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Contagion in Crude Oil Futures Market and 3Y, 4Y and 5Y CDS Markets for the Post-Global Financial Crisis Period: A Multivariate GARCH-cDCC Approach

Konstantinos TSIARAS [a*]

[a] *Department of Economic Sciences, Faculty of Economic and Administrative Sciences, University of Ioannina, University Campus, 45110, Ioannina, Greece.*

Abstract

This paper seeks to investigate the time-varying conditional correlations to the crude oil futures contract returns and the private Credit Default Swap market returns of Germany and France. We employ a dynamic conditional correlation (DCC) Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model to find potential contagion effects between the markets. The time under investigation is the 2011–2018 period. We focus on the CDSs of the biggest banks in Germany and France, namely: Société Générale and Deutsche Bank AG, using 3-, 4- and 5-year maturity CDSs. Empirical results show an increase in conditional correlation or contagion for the following pairs of markets: Société Générale CDS 3Y-Crude oil futures; Société Générale CDS 4Y-Crude oil futures; and Société Générale CDS 5Y-Crude oil futures for two periods (10/2014–12/2014 and 04/2017–11/2017). The results are of interest to policymakers who provide regulations for the CDS markets.

Keywords

cDCC-GARCH model, CDS market, crude oil futures market, financial contagion, dynamic conditional correlations

JEL Classification: C58, C61, G11, G15

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[*]konstantinos.tsiaras1988@gmail.com (corresponding author)
The research was carried out by me independently. The research is original and has not been submitted to any other journal. I wish to thank the anonymous referees for their many constructive comments and suggestions, which have improved the paper. Responsibility for any errors in the resulting work remains my own.

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Contagion in Crude Oil Futures Market and 3Y, 4Y and 5Y CDS Markets for the Post-Global Financial Crisis: A Multivariate GARCH-cDCC Approach

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1. Introduction

The purpose of this paper is to investigate the potential contagion[1] effects among crude oil futures contract returns and the private Credit Default Swap market returns of the biggest banks in Germany and France. We consider the 3-, 4- and 5-year maturity CDSs of Société Générale and Deutsche Bank AG during the period from 2011 to 2018. We quantify contagion by producing the dynamic conditional correlations using the dynamic conditional correlation (DCC) Generalized ARCH (GARCH) model.

The motivation for examining contagion is as follows: first, there is no other empirical research investigating the conditional second moments of the distribution of crude oil futures contracts and the 3-, 4- and 5-year maturity CDSs of Société Générale and Deutsche Bank AG (spillover effects). Spillovers[2] refer to the impact that events in one market can have on another market. Second, the existence of contagion between the aforementioned markets is of great importance, since policymakers may provide a reformulated regulation framework for the CDS markets.

Furthermore, three interesting aspects emerged from this paper. First, based on the descriptive statistics, Société Générale CDS 3Y demonstrates the largest fluctuations compared to the rest of the markets, indicating that Société Générale CDS 3Y is the most immune CDS market. Second, the results of the cDCC- GARCH(1,1) model show the existence of volatility spillovers. Third, dynamic conditional correlations show evidence of contagion for the following pairs of markets: Société Générale CDS 3Y-Crude oil futures; Société Générale CDS 4Y-Crude oil futures; and Société Générale CDS 5Y-Crude oil futures, for two periods (10/2014–12/2014 and 04/2017–11/2017).

This paper is structured as follows. Section 2 presents the literature review, and Section 3 shows the data used for the analysis. Section 4 gives a brief introduction to the econometric methods used in this study. Section 5 provides an explicit analysis of the econometric results. Section 6 summarizes the major findings.

2. Literature review

The main body of the current literature explores the linkages between CDS markets with financial markets (Lake and Apergis 2009; Belke and Gokus 2011; Fonseca and Gottschalk; 2012; Tokat 2013). Lake and Apergis (2009) investigate the spillovers among the US and European (German, UK and Greek) 5-year maturity CDS spreads and equity returns in the period of 2004–2008. By making use of daily observations, they employ an MVGARCH-M model, finding evidence of spillover effects. Belke and Gokus (2011) examine the volatility transmission among the daily equity prices, CDS premiums and bond yields returns for four large US banks for the period of 2006–2009. By employing a Baba-Engle-Kraft-Kroner-GARCH model, they capture spillover effects. Fonseca and Gottschalk (2012) examine the volatility spillovers among CDS premium and equity returns for Australia, Japan, Korea and Hong Kong at the firm- and index levels. They use weekly data during the period of 2007–2010 and present empirical evidence of spillover effects. Tokat (2013) empirically[3] investigates the spillover effects between daily 5-year maturity sovereign CDS values for Brazil and Turkey denominated in USD, the iTraxx XO index and the CDX index during the period from 2005 to 2011. He employs a full BEKK-GARCH model and empirically proves the existence of spillovers.

[1] Contagion is a significant increase in the cross-market positive correlation (Forbes and Rigobon 2002).

[2] Spillovers are important because they support the existence of contagion.

[3] Financial researchers and academics are interested in 5-year maturity CDSs, investigating the underlying contagion mechanisms in the short-term period.

Additionally, there are several studies investigating linkages between oil crude oil futures contracts with macroeconomic figures, financial markets and commodities (Haigh and Holt 2002; Guo and Kliesen 2005; Malik and Hammoudeh 2007; Driesprong, Jacobsen, and Maat 2008; Geman and Kharoubi 2008; Ewing and Malik 2010; Wu, Guan, and Myers 2011). Haigh and Holt (2002) develop a theoretical model for a representative energy trader that simultaneously employs crude oil, heating oil and natural gas futures to hedge futures price uncertainty. They use weekly spot and futures price data during the period from 7th December 1984 through 26th September 1997 for crude oil, unleaded gasoline and 2 heating oil sourced from Bridge/Concurrent Routing Bridging. They find that the multivariate GARCH methodology, which takes into account volatility spillovers between markets, significantly reduces the uncertainty. Guo and Kliesen (2005) examine whether crude oil futures prices have a negative and significant effect on future gross domestic product (GDP) growth. They use daily values of crude oil futures traded on the New York Mercantile Exchange (NYMEX) during the period of 1984–2004 by employing Granger causality tests. The results confirm their hypothesis of a negative effect from crude oil futures prices to future gross domestic product (GDP)

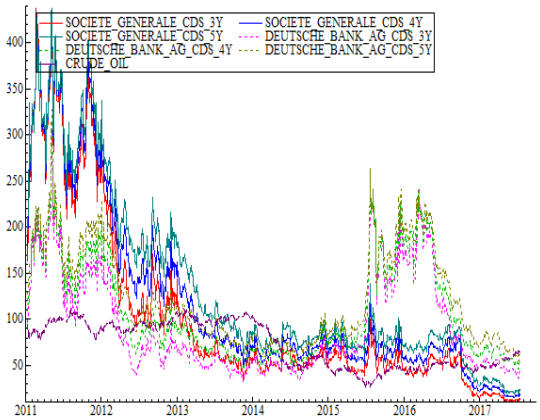


Figure 1 Actual series of the markets

growth. Malik and Hammoudeh (2007) examine the volatility and shock transmission mechanisms among US equity, global crude oil markets and equity markets of Saudi Arabia, Kuwait and Bahrain. They use daily data for a period from 12th February 1994 to 25th December 2001, sourced from Reuters. They use a multivariate GARCH model, finding significant volatility and shock transmission among US equity, Gulf equity and global crude oil markets. Driesprong, Jacobsen and Maat (2008) examine the relationship between changes in oil prices with stock market returns. They use monthly data during the period from October 1973 to April 2003. They run regressions, finding evidence of the predictability of stock returns when incorporating oil price changes into their model. Geman and Kharoubi (2008) examine the diversification effect from including crude oil futures into a portfolio of stocks. They use daily data for a period from 2nd May 1990 to 1st September 2006. By using copula functions, they find that the desirable negative correlation effect is more pronounced in the distant maturity oil futures. Ewing and Malik (2010) investigate the way that shocks affect the volatility of oil prices over time. They use daily data for the period from 1st July 1993 to 30th June 2008. By employing univariate GARCH models, they find that oil shocks have a strong initial impact on volatility, but dissipate very quickly. Wu, Guan and Myers (2011) investigate spillovers across two types of market, focusing on the impact of external shocks from the crude oil futures market on corn prices, examining corn cash and futures markets simultaneously. They use weekly data for a period from 2nd January 1992 to 30th June 2009. Using a volatility spillover model, they find evidence of significant spillovers from crude oil prices to corn futures prices and show that these spillover effects are time-varying.

3. Data and descriptive statistics

The data on seven CDS and futures markets – namely, crude oil, Société Générale CDS 3Y, Société Générale CDS 4Y, Société Générale CDS 5Y, Deutsche Bank AG CDS 3Y, Deutsche Bank AG CDS 4Y and Deutsche Bank AG CDS 5Y – which are used in this study are obtained from the Datastream® Database (Figure 1). Crude oil is traded on the NYMEX, and we use its setting price (NYM-LIGHT CRUDE OIL CONTINUOUS – SETT. PRICE). Furthermore, we use the premium mid prices for CDSs (SNR CR – CDS PREM. MID). We set the period from August 1, 2011–February 5, 2018 (1702 obs.), one week before Black Monday, when US and global stock markets crashed, following Standard & Poor's Friday night credit rating downgrade of the US sovereign debt from AAA to AA+. We generate the market returns using the equation $r_t = \log(p_t) - \log(p_{t-1})$, where p_t is the price of the futures market on day *t*, and p_{t-1} is the price of the futures market on day *t*-1.

Table 1 shows descriptive statistics of CDS and futures market returns. Crude oil exhibits the highest mean value (-0.00010001). According to the highest maximum (0.15263) and the lowest minimum (-0.17832), and the highest standard deviation (0.021968) values, Société Générale CDS 3Y returns demonstrate the largest fluctuations. The returns are positively skewed, except for the case of Société Générale CDS 3Y returns, while the excess kurtosis suggests leptokurtic behaviour. Jarque-Bera statistic results reject the null hypothesis of normality for all

market returns, indicating the use of a non-normal distribution as the most appropriate. The Augmented Dickey-Fuller (Dickey and Fuller, 1979) test results reject the null hypothesis of a unit root at the 1% level, and hence, stationarity is guaranteed.

Appendix A plots the actual and the return series for crude oil futures (Graph A), Société Générale CDS 3Y (Graph B), Société Générale CDS 4Y (Graph C), Société Générale CDS 5Y (Graph D), Deutsche Bank AG CDS 3Y (Graph E), Deutsche Bank AG CDS 4Y (Graph F) and Deutsche Bank AG CDS 5Y (Graph G). The return series exhibit high volatility levels, suggesting the presence of heteroscedasticity.

4. Econometric estimation framework

The cDCC[4] model proposed by Aielli (2009) involves two stages to estimate the conditional covariance matrix H_t.

In the first stage, we estimate conditional variance h_t by employing univariate volatility models for the CDS and crude oil futures returns. We generate the daily logarithmic returns by the following expression:

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

$$\text{with } \varepsilon_t = \sqrt{h_t} u_t,$$

where $\mu \epsilon [0,\infty)$, $\varepsilon_t \sim N(0, H_t)$, u_t are i.i.d. random variables, and h_t is positive with probability one.

We use Bollerslev's (1986) GARCH(1,1) model to generate the conditional variance (h_t). h_t is depending on h_t and ε_t for each market lagged one period. The equation of h_t can be expressed as:

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

where $\omega > 0$, $a \geq 0$ and $b \geq 0$ is sufficient for the condi-

conditional variance to be positive.

In the second stage, we estimate conditional correlations using the standardized residuals from the first stage. We define the multivariate conditional variance matrix (H_t) (N x N matrix), using the cDCC model of Aielli (2009) as follows:

$$H_t = D_t R_t D_t, \qquad (3)$$

where $D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right)$ is the conditional variance obtained from the univariate GARCH(1,1) model, and $R_t = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}})$ is the conditional correlation matrix, with N is the number of markets (i = 1,…,N).

Table 1 Summary statistics of daily market returns

	Crude oil futures	Société Générale CDS 3Y	Société Générale CDS 4Y	Société Générale CDS 5Y	Deutsche Bank AG CDS 3Y	Deutsche Bank AG CDS 4Y	Deutsche Bank AG CDS 5Y
Mean	-0,00010001	-0,00063503	-0,00058018	-0,00053869	-0,00020373	-0,00017834	-0,00016166
Minimum	-0,046879	-0,17832	-0,15129	-0,13351	-0,14712	-0,12917	-0,10626
Maximum	0,050471	0,15263	0,12664	0,10764	0,10836	0,10803	0,1076
Std. dev.	0,0089838	0,021968	0,018166	0,016192	0,019925	0,01713	0,015375
Skewness	0,13420**	-0,020508	0,12255**	0,19544***	0,17340***	0,16012***	0,24163***
Excess Kyrtosis	3,3131***	6,3057***	6,0935***	6,1160***	4,4060***	5,2038***	5,6732***
Jarque-Bera	782,63	2816,6	2634,4	2660,4	1383,6	1925,4	2296,3
ADF Test	-23,9799***	-23,3547***	-23,0817***	-23,2444***	-23,1639***	-23,6349***	-23,9865***

[4] To obtain the cDCC model, first, 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:

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

where $\bar{Q}$ is the N x N unconditional variance matrix of u_t^* (since $E[u_t^* u_t^{*\prime} | \Omega_{t-1}] = Q_t$)[4]. 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,…,N), Aielli (2009) proposed to obtain these values $q_{11,t}$,.., $q_{NN,t}$ as follows:

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

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

We use the full information maximum likelihood (FIML) method with student's t-distributed errors to estimate the model as follows:

$$\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{v+N}{2}\right)}{[v\pi]^{\frac{N}{2}}\Gamma\left(\frac{v}{2}\right)v-2^{\frac{N}{2}}}-\frac{1}{2}\log\left(|H_t|\right)-\left(\frac{N+v}{2}\right)log\left[1+\frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{v-2}\right]\right], \quad (4)$$

where N is the number of markets, Γ(.) is the gamma function, and ν is the degrees of freedom.

5. Empirical results

This section is organized into three sub-sections. Sub-section 1 presents the empirical results from the MGARCH model. Sub-section 2 demonstrates the estimates of the dynamic conditional correlations.

5.1 Empirical results of the cDCC- GARCH(1,1) model

Table 2 presents the estimated GARCH(1,1) model. Estimates of the mean equation (Equation 1) show a statistically insignificant constant (μ) for all market returns. Estimates of the variance equation (Equation 3) reveal statistical significant constant (ω) for Société Générale CDS 3Y and 4Y, as well as for Deutsche Bank AG CDS 3Y, 4Y and 5Y returns. All ARCH (α) and GARCH effects (b) are statistically significant.

Table 3 presents the estimates of cDCC model, the diagnostic tests and the information criteria. Estimates of the cDCC model (Equation 7 and Equation 9) reveal a statistically significant average correlation (CORij) between crude oil and Deutsche Bank AG CDS 3Y, 4Y and 5Y returns. All the ARCH (α) and GARCH effects (β) are statistically significant. Additionally, we see the estimates of log-likelihood. Estimates of $x^2(4)$ statistics suggest the rejection of the null hypothesis of no spillovers at a 1% significance level. Ljung-Box test results (Hosking 1980; McLeod and Li 1983) show evidence of no serial autocorrelation, suggesting no misspecification errors. Additionally, estimates of the Akaike and Schwarz information criteria are stated.

Figure 2 presents the evolution of conditional variances for all the variables. We observe a tremble trend for all market returns. Furthermore, important economic shocks are observable (i.e. the Brexit decision in June 2016, among others).

In Figure 3, we report the estimates of conditional covariances generated by the cDCC-GARCH(1,1) model for all the pairs of market returns. The significant $x^2(4)$ states clearly the existence of spillovers. We can see how the pairs of market are presenting the spillover effects, by a visual inspection of the conditional covariances.

Table 2 Estimates of GARCH(1,1) model

	Crude oil futures	**Société Générale CDS 3Y**	**Société Générale CDS 4Y**	**Société Générale CDS 5Y**	**Deutsche Bank AG CDS 3Y**	**Deutsche Bank AG CDS 4Y**	**Deutsche Bank AG CDS 5Y**
constant *(μ)*	0,00035	-0,000383	-0,000416	-0,000423	-0,000396	-0,000499	-0,000546
t-Statistic	0,2186	-0,7485	-0,9372	-1,074	-0,9171	-1,373	-1,691
p-Value	0,8270	0,4543	0,3488	0,2831	0,3592	0,1700	0,0909
constant *(ω)*	0,448754	0,844253**	0,514385**	0,380671	0,127462**	0,078536**	0,057582**
t-Statistic	1,860	2,099	2,013	1,907	2,439	2,452	2,483
p-Value	0,0631	0,0360	0,0442	0,0567	0,0148	0,0143	0,0131
ARCH *(a)*	0,061119***	0,126572***	0,139357***	0,151670***	0,096656***	0,090994***	0,089231***
t-Statistic	3,901	3,215	2,669	2,808	3,849	3,899	4,105
p-Value	0,0001	0,0013	0,0077	0,0050	0,0001	0,0000	0,0000
GARCH *(b)*	0,933669***	0,706792***	0,715082***	0,713092***	0,875135***	0,884982***	0,888493***
t-Statistic	57,16	7,239	6,709	6,593	28,63	31,56	34,08
p-Value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Table 3 Estimates of cDCC model, diagnostic tests and information criteria

	Crude oil futures-Société Générale CDS 3Y	**Crude oil futures-Deutsche Bank AG CDS 3Y**	**Crude oil futures-Société Générale CDS 4Y**	**Crude oil futures-Deutsche Bank AG CDS 4Y**	**Crude oil futures-Société Générale CDS 5Y**	**Crude oil futures-Deutsche Bank AG CDS 5Y**
Average CORij	-0,112363	-0,120549**	-0,112669	-0,128371***	-0,119266	-0,139105***
t-Statistic	-1,592	-2,396	-1,732	-2,612	-1,919	-2,895
p-Value	0,1117	0,0167	0,0835	0,0091	0,0551	0,0038
alpha *(α)*	0,015119***	0,011674**	0,014115**	0,010920**	0,013557**	0,010605***
t-Statistic	2,647	2,491	2,391	2,476	2,167	2,476
p-Value	0,0082	0,0128	0,0169	0,0134	0,0304	0,0134
beta *(β)*	0,9777859***	0,979069***	0,978193***	0,980101***	0,978216***	0,980077***
t-Statistic	115,5	134,6	105,6	138,5	92,75	137,6
p-Value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
degrees of freedom (*df*)	5,619929***	5,807968***	5,784588***	5,979557***	5,797616***	5,929854***
t-Statistic	12,50	12,18	11,93	11,76	11,97	12,03
p-Value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
log-likelihood	9987,103	10229,283	10316,928	10509,708	10532,610	10719,991
$x^2(4)$	1359,1**	459,21**	1157,7**	432,97**	1226,3**	453,48**
p-Value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Hosking (50)	206,559	218,145	216,377	221,851	213,930	219,604
p-Value	0,3602921	0,1802859	0,2030860	0,1382624	0,2375835	0,1628158
Hosking^2 (50)	189,958	168,803	178,726	178,411	181,762	174,386
p-Value	0,6465818	0,9347746	0,8335113	0,8377002	0,7897824	0,8856128
Li-McLeod (50)	207,015	218,685	216,862	222,308	214,491	220,022
p-Value	0,3519834	0,1736794	0,1966569	0,1336172	0,2293734	0,1580260
Li-McLeod^2 (50)	189,953	169,239	179,024	178,702	182,046	174,706
p-Value	0,6466843	0,9316162	0,8294737	0,8338272	0,7854014	0,8821979
AIC	0,006030	0,005862	0,005801	0,005668	0,005652	0,005522
SIC	0,041219	0,041052	0,040991	0,040858	0,040842	0,040712

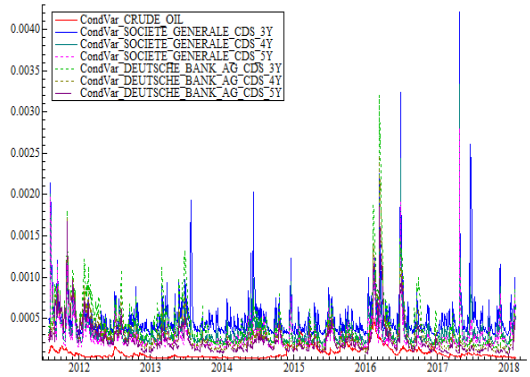


Figure 2 Conditional variances of the univariate GARCH (1,1) model

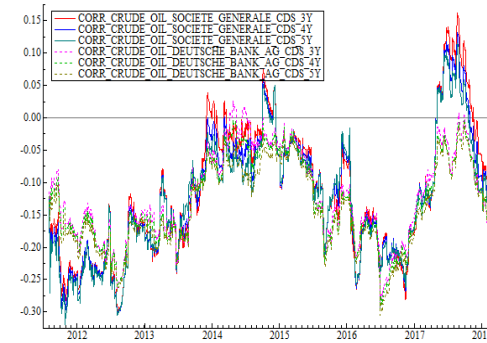


Figure 3 Conditional covariances of the GARCH(1,1)-cDCC model

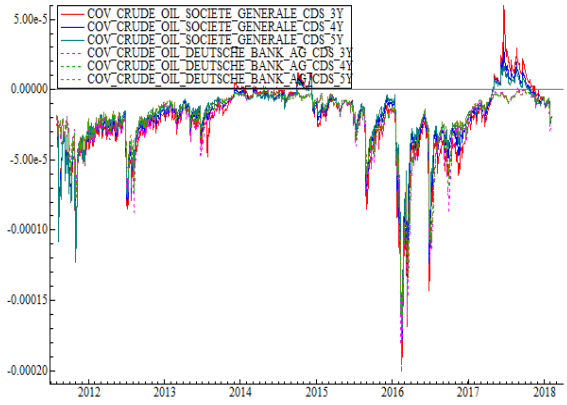


Figure 4 Dynamic conditional correlations of the GARCH(1,1)-cDCC model

5.2 Dynamic conditional correlations (DCCs) analysis

The DCCs for market pairs of Société Générale CDS 3Y-Crude oil futures, Société Générale CDS 4Y-

Crude oil futures and Société Générale CDS 5Y-

Crude oil futures returns demonstrate strong co-movements and are graphed in Figure 4. Additionally, they present common positive values and are extremely volatile in two periods (from October 2014 to December 2014, from April 2017 to November 2017), suggesting contagion and risky correlations for any investor. DCCs present some common extreme jumps for various reasons, such as: (a) the President of the Catalonia's announcement for a referendum on independence on 9/11/2014 in Spain (14/10/2014); (b) Black Monday (24/08/2015); and (c) when Standard & Poor's credit rating agency downgraded the credit rating of the US (from AAA to AA+) (5th August 2011), among others. Next, the DCCs for the market pairs of Deutsche Bank AG CDS 3Y -Crude oil futures, Deutsche Bank AG CDS 4Y -Crude oil futures and Deutsche Bank AG CDS 5Y -Crude oil futures present strong co-movements. Furthermore, we do not find strong evidence to support the existence of contagion effects.

Additionally, DCCs show common extreme jumps due to major reasons, such as: (a) the European Central Bank's announcement of an aggressive money-creation programme, printing more than one trillion new euros (22/01/2015); (b) the United Kingdom's referendum on Brexit (23/06/2016); and (c) when Standard & Poor's credit rating agency downgraded the credit rating of the US (from AAC58A to AA+) (5th August 2011), among others.

6. Conclusions

This paper investigates the impact of crude oil futures contracts on 3-year, 4-year and 5-year maturity CDSs returns from Société Générale and Deutsche Bank AG. Specifically, we quantify volatility transmission by employing a bivariate cDCC-GARCH model. The period under investigation is from 2011 until 2018. To the best of our knowledge, this is the first empirical study investigating volatility spillover effects between crude oil futures contracts and private CDSs returns from Société Générale and Deutsche Bank AG.

We identified interesting results. According to the descriptive statistics, Société Générale CDS 3Y returns presents the largest fluctuations compared to the rest of the markets. Subsequently, we estimated the Jarque-Bera statistic. These results suggest that the daily returns are not distributed normally for all markets. Additionally, we employ the cDCC- GARCH(1,1) model. These results indicate strong evidence of volatility spillover effects. The analysis of DCCs shows evidence of common contagion effects for the following pairs of market returns: Société Générale CDS 3Y-Crude oil futures, Société Générale CDS 4Y-Crude oil futures and Société Générale CDS 5Y-Crude oil futures (during two periods: 10/2014–12/2014 and 04/2017–11/2017).

A natural extension to this article would be to investigate the potential contagion mechanisms during the 2007–2012 global financial crises. In particular, we focus on the revelation of possible contagion effects between crude oil futures contracts and 3-year, 4-year and 5-year maturity CDSs from Société Générale and Deutsche Bank AG.

References

AIELLI, G. P. (2009). *Dynamic conditional correlations: on properties and estimation*. Department of Statistics, University of Florence.

BELKE, A., GOKUS, C. (2011). *Volatility Patterns of CDS, Bond and Stock Markets before and during the Financial Crisis Evidence from Major Financial Institutions*. Deutsches Institut fur Wirtschaftsforschung. https://doi.org/10.2139/ssrn.1777004, https://doi.org/10.2139/ssrn.1793135

BOLLERSLEV, T. (1986). Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31: 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

DICKEY, D. A., FULLER, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association* 74: 427–431. https://doi.org/10.1080/01621459.1979.10482531

DRIESPRONG, G., JACOBSEN, B., MAAT, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics* 89: 307–327. https://doi.org/10.1016/j.jfineco.2007.07.008

ENGLE, R. F. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics* 20: 339–350. https://doi.org/10.1198/073500102288618487

EWING, B. T., MALIK, F. (2010). Estimating Volatility Persistence in Oil Prices Under Structural Breaks, *The Financial Review* 45: 1011–1023.

FONSECA, J. D., GOTTSCHALK, K. (2012). *The Comovement of Credit Default Swap Spreads, Stock Market Returns and Volatilities:* Evidence from Asia-Pacific Markets.

FORBES, K., RIGOBON, R. (2002). No contagion, Only Interdependence: Measuring Stock Market Co-Movements. *Journal of Finance* 57: 2223–2261.

GEMAN, H., KHAROUBI, C. (2008). WTI crude oil futures in portfolio diversification: The time-to-maturity effect, *Journal of Banking and Finance* 32: 2553–2559. https://doi.org/10.1016/j.jbankfin.2008.04.002

GUO, H., KLIESEN, K. L. (2005). Oil price volatility and U.S. macroeconomic activity, *Federal Reserve Bank of St. Louis Review* 87: 669–684. https://doi.org/10.20955/r.87.669-84

HAIGH, M. S., HOLT, M. T. (2002). Crack spread hedging: Accounting for time-varying volatility spillovers in the energy futures markets, *Journal of Applied Econometrics* 17: 269–289. https://doi.org/10.1002/jae.628

HOSKING, J. R. M. (1980). The multivariate portmanteau statistic, *Journal of the American Statistical Association* 75: 602–608. https://doi.org/10.1080/01621459.1980.10477520

LAKE, A., APERGIS, N. (2009). *Credit default swaps and stock prices: Further evidence within and across markets from mean and volatility transmission with a MVGARCH-M model and newer data*, University of Pireaeus. https://doi.org/10.2139/ssrn.1330011

MALIK, F., HAMMOUDEH, S. (2007). Shock and volatility transmission in the oil, US and gulf equity markets, International *Review of Economics and Finance* 16: 357–368. https://doi.org/10.1016/j.iref.2005.05.005

MCLEOD, A.J., LI, W.K. (1983). Diagnostic checking ARMA time series models using squaredresidual autocorrelations, *Journal of Time Series Analysis* 4: 269–273. https://doi.org/10.1111/j.1467-9892.1983.tb00373.x

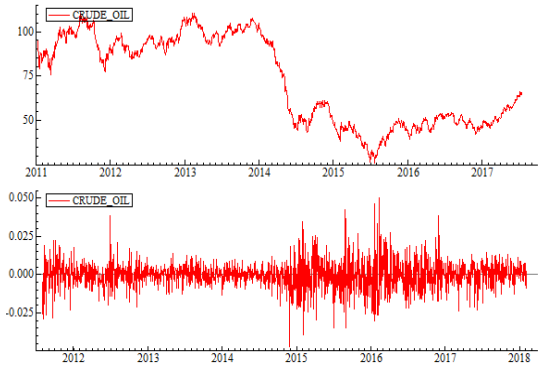
TOKAT, H. A. (2013). Understanding volatility transmission mechanism among the cds markets: Europe & North America versus Brazil & Turkey, *Economia Aplicada*. https://doi.org/10.1590/S1413-80502013000100001

WU, F., GUAN, Z., MYERS, R. J. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures, *Journal of Futures Markets* 31: 1052–1075. https://doi.org/10.1002/fut.20499

Appendix

Appendix-A Actual series of markets and their respective logarithmic returns

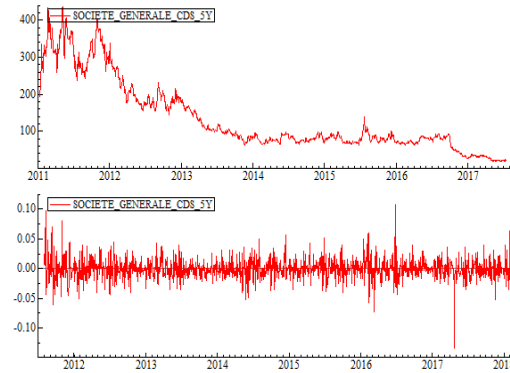
Graph A. Crude oil futures



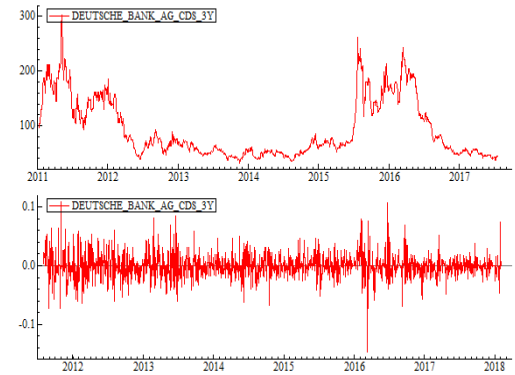
Graph B. Société Générale CDS 3Y

Graph C. Société Générale CDS 4Y

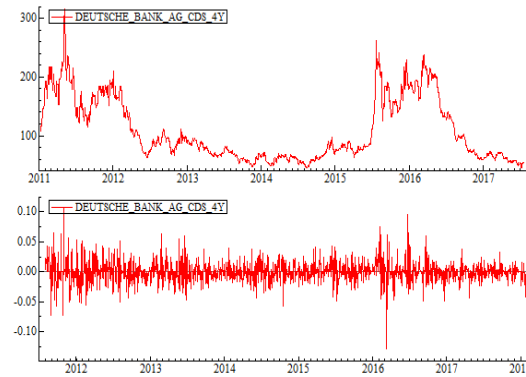
Graph D. Société Générale CDS 5Y



Graph E. Deutsche Bank AG CDS 3YGraph F. Deutsche Bank AG CDS 4Y



Graph F. Deutsche Bank AG CDS 4Y



Graph G. Deutsche Bank AG CDS 5Y