

# Measuring Contagion between Energy and Stock Market during Financial Crisis: Asymmetric Dynamics in the Correlations

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**Abstract:** This paper deals with the study of the Asymmetric Dynamic Conditional Correlation (ADCC) model developed by Cappiello *et al.* (2006). The A-DCC models carry out better than the non-asymmetric ones. The methodological design is an appropriate multivariate vector and autoregressive exponential GARCH (M-VAR-EGARCH) process which investigate the nature of the volatility and return spillover mechanism across markets. This article examines the dynamic linkages between the stock market and oil price in the US and the Euro-Zone from January 2, 2004 to July 5, 2013. The findings support the existence of a contagion effect during the Greek debt crisis but not the subprime crisis. The correlations between oil prices and stock return of the financial market reveal a certain degree of interdependence among oil market that is lower during the debt crisis.

**Keywords:** Asymmetric Dynamic Conditional, Correlation model, M-VAR-EGARCH, Oil prices, Debt Crisis.

## I. INTRODUCTION

The relationship between oil price and stock market is very prominent in energy economics. With the increasing importance of oil price in the economy, policy makers, economists and investors have focused on the correlations between stock markets and energy.

Crude oil can be an influential commodity with extraordinary ramifications for the real economy and financial markets. While the negative impact of oil price shocks on the macro-economy is well recognized (see Hamiltom, 1983, 2003; Mork, 1994,

Hooker, 2002; Hamiltom and Herrera, 2004; Kilian, 2008 among others), there is a less consensus among economists concerning the response of stock markets of oil price movements. However, some empirical researches into the oil-stock market relationship gives evidence of a negative impact of an oil shock on the stock returns (Kling, 1985; Kaul and Jones, 1996; Sadorsky, 1999; Ciner, 2001; Kilian and Park, 2009, among others). Another strand of literature reports the evidence of a positive and significant link (see, Arouri and Rault, 2012; El-Sharif, Brown, Nixon, and Russel, 2005; Narayan and Narayan, 2010), an insignificant one (see, Henriques and Sadorsky, 2008; Apergis and Miller, 2009) or a conditional and nonlinear link (see, Park and Ratti, 2008; Reboredo, 2010). However, have these co-movement patterns of stock markets and crude oil been retained during the recent financial crisis?

Usually, global financial crisis causes asset prices to plunge through markets and causes capital flight and speculative runs, leading to considerable market instability. Moreover, it produces a huge loss of confidence among investors, will be affected by the crisis. As the propagation of the shock among markets is hard to explain based on changes in macroeconomic fundamentals, many articles use the word “contagion” to refer to this phenomenon and focus on measuring contagion by indicating evidence of a significant increase in cross-market linkages. Thus, to determine the co-movement patterns of stock markets and crude oil during the global financial crisis, it is necessary to test if such a contagion effect exist the markets.

This empirical study contributes to analyze us the contagion effect between stock markets and crude oil during the recent financial crisis. Although some very recent researchers use the evolution of correlations between commodities and financial assets in a period that includes the crash of Lehman Brothers and its aftermath (Buyuksahin and Robe, 2010; Lautier and Raynaud, 2011; Silvennoinen and Thorpy, 2010; Tang and Xiong, 2010), their focus was not on the contagion effect between stock markets and oil prices during the recent financial crisis. For example, Buyuksahin and Robe (2010), Silvennoinen and Thorpy (2010) and Tang and Xiong (2010) put stress on how financialization of commodities influences the linear correlations between different commodities or the correlations between financial assets and commodities, while Lautier and Raynaud (2011) focused on integration in energy-derivative markets.

The familiarity of volatilities or correlations is powerful for both policy authorities and investors. If the volatilities or correlations vary over time, the forecast of their future values is the key to any asset pricing formula. Thus, many researchers have

been examining the dynamics of the correlation of asset returns. Bollerslev (1990), proposed in other studies, the constant conditional correlation (CCC) process, which supposes that the correlation between the five nominal European-US dollar exchange rates is constant over time.

Engle (2002) developed the new class of model called Dynamic Conditional Correlation (DCC), which allows the correlation of asset returns to time varying. In this model, the correlation across asset returns is adjusted to account for new information. Engle (2002) assumes a two-stage approach to estimate the dynamic conditional correlation. The first stage is to estimate a series of univariate GARCH processes, and the second one is to estimate the correlation. As it is indicated by Engle (2002), this model has the flexibility of univariate GARCH, but not the complexity of multivariate GARCH. Furthermore, Cappiello *et al.* (2006) modified the DCC model by considering the possibility of occasionally observed events in which the conditional correlation of the stock or bond returns is more significantly influenced by negative than positive shocks. The Asymmetric Generalized Diagonal (AGD) DCC-MGARCH model was considered to capture the heterogeneity, so as to allow for different news impact and smoothing parameters among the assets.

Our process of study includes three steps. First of all, we apply the Iterated Cumulative Sums of Squares algorithm (ICSS) of Inclan and Tiao (1994) to detect the presence of structural breaks of oil price markets. Second, in order to take structural breaks and asymmetry into estimation, we develop the univariate EGARCH model and bring the dummy variables for structural breaks into variance equation. The EGARCH process has several advantages compared to the standard GARCH specification: there is no need to artificially impose a non-negative constraint on the model parameters and asymmetries are allowed under the EGARCH formulation.

The remainder of this article is organized as the following. Section two presents the empirical techniques. Section three discusses the data and descriptive statistics as well as presents the empirical results and discusses the findings. The closing section offers the summary and conclusion.

## II. Econometric Methodology

### A. Detecting Structural Breakpoints

We employ the ICSS algorithm developed by Inclan and Tiao (1994) to detect the structural breakpoints on the stock markets of six indicators during the study period.

As a starting point, the stock return for market  $i$  on day  $t$  can be written as the following:

$$r_{i,t} = (\log P_{it} - \log P_{i,t-1}) \times 100 \quad (2.1)$$

While  $(P_{i,t})$  is the closing stock price:

Next, we define

$$a_{i,t} = r_{i,t} - \mu_i \quad (2)$$

While  $\{a_{i,t}\}$  is with zero mean and unconditional variance,  $\sigma_i^2$ ,  $\mu_i$  denotes the average return of market  $i$ . Let  $C_k = \sum_{t=1}^k a_{i,t}^2, k = 1, \dots, T$  be the cumulative sums of squares of  $\{a_{i,t}\}$  series, then  $D_k$  statistic can be calculated as the following:

$$D_k = \left( \frac{C_k}{C_T} \right) - \frac{k}{T}, k = 1, \dots, T \text{ and } D_0 = D_T = 0 \quad (3)$$

We adopt the ICSS algorithm to detect the multiple breaks in the unconditional variance of  $\{a_{i,t}\}$  series. Thus, the ICSS algorithm based on the statistic  $D_k$  begins with testing the structural breaks over the whole sample. The ICSS case depicts a significant break; the algorithm applies the new statistics to examine the break for each of the two sub-samples (defined by the break). The algorithm proceeds in this manner until the statistics is insignificant for all of the sub-samples defined by any significant break. Finally, we create a set of dummy variables in order to capture seize the normalized volatility of returns.

### ***B. Multivariate VAR-EGARCH process***

From the very beginning, we examine the market's interdependence and the volatility propagation through stock markets and oil price using the M-VAR-EGARCH. Due to both modelling movements in the three markets, we can study the nature of interdependence and interaction between oil price and stock markets to find out whether innovation and volatility in a given market is a sign of the conditional mean and variance in other markets. The M-VAR-EGARCH is utilized since the return of the three markets that display asymmetric conditional variance. Thus, this process helps conclude whether the impacts of one market innovations on other markets are asymmetric, for examples whether bad news from one market has a greater (or lesser) impact on other markets volatility than good news. In addition, this process is

prominent since it does not necessitate any parameter restriction ones to insure those conditional variances that are positive all three time. The multivariate VAR-EGARCH process can be expressed in the following way:

We suppose  $R_{it}$ ,  $i = 1, \dots, 3$

$$R_{it} = \alpha_{i0} + \sum_{j=1}^4 \alpha_{ij} R_{jt-1} + \varepsilon_{it} \text{ for } i=1, \dots, 3 \tag{4}$$

This process indicates where the conditional mean in each markets,  $R_{it}$  is a function of own past returns and between-market returns,  $R_{jt}$ . The statistics  $\alpha_{i0}$  indicates long-term drift coefficients.  $\alpha_{ij}$ , for  $i \neq j$ , characterize the degree of the mean spillover effect between-markets, or put differently the actual returns in market  $i$  that can be utilized to predict the future returns in market  $j$ .

The conditional variance process can be expressed in the following way:

$$\sigma_{it}^2 = \exp \left\{ \beta_{i,0} + \sum_{j=1}^3 \beta_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{it-1}^2) \right\}, \text{ for } i,j=1,2,3 \tag{5}$$

The persistence of volatility is measured by  $\gamma_i$ . If  $\gamma_i = 1$ , then the unconditional variance does not exist and the conditional variance follows an integrated process of  $I(1)$ . The Equation (5) permits its own lagged and among-market standardized innovations to use an asymmetric impact on the volatility of market  $i$ . If  $\beta_{i,j}$ , for  $i \neq j$ , is significantly different from zero, then volatility of market  $i$  will spillover to that of market  $j$ .

The asymmetry effect is modelled in the following way:

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E(|z_{j,t-1}|) + \delta_j z_{j,t-1}) \text{ for } i,j=1,2,3 \tag{6}$$

while  $z_{j,t-1}$  is the standardized residual at time  $t - 1$ , which is defined as  $\frac{\varepsilon_{j,t-1}}{\sigma_{j,t-1}}$ , and

$E(|z_{j,t-1}|)$  is the expected absolute value of  $z_{j,t-1}$ . Statistics  $\delta_j$  in equation (6) measures the asymmetric impact on the volatility of market  $i$  through the following partial derivatives:

$$\begin{aligned} \frac{\partial f_j(z_{j,t})}{\partial z_{j,t}} &= 1 + \delta_j, \text{ for } z_j > 0 \\ \frac{\partial f_j(z_{j,t})}{\partial z_{j,t}} &= -1 + \delta_j, \text{ for } z_j < 0 \end{aligned} \tag{7}$$

Generally, the asymmetry effect exists if parameter  $\delta_j$  is negative and, statistically is significant. The term  $|z_{j,t-1}| - E(|z_{j,t-1}|)$  indicates the size effect of an innovation, yet,  $\delta_j z_{j,t-1}$  indicates the corresponding sign effect. A negative parameter  $\delta_j$  with positive and significant parameter  $\beta_{i,j}$  imply that a negative shock in market  $i$  increases volatility in market  $j$  more than a positive shock of an equal magnitude. The reverse holds true for positive values of coefficient  $\delta_j$ . Such results would reveal the asymmetric nature of the spillovers mechanism. This specification, with all parameters  $\beta_{i,j}$ , can also determine the volatility spillovers between markets, as explained above. Furthermore, a negative (positive)  $z_{j,t}$  coupled with a negative  $\delta_j$  enhance (minimize) the size effect.

Finally, the residuals considered of equation (4) are supposed to be normal and the conditional covariance specification is supposed to be constant correlation coefficients (Bollerslev, 1990). The interpretation ought to be based on the fact that these coefficients determine contemporaneous relationships. Similarly the covariance is proportional with the product of the standard deviations, assuming a constant between market correlations over time, as described by the following equations:

$$\varepsilon_i | \Omega_{t-1} \sim N(0, H_t / \Omega_{t-1}) \text{ for } i=1,2,3 \quad (8)$$

Where  $\Omega_{t-1}$  is the information set at time period  $t-1$ , and  $H_t$  is conditional variance-covariance matrix  $t$  is  $(3 \times 3)$ .

$$\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t} \quad (9)$$

Parameter  $\rho_{i,j}$  is the in-market correlation parameter between volatilities of returns of two markets. Statistically, the significant estimates of  $\rho_{i,j}$  that measure time-varying volatilities between markets  $i$  and  $j$  are correlated over time (Racine and Ackert, 1998). This supposition greatly simplifies the estimation and is reasonable for many applications (Bollerslev et al, 1992). With the assumption of normality, the log-likelihood function of the M-VAR-EGARCH process is expressed as:

$$L(\theta) = -(0.5)(NT) \ln(2\pi) - 0.5 \left( \sum_{t=1}^T H_t + \sum_{t=1}^T \varepsilon_t' H_t^{-1} \varepsilon_t \right) \quad (10)$$

where  $N$  is the number of equations,  $T$  the number of observations,  $\theta$  the parameter vector to be estimated.

**C. Multivariate M-GARCH-GDCC process**

Second, having obtained the conditional variances from equation (5), we study the conditional correlations. We, first, illustrate the conditional covariance matrix as the following:

$$H_t = D_t \cdot P_t \cdot D_t \tag{11}$$

Where the diagonal matrix  $D_t$ , it is the conditional standard deviation obtained from equation (5). The matrix of the standardized residuals  $Z_t$ , is utilized to estimate the parameters of the A-DCC process, introduced by Cappiello *et al.* (2006). The progression of the asymmetric generalized DCC (AG-DCC) process is specified as the following:

$$Q_t = (\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G) + A' Z_{t-1} Z'_{t-1} A + B' Q_{t-1} B + G' \eta_{t-1} \eta'_{t-1} G \tag{12}$$

Where  $\bar{Q}$  and  $\bar{N}$  are the unconditional correlation matrices of  $Z_t$  and  $\eta_t$ ,  $\eta_t = I[Z_t < 0] \otimes Z_t$ , ( $I[\cdot]$  is a  $(k \times 1)$  indicator function that takes value one if the argument is true and zero otherwise, while  $\otimes$  indicates the Hadamard product), and  $\bar{N} = E[\eta_{t-1} \eta'_{t-1}]$ . A-DCC(1,1) is recognized as a special case of the AG-DCC(1,1) process if the matrices A, B, and G are replaced by the scalars ( $a_1$ ,  $b_1$  and  $g_1$ ). Cappiello *et al.* (2006) explain that  $Q_t$  is positive definite with a probability of one if  $(\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G)$  is positively defined. Then, we estimate the correlation matrix  $P_t$  that is:

$$P_t = Q_t^{*^{-1}} \cdot Q_t \cdot Q_t^{*^{-1}} \tag{13}$$

Where  $Q_t^* = \sqrt{q_{ii,t}}$  is a diagonal matrix through a square root of the  $i^{\text{th}}$  diagonal components of  $Q_t$  on its  $i^{\text{th}}$  diagonal position.

The standardised residuals and standardised negative residuals, the dynamics of  $P_t$  in the asymmetric DCC process of order (s,u) are given by the following two equations:

$$Q_t = \left( 1 - \sum_{j=1}^s a_j - \sum_{j=1}^u b_j \right) \bar{P} - \sum_{j=1}^s g_j \bar{N} + \sum_{j=1}^s a_j \bar{\varepsilon}_{t-j} \bar{\varepsilon}'_{t-j} + \sum_{j=1}^s g_j \eta_{t-j} \eta'_{t-j} + \sum_{j=1}^u b_j Q_{t-j} \tag{14}$$

Where  $\bar{P} = E[\bar{\varepsilon}_t \bar{\varepsilon}_t']$ ,

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^T \left\{ n \log(2\pi) + 2 \log \det(D_t) + \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t \right\} + (\log \det(P) + \bar{\varepsilon}_t' P^{-1} \bar{\varepsilon}_t - \bar{\varepsilon}_t' \bar{\varepsilon}_t) \quad (15)$$

Finally, AR(1) process is utilized to the conditional correlations derived from the second stage. Purposely, the dummy variables that signify the periods of the subprime crisis and global financial crisis are included in order to test whether the above events significantly altered the studied dynamics; from the following equation:

$$D\hat{C}_t = \mu_0 + \mu_1 D\hat{C}_{t-1} + \theta_1 \text{crisis}_{1t} + \theta_2 \text{crisis}_{2t} + v_t \quad (16)$$

where the series of  $D\hat{C}_t$  is the conditional correlation estimated from equation (16) and  $v_t$  is the white noise. For equation (13), the dummy variables  $\text{crisis}_t$  represent the Asian financial subprime crisis and the global financial one.

$$\text{crisis}_t = \begin{cases} 0 & \text{calm period} \\ 1 & \text{crisis period} \end{cases} \quad (17)$$

### III. Empirical Results

The data comprise, weekly, total return indices calculated by “yahoo.finance” for markets of developed countries. We have chosen the S&P500 index for the American market, the WTI (West Texas Intermediate grade) spot oil prices and Brent to represent, respectively, the US and European energy markets. These series cover the period from 2 January 2004 to 5 July 2013 yielding 496 observations for each series.

As a first investigation, we present in figure 1 the closing weekly Brent and WTI crude oil prices index and S&P500 of stock market.

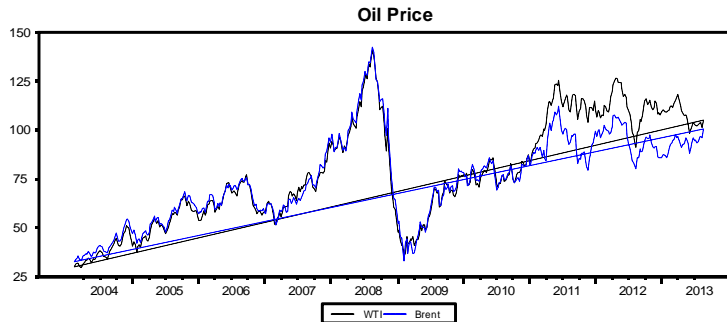


Figure 1 (a): oil prices indices



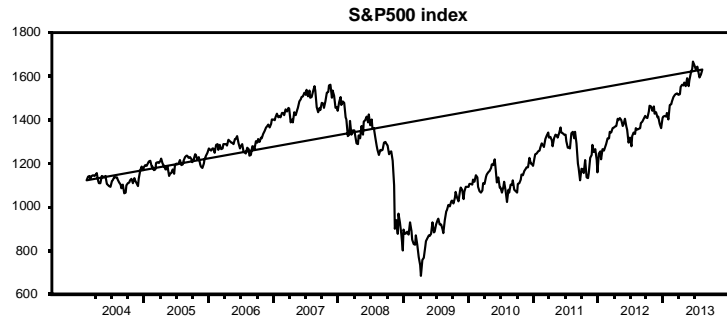


Figure 1 (b): S&P500 indices

Examining the oil price index trends depicted, graphically, in Figure 1(a-b), it is clear that the down gliding tendency of S&P500 stock market and oil price indices appeared, clearly, in the second half of 2007 and continued with aggravated prices during 2008. Even after August 2007, the S&P500 stock market and both oil price and markets' indices displayed the same down trend. This phenomenon shows the availability of contagion effect between these markets. We observe from the comparison of the American oil price index and those of the European big examined countries that the WTI indices increased after 2011. As long as, there is a contagion relationship between countries, the capital stream of these countries inflows from low return countries to high return ones.

Table I: The descriptive statistics

	<i>S&amp;P500</i>	<i>WTI</i>	<i>Brent</i>
T	496	496	496
Mean	-0.0008	-0.003	-0.002
Std.dev	0.025	0.04	0.04
Skewness	0.949	0.27	0.24
kurtosis	9.074	1.95	4.05
J.B	1776.218(0.00)	85.11 (0.00)	343.90(0.00)
ARCH(4)	0.055(0.00)	0.227(0.00)	0.193(0.00)
	61.05(0.00)	45.33(0.00)	59.51(0.00)
	678.35(0.00)	453.08(0.00)	573.69(0.00)
ADF	-32.21(S)	-14.01(S)	-18.63(S)

Notes (i) J-B is the statistic of Jarque-Bera normal distribution test.  $Q(20)$  and  $Q^2(20)$  are the Ljung-Box statistics with 20 lags for the standardized residuals and their squares. The value between (.) indicates the P-value. (S) indicates the stationarity of the process.

### *A. Data and Descriptive Statistics*

Our data set consists of daily ones on the S&P500 stock market, Brent and WTI crude oil prices from January 2, 2004, to July 05, 2013 (see Figure 1). The entire sample period is divided into the following four sub-periods based on the dates of major economic events that have influenced the S&P500 stock market, Brent and WTI crude oil prices during this time.

Table 1 gives the descriptive statistics of the asset returns. The returns are calculated as 100 times the difference in the log of the indices or price. As shown, for risk-neutral investors, the S&P500 stock market seems to outperform WTI and Brent oil prices markets in the sense that it provides a higher average return with a lower standard deviation. It is also evident that the S&P500 stock market is significantly more volatile than the other oil price markets studied. This result indicates that S&P500 stock market is the riskiest among these three markets. Furthermore, the summary statistics show that the three markets display a wide level of standard deviation ranging from 0.025 (stock market) to 0.044 (oil prices). The wide range of standard deviations indicates that a better efficient frontier can be reached if investors include the three markets in their asset allocation strategy. The coefficients of skewness indicate that the series, typically, have asymmetric distribution skewed to the right. This implies that there is a higher probability for investors to get positive rather than negative generated returns as in the case of the three markets studied. Thus, the global investors are optimistic to get positive returns by including the American and European markets in their portfolio.

In the USA and Europe, oil price return mean is negative. Meanwhile, the standard deviation shows the same risk (Std. dev= 0.04). We observe high negative returns with high standard deviation. A shift in the levels of returns from high to low is found as in the case of the American and European oil price markets. The skewness coefficients present the asymmetric and left-skewed distribution of the American and European oil price returns. The excess of 3 kurtosis coefficients exhibit a leptokurtic distribution of S&P500 stock market, the WTI and Brent market's returns.

The positive skewness in the three markets returns studied can be explained for many reasons. First, the recent privatization schemes were executed in these three markets. Second, the extensive sale of government assets to private firms has focused in the correlations. Third, the significant efforts devoted during that period towards enhancing the efficiency, depth, and liquidity of both stock markets. The excess of

kurtosis statistics ranges in value from 9.074 of the S&P500 stock market to 1.95 and 4.05 respectively for WTI and Brent oil prices market<sup>3</sup>. This means that the probability of outliers of returns in both signs is higher than the normal in these markets. The measures for skewness and kurtosis, together with the Jarque-Bera (1978) statistics, are also reported in order to demonstrate whether oil prices are normally distributed. The Jarque-Bera statistics reject normality at any significance level for all the variables. This result indirectly supports the existence of an ARCH effect in the distribution of Brent and WTI oil prices.

Jarque-Bera (J-B) normal distribution test shows that all the returns are not normal distributions. This also means that the heteroscedasticity of return should change according to time. This result suggests the use of the estimation and variance of the autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982). As a first step, stationarity in the time series is checked by applying the Augmented Dickey Fuller (ADF) test. The results allow us to reject the null hypothesis that the returns have a unit root in favor of the alternative hypothesis (even at 5% critical value).

The diagnostics of the empirical results of the AR (1) process is important, yet  $Q(20)$  is a test statistic for the null hypothesis that there is no autocorrelation up to ordering 20 for standardized residuals,  $Q^2(20)$  is a test statistics for the null hypothesis that there is no autocorrelation up to order 20 for standardized squared residuals. As shown in this table, both statistics are above 0.05 in all cases. Thus, the null hypotheses of no autocorrelation up to order 20 for standardized residuals and standardized squared residuals are accepted. These results empirically support the specification of the M-VAR-EGARCH process.

Domestic and international investors perceived these favorable structural changes positively and started buying, heavily, in those markets driving up stock returns during the period under consideration. Table 2 also reports unconditional variances among markets. This is very important information for international investors, since the variance of returns may inform the construction of investment portfolios and hedging approaches. Table 2 displays the structural breaks for the samples of the stock market and oil prices.

Table 2 reports the structural breaks of the S&P500 stock market and oil price return volatility and their emergence dates. The ICSS algorithm detects six, three and two breaks in the unconditional variance of the S&P500 stock market, WTI

**Table 2: The structural breaks and their emergence dates**

$n_i$	<i>S&amp;P500</i>	<i>WTI</i>	<i>Brent</i>
1	16/02/07	29/08/08	18/07/08
2	19/09/08	27/03/09	07/08/09
3	20/03/09	28/10/11	-
4	06/08/10	-	-
5	17/06/11	-	-
6	16/12/11	-	-

*Notes:*  $n_i$  indicate the number of structural break.

crude oil price, and Brent oil price, respectively. The structural breaks in 2008 for all the markets studied can be done to some of the major crisis events during 2008-2010 periods. The subprime financial crisis was marked by two phases. The first one started in February 2007 when the Europe's biggest bank, HSBC Holdings, blamed soured U.S. subprime loans for its first-ever profit warning. Two months later, Subprime lender New Century Financial Corporation filed in bankruptcy. In June 2007, two Bear Stearns funds sold \$4 billion of assets to cover redemptions and expected margin calls arising from subprime losses. In July 10<sup>th</sup>, 2007, Standard & Poor's said it might cut ratings on some \$12 billion of subprime debts. A week later, Bear Stearns said two hedge funds with subprime exposure had very little value and credit spreads soared. In the 20<sup>th</sup> of July, Home foreclosures soared 93% from the previous year. This phase, especially in August 2007, marked the start of the subprime crisis in the American stock market when BNP Paribas suspended redemptions in \$2.2 billion of asset-backed funds and announced that it could not determine security values (Longstaff, 2010). In January 2008, Bank of America purchased wide financial in all-stock transaction.

The year 2008 was characterized by a rise in oil prices which peaked in July 2008; (The price of oil underwent a significant decrease after the record peak of US\$145 it reached in July 2008.) but the aftermath of the crisis is distinguished from the other periods of rise because the correlation between the oil and stock markets is positive.

The second phase began in July 2008 when Standard & Poor's announced the downgrading of monoline insurers AMBAC and MBIA. July 11, 2008, the Office of Thrift Supervision closed Indy Mac Bank and F.S.B. September 7<sup>th</sup>, 2008; the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in government

conservatorship. A week later, the Bank of America announced the purchase of Merrill Lynch and Lehman Brothers filed Chapter 11 bankruptcy. The Federal Reserve authorized lending up to \$85 billion to AIG. In the last week of this month, two other important events took place. The Office of Thrift Supervision closed Washington Mutual Bank and the Federal Deposit Insurance Corporation (FDIC) announced that Citigroup would purchase the banking operations of Wachovia Corp. In the 3<sup>rd</sup> of October 2008, the congress passed Emergency Economic Stabilization Act establishing \$700 the Troubled Asset Relief Program (TARP). 31 January 2011, the Brent price hit \$100 a barrel for the first time since October 2008.

The breaks of 2011 (S&P500 and WTI) confirm the presence of recession, which is projected to continue during 2012. The recycling of debt appeared to stop rumors of Greece's default and represented a response to hedge funds and investors that had bet on the Euro zone's destruction. December 23, 2008, WTI crude oil spot price fell to US\$30.28 a barrel, the lowest since the financial crisis of 2007-2010, and traded at between US\$35 and US\$82 a barrel in 2009.

One of our interests is comparing the difference between the impact of the Asian financial crisis and the current financial one on the dynamics of the correlation between the Asian markets and the US market. To this end, we adopt a dummy variable regression framework to answer this question. For the current global financial turmoil, it is commonly agreed that its effect on the Asian region, as well as the LA region, began in August 2007 because of the outbreak of the sub-prime crisis. Thus, we define the second crisis dummy variable (Crisis2) that took value 1 from August 2007 to the end of March 2009 and zero otherwise. On the other hand, it is difficult to come out with a unanimous agreement on the period of the Asian financial crisis for different economies in the group in defining the first crisis dummy variable. The examination period is divided into 4 periods:

- Sample A: from January 2, 2004, to February 15, 2007 (Pre-Crisis period);
- Sample B: from February 16, 2007, to March 20, 2009 (Subprime Crisis period);
- Sample C: from March 21, 2009, to December 16, 2011 (Greek debt crisis period); and
- Sample D: from December 17, 2011, to July 05, 2013 (after crisis period).

Table 3: Empirical results of the VAR-EGARCH model

	<i>S&amp;P500</i> ( <i>i</i> = 1)		<i>WTI</i> ( <i>i</i> = 2)		<i>Brent</i> ( <i>i</i> = 3)	
	<i>coefficient</i>	<i>Std.error</i>	<i>coefficient</i>	<i>Std.error</i>	<i>coefficient</i>	<i>Std.error</i>
<i>Price spillovers parameters</i>						
$\alpha_{i0}$	0.154**	0.07	0.04	0.039	0.152*	0.04
$\alpha_{i1}$	-0.08**	0.04	0.176	0.04*	0.161*	0.03
$\alpha_{i2}$	-0.04	0.02	0.272	0.016*	0.338*	0.017
$\alpha_{i3}$	-0.009	0.02	-0.08	0.019*	-0.069*	0.019
$\beta_{i0}$	0.241***	0.015	0.187***	0.002	0.175***	0.002
$\beta_{i1}$	0.418***	0.035	0.142***	0.016	0.107***	0.012
$\beta_{i2}$	0.0001***	0.00003	-0.0002***	0.00	-0.002***	0.00
$\beta_{i3}$	-0.026*	0.015	0.092***	0.004	0.027***	0.004
<i>Others parameters and statistics</i>						
$\gamma_i$	0.837***	0.009	0.930***	0.001	0.934***	0.0008
Halfe-Life	3.895		9.551		10.151	
$\delta_i$	-0.600***	0.07	-0.787***	0.349	-0.761***	0.172

Notes: \* Statistical significance at 10%, \*\* Statistical significance at 5%, \*\*\* Statistical significance at 1%.

Before the MVAR-EGARCH process is estimated, it is necessary to check up the stationarity of the variables and possible cointegration relation through them. This step is necessary since error correction terms should be included in the VAR terms (Equation 2.4) if the series are cointegrated (Engle and Granger (1987)). We, first, test for the stationarity of the logarithm of stock indices and the returns using the augmented Dickey-Fuller (ADF) test with and without trend. Table 1 indicates that the return indices can be considered as I(0). Therefore, the results signify the absence of a long-run relationship through the long-term returns between market groups. This implies that the construction of the empirical model of modeling the volatility linkages between these series won't include an error-correction term.

The maximum likelihood estimates the MVAR-EGARCH process is reported in Table 4. It is clear from the results which are linked to the mean equation returns that mean-spillovers effect does not exist in any of the stock markets and oil prices. Considering that at the parameters indicate the first moment interdependences ( $\alpha_{ij}$ ) (price spillovers parameters of Table 3), the results propose the absence of any

significant lead-lag relationship between the oil price and stock market. These results indicate that past information in any series cannot be used to predict other markets' returns and no market play a role as information producers. In addition, this conclusion shows that these markets may be at least, weak-form efficient.

The autoregressive coefficients  $\alpha_{jt}$  are statistically significant for the WTI and Brent oil price markets, indicating that either non-synchronous trading or market inefficiency induces autocorrelation in the return series, therefore S&P500 market  $\alpha_{jt}$  is insignificant. Conditional heteroskedasticity is perhaps the most important single property describing the short-term dynamics of all the three markets. The conditional variance is a function of past innovations and past conditional variances.

The second moment interdependences (spillover-volatility) are measured by coefficient  $\beta_{jt}$ . The empirical study shows that the impact of past own innovations on current volatility are all positive and significantly different from zero at 5% level for the oil price and S&P500 stock market. These results indicate the presence of significant own-volatility spillovers in these markets. In other words, past own innovations increase current volatility in the studied markets.

Estimates at cross-market spillover volatility parameters show that, at 5% significant level, reciprocal spillovers exist for any market pair, with the exception of the spillovers from S&P500 to WTI and Brent for which the coefficient (0.142) is significant at 1% level. Specifically, the 10% level, significant reciprocal spillovers exist between the S&P500 and Brent oil price, and unidirectional spillovers from the S&P500 to oil price markets. From these results, we can conclude that there are feedback effects between most of the markets under investigation.

Regarding the magnitude of cross-market spillover coefficients, the coefficient of spillovers from the WTI and Brent are comparatively greater than those of spillover results from the other two markets. This indicates that almost every market exports its volatility to the other, where the WTI and Brent, being the largest among these four markets in terms of market capitalization, exporting volatilities which have comparatively the greatest influence. In other words, the result indicates that the WTI and Brent exercise the greatest influence on the others and receive relatively the weakest influence from the others. Thus, we conclude that the WTI and Brent stock markets are relatively dominated the transmission of volatility in the region. Moreover, compared to the cross-market spillover coefficients, own-volatility spillovers coefficients appear to be consistently higher indicating that changes in

volatility in the stock and oil price markets from domestic factors are relatively more important than the external factors.

The degree of volatility persistence is captured by the coefficient  $\gamma_i$ . The estimated values for all the three markets are approximately close to unity. From these results, we conclude that all the stock markets under investigation have very strong volatility persistence. The volatility shocks in the S&P500, WTI and Brent markets lasted for weekly data, respectively on average (based on the half-life of a shock, defined as  $HL = \ln(0.5) / \ln(\gamma_i)$ ) regarding the nature of spillovers, measured by  $\delta_p$ , Table 3 shows that all the spillovers are asymmetric. More specifically, the significant and negative coefficient of  $\delta_i$  in all the markets suggests that bad news (negative innovations) in every market has a greater effect on the volatility of the other markets than good news. The negative innovations of stock return and oil prices in every market have an impact on conditional volatility approximately two times larger than positive innovations.

Table 3 reports estimates at the cross-market correlation coefficient among the volatilities of returns of the markets investigated. All the estimates are significantly different from zero. These estimates suggest that the time-varying volatilities across the four series are correlated over time.

We utilize the A-DCC methodology to test the correlation through the selected three markets. Therefore, the outcome views the relationship between the indices of interest. Besides, the sub-periods help us obtain the required results. Table 4 describes the asymmetric conditional correlation as well.

The second step is to estimate the A-DCC process. Table 4 shows the empirical results of the entire sample period. The estimates at the parameter of standardized residuals ( $a_i$ ) and innovation in the dynamics of the conditional correlation matrix ( $b_i$ ) are both statistically significant at 1% level, whereas the parameter of the asymmetric term ( $g_i$ ) is statistically significant at 5% level. Thus, the conditional correlation of the stock returns is influenced more significantly by negative innovations than by positive ones. Table 4 shows the empirical results by sub-period.

We infer that the parameter of the asymmetric term  $g_1$  for all period is not statistically significant at conventional levels, and statistically significant at 1% level for Greek debt crisis. These results suggest that the interdependent relationship between the S&P500 stock market and Brent oil price has evolved since the Greek debt crisis came into effect.



**Table IV: Empirical results of the asymmetric conditional correlation model  
(subsample analysis)**

	<i>All period</i>	<i>Pre-crisis</i>	<i>Subprime crisis</i>	<i>Debt crisis</i>	<i>After the crisis</i>
$a_1$	-0.289 (0.09)	0.365 (0.02)	-0.867 (0.22)	0.051 (0.12)	0.151 (0.04)
$a_2$	0.430 (0.05)	0.231 (0.03)	0.204 (0.01)	0.247 (0.15)	-0.46 (0.09)
$a_3$	0.277 (0.05)	0.140 (0.02)	0.183 (0.04)	-0.01 (0.12)	0.06 (0.18)
$b_1$	0.478 (0.28)	-1.01 (0.01)	0.302 (0.32)	-1.002 (0.01)	-1.01 (0.00)
$b_2$	0.760 (0.06)	0.565 (0.06)	0.988 (0.00)	0.540 (0.08)	0.788 (0.04)
$b_3$	0.862 (0.07)	0.848 (0.03)	0.883 (0.04)	0.864 (0.06)	-0.41 (0.34)
$g_1$	-0.04 (0.18)	-0.24 (0.02)	0.00 (0.00)	0.278 (0.134)	0.011 (0.06)
$g_2$	0.299 (0.171)	0.595 (0.08)	0.00 (0.00)	0.624 (0.153)	0.623 (0.18)
$g_3$	0.337 (0.185)	0.409 (0.06)	0.00 (0.00)	0.290 (0.10)	-0.769 (0.30)
<b>Log L</b>	-3382.489	-972.24	-878.9	-998.46	-813.90

*Notes:* \* Statistical significance at 10%, \*\* Statistical significance at 5%, \*\*\* Statistical significance at 1%. *Log L* is the maximum likelihood function.

The  $g_i$  parameter is higher than zero of all the series during the debt crisis, implying the presence of asymmetric movements. Both variables  $a_i$  and  $b_i$  were found to be positive, and  $a_i + b_i < 1$  for Brent and WTI crude oil prices and the S&P500 stock market during the Pre-crisis period, supporting the presence of dynamic correlations over time and the existence of a contagion effect. More specifically, the results verify that the correlations increase significantly during the crash period through the studied markets. Brent and WTI crude oil prices share a higher correlated level during the turbulent period in the Greek economy. However, the S&P500 stock market appears to follow the WTI crude oil price, but do not do, closely, during all the sub-periods.

During the while period, the studied oil price markets have similar correlation levels. The  $g_i$  term is more significant and higher than 0.27 in all cases during the

debt crisis. The WTI crude oil price produced the highest  $g$  parameter at 0.624, followed by the S&P500 stock market and the Brent oil price, which produced similar values (respectively 0.278 and 0.290). The  $g$  parameter of subprime crisis was close to zero in the whole series. The  $g_i$  parameters of the pre-crisis period were much lower than expected, at -0.24 for the S&P500 stock market; the WTI oil price (0.595) is lower than the Greek debt crisis after the crisis parameter. The parameter Brent oil price is not significant.

After the crisis, the Brent oil price index had a  $g_i$  parameter (-0.769) slightly lower than the other two studied series, whereas the S&P500 stock market index was found to be 0.8644. The results of the pre-crisis period clearly portray the difference. The subprime crisis period features an increase in the  $g_i$  parameter for all the indices apart from the Brent European countries of our sample. The  $g$  parameter of the Brent oil price index decreased significantly, falling from 0.624 to 0.623.

However, the  $g_i$  parameters for the three markets increased between the pre-crisis period and the Greek debt crisis. The S&P500 stock market increased to 0.278. The WTI oil price increased slightly to 0.624 and the highest increase was observed for the WTI crude oil. The  $g$  term was found to increase significantly in the case of the Brent oil price index (0.290).

Finally, the Greek debt crash leads to different consequences for the selected markets. The Brent oil price, accompanied with 3 indices, had  $g_i$  parameters lower than in the pre-crisis period. This significant drop occurred although Greece has a weak economy that may not influence other stock markets, the structure of the EU and the Eurozone enable third parties, like speculators, to take benefit of it and use aggressive approaches, such as naked short selling, to gain profits. Despite the decrease in the  $g_i$  parameters in all cases, the positive  $g_i$  parameters confirm asymmetric movements. Consequently, the contagion phenomenon exists because all  $a_i$  and  $b_i$  parameters are positive and lower than 1.

Generally, the subprime crisis period increased the level of dependence between the three studied markets, including both the oil price indices and the so-called “big” (S&P500). To conclude, during the third period “the Greek debt crisis”, the relationship among the aforementioned markets remains high but not at the previous level. The main cause of this decrease is the low level of the Greek market correlation dynamics as well as the limited contribution and influence on the global finance market.

**Table IV: Regression of the correlation evolution for the Japanese and Singaporean stock market returns**

	<i>SP500-WTI</i>	<i>SP500-Brent</i>
$\mu_0$	-0.046*** (0.006)	-0.046*** (0.007)
$\mu_1$	0.270*** (0.043)	0.273*** (0.043)
$\theta_1$	0.021 (0.019)	0.010 (0.016)
$\theta_2$	0.0075 (0.010)	0.006 (0.010)

The final step is to apply the AR(1) process to the evolution of the estimated dynamic conditional correlations, with a dummy variable representing the major economic events investigated in this article. Table 5 shows the estimation results of these AR(1) process. The constant term  $\mu_0$  is positive and significant at 1% significance level, but the coefficient of AR terms  $\mu_1$  is also significant at 1% significant level through the values of less than unity. The dummy variables of subprime crisis  $\theta_1$  and the global financial crisis  $\theta_2$  are positively significant at 1% significance level, but that for the Asian financial crisis  $\theta_1$  is not significant at conventional levels. Table 5 evidently shows that not only the subprime crisis but also the global financial crisis affected the interdependent relationship between the S&P500 stock market and Brent oil price. The period after the crisis, however, had no impact.

#### IV. Conclusion

This article demonstrates the conditional correlation between the S&P500 stock market, Brent and WTI crude oil prices using the A-DCC model developed by Cappiello *et al.* (2006) and the AR model developed by Yiu *et al.* (2010) while considering the major economic events of 2008 and 2011 as dummies. We have two principal results. First, financial integration has advanced because of the subprime crisis, thereby strengthening the interdependent relationship between Brent and WTI crude oil prices. Second, the portfolio within the European region has increased since the recent global financial crisis, and increased the interdependent relationships through the European regional economies.

### *Notes*

1. We use weekly data here to get meaningful statistical generalizations and obtain a good picture of the movements of the stock market returns and oil price indices.
2. See Ljung and Box (1978).

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