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FINANCIAL CONNECTEDNESS AND CONTAGION RISK IN A DUAL BANKING SYSTEM

CONNEXIONS FINANCIERES ET RISQUE DE CONTAGION DANS UN SYSTEME BANCAIRE DUAL

Rachid Ouchchikh
Cadi Ayyad University, Morocco
(ouchchikhra@yahoo.fr)

Khalil Belghouat
Cadi Ayyad University, Morocco
(khalil.belghouat@gmail.com)

Abstract:
The 2008 subprime mortgage crisis laid bare the vulnerabilities inherent in financial interdependencies, where shocks originating from one sector and entity rapidly disseminated through complex networks, engendering a contagion effect that reverberated across the banking system. The present paper offers a comprehensive exploration of systemic risk, financial interconnectedness, and contagion within the context of a dual banking system. This appears to be a particular problem because of the heterogeneous market structure, which raises major questions about financial stability. Recognizing the profound implications of the interplay between Islamic and conventional banks, this study employs a comprehensive framework to dissect the intricate dynamics at play. The results reveal the existence of significant interconnectivity, which experiences a notable augmentation during periods of turmoil. Additionally, we provide an analysis of the topological structure of the interlinkage between Islamic and conventional banks, indicating substantial transmission of volatility, both unidirectionally and bidirectionally, across intersectoral and intrasectoral domains. However, our findings indicate that both incoming and outgoing connectivities are primarily influenced by the conventional banking sector.

Keywords: Contagion risk, Financial connectedness, Complex networks, Dual banking system.

JEL Classification — C58, G01, G21.

1. Introduction

Systemic risk pertains to the probability of an interconnected sequence of failures or a pervasive disruption resulting from a deficiency within a specific segment or the entirety of a market. This deficiency has the potential to curtail the effective operation of the system as a whole, thereby inducing a state of compromised functionality. Due to its pivotal role in financial intermediation, the banking sector conventionally assumes a foundational position within the domain of systemic risk analysis. The rationale for this emphasis emanates from the recognition that its potential collapse possesses the capacity to impede economic expansion and inflict enduring harm upon the overall system. This notion was starkly illuminated by the seismic descent of global financial markets during the 2008 subprime mortgage crisis, subsequent to the cataclysmic downfall of Lehman Brothers, and underscored the critical role that existing links between banks and financial institutions assume, serving as conduits for the propagation and amplification of shocks. In the context of a dual banking system encompassing both Islamic and conventional banks, the importance of systemic risk analysis becomes even more pronounced. Such dual banking systems introduce a multifaceted landscape of interactions, synergies, and interdependencies that are distinct from those of conventional financial systems. By accommodating both Islamic and conventional banks, this dual framework generates intricate relationships that can potentially magnify the impact of adverse events across various sectors. The interplay between these different banking paradigms becomes a source of complexity that must be thoroughly understood to assess their implications for systemic stability. Particularly, the juxtaposition of distinct risk profiles, business practices, and customer preferences within a dual banking system can accentuate the channels through which shocks propagate and interconnect. Amidst the recent revelations concerning financial challenges encountered by prominent banking institutions, specifically Credit Suisse and Deutsche Bank, the imperative to evaluate and comprehend systemic risk and contagion has taken center stage in the agendas of central banks, supervisory authorities, and regulatory agencies. The assessment of potential vulnerabilities within a dual banking system is indispensable for devising effective regulatory measures and proactive strategies that can mitigate the propagation of shocks and the consequent contagion effects. As the intricacies of financial interactions continue to evolve in an increasingly interconnected global landscape, a comprehensive understanding of systemic risk within dual banking systems becomes instrumental in safeguarding financial stability and fortifying the resilience of the broader economy. The rest of the article is thus structured as follows. The second section is devoted to a review of the literature on financial connectedness, systemic risk and their measures. The third section presents information with regard to the employed methodology. The fourth section details the data used, reports and discusses the empirical results found in relation to the dual banking system. The fifth section concludes the study.

2. Literature Review

The subprime mortgage crisis of 2008 starkly exposed the susceptibilities intrinsic to financial interconnectedness. It unveiled a scenario where shocks, originating from a single sector or entity, swiftly propagated through intricate networks, resulting in a contagion effect that echoed throughout the banking system. Consequently, a paramount concern is the quantification of systemic risk and the identification of financial institutions whose distress or disorderly failure, because of their size, complexity and interconnectedness, would cause significant disruption to the wider system and economic activity. Caccioli *et al.* (2015) lists several channels through which the transmission of shocks from one financial institution to another occurs. These channels encompass losses stemming from counterparty exposures, the incapacity to refinance debt and secure short-term funding, and portfolio devaluations due to common asset holdings. Systemic risk is a multidimensional phenomenon, and each measure emphasizes particular facets of this complexity. Assessing an individual financial institution's contribution to systemic risk can be approached through the utilization of confidential data encompassing the firm's positions and risk exposures, or alternatively, by employing publicly available market data. The latter includes metrics such as stock returns, option prices, and credit default swap (CDS) spreads, which are regarded as comprehensive indicators, as they are believed to encapsulate all pertinent information regarding publicly traded firms. In the aftermath of the global financial crisis, there has been a plethora of studies aimed at formulating alternative measures of systemic risk. Notable illustrations of these measures encompass the Marginal Expected Shortfall (MES) and the Systemic Expected Shortfall (SES) proposed by Acharya *et al.* (2010), the Systemic

Risk Measure (SRISK) advanced by Acharya *et al.* (2012), in conjunction with the work by Brownlees and Engle (2017), the Delta Conditional Value-at-Risk (ΔCoVaR) devised by Adrian and Brunnermeier (2011), and the Conditional Autoregressive Value-at-Risk (CaViaR) by White *et al.* (2015). While the papers that analyze financial connectedness and systemic risk, does so exclusively in a conventional banking setting (Liu, 2016; Demirer *et al.*, 2017; Barunik and Krehlik, 2018; Zhang *et al.*, 2020; Zedda and Spinace-Casale, 2021; Zou *et al.*, 2022). The study of shock transmission within the context of dual banking systems appears to be a particular problem because of the heterogeneous market structure. Such area of research has emerged to be critical, given its implications for financial stability and the broader economy. Abedifar *et al.* (2017) conducted a study examining the impact of Islamic and conventional finance coexistence on the stability of banking systems. They assessed the resilience of three types of banks in six Gulf Cooperation Council (GCC) member countries that have dual banking systems. Using market-based measures of systemic risk and analyzing data from 79 publicly traded banks, their findings revealed that conventional banks with Islamic windows exhibited the lowest level of resilience in the face of systemic events. These banks displayed the highest degree of correlation with the overall market and demonstrated the most significant interconnections within the banking sector, particularly during times of financial crisis. Abdul Manap (2019) analyzes systemic risk within the Malaysian banking sector, with specific focus on Islamic banks. Following the estimation approach developed by Adrian and Brunnermeier (2011), the paper concludes that the size of a bank is typically associated with the extent of risk spillover. Furthermore, it observes that various depository institutions tend to contribute more significantly to systemic risk during financial crises. Addi and Bouoiyour (2023) investigated using the Tail Event driven NETwork (TENET) technique introduced by Härdle *et al.* (2016) financial connectedness between Islamic and conventional banks and the transmission of extreme risk among a group of 20 Islamic and 34 conventional banks across six GCC member countries. Their findings unveiled a strong interconnectedness that notably intensifies during times of financial instability. The analysis of this interconnection structure indicated substantial one-way and two-way transmissions of extreme risk both between sectors and within sectors, as well as across countries. Moreover, when assessing individual systemic significance, the study identified an uneven impact of extreme risk spillovers between conventional and Islamic banks. Our study makes a valuable contribution to the current literature by being the first to apply Gabauer's (2020) novel methodology, the volatility impulse response functions (VIRF) for the dynamic conditional correlation class of multivariate generalized autoregressive conditional heteroskedasticity (DCC-GARCH) models, to analyze financial connectedness and volatility spillover within a dual banking system. This framework offers several advantages, notably that it does not rely on a rolling-window approach to capture time-varying dynamics, and it enables us to assess whether the propagation mechanism exhibits time-varying characteristics or remains constant. By utilizing this innovative approach, our research offers fresh insights and addresses the scarcity of academic research on the dynamic interlinkages in this critical area of study. Furthermore, this study examines the interdependence and the underlying relationship between the different banks during periods of market stability and crises. Finally, we provide an in-depth analysis of the topological structure governing the interconnectedness between Islamic and conventional banks and examine the transmission of risk across both intersectoral and intrasectoral levels.

3. Methodology

3.1. DCC-GARCH

The DCC-GARCH model is an approach that allows modeling both the conditional variance and correlation of multiple time series. It was introduced by Engle (2002) to address the issue of the CCC-GARCH model, where the matrix of conditional correlations, which is constant, becomes dynamic. The DCC-GARCH model can be written as follows:

$$y_t = \mu_t + \epsilon_t, \quad \epsilon_t | F_{t-1} \sim N(0, H_t)$$

$$\epsilon_t = H_t^{\frac{1}{2}} u_t, u_t \sim N(0, I)$$

$$H_t = D_t R_t D_t$$

where F_{t-1} is the information set observed up to time $t-1$. The vectors y_t, μ_t, ϵ_t, and u_t are all of dimension $N \times 1$, representing the time series under analysis, conditional mean, error term, and standardized error term, respectively. Moreover, the matrices R_t, H_t, and D_t are of size $N \times N$, denoting the dynamic conditional correlations, time-varying conditional variance-covariance matrices, and time-varying conditional variances, respectively. $D_t = \mathrm{diag}\left(\nu_{11,t}^{\frac{1}{2}},\ldots,\nu_{NN,t}^{\frac{1}{2}}\right)$ is created by estimating a Bollerslev (1986) GARCH(1, 1) model for each series:

$$\nu_{ii,t} = \omega + \alpha\epsilon_{i,t-1}^{2} + \beta\nu_{ii,t-1}$$

To ensure positivity, we require that $\omega > 0$, $\alpha > 0$, and $\beta \geq 0$. The dynamic conditional correlations are computed as follows:

$$R_t = \mathrm{diag}\left(q_{11,t}^{-\frac{1}{2}},\ldots,q_{NN,t}^{-\frac{1}{2}}\right)Q_t\mathrm{diag}\left(q_{11,t}^{-\frac{1}{2}},\ldots,q_{NN,t}^{-\frac{1}{2}}\right)$$

$$Q_t = (1-\gamma-\lambda)\bar{Q} + \gamma u_{t-1}u_{t-1}^{T} + \lambda Q_{t-1}$$

where Q_t and $\bar{Q}$ are $N \times N$–dimensional positive definite matrices that depict the variance-covariance matrices of the conditional and unconditional standardized residuals, respectively. While (γ, λ) and (α, β) fulfill the conditions $\gamma + \lambda < 1$ and $\alpha + \beta \leq 1$. Provided that $\gamma + \lambda < 1$ is satisfied, the matrices Q_t and consequently R_t exhibit time variation. Conversely, failing to meet this condition would result in the model converging to the CCC-GARCH framework, in which R_t remains constant over time.

3.2. Volatility Impulse Response Function

The connectedness approach introduced by Diebold and Yilmaz (2012, 2014) is founded upon the generalized impulse response functions (GIRF) introduced by Koop *et al.* (1996) and Pesaran and Shin (1998). GIRF possess the advantage of being invariant to the order of the variables and offer an interpretation of the impact of a shock in variable i on variable j over J time steps ahead:

$$\mathrm{GIRF}(J,\delta_{j,t},F_{t-1}) = E(y_{t+J}|\epsilon_{j,t} = \delta_{j,t},F_{t-1}) - E(y_{t+J}|\epsilon_{j,t} = 0,F_{t-1})$$

Consistently, the volatility impulse response function (VIRF) encapsulates the effect of a shock in variable i on the conditional volatility of variable j, and this relationship can be expressed as follows:

$$\Psi^{g} = \mathrm{VIRF}(J,\delta_{j,t},F_{t-1}) = E(H_{t+J}|\epsilon_{j,t} = \delta_{j,t},F_{t-1}) - E(H_{t+J}|\epsilon_{j,t} = 0,F_{t-1})$$

where $\delta_{i,t}$ is a selection vector with a 1 at the j–th position and 0 otherwise. Central to the VIRF is the forecasting of conditional variance-covariance matrices using the DCC-GARCH model (Engle and Sheppard, 2001). The univariate GARCH(1, 1) model is employed to forecast the conditional volatilities $(D_{t+h}|F_t)$, and this is given by:

$$E(\nu_{ii,t+1}|F_t) = \omega + \alpha\delta_{1,t}^2 + \beta\nu_{ii,t}, \quad \text{for} \quad h = 1$$

$$E(\nu_{ii,t}|F_t) = \sum_{i=0}^{h-1} \omega\,(\alpha + \beta)^i + (\alpha + \beta)^{h-1}E(\nu_{ii,t-1}|F_t), \quad \text{for} \quad h > 1$$

whereas $E(Q_{t+h}|F_t)$ is predicted according to:

$$E(Q_{t+1}|F_t) = (1-\gamma-\lambda)\bar{Q} + \gamma u_t u_t^T + \lambda Q_t, \quad \text{for} \quad h = 1$$

$$E(Q_{t+h}|F_t) = (1-\gamma-\lambda)\bar{Q} + \gamma E(u_{t+h-1}u_{t+h-1}^T|F_t) + \lambda E(Q_{t+h-1}|F_t), \quad \text{for} \quad h > 1$$

where $E(u_{t+h-1}u_{t+h-1}^T|F_t) = E(Q_{t+h-1}|F_t)$[1], which helps in forecasting the dynamic conditional correlations and, ultimately, the conditional variance-covariance:

$$E(R_{t+h}|F_t) = \text{diag}\left(E\left(q_{11,t+h}^{-\frac{1}{2}}|F_t\right),\ldots,E\left(q_{NN,t+h}^{-\frac{1}{2}}|F_t\right)\right)$$
$$Q_t \text{diag}\left(E\left(q_{11,t+h}^{-\frac{1}{2}}|F_t\right),\ldots,E\left(q_{NN,t+h}^{-\frac{1}{2}}|F_t\right)\right)$$

$$E(H_{t+h}|F_t) = E(D_{t+h}|F_t)E(R_{t+h}|F_t)E(D_{t+h}|F_t)$$

In the long run, the forecast of the conditional correlation matrix will converge to the unconditional correlation matrix of the standardized residuals.

3.3. Dynamic Connectedness Approach

Based on the VIRF, the generalized forecast error variance decomposition (GFEVD) is computed, and can be interpreted as the proportion of variance that a single variable explains in relation to the others. These proportions are adjusted to ensure that each row

[1] See Engle and Sheppard (2001).

totals to one, signifying that collectively, all variables account for 100% of the forecast error variance of variable i. The calculation is as follows:

$$\tilde{\varphi}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}$$

where $\sum_{j=1}^{N} \tilde{\varphi}^{g}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\varphi}^{g}_{ij,t}(J) = N$. The numerator embodies the cumulative impact of the shock pertaining to variable i, while the denominator represents the aggregate cumulative effect of all shocks. Using the GFEVD, the comprehensive total connectedness index (TCI) can be constructed by:

$$C^{g}_{t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\varphi}^{g}_{ij,t}(J)}{N}$$

The spillovers which variable i transmits to variables j, known as the total directional connectedness TO others, are calculated as follows:

$$C^{g}_{i\to j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\varphi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N} \tilde{\varphi}^{g}_{ji,t}(J)}$$

While the spillovers that variable i receives from variables j, known as the total directional connectedness FROM others, are computed by:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\varphi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N} \tilde{\varphi}^{g}_{ij,t}(J)}$$

By subtracting the aforementioned measures from each other, we arrive at the net total directional connectedness, representing the extent of influence that variable i exerts on the analyzed network:

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(J) - C^{g}_{i\leftarrow j,t}(J)$$

Should the net total directional connectedness of variable i be positive (negative), this indicates that variable i functions as a net transmitter (receiver) of shocks, signifying its role in driving (being driven by) the network dynamics. Finally, the net pairwise directional connectedness (NPDC) linking variable i with variable j is calculated in the subsequent manner:

$$NPDC_{ij}(J) = \tilde{\varphi}^{g}_{ji,t}(J) - \tilde{\varphi}^{g}_{ij,t}(J)$$

In cases where $NPDC_{ij}$ is positive (negative), it signifies that variable i dominates (is dominated by) variable j.

4. Empirical Study

4.1. Data

This paper analyzes the financial connectedness and contagion risk of a panel consisting of 3 Islamic and 5 conventional listed banks on the Saudi Exchange, spanning from early January 2004 to the end of July 2023 and covering a multiplicity of systemic events, including, the subprime mortgage crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict. In line with Yoon *et al.* (2019), Antonakakis *et al.* (2020), and Chatziantoniou and Gabauer (2021), we use the daily closing prices of each financial institution.

Table 1: Sample of banks.

Name	Ticker	Type
Riyad Bank	1010	Conventional Bank
Bank Aljazira	1020	Islamic Bank
Saudi Investment Bank	1030	Conventional Bank
Banque Saudi Fransi	1050	Conventional Bank
Saudi Awwal Bank	1060	Conventional Bank
Arab National Bank	1080	Conventional Bank
Al Rajhi Bank	1120	Islamic Bank
Bank Albilad	1140	Islamic Bank

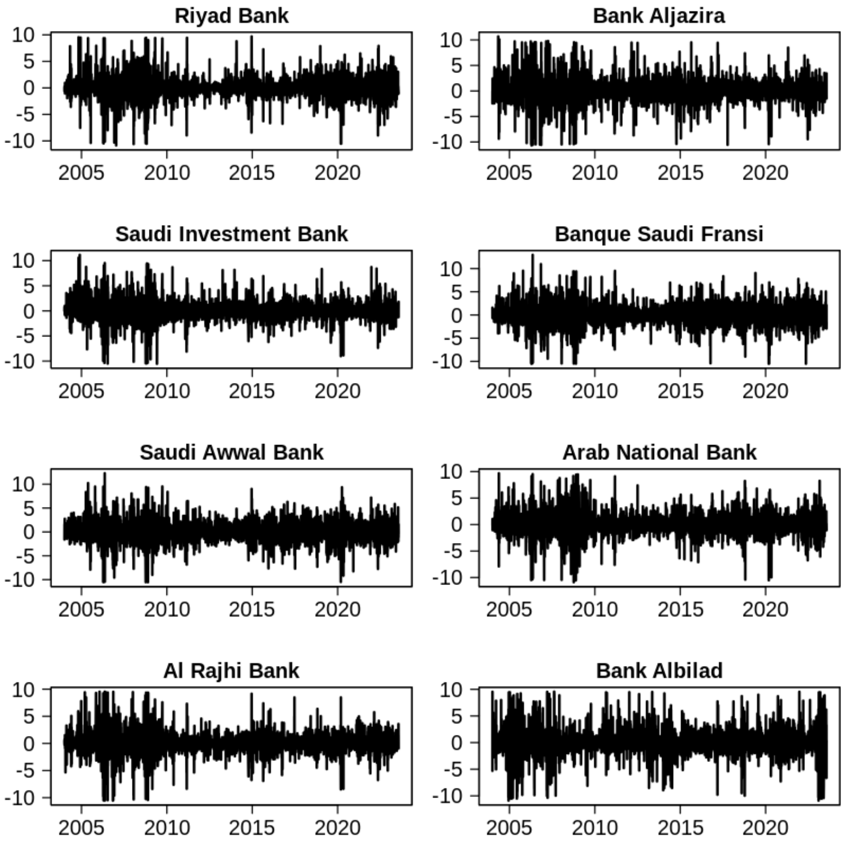


Figure 1: Banks' daily returns.

We can see strong fluctuations going from 2006 until 2009, the interval in which the subprime mortgage crisis occurred, during the 2015 decline in oil prices, beginning of 2020 corresponding to the stock market panic due to the appearance of the COVID-19 epidemic, and the first quarter of 2022 following the Russo-Ukrainian conflict.

Table 2: Summary statistics.

	1010	**1020**	**1030**	**1050**	**1060**	**1080**	**1120**	**1140**
Minimum	-10.83	-10.666	-10.536	-10.508	-10.536	-10.88	-10.53	-10.89
Mean	0.0212	0.02306	0.0170	0.0209	0.0224	0.0217	0.0389	0.0016
Maximum	9.7045	10.6786	11.158	12.947	12.296	9.6849	9.5382	9.5604
Median	0.0000	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Variance	3.1965	4.76897	3.1574	4.2668	3.8679	3.7834	3.3939	4.5375
Skewness	-0.1744	-0.0445	-0.0522	-0.0979	-0.0895	-0.2104	-0.119	-0.0312
Kurtosis	7.6297	5.37120	7.0706	4.3327	4.5110	5.5738	7.4357	5.5764
ADF Test	0.0100	0.01000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
JB Test	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16
LB Test	6.569e-10	< 2.2e-16	3.028e-11	1.802e-07	7.553e-07	1.102e-08	< 2.2e-16	5.992e-15
				Correlation Matrix				
1010	1.0000	0.50651	0.4915	0.5221	0.5120	0.5613	0.5446	0.0193
1020	0.5065	1.00000	0.5131	0.4257	0.4153	0.4894	0.6159	0.0035
1030	0.4915	0.51312	1.0000	0.4704	0.4520	0.5113	0.5080	0.0083
1050	0.5221	0.42575	0.4704	1.0000	0.5781	0.5714	0.4968	0.0090
1060	0.5120	0.41538	0.4520	0.5781	1.0000	0.5329	0.4613	0.0090
1080	0.5613	0.48941	0.5113	0.5714	0.5329	1.0000	0.5190	0.0078
1120	0.5446	0.61596	0.5080	0.4968	0.4613	0.5190	1.0000	-0.0136
1140	0.0193	0.0035	0.0083	0.0090	0.00903	0.00780	-0.013	1.00000

The skewness coefficient of the different bank stock returns are all less than 0, which suggests that the distribution of the data is negatively asymmetric. For the kurtosis, we obtain values higher than 3, implying that the set of fluctuations is leptokurtic. In other words, the banking sector is subject to extreme events. Thus, to check whether the returns follow a Gaussian distribution, we refer to the Jarque-Bera test which indicates the time series does indeed not follow a Normal distribution since the $p-$value is well below the risk level $\alpha = 0.05$. The correlation matrix contains figures ranging from 40% to 65% between Islamic and conventional banks, underscoring a degree of comovement between their respective logarithmic returns. This suggests that, in general, these two banking models exhibit similar trends and behaviors in response to various economic and financial conditions. However, it is worth noting that a notable exception exists within this pattern. Particularly, Bank Albilad stands out due to its considerably lower unconditional correlation, which appears to converge towards 0 when compared to the other banks. This distinct behavior could potentially be attributed to idiosyncratic factors.

4.2. Volatility Transmission

Figure 2: Volatility impulse response functions.

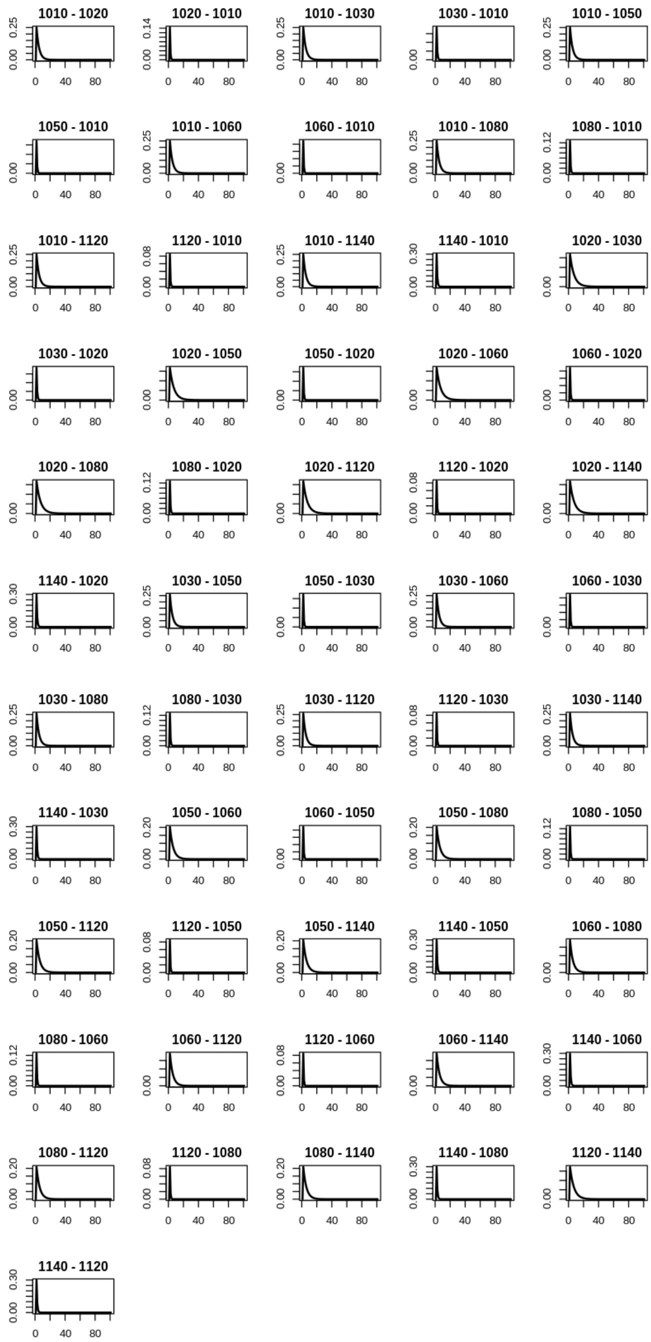
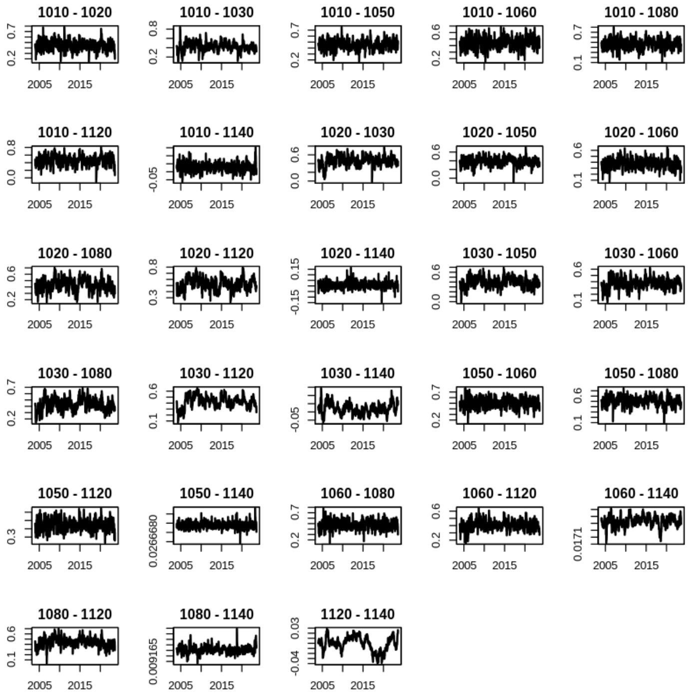


Figure 3: Dynamic conditional correlations.



The results, which are illustrated in Figure 2, demonstrate that the volatility spillovers tend to exhibit a generally modest to moderate level of persistence. Furthermore, the cross-volatility spillovers reveal that an augmentation in the volatility of one series leads to a corresponding increase in the volatility of the others. The effects exhibit variations primarily in their magnitude and persistence. Moreover, it is noteworthy that the levels of persistence among conventional banks surpass those observed among their Islamic counterparts. This could suggest the presence of higher contagion risk in the conventional banking sector, aligning with the findings of Abdul Manap (2019) and Addi and Bouoiyour (2023). In addition, this result provides essential insights with regard to financial stability within a dual banking system. Finally, the DCC test[2] (Engle and Sheppard, 2001) provides strong evidence that spillovers are changing over time.

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[2] p−value of 0.00397

4.3. Dynamic Total Connectedness

Table 3: Dynamic connectedness in the banking sector.

	1010	1020	1030	1050	1060	1080	1120	1140	FROM
1010	37.69	13.35	7.06	12.67	9.95	10.27	8.84	0.18	62.31
1020	7.39	53.08	7.00	8.13	6.40	7.72	10.16	0.12	46.92
1030	8.33	15.06	39.90	10.59	7.99	9.53	8.34	0.26	60.10
1050	7.58	8.68	5.31	49.52	11.22	10.20	7.35	0.13	50.48
1060	7.88	9.10	5.24	14.82	45.95	10.06	6.78	0.17	54.05
1080	8.67	11.76	6.76	14.36	10.78	39.85	7.67	0.16	60.15
1120	8.51	17.56	6.66	11.81	8.34	8.80	38.17	0.16	61.83
1140	0.21	0.32	0.21	0.26	0.20	0.16	0.17	98.48	1.52
TO	48.58	75.83	38.24	72.63	54.87	56.74	49.31	1.18	397.37
Inc. Own	86.27	128.91	78.14	122.16	100.82	96.59	87.47	99.65	**cTCI/TCI**
NET	-13.73	28.91	-21.86	22.16	0.82	-3.41	-12.5	-0.35	56.77/49.67
NPT	2.00	7.00	0.00	6.00	5.00	4.00	3.00	1.00	

Table 3 illustrates the averaged dynamic connectedness measures. The standrad and corrected TCI, which are equal to 49.67% and 56.77%, respectively, indicate that the financial system is relatively interconnected. Furthermore, the findings suggest that Bank Aljazira plays a significant role as the primary net transmitter, extending its influence to all seven other banks, closely followed by Banque Saudi Fransi. Conversely, the prominent net receiver emerges as the Saudi Investment Bank, drawing from all the other banks, with Riyad Bank following closely, slightly outweighing Bank Albilad but also being influenced by the remaining banks.

Table 4: Dynamic connectedness among conventional banks.

	1010	1030	1050	1060	1080	FROM
1010	48.33	9.26	16.30	12.79	13.31	51.67
1030	10.86	52.48	13.81	10.40	12.45	47.52
1050	9.03	6.40	59.10	13.29	12.18	40.90
1060	9.42	6.31	17.57	54.69	12.00	45.31
1080	10.76	8.52	17.78	13.31	49.63	50.37
TO	40.08	30.50	65.46	49.79	49.95	235.77
Inc. Own	88.41	82.97	124.56	104.48	99.58	**cTCI/TCI**
NET	-11.59	-17.03	24.56	4.48	-0.42	58.94/47.15
NPT	1.00	0.00	4.00	3.00	2.00	

Table 5: Dynamic connectedness among Islamic banks.

	1020	1120	1140	FROM
1020	83.07	16.60	0.33	16.93
1120	31.36	68.15	0.49	31.85
1140	0.57	0.30	99.13	0.87
TO	31.93	16.90	0.83	49.65
Inc. Own	115.00	85.05	99.96	**cTCI/TCI**
NET	15.00	-14.95	-0.04	24.83/16.55
NPT	2.00	0.00	1.00	

Table 4 showcases the extent of financial interconnectedness within the conventional banking sector. The static measures stand at 47.15% and 58.94%, respectively, indicating a considerable level of interdependence among the distinct financial institutions. In contrast, Table 5 delves into the extent of financial interconnectedness within Islamic banks. The standard and corrected TCI values of 16.55% and 24.83% unveil that Islamic banks demonstrate comparatively modest levels of interconnectivity.

Figure 4: Dynamic total connectedness index of the banking sector.

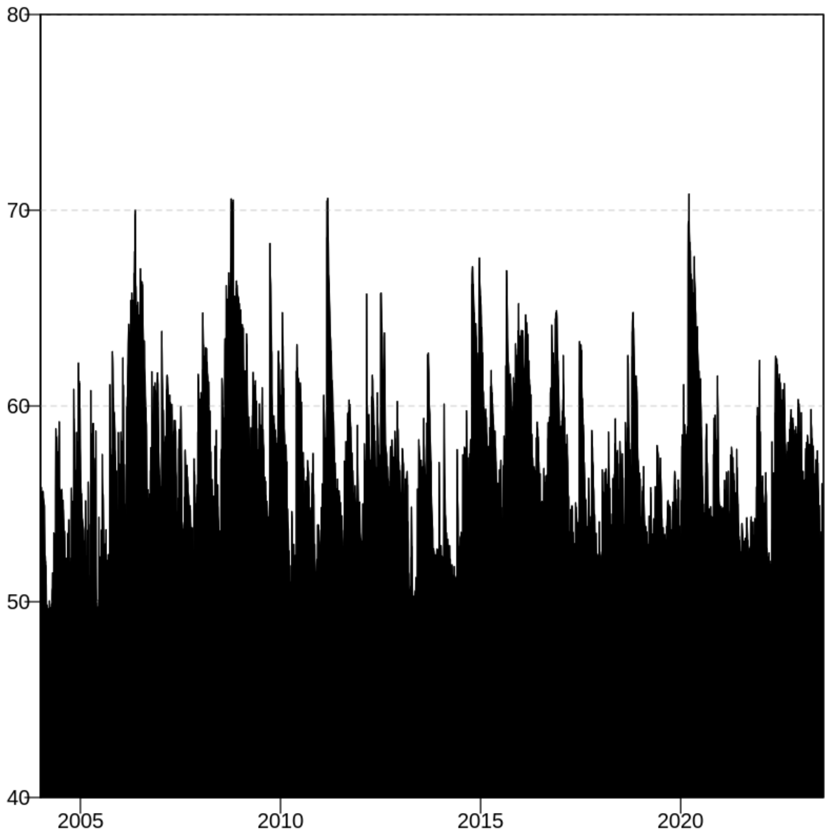


Figure 5: Dynamic total connectedness index of conventional banks.

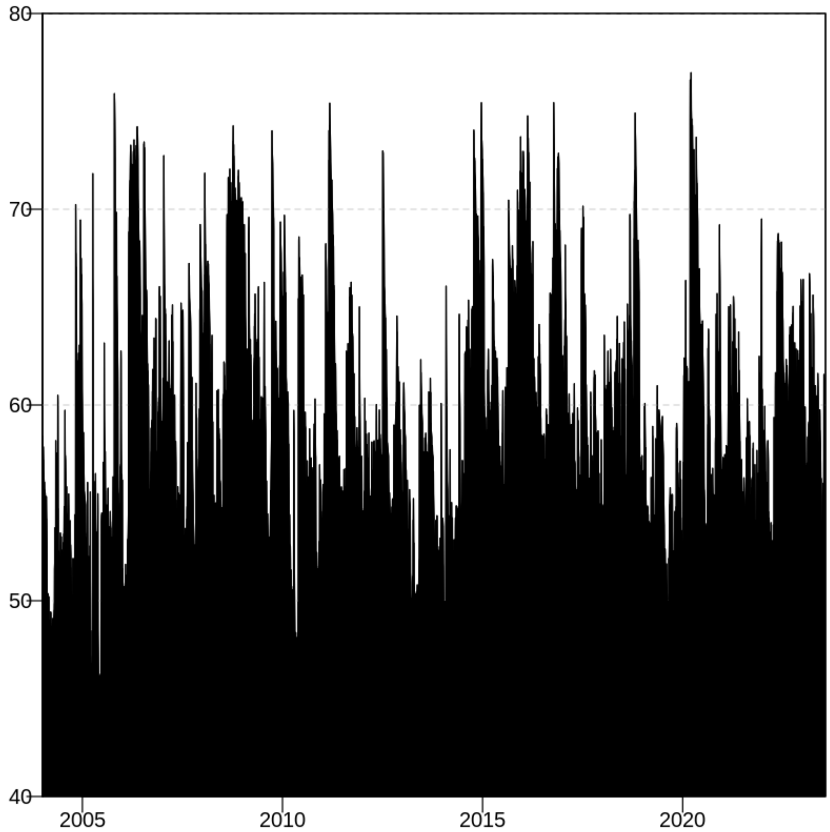


Figure 6: Dynamic total connectedness index of Islamic banks.

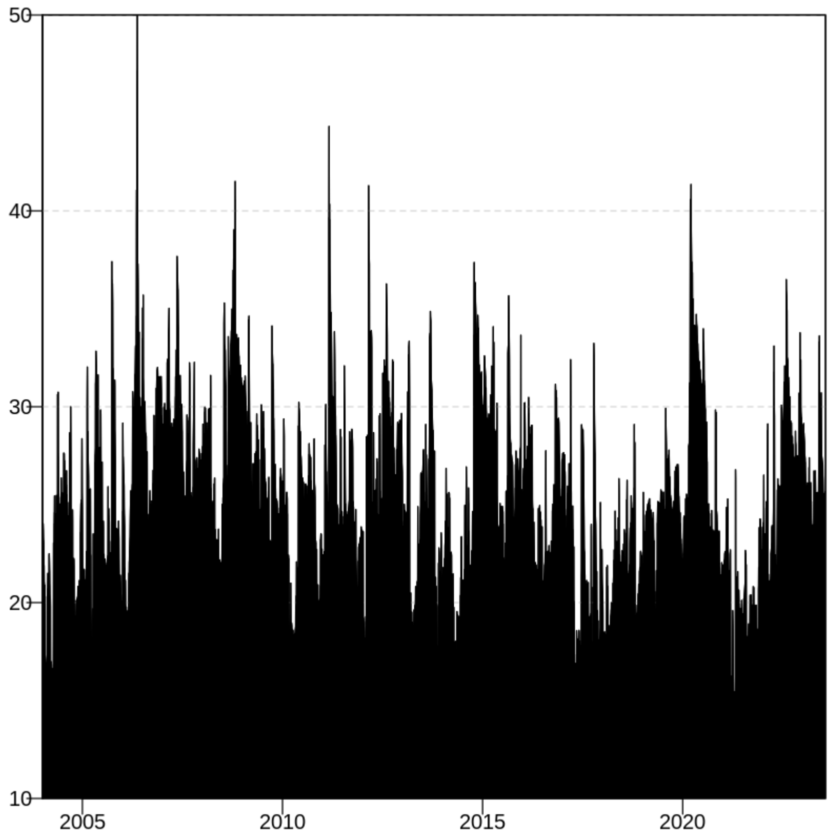


Figure 4 depicts the dynamic TCI, spanning approximately between 50% and 70%. This practically implies that connectedness across financial institutions is strong and time varying, a characteristic often concealed by the nature of static TCI. To elaborate further, two noticeable peaks emerge in Figure 4. The first corresponds to the 2008 subprime mortgage crisis, while the second aligns with the 2020 COVID-19 pandemic. The identified peaks exhibited both persistence and strong associations with crisis episodes, underscoring their significance. In contrast, periods of stability were marked by a prevailing lower level of interconnectedness. This observation hints at a decreased risk level within the banking system during these phases. Figure 5 illustrates the dynamic TCI covering between 50% to 75%. This indicates a substantial level of connectedness across conventional banks, signifying their strong interrelationships. Additionally, beyond the previously noted spikes, further instances are discernible in the year 2015. The Saudi capital market experienced significant fluctuations, highest level since 2009, due to pronounced embedded correlation with the energy sector, emphasized by numerous preceding research endeavors (Alqattan and Alhayky, 2016; Maghyereh *et al.*, 2017; Abuzayed and Al-Fayoumi, 2021), which had directly and indirectly impacted various industries. Moreover, throughout this period, macroeconomic indicators showed a noticeable slowdown as the oil prices continued their decline. Finally, Figure 6 displays the dynamic TCI, spanning a range from 15% to 50%. The representation indicates a predominantly modest to moderate degree of interconnectedness among Islamic banks. This insight resonates with the overarching deduction that these financial institutions exhibit a noteworthy level of resilience, making them less vulnerable to the potential contagion effects that may arise during periods of financial turmoil.

4.4. Net Directional Connectedness

Figure 7: Net total directional connectedness.

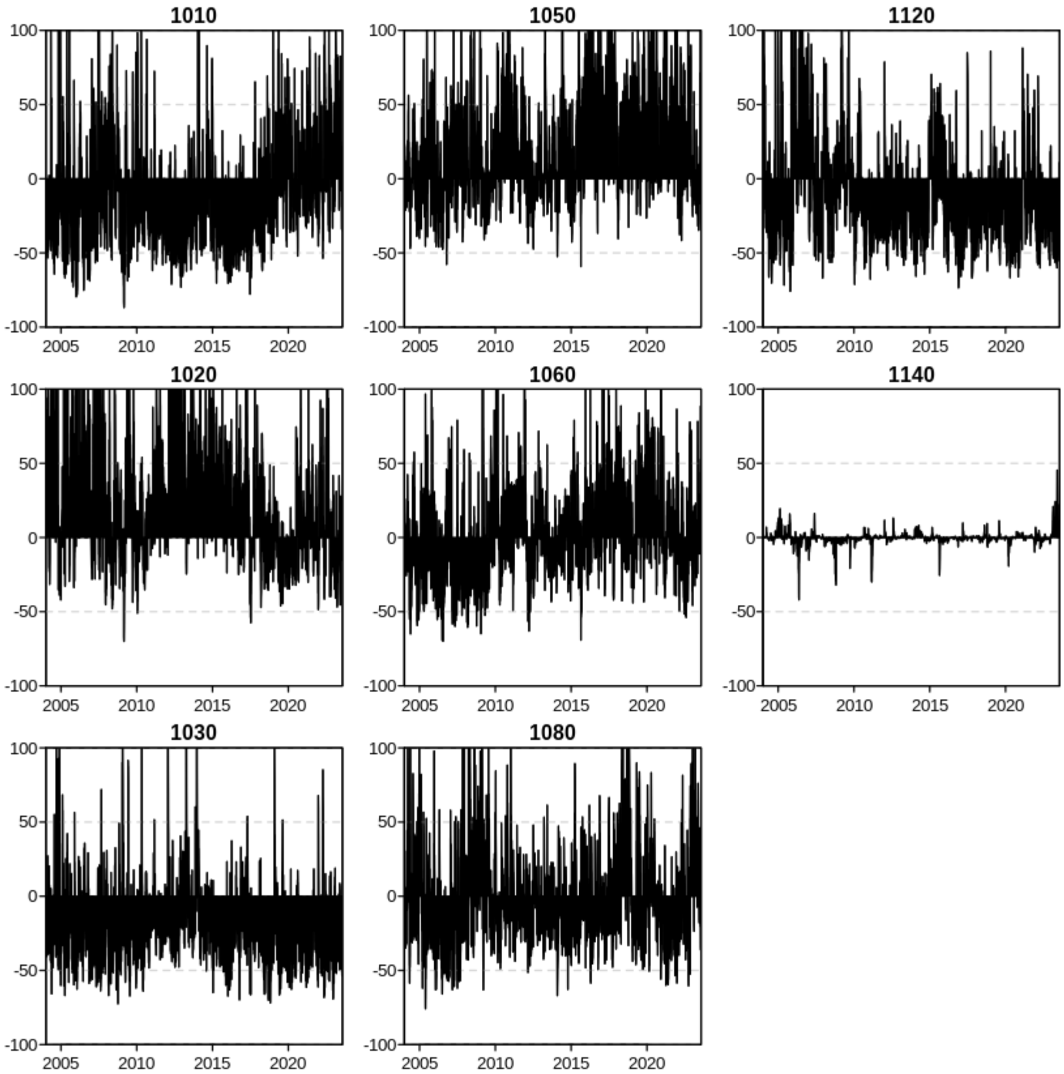


Figure 8: Total directional connectedness to other banks.

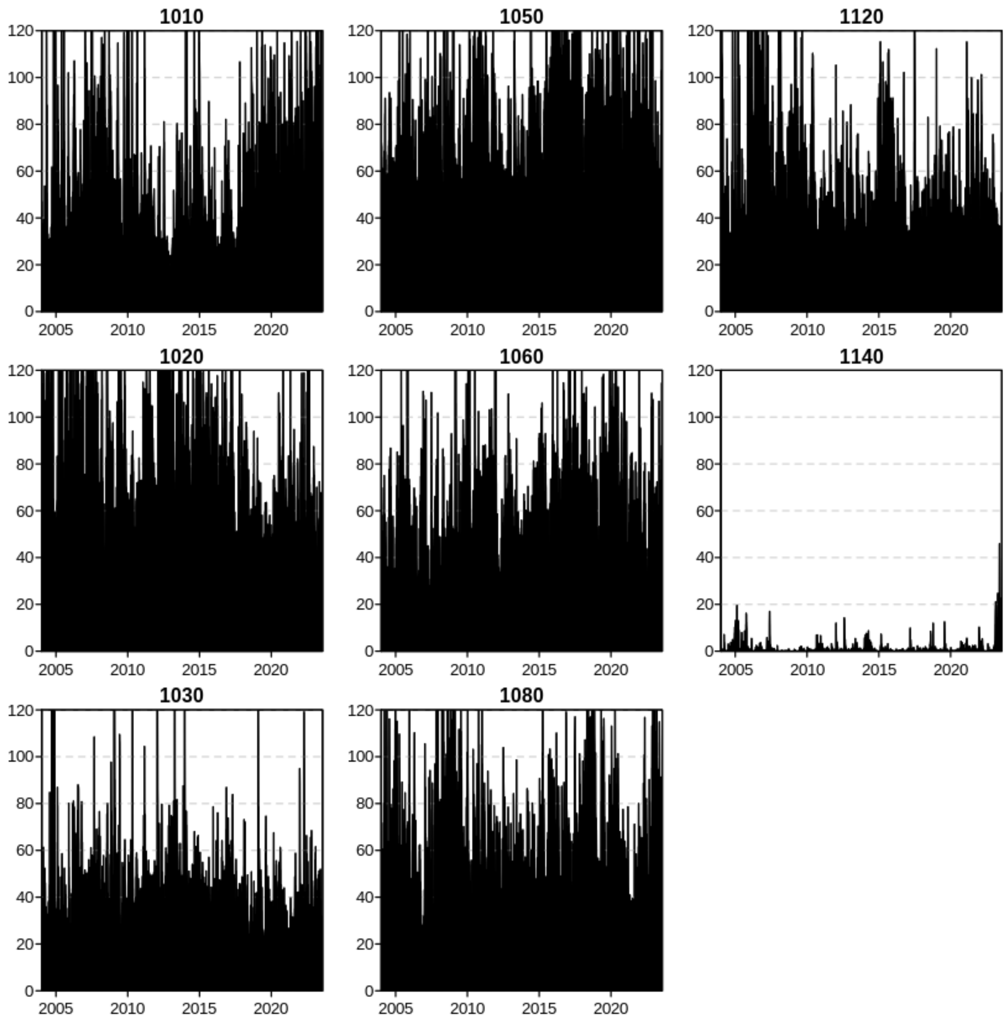
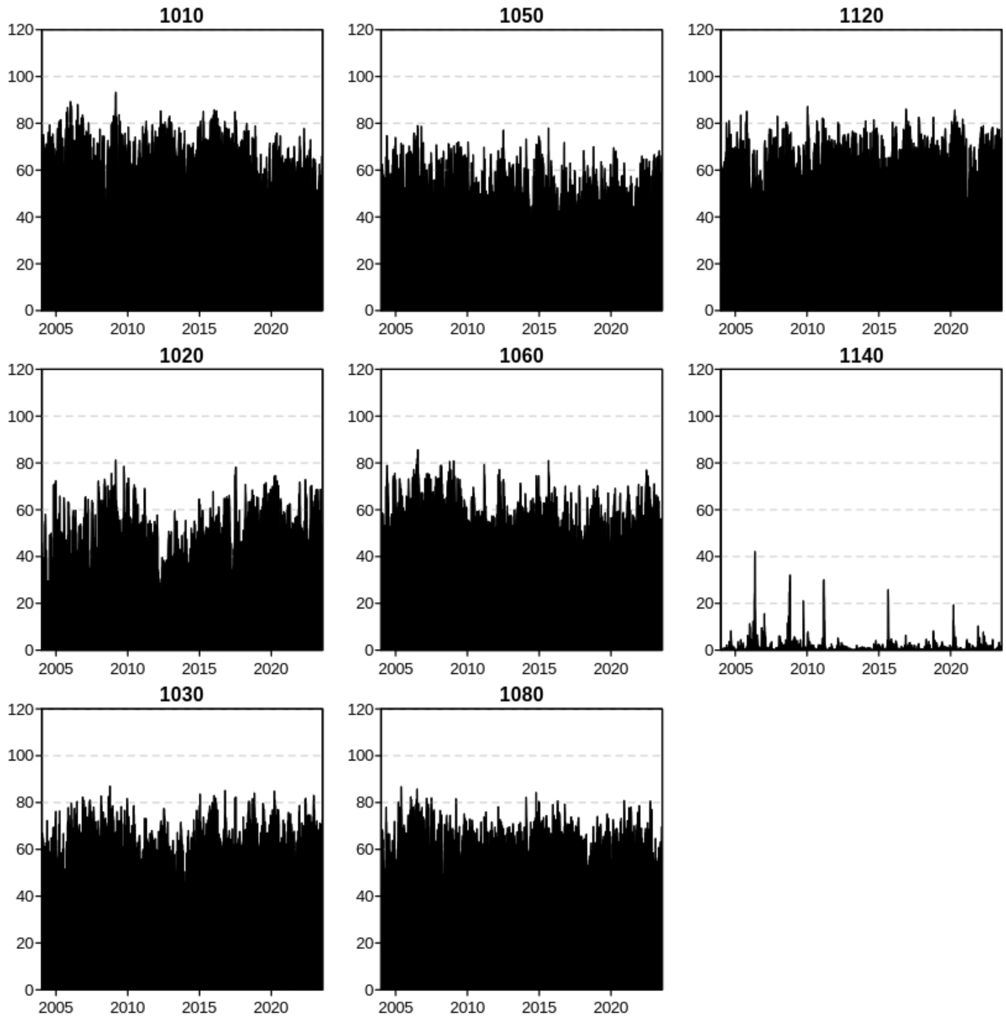


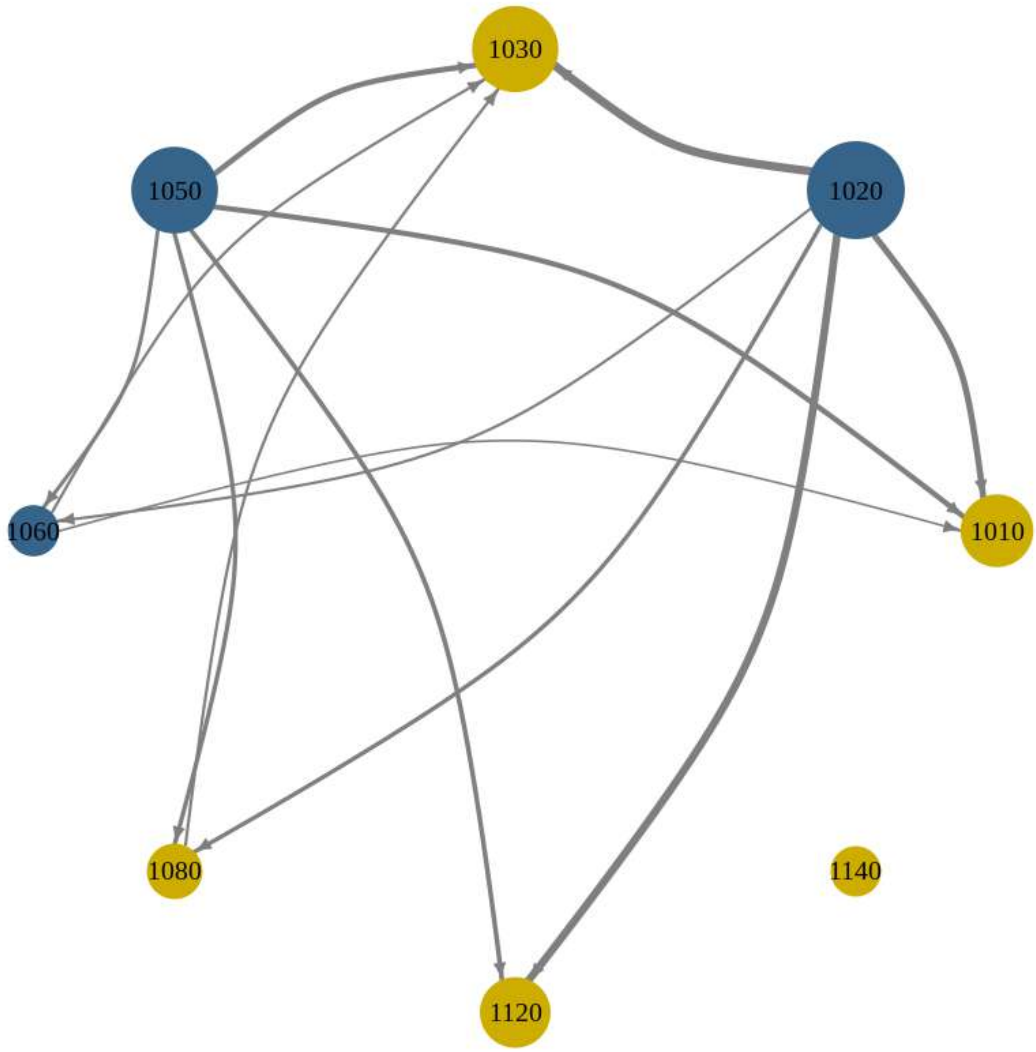
Figure 9: Total directional connectedness from other banks.



The dynamic net total directional connectedness measures are illustrated in Figure 7. The findings suggest that Bank Aljazira exerted the most significant influence throughout the interpretable period. The negative spikes, generally persistent, can be attributed to the 2008 subprime mortgage crisis, the 2020 COVID-19 pandemic, and the economic fallout from the Russia-Ukraine conflict. Similar patterns were observed for Banque Saudi Fransi, which has consistently acted as a net transmitter of shocks. The results reveal that Saudi Investment Bank tends to receive higher levels of volatility. While Al Rajhi Bank has shown a role as a net transmitter during critical junctures like the 2008 subprime mortgage crisis, the 2015 decline in oil prices, and the 2020 COVID-19 pandemic. In the case of

Bank Albilad, its influence on other series is notably limited, and conversely. Figure 8 exhibits the evolving influence of each bank on the others. The outcomes highlight Saudi Awwal Bank, Bank Aljazira, and Banque Saudi Fransi as the most impactful, while Bank Albilad emerges as the least influential, thus corroborating earlier findings. In Figure 9, the impact of all series on each bank is showcased. The results unveil that all banks were, overall, equally affected by the others, with the exception of Bank Albilad.

Figure 10: Topological representation of the interconnectedness between Islamic and conventional banks.



Moving to Figure 10, it presents a topological representation of the interconnectedness between Islamic and conventional banks, revealing significant unidirectional and bidirectional volatility spillovers both at the intersectoral and intrasectoral levels. However, our findings indicate that both incoming and outgoing connectivities are primarily influenced by the conventional banking sector. Approximately half of the conventional banks act as net transmitters, while among the Islamic banks, two thirds function as net receivers showing weaker links to the broader system, except for Bank Aljazira, which has consistently transmitted shocks to the rest of the banking sector.

5. Conclusion

This paper investigates financial connectedness and volatility spillover within a dual banking system. In pursuit of this objective, we employ the framework introduced by Gabauer (2020). This methodology offers several advantages, notably that it does not rely on a rolling-window approach to capture time-varying dynamics, and it enables us to assess whether the propagation mechanism exhibits time-varying characteristics or remains constant. The findings of our investigation uncover significant interconnectivity, which intensifies during periods of financial turbulence. Additionally, our analysis of the topological structure of interlinkages between Islamic and conventional banks reveals substantial transmission of volatility, both unidirectionally and bidirectionally, across intersectoral and intrasectoral domains. Nevertheless, our research suggests that both incoming and outgoing connectivities are primarily influenced by the conventional banking sector.

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