Evaluating the Impact of Oil Market Shocks on Sovereign Credit Default Swaps in Major Oil-Exporting Economies

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ABSTRACT

This study analyzes the impact of oil market fluctuations on Sovereign Credit Default Swaps (SCDS) in three key oil-exporting economies: Saudi Arabia, Russia, and the United Arab Emirates (UAE). The study investigates how various oil shocks, namely demand, supply, and market risk, affect sovereign credit risk and how these effects are transmitted within and across these economies. Time-domain and frequency-domain analyses were used to categorize oil market shocks and structural break analysis was incorporated to account for significant global events. The findings indicate that Saudi Arabia is a primary source of credit risk volatility, influencing Russia and the UAE, with the latter being significantly affected as a net recipient of such risks. Structural breaks, such as those associated with the COVID-19 pandemic, introduce shifts in impact patterns. This study underscores the significant role of demand shocks in shaping sovereign credit risk across the countries examined. These insights are essential for policymakers, investors, and financial analysts focused on sovereign credit risk management in oil-exporting economies, highlighting the importance of considering structural changes in economic conditions.

Keywords-oil market shocks; sovereign credit risk; frequency connectedness; sovereign credit default swaps

I. INTRODUCTION

The interconnections within the global financial ecosystem, particularly between oil markets and Sovereign Credit Default Swaps (SCDS), show the importance of dissecting the pathways for shock transmissions in these segments. SCDS spreads are now widely regarded as a reliable measure of a country's fiscal health, reflecting investor perceptions and serving as a crucial indicator for investing in global markets [1-4]. Concurrently, the oil sector, integral to global energy supply and demand, experiences volatility that directly influences economic indicators and fiscal stability. Oil price fluctuations affect economies differently, depending on their status as oil importers or exporters. This affects inflation, government budgets, and general economic health [5]. Both supply and demand shocks in the oil market carry significant implications for sovereign credit risk, affecting public finances, inflation, trade balances, and vulnerability to default. The primary goal of this study is to quantify the frequency and extent of the connection between oil market shocks and sovereign CDS of major oil-exporting countries, namely Saudi Arabia, Russia, and the United Arab Emirates (UAE), across different time frames and dominant transmission frequencies.

The motivation for this study lies in the fundamental role of oil exports for the economies of Saudi Arabia, Russia, and the UAE, coupled with the potential financial destabilization stemming from oil market shocks. The relationship between the oil market and these countries' sovereign credit risk profiles merits rigorous analysis due to its implications for economic policy and financial risk management. Understanding how oil price volatility translates into sovereign credit risk becomes imperative as these countries maneuver through global oil dependency and economic diversification complexities. Understanding domain and frequency connectedness aids in risk assessment and effective portfolio diversification [6]. The existing literature has examined oil price shocks, sovereign credit risk, and their interconnections, including the effects of oil price fluctuations on economic parameters and the financial system [7, 8]. SCDS spreads are sensitive to macroeconomic factors, and the SCDS market shows pricing efficiency and contagion effects [9]. Some studies explored the relationship between commodity prices and sovereign bond spreads [10, 11] and the impact of oil price volatility on sovereign credit risk [12, 13]. Many recent studies have investigated the multifaceted impact of oil price shocks across various economic sectors. This surge in scholarly attention emphasizes the critical role of oil price shocks in shaping global economic landscapes. The nexus between oil prices and stock market volatility has been extensively explored, with notable contributions from [14, 15]. The study in [14] investigated oil price shocks on the systematic risk of the G7 stock markets, providing insights into how these shocks can propagate through financial systems. Similarly, in [15], the frequency of spillovers between oil shocks and the stock markets of leading oil-producing and consuming economies was investigated, highlighting the global interconnectedness of the oil markets and stock market dynamics.

The sensitivity of the burgeoning green bond market to oil price fluctuations has been documented in [16, 17]. In [16], the return and volatility spillovers between oil price shocks and the international green bond markets were investigated, suggesting a complex dynamic in which oil prices significantly influence green bond market movements. In [17], this theme was further explored, examining the direct effects of oil shocks on the green bond market, thus underscoring the broader implications of energy prices on sustainable finance. Furthermore, the impact of oil price shocks on global uncertainty has been a topic of interest, with [18, 19] offering valuable perspectives. In [18], a nuanced view of the time-varying and asymmetric impacts of oil price shocks on geopolitical risks was presented, indicating that the nature of these shocks (positive or negative) may have differential effects on global uncertainty levels. In [19], this analysis was extended by examining the dynamic spillovers among global oil shocks, economic policy uncertainty, and inflation expectation uncertainty under extreme conditions, providing a comprehensive overview of how oil prices interact with broader economic indicators of uncertainty. In [20, 21] the repercussions of oil price movements on commodity markets were analyzed. In [20], the asymmetric influence of oil demand and supply shocks on meat commodities was investigated, highlighting the sector-specific impacts of oil price fluctuations. In [21], this discussion was further expanded by examining the role of biofuels in mediating the relationship between exogenous oil supply shocks and global agricultural commodity prices, illustrating the intricate links between energy markets and global food supplies.

These studies demonstrate the multifaceted impact of oil prices across various economic domains. Oil shocks have a differential impact on sovereign credit risk, as evidenced by the movements in credit CDS spreads. Oil demand shocks generally decrease CDS spreads across G10 and major oil-exporting countries, suggesting a perceived reduction in sovereign default risk associated with increased oil demand. On the contrary, oil supply shocks tend to increase CDS spreads for G10 countries while decreasing them for oil-exporting ones, reflecting the varied implications of reduced oil supply in different economies. In addition, uncertainty in the oil market has been found to predictably affect sovereign CDS spreads of oil-exporting countries, especially during periods of significant oil price volatility, such as the collapse of 2014-2015. Additionally, the spillover effects from crude oil prices and volatilities to sovereign risk premiums have been documented, with these effects being moderated by both local and global factors. Events such as the European sovereign debt crisis, the COVID-19 pandemic, and oil price crashes further influence the interconnectedness within the CDS market, altering the dynamics of sovereign credit risk in the context of oil demand and supply shocks [8, 22-24].

Although recent research has examined the broad impact of oil price shocks on sovereign credit risk, studies focused specifically on Saudi Arabia, Russia, and the UAE provide crucial insight into the unique dynamics within these major oil-exporting countries. In [25], the impact of oil shocks on the economies of Gulf Cooperation Council (GCC) countries was discussed, focusing on economic growth, inflation, and trade balance. Empirical results indicate that GCC countries, particularly Saudi Arabia, are significantly affected by oil price shocks, impacting economic growth, trade balance, and inflation. There are notable differences in the responses of GCC economies to oil shocks, with Saudi Arabia, Bahrain, and Kuwait showing the highest sensitivity to oil price fluctuations. In [26], it was found that the VIX index and oil prices are the most crucial factors in explaining Russian sovereign credit risk. In [8], the dynamic spillover of crude oil prices and volatilities on the sovereign risk premia of ten oil-exporting countries was investigated. This study explored the impact of oil shocks on sovereign debt and financial markets. The findings suggested that the spillover effects from oil markets varied over time and depended on the country. This study showed that Russia was among the top recipients of crude oil spillover effects in sovereign debt markets, indicating that changes in crude oil prices notably impact Russia's sovereign debt spreads. The impact of extreme oil price movements on SCDS spreads in G7 and BRICS countries was studied in [4], with empirical results revealing varying dependence structures between oil and sovereign CDS markets in different countries. This study concluded that oil exporters (Russia and Brazil) were more sensitive to positive shocks in oil volatility. In [3], the impact of global and local financial factors was investigated on SCDS spreads in GCC countries. Empirical results indicated that oil prices positively impact the sovereign CDS of the UAE.

Despite the extensive examination of the impact of oil price shocks on various economic sectors, the literature reveals a conspicuous gap in understanding the specific mechanisms and spillover patterns between oil market shocks and sovereign credit risk within the context of major oil-exporting countries, notably Saudi Arabia, Russia, and the UAE. While previous studies have broadly investigated the repercussions of oil price fluctuations on sovereign credit risk, detailed analyses focusing on the relationship between oil shocks (demand, supply, and risk) and sovereign credit risk, especially through the lens of time-domain and frequency-domain analyses, remain sparse. This study seeks to bridge this gap by employing a comprehensive methodological approach to dissect how oil shocks affect sovereign credit risk across these countries. This study fills a literature gap by examining the domain and frequency connectivity between oil market shocks and sovereign credit risk in major oil-exporting countries, offering insights for risk management and informed decision-making in a globally interconnected financial system. The findings reveal that Saudi Arabia is the primary source of volatility transmission to Russia and the UAE, with the latter being a major recipient of oil market shocks. Importantly, oil demand shocks emerge as significant influencers of sovereign credit risk across all timelines, while oil supply shocks predominantly absorb sovereign credit risk during heightened risk perception periods. These insights are vital for policymakers, investors, and financial institutions looking to navigate the complexities of a globally interconnected financial landscape.

II. EMPIRICAL METHODOLOGY

In [27], real oil price increases were identified as demand, supply, and specific market shocks, emphasizing the need for correlated series in structural VAR models. In [28], oil price changes were decomposed into demand, supply, and risk shocks using financial asset prices. This approach was advanced in [29] using VIX for expected returns, NYMEX crude futures for price changes, and the World Integrated Oil and Gas Producer Index for oil producers.

A. *Standard Spillover Approach*

This study used the standard network connectedness method of [30]. The connectedness measure is based on the spillover table, with $\theta_{ij}^{g}(H)$ representing the estimation of oil shock j's impact on SCDS and i's forecast error variance obtained from the H-step-ahead generalized forecast:

$$\theta_{ij}^{g}(H)\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i{}'A_h\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i{}'A_h\Sigma A_h{}'e_i\right)^2},\quad H=1,2,.... \tag{1}$$

The term σ_{jj} represents the standard deviation of the error term in the j^{th} equation. The normalized entry is denoted as follows:

$$\widetilde{\theta_{ij}}(H)\frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)} \tag{2}$$

where $\sum_{j=1}^{N}\widetilde{\theta_{ij}}(H)=1$ and the sum of the total variance decompositions is $\sum_{i,j=1}^{N}\widetilde{\theta_{ij}}(H)=K$ and $\widetilde{\theta_{ij}}(H)$ represents the directional pairwise connectedness from oil shocks to SCDS. The aggregate connectedness measure of oil shocks on SCDS can be calculated as follows:

$$C(H)=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\theta_{ij}}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta_{ij}}(H)}=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\theta_{ij}}(H)}{K} \tag{3}$$

B. *Frequency Connectedness Approach*

Consider the spectral behavior of series X_t at frequency ω:

$$S_x(\omega)=\sum_{h=0}^{\infty}E(X_tX_{t-h})e^{-ih\omega}=\Psi(e^{-ih\omega})\sum\Psi(e^{ih\omega}) \tag{4}$$

where $\Psi(e^{-ih\omega})=\sum_{h=0}^{\infty}\Psi_h e^{-ih\omega}$ and ∞ implies infinite horizon relations. The generalized forecast error variance decomposition on a specific frequency ω can be determined as follows:

$$(\Theta(\omega))_{i,j}=\frac{\sum_j^{-1}\sum_{h=0}^{\infty}(\Psi(e^{-ih\omega})\Sigma)_{i,j}^2}{\sum_{h=0}^{\infty}(\Psi(e^{-ih\omega})\Sigma\Psi(e^{ih\omega}))_{i,j}} \tag{5}$$

This equation can be standardized as follows:

$$(\tilde{\Theta}(\omega))_{i,j}=\frac{(\Theta(\omega))_{i,j}}{\sum_{j=1}^{k}(\Theta(\omega))_{i,j}} \tag{6}$$

The overall connectedness within the frequency band d can be defined as follows:

$$C^d=\frac{\sum_{i=1,i\neq j}^{k}(\tilde{\Theta}_d)_{i,j}}{\sum_{i,j}(\tilde{\Theta}_d)_{i,j}}=1-\frac{\sum_{i=1}^{k}(\tilde{\Theta}_d)_{i,j}}{\sum_{i,j}(\tilde{\Theta}_d)_{i,j}} \tag{7}$$

$$C_{i\rightarrow\cdot}^{d}=\sum_{j=1,i\neq j}^{k}(\tilde{\Theta}_d)_{j,i} \tag{8}$$

$$C_{i\leftarrow\cdot}^{d}=\sum_{j=1,i\neq j}^{k}(\tilde{\Theta}_d)_{i,j} \tag{9}$$

III. DATA AND PRELIMINARY STATISTICS

This study used SCDS data with a 5-year maturity from Saudi Arabia, Russia, and the UAE from September 30, 2011 to October 21, 2021. According to the Observatory of Economic Complexity (OEC), the top exporter of crude oil in 2019 was the UAE (\$175B), representing 16.08% of global oil exports, followed by Saudi Arabia (\$128B), which represented 11.79% of global oil exports. Russia was the third top oil exporter (\$113B), representing 10.39% of global oil exports [31]. So, the three countries export around 38% of global oil. This study used SCDS data with a 5-year maturity from Saudi Arabia, Russia, and the UAE from September 30, 2011, to October 21, 2021. The choice of this period was influenced by the significant global and regional economic events that profoundly shaped the financial and oil markets. Analyzing this period provides insights into how sovereign credit risk and oil market shocks interact during significant economic stress and recovery phases. Moreover, including data beyond 2021, particularly from 2022 onwards, could introduce significant bias due to the Russia-Ukraine conflict, which caused a massive spike in Russia's SCDS levels. This spike would disproportionately influence the results and potentially skew the analysis. Focusing on the period up to 2021 ensures a more stable and representative analysis of the typical relationships between oil market shocks and sovereign credit risk. To work with stationary data, the log spread returns were calculated, $r_t=ln\left(\frac{S_t}{S_{t-1}}\right)$, where r_t is the return on the SCDS spreads at time t, and S_t and S_{t-1} are the SCDS spreads at t and $t-1$, respectively. The SCDS volatility is estimated using the generalized autoregressive conditional heteroskedasticity model $GARCH(p,q)$. Using AIC and BIC information metrics, $GARCH(1,1)$ was selected. All data were collected from the Bloomberg database. Table I shows the descriptive statistics of the datasets.

TABLE I. DESCRIPTIVE STATISTICS

	Saudi Arabia	**Russia**	**UAE**	**Supply shock**	**Demand shock**	**Risk shock**
Mean	0.000164	0.000165	-0.000124	0.006797	-0.040837	-0.263721
Median	0.000000	-0.000117	0.000000	0.042429	-0.072359	-1.048142
Maximum	0.623646	0.558237	0.356089	28.15524	14.01063	78.94120
Minimum	-0.216286	-0.191859	-0.169899	-29.35763	-14.21779	-30.13487
Std. Dev.	0.031895	0.037604	0.024267	2.270718	1.153730	7.878708
Skewness	5.066386	2.119642	3.104156	0.616517	-0.641081	1.379050
Kurtosis	88.44173	29.65188	42.26261	37.03233	31.76599	10.59950
Jarque-Bera	777311***	76470.9***	165910***	121770.6***	87058.27***	6862.748***
ADF	-31.10848***	-22.7873***	-23.6327***	-15.45969***	-17.29549***	-49.56472***
Q(1)	747.51***	622.96***	559.76***	620.62***	610.54***	574.43***
Q(5)	785.57***	680.63***	567.09***	702.54***	635.35***	584.17***
Observations	2520	2520	2520	2520	2520	2520

Notes: ADF is the Augmented Dickey-Fuller test of the null hypothesis of a unit root.
*** denotes statistical significance at the 1% level.

Saudi Arabia's CDS has a mean return of 0.000164 and a standard deviation of 0.0318. The positive skewness of 5.066 indicates that the returns distribution is skewed to the right, with longer tails on the right side. The high kurtosis of 88.44 indicates a leptokurtic distribution, with fatter tails and more extreme values. For Russia, the mean return of the CDS is slightly higher at 0.000165, and the standard deviation of 0.037604 indicates higher volatility than Saudi Arabia. The skewness is 2.119, which is positive but less skewed than in Saudi Arabia. The kurtosis of 29.65 suggests a relatively leptokurtic distribution but not as extreme as Saudi Arabia. For the UAE, the CDS returns have a negative mean of -0.000124 and a standard deviation of 0.024267, which is the lowest among the three countries. The skewness of 3.104156 shows that the distribution is positively skewed, and the kurtosis of 42.26261 suggests a leptokurtic distribution, indicating more extreme values and fatter tails than a normal distribution.

IV. EMPIRICAL RESULTS AND DISCUSSION

A. Time-Domain Spillover Analysis

Table II shows the average return and volatility spillovers over the full sample period.

TABLE II. SPILLOVER MEASURES

Return Spillover							
	SS	DS	RS	SA	RU	UAE	From
SS	85.34	5.10	1.45	3.88	2.96	1.26	2.44
DS	3.23	71.11	5.49	6.92	12.22	1.02	4.81
RS	0.75	4.09	83.85	3.36	7.52	0.43	2.69
SA	1.98	3.76	1.92	75.83	15.32	1.19	4.03
RU	1.92	2.84	2.29	13.53	78.69	0.73	3.55
AE	2.83	2.86	1.65	29.41	17.71	45.54	9.08
To	1.79	3.11	2.13	9.52	9.29	0.77	Total
Net	-0.65	-1.70	-0.56	5.49	5.74	-8.31	26.61
Volatility Spillover							
	SS	DS	RS	SA	RU	UAE	From
SS	79.51	4.34	1.50	5.53	7.57	1.55	3.41
DS	2.93	68.31	4.50	11.28	11.18	1.82	5.28
RS	0.98	2.03	90.75	3.09	2.43	0.72	1.54
SA	1.52	2.90	2.85	61.03	29.23	2.47	6.49
RU	1.41	2.21	4.63	26.85	62.36	2.54	6.27
AE	1.68	2.77	3.32	35.95	29.71	26.57	12.24
To	1.42	2.37	2.80	13.78	13.35	1.52	Total
Net	-1.99	-2.91	1.26	7.29	7.08	-10.72	35.25

Note: The lag order of the VAR models is selected using the Akaike information criterion (AIC).

Table II illustrates the spillover measures estimated using the approach in [30], which aims to quantify the transmission of oil shocks across SCDS returns and volatility. The table is divided into two parts: return spillover and volatility spillover. The return spillover looks at how oil shocks spillover into the SCDSs. The volatility spillover focuses on how one variable's volatility influences the other variables' volatility. Table II indicates that the UAE SCDS has the highest negative net spillover in both return and volatility, meaning that it mostly receives rather than sends shocks. However, the SCDS of SA and RU have positive net spillovers, suggesting that they transmit shocks more than they receive. SA and RU are net senders of shock returns and volatility, with net values of 5.49% (7.29%) and 5.74% (7.08%), respectively. These findings are consistent with the results that the impact of oil price volatility on SA CDS spreads is minimal due to its substantial sovereign wealth funds, which provide a buffer against oil price fluctuations. In contrast, RU CDS spreads are highly sensitive to oil price changes, with both the price level and volatility being critical determinants of sovereign debt risk. This sensitivity is exacerbated during economic downturns, highlighting the country's dependence on oil revenues. On the contrary, UAE SCDS is a major net receiver in terms of return and volatility, with a value of -8.31% and -10.72%, respectively. UAE SCDS receives the highest return spillover from other countries, with a "From" value of 9.08%. SA SCDS particularly influences it. The UAE SCDS stands out with a "From" value of 12.24%, indicating that it receives considerable volatility spillovers from other variables. The findings contrast with the results of [32], which showed that the impact of oil price shocks on CDS spreads is relatively muted, again due to the presence of large sovereign wealth funds that mitigate the financial risks associated with oil price volatility. SA SCDS has the highest "To" value of 9.52%, indicating that it contributes the most in terms of return spillover to UAE (29.41%) and RU (13.53%) SCDSs.

B. Frequency-Domain Spillovers Analysis

Tables III and IV show the frequency-domain return spillovers over the full sample period.

TABLE III. SPILLOVER RETURNS

Short Run (up to 5 days)								
	SS	DS	RS	SA	RU	AE	FROM_ABS	FROM_WTH
SS	73.23	4.73	1.39	3.77	2.84	0.79	2.25	2.93
DS	2.45	56.73	5.22	4.15	6.48	0.95	3.21	4.17
RS	0.54	3.45	69.19	1.70	4.82	0.33	1.81	2.35
SA	1.33	3.38	1.42	58.75	9.79	1.02	2.82	3.67
RU	1.35	2.17	1.62	9.76	60.70	0.62	2.59	3.36
AE	1.74	2.32	0.80	17.58	9.02	35.78	5.24	6.81
To_ABS	1.23	2.68	1.74	6.16	5.49	0.62	17.92	
To_WTH	1.60	3.48	2.26	8.00	7.13	0.80		23.28
Long Run (from 5 days onwards)								
	SS	DS	RS	SA	RU	AE	FROM_ABS	FROM_WTH
SS	11.75	0.45	0.10	0.19	0.25	0.51	0.25	1.09
DS	0.79	14.11	0.34	2.85	5.80	0.13	1.65	7.18
RS	0.23	0.66	14.61	1.67	2.70	0.11	0.89	3.89
SA	0.68	0.44	0.54	16.89	5.54	0.22	1.24	5.38
RU	0.62	0.69	0.69	3.77	17.87	0.14	0.98	4.27
AE	1.13	0.61	0.89	11.80	8.70	9.63	3.86	16.75
To_ABS	0.58	0.48	0.43	3.38	3.83	0.19	7.87	
To_WTH	2.50	2.07	1.85	14.69	16.64	0.81		38.55

Note: SS: Supply Shocks, DS: Demand Shocks, RS: Risk Shocks, FROM_ABS: Absolute spillover received from other variables, FROM_WTH: Within spillover received from other variables, TO_ABS: Absolute spillover transmitted to other variables, TO_WTH: Within spillover transmitted to other variables.

TABLE IV. SPILLOVER VOLATILITY

Short Run (up to 5 days)								
	SS	DS	RS	SA	RU	AE	FROM_ABS	FROM_WTH
SS	67.83	4.06	1.30	5.00	6.86	1.37	3.10	4.31
DS	2.11	55.26	3.41	9.08	6.93	1.52	3.84	5.34
RS	0.72	1.75	74.90	1.64	1.80	0.62	1.09	1.51
SA	1.05	1.94	1.01	43.08	18.39	2.04	4.07	5.66
RU	0.72	1.29	1.07	15.64	37.77	2.23	3.49	4.85
AE	1.12	1.57	0.58	21.59	14.39	19.95	6.54	9.09
To_ABS	0.95	1.77	1.23	8.83	8.06	1.30	22.13	
To_WTH	1.32	2.46	1.71	12.27	11.20	1.80		30.77
Long Run (from 5 days onwards)								
	SS	DS	RS	SA	RU	AE	FROM_ABS	FROM_WTH
SS	11.68	0.27	0.19	0.53	0.71	0.18	0.31	1.12
DS	0.82	13.05	1.09	2.20	4.25	0.30	1.44	5.14
RS	0.26	0.28	15.85	1.46	0.63	0.10	0.45	1.62
SA	0.47	0.96	1.84	17.95	10.85	0.43	2.42	8.63
RU	0.70	0.92	3.56	11.21	24.59	0.31	2.78	9.91
AE	0.56	1.20	2.74	14.37	15.32	6.62	5.70	20.30
To_ABS	0.47	0.60	1.57	4.96	5.29	0.22	13.11	
To_WTH	1.66	2.15	5.59	17.67	18.86	0.79		46.72

Note: SS: Supply Shocks; DS: Demand Shocks; RS: Risk Shocks; FROM_ABS: Absolute spillover received from other variables; FROM_WTH: Within spillover received from other variables; TO_ABS: Absolute spillover transmitted to other variables; TO_WTH: Within spillover transmitted to other variables.

Table III illustrates the frequency domain connectedness measures in the short and long term. The spillover returns in the short term (5 days) are lesser than those in the long term (over 5 days to infinity). This is consistent with the findings of [32], who reported that the intensity of the spillovers and the extent of connectedness over the long term were significantly elevated. The overall spillover index reveals that 23.28% of the forecast error variance breakdown is due to short-term spillovers among oil shocks and SCDS. In contrast, in the long term, spillovers between these variables account for about 38.55% of the forecast error variance. In the short run (up to 5 days), the SCDS of the UAE receives the highest spillover from other variables, with a frequency connectedness in the absolute sense of 5.24% and a measure of "within" connectedness of 6.81%. Specifically, Saudi Arabia and Russia contribute significant spillovers to the UAE. Regarding oil market shocks (SS, DS, RS), their spillover to the CDS of countries is limited compared to the interactions between the countries themselves. Saudi Arabia and Russia are more sensitive to oil DS, with values of 4.15% and 6.48%. Oil DS exerts the most substantial influence on RU SCDS, with a value of 6.48%. The UAE SCDS is less influenced by oil market shocks in the short term, particularly by an RS of only 0.33%.

In the long term, the UAE SCDS continues to stand out as the primary recipient of spillovers, with an absolute value of 3.86% and a measure of "within" connectedness of 16.75%. Saudi Arabia and Russia are more sensitive to oil DS, with values of 2.85% and 5.80%, respectively, indicating the prominence of demand-side factors for these countries in the short and long term. RU SCDS is more reactive to DS (5.80%) long-term, emphasizing the sustained significance of demand-side oil shocks for Russia's credit risk. However, the UAE is least affected by long-term oil shocks, with RS influencing it by only 0.11%.

Table IV shows the frequency-domain volatility spillovers over the full sample period. In the short run, oil DS seems to be the most significant influencer for all three SCDS volatilities. The SCDS volatility of Saudi Arabia is the most influenced by oil DS, with a value of 9.08%. Oil SS and RS impacts are comparatively lower, with values of 1.05% and 1.01%, respectively. For Russia, SCDS volatility is mainly influenced by oil DS, followed by oil RS and oil DS. For the SCDS volatility of the UAE, the most substantial impact comes from Saudi Arabia, with a value of 21.59%.

In the long term, DS again stands out as the most influential factor for the SA SCDS volatility, with a value of 2.20%. RS and SS have values of 1.84% and 0.47%, respectively, indicating less influence than DS. In the case of Russia, DS remains the main influencer of SCDS volatility, with a value of 4.25%. RS has a greater impact than in the short term, with a value of 3.56%, whereas the SS influence decreases to 0.70%. In the case of the UAE, RS emerges as the most significant influencer, with a value of 2.74%. DS and SS follow, with values of 1.20% and 0.56%, respectively.

C. Dynamic Spillovers Analysis

The dynamics of spillover trends were assessed, including their evolution and response to economic fluctuations, by analyzing time-varying spillover metrics in both time-domain and frequency-domain models. This was carried out using a 200-day rolling window and 10-day forecasts. Figure 1 displays these time-domain spillover indices. Figure 1(a) shows the time variation of the total return spillover index. The index reacts notably to significant financial, political, and economic disruptions throughout the observed time frame. For example, the 2015-2016 peak aligns with significant volatility in global oil prices. The prices sharply declined, primarily due to an oversupply in the global market and a slowdown in demand, particularly from emerging economies. The decline in oil prices put pressure on their national budgets, leading to increased perceived credit risk and higher SCDS spreads. The 2020-2021 peak aligns with the emergence of the COVID-19 pandemic, which resulted in an unprecedented global economic slowdown. Travel bans and lockdowns led to a sharp contraction in oil demand. Furthermore, in early 2020, there was a brief oil price war between Russia and Saudi Arabia, leading to an increased supply in an already depressed market, further pushing down prices. Figure 1(b) shows the time variation of the total volatility spillover index, showing additional peak periods. For example, the prominent peaks in 2018-2019 can be related to several pivotal financial, geopolitical, and economic events. Fluctuations in oil prices marked this period due to a combination of factors, such as production changes by OPEC and global economic growth concerns. The oil market was affected by both SS and SDs. In addition, by the end of 2014, a drastic decline in oil prices commenced, largely due to a surplus in global oil supply coupled with tepid demand. This drop in oil prices cascaded oil-dependent economies, leading to increased volatility in their SCDS.

(a)

(b)

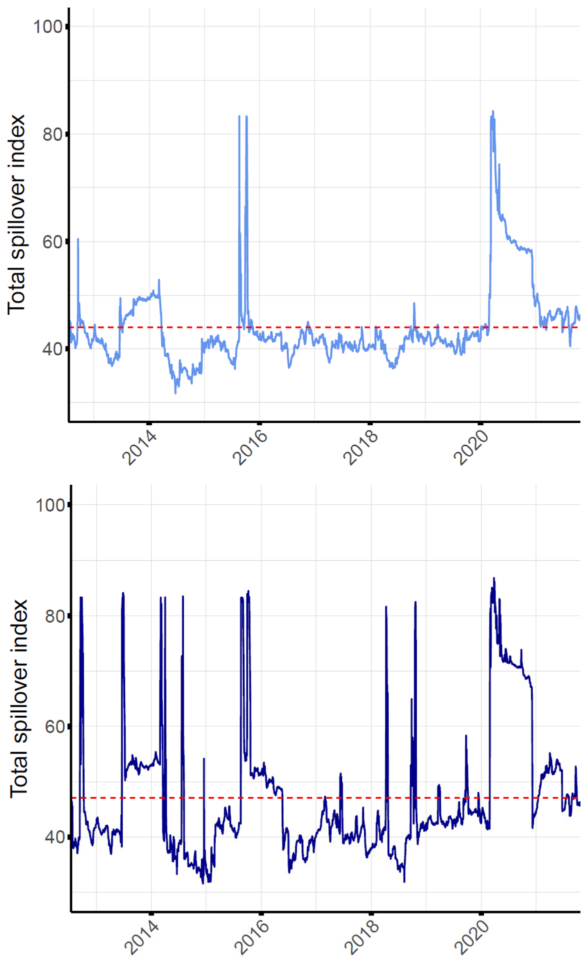

Fig. 1. Rolling spillover index estimates (time-domain spillovers): (a) Total return spillover index, (b) Total volatility spillover index.

Figure 2 illustrates the frequency domain variation of the total spillover index in both the short and long run, showing similar patterns. Long-term spillovers and the extent of interconnectedness appear significantly greater than short-term spillovers. This observation suggests that the sovereign credit risk of the three countries tends to exhibit delayed reactions to oil shocks, making them slow to adapt to new information. The observed peaks in the spillover indexes during these periods (full-time period, short and long run) underscore the intricate ties between oil market dynamics, geopolitical events, and the perceived creditworthiness of major oil-exporting countries. The index effectively captures the increased interdependencies and contagion risks during global crises.

(a)

(b)

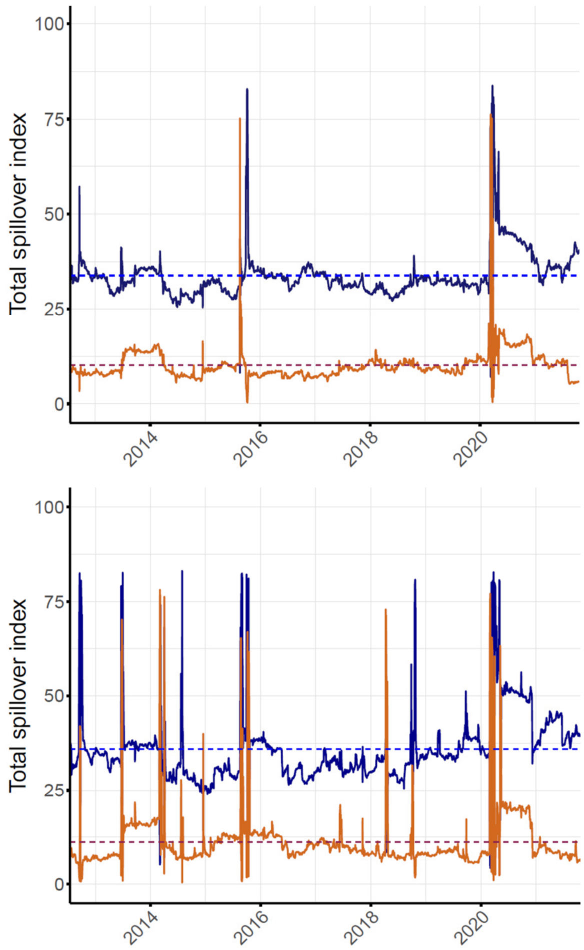

Fig. 2. Rolling spillover index estimates (frequency-domain spillovers): (a) Total return spillover index, (b) (b) Total volatility spillover index. Note: The short run with 5-day and less (Orange line) and the long run greater than 5-day periods (blue line) rolling spillover indexes are obtained from the frequency domain approach of [33].

D. Network Spillovers Analysis

Figures 3-5 present network diagrams of pairwise return and volatility connectedness. Figure 3 shows the return and volatility network, whereas Figures 4 and 5 depict short- and long-term total connectedness networks, respectively.

(a)

(b)

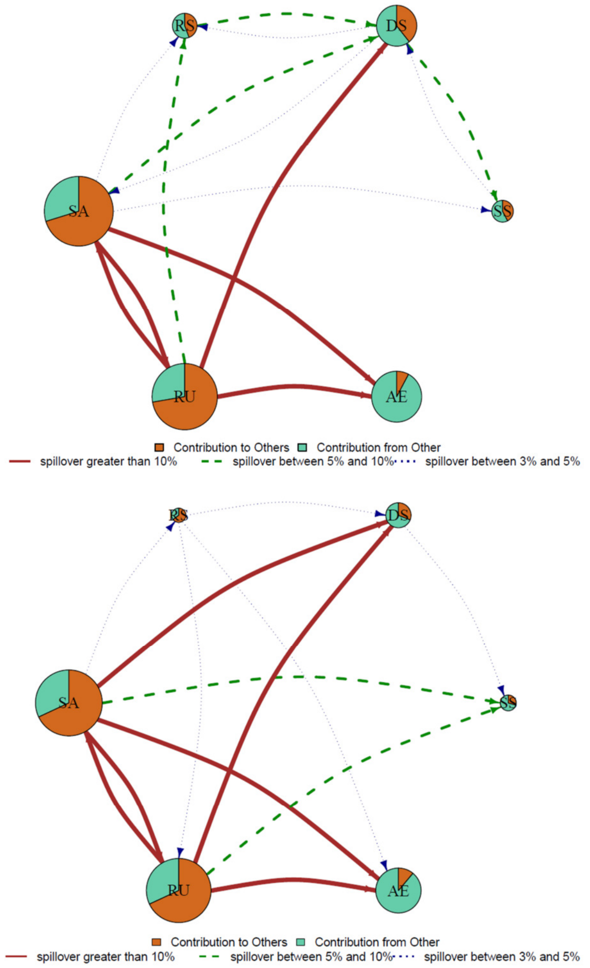

Fig. 3. Total connectedness network from the time-domain spillover analysis: (a) Total return connectedness network, (b) Total volatility connectedness network.

(a)

(b)

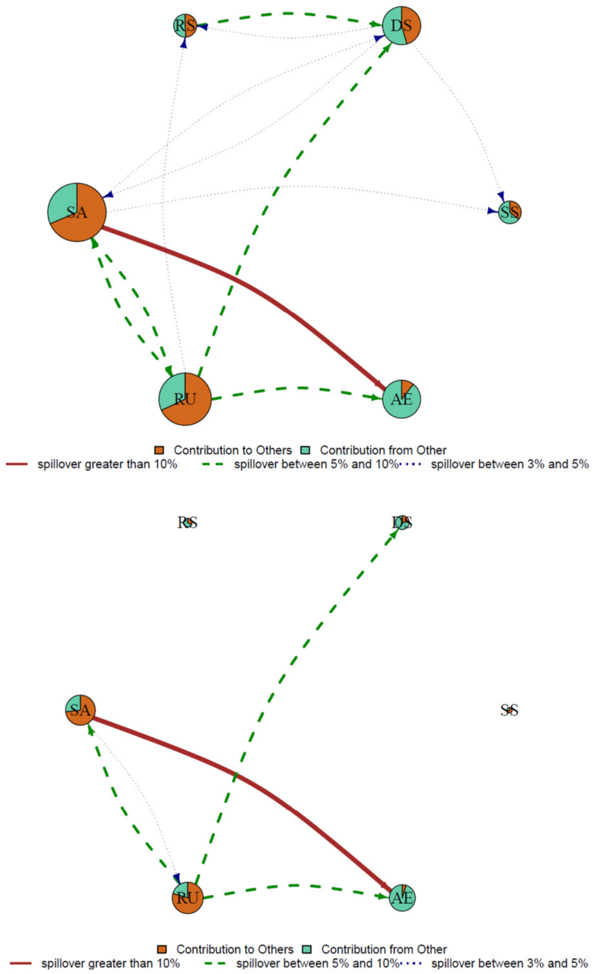

Fig. 4. Total connectedness network (short term) from the frequency-domain spillovers analysis: (a) Total return connectedness network (short term), (b) Total volatility connectedness network (short term).

For Figures 3-5, the size of each node is determined by the sum of its "From others" and "To others" values, which is essentially the sum of in-degree and out-degree for total connectedness. Figures 4(a) and 4(b) show that the SCDS of Saudi Arabia has the largest node, followed closely by the SCDS of Russia. The SCDS of the UAE is the next in line, with DS, RS, and SS being smaller, respectively. The arrows' orientation illustrates the incoming and outgoing returns (volatilities). In this network depiction, weights are assigned based on the intensity of each spillover. The breadth of each arrow serves as an indicator of the spillover's strength. Saudi Arabia and Russia have positive net spillover, transmitting more shocks than they receive. In contrast, the UAE has the most negative, which indicates it is more of a receiver than a transmitter. Within these networks, Saudi Arabia predominantly acts as a chief conduit of sovereign credit risk volatility, whereas the UAE predominantly serves as a key recipient of such risks. To better understand the distinction in the dynamic connectedness of short- and long-term financial risks, these impacts are broken down into short- (less than 5 days) and long-term (beyond 5 days).

Figures 4 and 5 illustrate the total returns and volatility connectedness network from the frequency domain spillover analysis. Examining the short-term pairwise connectedness in Figures 4(a,b), the pattern of returns connectedness is analogous to the outcomes from the time-domain spillovers model, highlighting that Saudi Arabia is the largest transmitter of credit risk-return and volatility to the UAE. Figure 5(a) shows the return connectedness networks for periods extending beyond 5 days. A striking observation from this network is its resemblance to the patterns seen in Figure 3(a), about the time-domain spillovers scenario. Figure 5(b) shows that a substantial portion of SCDS volatility occurs in the long term, whereas the short-term volatility spillover does not have a significant effect (except for SCDS volatility transmission from Saudi Arabia to the UAE). Visualizing the network provides an intuitive understanding of the strength and direction of spillovers between oil shocks and sovereign credit risks. Observers can immediately discern the stronger connections (thick chocolate arrows) from the weaker ones (fine dark blue lines), making the network analysis more insightful.

(a)

(b)

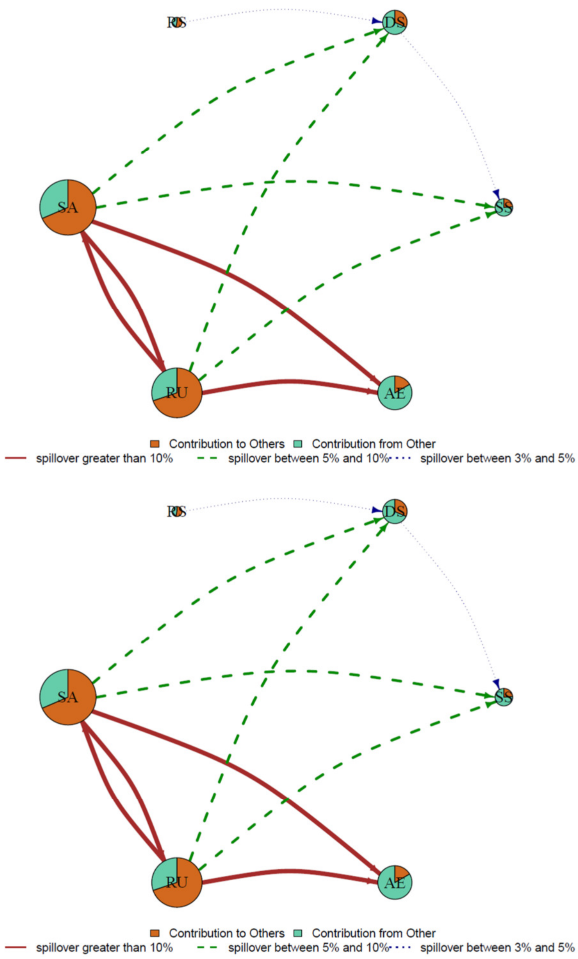

Fig. 5. Total connectedness network (long term) from the frequency-domain spillovers analysis: (a) Total volatility connectedness network (short term), (b) Total volatility connectedness network (long term).

E. Structural Break Analysis

1) Structural Break Test with an Unknown Break Date

To handle structural breaks in the time series data, a structural break was tested with an unknown break date using the sup-Wald (swald) test for the SCDS of Saudi Arabia, Russia, and the UAE. This test allows the identification of the precise points where significant changes occurred in the relationships between oil market shocks and sovereign credit risk. Table V illustrates the results of the structural break tests.

TABLE V. STRUCTURAL BREAK TESTS

Country	Statistic (swald)	p-value	Estimated break date
Saudi Arabia	16.4294	0.0464	10 March 2020
Russia	20.5127	0.0094	18 April 2020
UAE	26.0053	0.0009	17 April 2020

The results of the structural break test reveal significant changes in the relationships between oil market shocks and sovereign credit risk for Saudi Arabia, Russia, and the UAE. Saudi Arabia's swald statistic of 16.4294 with a p-value of 0.0464 indicates a structural break on March 10, 2020, possibly corresponding to the initial global response to the COVID-19 pandemic, severely impacting oil demand and prices. For Russia, the swald statistic of 20.5127 and p-value of 0.0094 pinpoint a break on April 18, 2020, a period marked by further escalations in the pandemic and geopolitical tensions affecting oil markets. The UAE shows the most pronounced break with a swald statistic of 26.0053 and a p-value of 0.0009 on April 17, 2020, aligning with significant economic disruptions and policy shifts in response to the ongoing global crisis. These break dates highlight the profound impact of the COVID-19 pandemic on economic stability and sovereign risk perceptions in these major oil-exporting countries.

To enhance the accuracy and robustness of this analysis, the structural breaks identified in the time series data were incorporated by introducing dummy variables. These dummy variables were created to account for the specific break dates detected for each country: March 10, 2020, for Saudi Arabia; April 17, 2020, for the UAE; and April 18, 2020, for Russia. By integrating these dummy variables into the regression models, the shifts in the relationships between oil market shocks and sovereign credit risk were captured before and after structural breaks. A dummy variable was created for each country, equal to one from the break date onward and zero before the break date. These dummy variables and their interaction were then included with the independent variables (SS, DS, and RS) in the regression models. This allowed us to separately estimate the effects of the oil market shocks on sovereign credit risk during the pre-break and post-break periods. This methodological improvement provided a better analysis of how the impacts of oil market shocks on sovereign credit risk changed after structural breaks, allowing the identification of significant differences in the magnitude and direction of these relationships over different periods and offering critical insights into the evolving economic and financial dynamics in Saudi Arabia, the UAE, and Russia. Table VI illustrates the impact of oil shocks on SCDS returns.

TABLE VI. THE IMPACT OF OIL SHOCKS ON SCDS RETURNS

	Saudi Arabia	Russia	UAE
Pre-break period			
SS	.0001983	-.0019713***	.0009876
DS	-.0031147***	-.0046405***	-.0044653***
RS	.0005746***	.0007579***	.0006117***
Post-break period			
SS	-.0030913***	.0011426	-.0000401***
DS	-.0049405	-.0093445***	0026917***
RS	-.0001872	.0009257***	-.0005401***

2) Overall Impact of Structural Breaks Across Countries

Table VI shows that for Saudi Arabia, the structural break led to notable changes in how SSs and DSs affect its sovereign credit risk. Before the break, DSs significantly negatively affected SA SCDS, while RSs had a positive impact. Post-break, the impact of SSs became significantly negative, indicating an increased sensitivity to supply fluctuations. However, the influence of DSs and RSs decreased, suggesting a shift in the country's underlying factors driving sovereign risk perceptions. Russia experienced a structural break on April 18, 2020, with significant changes in the influence of DSs and RSs on its sovereign credit risk. Before the break, SSs and DSs significantly negatively affected Russian CDS, while RSs had a positive impact. Post-break, the effect of demand shocks intensified negatively, and the positive impact of risk shocks increased. However, the interaction term for supply shocks was insignificant post-break, indicating a reduced sensitivity to supply variations. In the UAE, the structural break highlighted changes in the relationship between oil market shocks and sovereign credit risk. Before the break, DSs had a significant negative effect and RSs positively affected the UAE SCDS. After the break, the effects of DSs turned positive, and the impact of RSs turned negative. This reversal indicates a significant shift in market dynamics and risk assessments, potentially driven by policy responses and economic adjustments in the face of the pandemic.

These findings highlight that while the three countries experienced structural breaks around the same period, the nature and impact of these breaks varied. Saudi Arabia, the UAE, and Russia displayed unique responses to the global economic environment, reflecting their differing economic structures, policy responses, and levels of exposure to global oil market dynamics. Policymakers in these countries must consider these structural changes when designing strategies to mitigate sovereign credit risk and enhance economic stability.

F. Robustness Checks

This study assessed the dynamics of spillover trends, including their evolution and response to economic fluctuations, by analyzing time-varying spillover metrics in both time and frequency domain models. To ensure the robustness of the findings, additional tests were carried out to verify the stability of the spillover connectedness measures under different forecast horizons. Although the primary analysis was based on a 200-day rolling window with a 10-step forecast horizon using daily data, portfolio managers and other financial professionals may operate on varying time frames, often adjusting their portfolios monthly, bimonthly, or quarterly. In response, robustness checks were extended to include forecast horizons of 30, 60, and 90 days, which correspond more closely to the shorter decision cycles of active portfolio management. The core conclusions drawn from the primary analysis hold across these varying forecast horizons, affirming the stability and reliability of the spillover connectedness measures under different temporal frameworks.

Furthermore, Granger causality tests were employed within the Vector Auto-Regression (VAR) framework to establish causality between oil market shocks and sovereign credit risk. This approach allows to test whether one variable's past values can predict another's future values, thereby establishing a directional influence. The results showed that oil demand shocks Granger-cause SCDS spread across the three countries, suggesting that changes in oil demand have predictive power over sovereign credit risk. Similarly, oil supply and risk shocks were found to have significant causal effects on SCDS spreads. However, the strength and direction of these relationships varied across countries and periods.

V. CONCLUSIONS AND POLICY IMPLICATIONS

This study analyzed the time-frequency connectedness between oil market shocks and sovereign credit risk in Saudi Arabia, Russia, and the UAE using methods from [30] and [33]. Empirical results indicated several notable findings: Spillover behaviors were identified to show marked differences based on frequencies and countries in focus. Saudi Arabia was prominently the predominant transmitter of credit risk volatility, particularly toward Russia and the UAE. In contrast, the role of the UAE was consistently highlighted as the major net receiver of such risks. In both short- and long-term scopes, oil demand shocks were the most influential determinants of sovereign credit risk volatilities across the three countries. The structural break analysis identified significant shifts in the relationships between oil market shocks and sovereign credit risk corresponding to global economic disruptions, such as the COVID-19 pandemic. Specifically, structural breaks were identified on March 10, 2020, for Saudi Arabia, April 17, 2020, for the UAE, and April 18, 2020, for Russia. These breaks highlight the changing dynamics and underline the importance of accounting for such events in risk management and policy formulation. Including more recent data from 2022 onward could introduce significant bias due to the Russia-Ukraine conflict, which caused a massive spike in Russia's SCDS levels. This spike would disproportionately influence the results and potentially skew the analysis. Focusing on the period up to 2021 ensures a more stable and representative analysis of the typical relationships between oil market shocks and sovereign credit risk.

The empirical findings of this study have several key policy implications for various stakeholders. For policymakers in Saudi Arabia, as the predominant transmitter of credit risk volatility, there is a pressing need to strengthen financial oversight and develop more resilient fiscal policies. These policies should aim to buffer against economic shocks by diversifying the economy beyond oil. On the contrary, the UAE, being a major net receiver of such risks, should focus on enhancing risk management strategies and developing robust mechanisms to monitor international financial flows to mitigate the impacts of external shocks. Russian policymakers should stabilize the financial system by enhancing transparency and regulatory frameworks to better manage and anticipate spillovers from Saudi Arabia. Additionally, the three countries could benefit from establishing strategic petroleum reserves and employing financial instruments to hedge against oil price volatility, which would stabilize government revenues and manage sovereign credit risk more effectively.

On the other hand, investors should be particularly aware of the high risk from Saudi Arabia's volatility transmission and the UAE's sensitivity to external shocks. This study suggests that diversifying investment portfolios by including assets from multiple regions and sectors can reduce exposure to geopolitical and economic risks associated with the oil market. Investors in sovereign bonds and CDSs should also closely monitor oil demand shocks, as they are significant determinants of credit risk volatility, informing better timing and selection of investment opportunities in these countries. Financial analysts should include oil market dependencies in their risk assessments of sovereign credit risk, especially for countries that rely heavily on oil exports. In addition, financial analysts can offer customized advice on currency risks, interest rates, and commodity investments, considering the connectedness highlighted in this study. While this study focuses on the spillover effects between oil market shocks and sovereign credit risk in Saudi Arabia, Russia, and the UAE, it is important to recognize the potential impact of other major oil-producing countries that collectively account for approximately 62% of the global oil supply. Countries such as the United States, Canada, Brazil, and Iraq play significant roles in the global oil market, and their production levels, geopolitical decisions, and economic policies can substantially influence oil prices and market stability. Future research could extend the analysis to incorporate these additional countries, offering a more complete view of the interconnectedness and spillover effects within the global oil market.

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