International Journal of Multidisciplinary Research and Growth Evaluation.

Volatility spillover effects among crude oil future market, SAR/EUR and Saudi Arabia CDS Market: The evidence of DCC-FIGARCH model

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Article Info

ISSN (online): 2582-7138
Volume: 03
Issue: 02
March-April 2022
Received: 19-03-2022
Accepted: 08-04-2022
Page No: 504-511
DOI:
https://doi.org/10.54660/anfo.2022.3.2.17

Abstract
This empirical study examines the time-varying spillover and contagion effects between one major future market, one major FOREX market and six major Islamic CDS markets. We use daily data for crude oil future, SAR/EUR and Saudi Arabia CDS markets. The data spans from February 15, 2011 to August 27, 2020, which entails major economic events. In this paper, we deploy DCC-FIGARCH process. The empirical findings indicate volatility effects spilling over from crude oil future returns to SAR/EUR returns and CDS market returns. Dynamic Conditional Correlations provide empirical evidence of strong contagion effects between the market returns. Conclusions of this paper are of interest to investors diversifying their portfolios of the above markets and to financial derivative markets regulators providing regulations for the under investigation derivative markets.

Keywords: Contagion, DCC-FIGARCH model, dynamic conditional correlations, Saudi Arabia CDS market

Introduction

Understanding the dynamics of time varying conditional volatility spillover effects between crude oil future, SAR/EUR and Saudi Arabia CDS markets is very important and it helps in better understanding of investors related to portfolio diversification. This study attempts to fill this gap and examines the spillovers and dynamic correlations between the under investigation markets. For this purpose the study uses a multivariate DCC-FIGARCH framework. The under investigation period spans from 15th February 2011 to 27th August 2020, including major economic crises: i.e. the European Sovereign Debt Crisis.

In the last few decades, the crude oil market returns have been highly volatile (Lee, Ni, 2002; Bernanke, 2006; Hamilton, 2008; Hamilton, 2009; Kilian, 2009) [21, 4, 16, 17, 6, 19]. The dramatic shocks that result from a financial crisis lead to major effects on stock returns (Park, Ratti, 2008; Apergis, Miller, 2009; Filis, Degiannakis, Floros, 2011; Basher, Haug, Sadorsky, 2012; Abhuankar, Xu, Wang, 2013, Wang, Wua, Li, 2013; Degiannakis, Filis, Kizys, 2014) [24, 2, 12, 4, 25, 1, 8]. Moreover, the investors, who are averse to risk become reluctant to intvest in bond markets (Bernanke, Gertler, Watson, 1997; Kilian, Lewis, 2011) [5, 20] due to unexpected shocks and high volatility. Other empirical studies examine the volatility between crude oil future market and financial markets (Haigh, Holt, 2002; Guo, Kliesen, 2005; Malik, Hammoudeh, 2007; Driesprong, Hacobsen, Maat, 2008; Geman, Kharoubi, 2008; Ewing, Malik, 2010; Wu, Guan, Myers, 2011) [15, 14, 22, 13, 26]. To the best of our knowledge this is the first such investigation of spillovers and contagion between crude oil future SAR/EUR and Saudi Arabia CDS markets.

The rest of the article is organized as follows. The second section displays the objectives. The third section presents the trivariate DCC-FIGARCH model. The fourth section provides the empirical application. The fifth section provides our conclusions.

Objectives

The objective for this article is to add to the related literature in several ways. First, we investigate the dynamic links between crude oil future, SAR/EUR and Saudi Arabia CDS markets based on a time-varying framework, which had not been researched before in the literature. We examine whether the crude oil future market returns is exposed to volatility in USA bond markets.

Based on dynamic links, we present the existence of potential contagion effects. The sample period allowed us to investigate the potential effects of major economic events on the dynamic links between the markets.

Methodology

As mentioned earlier, we use the DCC-FIGARCH which compines the DCC process of Engle (2002) and the FIGARCH specification. This model allows us to model jointly the long-memory feature for the series and to follow the evolution of the dynamic correlation over time. We assume that the conditional mean equation is defined as follows:

$$y_t = \mu + \varepsilon_t, \text{ with } t = 1, \dots, T. \quad (1)$$

Where (μ) is constant and the empirical set-up of the mean equation for the daily future market returns (y_t) and ε_t is the standardized residuals such that:

$$\varepsilon_t = \sqrt{h_t} u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \sim N(0,1) \quad (2)$$

where h_t is defined as the univariate conditional variance matrix and u_t is the standardized errors. Furthermore, H_t is the multivariate conditional variance matrix.

It follows the definition of the univariate FIGARCH(p,d,q) model (Baillie, Bollerslev and Mikkelsen, 1996) to generate the conditional variance matrix (h_t):

$$h_t = \omega[1 - b(L)]^{-1} + \{1 - [1 - b(L)]^{-1}\Phi(L)(1 - L)^d\}\varepsilon_t^2 \quad (3)$$

where ω is mean of the logarithmic conditional variance, $\Phi(L) = [1 - a(L) - b(L)](1 - L)^{-1}$ is lag polynomial of order p and $(1 - L)^d$ is fractional difference operator. Additionally, $b(L)$ and $a(L)$ are autoregressive polynomials of order p and q so that: $b(L) = 1 - \sum_{k=1}^{p} b_k L^k$ and $a(L) = 1 + \sum_{l=1}^{q} a_l L^l$.

Furthermore, the selected lag order is equal to 1, as many other researchers have mentioned as sufficient to estimate the univariate conditional variance matrix, i.e. Bolleslev, Chou and Kroner (1992), among others.

In the second stage, we employ the Engle (2002) representation of the multivariate GARCH model in order to estimate the multivariate conditional variance matrix (H_t is N x N matrix, with N the number of markets, i = 1,…,N) as follows:

$$H_t = D_t R_t D_t \quad (4)$$

D_t is the conditional variance matrix given by:

$$D_t = \mathrm{diag}\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right) \quad (5)$$

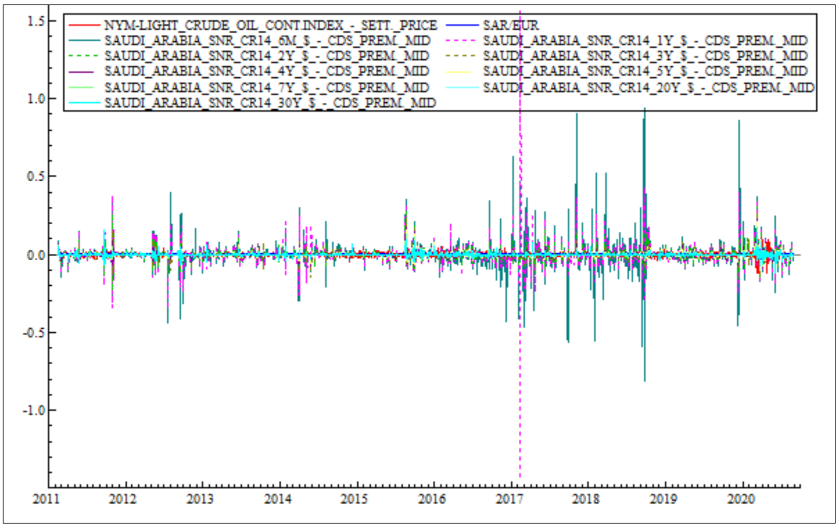
R_t is the condition correlation matrix of N x N dimension, and is defined as follows.

$$R_t = (\rho_{iit}) = \mathrm{diag}(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) Q_t \mathrm{diag}(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \quad (6)$$

where the N x N symmetric positive definite matrix $Q_t = (q_{ii,t})$ is given by:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \quad (7)$$

$\overline{Q}$ is the N x N unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.



***Source*:** Datastream® Database

Fig 1: Actual series of the logarithmic returns of the markets

Data description

In this article, we use the daily returns of NYM-LIGHT_CRUDE_OIL_CONT.INDEX_-_SETT._PRICE, SAR/EUR, 6M, 1Y, 2Y, 3Y, 4Y, 5Y, 7Y 20Y and 30Y SAUDI_ARABIA_SNR_CR14_$_-_CDS_PREM._MID. The under investigation period covered is defined from 15th February 2011 until 27th August 2020 leading to a sample of 2488 observations. The data were obtained from

Datastream® Database. We compute the continuously compounded return by taking the first difference of the logarithm of the two successive prices i.e. $r_t = log(p_t / p_{t-1})$.

Figure 1 (above) illustrates the evolution of all market logarithmic returns during 2011-2020. Figure 1 shows extreme volatile logarithmic returns. We observe significant picks and troughs, revealing volatility clustering phenomenon.

Results and Discussion

In this section, we present the empirical results for the univariate FIGARCH model, the multivariate DCC-FIGARCH model, the hypothesis and diagnostic tests. In addition, we show a Dynamic Conditional Correlation analysis of the trivariate DCC-FIGARCH (1,d,1) model.

Table 1: Estimates of univariate FIGARCH (1,d, 1) model

	NYM-Light_Crude_Oil_Cont.Index_-_Sett._Price	SAR/EUR	Saudi_arabia_snr_cr14_6m_$_-_cds_prem._mid
constant (μ)	-0,000026	-0,0000383	-0,000499
t-Statistic	-0,1731	-0,9739	-0,4298
p-Value	0,8626	0,3302	0,6673
constant (ω)	0,016655*	0,112713*	0,561009*
t-Statistic	1,726	1,394	1,558
p-Value	0,0844	0,1633	0,1193
d-figarch	0,585345***	0,453121***	0,502823**
t-Statistic	3,069	3,730	2,382
p-Value	0,0022	0,0002	0,0173
ARCH (a)	0,307151***	0,278890***	0,709656***
t-Statistic	3,112	5,227	4,455
p-Value	0,0019	0,0000	0,0000
GARCH (b)	0,762059***	0,710343***	0,885116***
t-Statistic	5,988	6,302	19,90
p-Value	0,0000	0,0000	0,0000

Source: Datastream® Database

Table 2: Estimates of univariate FIGARCH (1,d,1) model

	Saudi_arabia_snr_cr14_1Y_$_-_cds_prem._mid	Saudi_arabia_snr_CR14_2Y_$_-_cds_prem._mid	Saudi_arabia_snr_cr14_3Y_$_-_cds_prem._mid
Constant (μ)	0,001122	-0,000838*	-0,000574*
t-Statistic	0,7218	-1,593	-1,665
p-Value	0,4705	0,1112	0,0960
constant (ω)	2,189635***	0,028794*	0,041687
t-Statistic	3,262	1,930	0,8066
p-Value	0,0011	0,0538	0,4200
d-figarch	0,800598***	0,269133***	0,259230**
t-Statistic	6,986	3,661	2,517
p-Value	0,0000	0,0003	0,0119
ARCH (a)	-0,012886	0,971962***	0,937357***
t-Statistic	-0,1062	60,17	12,45
p-Value	0,9154	0,0000	0,0000
GARCH (b)	0,664626***	0,984458***	0,952265***
t-Statistic	12,47	102,7	15,73
p-Value	0,0000	0,0000	0,0000

Source: Datastream® Database

Table 3: Estimates of univariate FIGARCH (1,d,1) model

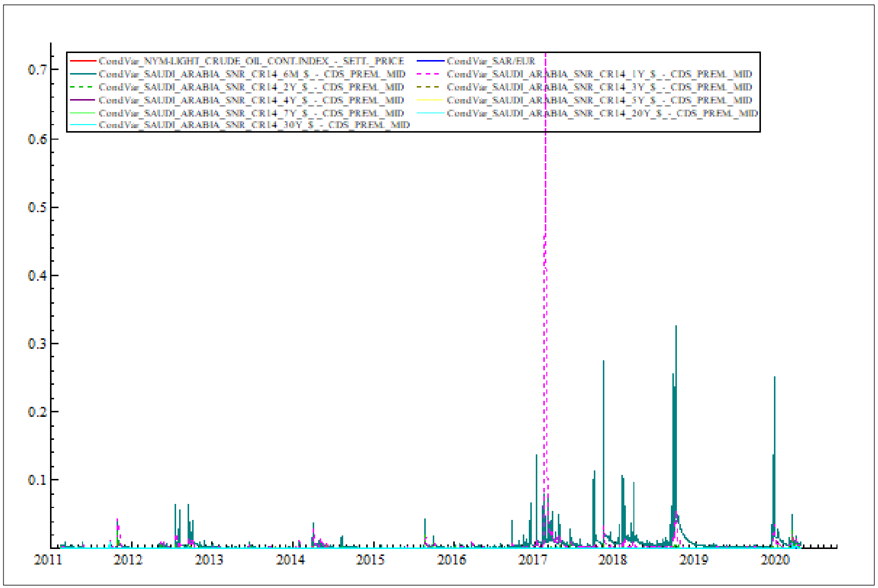
	Saudi_arabia_snr_cr14_4Y_$_-_cds_prem._mid	Saudi_Arabia_Snr_Cr14_5Y_$_-_Cds_Prem._mid	saudi_arabia_snr_cr14_7Y_$_-_cds_prem._mid
Constant (μ)	-0,000467*	-0,000319*	-0,000288*
t-Statistic	-1,908	-1,585	-1,789
p-Value	0,0566	0,1132	0,0738
constant (ω)	0,200451**	0,188591**	0,248524***
t-Statistic	2,460	2,555	3,665
p-Value	0,0140	0,0107	0,0003
d-figarch	0,122038**	0,475830**	0,310605***
t-Statistic	2,180	2,052	3,201
p-Value	0,0294	0,0403	0,0014
ARCH (a)	0,749173***	0,021770	-0,721353***
t-Statistic	8,938	0,1141	-9,675
p-Value	0,0000	0,9002	0,0000
GARCH (b)	0,632103***	0,278146	-0,604416***
t-Statistic	6,714	0,9493	-6,883
p-Value	0,0000	0,3425	0,0000

Source: Datastream® Database

Table 4: Estimates of univariate FIGARCH (1,d,1) model

	Saudi_arabia_snr_cr14_20Y_$_-_cds_prem._mid	Saudi_arabia_snr_cr14_30Y_$_-_cds_prem._mid
Constant *(μ)*	-0,000205*	-0,000132
t-Statistic	-1,099	-0,5932
p-Value	0,2718	0,5531
constant (ω)	0,134686*	0,132653**
t-Statistic	1,881	2,930
p-Value	0,0600	0,0034
d-figarch	0,673286*	0,845828**
t-Statistic	1,252	2,881
p-Value	0,2108	0,0040
ARCH *(a)*	0,072216	0,058981
t-Statistic	0,3486	0,2836
p-Value	0,7274	0,7768
GARCH *(b)*	0,459277*	0,560990***
t-Statistic	1,062	3,158
p-Value	0,2885	0,0016

***Source*:** Datastream® Database



***Source*:** Datastream® Database

Fig 2: Conditional variances of the univariate FIGARCH (1,d,1) model

Results of the univariate FIGARCH (1, d, 1) model

Estimates of the univariate FIGARCH (1,d,1) model are displayed in Tables 1 to 4 (above). From this tables, μ has significant value only for 2Y-3Y-4Y-5Y-7Y and 20Y CDSs. Constant ω is significant for all markets except the case of 3Y-CDSs. The ARCH (*a*) and GARCH (*b*) terms are highly significant for the most markets. Additionally, all markets demonstrate strong persistent behaviour (significant d-Figarch).

Figure 2 (above) illustrates the evolution of the estimated conditional variances for all market logarithmic returns from 2011 to 2020. Variances present a common movement. Additionally, they demonstrate mostly extreme picks during the whole period.

Table 5: Estimates of the DCC-FIGARCH (1,d,1) model, degrees of freedom

	Crude oil-Sar/Eur-6M Cds	Crude oil-sar/eur-1Y cds	Crude oil-sar/eur-2Y cds
Alpha *(α)*	0,005273***	0,005516***	0,004575***
t-Statistic	3,336	3,426	3,178
p-Value	0,0009	0,0006	0,0015
beta *(β)*	0,988613***	0,988422***	0,989877***
t-Statistic	290,9	294,6	325,1
p-Value	0,0000	0,0000	0,0000
degrees of freedom *(df)*	3,677144***	3,726771***	3,931701***
t-Statistic	33,44	32,28	29,26
p-Value	0,0000	0,0000	0,0000

***Source*:** Datastream® Database

Table 6: Estimates of the DCC-FIGARCH (1,d,1) model, degrees of freedom

	Crude Oil-Sar/Eur-3Y CDS	Crude Oil-Sar/Eur-4Y CDS	Crude Oil-Sar/Eur-5Y CDS
Alpha (α)	0,005035***	0,005155***	0,006253***
t-Statistic	3,281	3,268	3,449
p-Value	0,0011	0,0011	0,0006
beta (β)	0,989382***	0,989128***	0,987183***
t-Statistic	302,8	295,2	255,0
p-Value	0,0000	0,0000	0,0000
degrees of freedom (*df*)	3,965759***	4,025645***	3,969599***
t-Statistic	28,73	28,11	28,74
p-Value	0,0000	0,0000	0,0000

***Source*:** Datastream® Database

Table 7: Estimates of the DCC-FIGARCH (1,d,1) model, degrees of freedom

	Crude Oil-Sar/Eur-7Y CDS	Crude Oil-Sar/Eur-20Y CDS	Crude Oil-Sar/Eur-30Y CDS
Alpha (α)	0,006468***	0,007101***	0,006992***
t-Statistic	3,418	3,053	3,051
p-Value	0,0006	0,0023	0,0023
beta (β)	0,986715***	0,985007***	0,985220***
t-Statistic	239,8	172,2	173,6
p-Value	0,0000	0,0000	0,0000
degrees of freedom (*df*)	3,973142***	3,748084***	3,686977***
t-Statistic	29,02	32,16	33,45
p-Value	0,0000	0,0000	0,0000

***Source*:** Datastream® Database

Results of the trivariate DCC-FIGARCH (1, d, 1) model

Tables 5 to 7 (above) reports the estimation results of the trivariate DCC model. The estimates of the α and β are statistically significant showing strong ARCH and GARCH effects. Besides, we observe the estimated degrees of freedom (v) and the log-likelihood.

Table 8: Average correlations

	Crude Oil-Sar/Eur-6M CDS	Crude Oil-Sar/Eur-1Y CDS	Crude Oil-Sar/Eur-2Y CDS
Rho12	0,071750**	0,073696**	0,083231**
t-Statistic	2,322	2,334	2,675
p-Value	0,0203	0,0197	0,0075
Rho13	-0,081525**	-0,094133**	-0,087627**
t-Statistic	-2,437	-2,672	-2,636
p-Value	0,0149	0,0076	0,0085
Rho23	-0,027576	-0,049969*	-0,042811*
t-Statistic	-0,8992	-1,553	-1,387
p-Value	0,3687	0,1206	0,1656

***Source*:** Datastream® Database

Table 9: Average correlations

	Crude Oil-Sar/Eur-3Y CDS	Crude Oil-Sar/Eur-4Y CDS	Crude Oil-Sar/Eur-5Y CDS
Rho12	0,081713**	0,086185**	0,079526**
t-Statistic	2,534	2,657	2,402
p-Value	0,0113	0,0079	0,0164
Rho13	-0,087803**	-0,085686**	-0,079463**
t-Statistic	-2,500	-2,417	-2,186
p-Value	0,0125	0,0157	0,0289
Rho23	-0,041067*	-0,039972*	-0,051441*
t-Statistic	-1,274	-1,220	-1,518
p-Value	0,2029	0,2224	0,1290

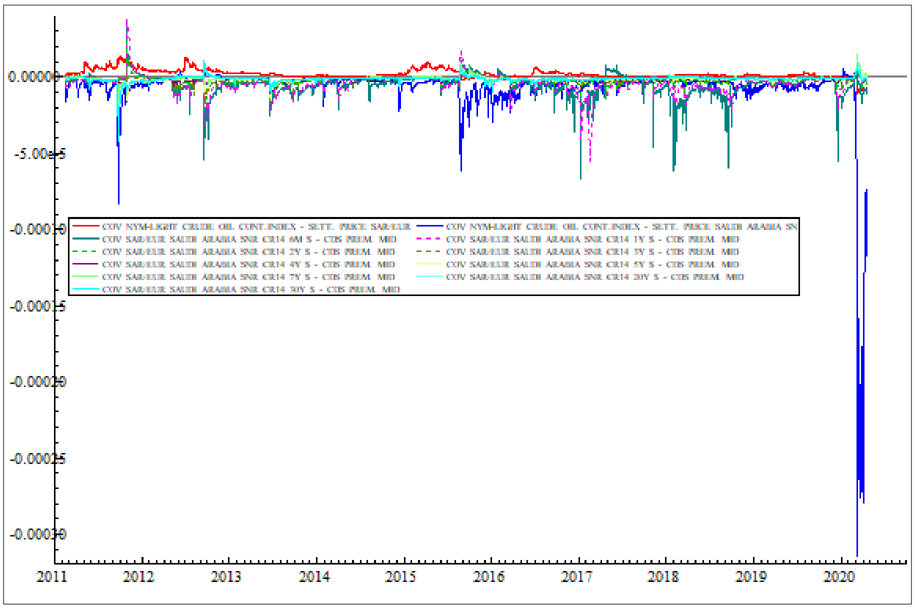
***Source*:** Datastream® Database

Table 10: Average correlations

	Crude Oil-Sar/Eur-7Y CDS	Crude Oil-Sar/Eur-20Y CDS	Crude Oil-Sar/Eur-30Y CDS
Rho12	0,076418**	0,066634**	0,065101**
t-Statistic	2,297	2,096	2,067
p-Value	0,0217	0,0362	0,0389
Rho13	-0,069033*	-0,054125*	-0,060246*
t-Statistic	-1,915	-1,550	-1,740
p-Value	0,0556	0,1214	0,0820
Rho23	-0,043839*	-0,064538*	-0,069840**
t-Statistic	-1,296	-1,963	-2,131
p-Value	0,1951	0,0498	0,0332

***Source*:** Datastream® Database

The average correlation are displayed in Tables 8 to 10 (above). Average correlation is statistically significant for the most pairs of markets.



***Source*:** Datastream® Database

Fig 3: Conditional covariances of the univariate FIGARCH (1, d,1) model.

Figure 3 (above) presents the estimated conditional covariances for all the pairs of market logarithmic returns. As the aforementioned findings of variances, conditional covariances present a common movement and they are extreme volatile. Additionally, they present both negative and positive values.

Table 11: Diagnostic tests

	Crude Oil-Sar/Eur-6M CDS	**Crude Oil-Sar/Eur-1Y CDS**	**Crude Oil-Sar/Eur-2Y CDS**
$x^2(6)$	8820,3**	6858,3**	5346,0**
p-Value	0,0000	0,0000	0,0000
Hosking (50)	449,183	462,080	502,862
p-Value	0,5020021	0,3367758	0,1147311
Li-McLeod (50)	449,201	461,948	502,384
p-Value	0,5017630	0,3383553	0,1141558

***Source*:** Datastream® Database

Table 12: Diagnostic tests

	Crude Oil-Sar/Eur-3Y CDS	**Crude Oil-Sar/Eur-4Y CDS**	**Crude Oil-Sar/Eur-5Y CDS**
$x^2(6)$	5534,3**	4463,4**	4761,7**
p-Value	0,0000	0,0000	0,0000
Hosking^2 (50)	489,258	495,365	470,658
p-Value	0,0977591	0,0686150	0,2418160
Li-McLeod^2 (50)	488,953	495,212	470,787
p-Value	0,0994291	0,0692503	0,2405130

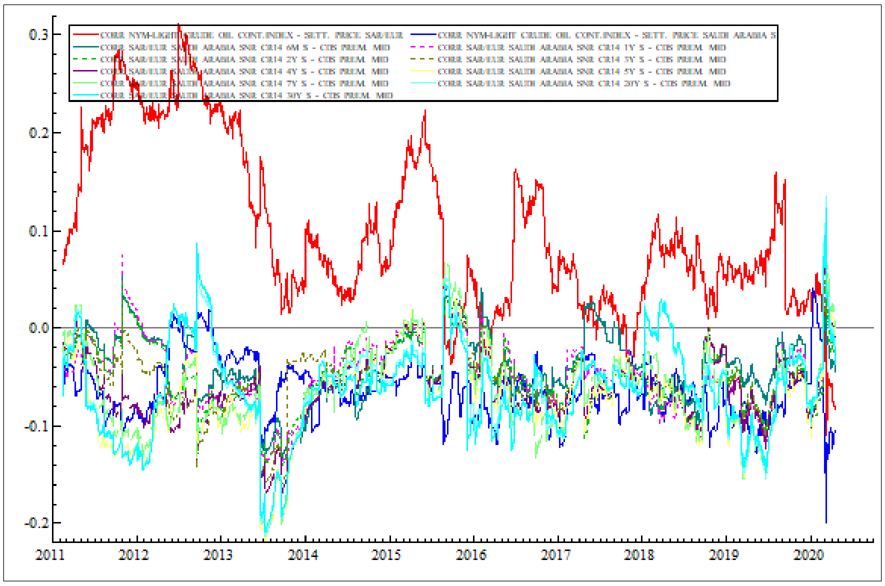
***Source*:** Datastream® Database

Table 13: Diagnostic tests

	Crude oil-Sar/Eur-7Y CDS	**Crude Oil-Sar/Eur-20Y CDS**	**Crude Oil-Sar/Eur-30Y CDS**
$x^2(6)$	4156,6**	8425,4**	11370,0**
p-Value	0,0000	0,0000	0,0000
Hosking (50)	469,245	450,081	451,987
p-Value	0,2563259	0,4900604	0,4648048
Li-McLeod (50)	469,399	450,343	452,190
p-Value	0,2547140	0,4865778	0,461202

***Source*:** Datastream® Database

Results of the hypothesis tests, diagnostic tests and information criteria: Tables 11, 12 and 13 (above) report the estimation results of $x^2(4)$ statistic, hypothesis tests and selected information criteria (AIC, SIC). Overall, test results do not accept the hypothesis of no spillovers at 1% significance level. Multivariate diagnostic tests detect no serial correlation on squared standardized residuals (Hosking, 1980; Li-McLeod, 1983).



Source: Datastream® Database

Fig 4: Dynamic conditional correlations of the trivariate DCC-FIGARCH (1, d,1) model

Dynamic Conditional Correlation analysis of the trivariate DCC-FIGARCH (1, d, 1) model

Figure 4 (Above) displays the Dynamic Conditional Correlations (DCCs) for all the pairs of market returns. In what follows, the alternate between bull and bear phases on the figure indicate the dynamic nature of DCCs. DCCs are extreme volatile and have positive values. Moreover, some major time-varying jumps are highlighted. The results present a less reliable stability of the DCCs from an investors point of view, rationalizing the market-portfolio diversification. Additionally, We can see the effects of major economic crises on the figure i.e. the Standard & Poor's credit rating agency downgraded the credit rating of the USA from AAA to AA+ (5/8/2011), the European Central Bank announcement of an aggressive money-creation program, printing more than one trillion new euros (22/01/2015), the Black Monday (24/08/2015), and the United Kingdom referendum (23/06/2016).

Conclusions

The aim of this paper is to increase the empirical evidence reported in the literature by examining potential volatility spillover and contagion effects between crude oil future, SAR/EUR and Saudi Arabia CDS markets. We defined the under investigation period from 15 Februry 2011 to 27 August 2020. To this end, we employ a trivariate DCC-FIGARCH process in order to quantify major spillovers and contagion.

These empirical results prove the existence of strong volatility spillover effects for all the pairs of markets. Then, Dynamic Conditional Correlations highlight strong contagion effects for all the pairs of markets, implying that investors should diversify their portfolios during bearish time periods. Additionally, the empirical results if this article are of interest to regulators of financial derivatives markets, who provide regulations for the future, FOREX and CDS markets.

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