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SYSTEMIC RISK AND INTERCONNECTEDNESS IN GULF COOPERATION COUNCIL BANKING SYSTEMS

Abstract

Nowadays, financial interconnectedness is the main driver of systemic risk. Thus, there is a constant need for tools to assess and manage systemic risk. This paper offers an alternative model framework to measure systemic risk and examine interconnectedness between direct exposures across banking systems in the emerging markets of the Gulf Cooperation Council (GCC). To ensure consistency and efficiency of systemic risk estimates and to capture its multifaceted nature, the methodology measures systemic risk using a combination of Filtered Historical Simulation and nonparametric regression and then examines the interconnectedness using a network analysis. The results reveal that shocks originating in the banking systems in Saudi Arabia may potentially cause a cascade of failures in the banking systems of most GCC countries. The banking system in Oman, however, is robust enough to withstand any ripple effect from adverse shocks affecting GCC's major banking systems. Such results present some policy implications for regulators and supervisors and may benefit asset managers and investors in making portfolio allocation decisions.

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JEL Classification C58, G21, G32

INTRODUCTION

There is an ongoing concern that the financial system has continued to experience negative consequences since the last financial crisis. Among other things, the effects of financial integration have certainly triggered problems such as the interconnectedness risk. There is a general consensus that the main vehicle for systemic risk is financial interconnectedness (e.g., Castren & Rancan, 2014). Consequently, this has prompted regulators and policy makers to look for better means to control this risk. In a simpler sense, the interconnectedness risk is that when one institution fails, other institutions fail too in the financial system. This cascade is the consequence of the existence of links between institutions in the system, direct or indirect. Regulatory authorities, such as the Bank for International Settlements (BIS) and the International Monetary Fund (IMF), have, therefore, requested means to quantify and manage systemic risk and to properly identify financial institutions that pose a threat to the financial system.

Consequently, scholars have suggested identifying and measuring systemic risk using different modelling frameworks. Several mechanisms have been identified that contributed to financial instability during recent financial crises, such as counterparty risk, correlated exposures, funding mechanisms, and price contagion. Besides, many indicators were proposed to measure systemic risk and the systemic importance of a financial institution. These indicators were mainly market-based,

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such as equity returns, CDS spreads, option-implied volatility, interbank exposures, liquidity and leverage ratios, and exposures to other risk factors. Some others dealt with interbank risk exposures and balance sheet information to form a financial network. Nevertheless, the implementation of these indicators is still dependent on the availability of the secondary market data.

However, with regard to market-based quantitative systemic risk measures, there is a need to consider the stylized facts of financial time series. There is overwhelming evidence that returns on financial asset classes display deviation from the normality assumption with high kurtosis as well as volatility clustering and heteroskedasticity. On a regulatory level, it is important to highlight the extent of volatility transmission. There are countries that emit volatility, while others, depending upon their exposure to foreign debt holdings, are exposed to external financial shocks (like sub-prime crisis), or government policies (such as quantitative easing). Naturally, a critical measure of the global connectedness relies on the extent to which volatility is home-grown or imported. To solve these problems, some suggested econometric models that helped explain financial price series in times of crisis, based on linear accommodating variances and correlations. Although such models have proven that they provide an idea of the risk sharing in financial systems, they cannot guarantee consistency and efficiency of systemic risk estimates.

This paper offers an alternative framework. It first adopts a different approach to addressing the heteroskedasticity problem using a distributional free dynamic system, and combines two techniques, namely the Filtered Historical Simulation (FHS), as introduced by Barone-Adesi, Giannopoulos, and Vosper (1999), and nonparametric smoothing. The aim is to use standardized residuals to get consistent variance-covariance estimates and, therefore, to obtain efficient systemic risk assessments. Such approach was earlier adopted by Giannopoulos, Nekhili, and Koutmos (2010) to examine dependencies in changes in covariance of some major equity markets. Secondly, the paper follows a similar methodology suggested by Giudici and Spelta (2016) to examine interconnectedness and see how systemic risk is diffused between various banking systems. This is achieved by using a network analysis based on “statistical financial networks” using partial correlations.

Empirically, this paper quantifies the interconnectedness risk from direct exposures across banking systems in GCC countries. These economies operate in a similar environment in the sense that their businesses and banks have cross-exposures and are oil dependent. They are also characterized by a low sectoral diversification with a high dominance in the banking sector. Hence, their banking systems may be vulnerable to shocks and events specific to the region. Recently, there has been growing concern among policy makers on how to implement an effective regulatory framework across the GCC banking systems. Banks in the Arabian Gulf countries have one of the highest advances to deposit ratios in the region and any further pressure on deposits will crimp the ability of banks to lend to companies that need cash to fund their businesses. Therefore, it is motivating to examine the interconnectedness risk of the GCC banking systems and to look at how this can change the structure of the network banking system.

This paper aims to shed light on regulators in the GCC countries on systemic risk and interconnectedness of banking systems. The results can also help asset managers and investors make portfolio decisions. The paper is structured as follows: Section 1 overviews the relevant literature on systemic risk and interconnectedness; Section 2 discusses the methodology; Section 3 presents the banking data and discusses the empirical findings; the last section concludes.

1. LITERATURE REVIEW

The literature on quantifying systemic risk has been developed using methodologies that follow two approaches. The first approach is a top down approach, where a global indicator of global risk is first defined, it is decomposed into the marginal constituents of each financial system or institution. The second approach, a bottom-up approach, examines a system-wide impact of losses of one institution on the financial system.

Adopting the first approach, Acharya, Pedersen, Philippon, and Richardson (2017) suggested a model that predicts financial institutions contributing to systemic risk during financial crises. They measured systemic risk using systemic expected shortfall, which they defined as "equity loss below target level in a crisis scenario". Using equity returns, leverage ratios and CDS spreads of US banks, they tested their model's performance in times of crisis and suggested that a combination of leverage and Marginal Expected Shortfall (MES) provided good explanation of systemic risk. One drawback, however, is that their framework doesn't take into account counterparty risk and, therefore, network effects. Brownlees and Engle (2012) suggested an improved the MES version by employing time-varying correlations and conditional volatilities. Through a combination of balance-sheet data on leverage and equity with market price data, they assessed the probability that a firm witnesses a decrease in its market capitalization as an effect of systemic risk. Similarly, Adrian and Brunnermeier (2016) suggested a new measure of systemic risk, Conditional Value at Risk (CoVaR). According to these authors, "This measure assesses the financial system's Value at Risk (VaR) conditional on another being under stress." They argued that CoVaR provides how much a financial system contributes to systemic risk. In a broader context, Benoit, Colliard, Hurlin, and Perignon (2017) provided an exhaustive literature review on systemic risk and its measurement. They discussed two main approaches adopted in the literature to measure systemic risk, one is "source-specific" and the other is a "global approach" alternating between qualitative and quantitative measures used by banking regulatory agencies and central banks. They identified gaps between the two approaches and indicated that not all the measures could reflect the systemic risk multiple facets. Nevertheless, they argued that these measures were considered to be coherent risk measures.

As an alternative and within the second approach, network analysis has served for recent and emerging literature that studies cross-border contagion and spillover effects spreading a financial crisis from one country to another. This analysis has become a trending framework for central banks and regulatory authorities right after the 2008 financial crisis. With it, regulators can monitor systemic risk by looking at the interconnectedness in the banking sector. Consequently, the existing literature delved into the role of international banks in transmitting financial shocks across borders. As such, many scholars have attempted to assess systemic risk within various jurisdictions and using various network models. For example, Allen and Dale (2000) used various network structures to investigate the contagion effect on a banking system. They showed that when banks are involved in risk sharing, within interbank markets, the likelihood of banks defaulting is reduced. However, they proved that indirect links between banks can still cause contagion between them. Von Peter (2007) topologically focused on the properties of the global banking system using over 30 years of BIS Locational Banking Statistics. He looked at the evolution of connectivity and density of transactions over the period 1978–2010 and found that the main trend in global banking network connectivity has a procyclical path with global capital flows more during 2000s than the previous decades. His results showed that the network displayed a high connectivity and clustering before the global financial crisis and less so after that. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) studied contagion of counterparty risk using two types of networks, such as the ring network, where bank credit claims are unidirectional, and the complete network, where all banks lend equally to all others. They tested the resilience and stability of these two networks and showed that small-size negative shocks have a significant effect on the ring network but have no effect on the complete network. While large-size negative shocks have effects on both networks, therefore, they do not show resilience and stability. Nevertheless, the authors concluded that due to risk sharing, a complete financial network has the least probability of contagion. Glasserman and Young (2016) extensively reviewed the literature on financial network and discussed various financial network models to investigate the relationship between financial stability and interconnectedness. They referred to the network model with extensions, attributed to Eisenberg and Noe (2001), to look at the transmission of defaults from one institution to another. They found that the financial network models do present some limitations in the sense that they do not consider factors such as bankruptcy costs, in-

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terbank equity claims, interbank debt obligations, and the quality of banks' assets. The authors claim that these factors are important predictors of financial contagion. They, therefore, argued that more empirical research is required to delve into more details on the mechanisms causing financial contagion and the measurement of their relative magnitudes.

In the Gulf region, however, there are few studies that looked at the systemic risk in banking systems. A study by Abedifar, Giudici, and Hashem (2017) is one of the recent literatures that worked on the effect of combining conventional and Islamic finance on the stability of the banking system. They combined two frameworks to study the systemic resilience of banks operating in the GCC: one framework based on market values to measure systemic risk and another framework based on network analysis to examine interconnectedness. Their finding highlighted that conventional banks offering Islamic financial services display high vulnerability to systemic risk and high interconnectedness with other conventional banks during crises.

Therefore, it seems evident that the literature has provided scholars and regulators with several alternative measures of systemic risk and still offers rooms for more research on measuring systemic risk and examining the interconnectedness of banking systems. The ground is still open to monitor the financial stability both globally and regionally.

2. METHODOLOGY

Let's consider N markets with one banking portfolio i with returns

$$r_{i,t} = \sum_{k=1}^{n_k} w_k r_{k,t}, \text{ and where } w_k = \frac{MV_k}{\sum_{m=1}^{n_k} MV_m},$$

$r_{k,t} = \ln\left(p_t - p_{t-1}\right)$, p_t is the price at time t, MV_k denotes the market capitalization value of n_k number of listed banks in country i. To capture spillover effects of returns and other volatility stylized facts, such as clustering, persistence, and transmission, among different banking systems, a GARCH (1,1) volatility specification is used to model the returns as follows:

$$\begin{aligned} r_{i,t} &= \mu_i + \sum_{j=1}^{n} \mu_{i,j} r_{j,t-1} + \varepsilon_{i,t}, \varepsilon_{i,t} \to D\left(0, h_{i,t}\right) \\ h_{i,t} &= w_i + \beta_i h_{i,t-1} + \alpha_i \varepsilon_{i,t-1}^2, \end{aligned} \tag{1}$$

where i is the banking portfolio of country i, j is the banking portfolio of country j, and $D(0,h_{i,t})$ is the distribution of the error terms. The error terms' distribution D will be assumed to follow a Student-$t(v)$ distribution, with v degrees of freedom, as a result of the departure of financial time series from normality, which is a common stylized fact in the financial modelling literature. Interestingly, from an econometric point of view, most of the market-based measures accounted for periods with high volatility have addressed the heteroskedasticity problem and the distortion in correlation coefficients. For instance, this was achieved by using robust models such as the DCC-GARCH that was introduced by Engle (2002). However, there was little attention to challenge the unrealistic assumption of adopting a specific distribution in the conditionally heteroskedastic error terms. The study then suggests re-working on the return series using the Filtered Historical Simulation (FHS). Unlike Brownlees and Engle (2012), who suggested time varying linear dependencies in their model, FHS does not impose either linearity of conditional variance-covariance matrix or conditional distribution of the residuals, $z_{i,t} = \varepsilon_{i,t} / h_{i,t}^{1/2}$. The time-varying variance-covariance matrix H_t is decomposed into a diagonal matrix containing GARCH conditional variances and conditional correlations such as $H_t = D_t R D_t$, where

$$D_t = diag\left(h_{1,t}^{\frac{1}{2}}, \ldots, h_{N,t}^{\frac{1}{2}}\right),$$

N is the number of banking indices, and $R = \left[\rho_{ij}\right]$ is a positive definite with $\rho_{ii} = 1, i = 1, \ldots, N$. The off-diagonal elements $\left[H_t\right]_{ij} = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij},$, $i \neq j$.

The study then proceeds by performing a nonparametric estimation of the conditional covariance matrix H_t using the Nadaraya-Watson (NW) estimator. This will guarantee accommodating for the non-linearity in the conditional covariance. The nonparametric estimator is the following:

$$H_t = \frac{\sum_{t-1}^{N} z_t \overset{ÿ}{z_t} K_\tau\left(s_N - s_t\right)}{\sum_{t-1}^{N} K_\tau\left(s_N - s_t\right)}, \tag{2}$$

where s_t is a conditioning variable, and $K_\tau(.) = K(./\tau)/\tau$, representing a kernel function with a bandwidth parameter τ.

The adjusted standardized residuals, $z^*_{i,t}$, are then orthogonalized using Choleski factorization to accommodate for contemporaneous independence of the innovation and will serve as an input to generate the conditional variance and the conditional mean in the model: for $i = 1,\ldots,N$ and $i \neq j$

$$\begin{aligned} h^*_{i,t+j} &= w^*_i + \beta^*_i h_{i,t+j-1} + \\ &+\alpha^*_i \left(z^*_{i,t+j-1} \sqrt{h^*_{i,t+j-1}} \right)^2, j = 1,\ldots,N \\ r^*_{i,t+j} &= \mu^*_i + \sum_{j\neq i} \mu^*_{i,j} r^*_{j,t} + \\ &+ z^*_{i,t+j} \sqrt{h^*_{i,t+j}}, j = 1,\ldots,N. \end{aligned} \tag{3}$$

The model is then simulated several times to obtain simulated pathways for each return, and the outcome of this model is a sequence of simulated returns serving to compute the systemic risk of banking portfolios. With these returns, the study generates a series of Value-at-Risk, VaR^i_θ, defined as the quantiles for each banking portfolio *i* at a given confidence level θ. These *VaR*s will serve in calculating the Conditional Value-at-Risks of each banking portfolio, as in Adrian and Brunnermeier (2016). $CoVaR^{j|i}_\theta$ is the θ-percent *VaR* value for banking system *j* when banking system *i* is at its θ-percent *VaR* value. In other words, it simply tells the boundary on a large loss for some banking systems given that a particular banking system is stressed to a certain degree. The calculations are as follows:

$$\Pr(r^*_i \leq CoVaR^{j|i}_\theta | r^*_i = VaR^i_\theta) = \theta \tag{4}$$

At a final stage, the contribution of a banking system *i* to systemic risk represented by a banking system *j* is estimated, using $\Delta CoVaR$. The computations of the systemic risk measures go as follows:

$$\begin{aligned} \Delta CoVaR^{j|i}_\theta &= CoVaR^{j|r^*_i = VaR^i_\theta}_t - \\ &- CoVaR^{j|r^*_i = Median(r_i)}_t. \end{aligned} \tag{5}$$

The methodology proceeds by looking at the interconnectedness of the banking systems using a network approach. The study applies a financial network based on statistical measures, often called "statistical network model" as in Giudici and Spelta (2016). These latter argued that correlation-based statistical networks are best used to investigate the structure of pairwise correlations among financial time series. In this network, the edges connecting two banking systems are based on statistically significant correlations and partial correlations. This study is motivated by the fact that since correlations can capture both direct and indirect effects between two banking systems, partial correlations will be more representative in a network model as they capture only the direct effects between two banking systems. Therefore, the current financial network model is composed of systemic risk measures of *N* nodes, which will have an $N \times N$ adjacency matrix with $a_{i,j}$ weights. These weights represent the interconnections of banking systems taking values of 1 if partial correlations are significant, otherwise 0. Finally, the partial correlation network's centrality measures are expressed in terms of rank concentration ratio (RC%).

3. DATA AND RESULTS

For the empirical application, a market capitalization weighted index is used, which consists of the daily closing prices of listed banks of five GCC markets, Bahrain, Kuwait, United Arab Emirates, Oman, and Saudi Arabia, for the period of January 2, 2014 until March 2, 2019. The daily closing prices and market capitalizations of seven Bahraini banks, 12 Kuwaiti banks, 28 UAE banks, eight Omani banks, and 12 Saudi banks were obtained from the Thomson Reuters Zawya database. These banks are a mix of both conventional and Islamic banks. It is worth to mention that some observations had to be deleted to accommodate the differences in holidays across the GCC countries. Banking portfolios are then constructed and their descriptive statistics are presented in Table 1. It is observed that the average banking portfolio returns alternate between positive and negative values with the lowest for UAE and the highest for Bahrain. In terms of volatility, the lowest is for Bahrain, and this seems the trend as it is the least liquid of the GCC markets, and the highest for UAE. The daily returns in all banking portfolios display skewness and a high kurtosis, which indi-

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Table 1. Descriptive statistics for GCC banking portfolio daily returns

Statistics	Bahrain	Kuwait	UAE	Oman	Saudi Arabia
Mean	0.004	–0.144	–0.004	–0.014	0.002
S.D.	0.645	1.081	3.219	1.31	1.475
Skewness	0.441	–0.612	0.264	–0.737	0.085
Kurtosis	4.853	6.22	5.826	10.234	9.85
Jarque-Bera	7,541.58	6,832.40	4,602.30	1207.48	12,969.03

cates a deviation from normality. The descriptive statistics also show that daily returns have high serial correlations, as indicated by Jarque-Bera statistics.

Table 2 displays the estimation results of the return model. The results show that banking systems of Bahrain, Oman, and Kuwait display positive return spillover on Saudi banking system, with a higher magnitude from Bahrain and Kuwait (0.377 and 0.407, respectively). Also, while Kuwaiti and Saudi banking systems have a positive return spillover on the banking system of Bahrain (0.092 and 0.080), Oman has a negative bank spillover (–0.050). This is normal as Bahrain economy has a great deal of trade with Saudi Arabia and Kuwait than with Oman. It is also noticed that for UAE banking system, the only return spillover is coming from Saudi Arabia due to a high exposure of UAE banks to Saudi businesses. Moreover, there is a highly significant GARCH effect on all banking portfolios, which indicates at the presence of own-banking volatility persistence. Also, all banking portfolios have high own-market volatility spillover effects ranging from 0.790 in UAE to 0.948 in Bahrain. This indicates a positive sensitivity to past own volatility in all GCC banking portfolios.

The results of the estimation of $\Delta CoVaR$ at $\theta = 5\%$ confidence level in Table 3 display the systemic risk contribution of each banking system. $\Delta CoVaRs$ are presented as standard values as in equation (5) and "netted" values with partial correlations. In terms of the within market risk contribution and the standard measures of systemic risk, Saudi Arabia has the highest contribution, whereas Oman has the least risk contribution. In terms of risk contribution across banking sectors and with the partial correlation measures of systemic risk, it is similarly observed that Saudi Arabia has the highest contribution across all GCC banking systems and Oman has the least contribution.

Table 2. Estimation results

Country		Bahrain	Kuwait	UAE	Oman	Saudi Arabia
Bahrain	μ_{ij}	0.016	0.244*	0.235	–0.223**	0.377*
		(0.413)	(2.351)	(0.715)	(–1.654)	(2.732)
Kuwait	μ_{ij}	0.092*	–0.144*	0.313	–0.053	0.407*
		(2.351)	(–2.237)	(1.557)	(–0.644)	(4.953)
UAE	μ_{ij}	0.009	0.032	0.030	0.032	–0.402
		(0.715)	(1.557)	(0.148)	1.212	(–1.541)
Oman	μ_{ij}	–0.050**	–0.032	0.190	–0.018	0.142*
		(–1.654)	(–0.644)	(1.212)	(–0.218)	(2.151)
Saudi	μ_{ij}	0.080*	0.229*	–0.233**	0.133*	0.055
		(2.732)	(4.953)	(–1.641)	(2.151)	(0.641)
	w	0.0004	0.001	0.022	0.002	0.018
		(0.023)	(0.092)	(0.423)	(0.394)	(1.021)
	α_i	0.046*	0.085*	0.203*	0.091*	0.095*
		(7.888)	(3.168)	(3.800)	(3.766)	(2.799)
	β_i	0.948*	0.908*	0.790*	0.893*	0.902*
		(25.555)	(24.639)	(14.942)	(29.793)	(27.143)
	v	5.951*	5.010*	6.792*	4.089*	5.494*
		(4.760)	(4.593)	(2.989)	(5.779)	(3.177)
	LogLik	–226.15	–330.15	–591.7	–325.57	–385.16

Note: *t*-values are in parentheses, * denotes 1% significance level, ** denotes 5% significance level.

Table 3. $\Delta CoVaR$ at the 5% confidence level for each country's banking system

Country	$\Delta CoVaR$	$\Delta CoVaR$ with partial correlation
Saudi Arabia	1.040	0.488
UAE	0.155	0.069
Bahrain	0.176	0.147
Kuwait	0.301	0.235
Oman	0.105	0.058

Let's now look at how the banking portfolios are interconnected with each other using a graphical network model. The graphical nodes represent the banking systems of the GCC countries, and the systemic risks associated with each node is based on partial correlations. Figure 1 shows the graphical network, using a significance level of $\theta = 5\%$. The links on the graph between nodes indicate significant partial correlation between banking portfolios. It can be observed that the banking system of Saudi Arabia has the highest number of connected edges, which highlights its role in the GCC financial network. It seems to correlate with all other GCC banking systems and can be explained by the fact that many Saudi banks have higher cross-border level operations than the other GCC countries. The direct effect between banking systems of UAE and Saudi Arabia is observed, and this can be explained by the high exposure of UAE banks to Saudi economy. The Omani banking sector has the least systemic importance in terms of contagion.

Table 4 summarizes the graph (see Figure 1) using centrality measures, which serve to rank banking portfolios from being the least systematically important to the most important in terms of contagion. This table displays the rank concentration ratios using both $\Delta CoVaRs$ as standard values as in equation (5) and "netted" values with partial correlations. For a specified banking system, a higher concentration ratio points out a higher contagion, and the opposite holds. It can be observed from the results that Saudi Arabia has much higher contagion capacity than its counterparts. The lowest concentration ratio is observed for the Omani banking system, which identifies it as having the lowest contagion capacity than the other GCC banking systems.

Table 4. Rank concentration ratio of banking systems

Country	$\Delta CoVaR$	$\Delta CoVaR$ with partial correlation
Saudi Arabia	0.201	0.245
UAE	0.164	0.152
Bahrain	0.176	0.147
Kuwait	0.18	0.208
Oman	0.125	0.091

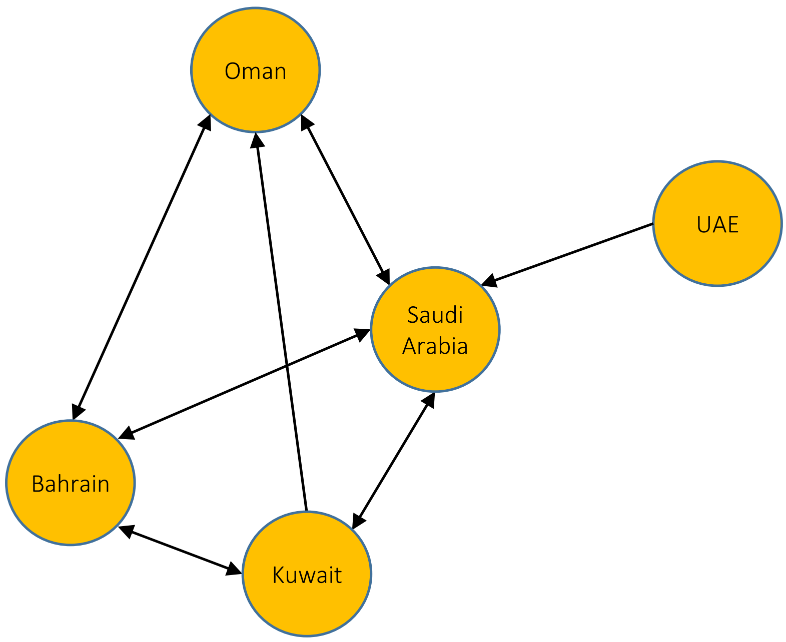

Figure 1. Partial correlation network

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By combining the data, it can be then concluded from Figure 1 and Table 4 that if shocks occur in the banking systems in the Saudi Arabia, there is great potential to cause a cascade of failures in the banking systems in most GCC countries. Hence, banks headquartered in Saudi Arabia may be at risk of bankruptcy from a GCC perspective. Also, systemic risk from shocks originating in the banking system of Saudi Arabia, primarily, and Kuwait, secondarily, appears to have an effect on the banking system of Bahrain. Besides, among these GCC countries analyzed, the banking system of Oman is the least exposed to systemic risks from other GCC banks. Therefore, it can be argued that the Omani banking system demonstrates sufficient robustness to withstand any ripple effect from adverse shocks affecting major GCC banking systems.

CONCLUSION

This paper offers an alternative model framework for measuring systemic risk and examining interconnectedness as a further refinement to existing models for estimating systemic risk. The framework is based on Filtered Historical Simulation with a nonparametric estimation of the conditional covariance matrix, which allows relaxing any assumption on its functional form or the distribution of residuals. The framework is empirically used in the GCC banking system to measure systemic risks, and a network analysis is conducted to examine interconnectedness. The results reveal that shocks originating in the banking systems of Saudi Arabia can potentially cause a cascade of failures in the banking systems of most GCC countries. The exception is the banking system of Oman, which demonstrates sufficient robustness to withstand any ripple effect from adverse shocks affecting major GCC banking systems. Such results will present some policy implications for regulators and supervisors and may benefit asset managers and investors in making portfolio allocation decisions. In fact, GCC banking systems have a lot to do to meet regulatory capital requirements in the event of severe economic shocks, mainly characterized by oil fluctuating prices. For instance, Saudi financial sector remains the most vulnerable to the oil price volatility. In general, despite significant regulatory developments made in accordance with Basel regulations, it is believed that GCC banks in general and Islamic banks in particular have yet to resolve many regulatory issues.

AUTHOR CONTRIBUTIONS

Conceptualization: Ramzi Nekhili
Data curation: Ramzi Nekhili
Formal analysis: Ramzi Nekhili
Investigation: Ramzi Nekhili
Methodology: Ramzi Nekhili
Validation: Ramzi Nekhili
Writing – original draft: Ramzi Nekhili
Writing – reviewing & editing: Ramzi Nekhili

REFERENCES

1. Abedifar, P., Giudici, P., & Hashem, S. Q. (2017). Heterogeneous market structure and systemic risk: evidence from dual banking systems. *Journal of Financial Stability, 33,* 96-119. https://doi.org/10.1016/j.jfs.2017.11.002
2. Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review, 105*(2), 564-608. https://doi.org/10.1257/aer.20130456
3. Acharya, V., Pedersen, T., Philippon, T., & Richardson, M. (2016). Measuring systemic risk. *The Review of Financial studies, 30*(1), 2-47. https://doi.org/10.1093/rfs/hhw088
4. Adrian, T., & Brunnermeier, M. (2016). CoVaR. *American Economic Review, 106*(7), 1705-1741. https://doi.org/10.1257/aer.20120555
5. Allen, F. & Gale, D. (2000). Financial contagion. *Journal of Political Economy, 108*(1), 1-33. https://doi.org/10.1086/262109

6. Barone-Adesi, G., Giannopoulos, K., & Vosper, L. (1999). VaR without correlations for non–linear portfolios. *Journal of Futures Markets, 19*(5), 583-602. https://doi.org/10.1002/(SICI)1096–9934(199908)19:5<583::AID–FUT5>3.0.CO;2–S

7. Benoit, S., Colliard, J.-E., Hurlin, C., & Perignon, C. (2017). Where the risks lie: A survey on systemic risk. *Review of Finance, 21*(1), 109-152. https://doi.org/10.1093/rof/rfw026

8. Brownlees, C. T., & Engle, R. F. (2012). *Volatility, Correlation and Tails for Systemic Risk Measurement* (Working Paper). New York University. Retrieved from https://faculty.washington.edu/ezivot/econ589/Volatility-Brownlees.pdf

9. Castren, O., & Rancan, M. (2014). Macro-Networks: An application to euro area financial accounts. *Journal of Banking & Finance, 46*(C), 43-58. https://doi.org/10.1016/j.jbankfin.2014.04.027

10. Eisenberg, L., & Noe, T. (2001). Systemic risk in financial systems. *Management Science, 47*(2), 236-249. https://doi.org/10.1287/mnsc.47.2.236.9835

11. 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. https://doi.org/10.1198/073500102288618487

12. Giannopoulos, K., Nekhili, R., & Koutmos, G. (2010). Volatility spillovers and price interdependencies, a dynamic non parametric approach. *International Research Journal of Finance and Economics, 45,* 115-121. Retrieved from https://www.researchgate.net/publication/228350571_Volatility_spillovers_and_price_interdependencies_A_dynamic_non_parametric_approach

13. Giudici, P., & Spelta, A. (2016). Graphical network models for international financial flows. *Journal of Business & Economic Statistics, 34*(1), 128-138. https://doi.org/10.1080/07350015.2015.1017643

14. Glasserman, P., & Young, H. P. (2016). Contagion in Financial Networks. *Journal of Economic Literature, 54*(3), 779-831. http://dx.doi.org/10.1257/jel.20151228

15. Von Peter, G. (2007). International banking centres: a network perspective. *BIS Quarterly Review,* December 2007, 33-45. https://doi.org/10.2139/ssrn.1075205

http://dx.doi.org/10.21511/bbs.15(1).2020.15