Multilayer information spillover networks between oil shocks and banking sectors: Evidence from oil-rich countries

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Abstract

There is no doubt that the oil price shocks significantly affect the macroeconomic fundamentals and financial stability of the oil-producing countries, mainly in crisis times. The recent oil price shocks coupled with the COVID-19 pandemic motivated us to investigate the connectedness and risk transmission among oil shocks and banking sectors in the Gulf Cooperation Council (GCC) economies over the period from June 30, 2006, to September 9, 2021. We use the multilayer information spillover networks to consider mean and volatility spillover effects, and extreme risk spillover effects between oil price shocks and GCC banking sectors. Empirical findings indicate a higher degree of spillover during the crisis sub-period. Further, we find a significant increase in the number of unique edges on extreme risk spillover and volatility spillover layers happened during COVID-19 pandemic period. The finding of this paper has several significant implications for regional portfolio selection and risk management, alleviating financial systemic risk and making hedging and investment strategies.

JEL classification: C32, E44, G15, G21
Keywords: Oil shocks; Banking sectors; Risk transmission, multilayer spillover networks; COVID-19; GCC

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1. Introduction

Oil price shocks are at the centre of the oil industry and are main driver of the future cash flows of industrial companies. The accurate prediction of crude oil price is of interest for a wide range of applications such as assessing macroeconomic risks, making macroeconomic policies and asset allocation (Dai and Kang, 2021). The oil price shocks can affect the financial systems in the GCC countries which are denominated by the banking sector and their economies are mainly dependent on oil-related products (Maghyereh and Abdoh, 2021). In addition, oil price shocks influence the government's spending, which impacts the business environment and the lending activity of a country's banks. The great Collapse of oil prices 2014-15 (The average oil price per year is $41.85), and the US – Russian – OPEC disagreements on March 2020 (The average oil price per year is $20.37), combined with COVID-19 virus outbreak have renewed the interest to the study of the connectedness of oil price shocks and financial sectors. The recent COVID-19 pandemic intensification generates a different set of challenges for the global economy and financial systems. Therefore, understanding the impact of oil price shocks on financial systems and systemic risk is vital for a country's financial stability.

In this paper, two main facts have motivated us to examine the connectedness and risk transmission between oil shocks and banking sectors in the GCC economies. The first fact relates to the significant influence of the recent oil price shocks on macroeconomic fundamentals and financial sectors in oil-rich countries including the GCC region. The oil prices have dropped due to the decline of the global economy demand (caused by lockdown measures and flights) and the rise abruptly and rapidly of supply (caused by the Saudi Arabia-Russia oil prices war in March 2020 and the failure of the OPEC+ to agree on the terms of stable supply cuts). The second fact relates to the absence of studies that address and combine the impact of the COVID-19 pandemic, regional political uncertainty, and recent demand/supply oil shocks on the dynamic connectedness between the oil market and banking sectors in GCC economies. Most of the literature in this area focused on the impact of oil price changes on stock markets (Arouri & Rault, 2012; Wang et al., 2013, Bastianin et al., 2016; Ding et al., 2017; Basher et al. 2018; among others). Despite this, the number of studies investigated the relationship between oil and banking sectors in oil-exporting economies are very scarce; and thus, very little attention has been paid to risk transmission across oil market and banking sectors in the GCC economies, notwithstanding its policy and industry importance (Alqahtani et al., 2020).

This paper adds to the existing literature from several novel aspects: First, we tend to fill the gap in the literature by examining the relationship and dynamic connectedness among oil price shocks and banking sectors in the GCC economies before and during the COVID-19 pandemic. This study provides a comparative analysis of the effect of oil supply and demand shocks on the banking sectors of GCC countries. Second, our methodology based on the multilayer information spillover networks considers the mean, volatility, and extreme risk spillover effects, which can better describe the connectedness among oil price shocks and banking sectors more efficiently. Multilayer information spillover networks are a powerful tool to investigate the connectedness and risk transmission with various relationships simultaneously and capture the diversity and heterogeneity of information transmission. The traditional Diebold and Yilmaz (DY) spillover index approach (Diebold and Yilmaz, 2009, 2012) only consider the return and the volatility spillover that respectively represent information spillover effects in the first and second moments of asset returns and ignore the extreme tail risk spillover in asset returns that indicates spillover effects in high moments (e.g., skewness and kurtosis). The DY spillover index is a single-layer network focusing on a specific type of information spillover effect and ignoring the diversity and heterogeneity of information spillovers (Wang et al. 2021 (a)). Moreover, with a single-layer network, it is difficult to capture the diversity and heterogeneity of information transmission and its interconnectedness among financial institutions (Wang et al. 2021 (b)). To the best of our knowledge, this study is the first that investigates the connectedness and risk transmission among oil shocks and banking sectors using multilayer information spillover networks. Third, the sample period of this study includes some important events (such as the global financial crisis, the European sovereign debt crisis, the 2014-15 oil price drop, political uncertainty caused by the Qatar diplomatic crisis, and Arab Spring, the oil price war, and the announcement of COVID-19 as a global pandemic in March 2020, and the oil price crash on April 20, 2020). Consequently, the sample period can lead to different multilayers information spillover on the return, volatility, and extreme risk between oil price shocks and GCC banking sectors.

The empirical results show that (I)The peak degree on each layer of multilayer information spillover networks mostly has a synchronization effect, however, there was a significant asynchronous effect during crisis times and COVID-19 pandemic. (Ⅱ) The pattern of the unique edge is different than the pattern of the degree, suggesting that the increasing connection between GCC banking sectors and oil price shocks is mainly attributed to the rise of similar edges. (Ⅲ) a significant increase in the number of unique edges on extreme risk spillover and volatility spillover layers happened during COVID-19 pandemic period (2020-2021). (Ⅳ) The average edge overlap is lower than 2 on average, so the information obtained by the network is one-sided no matter which layer is considered separately. The finding of this paper has several significant implications. First, controlling the demand and supply oil risk shocks alleviate financial systemic risk. Second, GCC banking systems are vulnerable to changes in oil prices during crises period. Third, understanding the connectedness and risk transmission improves the regional portfolio diversification, and hedging strategies, to make sound investment decisions.

The rest of this paper is organized as follows. In section 2 we review the related literature. Section 3 introduces the empirical methodology. Section 4 present the data specifications and preliminary results. Section 5 discusses the empirical findings. Finally, section 6 concludes the paper.

2. Literature review

The connectedness and risk transmission between the oil price shocks and financial markets has drawn much attention over the past decades. Most of the existing recent literature focused on the impact of oil price changes on stock markets (e.g., Escobari and Sharma, 2020; Enwereuzoh et al. 2021; Gupta et al. 2021; Jiang et al. 2021; Anand and Paul, 2021; Ziadat et al. 2022; *among others*). The oil price shocks may increase the marginal cost of production, decrease future cash flows, and negatively affect the value of the stock. According to Demirer et al. (2020), The oil demand shocks affect positively the stock market returns for 21 countries, regardless of the status of the country as an importer/exporter or advanced/emerging economy. However, the effect of supply-related shocks is more heterogeneous across markets, with mostly an adverse impact on stock market returns. Some research papers find a negative relationship between the oil market and stock market (e.g., Jones and Kaul, 1996, Chiou and Lee, 2009; Wang et al., 2013), positive relationship (e.g., Chen et al., 1986; Arouri and Rault, 2012), and no significant relationship between oil shocks and the stock market (e.g., Wei, 2003; Zhang, 2017).

The effect of oil price shocks is not limited to stock markets but also extended to bond markets (e.g., Kang et al., 2014; Gormus et al. 2018; Nguyen et al. 2018; *among others*).

According to Demirer et al. (2020), unanticipated changes in oil prices generates inflationary pressures, leading the central banks to tighten their monetary policy by raising the interest rates, which in turn get reflected in bond market yields. Shahzad et al. (2021) examine the Granger causal relationship from implied oil volatility to US high-yield and investment-grade corporate bonds. They find that oil price volatility predicts the future values of the high-yield bond market and its energy sector. Similarly, Dai and Kang (2021) find a significant Granger causal relationship from long-term government bond yield and corporate bond yields spread to oil returns. Nazlioglu et al. (2020) find that oil prices tend to predict bond prices in most oil exporting countries.

Another stand of literature has investigated the impact of oil price shocks on (I) macroeconomic fundamentals (e.g., Amiri et al. 2021; Sheng et al. 2020; Yildirim and Arifli, 2020; Ahmed et al. 2018; Ju et al. 2016; *among others*), (II) CO2 emissions (e.g., Kassouri et al. 2021; Zheng et al. 2021; *among others*), (III) commodities (e.g., Yang et al. 2021; Ezeaku et al. 2021; Zhang and Qu, 2015; among others), (Ⅳ) cryptocurrency (e.g., Jareño et al. 2021; Yin et al. 2020; *among others*), (Ⅴ) green investment (e.g., Kassouri and Altıntaş, 2021; Lee et al. 2020; Dutta et al. 2020; *among others*)

With the massive body of literature that investigated the effect of oil price shocks on stock markets, bond markets, and macroeconomic fundamentals, only a few studies have examined the impact of oil price shocks on the banking sectors and financial systemic risk. Maghyereh and Abdoh (2021) investigate the impact of oil shocks (oil supply and demand shocks) on GCC banking systems over the period from January 2006 to September 2020. Using data from 51 banks and two different systemic risk measures (Delta CoVAR and marginal expected shortfall), they find that oil supply shocks increase the systemic risk of GCC banks, and the effect of supply shocks is more important that the effect of demand shocks. Ma et al. (2021) study the impact of oil shock (supply shock, aggregate demand shock, specific demand shock, and speculative shock) on risk level in China's banking sector. Using data of 16 listed banks in China from January 2011 to December 2019, empirical results show that Oil speculative shock increases bank risk levels and the oil supply shock reduces the risk in China's banking sector. Qin (2020) apply structural VAR analysis to study how different oil structural shocks affect the Composite Indicator of Systemic Stress in twenty countries for the period from January 2004 to December 2015. The study shows the financial systemic risk of oil-importing economies, are affected negatively by oil supply and aggregate demand shocks and affected positively by oil-specific demand shocks.

In this paper, we tend to fill the gap in the literature by examining the relationship and dynamic connectedness among oil shocks and banking sectors in the GCC economies controlling for the impact of global banking sectors as well as international risk factors. Theoretically, an increase in the oil price for the oil-exporting countries will lead to an increase in economic growth due to the increase of government spending, thus leading to an economic expansion and the financial sector will be affected negatively. In this paper, we employ a novel framework of our methodology based on the multilayer information spillover networks that consider the mean, volatility, and extreme risk spillover effects to investigate the connectedness and risk transmission among oil shocks and banking sectors in the GCC economies.

3. Data and Econometric Methodology

3.1. Constructing oil price shocks

Several approaches have been used in the literature to classify changes in oil prices into demand-driven or supply-driven. In his seminal paper, Kilian (2009) decomposes changes in real oil prices into oil supply shocks, aggregate demand shocks, and specific demand shocks that are related to the crude oil market to examine the impact of higher oil prices on the U.S. macroeconomic aggregates. Results indicate that the impact of oil process changes on real GDP and inflation depends on the nature and source of the oil price shocks. Since then, Kilian's approach has been extensively used in the literature to investigate the structural impact of different oil shocks on both macroeconomic and financial conditions (e.g., Alsalman & Karaki, 2019; Wang et al., 2014, Zhao et al., 2016, *among others*). However, all series included in the Structural VAR model should be correlated with oil prices changes to accurately estimate and identify the oil price shocks.

To overcome this problem, Ready (2018) disentangles oil price changes into three shocks: demand, supply, and risk shocks, using prices of traded financial assets (Wen et al., 2021). Another unique advantage of this approach is its ability to decompose shocks on a daily frequency which is of paramount importance to our study and strengthens the empirical analysis (Malik and Umar, 2019). To this end, three main series have been collected to disentangle oil price changes into supply shocks, demand shocks, and risk shocks. These variables are the return of World Integrated Oil and Gas Producer Index as a proxy of oil producing-firms, the second nearest future maturity of NYMEX Crude—Light Sweet Oil futures contract as a measure of oil price changes, and the Chicago Board Options Exchange's Volatility Index (VIX) as a proxy for changes in expected returns.

Accordingly, supply, demand, and risk shocks are orthogonal and could be defined as follows:

$$X_t \equiv \begin{bmatrix} \Delta p_t \\ R_t^{\text{Prod}} \\ \xi_{\text{VIX},t} \end{bmatrix}, Z_t \equiv \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix}, A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{1}$$

Where Δp_trepresents oil price changes at time t, R_t^{Prod} is the return on the oil-producing firms, $\xi_{\text{VIX},t}$ denotes the residuals from an ARMA (1,1) model of the VIX index. Finally, $s_t, d_t, and\ v_t$ indicate supply shocks, demand shocks, and risk shocks, respectively. Next, Oil price shocks are mapped by matrix A into the observable variables so that:

$$X_t = AZ_t \tag{2}$$

The following restriction is introduced to ensure that orthogonality of the oil price shocks:

$$A^{-1}\Sigma_X(A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

Where Σ_X denotes the covariance matrix of the observable X_t whereas $\sigma_s^2, \sigma_d^2,$ and σ_v^2 are volatilities of the supply, demand, and risk shocks, respectively. Finally, volatilities are normalized so that they sum up to the total oil price changes.

3.2 Multilayer network measures

Our proposed multilayer information spillover networks including mean spillover layer, volatility spillover layer and risk spillover layer are based on the Granger causality tests in mean, volatility and risk of Hong (2001) and Hong et al. (2009). In this section, we firstly introduce how to examine the information spillover effects. We then construct the multilayer information spillover networks and finally describe some multilayer network measures to investigate the interconnectedness between oil shocks and banking sectors.

3.2.1 Information spillover effects test

We adopt the sample cross-correlation function (CCF)-based Granger causality test to estimate information spillover effects including mean spillover effect, volatility spillover effect and extreme risk spillover effect between two variables, proposed by Hong (2001) and Hong et al. (2009). This method is divided into two steps. The first step selects the appropriate model, e.g., the ARMA-GARCH model, to fit return series of variable i and obtain the estimations of the residuals $\hat{\varepsilon}_{i,t}$ and the conditional variances $\hat{h}_{i,t}$. The mean spillover effect is directly tested against the standardized residuals $\hat{u}_{i,t}$ (see, Eq. **Error! Reference source not found.**). The volatility spillover effect is tested against the centralized standard residuals (see Eq. **Error! Reference source not found.**). To test the risk spillover effect, we firstly estimate Value-at-Risk (VaR) series $\hat{V}_{i,t}$ of variable i through the standardized residuals and the conditional variances (see Eq. **Error! Reference source not found.**) and then obtain the risk indicator $\hat{Z}_{i,t}$ for testing, following Hong et al. (2009) (see Eq. **Error! Reference source not found.**).

$$\hat{u}_{i,t} = \hat{\varepsilon}_{i,t}/\left(\hat{h}_{i,t}\right)^{\frac{1}{2}} \tag{1}$$

$$\hat{v}_{i,t} = \hat{\varepsilon}_{i,t}^2/\hat{h}_{i,t} - 1 \tag{2}$$

$$\hat{V}_{i,t} = -\hat{\mu}_{i,t} - z_\alpha\sqrt{\hat{h}_{i,t}} \tag{3}$$

$$\hat{Z}_{i,t} = 1(r_{i,t} < -\hat{V}_{i,t}) \tag{4}$$

where Z_α is the left α −quantile for the standardized residuals, $r_{i,t}$ is the return of variable i, and $\mathbf{1}(\cdot)$ is an indicator function. When the condition is met, the risk indicator $Z_{i,t}$ takes a value of 1, otherwise it takes a value of 0.

The second step constructs a statistic Q based on the estimated series in the first step to test whether there is an information spillover effect between pairs of variables. We take the Granger causality test in risk for examining extreme risk spillover effect from variable 2 to variable 1 as an example. The null hypothesis of the Granger causality in risk is $H_0: E\left(Z_{1,i} \mid I_{1,t-1}\right) = E\left(Z_{1,t} \mid I_{t-1}\right)$ against the alternative $H_1: E\left(Z_{1,i} \mid I_{1,t-1}\right) \neq E\left(Z_{1,t} \mid I_{t-1}\right)$, where $I_{1,t-1}=\{Z_{1,t-1},\ldots, Z_{1,1}\}$ and $I_{2,t-1}=\{Z_{2,t-1},\ldots, Z_{2,1}\}$ are the information sets available at time t-1 for variables 1 and 2, and $I_{t-1}=\{I_{1,t-1}, I_{2,t-1}\}$.

suppose $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ are two series of estimated risk indictors of variables 1 and 2, the sample cross-correlation function (CCF) is defined

$$\hat{\rho}(j) = \frac{\hat{C}(j)}{(\hat{S}_1\hat{S}_2)}, \qquad j = 1,2,\ldots,T-1 \tag{5}$$

where $\hat{S}_i$ is the sample standard deviation of $\hat{Z}_{i,t}$, T is the sample size, and $\hat{C}(j)$ is the sample cross-covariance function between $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ at positive lag j and is defined by:

$$\hat{C}(j) = T^{-1} \sum_{t=1+j}^{T} \left(\hat{Z}_{1,t} - \hat{\bar{Z}}_1\right)\left(\hat{Z}_{2,t-j} - \hat{\bar{Z}}_2\right), 0 \leq j \leq T-1 \tag{6}$$

Where $\hat{Z}_i = T^{-1} \sum_{t=1}^{T} \hat{Z}_{i,t}\, , i = 1,2$. Following Hong et al. (2009), we construct a statistic Q that contains the weighted average sum of sample CCFs of all lag orders, given by:

$$Q = \left\{T \sum_{j=1}^{T-1} \left[k^2(j/M)/\hat{\rho}^2(j) - C_T(M)\right]\right\}/(2D_T(M))^{1/2} \tag{7}$$

where M is effective lag truncation order, and $k(\cdot)$ is the kernel function.

Hong et al. (2009) point out the Daniel kernel function has the best results. The Daniel kernel function not only takes all lag orders into account, but also considers a decreasing weight with an increasing time lag, which is consistent with the fact that financial markets are more susceptible to recent events than long-term events. Specifically, the Daniel kernel function is defined as

$$k(x) = \sin(\pi x)/(\pi x) \tag{8}$$

In Eq. (8), $C_T(M)$and $D_T(M)$ are the centering and standardization constants respectively, which are expressed as

$$C_T(M)\& = \sum_{j=1}^{T-1} (1 - j/T)k^2(j/M), \tag{9}$$

$$D_T(M)\& = \sum_{j=1}^{T-1} (1 - j/T)\{1 - (j+1)/T\}k^4(j/M) \tag{10}$$

If the null hypothesis of the Granger causality in risk is true, i.e., there is no extreme risk spillover effect from variable 2 to variable 1, the statistic Q is convergent to the standard normal distribution. Since Q tends to be positive infinity as T increases, the test value selects the right-hand side of the standard normal distribution. When the estimated value Q is higher than the right-tail critical value of the standard normal distribution at a given significance level β (in our case, $\beta = 0.05$), it is considered that variable 2 has an extreme risk spillover effect on variable 1. Similarly, when considering the standardized residuals and conditional variances of variables 1 and 2 in Eqs. (5)-(10), we can obtain mean and volatility spillover effects from variable 2 to variable 1 respectively.

3.2.2 Multilayer information spillover networks

We propose multilayer information spillover networks $\Omega = \left\{G^{[1]}, G^{[2]}, \dots, G^{[L]}\right\}$ with L layers and N nodes, where $G^{[\alpha]} = G(V, A^{[\alpha]})$ is the layer α of the multilayer information spillover networks, where $V = \{1, 2, \dots, N\}$ is the set of nodes, and $A^{[\alpha]}$ is the set of edges of layer α. In each layer, nodes represent variables, and a directed edge indicates that there is a corresponding information spillover effect from the starting financial variable to the terminal financial variable. In our case, $L = 3$， and we assume that from the first layer to the third layer correspond to the mean spillover layer, the volatility spillover layer and the extreme risk spillover layer, respectively. For any two variables $i, j \in V$, we draw a directed edge from i to j on the first (second, third) layer, if variable i has a mean (volatility, risk) spillover effect on variable j. $A^{[\alpha]} = \left\{a_{ij}^{[\alpha]}\right\}_{N \times N}$ is a directed binary connection matrix for all pairs of variables i and j in layer α, where the element $a_{ij}^{[\alpha]}$ in the matrix $A^{[\alpha]}$ is defined as:

$$a_{ij}^{[\alpha]} = \begin{cases} 1, \text{ if } i \neq j \text{ and } i \text{ has a corresponding spillover effect on } j \text{ on layer } \alpha \\ 0, \text{ else} \end{cases} \tag{11}$$

Thus, multilayer information spillover networks are simplified to a 3 dimensional $N \times N$ adjacency matrix by mathematical notation. Considering the unpredictability of the financial system and dynamic changes of the interconnectedness among variables, we build time-varying multilayer information spillover networks using the rolling window analysis. The sample interval of the investigated daily return series is divided into rolling windows with width w and size step δ, where the width w is the length of the daily return series in each window, and the size step δ is the interval between two continuous windows. Following Hong et al. (2009), we select a width w of 240 days and a step size δ of 20 days, corresponding to one trading year and one trading month. Thus, the period for the first window is from the first day to the 240th day of the sample period, the period for the second window is from the 21st day to the 260th day, and so on. Then, we note time-varying multilayer information spillover networks as Ω_t.

3.2.3 Multilayer network measures

3.2.3.1 Similarity measures

In multilayer information spillover networks, we explore whether there is similarity between different layers. First, we introduce the degree of layer α, which indicates the number of edges on layer α, to character the basic feature on layer α. The greater the degree of a layer has, the closer the connectedness among variables on the layer has. The degree of layer α is defined as

$$a^{[\alpha]} = \sum_{i,j=1, i \neq j}^{N} a_{ij}^{[\alpha]}, \alpha = 1,2, \dots, L \tag{12}$$

where $a_{ij}^{[\alpha]}$ represents the edge (or the corresponding information spillover effect) from i to j on layer α, which is defined in Eq. (18).

We introduce a similarity measure among different layers, i.e., the Spearman correlation coefficient$\rho^{[\alpha,\beta]}$, which is measured to explore the similarity about the rankings of variables between layers α and β and is formally defined as:

$$\rho^{[\alpha,\beta]} = 1 - \frac{6\sum_i \left(R_i^{[\alpha]} - R_i^{[\beta]}\right)^2}{N(N^2-1)}, \alpha, \beta = 1,2, \dots, L \tag{13}$$

where N is the number of variables, and $R_i^{[\alpha]}$ and $R_i^{[\beta]}$ represent the rankings of variable i on layers α and β, respectively.

3.2.3.2 Uniqueness measures

To quantify how peculiar the structure of layer α is, we introduce a uniqueness measure $U^{[\alpha]}$ by computing the number of unique edges on layer α, i.e.,

$$U^{[\alpha]} = \sum_{i,j=1,i\neq j}^{N} a_{ij}^{[\alpha]} \prod_{\beta=1,\beta\neq\alpha}^{L} \left(1 - a_{ij}^{[\beta]}\right), \alpha = 1,2, \dots, L \tag{14}$$

which captures the number of edges that exist only on the layer α rather than other layers. $U^{[\alpha]}$is 0, only if all edges on layer α exist on at least one of the other layers. A larger $U^{[\alpha]}$ represents layer α has a greater number of unique edges, indicating the peculiarity of layer α, because if layer α is absent, these unique edges will be ignored, i.e., the corresponding interconnectedness between variables will not be captured.

We also consider unique edges of each variable i on layer α, i.e.,

$$U_i^{[\alpha]} = \sum_{j=1,j\neq i}^{N} a_{ij}^{[\alpha]} \prod_{\beta=1,\beta\neq\alpha}^{L} \left(1 - a_{ij}^{[\beta]}\right), \alpha = 1,2, \dots, L, i = 1,2, \dots, N \tag{15}$$

3.2.3.3 Overlap measures

To comprehensively consider multilayer information spillover networks, we can obtain a projection network of information spillover networks, denoted as$\Pi(V, A)$, by ignoring the fact that the link between two variables belongs to different layers and drawing an edge from variable i to variable j if variable i has at least one information spillover effect on variable$j$. $A = \{a_{ij}\}$ is an adjacency matrix for all variables i and j in the projection network, and its element is defined as

$$a_{ij} = \begin{cases} 1, \exists \alpha, a_{ij}^{[\alpha]} = 1 \\ 0, \text{else} \end{cases} \tag{16}$$

We measure the number of edges in the projection network, i.e., the edges present on at least one layer between variables, given by

$$K = \sum_{i,j=1,i\neq j}^{N} a_{ij} = \sum_{i,j=1,i\neq j}^{N} \left(1 - \prod_{\alpha=1}^{L} \left(1 - a_{ij}^{[\alpha]}\right)\right) \tag{17}$$

In multilayer information spillover networks, the same directed edge between variables may exist on different layers. We introduce a measure of average edge overlap O to explore how many layers each edge appears on average, which is defined as

$$O = \frac{1}{K} \sum_{i,j=1, i \neq j}^{N} \sum_{\alpha=1}^{L} a_{ij}^{[\alpha]} \tag{18}$$

Note that the average edge overlap is 1, only when the connections of each layer are completely different, i.e., each edge appears only on one layer of multilayer networks. When all variables on all layers are connected identically, the average edge overlap is the number of layers. Thus, a greater average edge overlap indicates a higher similarity or homogeneity among layers in multilayer information spillover networks.

To identify relatively important variables, we describe the overlapping degree of variable i, which is the sum of edges on variable i at all layers. If the overlapping degree of a variable is high, it indicates that the variable has strong connection with other variables, so the variable is considered to be a central node in multilayer networks. The overlapping degree O_i of variable i is defined as:

$$o_i = \sum_{\alpha=1}^{L} \sum_{j=1, j \neq i}^{N} a_{ij}^{[\alpha]}, i = 1,2, \ldots, N \tag{19}$$

3.3 Data and preliminary analysis

In this study, we used daily closing prices of Refinitiv banking equity indices for GGC countries to examine connectedness patterns and risk transmission between oil shocks and banking returns in the GCC countries.[2] The sample period spans from June 30, 2006, to September 9, 2021, with 3958 observations. The sample period is determined by the data availability and covers several significant events such as the Global Financial Crisis in 2008; the Arab Spring that started in 2010; the oil crises during 2014 and 2016; Qatar diplomatic crisis and the COVID-19 pandemic.

In addition, we have collected data for the World Integrated Oil and Gas Producer Index, the second nearest future maturity of NYMEX Crude—Light Sweet Oil futures contract, and the CBOE volatility index (VIX) to calculate oil price shocks. All data has been collected from Thomson Reuters DataStream database.

The descriptive statistics of all series under consideration are reported in Table 1.

[2] Saudi Arabia has been excluded from the empirical analysis as Refinitiv Banks Price Index for Saudi Arabia only starts from March 29, 2018 which would limit our dataset.

Table 1. Descriptive statistics of GCC banking returns and oil shocks

	Bahrain	Kuwait	Oman	UAE	Qatar	Demand Shock	Supply Shock	Risk Shock
Mean	2.05E-07	8.30E-05	1.23E-05	0.0001	0.0002	-0.0223	0.0075	-0.0025
Median	0	0.0001	0	2.72E-05	2.75E-05	-0.0248	0.0021	-0.6507
Maximum	1.166	0.065	0.098	0.092	0.094	15.016	20.038	78.842
Minimum	-1.160	-0.104	-0.104	-0.095	-0.102	-13.221	-15.203	-31.702
Std. Dev.	0.029	0.011	0.011	0.013	0.014	1.253	2.002	7.512
Skewness	2.492	-0.651	-0.462	-0.189	-0.216	0.092	0.433	1.271
Kurtosis	1331.774	12.415	17.692	12.334	11.079	20.924	15.431	10.134
JB	2.91E+08***	14897***	35730***	14388***	10793***	52979***	25602***	9457***
ADF	-41.315***	-58.721***	-54.865***	-54.069***	-60.455***	-22.161***	-71.008***	-63.268***
ERS	-33.677***	-14.735***	-27.006***	-20.644***	-19.966***	-26.788***	-29.380***	-29.749***
Q(10)	644.221***	39.392***	83.285***	113.858***	20.191***	51.245***	73.305***	14.747***
$Q^2(10)$	920.373***	1684.181***	2109.441***	1935.708***	1282.210***	1354.552***	2081.461***	175.031***
ARCH(20)	478.703***	1028.617***	1053.206***	988.689***	877.908***	1237.054***	1265.788***	161.161***
Observations	3957	3957	3957	3957	3957	3957	3957	3957

Notes: This Table reports the summary statistics of GCC banking returns and oil shocks. JB is the Jarque-Bera test for normality; ADF is the Augmented Dickey–Fuller tests the null hypothesis of a unit root whereas ERS is the Elliott, Rothenberg and Stock modified ADF test. Q(20) and $Q^2(20)$ are the Ljung-Box statistic for serial correlation in the raw series and squared residuals, respectively. ARCH (20) is Engle's ARCH-LM test for autoregressive conditional heteroskedasticity up to 20 lags. *** denotes statistical significance at the 1% level.

Table 1 shows that the average returns for all banking sectors in the GCC countries are positive where Qatar and Bahrain provide the highest and lowest average returns over the sample period. The unconditional volatility is highest for the Bahrain banking sector but smallest for both Kuwait and Oman banking sectors. Regarding oil shocks, risk shocks have the highest volatility followed by supply shocks and demand shocks (7.5, 2, and 1.2 respectively). Banking returns for Kuwait, Oman, UAE, and Qatar are slightly left-skewed while banking return and oil shocks are right-skewed. The value of kurtosis is greater than 3 for all variables included in the analysis, which implies that the distributions of all the series are leptokurtic (higher peaked around the mean with fatter tails). These findings are confirmed by significant statistics of the Jarque-Bera test. All series under consideration, therefore, are not normally distributed. Furthermore, results from unit root tests, ADF and ERS, are significant indicating that all series are stationary at levels. Finally, the series suffer from serial correlation and exhibit an ARCH effect according to the Ljung–Box test statistics and Engle's ARCH-LM test.

4. Empirical Results

In the empirical results analysis of this paper, we follow Wang et al. (2021, (b)) and we focus on two types of multilayer information spillover networks: (i) static multilayer information spillover networks with different lag orders (i.e., M) and (ii) time-varying multilayer information spillover networks.

4.1. Results for similarity measures

To investigate the connectedness and risk transmission among oil shocks and banking sectors in the GCC economies, we used the multilayer information spillover networks based on mean spillover effects, volatility spillover effects, and extreme risk spillover effects. For each country's banking index, we compute the return, and for the other three shocks, we use the level value. We use AR(1)-GARCH (1,1)-t model to estimate each series. For time-varying multilayer spillover networks, the lag order M is set at 10. To discover whether there is similarity among the different information spillover layers, we examine the degree of each layer. Fig.1 plot the degree of each layer (mean, volatility and extreme risk) under different lag orders M.

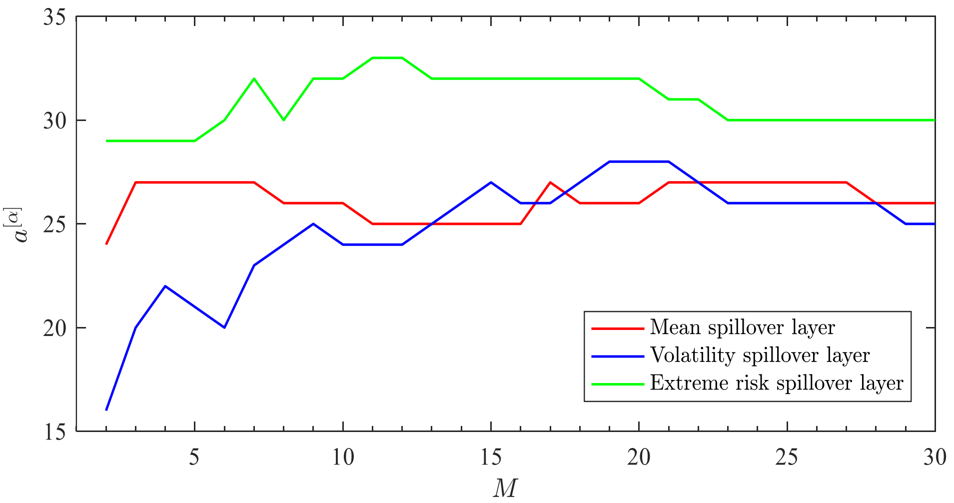


Fig 1. Degree of each layer in multilayer spillover networks as functions of lag order *M*.

Fig 1. Shows Extreme risk spillover layer has more interconnected edges than the mean and the volatility spillover layer at various lags. The strong interconnection on extreme risk spillover layer may be explained to the sample period of the study that covers numerous events such as the global financial crisis, the 2014-15 oil price drop, political uncertainty caused by the Qatar diplomatic crisis, the Arab spring, the oil price war, and the COVID-19 pandemic. The degree of the volatility layer increases rapidly when the lag orders increase from 2 to 5, 6 to 10 and 13 to 20. This pattern indicates that the market needs some time to respond to past information and needs at least 5 days to fully reflect the information. The degree of the mean layer shows a slightly upward trend only from 2 to 3. The degree of extreme risk spillover increases speedily when the lag order increases from 5 to 12. The degrees of extreme risk and volatility spillover layers start to decrease, when the lag order is at a high value ($M \geq 20$), while the degree of mean spillover layer shows a little upward trend.

In this empirical study, we set the lag order M = 10, which corresponds to the 10- day VaR required by the Bank for International Settlements. The degree of each layer when the lag order M = 10 is at a high level and relatively stable, and the networks at this lag order can fully reflect the past information (Wang et al. 2021 (b)).

To visualize the multilayer networks, Fig. 2 illustrate a snapshot of multilayer information spillover networks (mean spillover effects, volatility spillover effects, and extreme risk spillover effects) when M = 10.

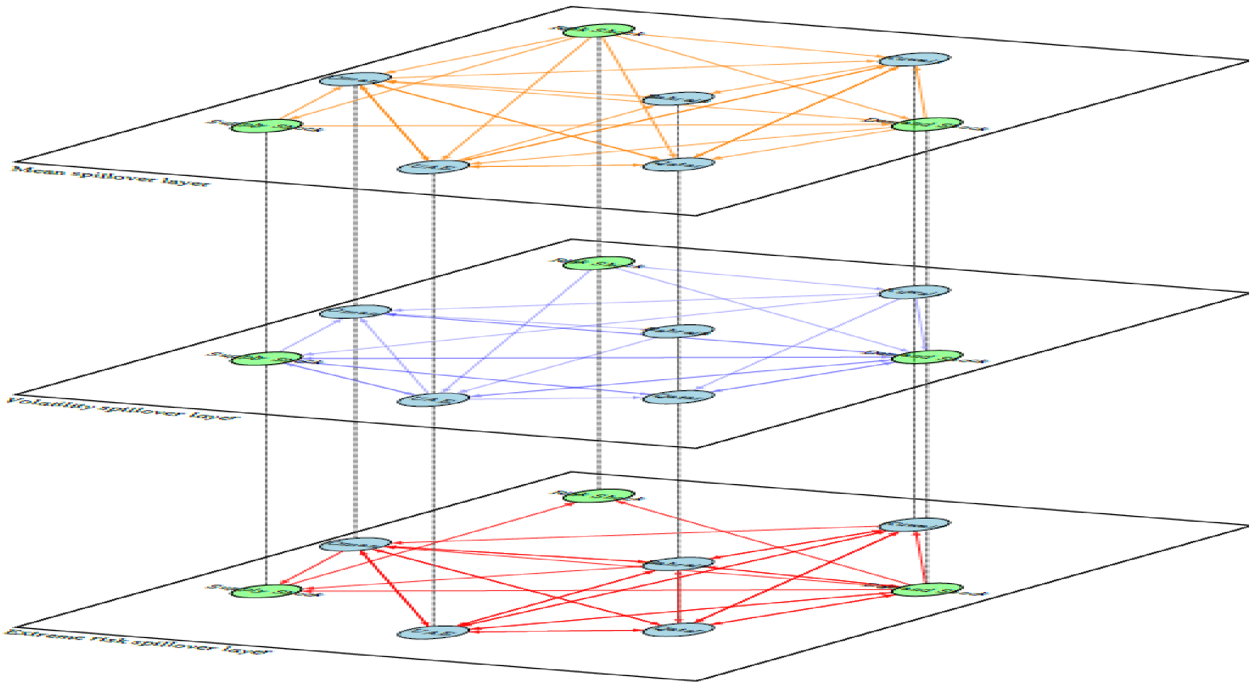


Fig 2. A snapshot of multilayer information spillover networks of GCC countries

Note: The GCC countries include Sultanate of Oman, United Arab Emirates, State of Qatar, Kingdom of Bahrain, and State of Kuwait over the period from June 30, 2006, to September 9, 2021. The first layer (from up to down) corresponds to mean spillover, the second spillover corresponds to the volatility spillover layer and the third layer to the extreme risk spillover layer.

Fig. 2 demonstrates that the connectedness of oil price shocks and GCC banking sectors at each layer is not consistent. For example, oil supply shocks (green cercle at the left side) have strong connectedness with GCC banking sectors on volatility and extreme risk spillover layers, but lower connectedness with GCC banking sectors on mean spillover layer. Also, risk shocks have weak connectedness with GCC banking sectors on extreme risk spillover layer, but strong on mean and volatility spillover layers.

Fig. 3 illustrates the dynamic degree of each layer in time varying multilayer information spillover networks.

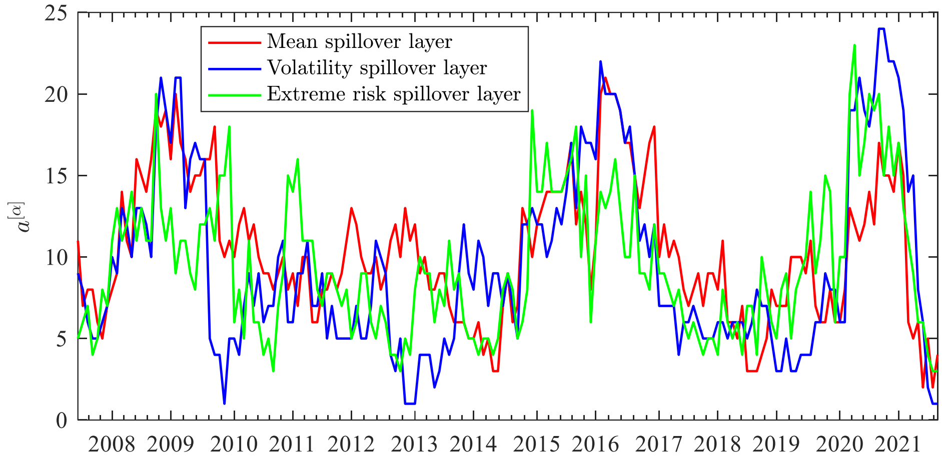


Fig 3. Dynamic degree of each layer in time-varying multilayer information spillover networks.

From Fig.3, we notice that the general trend of the degrees among the three layers is relatively consistent. When the degree of a layer increased and reached the peak, the degrees of other layers changed almost synchronously. For example, in the periods of 2008-2010 and the 2015- 2016, suggesting that the increased connectedness and risk transmission among oil shocks and banking sectors is consistent. However, during the period from 2014 to 2015, the peaks of the degree on the three layers show nonsynchronous, in which volatility spillover layer first reached the peak, followed by extreme risk and mean spillover layers. During the COVID-19 pandemic period, the peaks of the degree on the three layers show unsynchronized, in which extreme risk spillover layer first reached the peak, followed by volatility and mean spillover layers. This finding implies that extreme risk spillover layer followed by volatility spillover layer can offer early signals of risk transmission among oil shocks and banking sectors.

In the next step, we investigate the rang correlation (Spearman's correlation coefficients) between dynamic degree series of three layers (Fig. 4)

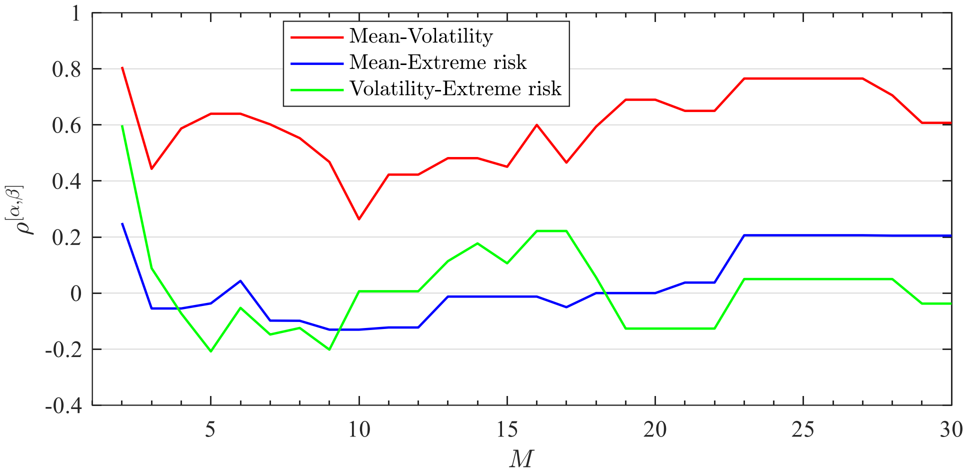


Fig 4. Spearman's correlation coefficients between three different layers

Fig. 4 shows the rank correlations between the three layers at different lag orders. We note that (I) the rank correlation between volatility spillover layer and extreme risk spillover layer is mostly negative (II) the correlation between the mean r layer and extreme risk spillover layer changes inversely across the lag orders. Fig. 5 illustrate the dynamic Spearman's correlation between the three layers.

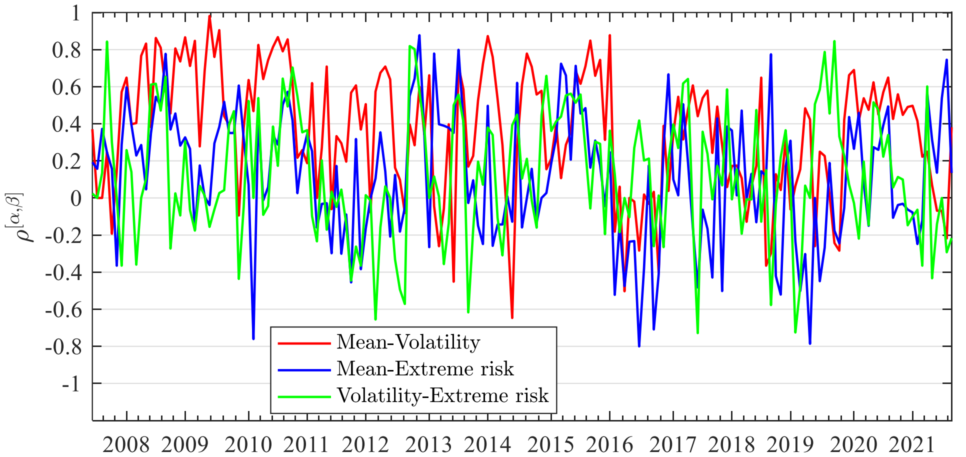


Fig 5. Dynamic Spearman's correlation coefficients between three different layers

Fig. 5 demonstrate the dynamic rank correlations between the three layers based on GCC banking sectors in time-varying multilayer information spillover networks. The dynamic correlations vary with time, but in most of the period the correlations fall between −0.2 and 0.8. This finding indicates that there is a time varying correlation between the different layers, and the overall correlation is large.

4.2. Results for uniqueness measures

In this part, we introduce unique edges to describe the uniqueness among three layers. The unique edges on layer α mean the edges only exist on layer α rather than on other layers. Fig.6 presents the number of unique edges on each layer under different lag orders

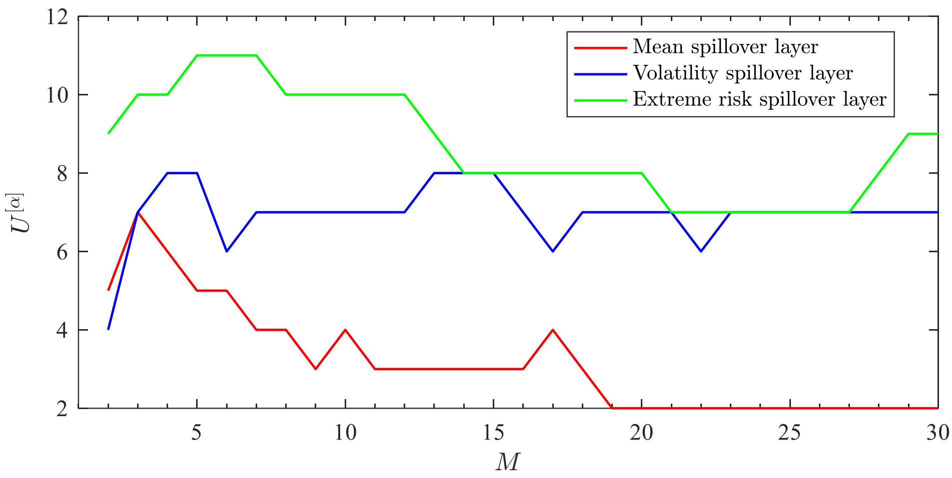


Fig 6. The number of unique edges on each layer in multilayer spillover networks as functions of lag order *M*.

Fig. 6 shows that the trend of the number of unique edges on each layer at different lags order is different than the trend on the corresponding layer. Also, we notice than t the number of unique edges of each layer tends to be stable when M ≥ 20. Fig.7 illustrate the dynamic number of unique edges on each layer.

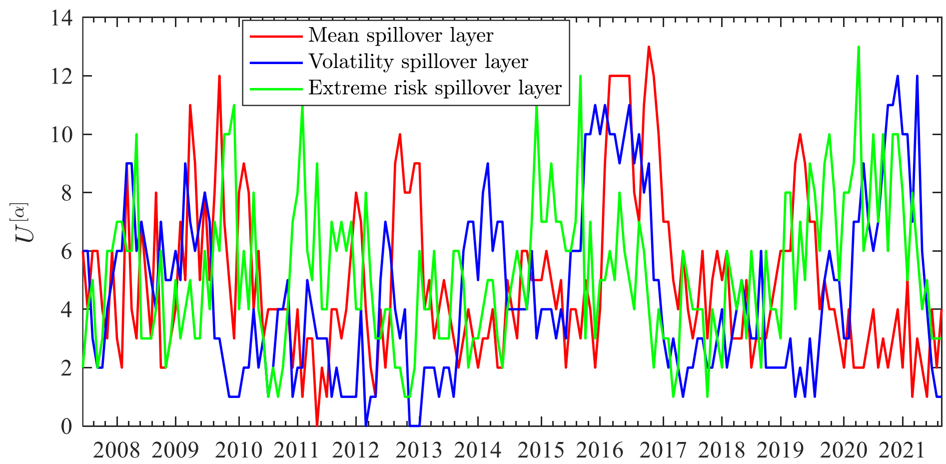


Fig 7. Dynamic number of unique edges on each layer in time-varying multilayer information spillover networks.

From figure 7, we note that in most of the time, the extreme risk spillover layer captures the largest number of unique edges, followed by the volatility and the mean spillover layers. Fig.8 illustrate the number of unique edges of each agent on multilayer information spillover networks as functions of lag order M.

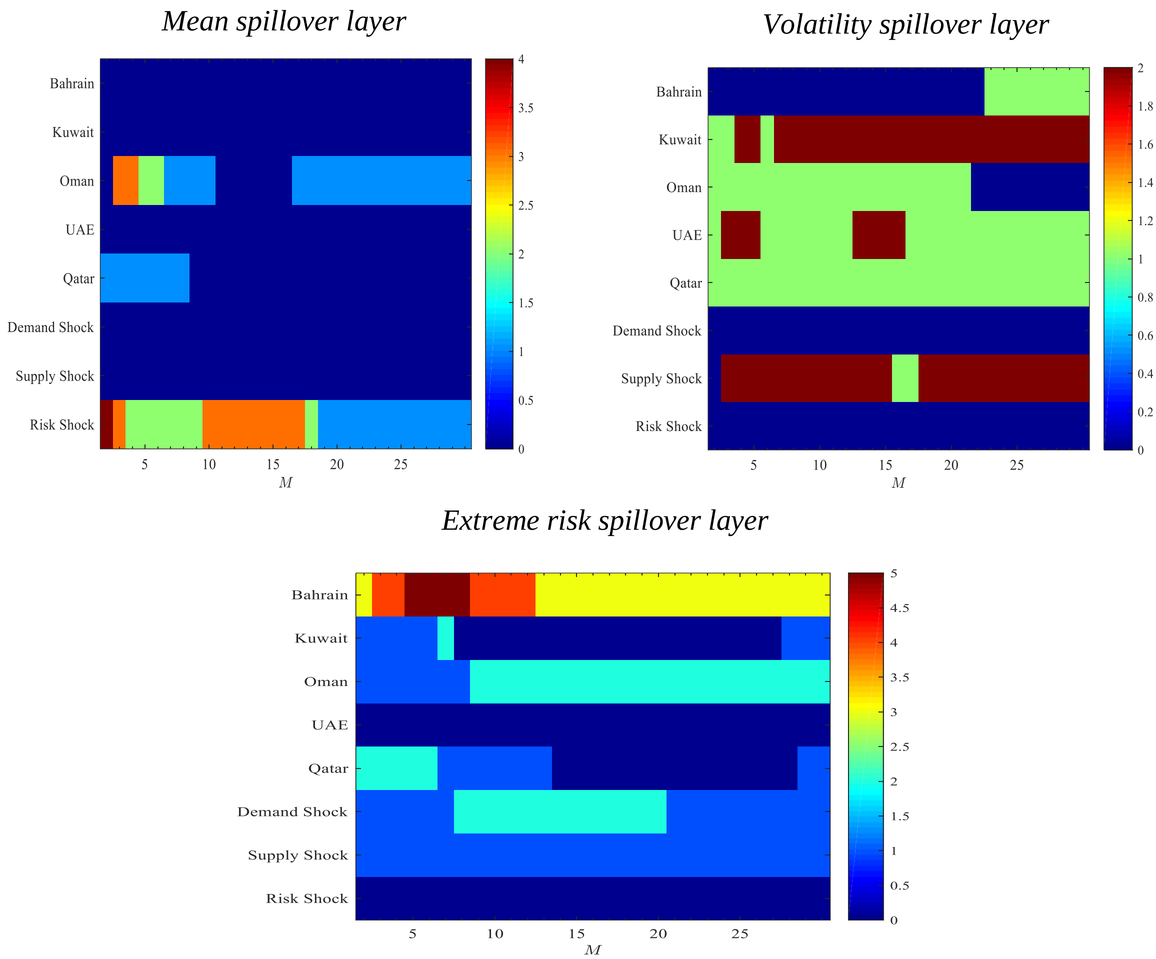
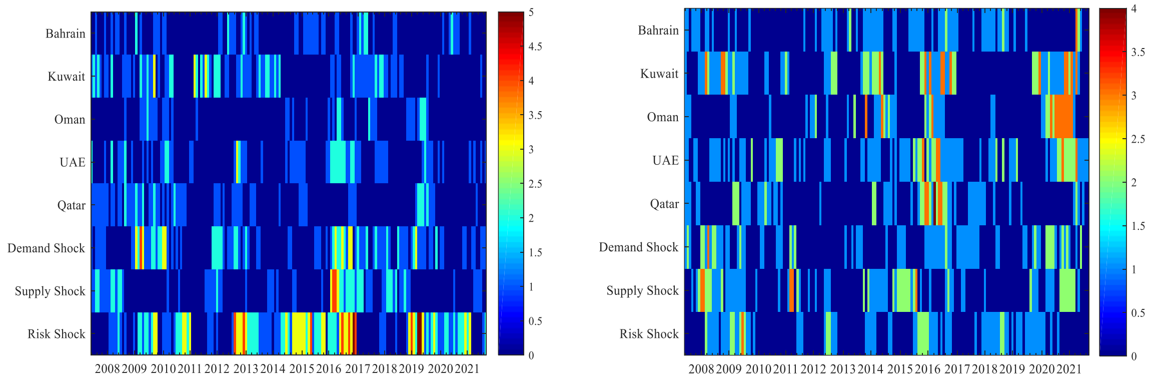


Fig 8. The number of unique edges of each agent on multilayer information spillover networks as functions of lag order *M*.

From Fig 8. note that the unique edges of GCC banking sectors on each layer are different and change with the lag order. Also, Bahrain banking sector have a large number of unique edges (i.e., the high connectedness and risk transmission with oil price shocks) on the extreme risk layer across most of lag orders. Fig. 9 illustrates the evolution for the number of unique edges of the GCC banking sectors on each layer.



Extreme risk spillover layer

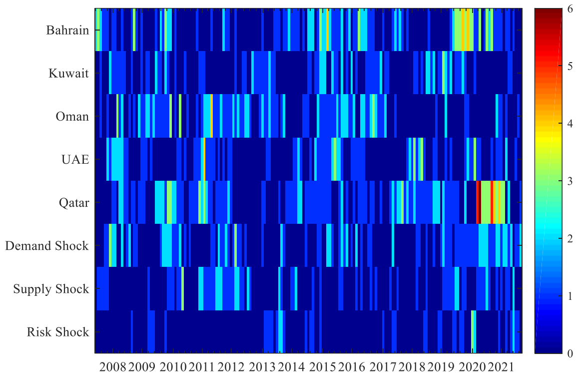


Fig 9. Dynamic evolution for the number of unique edges of agents in time-varying multilayer information spillover networks.

From Fig. 9, we notice that the dynamic patterns of unique edges on three layers also show the nonsynchronous effect during the crisis period. For example, we observe a significant increase in the number of unique edges on extreme risk spillover and volatility spillover layers happened during COVID-19 pandemic period (2020-2021). We note also a significant increase in the number of unique edges in mean spillover layer in the case of risk shocks happening during the oil crisis period 2014-2016.

4.3. Results for overlap measures

In this section, we consider the non-unique edges of GCC banking sectors through the projection network of multilayer information spillover. Fig 10 measure the average edge overlap of multilayer information spillover networks under different lag orders.

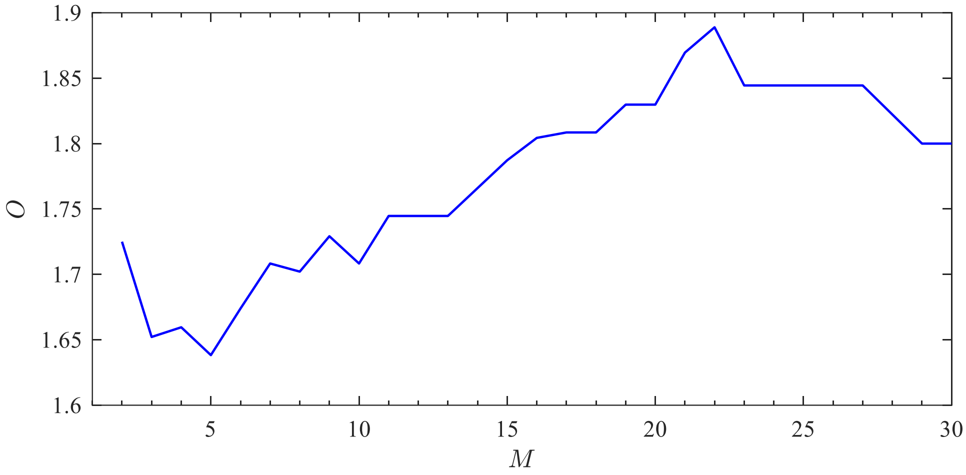


Fig 10. Average edge overlap of multilayer information spillover networks

Fig. 10 shows that the average edge overlap increases when the lag order M is greater than 5, and then is decreasing when M ≥ 27. The average edge overlap is in a stable state when 23 ≤ M ≤ 27. Fig. 11 illustrates the dynamic average edge overlap of multilayer information spillover networks.

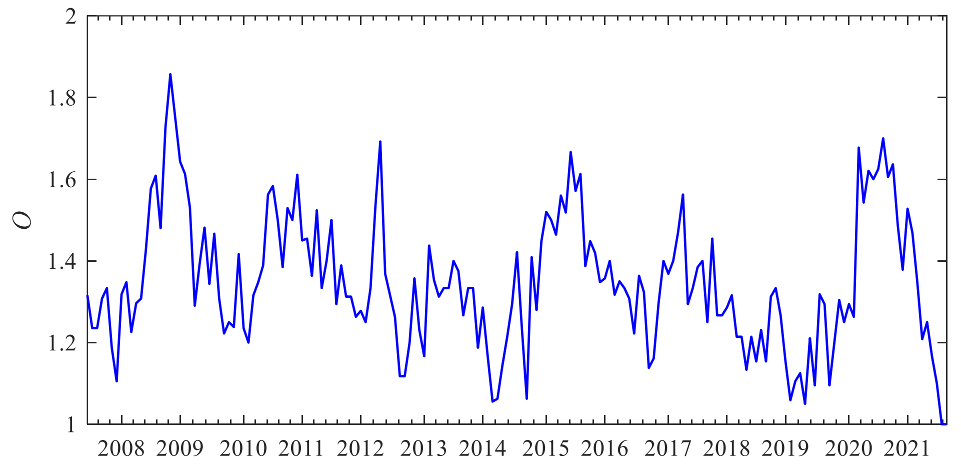


Fig 11. Dynamic average edge overlap of multilayer information spillover networks

From Fig 11, we note that the average edge overlap is relatively low and less than 2, indicating that (i) on average each edge will not simultaneously appear on two layers and (ii) each information spillover layer has a complementary effect. Fig. 12 illustrate the overlapping degree of GCC banking sectors at different lag orders.

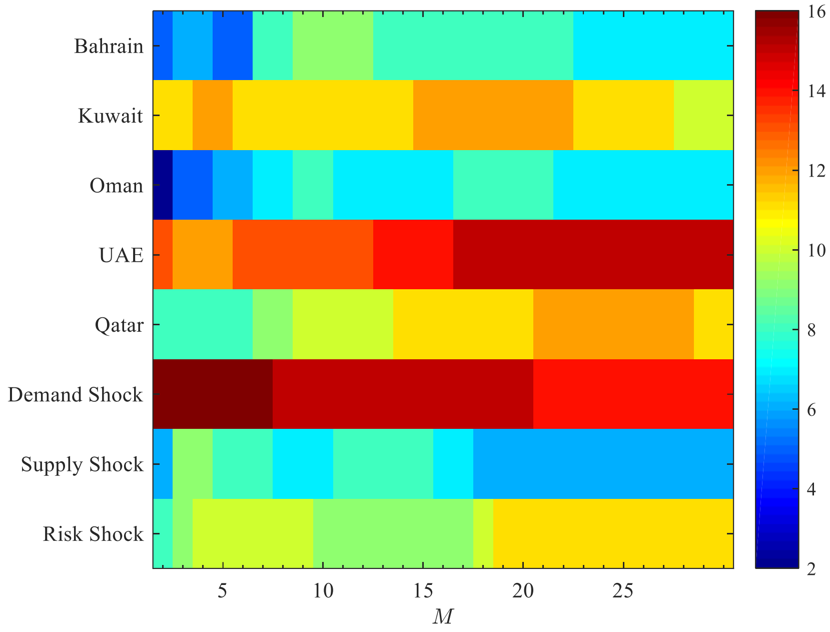


Fig 12. The overlapping degree of each agent in multilayer spillover networks as functions of lag order *M*.

Fig. 12 shows that Kuwait and UAE are highly connected with demand shocks because their overlapping degrees are large. Fig. 13 demonstrate the dynamic overlapping degrees of GCC banking sectors and oil price shocks in time-varying multilayer information spillover networks. Finally, Fig. 15 illustrates the time-varying participation coefficients of different GCC banking sectors. The higher the participation coefficient is, the more homogeneous the distribution of banking sector' activity is among layers.

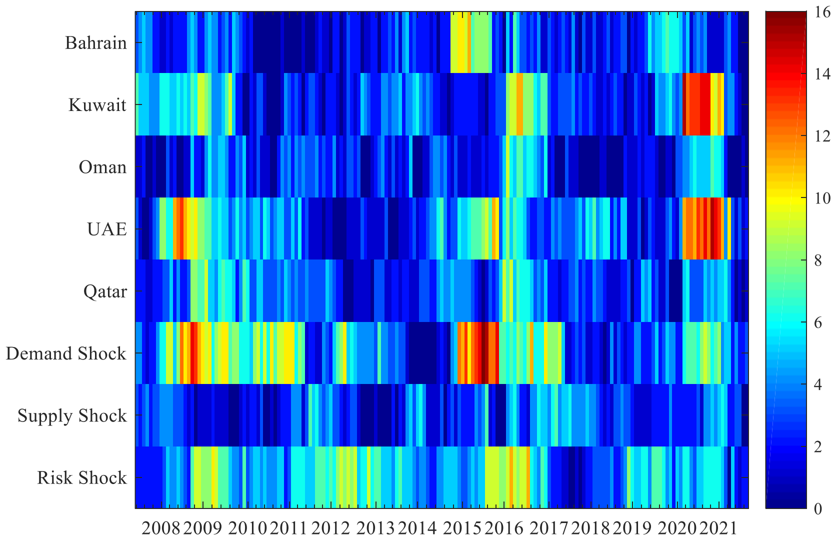


Fig 13. Dynamic overlapping degrees of agents in time-varying multilayer information spillover networks.

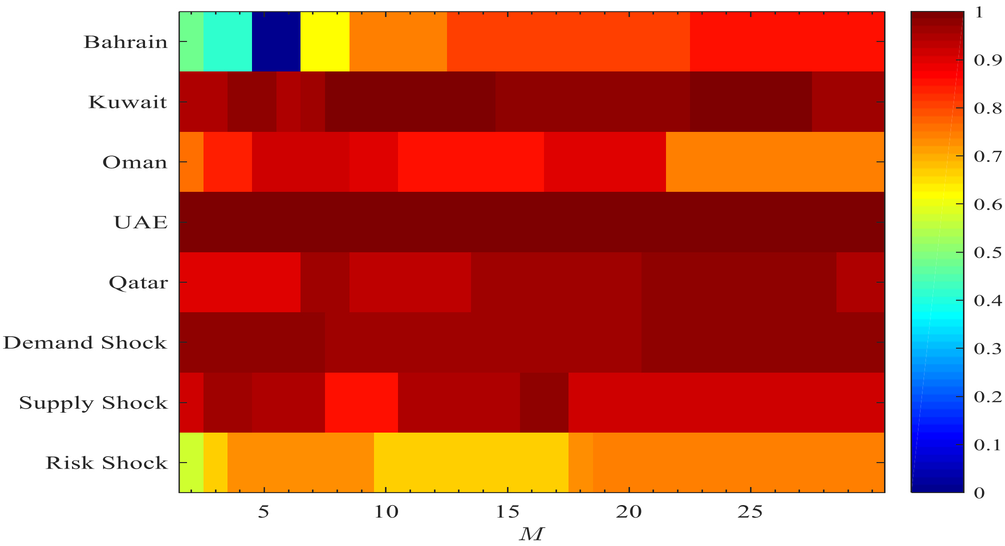


Fig 14. The participation coefficient of each agent in multilayer spillover networks as functions of lag order *M*.

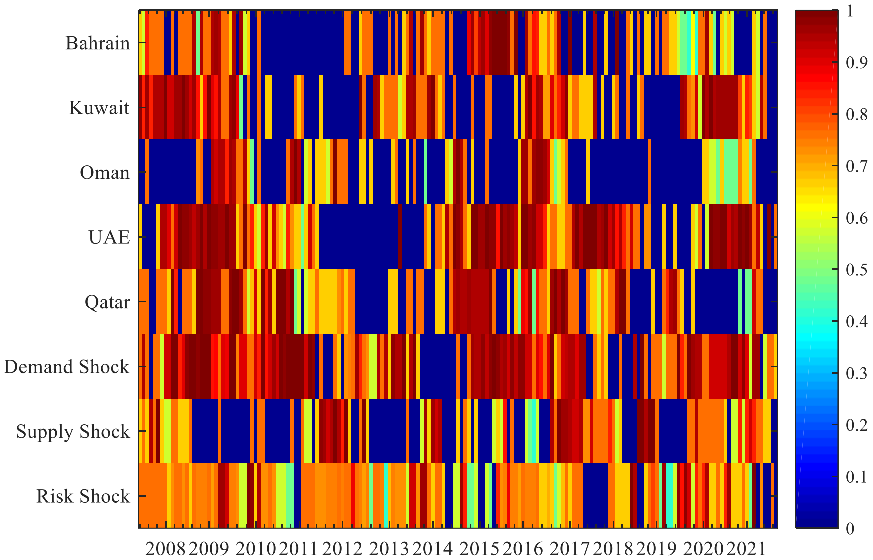


Fig 15. Dynamic participation coefficient of agents in time-varying multilayer information spillover networks.

5. Conclusion

In this paper, we investigated the connectedness and risk transmission among oil shocks and banking sectors in the GCC economies over the period from June 30, 2006, to September 9, 2021. We used the multilayer information spillover networks to consider mean and volatility spillover effects, and extreme risk spillover effects between oil price shocks and GCC banking sectors. We used multilayer measures to examine the connectedness between oil price shocks and GCC banking sectors.

The empirical results show that (I)The peak degree on each layer of multilayer information spillover networks mostly has a synchronization effect, however, there was a significant asynchronous effect during crisis times and COVID-19 pandemic. (II) The pattern of the unique edge is different than the pattern of the degree, suggesting that the increasing connection between GCC banking sectors and oil price shocks is mainly attributed to the rise of similar edges. (III) a significant increase in the number of unique edges on extreme risk spillover and volatility spillover layers happened during COVID-19 pandemic period (2020-2021). (Ⅳ) The average edge overlap is lower than 2 on average, so the information obtained by the network is one-sided no matter which layer is considered separately. This finding is similar to the finding of Wang et al. (2020).

Overall, these findings are of great importance to investors, policymakers, and market regulators in understanding the relationship and risk transmission between the oil market and banking sectors. A more informed understanding of the impact of the oil shocks on the banking sectors may help reveal promising domains for regional portfolio diversification, and trading and hedging strategies, enabling investors to make sound investment decisions. It would also help policymakers to regulate the banking sector more effectively and adopt the right policy measures to safeguard and maintain sound and stable financial systems.

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