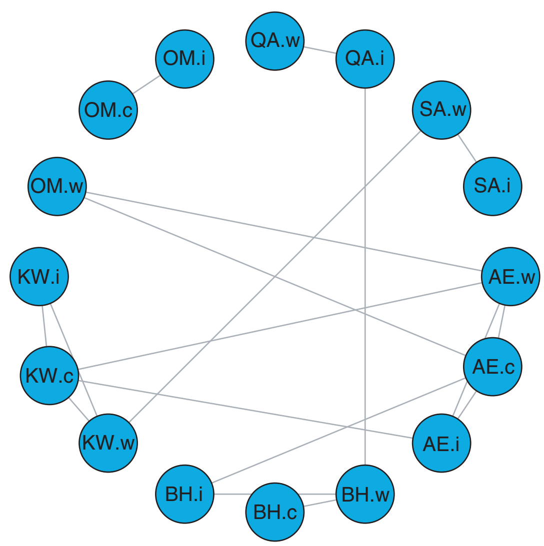


FIGURE 2 During-crisis network.

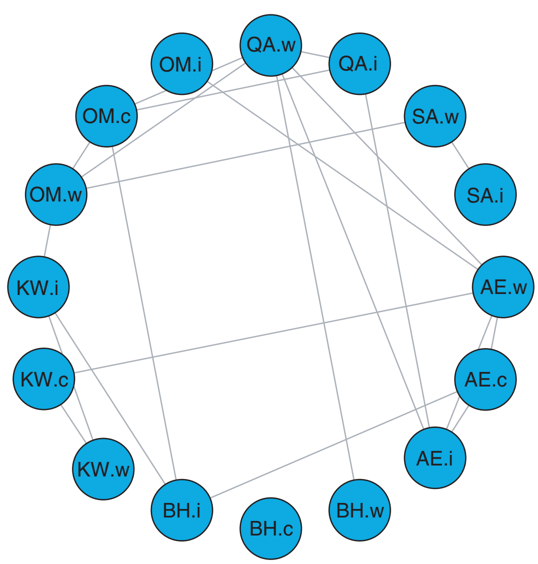


FIGURE 3 Post-crisis network.

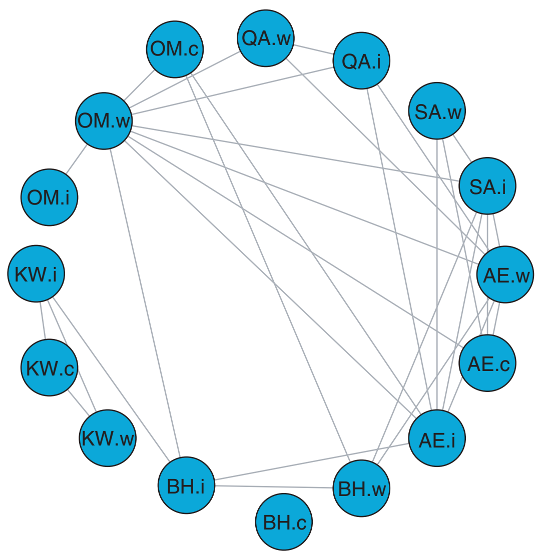


TABLE 6 Correlation model centrality rankings: pre-crisis (2005–6).

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

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

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

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

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

TABLE 9 RC% for correlation network model.

(a) Pre-crisis (2005–6)

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

(b) During crisis (2007–8)

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

(c) Post-crisis (2009–14)

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3.3 NetMES and Bayesian NetMES

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

TABLE 15 RC% for Bayesian model averaging.

(a) Pre-crisis (2005–6)

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

(b) Crisis (2007–8)

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

(c) Post-crisis, part 1 (2009–10)

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

(d) Post-crisis, part 2 (2011–12)

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

(e) Post-crisis, part 3 (2013–14)

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

TABLE 16 MES rankings.

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

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

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

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

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

TABLE 17 NetMES rankings.

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

TABLE 18 Bayesian NetMES rankings.

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

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

(a) RC% for MES

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

(b) RC% for NetMES

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

(c) RC% for Bayesian NetMES

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

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

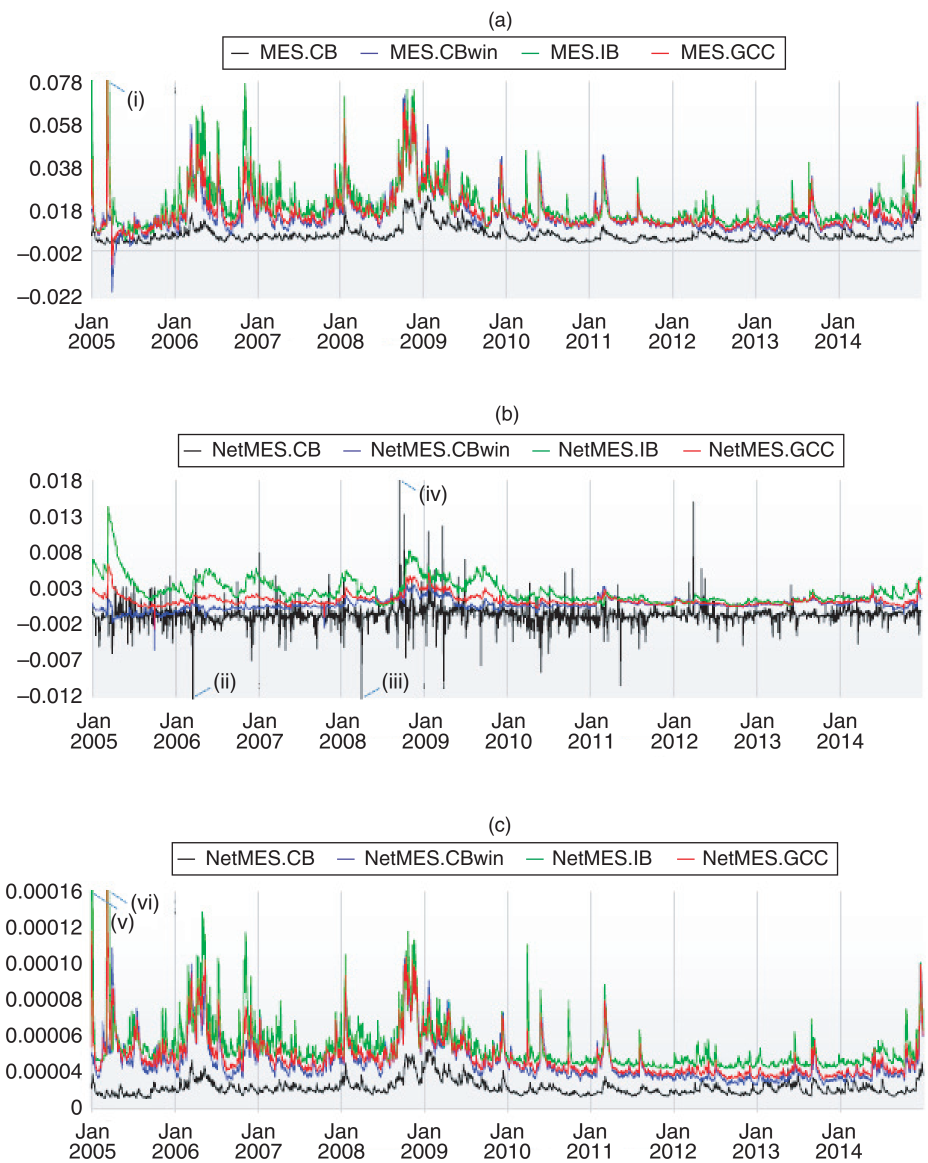
More formally, the timely aggregate systemic risk measure $\mathrm{RM}_{s,t}$ for each banking sector type is

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

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

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

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



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

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

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

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

4 CONCLUSIONS

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

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

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

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

DECLARATION OF INTEREST

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

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support from the PhD program in Economics and Management of Technology at Pavia University. The authors also acknowledge Pejman Abedifar of the University of St Andrews for the data.

REFERENCES

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. P. (2010). Measuring systemic risk. Working Paper, NYU (http://bit.ly/2d34SRi).

Acharya, V., Engle, R., and Richardson, M. (2012). Capital shortfall: a new approach to ranking and regulating systemic risks. *American Economic Review* **102**(3), 59–64 (http://doi.org/bqpk).

Adrian, T., and Brunnermeier, M. (2011). CoVaR. Working Paper 17454, National Bureau of Economic Research (http://doi.org/ft89nk).

Aharony, J., and Swary, I. (1996). Additional evidence on the information-based contagion effects of bank failures. *Journal of Banking and Finance* **20**(1), 57–69 (http://doi.org/chzkn4).

Ahelegbey, D. F., Billio, M., and Casarin, R. (2015). Sparse graphical vector autoregression: a Bayesian approach. Working Paper, Social Science Research Network (http://doi.org/bqpj).

Bank for International Settlements (1994). *64th Annual Report*. BIS.

Banulescu, G.-D., and Dumitrescu, E.-I. (2015). Which are the SIFIs? A component expected shortfall approach to systemic risk. *Journal of Banking and Finance* **50**, 575–588 (http://doi.org/bqpg).

Barigozzi, M., and Brownlees, C. T. (2014). NETS: network estimation for time series. Working Paper, Social Science Research Network (http://doi.org/bqph).

Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2015). Where the risks lie: a survey on systemic risk. Working Paper (http://bit.ly/2crX0HX).

Billio, M., Getmansky, M., and Pelizzon, L. (2012a). Dynamic risk exposures in hedge funds. *Computational Statistics and Data Analysis* **56**(11), 3517–3532 (http://doi.org/dxvnj2).

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012b). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* **104**(3), 535–559 (http://doi.org/bhxm).

Board of Governors of the Federal Reserve System (2001). Policy statement on payments system risk. Docket R-1107, May 30, Washington, DC, pp. 1–13 (http://bit.ly/2cetglE).

Brownlees, C. T., and Engle, R. F. (2012). Volatility, correlation and tails for systemic risk measurement. Working Paper, NYU.

Carvalho, C. M., and West, M. (2007). Dynamic matrix-variate graphical models. *Bayesian Analysis* **2**(1), 69–97 (http://doi.org/cqdc38).

Corander, J., and Villani, M. (2006). A Bayesian approach to modelling graphical vector autoregressions. *Journal of Time Series Analysis* **27**(1), 141–156 (http://doi.org/cjrfgt).

Crockett, A. (1997). Why is financial stability a goal of public policy? Working Paper, Economic Policy Symposium Jackson Hole, Federal Reserve Bank of Kansas City, pp. 7–36.

Dawid, A. P., and Lauritzen, S. L. (1993). Hyper Markov laws in the statistical analysis of decomposable graphical models. *Annals of Statistics* **21**(3), 1272–1317 (http://doi.org/cc6w4s).

Diebold, F. X., and Yılmaz, K. (2014). On the network topology of variance decompositions: measuring the connectedness of financial firms. *Journal of Econometrics* **182**(1), 119–134 (http://doi.org/v9t).

Engle, R. F. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics* **20**(3), 339–350 (http://doi.org/fb46f2).

Engle, R. F. (2012). Dynamic conditional beta. Working Paper, Social Science Research Network (http://doi.org/bqpd).

Engle, R. F., and Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. Working Paper 8554, National Bureau of Economic Research (http://doi.org/c7978t).

Furfine, C. (2003). Interbank exposures: quantifying the risk of contagion. *Journal of Money, Credit, and Banking* **35**(1), 111–128 (http://doi.org/ffjbf5).

George, E. A. J. (1998). The new lady of Threadneedle Street. Governor's Speech, February 24, Bank of England.

Giudici, P., and Spelta, A. (2016). Graphical network models for international financial flows. *Journal of Business and Economic Statistics* **34**(1), 128–138 (http://doi.org/bqpc).

Hasan, M., and Dridi, J. (2011). The effects of the global crisis on Islamic and conventional banks: a comparative study. *Journal of International Commerce, Economics and Policy* **02**(02), 163–200 (http://doi.org/ckzp9x).

Hautsch, N., Schaumburg, J., and Schienle, M. (2014). Forecasting systemic impact in financial networks. *International Journal of Forecasting* **30**(3), 781–794 (http://doi.org/bqpb).

Islamic Financial Services Board (2014). Islamic financial services industry stability report 2014. Technical Report, Islamic Financial Services Board, Bank Negara Malaysia, Kuala Lumpur, Malaysia.

Kaminsky, G. L., and Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of International Economics* **51**(1), 145–168 (http://doi.org/c398fw).

Kaminsky, G. L., and Schmukler, S. L. (1999). What triggers market jitters? *Journal of International Money and Finance* **18**(4), 537–560 (http://doi.org/b5g63q).

Kaufman, G. G. (1994). Bank contagion: a review of the theory and evidence. *Journal of Financial Services Research* **8**(2), 123–150 (http://doi.org/fj9979).

Lauritzen, S. L. (1996). *Graphical Models*. Oxford Statistical Science Series. Clarendon Press.

Peltonen, T. A., Piloiu, A., and Sarlin, P. (2015). Network linkages to predict bank distress. Working Paper, Social Science Research Network (http://doi.org/bqn9).

Shafique, A., Faheem, M. A., and Abdullah, I. (2012). Impact of global financial crises on the Islamic banking system: analysis of Islamic financial system during financial crunch 2008. *Oman Chapter of Arabian Journal of Business and Management Review AJBMR* **1**(9), 124–134 (http://doi.org/bqpw).

Whittaker, J. (1990). *Graphical Models in Applied Multivariate Statistics*. Wiley Series in Probability and Mathematical Statistics. Wiley.