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Original Research Article

Volatility Spillovers among Crude Oil, EUR/USD and Major ETS Markets during 2013-2017: A Trivariate cDCC-GARCH Application

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Abstract

This paper examines the time-varying conditional correlations among Crude oil. EUR/USD and major ETS markets. We apply a trivariate dynamic conditional correlation (cDCC) GARCH models in order to capture potential contagion effects between the markets for the period 2013-2017. Empirical results reveal contagion during the under investigation period regarding the trivariate models, showing potential volatility transmission channels among the markets. Findings have crucial implications for policymakers who provide regulations for the above derivative markets.
Keywords: cDCC-GARCH model, FOREX, Crude Oil, ETS, financial contagion, dynamic conditional correlations.

1. INTRODUCTION

In this paper, we explore the potential spillovers among Crude oil, EUR/USD and major ETS markets from 2013 until 2017. The recent global financial crisis has made assets with low correlations attractive for investors regarding the systematic risk protection. We extend the correlation analysis of Forbes and Rigobon (2002) by considering the corrected Dynamic Conditional Correlation GARCH (cDCC-GARCH) of Aielli (2009).

Our aim is to answer the following questions. First question is whether there are volatile Dynamic Conditional Correlations (DCCs). Next question is how those DCCs evolve over time. Third question is whether there are contagion effects.

We organize the paper as following: Section two shows the literature review. Section three presents the model and the data. Section four describes the empirical results, whilst Section five states the conclusions.

2. LITERATURE REVIEW

In the literature, there are many researches trying to explore the ETS market (Zou, *et al.*, 2022; Tan, *et al.*, 2020; Zhou, *et al.*, 2022; Liu, *et al.*, 2021; Meng, *et al.*, 2022; Yu, *et al.*, 2015; Song, *et al.*, 2020; Tiwari, *et al.*, 2022; Ali, *et al.*, 2022; Ali, *et al.*, 2021). Also, there are many papers examining the potential spillover effects of ETS market (Zhu, *et al.*, 2020; Zhu, *et al.*, 2020; Pan, *et al.*, 2021; Deng, *et al.*, 2019; Chen, *et al.*, 2021; Yi, *et al.*, 2020; Guo, *et al.*, 2021; Peng, *et al.*, 2020; Ji, *et al.*, 2021; Jiang, 2018). To the best of our knowledge, this is the first empirical research considering potential spillover effects among Crude oil, EUR/USD and major ETS markets.

3. MODEL AND DATA DESCRIPTION

3.1 The Trivariate cDCC-GARCH model

First, we define the daily logarithmic returns:

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

where μ is constant and ε_t is standardized residuals defined as follows:

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

where u_t is standardized errors and h_t is conditional variance depending on h_t and ε_t for each market lagged one period, generated by the univariate GARCH(1,1) model [24]:

$h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1}$ (3)

where ω is constant, a and b are ARCH and GARCH effects.

Next, we define the multivariate conditional variance matrix (H_t) ($N\,x\,N$ matrix), using the cDCC model of Aielli (2009) as follows:

$H_t = D_t R_t D_t$ (4)

And

$D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right)$, where N is the number of markets ($i = 1,\dots,N$) (5)

Additionally, we define the conditional correlation matrix (R_t):

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

We define $P_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}\right)$ and $u_t^* = P_t u_t$.

The cDCC model of Aielli (2009) is an extension of the DCC model of Engle (2002). In the cDCC model, $Q_t = (q_{ij,t})$ ($N\,x\,N$ symmetric positive definite matrix) is defined as follows:

$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}^* u_{t-1}^{*\prime} + \beta Q_{t-1}$ (7)

where $\bar{Q}$ is the $N\,x\,N$ unconditional variance matrix of u_t^* (since $\mathrm{E}[u_t^* u_t^{*\prime}|\Omega_{t-1}] = Q_t$) [1]. α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

For the cDCC model, the estimation of the matrix $\bar{Q}$ and the parameters α and β are intertwined, since $\bar{Q}$ is estimated sequentially by the correlation matrix of the u_t^*. To obtain u_t^* we need however a first step estimator of the diagonal elements of Q_t. Thanks to the fact that the diagonal elements of Q_t do not depend on $\bar{Q}$ (because $\overline{Q_{ii}} = 1$ for $i = 1,\dots,N$), Aielli (2009) proposed to obtain these values $q_{11,t},\dots, q_{NN,t}$ as follows:

$q_{ii,t} = (1 - \alpha - \beta) + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1}$ (8)

for $i = 1,\dots,N$. In short, given α and β, we can compute $q_{11,t},\dots, q_{NN,t}$ and thus u_t^*, then we can estimate $\bar{Q}$ as the empirical covariance of u_t^*.

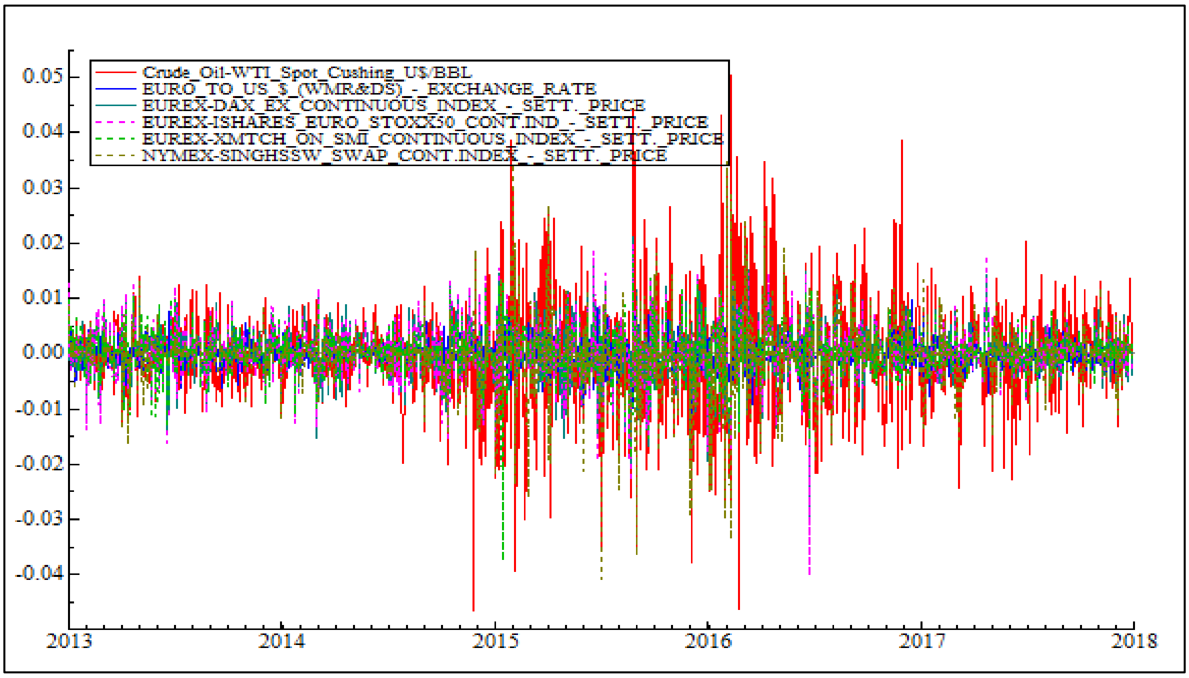

Figure 1: Actual series of the logarithmic returns of the markets

Source: Data stream Database

[1] Aielli (2009) has recently shown that the estimation of $\bar{Q}$ as the empirical correlation matrix of u_t is inconsistent because: $\mathrm{E}[u_t\ u_t\ ] = \mathrm{E}[\mathrm{E}[u_t' u_t\ |\Omega_{t-1}] = \mathrm{E}[R_t\ ] \neq \mathrm{E}[Q_t\ ]$.

3.2 Data Description

In this paper, we use daily data for the following markets: Crude Oil-WTI Spot Cushing U$/BBL, EURO TO US $ (WMR&DS) – EXCHANGE RATE, EUREX-DAX EX CONTINUOUS INDEX - SETT. PRICE, EUREX-ISHARES EURO_STOXX50 CONT.IND - SETT. PRICE, EUREX-XMTCH ON SMI CONTINUOUS INDEX - SETT. PRICE and NYMEX-SINGHSSW SWAP CONT.INDEX - SETT. PRICE. The period of observation starts at 1st January 2013, and ends at 31st December 2017. All prices have been extracted from *Datastream® Database.* For each market we use 1303 observations. Market logarithmic returns generated by $r_t = log(p_t) - log(p_{t-1})$, where p_t is the price of market on day t.

Figure 1 plots the actual series of market logarithmic returns. By contacting a visual inspection of the logarithmic returns, we can recognize the trend of the markets. The figure shows the presence of heteroskedasticity rationalizing the use of the dynamic conditional correlations in the multivariate GARCH (1,1) framework.

4. EMPIRICAL RESULTS

This section is divided into five subsections. In section 4.1, the results from the cDCC-GARCH (1,1) model are described. Section 4.2 presents the estimates of average correlations. Section 4.3 provides an explicit economic analysis based on dynamic conditional correlations (DCCs), whilst section 4.4 presents the diagnostic tests.

4.1 Results of the DCC-GARCH (1,1) model

Tables 1 and 2 state the estimated values for mean equation and univariate GARCH (1,1) model. Mean equation exhibits significant μ value for three markets: EUREX DAX EX CONTINUOUS INDEX - SETT. PRICE, EUREX ISHARES EURO STOXX50 CONT.IND - SETT. PRICE and EUREX XMTCH ON SMI CONTINUOUS INDEX - SETT. PRICE. Moreover, all the markets present statistically significant ω. In addition, the ARCH (a) and GARCH (b) terms are highly significant for all markets.

Table 1: Estimates of univariate GARCH (1,1) model

	Crude_Oil-WTI_Spot_Cushing_U$/BBL	**EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE**	**EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE**
constant *(μ)*	0,000047	0,0000485	0,000321**
t-Statistic	0,2661	0,8818	2,934
p-Value	0,7902	0,3780	0,0034
constant (ω)	0,333490*	0,013741*	0,234814*
t-Statistic	1,537	1,047	1,259
p-Value	0,1246	0,2954	0,2084
ARCH *(Alpha1)*	0,065189***	0,030745***	0,065101**
t-Statistic	4,936	5,181	2,501
p-Value	0,0000	0,0000	0,0125
GARCH *(Beta1)*	0,934968***	0,967251***	0,926351***
t-Statistic	72,96	166,8	30,20
p-Value	0,0000	0,0000	0,0000

Source: Data stream Database

Table 2: Estimates of univariate GARCH (1,1) model

	EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE	**EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE**	**NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE**
constant *(μ)*	0,000279**	0,0002749***	0,0000015
t-Statistic	2,458	3,035	0,01180
p-Value	0,141	0,0025	0,9906
constant (ω)	0,307016*	0,738860*	2,784130***
t-Statistic	1,154	1,884	4,162
p-Value	0,2486	0,0598	0,0000
ARCH *(Alpha1)*	0,064090**	0,106793***	0,384036***
t-Statistic	2,161	3,693	7,284
p-Value	0,0309	0,0002	0,0000
GARCH *(Beta1)*	0,923104***	0,845283***	0,543535***
t-Statistic	24,19	17,12	16,79
p-Value	0,0000	0,0000	0,0000

Source: Data stream Database

Figure 2 plots the behavior of conditional variances for all markets. By contacting a visual exploration, we observe that all markets exhibit strong ups and downs over time. Additionally, we observe large spikes in February 2016 revealing the effects of major economic crises.

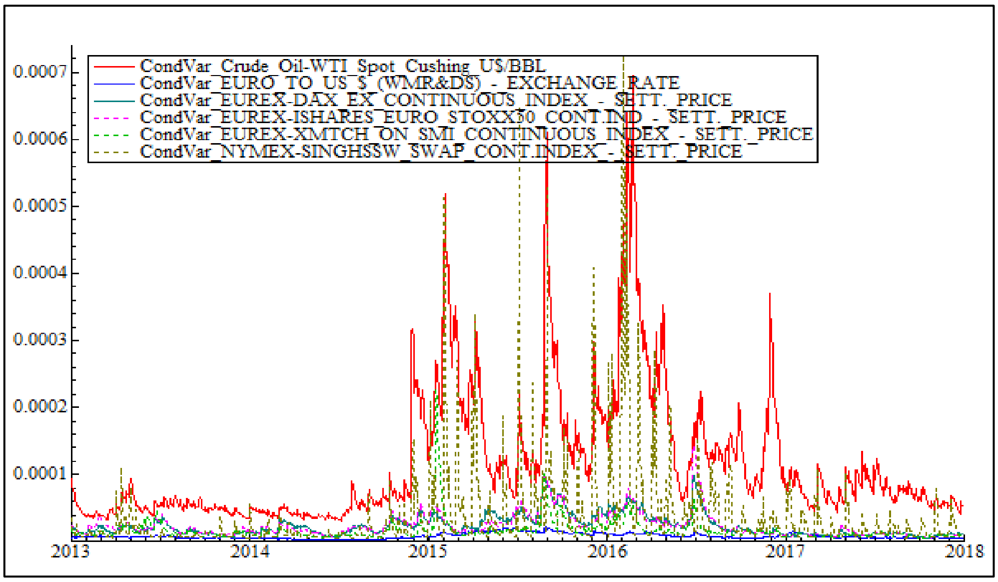

Figure 2: Conditional variances for the markets of the univariate EGARCH (1,1) model
Source: Data stream Database

In Tables 3 and 4, we see the normality test of the univariate GARCH model. All market returns are negatively skewed except the case of EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE. Moreover, all market returns present excess kurtosis (fat tails). According to the Jarque-Bera statistic, we reject the null hypothesis of normality for all markets, suggesting the use of student-t distribution as the most appropriate for the empirical analysis (Forbes and Rigobon, 2002).

Table 3: Normality Test of univariate GARCH (1,1) model

	Crude_Oil-WTI_Spot_Cushing_US$/BBL	**EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE**	**EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE**
Skewness	-0,38476***	0,17439**	-0,21108***
t-Statistic	5,6722	2,5709	3,1118
p-Value	1,4095e-008	0,010144	0,0018596
Excess Kurtosis	2,3471***	1,6206***	1,8780***
t-Statistic	17,314	11,955	13,854
p-Value	3,7130e-067	6,1381e-033	1,2066e-043
Jarque-Bera	330,72**	148,96**	200,85**
p-Value	1,5345e-072	4,5012e-033	2,4260e-044

Source: Data stream Database

Table 4: Normality Test of univariate GARCH (1,1) model

	EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE	**EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE**	**NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE**
Skewness	-0,27129***	-0,67701***	-1,3392***
t-Statistic	3,9993	9,9807	19,743
p-Value	6,3518e-005	1,8524e-023	9,1740e-087
Excess Kurtosis	3,2423***	4,2931***	30,294***
t-Statistic	23,918	31,669	223,47
p-Value	2,0052e-126	4,1334e-220	0,0000
Jarque-Bera	585,83**	1098,5**	50137**
p-Value	6,1562e-128	2,9301e-239	0,0000

Source: Data stream Database

Tables 7 and 8 report the results of the trivariate cDCC model estimations. The cDCC model results show significant α and β parameters, indicating strong ARCH and GARCH effects, suggesting empirical evidence that the markets are integrated. In addition, we provide the estimates of the degrees of freedom (v) and of the log-likelihood.

Table 7: Estimates of the trivariate cDCC-GARCH (1,1) model, degrees of freedom, log-likelihood

	Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE	**Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE**
alpha *(α)*	0,006354*	0,005602*
t-Statistic	1,364	1,982
p-Value	0,1728	0,0477
beta *(β)*	0,983539***	0,985409***
t-Statistic	54,13	114,7
p-Value	0,0000	0,0000
degrees of freedom (*df*)	8,041537***	7,799021***
t-Statistic	8,009	8,379
p-Value	0,0000	0,0000
log-likelihood	15813,976	15804,716

Source: Data stream Database

Table 8: Estimates of the trivariate cDCC-GARCH (1,1) model, degrees of freedom, log-likelihood

	Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE	**Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE**
alpha *(α)*	0,007208*	0,111920***
t-Statistic	1,760	3,442
p-Value	0,0786	0,0006
beta *(β)*	0,982139***	0,583688***
t-Statistic	78,31	6,465
p-Value	0,0000	0,0000
degrees of freedom (*df*)	8,007267***	3,437307***
t-Statistic	8,172	14,57
p-Value	0,0000	0,0000
log-likelihood	16050,394	16248,688

Source: Data stream Database

In figure 3 we graph the conditional covariances. Results suggest positive values for the most conditional covariances, while for some market pairs, conditional covariances present negative prices.

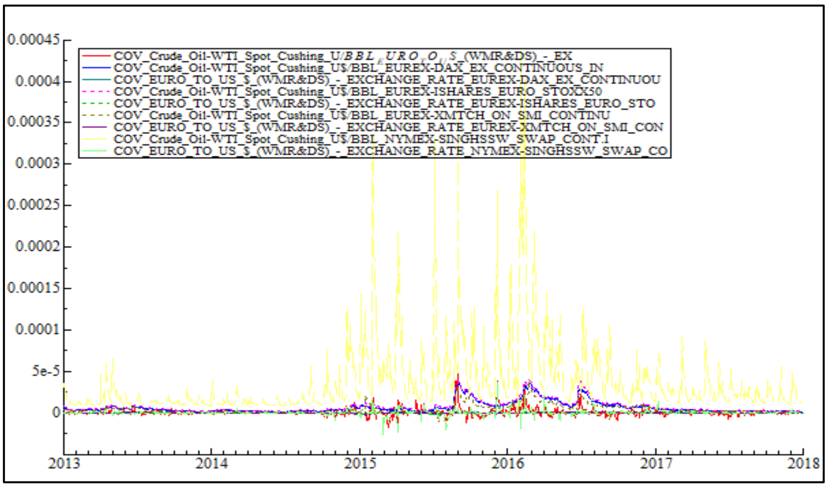

Figure 3: Conditional covariances for the pairs of markets of the trivariate DCC-EGARCH (1,1) model
Source: Data stream Database

4.2 Estimates of average correlations

Table 9 presents the estimated average correlations of the trivariate GARCH(1,1)-cDCC model. We observe that the most average correlations are not statistically significant and positive.

Table 9: Estimates for the average correlations of the trivariate cDCC-GARCH (1,1) model

	Coefficient	t-Statistic	p-Value
Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE	0,012193	0,2772	0,7817
EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE-Crude_Oil-WTI_Spot_Cushing_U$/BBL	0,128438**	2,890	0,0039
EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE	-0,007487	-0,1738	0,8620
EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE-Crude_Oil-WTI_Spot_Cushing_U$/BBL	0,156323***	3,515	0,0005
EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE	-0,005360	-0,1273	0,8987
Crude_Oil-WTI_Spot_Cushing_U$/BBL- EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE	0,102939**	2,278	0,0229
EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE	-0,009762	-0,2188	0,8269
Crude_Oil-WTI_Spot_Cushing_U$/BBL- NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE	0,611160***	23,76	0,0000
EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE	0,012553	0,4124	0,6801

Source: Data stream Database

Tables 12 to 14 present the descriptive statistcs of the DCCs. CORR Crude Oil-WTI Spot Cushing U$/BBL EUREX-DAX EX CONTINUOUS I exhibits larger fluctuations compared to the rest markets, considering the highest maximum and the lowest minimum return prices. All markets exhibit excess kurtosis. Based on Jarque-Bera statistics we reject the null hypothesis of normality for all the pairs of markets except the cases of CORR EURO TO US $ (WMR&DS) - EXCHANGE RATE EUREX-DAX EX CONTINUO and CORR Crude Oil-WTI Spot Cushing U$/BBL EUREX-ISHARES EURO STOXX5.

Table 12: Descriptive statistics of the DCCs

	CORR_Crude_Oil-WTI_Spot_Cushing_U$/BBL_EURO_TO_US_$_(WMR&DS)_-_E	CORR_Crude_Oil-WTI_Spot_Cushing_U$/BBL_EUREX-DAX_EX_CONTINUOUS_I	CORR_EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE_EUREX-DAX_EX_CONTINUO
Min	-0,6933	0,0098555	-0,092227
Mean	0,024448	0,12651	-0,0029697
Max	0,1007	0,26218	0,099294
Std.dev.	0,033163	0,05529	0,034114
Skewness	0,086151*	0,27182***	0,054167
t-Statistic	1,2701	4,0073	0,79854
p-Value	0,20406	6,1424e-005	0,42456
Excess Kurtosis	-0,35483**	-0,94117***	0,048352
t-Statistic	2,6175	6,9428	0,35668
p-Value	0,0088588	3,8453e-012	0,72133
Jarque-Bera	8,4342**	64,039**	0,76293
p-Value	0,014741	1,2420e-014	0,68286

Source: Data stream Database

Table 13: Descriptive statistics of the DCCs

	CORR_EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE_EUREX-ISHARES_EURO_ST	CORR_Crude_Oil-WTI_Spot_Cushing_U$/BBL_EUREX-ISHARES_EURO_STOXX5	CORR_Crude_Oil-WTI_Spot_Cushing_U$/BBL_EUREX-XMTCH_ON_SMI_CONTIN
Min	-0,089212	0,048995	-0,019425
Mean	-0,0031889	0,15445	0,10556
Max	0,075674	0,28142	0,26695
Std.dev.	0,034744	0,053772	0,062626
Skewness	-0,30293***	0,26475***	0,44880***
t-Statistic	4,4659	3,9030	6,6163
p-Value	7,9743e-006	9,4994e-005	3,6839e-011
Excess Kurtosis	-0,55166***	-1,1007***	-0,79491***
t-Statistic	4,0694	8,1198	5,8638
p-Value	4,7129e-005	4,6707e-016	4,5232e-009
Jarque-Bera	36,395**	80,977	77,927**
p-Value	1,2500e-008	2,7398e-018	1,1976e-017

Source: Data stream Database

Table 14: Descriptive statistics of the DCCs

	CORR_EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE_EUREX-XMTCH_ON_SMI_CO	CORR_Crude_Oil-WTI_Spot_Cushing_U$/BBL_NYMEX-SINGHSSW_SWAP_CONT.	CORR_EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE_NYMEX-SINGHSSW_SWAP_C
Min	-0,12444	0,019617	-0,50436
Mean	-0,0003885	0,61412	0,013635
Max	0,10304	0,872	0,49686
Std.dev.	0,039772	0,066693	0,095859
Skewness	-0,13091*	-1,1704***	-0,17811**
t-Statistic	1,9299	17,255	2,6257
p-Value	0,053617	1,0342e-066	0,0086462
Excess Kurtosis	0,036813	8,5493***	4,7676***
t-Statistic	0,27156	63,066	35,169
p-Value	0,78596	0,0000	5,9437e-271
Jarque-Bera	3,7895	4259,1**	1239
p-Value	0,15036	0,0000	8,9460e-270

Source: Data stream Database

4.3 Economic Analysis of Dynamic Conditional Correlation Coefficients

We proceed with the trivariate GARCH(1,1)-cDCC's estimation, using market logarithmic returns, illustrated graphically in Figure 4. The dynamic conditional correlation coefficient (DCC coefficient) estimates aim to give us a much clearer view of contagion effects. As depicted in figure 4, all the DCC coefficients are positive in sub-periods and extreme volatile, implying contagion effects and a less reliable correlation in guiding portfolio decision. Furthermore, all the DCC coefficients are negative in sub-periods, implying a more reliable correlation in guiding portfolio decision. Additionally, we can recognize the effects of major economic events on the Figure, i.e. (3) the begin of Russo-Ukrainian war (2/2014) and (1) the Chinese stock market crash (12/6/2015).

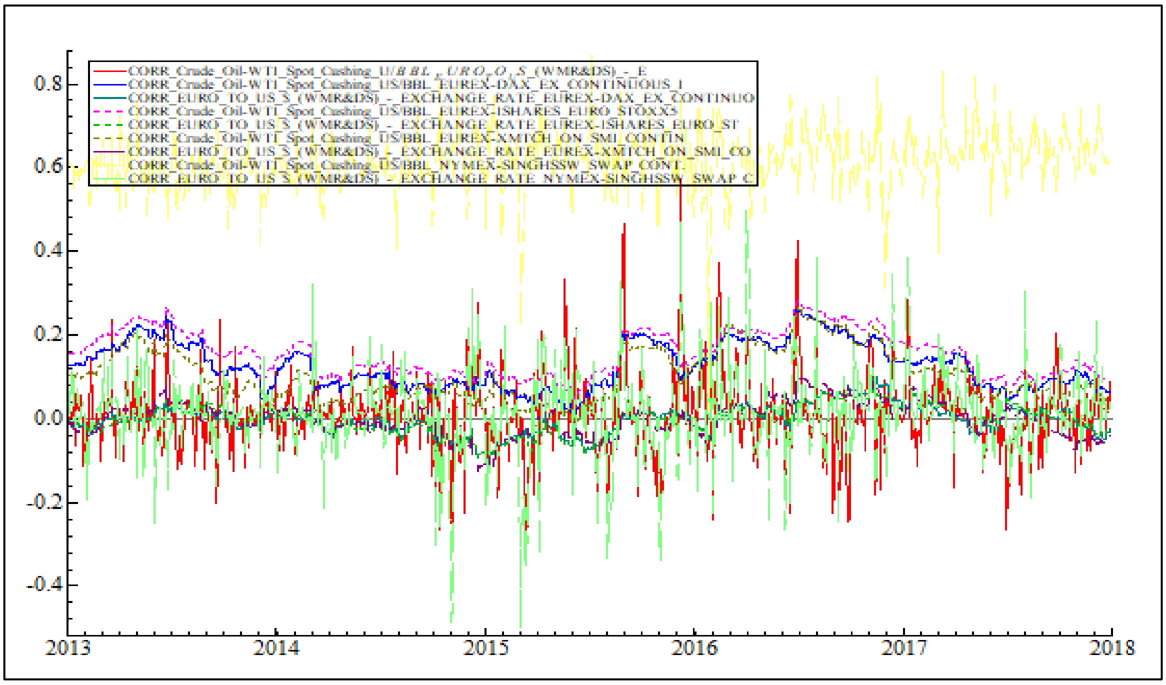

Figure 4: Dynamic conditional correlations for the pairs of markets of the trivariate DCC-EGARCH (1,1) model

Source: Data stream Database

4.4 Diagnostic Tests, Hypothesis Testing & Information Criteria

Hypothesis testing results and information criteria are exhibited in tables 5 and 6. Box/Pierce test results provide evidence of no serial autocorrelation, suggesting the absence of misspecification errors of the estimated GARCH model.

Table 5: Diagnostic tests tests of the univariate GARCH (1,1) model

	Crude_Oil-WTI_Spot_Cushing_U$/BBL	**EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE**	**EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE**
Box/Pierce^2 (10)	2,72877	9,77276	4,42994
p-Value	0,9871064	0,4606507	0,9258748

Source: Data stream Database

Table 6: Diagnostic tests tests of the univariate GARCH (1,1) model

	EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE	**EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE**	**NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE**
Box/Pierce^2 (10)	4,41624	13,1157	2,38789
p-Value	0,9266228	0,2172752	0,9924106

Source: Data stream Database

Hypothesis testing results and information criteria are exhibited in tables 10 and 11, x^2 (12) statistic results suggest that the null hypothesis of no spillovers is rejected at 1% significance level. In addition, Ljuing-Box test results (Hosking 1980; Li-McLeod 1983) provide evidence of no serial autocorrelation, suggesting the absence of misspecification errors of the estimated MGARCH model. Furthermore, AIC and SIC information criteria are provided for our model.

Table 10: Diagnostic tests and information criteria of the trivariate cDCC-GARCH (1,1) model

	Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-DAX_EX_CONTINUOUS_INDEX_-_SETT._PRICE	**Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-ISHARES_EURO_STOXX50_CONT.IND_-_SETT._PRICE**
$x^2(6)$	358,96**	512,44**
p-Value	0,0000	0,0000
Hosking (50)	483,418	488,003
p-Value	0,1335922	0,1047666
Li-McLeod (50)	483,590	487,898
p-Value	0,1324172	0,1053748
Akaike	0,008985	0,008996
Schwarz	0,080527	0,080538
Shibata	0,008609	0,008620
Hannan-Quinn	0,035827	0,035838

Source: Data stream Database

Table 11: Diagnostic tests and information criteria of the trivariate cDCC-GARCH (1,1) model

	Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- EUREX-XMTCH_ON_SMI_CONTINUOUS_INDEX_-_SETT._PRICE	**Crude_Oil-WTI_Spot_Cushing_U$/BBL-EURO_TO_US_$_(WMR&DS)_-_EXCHANGE_RATE- NYMEX-SINGHSSW_SWAP_CONT.INDEX_-_SETT._PRICE**
$x^2(6)$	530,33**	3931,6**
p-Value	0,0000	0,0000
Hosking (50)	487,582	521,312
p-Value	0,1072059	0,2105557
Li-McLeod (50)	487,699	519,134
p-Value	0,1065204	0,2128970
Akaike	0,008706	0,008471
Schwarz	0,080248	0,080013
Shibata	0,008330	0,008095
Hannan-Quinn	0,035547	0,035313

Source: Data stream Database

5. CONCLUSIONS

In this article, we study the volatility transmission among Crude oil, EUR/USD and major ETS markets using daily data for the period 2013 – 2017. We apply a trivariate cDCC-GARCH(1,1) framework. To the best of our knowledge no empirical study has attempted to analyze the volatility effects among the under investigation markets in order to quantify and measure potential contagion effects.

Using the GARCH-cDCC model, we find evidence of significant dynamic conditional correlations for all the pairs of markets. More importantly, we find positive and negative correlation in sub-periods, supporting that the investors (Pension funds, hedge funds and insurance companies) dealing can get diversifications benefits and face non-important losses during bearish times. Policy makers, who provide regulations for the markets, should examine possible strategies that take into account the spillovers of the above markets during future crises.

Jel Classification: C58, C61, E44, G10, G20

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