Journal of Infrastructure, Policy and Development 2025, 9(1), 10434.
https://doi.org/10.24294/jipd10434

Article

Risk spillovers among Islamic and conventional banks in Saudi Arabia: frequency TVP-VAR approach

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CITATION

Abdu M, Alruwaitee KA. (2025). Risk spillovers among Islamic and conventional banks in Saudi Arabia: frequency TVP-VAR approach. Journal of Infrastructure, Policy and Development. 9(1): 10434. https://doi.org/10.24294/jipd10434

ARTICLE INFO

Received: 20 November 2024
Accepted: 10 December 2024
Available online: 22 January 2025

Abstract: While extensive research has explored interconnectedness, volatility spillovers, and risk transmission across financial systems, the comparative dynamics between Islamic and conventional banks during crises, particularly in specific regions such as Saudi Arabia, are underexplored. This study investigates risk transmissions and contagion among banks operating in Islamic and conventional modes in the Kingdom of Saudi Arabia. Daily banking stock data spanning November 2018 to November 2023, encompassing two major crises—COVID-19 and the Russian-Ukraine war—were analyzed. Using the frequency TVP-VAR approach, the study reveals that average total connectedness for both banking groups exceeds 50%, with short-run risk transmission dominating over long-term effects. Graphical visualizations highlight time-varying connectedness, driven predominantly by short-run spillovers, with similar patterns observed in both Islamic and conventional banking networks. The main contribution of this paper is the insight that long-term investment strategies are crucial for mitigating potential risks in the Saudi banking system, given its limited diversification opportunities.

Keywords: frequency TVP-VAR; risk transmissions; contagion; Islamic banking; conventional banking; COVID-19; Russian-Ukraine war
JEL Classifications: C22; G15; G01; G21; L12; F15

1. Introduction

Systemic risk arises when distress in a financial institution precipitates the failure of an entire system (Acharya et al., 2012). The 2008 financial crisis was especially severe because a large number of institutions, operating in several countries and marketplaces, all suffered difficulties concurrently. For example, the collapse of Lehman Brothers on 15 September 2008, triggered a swift contagion throughout the financial system globally. This highlights how the interconnected nature of global financial system is crucial.

Interconnectedness and contagion can emerge in both normal and the crisis period; hence, contagion analysis may be directly related to banking sector stress tests by combining solvency and liquidity stress testing. Stress tends to spread more rapidly and widely throughout the financial system as interconnectedness increases (Badics, 2023). Thus, the financial sector, specifically banking, is regarded as the key source of potential systemic risk (Akhtaruzzaman et al., 2023).

During the 2007–2008 global financial crisis, the Islamic finance industry demonstrated greater resilience compared to the mainstream financial sector (Farooq and Zaheer, 2015; Lajis, 2017; Yarovaya et al., 2022). Additionally, the existing literature shows that Islamic indices and Islamic banks outperformed their conventional counterparts during periods of financial turmoil (Farooq and Zaheer, 2015; Ho et al., 2014). Furthermore, there are credible arguments for considering Islamic stocks as a safe haven and diversification asset against risks in other financial markets (Adekoya et al., 2021; Sherif, 2020; Yarovaya et al., 2020).

Another point which needs special consideration is motivated by Agoraki et al. (2023) whose study suggested that banks in Europe were not significantly affected by the COVID-19 despite being seriously affected by the global financial meltdown (GFM). Additionally, Badics (2023) examines the effect of the Russian-Ukraine invasion on the European banking network and finds that only banks from Central and Eastern Europe (CEE) exhibited a significant degree of exposure to the incident. These may also highlight that in addition to the mode of operation (Islamic or conventional), banks' reaction to particular event may differ according to a time and its geographical location (Boubaker et al., 2023).

While extensive research has explored interconnectedness, volatility spillovers, and risk transmission across financial systems, significant gaps remain. Firstly, the comparative dynamics between Islamic and conventional banks during crises, particularly in specific regions such as Saudi Arabia, are underexplored. Most studies, such as Adekoya et al. (2022) and Tabash et al. (2023), focus on broad market-level analyses or inter-market spillovers but do not delve into intra-market dynamics at the individual banking stock level.

Additionally, although frequency-based methods like Frequency TVP-VAR (Baruník and Křehlík, 2018) have been used to study financial connectedness (e.g., Da Silva et al., 2024; Furuoka et al., 2023), limited research applies this approach to separately analyze Islamic and conventional banks. There is a lack of detailed examination of short- and long-term risk transmission within these banking categories, especially during systemic crises like COVID-19 and geopolitical conflicts.

Furthermore, studies like Akhtaruzzaman et al. (2023) and Badics (2023) highlight the importance of regional and systemic contagion but do not integrate the unique operational frameworks of Islamic banking. This omission leaves a gap in understanding how Shariah principles influence resilience or vulnerability to financial shocks.

Lastly, while recent works (e.g., Mezghani et al., 2024) examine interdependencies in Islamic financial markets, few provide actionable insights for policymakers to tailor strategies for enhancing financial stability. This gap underscores the need for research that not only identifies risk dynamics but also offers practical recommendations, particularly in regions dominated by dual banking systems like Saudi Arabia

Thus, the study's contributions are three-folds: to begin with, it advances the understanding of intra-market dynamics in Saudi Arabia by examining comparatively a risk propagation among Islamic and conventional banks, addressing gaps in existing research that primarily focuses on broader market-level analyses. Similarly, using a Frequency TVP-VAR approach, decomposes risk transmissions into short- and long-term effects, offering a more insight into a systemic risk dynamic. Furthermore, by analyzing major crises like COVID-19 and the Russia-Ukraine war, the study provides valuable insights into the resilience and risk behavior of Islamic and conventional banks which enhancing knowledge on dual banking systems under stress.

2. Empirical literature review

The interconnectedness and risk transmission across financial markets and banking sectors have been widely studied using advanced econometric techniques. Adekoya et al. (2022) analyzed volatility connectedness between conventional and Islamic stock markets at the sectoral level using a TVP-VAR-based connectedness approach. Their findings revealed strong market interconnections, with technology, utilities, and oil and gas sectors being net receivers of volatility shocks. Notably, Islamic markets showed greater resilience to the COVID-19 pandemic compared to conventional markets. Similarly, Furuoka et al. (2023) examined the short- and long-run connectedness of energy and agricultural commodities using a Frequency TVP-VAR framework. The results demonstrated time-varying connectedness, with reduced interdependence during the 2020–2021 pandemic, offering portfolio diversification opportunities.

Beraich and El Main (2022) explored the Moroccan interbank sector's volatility spillovers during COVID-19 using the Diebold and Yilmaz (2012, 2014) methodology. They found heightened spillover effects and increased interdependence during the crisis. In a different context, Akhtaruzzaman et al. (2023) investigated the contagion effect following the failure of Silicon Valley Bank using dynamic conditional correlation and Diebold-Yilmaz analyses. Their study concluded that contagion was significant among global banks but limited in other sectors, and it subsided quickly after the initial shock.

In the context of the Russo-Ukrainian war, Badics (2023) applied the Diebold-Yilmaz framework to analyze European banking networks, finding peak volatility-connectedness during the war's early stages. Institutions from the CEE region played a key role in risk transmission during this period. Tabash et al. (2023) investigated return spillovers across GCC Islamic and conventional banks using Diebold-Yilmaz and Barunik-Krehlik methods. Their findings highlighted time-varying, asymmetric, and crisis-sensitive spillovers, with Islamic banks exhibiting weaker connectedness compared to conventional counterparts.

Balcilar et al. (2023) examined financial connectedness in MENA economies under extreme market conditions using Diebold-Yilmaz and frequency connectedness methods. Their study found strong financial stress co-movements and spillovers during high-stress periods, particularly among Gulf countries. Agoraki et al. (2023) assessed the euro area banking system's performance using time-varying parameter models and found that COVID-19 did not statistically impact the banking sector's performance significantly.

Da Silva et al. (2024) explored contagion risk among Brazilian bank stocks using a Frequency TVP-VAR approach, revealing short-run risk transmission as the dominant factor. Amar (2019) employed a TVP-VAR model to evaluate monetary policy transmission in a dual banking system, finding varying impacts on Islamic and conventional banks. Rudari et al. (2023) applied a TVP-VAR-BK approach to examine spillovers among exchange rates, inflation, and liquidity in Iran, uncovering significant interdependencies.

Further, Tabash et al. (2023) used a Frequency TVP-VAR approach to analyze the dynamic dependency between Shariah-compliant and traditional stock markets during crises, demonstrating diversification benefits of Shariah stocks. Mezghani et al. (2024) and Sahabuddin et al. (2023) investigated volatility spillovers and dynamic connectedness in Islamic and conventional markets, highlighting substantial interdependencies and hedging opportunities. Finally, Bouri et al. (2024) explored asymmetric spillovers in Islamic and conventional cryptocurrencies, showing distinct responses to market shocks.

3. Methodology

To begin with, the Frequency TVP-VAR approach is adopted in this study as it captures time-varying relationships in high-frequency data, essential for understanding dynamic contagion in the banking system (Badics, 2023). It allows for the decomposition of total connectedness into short-run and long-run effects, which is crucial during periods of crises (Boubaker et al., 2023). This method also enables a detailed bank-level analysis, addressing gaps in previous studies that focused on aggregate data (Agoraki et al., 2023). Additionally, it accounts for the evolving nature of financial interconnectedness, particularly during external shocks like COVID-19 (Diebold and Yilmaz, 2014). Lastly, the approach provides a more accurate understanding of contagion across the selected banks.

3.1. The time-varying parameter-vector autoregressive (TVP-VAR) model

The TVP-VAR method, as proposed by Antonakakis et al. (2020), is described by the following TVP-VAR (p).

$$\phi_t x_t = \phi_{1t} x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + u_t \tag{1}$$

where xt, $xt-1$, …, $xt-p$ and ut are $N \times 1$ vector, and $ut \sim N(0, \Sigma t)$. The parameters ϕit, $i = 1, ..., p$ are $N \times N$ TVP-VAR represents a matrix of time-varying variance-covariance coefficients. For any given vector of stationary series $\{xt\}$, equation (1) can be presented in form of TVP-VMA (∞) model, where $xt = \psi(B)ut$. Here, $\psi(B)$ denotes the moving average lag polynomial matrix derived from $\phi(B) = [\psi(B)]-1$ and $\phi(B) = [IN - \phi itB - \cdots, \phi ptBp]$ with IN as matrix of identity. The $\psi(B)$ encompasses an infinite lags approximated by ψh (B) for $h = 1, \ldots, H$ time period.

3.2. Time-varying frequency connectedness models

The Frequency TVP-VAR methodology developed by Baruník and Křehlík (2018) extends the standard connectedness framework by allowing for the decomposition of connectedness into distinct frequency bands, offering a nuanced view of short-, medium-, and long-term dynamics in financial systems. Unlike traditional connectedness frameworks, which only capture time-based variations in relationships among variables, this approach enables the measurement of connectedness across frequency ranges, enhancing our ability to analyze how shocks impact systems over different time horizons.

For example, while high-frequency shocks may indicate short-term fluctuations driven by temporary market conditions, low-frequency shocks highlight long-lasting impacts that might stem from structural changes, such as shifts in dividend policies or regulatory reforms (Balke and Wohar, 2002). By leveraging a spectral representation of the generalized forecast error variance decomposition (GFEVD)—as introduced by Pesaran and Shin (1998)—and Fourier transforms, the method produces a frequency-based connectedness measure. This spectral approach distinguishes between immediate and persistent effects of shocks, offering deeper insights into systemic risk and contagion.

The methodology's ability to isolate connectedness at specific frequencies makes it particularly valuable in analyzing the multi-dimensional nature of financial interconnectedness, especially in contexts of heightened volatility or during crises. For instance, short-term connectedness may dominate during a crisis, whereas long-term relationships might reveal systemic vulnerabilities or resilience that are less apparent in the short term. This granular perspective is critical for policymakers and investors, as it allows for tailored strategies to mitigate risks and optimize portfolio allocations over varying time horizons. The Frequency TVP-VAR approach is a sophisticated tool for dissecting the temporal and structural layers of connectedness in financial systems, making it ideal for assessing risk transmission and contagion in contexts with both short-lived shocks and enduring systemic changes (Baruník and Křehlík, 2018; Diebold and Yilmaz, 2016).

Furuoka et al. (2023) introduce an orthogonalized generalized forecast error variance decomposition (GFEVD) which is used to measure how all variables j respond to a shock in variable i.

$$\tilde{\theta}_{jk,t}(H) = \frac{(\Sigma_t)_{kk}^{-1}\Sigma_{h=0}^{H}[(\psi_h\Sigma_t)_{jkt}]^2}{\Sigma_{h=0}^{H}(\psi_h\Sigma_t\psi'_h)_{jj}} \tag{2}$$

where $\tilde{\theta}_{jk,t}(H)$ denotes the total influence of jth in terms of VFE, to the ith variable at forecast horizon H. The numerator of (2) represents the cumulative impact of the shocks to variable j from the network, while the denominator represents the cumulative effect of all shocks in the system's of connectedness. By definition, the rows of Equation (2) require normalization in order to add to one. Therefore, Equation (2) is normalized as follows,

$$\tilde{\theta}_{jk,t}(H) = \frac{\tilde{\theta}_{jk,t}(H)}{\Sigma_{k=1}^{n}\tilde{\theta}_{jk,t}(H)} \tag{3}$$

where $\sum_{k=1}^{n}\tilde{\theta}_{jk,t}(H)$=1 and $\sum_{j,k=1}^{n}\tilde{\theta}_{jk,t}(H) = n$.

In addition, Furuoka et al. (2023) subjected (2) into series of modifications including the decomposition of the FEV for connectedness into short-run and long-run to generate the measure of frequency TVP-VAR total connectedness.

Following Baruník and Křehlík (2018) and Chatziantoniou et al. (2021), the decomposition into short- and long-term connectedness is achieved by analyzing variance contributions over specific frequency bands. Using the frequency response function derived via Fourier transformation, the variance of variables is examined across different frequencies. High-frequency bands capture short-term, transitory effects, while low-frequency bands represent long-term, persistent influences. The Generalized Forecast Error Variance Decomposition (GFEVD) is adapted for the frequency domain to attribute variance to shocks within specific frequency ranges. By aggregating GFEVD values over these bands, the method distinguishes between short- and long-term connectedness, providing insights into temporal relationships between variables.

The authors initially reported the below given normalized version of this frequency GFEVD

$$\bar{\phi}_{jk,t}(H) = \frac{\widetilde{\theta}_{jk,t}(\omega)}{\sum_{k=1}^{n}\widetilde{\theta}_{jk,t}(\omega)} \tag{4}$$

and subsequently Equation (5) which state that the information about spillovers offered by the frequency connectedness lies within a given frequency range d.

$$\bar{\phi}_{jk,t}(d) = \int_{a}^{b} \bar{\phi}_{jk,t}(\omega)d\omega \tag{5}$$

3.3 Connectedness measures

Using the frequency decomposition of GFEVD from Equation (5), the following measures are derived.

The average effect of a shock from a variable j to another group of variables k is the measure of overall connectedness of the network, and it is called the Average Total Connectedness Index, ($TFCIjk$) of j to any of k variables. This assesses market risk by calculating the average size of spillovers between variables j and k. Hence, $TFC\text{U}jk$ is determined by averaging overall connectedness in the network over the different time periods ($TFO\text{U}t(d)$)

$$TFCI_t = n^{-1}\sum_{j=1}^{n} TO_{j,t}(d) = n^{-1}\sum_{j=1}^{n} FROM_{j,t}(d) \tag{6}$$

where TOj, $t(d)$ is the size of shock the variable j propagates to all other variables k. This represents the overall directional connectedness to other variables and is defined as,

$$TO_{j,t}(d) = \sum_{j=1,j\neq k}^{n} \phi_{kj,t}(d) \tag{7}$$

The $FROMj$, $t(d)$ represents the size of shocks received by the variable j from the system. This is the complete directional spillover received from the rest of the system, expressed as:

$$FROM_{j,t}(d) = \sum_{j=1,j\neq k}^{n} \phi_{kj,t}(d) \tag{8}$$

The difference between Equations (7) and (8) is the net-directional spillover, specified as,

$$NET_{j,t}(d) = \sum_{j=1,j\neq k}^{n} \phi_{kj,t}(d) - \sum_{j=1,j\neq k}^{n} \phi_{kj,t}(d) \tag{9}$$

If the ($NET_{j,t}(d)$) > 0, variable j is the net emitter of risks in the system, while variables k are the net receivers. If ($NET_{j,t}(d)$) < 0, then the reverse is the case.

The NPDFC which stands for Net Pairwise Directional Frequency Connectedness measures the bidirectional transmissions of risks between variables j and i. It is given as follows:

$$NPDFCj\mathrm{i}, t(d) = NETj, t(d) - NET\mathrm{i}, t(d) \tag{10}$$

3.4. Data source and type

This study employs daily spot price data for the stocks of 10 selected banks, obtained from Data Stream, spanning five working days from 23 November 2018, to 26 November 2023. This timeframe encompasses two significant events: the COVID-19 pandemic and the Russian-Ukraine war, making it well-suited for conducting frequency- and time-varying analysis. The selection of 10 banks is based on data availability, while the focus on Saudi Arabia is driven by the limited comparative studies on Islamic and conventional banks during crises, particularly in specific regions such as Saudi Arabia. The names of the banks, their modes of operation, and stock proxies are detailed in **Table 1**. In this study, log-returns are used for the analysis and are calculated using the given conventional formula: ret= log $\left(\frac{p_t}{p_{t-1}}\right)$, where p_t and p_{t-1} is the current and previous price respectively.

Table 1. List of the selected banks.

BANKS NAME	MODE OF OPERATION	PROXY
Bank Aljazira	Islamic Banking	BZJ
Arab National Bank	Conventional Banking	ANB
Bank Albilad	Islamic Banking	BABD
Alinma Bank	Islamic Banking	ALB
Riyad Bank	Conventional and Islamic	RB
Al Rajhi Bank	Islamic Banking	RJH
The Saudi Investment Bk	Conventional and Islamic Banking	SIB
Banque Saudi Fransi	Conventional and Islamic Banking	BSF
Saudi Awwal Bank	Conventional and Islamic Banking	SAB
The Saudi National Bank	Conventional and Islamic Banking	SNB

Source: Alsharif (2021), mode of operations: Banks that operate purely Islamic banking is considered an Islamic bank, while banks operate either purely conventional banking or Both Islamic and conventional banking are considered conventional banks.

The plots of the stock prices and returns are given in **Figures 1–4**. **Figure 1** portrays the behavior of Islamic banking stock prices, which include Alinma Bank (ALB), Bank Albilad (BABD), Bank Aljazira (BZJ), and Alrajhi Bank (RJH). It is observed that all the price indexes exhibited a common trend, which swiftly fell in the first quarter of 2020 and jumped to reach a peak between the first and second quarters of 2022, eventually starting to fall in the middle of the second quarter of 2022. Corresponding to these two different periods are the events of COVID-19 and the Russian-Ukraine war.

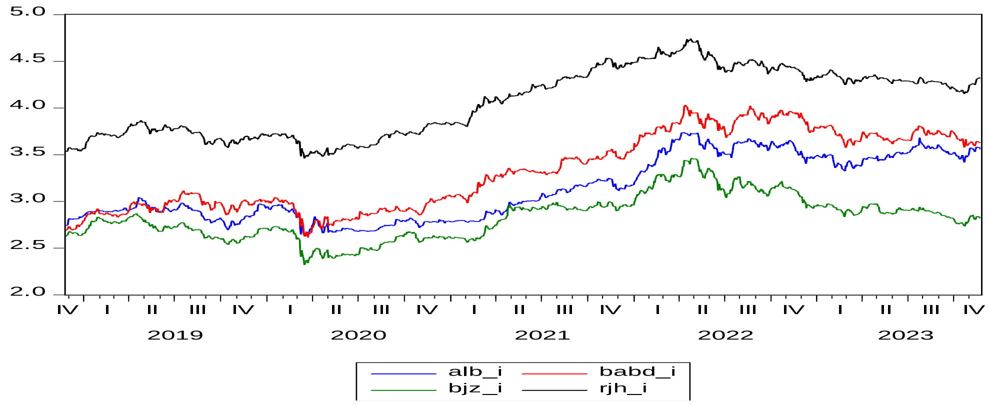

Figure 1. Islamic banks stock prices.

The stock prices for the conventional banks are reported in **Figure 2**. The conventional banks' stocks covered are: Saudi National Bank (SNB), Saudi Investment Bank (SIB), Saudi Awwal Bank (SAB), Banque Saudi Fransi (BSF), Arab National Bank (ANB), and Riyad Bank (RB). All the stocks have exhibited the same trends as Islamic banks in terms of their reaction to the events of COVID-19 and the Russian-Ukraine war.

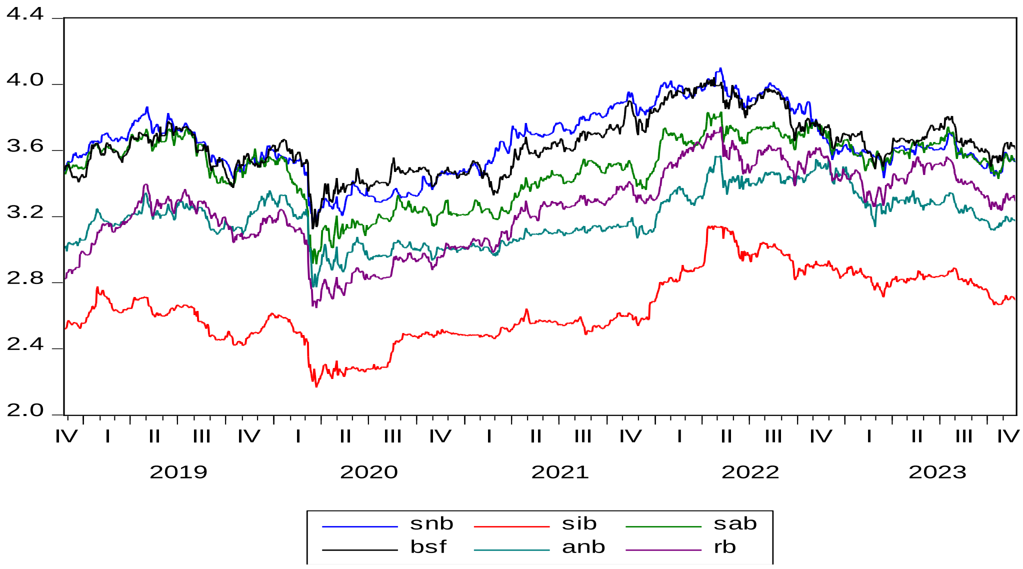

Figure 2. Conventional banks stock prices.

The returns series of Islamic and conventional banks are depicted in **Figures 3** and **4**, respectively. The volatility clustering is observed in the first quarter of 2020 and midway through the second quarter of 2022 for all the Islamic banks' stocks. This shows how they responded to these two major events, as documented in (1). The same behavior has been observed in the conventional banks' stocks in **Figure 2**. These common behaviors could reveal how interconnected each group is and the possibility of risk contagion in the event that one of the banks is in crisis.

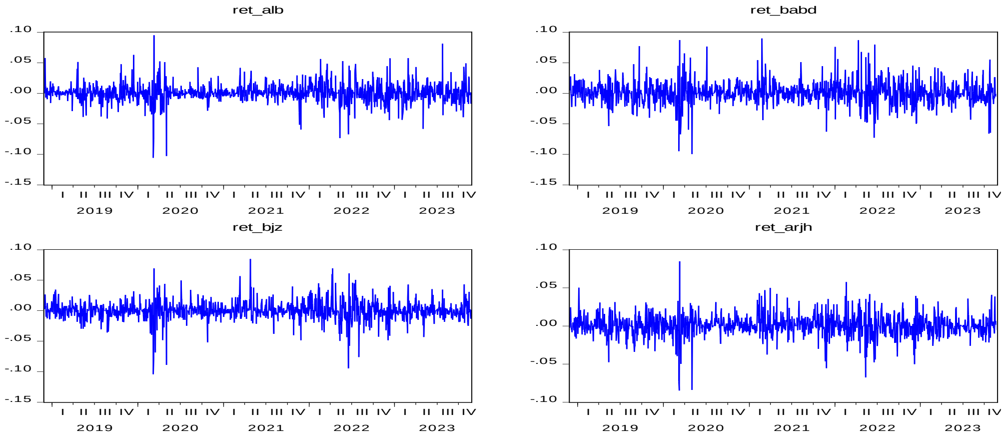

Figure 3. Islamic banks stocks' returns volatility.

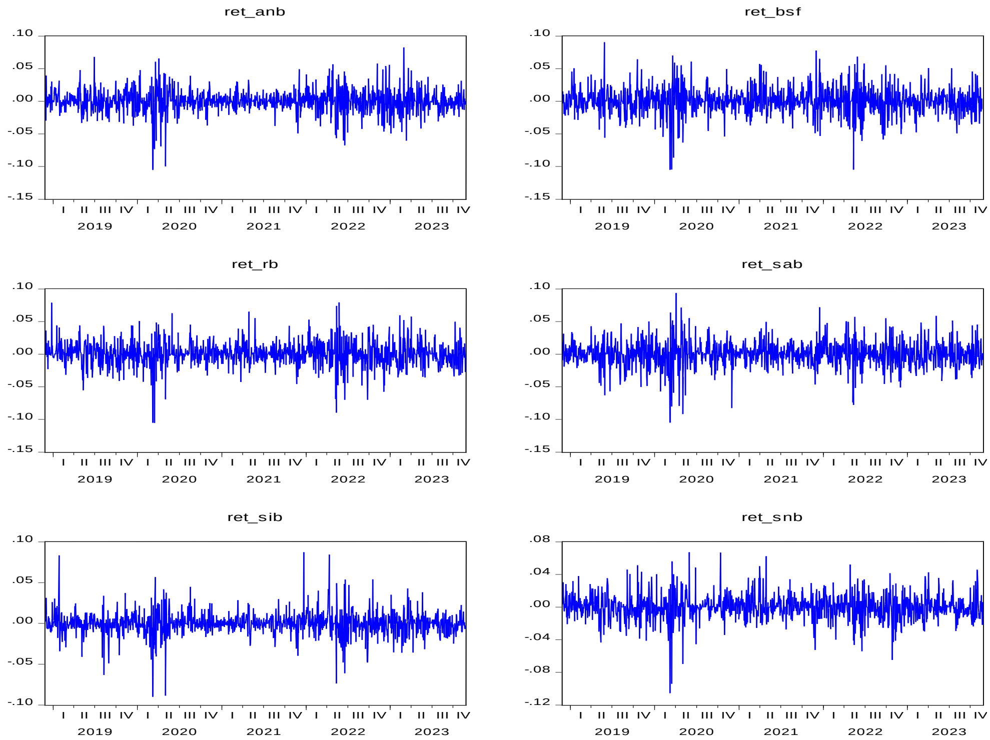

Figure 4. Conventional banks stocks' returns volatility.

4. Results discussions

Table 1, Panel -A, reports the average log-returns of Islamic banks ranging from 0.073% (BABD) to 0.0015% (BJZ), which is quite higher than that of conventional banks reported in the lower Panel-B. The unconditional volatilities of the returns range between 1.84% and 1.41%, which means that the Islamic banks are less volatile than their conventional counterparts. All the returns are left-skewed and fat-tailed except BABD, which is right-skewed. They are also not normally distributed, according to Jarque-Bera statistics.

Similarly, the Conventional Bank's statistics are reported in the panel-B of the table; the average returns range from 0.036% (RB) to 0.0040% (SNB); the returns' unconditional volatilities range from 2.02% to 1.92%; all the returns are left-skewed and fat-tailed. They are also not normally distributed, according to Jarque-Bera statistics. The ADF-test has rejected the unit root hypothesis for all the returns.

Table 2. Returns descriptive statistics and unit-roots-test.

RETURNS	MEAN	SD	SKEWNESS	KURTORSIS	JB-STATISTICS	ADF-UNITROOTs
ISLAMIC BANKS						
RET_RJH	0.0006	0.0141	−0.306928	7.813433	1279.330***(0.0000)	−33.312***(0.0000)
RET_ALB	0.0006	0.0156	−0.147499	9.868499	2567.973***(0.0000)	−32.509***(0.0000)
RET_BABD	0.0007	0.0184	0.183732	7.015707	883.5108***(0.0000)	−32.720***(0.0000)
RET_BJZ	0.0002	0.0153	-0.395719	9.959308	2665.503***(0.0000)	−33.550***(0.0000)
CONVENTIONAL BANKS						
RET_ANB	0.0001		−0.491771	7.844653	1327.799***(0.0000)	−33.910***(0.0000)
RET_BSF	0.0001		−0.274207	6.164340	560.3834***(0.0000)	−34.383***(0.0000)
RET_RB	0.0004		−0.348082	7.064421	923.8931***(0.0000)	−34.152***(0.0000)
RET_SAB	0.00005		−0.373710	6.464080	682.3444***(0.0000)	−34.210***(0.0000)
RET_SIB	0.0001		−0.100128	10.98011	3462.247***(0.0000)	−33.760***(0.0000)
RET_SNB	0.00004		−0.295298	7.405314	1073.387***(0.0000)	−31.378***(0.0000)

Source: Authors computation, *, **, *** indicate 10%,5% and 1% level of significant respectively.

Tables 3–5 show the average time-varying and frequency total, as well as the short- and long-term risk spillover. Based on panel A, the average total frequency spillover is 50.73%, indicating that interconnectivity among Islamic banks accounts for slightly more than half of the network's connectedness, while the remaining 49.27% of volatility originates from individual banks. BJZ (1.87%) and ALB (1.19%) are the first and second net transmitters of volatility transmissions in the Islamic banking network, respectively. This finding contradicts Hernandez et al. (2020), who reported lower connectedness within the financial network.

Looking at disaggregated connectedness in Panel B, the average short-term frequency spillover reveals that BABD (−2.20%) is the only net recipient of volatility, while ALB (1.22%), BJZ (0.95%), and RJH (0.03%) all contributed to the total spillover, with ALB as the main contributor, followed by BJZ as a second.

Table 3. Time frequency total connectedness, averages (Islamic banks).

RETURNS	RET_RJH	RET_ALB	RET_BABD	RET_BJZ	FROM
RET_RJH	50.16	16.96	15.24	17.64	49.84
RET_ALB	16.22	47.75	15.56	20.47	52.25
RET_BABD	16.07	16.23	51.55	16.14	48.45
RET_BJZ	17.25	20.25	14.89	47.61	52.39
TO	49.54	53.44	45.68	54.26	202.92
INC.OWN	99.71	101.19	97.23	101.87	TCI: 50.73%
NET	−0.29	1.19	−2.77	1.87	
NPDC	1.00	2.00	0.00	3.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

Table 4. Time frequency total connectedness, short-run averages (Islamic banks).

RETURNS	RET_RJH	RET_ALB	RET_BABD	RET_BJZ	FROM
RET_RJH	37.74	12.51	11.05	12.95	36.51
RET_ALB	12.19	36.76	11.42	15.33	38.94
RET_BABD	11.50	12.26	39.32	11.97	35.73
RET_BJZ	12.85	15.38	11.06	36.80	39.29
TO	36.53	40.16	33.53	40.24	150.46
INC.OWN	74.27	76.91	72.85	77.04	TCI: 37.61%
NET	0.03	1.22	−2.20	0.95	
NPDC	1.00	3.00	0.00	2.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

Table 5. Time frequency total connectedness, long-run averages (Islamic banks).

RETURNS	RET_RJH	RET_ALB	RET_BABD	RET_BJZ	FROM
RET_RJH	12.42	4.44	4.19	4.70	13.33
RET_ALB	4.02	11.00	4.14	5.14	13.31
RET_BABD	4.58	3.97	12.23	4.18	12.72
RET_BJZ	4.41	4.87	3.82	10.82	13.10
TO	13.01	13.28	12.15	14.01	52.46
INC.OWN	25.43	24.28	24.39	24.83	TCI: 13.12%
NET	−0.32	−0.03	−0.57	0.92	
NPDC	1.00	1.00	1.00	3.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

In **Table 5**, the BJZ (0.92%) index is the sole source of spillover to the system in the long run, while BABD (–0.57%), RJH (–0.32%), and RJH (–0.03%) are all recipients of the volatility spillover. The average short-term frequency spillover is around 37.61%, which is much higher compared with the 13.12% volatility spillover in the long run. This means that the short-run shock is the main driver of the risk spillover in the Saudi Islamic banking network, and the same scenario is observed in the commodities network by Furuoka et al. (2023). The possible explanation of this result is that risk transmission among the Islamic banking network in Saudi Arabia is done within 5 working days, and all the past information or volatility plays an inconsequential role in the current time connectedness and risk spillover among the Islamic banking network in Saudi Arabia.

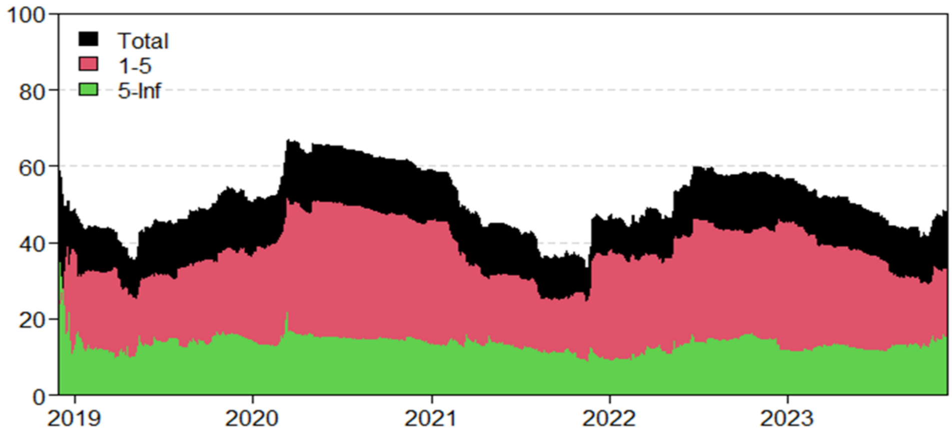

Figure 5. Total frequency connectedness between Islamic banks' stocks.

Figure 5 illustrates the dynamic connectedness over time, highlighting major events such as COVID-19 and the Russia-Ukraine war. The total dynamic connectedness is divided into short-term (within five working days) and long-term (beyond five working days). The index shows a notable surge during the first quarter of 2020 (COVID-19) and the first quarter of 2022 (Russia-Ukraine war), consistent with findings from Beraich and El Main (2022) for Moroccan banks during COVID-19 and Badics (2023) for European banks' reaction to the Russia-Ukraine war. A key characteristic of the Saudi Islamic banking network is the dominance of short-term connectedness in total risk transmission, which becomes more pronounced during crises. This observation aligns with recent studies by Alsubaie et al. (2023), Dammak et al. (2024), Da Silva et al. (2024), Furuoka et al. (2023) and Tabash et al. (2023).

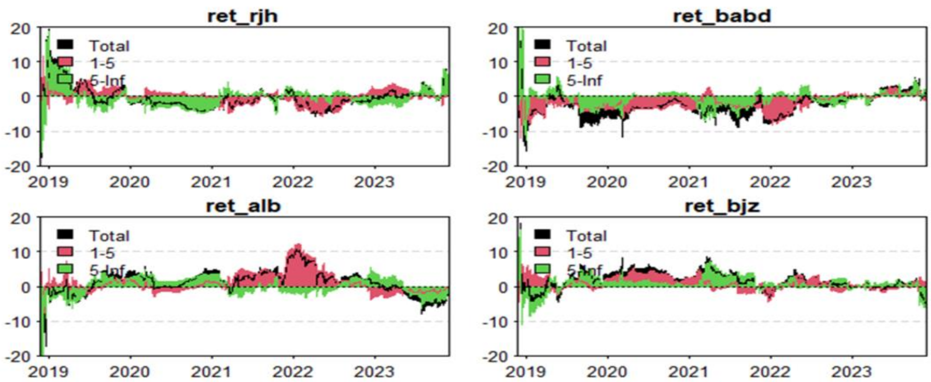

Figure 6. Net total directional frequency connectedness of individual Islamic banking stocks.

Figure 6 gives the net frequency connectedness of each index, which explains the role of each stock in the total connectedness of the system. The BJZ and ALB are the only net transmitters, and their influences on short- and long-term volatility have been oscillating, with short-term becoming dominant in the majority of the time horizon. Further analysis of the results is done using the one-on-one net-directional frequency connectedness in **Figure 7**, and it is observed that BJZ turns out to be dominant on two occasions and ALBD and ALB each on one occasion.

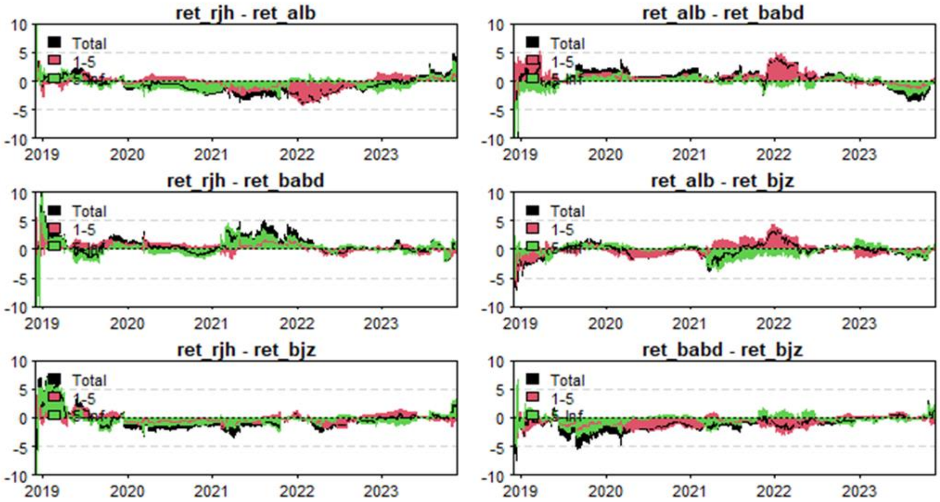

Figure 7. Net pairwise directional frequency connectedness among the Islamic banking stocks.

Tables 6–8 reports the average connectedness index of the conventional banks, which is reported in three forms: total (**Table 6**), short-run (**Table 7)**, and long-run (**Table 8**). The average total connectedness index is 52.12%, which is decomposed into 37.71% and 14.00%, respectively, for the short run and the long run. This demonstrated that, on average, 52.12% of the risk transmission within the system is attributed to the interrelationship between the banks under the same mode of operation, while the remaining 47.98% is associated with the internal circumstances within each bank. Additionally, the overall average connectedness of the entire network of conventional banking is dominated by short-run volatility. The high level of connectedness between banks in a particular market could be the signs of high degree of inter-banks activities (Hernandez et al., 2020).

Table 6. Time frequency total connectedness, averages (conventional banks).

RETURNS	RET_SNB	RET_SAB	RET_BSF	RET_SIB	RET_RB	RET_ANB	FROM
RET_SNB	47.39	11.41	9.58	7.09	14.45	10.08	52.61
RET_SAB	11.03	45.16	12.92	7.40	12.72	10.78	54.84
RET_BSF	9.75	13.71	47.16	6.45	12.25	10.69	52.84
RET_SIB	8.48	8.61	7.41	56.08	9.60	9.82	43.92
RET_RB	13.40	11.77	11.40	7.73	44.45	11.25	55.55
RET_ANB	10.57	11.39	10.31	8.73	11.93	47.07	52.93
TO	53.22	56.89	51.62	37.41	60.94	52.63	312.70
INC.OWN	100.61	102.04	98.78	93.49	105.39	99.70	TCI: 52.12%
NET	0.61	2.04	−1.22	−6.51	5.39	−0.30	
NPDC	3.00	4.00	1.00	0.00	5.00	2.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

Table 7. Time frequency total connectedness, short-run averages (conventional banks).

RETURNS	RET_SNB	RET_SAB	RET_BSF	RET_SIB	RET_RB	RET_ANB	FROM
RET_SNB	35.26	8.26	6.96	4.94	10.73	7.19	38.08
RET_SAB	7.87	35.34	9.67	5.32	9.42	7.85	40.13
RET_BSF	6.86	9.87	36.65	4.59	9.19	7.71	38.22
RET_SIB	5.70	6.06	5.27	43.01	6.87	7.01	30.91
RET_RB	9.91	8.90	8.60	5.56	34.61	8.14	41.11
RET_ANB	7.28	8.08	7.55	6.09	8.82	36.79	41.11
TO	37.62	41.16	38.05	26.49	45.03	37.90	37.82
INC.OWN	72.88	76.50	74.70	69.50	79.64	74.68	226.25
NET	−0.46	1.03	−0.16	−4.41	3.92	0.08	TCI: 37.71%
NPDC	2.00	4.00	2.00	0.00	5.00	2.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

Table 8. Time frequency total connectedness, long-run averages (conventional banks).

RETURNS	RET_SNB	RET_SAB	RET_BSF	RET_SIB	RET_RB	RET_ANB	FROM
RET_SNB	12.12	3.15	2.61	2.61	3.72	2.90	14.54
RET_SAB	3.15	9.82	3.25	2.09	3.29	2.93	14.71
RET_BSF	2.89	3.84	10.51	1.86	3.05	2.98	14.62
RET_SIB	2.78	2.55	2.13	13.07	2.74	2.81	13.02
RET_RB	3.49	2.87	2.80	2.17	9.84	3.11	14.45
RET_ANB	3.28	3.31	2.77	2.64	3.11	10.28	15.11
TO	15.61	15.72	13.56	10.91	15.91	14.73	15.11
INC.OWN	27.73	25.54	24.07	23.98	25.75	25.01	86.44
NET	1.07	1.01	−1.06	−2.10	1.46	−0.38	TCI: 14.41%
NPDC	4.00	3.00	1.00	0.00	4.00	3.00	

From: The spillover from other banks.
To: spillover transmission to other banks.
TCI: averaging overall connectedness index.

Generally, RB is the net transmitter of the risk, contributing 5.39% to the system, followed by 2.04%. The net recipient of the risk is SIB (−6.51%), followed by BSF (−1.22%) on average.

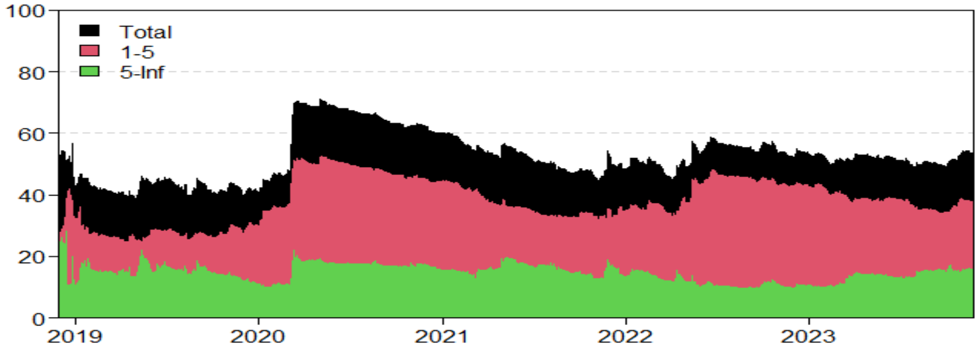

Figure 8. Total frequency connectedness among the conventional banking stocks.

Figure 8 portrays a decomposed frequency- and time-varying spillover of the conventional banks. The highest level of total connectedness has been observed during the first quarter (March) of 2020, which corresponds to the time in which the first case of COVID-19 was declared by the Ministry of Health, the subsequent closure of all domestic and international air travel, and the declaration of a curfew (Alghalyini et al., 2023; Saudi Research and Marketing Group, 2020). This period is also characterized by a massive crash in the oil price, leading to a huge budget deficit of about 9 billion USD in Saudi Arabia (Al Jazeera, 2020). The jump in the total dynamic connectedness index was also witnessed in the first quarter of 2022, which showed a slight downward trend but settled and remained around 40% throughout the sampling. This is in response to the Russian-Ukraine war which in line with finding by Badics (2023) and Bouri et al. (2024). It is also observed that the short-run volatility has been driven the total connectedness and consequently, dominated the long-run component in any other periods of crises (2020 and 2022) in the entire horizon and this result agreed with Da Silva et al. (2024).

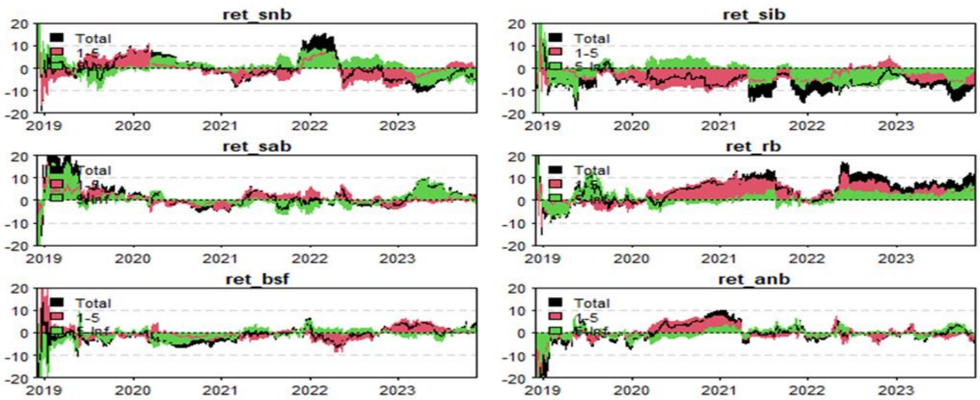

Figure 9. Net total directional frequency connectedness of individual conventional banking stock.

From **Figure 9**, RB and sab have been the net transmitters of the risk in a normal period, and both remain neutral during the crisis. SIB is the net recipient of the risk throughout the sampling period, and it received the highest risk during 2022, which corresponds to the Ukraine-Russian invasion. In addition, the SNB has been a net transmitter of short-run volatility since 2022.

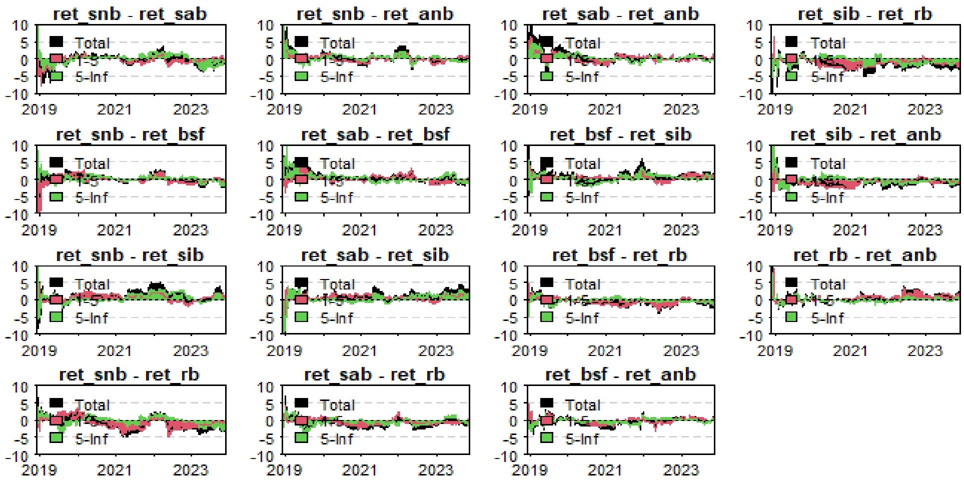

Figure 10. Net pairwise directional frequency connectedness between the conventional banking stocks.

From **Figure 10,** which is the pairwise view, no strong connectedness has been observed. This means that the volatility spillover is triggered by the interrelation among all banks rather than a bivariate interrelation. RB has been dominant in two instances, while SNB is dominant in only one instance.

5. Robustness check: Dynamic conditional correlation GARCH (1.1) model

To ascertain the robustness of the results, the DCC model for each category is estimated and result is reported in (Table 9). From the model, the sum of arch and garch terms is less than one for most of the banks, which shows the absence of volatility persistence in all but three banks' returns (ALB, RB and ANB). The significance of the two DCC parameters ($\alpha + \beta$) suggests the existence of both short- and long-run correlation over time and, hence, time-varying spillover within both Islamic and conventional banking networks. Finally, the sum of the parameters of the DCC (α + β) model is less than unity for both groups, which signifies the mean-reverting nature of the volatility. These results have strengthened the findings that have been obtained in the preceding section from the frequency TVP-VAR, thus confirming that the results are robust to the change of techniques. The results are also consistent with Hasan (2019). This scenario has been observed in the bivariate plots of the conditional correlations between returns (see Appendix A, **Figures A1** and **A2**). In each category, the plots have shown that the positive and time-varying correlation between each pair of returns is stronger at different times of turbulence. Finally, the figures strongly support the plots of frequency-time-varying connectedness depicted in the previous section. It also supported the existing DCC studies by Tabash et al. (2023) and Saadaoui and Boujelbene (2015).

Table 9. The DCC-GARCH (1, 1).

RETURNS	COFFIENTS	RETURNS	COEFFECIENTS
Islamic		Conventional	
RJH	*Arch + Garch=0.911*	SNB	*Arch + Garch = 0.943*
Const.	0.000020***(0.0049)	Const.	0.000016 **(0.0149)
AR(1)	0.000636*(0.0724)	AR(1)	0.000390(0.3247)
Arch	0.190770***(0.0000)	Arch	0.121417***(0.0000)
Garch	0.719540***(0.0000)	Garch	0.819473***(0.0000)
ALB	*Arch + Garch=0.974*	SAB	*Arch + Garch = 0.956*
Const.	0.000009***(0.0095)	Const.	0.000017*(0.0799)
AR(1)	0.000969***(0.0057)	AR(1)	0.079936(0.5931)
Arch	0.131310***(0.0000)	Arch	0.114974***(0.000647)
Garch	0.843452***(0.0000)	Garch	0.840963***(0.0000)
BABD	*Arch + Garch=0.949*	BSF	*Arch + Garch = 0.938*
Const.	0.000018**(0.0383)	Const.	0.000025**(0.0219)
AR(1)	0.001024**(0.0193)	AR(1)	0.000507(0.2934)
Arch	0.114216***(0.0019)	Arch	0.111414***(0.0010)
Garch	0.834709**(0.0000)	Garch	0.827037***(0.0000)
BJZ	*Arch + Garch=0.951*	SIB	*Arch + Garch = 0.937*
Const.	0.000013***(0.0000)	Const.	0.000018***(0.0000)
AR(1)	0.000154(0.670)	AR(1)	0.00016(0.606373)
Arch	0.119821***(0.0000)	Arch	0.222355***(0.0011)
Garch	0.830693***(0.0000)	Garch	0.714728***(0.0000)
		RB	*Arch + Garch =0.978*
		Const.	0.000021(0.251871)
		AR(1)	0.000817*(0.0673)
		Arch	0.080808*(0.0618)
		Garch	0.854251***(0.0000)
		ANB	*Arch + Garch =0.979*
		Const.	0.000007 (0.5410)
		AR(1)	0.000416(0.264939)
		Arch	0.123185*** (0.0000)
		Garch	0.856458*** (0.0000)
DCC-Islamic		DCC-Conventional	
α	0.029487**(0.0501)	α	0.009162***(0.00129)
β	0.929822***(0.0000)	β	0.970600***(0.0000)
Diagnostics			
AIC	−24.063		−34.448
SC	−23.968		−34.285
Log-likelihood	15713.1		22500.97

Source: Authors computation; *,**,*** is the significant at 10%, 5% and 1%; *Arch* + *Garch* test persistent of univariate model.

6. Conclusion and implications

This study provides a comprehensive analysis of risk spillovers and contagion dynamics within Islamic and conventional banks in Saudi Arabia, utilizing the Frequency Time-Varying Parameter Vector Autoregression (Frequency TVP-VAR) approach. By examining daily banking stock data from November 2018 to November 2023, the research reveals significant interconnectedness among both banking groups, with average total connectedness exceeding 50%. Notably, short-run risk transmission dominates over long-term effects, indicating that immediate market reactions to external shocks are more pronounced than sustained impacts.

The findings highlight the critical nature of major crises, such as the COVID-19 pandemic and the Russian-Ukraine war, in shaping the financial landscape. During the COVID-19 pandemic, both Islamic and conventional banks experienced heightened volatility and interconnectedness, with substantial spillover effects observed. Similarly, the Russian-Ukraine war further exacerbated these dynamics, leading to increased risk transmission among banks. These events underscore the importance of understanding how shocks propagate through interconnected banking systems.

Thus, this study's contributes to advance the understanding of intra-market dynamics in Saudi Arabia by comparatively examining risk propagation among Islamic and conventional banks. It employes a Frequency TVP-VAR approach to decomposes risk transmissions into short- and long-term effects, providing deeper insights into systemic risk dynamics. Finally, by analyzing major crises like COVID-19 and the Russian-Ukraine war, this study offers valuable insights into the resilience and risk behavior of both Islamic and conventional banks, enhancing knowledge on dual banking systems under stress.

The findings also highlight the need for Saudi financial regulatory authorities to implement regular monitoring of daily banking operations to facilitate timely interventions when necessary. For investors, it underscores the importance of closely tracking daily activities within the banking sector to safeguard their portfolios against potential risks. Additionally, the study does not support portfolio diversification solely within Saudi banks; instead, it suggests that investors diversify their holdings across different asset classes to achieve better risk hedging. Lastly, the results emphasize the relative safety of long-term investments, encouraging policies and strategies that promote and support long-term investment horizons.

In conclusion, this research not only enriches our understanding of intra-market dynamics during periods of crisis but also provides actionable insights for policymakers. It emphasizes the necessity for long-term investment strategies to mitigate potential risks within the Saudi banking system, particularly given its limited diversification opportunities. Policymakers are encouraged to develop tailored strategies that enhance resilience against systemic shocks, ensuring stability within both Islamic and conventional banking sectors.

7. Limitations of the study

The study focuses on Islamic and conventional banks separately, tracing the patterns of volatility spillover within each banking operation. Based on the observed co-movement within the two groups, the study could not identify the possibility of diversification. Additionally, due to data limitations, the study is confined to Saudi Arabia, and while the findings are significant, they cannot be generalized to the entire Gulf region.

Author contributions: Conducted an extensive review of the literature, drafted the manuscript, performed the data analysis and presentation, led the discussion of the results, wrote the conclusion and recommendations, MA; conceived the idea for the manuscript, provided the data, edited and proofread the document, identified several key issues that required attention before finalizing the manuscript, KA; development and completion of this manuscript, MA and KA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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Appendix

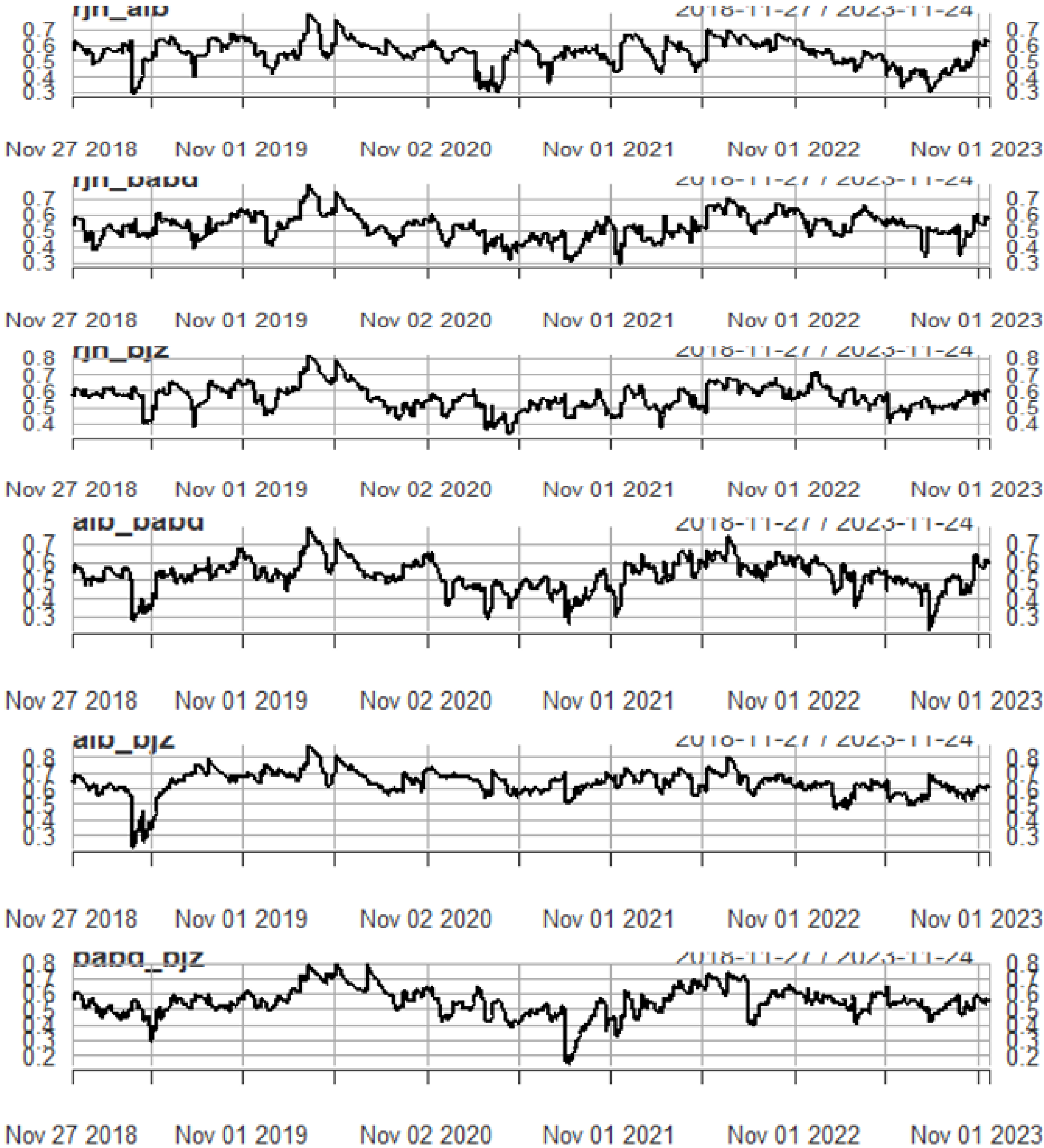


Figure A1. Time-Varying correlation among Islamic banks.

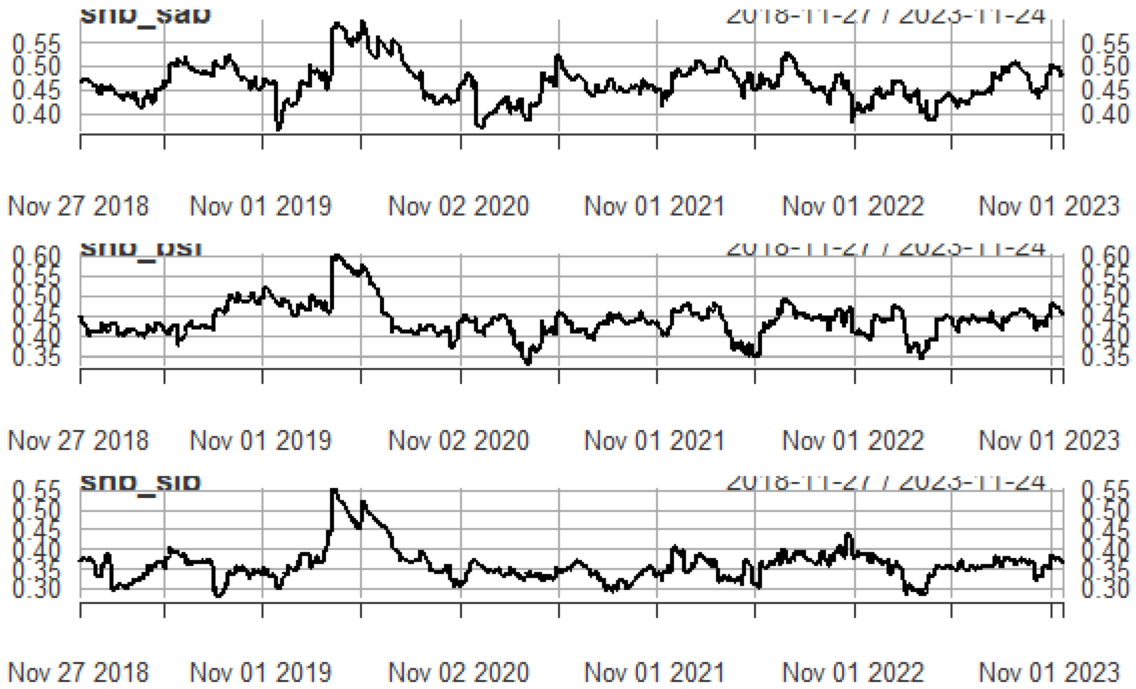
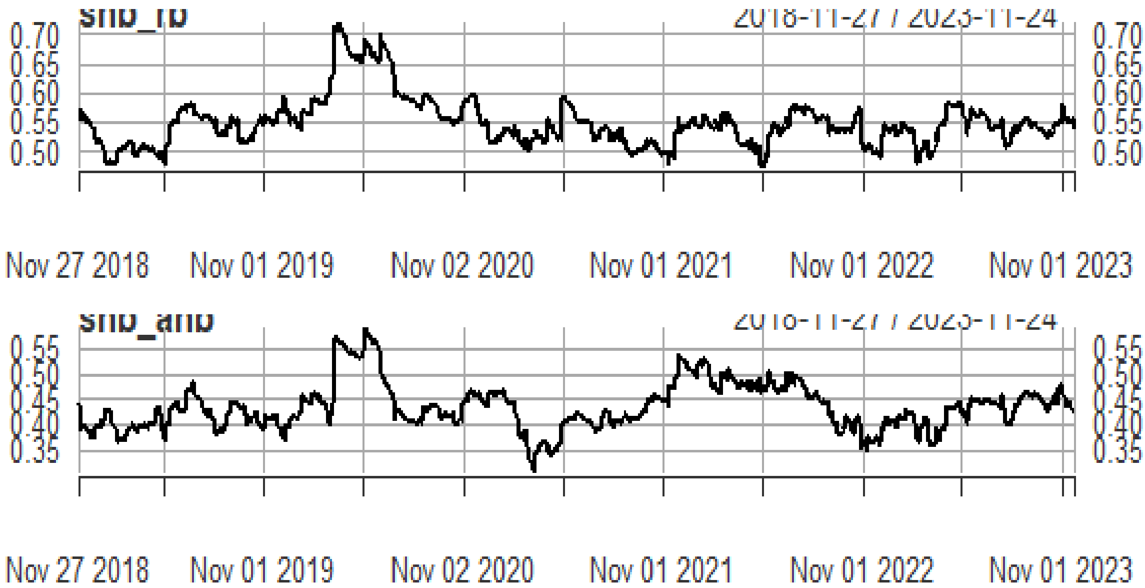


Figure A2. (*Continued*)



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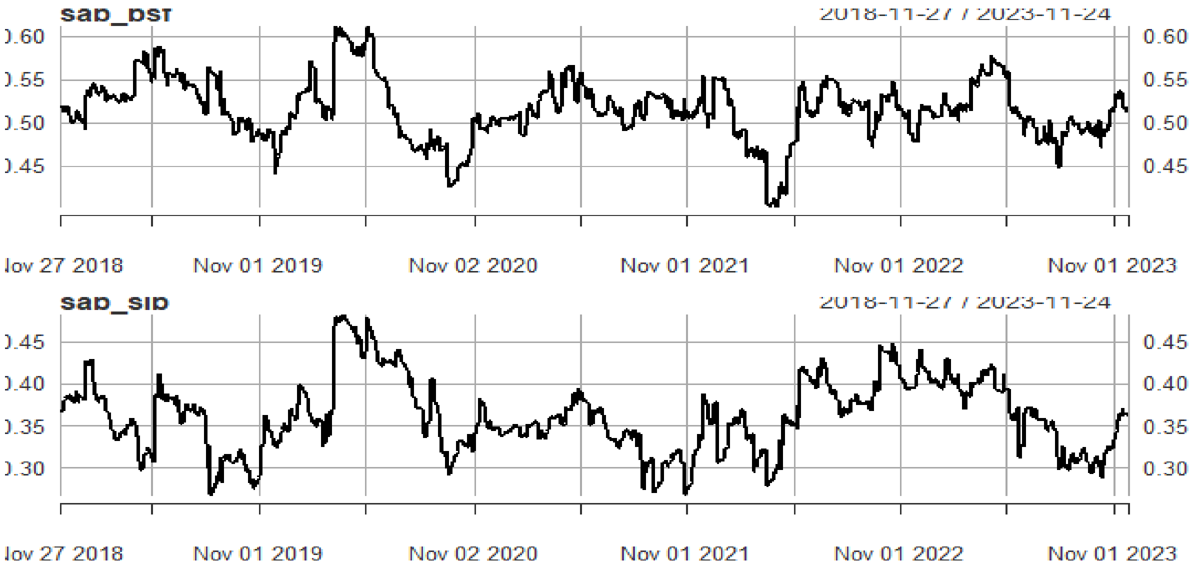

Figure A2. (*Continued*).

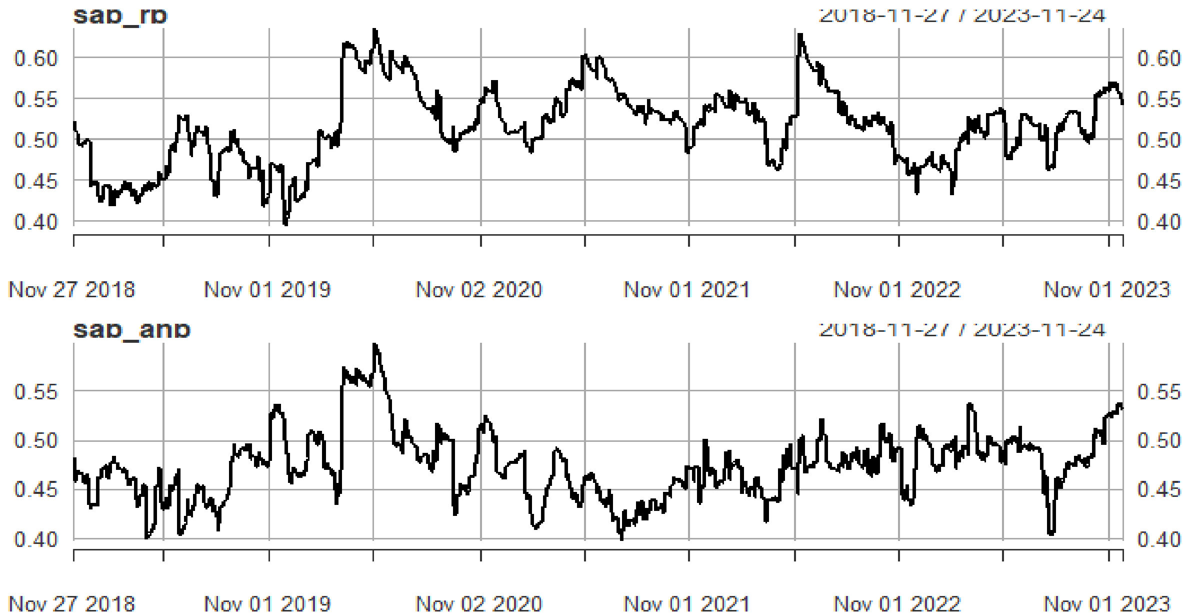

Figure A2. (*Continued*).

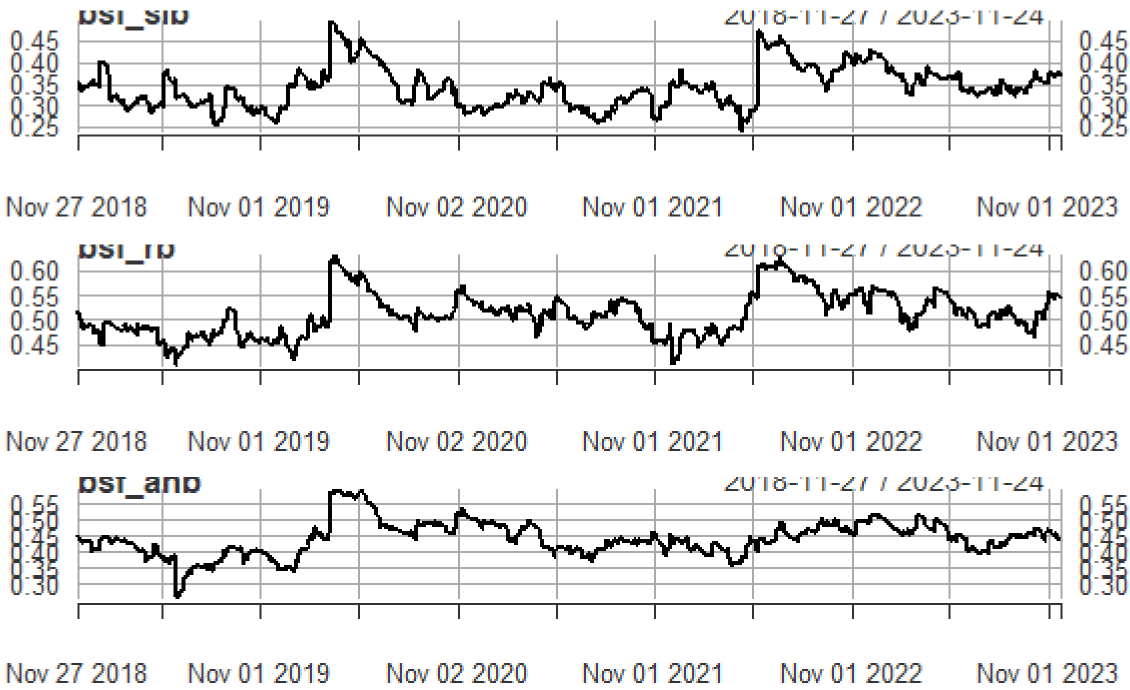

Figure A2. (*Continued*).

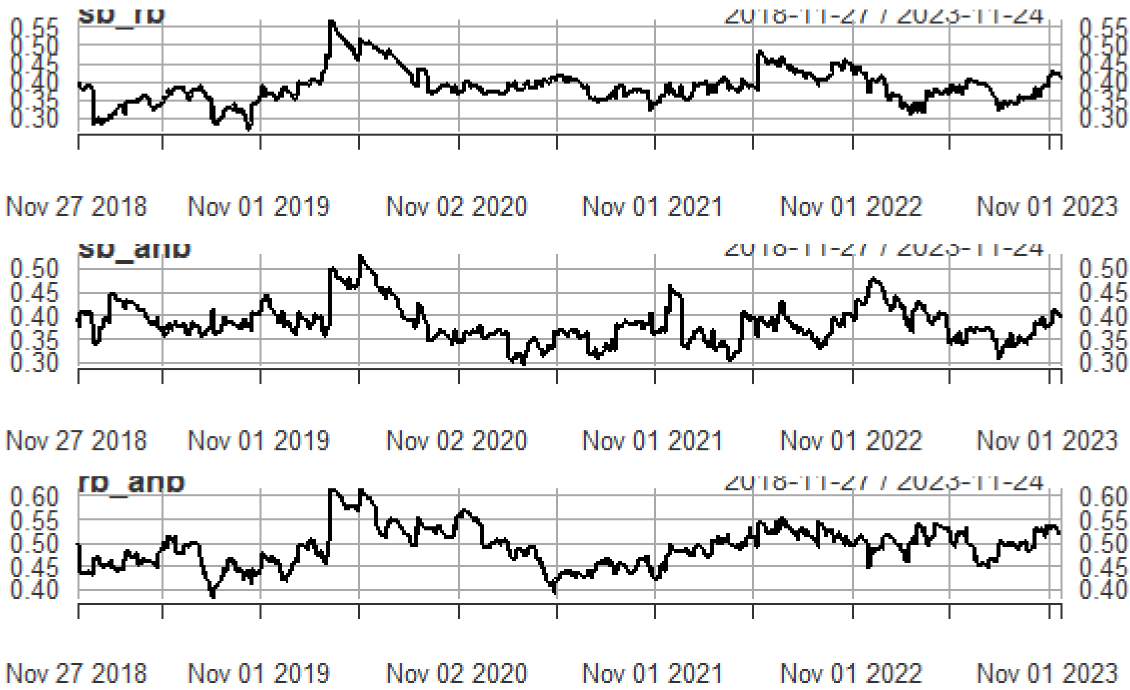

Figure A2. Time-Varying correlation among convention banks.