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Original Research Article

The Time-Varying Correlation between Crude oil Future and USA Bond Markets During 2005-2020: Evidence from a DCC-GARCH Model

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Abstract

In this paper, we examine potential time-varying correlations between crude oil future and USA bond markets. We employ a dynamic conditional correlation (DCC) multivariate GARCH model in order to quantify potential contagion effects between the markets for the period 2005-2020. We divide the period in two sub-period to make the empirical analysis easier. Empirical results reveal increased conditional correlation in the first sub-period (2005-2012) and no contagion in the second sub-period (2012-2020). Results are of interest to investors, who invest long-term into the under investigation financial markets, as well as, to policymakers, who provide regulations for the under investigation derivate market.

Keywords: DCC-GARCH, Crude oil future market, USA bond market, financial contagion, dynamic conditional correlations.

Jel Classification: C58, C61, G10.

INTRODUCTION

In this paper we empirically investigate the spillovers and contagion between crude oil future market and six USA bond markets from 3rd January 2005 to 31st August 2012, including the USA subprime crisis, and from 3rd September 2012 to 27th August 2020, including the European Sovereign Debt Crisis. To quantify volatility spillover effects, we use a multivariate DCC-GARCH process [1]. According to Forbes and Rigobon [2] contagion is defined as a significant increase in cross-market linkages after a shock. We use the produced dynamic conditional correlations to measure contagion. Our empirical findings support the conclusion that investors can benefit from diversifying into the under investigation financial markets. Furthermore, the policy implications of the empirical results are also crucial. Policymakers can expect the markets to recover without additional measures are taken.

In recent years it has been noted that the effects of crude oil market influence major economic activity [3-7]. It has been identified the effects of crude oil market returns on stock returns [8-14]. A few studies have discussed the effects of crude oil market on bond markets [15, 16]. There are several studies investigating the linkages between crude oil future market and financial markets [17-23]. To the best of our knowledge this is the first such investigation of spillovers and contagion between crude oil future and USA bond markets.

Our paper adds to the related literature in several ways. First, we investigate the dynamic links between crude oil future and USA bond 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.

The remainder of this paper is organized as follows: Section two presents the methodology. Section three analyzes the empirical results. Section four gives concluding comments.

METHODOLOGY

Model Description

First we define the daily logarithmic returns:

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

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

$\varepsilon_t = \sqrt{h_t} u_t$, where $\varepsilon_t \sim N(0, H_t)$ and u_t are i.i.d. ……………….. (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]:

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

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

Next, we employ the Engle [1] representation of the bivariate GARCH model in order to estimate the bivariate conditional variance matrix (H_t is N x N matrix, with N the number of markets, i = 1,…,N) as follows:

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

D_t is the conditional variance matrix given by:

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

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

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

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

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1}, \ldots (7)$$

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

Data Description

In this paper, we use daily data for NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE, US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX, US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX, US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX, US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX, US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX and US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX. Based on the Global Financial Crisis of 2008, we divide the sample period into two sub-periods: the first period from 03/01/2005 until 31/08/2012 (2000 obs.) and the second period from 03/09/2012 until 27/08/2020 (2084 obs). We extracted the data from Datastream® Database. We generate market logarithmic returns using the equation: y $r_t = \log(p_t) - \log(p_{t-1})$, where p_t is the price of market on day t.

Figure 1 and 2 show the dynamics of market logarithmic returns during the under investigation periods. We observe the presence of volatility clustering and ARCH effects in all series, rationalizing the adoption of the GARCH models.

RESULTS AND DISCUSSION

In this section, we present the empirical results for the two under investigation periods: 3 January, 2005 – 31 August, 2012 and 3 September, 2012 – 27 August, 2020.

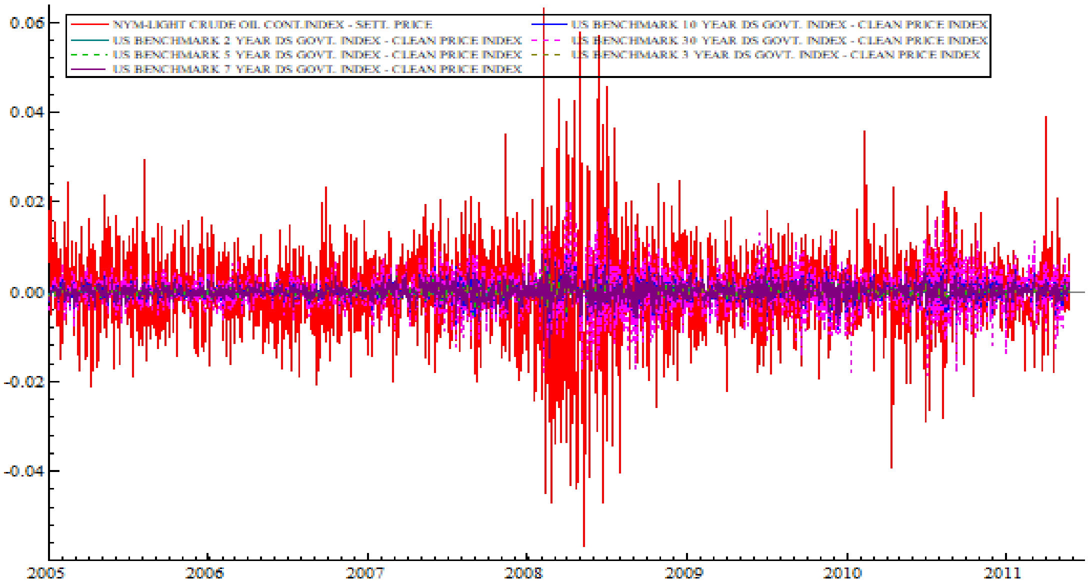

Fig-1: Actual series of the logarithmic returns of the markets, sample period: 3 January, 2005 – 31 August, 2012

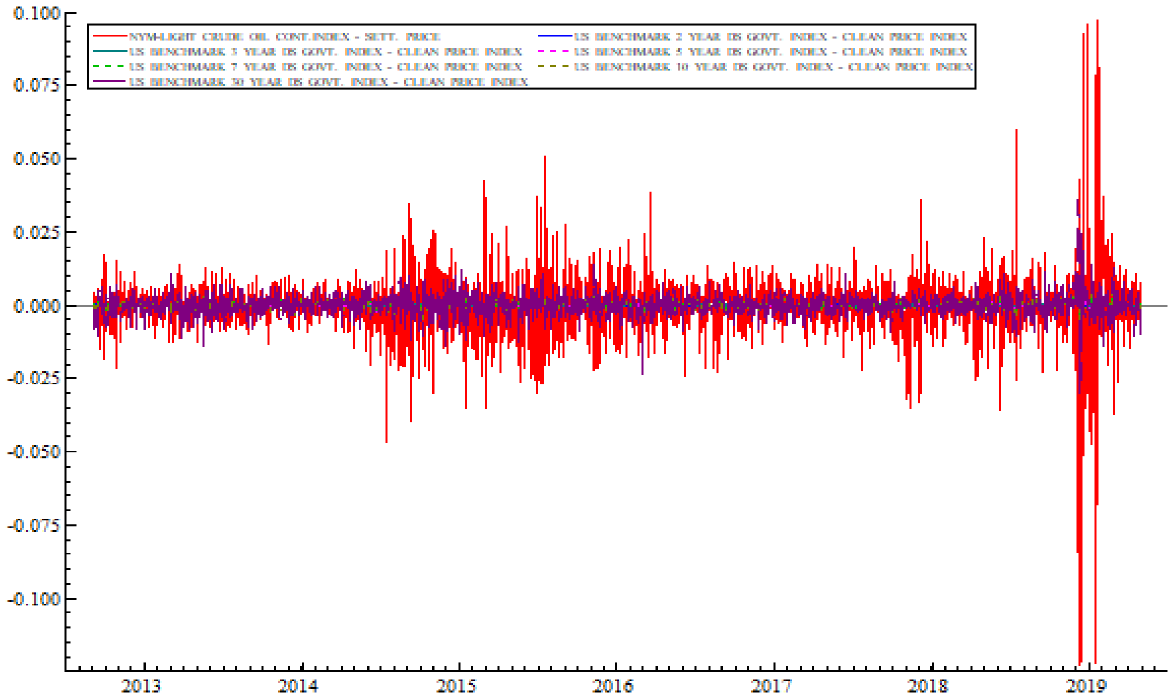

Fig-2: Actual series of the logarithmic returns of the markets, sample period: 3 September, 2012 – 27 August, 2020

Figure 3 and 4 plot the conditional variances for all market logarithmic returns in the two under investigation periods. Variances are extreme volatilite during both periods. Interestingly, we see a common movement.

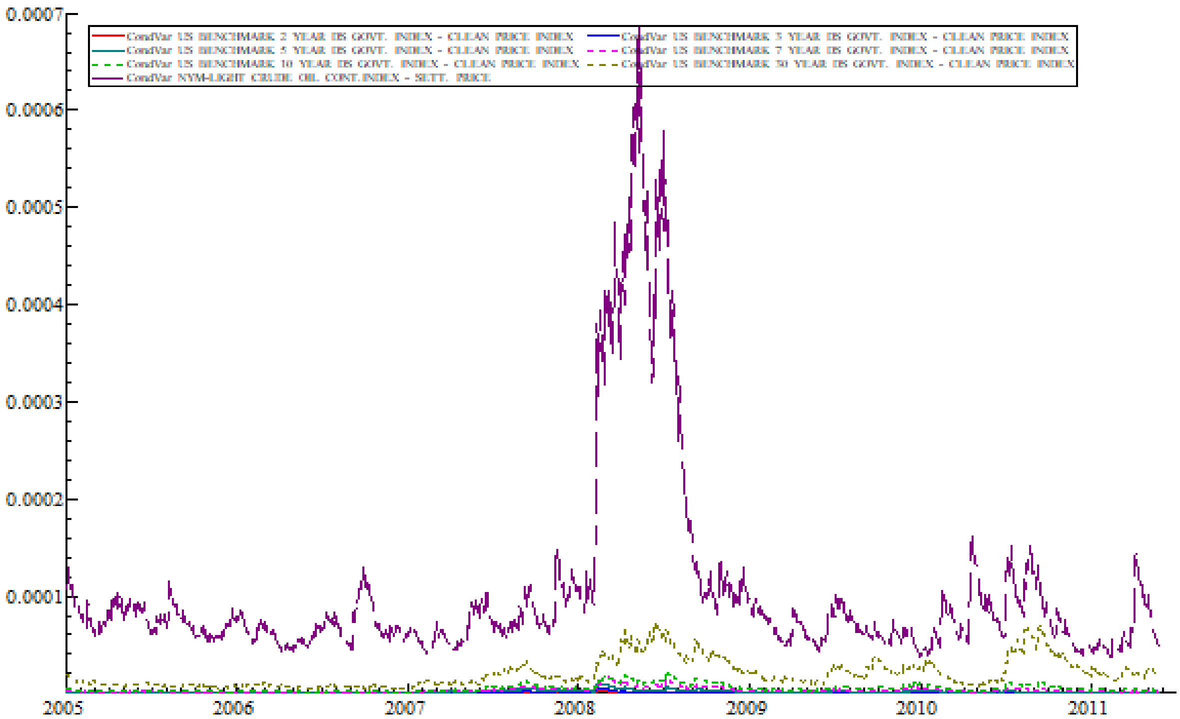

Fig-3: Conditional variances of the univariate GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

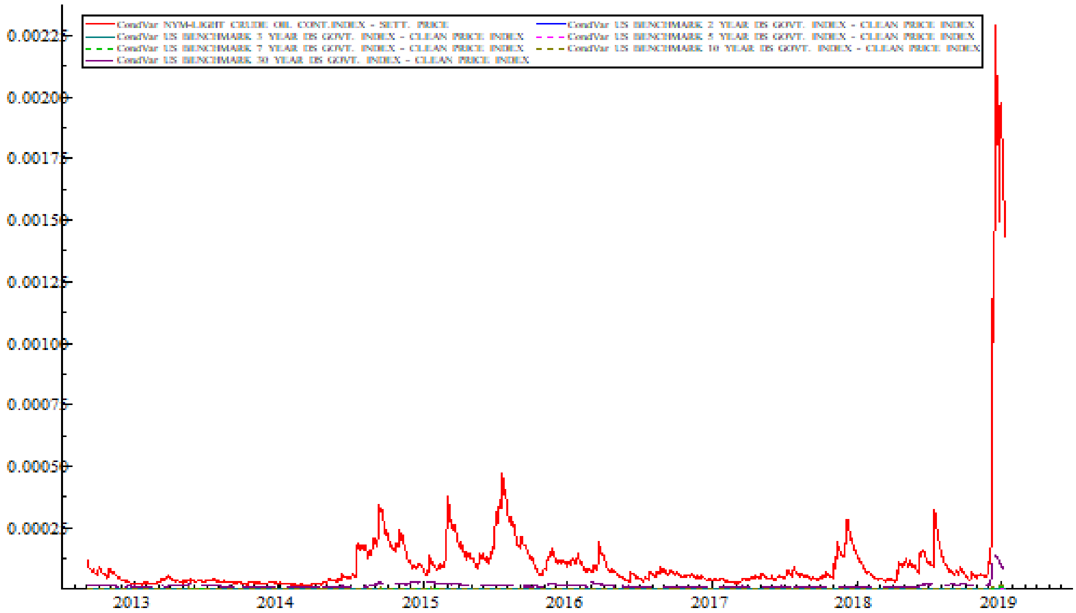

Fig-4: Conditional variances of the univariate GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

Sample period: 3 January, 2005 – 31 August, 2012

In Tables 1 to 3 we report the estimates of the univariate GARCH(1,1) model. We see significant μ value only for US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX. Constant ω is significant for all markets. In addition, all the ARCH (a) and GARCH (b) terms are highly significant for all markets.

Table-1: Estimates of univariate GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE	**US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX**	**US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX**
constant (μ)	0,000316*	0,0000028	0,0000081
t-Statistic	1,693	0,2718	0,6418
p-Value	0,0906	0,7858	0,5211
constant (ω)	0,012796**	0,000169*	0,001208*
t-Statistic	2,564	1,653	1,364
p-Value	0,0104	0,0984	0,1728
ARCH (a)	0,051460***	0,062458***	0,055245***
t-Statistic	4,402	4,526	3,813
p-Value	0,0000	0,0000	0,0001
GARCH (b)	0,935545***	0,938012***	0,942911***
t-Statistic	64,28	76,87	65,77
p-Value	0,0000	0,0000	0,0000

Table-2: Estimates of univariate GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

	US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	**US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX**
constant (μ)	0,0000172	0,0000353*
t-Statistic	0,7413	1,099
p-Value	0,4586	0,2720
constant (ω)	0,008120*	0,015867*
t-Statistic	1,604	1,838
p-Value	0,1088	0,0661
ARCH (a)	0,042338***	0,038444***
t-Statistic	3,070	3,535
p-Value	0,0022	0,0004
GARCH (b)	0,952285***	0,956322***
t-Statistic	60,62	78,39
p-Value	0,0000	0,0000

Table-3: Estimates of univariate GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

	US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
constant (μ)	0,0000243	0,0000247
t-Statistic	0,5926	0,3238
p-Value	0,5535	0,7462
constant (ω)	0,021935*	0,070534**
t-Statistic	1,907	2,029
p-Value	0,0567	0,0426
ARCH (a)	0,041466***	0,045121***
t-Statistic	4,894	6,353
p-Value	0,0000	0,0000
GARCH (b)	0,954529***	0,951933***
t-Statistic	102,5	127,7
p-Value	0,0000	0,0000

Table-4: Estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood, sample period: 3 January, 2005 – 31 August, 2012

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
rho	0,060952	0,046963	-0,200572*
t-Statistic	0,1503	0,2371	-1,731
p-Value	0,8805	0,8126	0,0836
alpha (α)	0,007692	0,008767*	0,016884**
t-Statistic	0,8772	1,554	2,731
p-Value	0,3805	0,1204	0,0064
beta (β)	0,992298***	0,991223***	0,979673***
t-Statistic	81,24	143,4	102,1
p-Value	0,0000	0,0000	0,0000
degrees of freedom (df)	7,995271***	8,317341***	9,844983***
t-Statistic	7,365	7,619	6,618
p-Value	0,0000	0,0000	0,0000
log-likelihood	19794,136	18659,095	17372,988

Table-5: Estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood, sample period: 3 January, 2005 – 31 August, 2012

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
rho	-0,221896*	-0,230786**	-0,241048**
t-Statistic	-1,956	-2,338	-2,484
p-Value	0,0506	0,0195	0,0131
alpha (α)	0,017240**	0,020046***	0,018622***
t-Statistic	2,680	3,060	3,215
p-Value	0,0074	0,0022	0,0013
beta (β)	0,979344***	0,975134***	0,976781***
t-Statistic	102,0	97,86	107,3
p-Value	0,0000	0,0000	0,0000
degrees of freedom (df)	10,215849***	10,799979***	12,182784***
t-Statistic	6,271	6,190	5,685
p-Value	0,0000	0,0000	0,0000
log-likelihood	16707,576	16250,902	14952,826

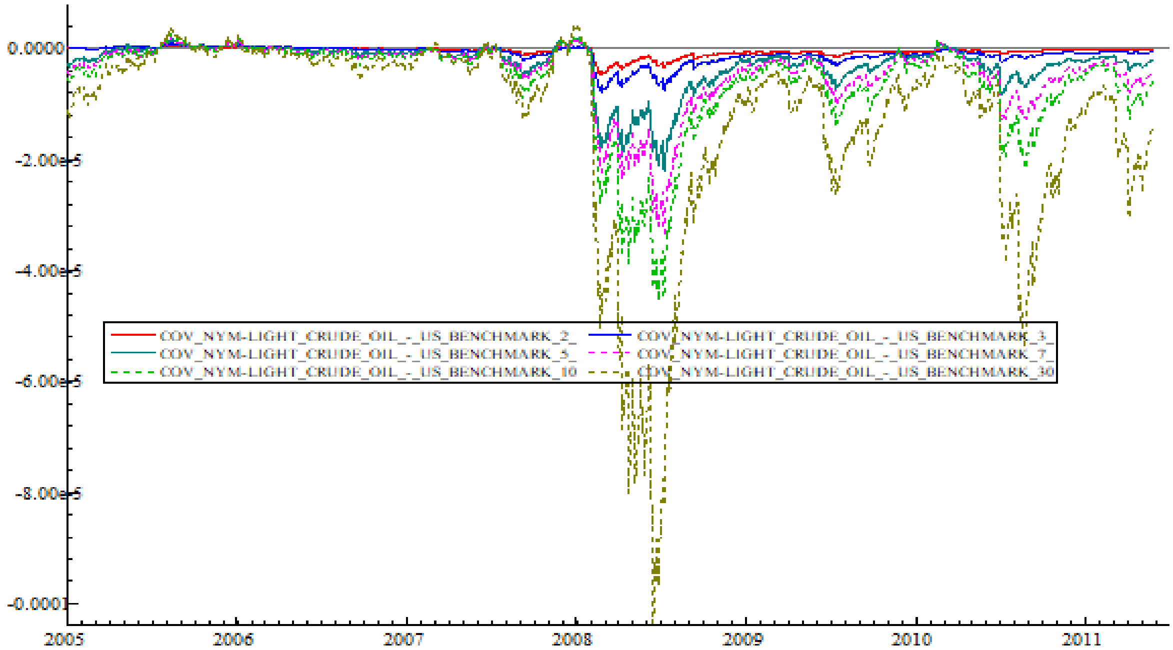

Fig-5: Conditional covariances of the univariate GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

Tables 4 and 5 present the estimates of the bivariate DCC model. Average correlation is significant for all the pairs of markets except the cases of NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX and NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX. As shown in tables, α and β are significant, showing strong ARCH and GARCH effects, except the insignificant ARCH effects of NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX. We also see the estimates of the degrees of freedom (v) and of the log-likelihood.

In Figure-5, we see the conditional covariances for all the pairs of market logarithmic returns. Covariances present a tremble trend and are extreme volatile in 2008 and after. In addition, they have mostly negative values.

Tables 6 and 7 shows the estimates of $x^2(12)$ statistic. Results do not accept the hypothesis of the absence of spillovers at 1% significance level. Hypothesis testing results and information criteria are exhibited in the two tables. Following Hosking [25] and Li and McLeod [26], the multivariate diagnostic tests detect no serial correlation on squared standardized residuals. Also, in Tables 6 and 7 we present the estimates of AIC and SIC information criteria.

Table-6: Diagnostic tests and information criteria, sample period: 3 January, 2005 – 31 August, 2012

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	**NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX**	**NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX**
$x^2(4)$	1359,4**	443,75**	244,88**
p-Value	0,0000	0,0000	0,0000
$Hosking^2$ (50)	149,666	191,808	201,207
p-Value	0,9956837	0,6106019	0,4231769
$Li\text{-}McLeod^2$ (50)	150,304	192,255	201,492
p-Value	0,9951681	0,6017671	0,4176548
Akaike	0,002103	0,002670	0,003314
Schwarz	0,035708	0,036276	0,036919

Table-7: Diagnostic tests and information criteria, sample period: 3 January, 2005 – 31 August, 2012

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
$x^2(4)$	247,96**	186,51**	122,93**
p-Value	0,0000	0,0000	0,0000
Hosking^2 (50)	201,193	184,428	211,385
p-Value	0,4234518	0,7468346	0,2446697
Li-McLeod^2 (50)	201,359	184,568	211,119
p-Value	0,4202317	0,7444735	0,2487072
Akaike	0,003646	0,003875	0,004524
Schwarz	0,037252	0,037480	0,038129

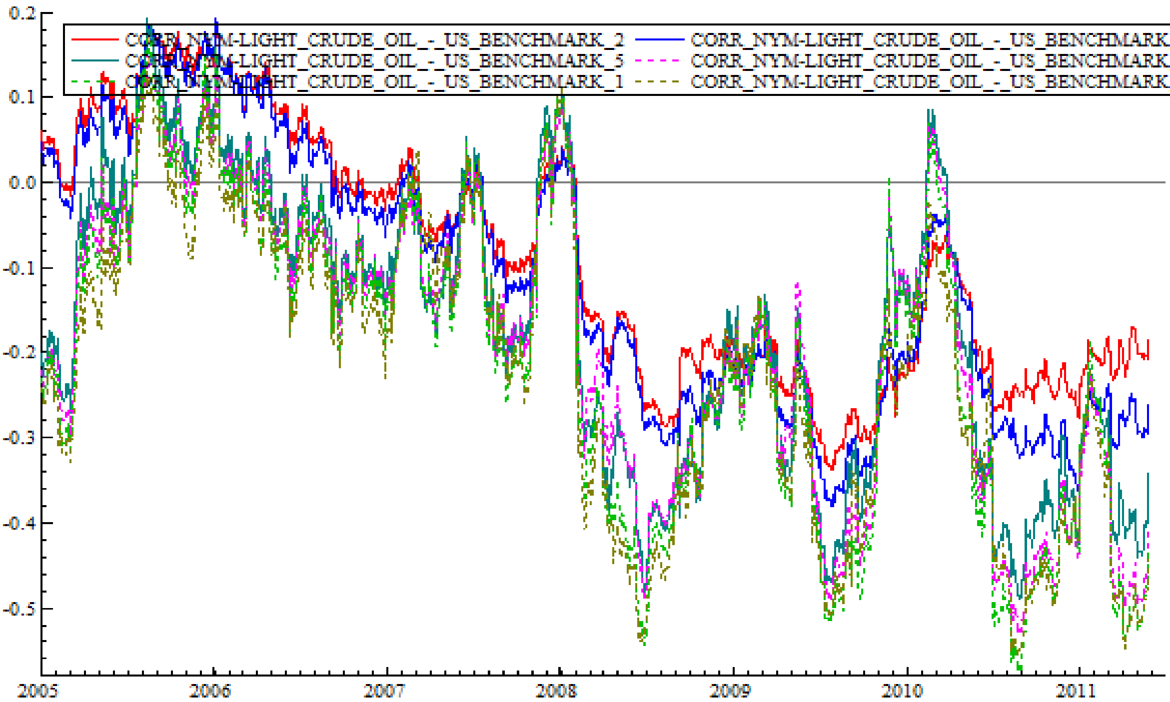

Fig-6: Dynamic conditional correlations of the bivariate DCC-GARCH (1,1) model, sample period: 3 January, 2005 – 31 August, 2012

Figure 6 shows the dynamic conditional correlations (DCCs) between time series. DCCs are extremely volatile. Interestingly, DCCs were seen to be persistently high and positive with some jumps over time. Positive and high correlation implies a less reliable stability of the correlation and that the benefit from market-portfolio diversification diminishes. In what follows, we can recognize the effects of major economic crises on the graph by taking into consideration the numerous picks and troughs: i.e. (1) the Lehman Brother bankruptcy on 15/9/2008, (2) the USA presidential election on 4/11/2008, and (3) Standard & Poor's credit rating agency downgraded the credit rating of the USA from AAA to AA+ on 5/8/2011.

Sample period: 3 September, 2012 – 27 August, 2020

Tables 8 to 10 present the estimates of the univariate GARCH(1,1) model. μ is significant only for US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX and US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX. Constant ω is significant for all markets. ARCH (a) and GARCH (b) terms are significant for all markets.

Table-8: Estimates of univariate GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE	US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
constant (μ)	0,000074	-0,0000056	-0,0000129*
t-Statistic	0,5172	-0,6970	-1,275
p-Value	0,6051	0,4859	0,2024
constant (ω)	0,004325**	0,0001087*	0,000887*
t-Statistic	2,019	1,399	1,144
p-Value	0,0436	0,1619	0,2528
ARCH (a)	0,065060***	0,066304***	0,048292***
t-Statistic	5,987	5,403	4,016
p-Value	0,0000	0,0000	0,0001
GARCH (b)	0,937153***	0,939544***	0,951247***
t-Statistic	95,66	88,64	68,66
p-Value	0,0000	0,0000	0,0000

Table-9: Estimates of univariate GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

	US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
constant (μ)	-0,0000161	-0,0000002
t-Statistic	0,9056	-0,01089
p-Value	0,3653	0,9913
constant (ω)	0,007142*	0,017218*
t-Statistic	1,322	1,399
p-Value	0,1862	0,1620
ARCH (a)	0,038931***	0,034960***
t-Statistic	3,472	3,491
p-Value	0,0005	0,0005
GARCH (b)	0,954568***	0,956789***
t-Statistic	58,57	60,78
p-Value	0,0000	0,0000

Table-10: Estimates of univariate GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

	US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
constant (μ)	0,0000133	0,0000917*
t-Statistic	0,3759	1,252
p-Value	0,7070	0,2106
constant (ω)	0,027560*	0,107850*
t-Statistic	1,563	1,956
p-Value	0,1181	0,0506
ARCH (a)	0,033339***	0,032141***
t-Statistic	4,067	4,936
p-Value	0,0000	0,0000
GARCH (b)	0,959401***	0,962244***
t-Statistic	77,44	114,7
p-Value	0,0000	0,0000

Tables 11 and 12 show the estimates of the bivariate DCC process. Average correlation is significant for all the pairs of markets. As presented in tables, α and β are significant, implying strong ARCH and GARCH effects. In addition, we observe the estimates of the degrees of freedom (v) and of the log-likelihood.

Figure-7 graphs the estimated conditional covariances. They are extreme volatile and have mostly negative values. Interestingly, the pair of markets NYM-LIGHT_CRUDE_OIL-US_BENSCHMARK_10 present the most volatile covariance among the covariances for all the pairs of markets.

Table-11: Estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood, sample period: 3 September, 2012 – 27 August, 2020

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
rho	-0,156709***	-0,157951***	-0,179411***
t-Statistic	-3,504	-3,573	-4,476
p-Value	0,0005	0,0004	0,0000
alpha (α)	0,003644*	0,004562**	0,004683*
t-Statistic	1,940	2,158	1,886
p-Value	0,0525	0,0311	0,0594
beta (β)	0,993091***	0,991191***	0,989257***
t-Statistic	293,8	330,4	254,6
p-Value	0,0000	0,0000	0,0000
degrees of freedom (df)	5,076738***	5,785807***	6,117417***
t-Statistic	11,14	10,41	10,06
p-Value	0,0000	0,0000	0,0000
log-likelihood	20893,822	19546,299	18128,215

Table-12: Estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood, sample period: 3 September, 2012 – 27 August, 2020

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
rho	-0,190665***	-0,203642***	-0,208213***
t-Statistic	-4,874	-5,088	-5,595
p-Value	0,0000	0,0000	0,0000
alpha (α)	0,005010*	0,005607*	0,004901*
t-Statistic	1,883	1,883	1,770
p-Value	0,0598	0,0598	0,0768
beta (β)	0,988175***	0,986919***	0,987380***
t-Statistic	232,1	175,8	193,6
p-Value	0,0000	0,0000	0,0000
degrees of freedom (df)	6,357867***	6,493858***	6,620931***
t-Statistic	9,609	9,345	8,776
p-Value	0,0000	0,0000	0,0000
log-likelihood	17372,765	16810,690	15244,207

Source: Datastream® Database

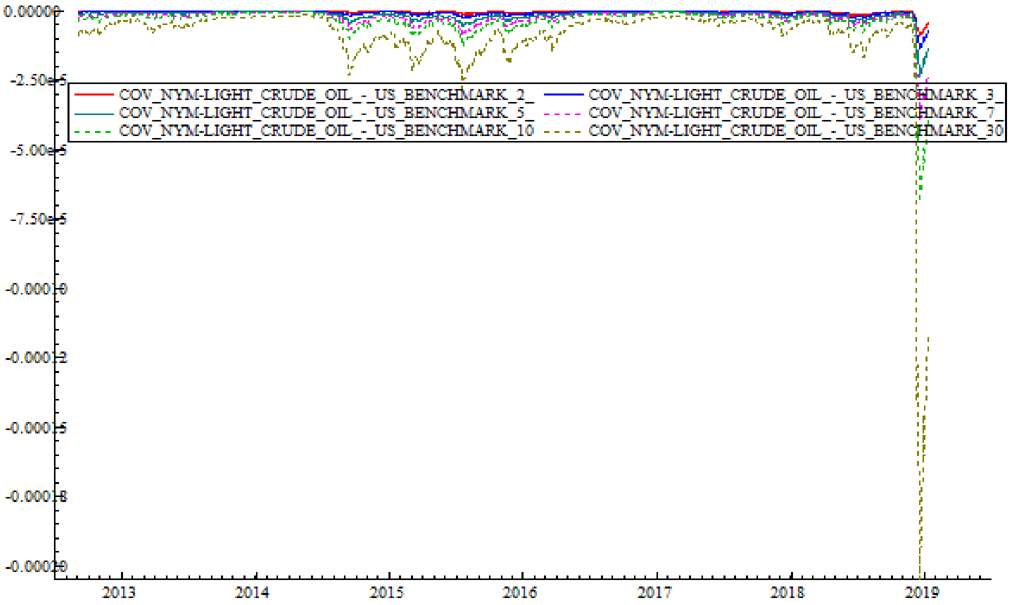

Fig-7: Conditional covariances of the univariate GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

Tables 13 and 14 show that the estimated x^2 (12) statistic imply the rejection of the null hypothesis of no spillover effects at 1%. Estimates of Hosking [25] and Li and McLeod [26] tests show no serial correlation the estimates of AIC and SIC information criteria are stated.

Table-13: Diagnostic tests and information criteria, sample period: 3 September, 2012 – 27 August, 2020

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 2 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 3 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE- US BENCHMARK 5 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
x^2(4)	861,08**	696,40**	623,94**
p-Value	0,0000	0,0000	0,0000
Hosking^2 (50)	232,246	228,028	254,407
p-Value	0,0586849	0,0705267	0,0041997
Li-McLeod^2 (50)	201,856	227,966	254,087
p-Value	0,0607411	0,0709111	0,0043714
Akaike	0,001504	0,002185	0,002902
Schwarz	0,035262	0,035943	0,036660

Table-14: Diagnostic tests and information criteria, sample period: 3 September, 2012 – 27 August, 2020

	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 7 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	NYM-LIGHT CRUDE OIL CONT.INDEX - SETT. PRICE-US BENCHMARK 30 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX
x^2(4)	604,07**	615,43**	904,36**
p-Value	0,0000	0,0000	0,0000
Hosking (50)	219,226	220,535	227,388
p-Value	0,1672193	0,1522965	0,0894029
Li-McLeod (50)	218,998	220,246	227,012
p-Value	0,1699185	0,1555091	0,0922270
Akaike	0,003284	0,003568	0,004360
Schwarz	0,037042	0,037326	0,038118

In Figure-8, we see the DCCs between time-varying series. We observe that DCCs are extremely volatile and have mostly negative values with some time-varying jumps supporting that investors benefit from market-portfolio diversification. On the graph, we can clearly see the effects of major economic crises: i.e. (1) the European Central Bank announcement of an aggressive money-creation program, printing more than one trillion new euros on 22/01/2015, (2) the Black Monday on 24/08/2015, (3) the United Kingdom referendum on 23/06/2016, and (4) the Covid-19 pandemic on 03/2020.

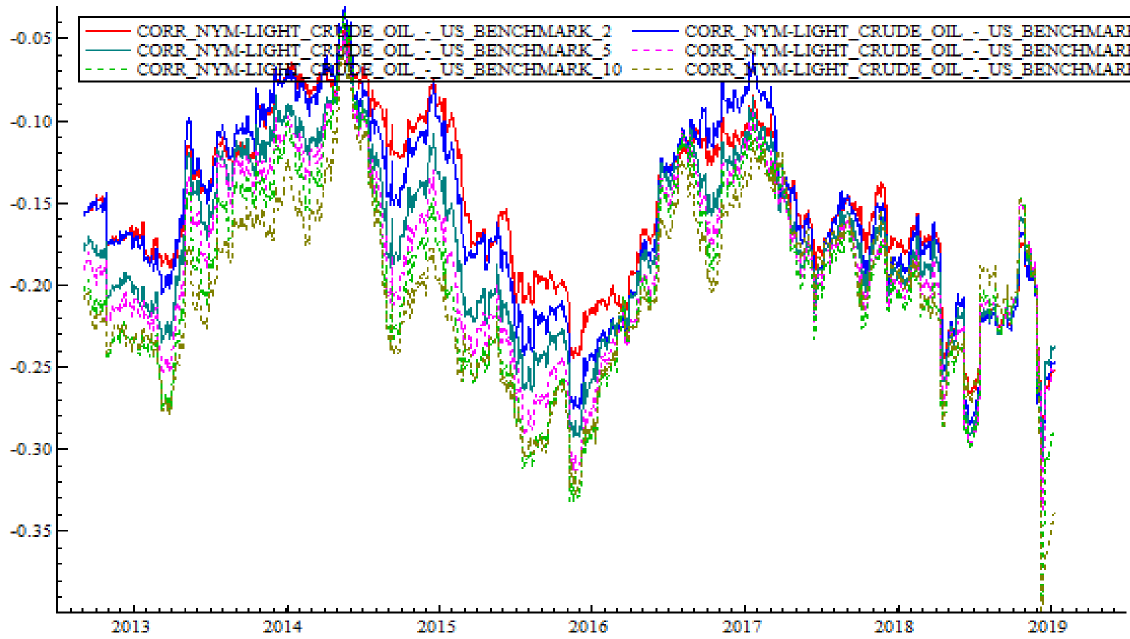

Fig-8: Dynamic conditional correlations of the bivariate DCC-GARCH (1,1) model, sample period: 3 September, 2012 – 27 August, 2020

CONCLUSIONS

This empirical paper is a contribution to the empirical literature on financial and derivative markets contagion effects. We examine the volatility transmission between Crude oil future and USA bond markets during the period 2005-2020. To measure volatility spillovers and contagion phenomenon, we use the multivariate DCC-GARCH process. We divide the under investigation period into sub-periods: 2005-2012 and 2012-2020. Empirical results suggest the existence of spillover effects during the both sub-periods. In the first sub-period, our results indicate the existence of contagion effect at the beginning of the period. Interestingly, during the second sub-period, there are no contagion effects.

A natural extension to this empirical research would be to investigate potential volatility spillover effects during the 2005-2020 period by taking into consideration different elements of financial analysis such as long memory and speed of market information.

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