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Were Oil Price Markets the Source of Credit Crisis in European Countries? Evidence Using a VAR-MGARCH-DCC Model

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ABSTRACT: This paper examines the role of oil prices, credit, financial and commercial linkages in the propagation of industrial market crises during the period 2004-2012. Using VAR-MGARCH-DCC model regressions on seven markets finds that credit linkage played a significant role in the subprime, financial and global crises. Our results also show that the European debt crisis has already spread like a crisis from oil prices to Ireland and Portugal, and other countries are now at risk: Spain is a probable candidate for financial crisis.

Keywords: Oil price; Contagion; Crisis; VAR-MGARCH-DCC.
JEL Classifications: C32; C52

1. Introduction

Research on the relationship between oil price shocks, stock markets and banking sectors has gained ground only very recently. Usually, oil shocks may influence stock prices through multiple channels, but most of them evoked the effects of oil prices shocks of the economic growth industrial production and business environment. The stock prices indices including the present value of the expected future cash flows of firms which depends directly on the role in macroeconomic policy. The effects of oil price fluctuations response are positive for oil-related companies, and negative for non-integrated oil companies. Note also those sharp oil prices changes, whatever sign, may reduce collective output temporarily since they put back investments due to rising uncertainties or induce expensive resource reallocation (Guo and Kliesen, 2005).

We agree with Forbes and Rigobon (2002), there is contagion when market co-movements are significantly more during the financial crisis than pre-financial crisis, for example due to the behavior of international investors. We mobilize the evolution of weekly returns indices for 7 assets markets over the period January 2004 to June 2012[1]. The choice of countries is motivated by the goal to study the co-movement between developed markets. We choose a model of the conditional variance of Multivariate GARCH (MGARCH). In our model, a specification Vector Autoregressive (VAR) yields clues to identify the transmission medium. The transmission variance is estimated through modeling conditional covariance. We also introduce variables of regime shifts in the variances. These allow the bias reduction heteroscedasticity responsible for the persistence of shocks to volatility and cross-correlations overestimate.

Generally, financial crisis will cause asset prices to plunge across multiple markets but also created speculative runs and capital flight to cause considerable market instability. Moreover, it can

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[1]The markets studied are oil prices (WTI for U.S and Brent for E.U), banking sectors: (Banco BPI) for Portugal (Banco Santander (BAS)) for Spain and Allied Irish Bank (AIB) for Greece and stock markets IBEX and ISEQ respectively for Spain and Ireland.

produce a huge loss of confidence from investors, which will cause economic growth. As a transmission of a shock across markets is hard to explain based to changes in macroeconomic fundamentals, many researchers who use the word "contagion" refer to the phenomenon and focus to measuring financial contagion by providing evidence of a significant increase in cross-market linkages. Thus, to discover the co-movement patterns of crude oil and stock markets during the recent financial crisis, it is necessary to test whether such a contagion effect exists between the markets.

Our process of study includes three steps: we firstly apply the Iterated Cumulative Sums of Squares algorithm (ICSS) of Inclan and Tiao (1994) to detect the presence of structural breaks of oil prices (WTI and Brent), banking sectors and stock markets studied. Secondly, in order to take structural breaks and asymmetry into estimation, we develop univariate Generalized Error Distribution-EGARCH model and bring dummy variables for structural breaks into variance equation. GED-EGARCH model has several advantages in comparison to the standard GARCH specification: there is no need to artificially impose a non-negative constraint on the model parameters and asymmetries are allowed for under the GED-EGARCH formulation.

Thirdly, we use DCC multivariate GARCH model of Engle (2002) to estimate the dynamic conditional correlation coefficients with structural break to test the existence of contagion effects. In order to test contagion, this study takes the asymmetric effect into account to get a more accurate estimation of dynamic conditional correlation coefficients.

This paper is organized in the following manner. In Section 2, we present the empirical techniques. Section 3 reports the results of cross-market contagion.

2. Econometric Methodology

2.1. Local Whittle method

The classes of semiparametric frequency domain estimators follow the local Whittle approach suggested by Künsch (1987) which was analyzed by Robinson (1995) (who called it a Gaussian semiparametric estimator). The Local Whittle estimator is defined as the maximization of the local Whittle likelihood purpose:

$$Q(g,d) = -\frac{1}{m}\sum_{j=1}^{m}\left[\log\left(g\lambda_j^{-2d}\right) + \frac{I(\lambda_j)}{g\lambda_j^{-2d}}\right] \tag{2.1}$$

Where $m = m(T)$ is a bandwidth number which tends to infinity $T \to \infty$ except at a slower speed than T ;

$I(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} e^{it\lambda}\right|^2$, is the periodogram of X_t,

$g_x(\lambda)$ is the spectral density of X_t, $\lambda_j = \frac{2\pi j}{n}$, and $j = 1,...,n$.

One disadvantage compared to log-periodogram estimation is that a statistical optimization is needed. On the other hand, the assumptions underlying this estimator are weaker than the log-periodogram regression (LPR) estimator. Robinson (1995) showed that while $d \in \left(-\frac{1}{2},\frac{1}{2}\right)$;

$$\sqrt{m}\left(\hat{d}_{LW} - d\right) \xrightarrow{d} N(0,1/4) \tag{2.2}$$

Therefore, the asymptotic distribution is extremely simple, facilitating easy asymptotic inference. In particular the estimator is more efficient than the LPR estimator. The ranges of reliability and asymptotic normality for the Local Whittle estimator have been shown by Velasco (1999) and by Shimotsu and Phillips (2006) to be the same as those of the LPR estimator. To determine the point's structural changes we will use the ICSS algorithm to determine the points of structural changes.

2.2. Detecting structural breakpoints

We employ the ICSS algorithm developed by Inclan and Tiao (1994) to detect the structural breakpoints on 7 series during the study period. As a starting point, the stock return for market i on day t can be written as:

$$r_{i,t} = \left(\log P_{it} - \log P_{it-1}\right) \times 100 \tag{2.3}$$

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

Next, we define

$$a_{i,t} = r_{i,t} - \mu_i \tag{2.4}$$

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

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, k = 1,....,T \text{ and } D_0 = D_T = 0 \tag{2.5}$$

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

In this section we describe in detail the wavelet transform used for the crude oil data decomposition together with the multivariate GARCH model used in our analysis.

The co-movement of markets is the result of transmissions from each market, and secondly, the transmission of a global market often represented by the oil prices markets to other markets. To account for these interdependencies, we consider a VAR model with errors including MGARCH structural changes in the variances introduced by Elder and Serletis (2010). The dynamic model is VAR (n1) as follows.

2.3. VAR-MGARCH-DCC process

The VAR process is written in the following form:

$$\alpha\left(L\right)\left(y_t - \mu\right) = u_t \tag{2.6}$$

where $\alpha(L)$ is the delay function VAR (n1) process[2]. Assuming that u_t is a vector of zero mean, non auto-correlated as:

$$u_t = H_t^{-1/2}\varepsilon_t \tag{2.7}$$

Where $\varepsilon_t \to N\left(0,1\right)$ and H_t denotes the matrix of conditional variance-covariance u_t.

We use the MGARCH model, with modifications capturing the transmission variance and structural change in the variance. We call this model MGARCH-VAR-DCC.

$$H_t = \{h_{it}\} \tag{2.8}$$

where

$$h_{it} = b_{0i} + b_{1i}\varepsilon_{t-1}^2 + b_{2i}h_{t-1}\ ,\ i = 1,...,n \tag{2.9}$$

$$H_t = E\left[u_t^{tr}u_t\right] = \begin{pmatrix} E(u_{1t}^2) & ... & E(u_{1t}u_{Mt}) \\ .. & .. & .. \\ E(u_{1t}u_{Mt}) & .. & E(u_{Mt}^2) \end{pmatrix} = \begin{pmatrix} h_{11t} & ... & h_{1Mt} \\ .. & .. & .. \\ h_{1Mt} & .. & h_{MMt} \end{pmatrix} \tag{2.10}$$

$$H_t = \begin{pmatrix} h_{11t} & \rho_{12t}\sqrt{h_{11t}h_{22t}} & ... & \rho_{1Nt}\sqrt{h_{11t}h_{NNt}} \\ \rho_{12t}\sqrt{h_{11t}h_{22t}} & h_{22t} & ... & \rho_{2Nt}\sqrt{h_{22t}h_{NNt}} \\ ... & ... & ... & ... \\ \rho_{N1t}\sqrt{h_{11t}h_{NNt}} & \rho_{N2t}\sqrt{h_{22t}h_{NNt}} & ... & h_{NNt} \end{pmatrix} \tag{2.11}$$

Therefore

[2] $\alpha\left(L\right) = I_m - \alpha^1 L - ... - \alpha^{n1}L^{n1}$ where $n1$ is the order of the VAR process which can be determined by the sequential LR test.

$$H_t = D_t.R_t.D_t \tag{2.12}$$

where R_t is the conditional correlation matrix of the return vector $r_t = (r_{1t},...,r_{nt})'$ and $D_t = \{diag(H_t)\}^{\frac{1}{2}}$ is the diagonal matrix whose i-th diagonal entry is given by the conditional standard deviation $\sqrt{H_{iit}}$ of asset i.

Otherwise, the correlation matrix R_t can be indicated as:

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{2.13}$$

Where

$$Q_t = (1-\alpha_c-\beta_c)\bar{Q} + \alpha_c(u_{t-1}u'_{t-1}) + \beta_c Q_{t-1} \tag{2.14}$$

Where $Q_t = (q_{ijt})$ the $(n \times n)$ covariance matrix of u_t is mean reverting as long as $\alpha_c + \beta_c < 1$, $\bar{Q} = E[u_t u_t']$ is the $(n \times n)$ unconditional variance matrix of u_t.

A typical element of R_t is presented as:

$$R_t = \{\rho_{ijt}\} \tag{2.15}$$

Where

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit}q_{jjt}}}, \ i,j = 1,2...,n \text{ and } i \neq j \tag{2.16}$$

In a bivariate case the correlation coefficient can be expressed as:

$$\rho_{12t} = (1-\alpha_c-\beta_c)\bar{\rho} + \alpha_c(u_{t-1}u'_{t-1}) + \beta_c \rho_{12t-1} \tag{2.17}$$

The DCC model used in this study includes two stages in the estimation process to maximize the log-likelihood function. Hence, this function can be written as the sum of one volatility part and one correlation part:

$$l_t(\Theta,\Phi) = \left[-\frac{1}{2}\sum_{t=1}^{T}\left\{n\log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-2}\varepsilon_t\right\}\right] + \left[-\frac{1}{2}\sum_{t=1}^{T}\left\{\log|R_t| + u_t' R_t^{-1} u_t - u_t' u_t\right\}\right] \tag{2.18}$$

We estimate the dynamic conditional correlation for all series studied, and calculate the stable period DCC and the crisis period DCC coefficients. The correlations tests for contagion are conducted for the sub-sample periods using DCC coefficients.

2.4. Stability test of the dynamic conditional correlation

The contagion between the dynamic conditional correlation pre-crisis and crisis periods are then examined by calculating $\bar{C}_{ij}^{crisis}$ for the crisis period and $\bar{C}_{ij}^{\text{pre-}crisis}$ for the pre-crisis period. The test for contagion is then:

$$\begin{cases} H_{0,i\to j}^{c_2} : \bar{C}_{ij}^{crisis} \leq \bar{C}_{ij}^{\text{pre-}crisis} \\ H_{1,i\to j}^{c_2} : \bar{C}_{ij}^{crisis} > \bar{C}_{ij}^{\text{pre-}crisis} \end{cases} \tag{2.19}$$

In fact the volatility they propose is only necessary if one draws all information from a system estimated across both crises and non-crisis periods under the null of non contagion. To conduct the test of $H_{0,i\to j}^{c_2}$ versus $H_{1,i\to j}^{c_2}$, the Student on the estimated dynamic conditional correlation is required to achieve. The two sample tests on independent means is performed as:

$$t = \frac{\bar{C}_{ij}^{crisis} - \bar{C}_{ij}^{\text{pre-}crisis}}{\sqrt{\frac{S_p^2}{n_1} + \frac{S_p^2}{n_2}}} \tag{2.20}$$

Where S_p^2 is the Common variance of the two sub-periods before and during the crisis is equal to:

$$S_p^2 = \frac{(n_1-1)V_1 + (n_2-1)V_2}{n_1+n_2-2} \text{ where } V_i = \frac{1}{n_i-1}\sum_{j=1}^{n_i}\left(C_{ij}^{crisis} - \bar{C}_{ij}^{crisis}\right)^2 \text{ for i=1,2.} \tag{2.21}$$

Where n_i is the number of observations in the sample. We use a test of equality of means of correlations in sub-periods based on analysis of variance intra-periods. If the two sub-periods have average correlations equal, then the variability of the intra-period and inter-period correlation are not significantly different. To account for the non-homogeneity of variance in each sub-period, we will divide that total period into two sub-periods before and during the crisis.

3. Empirical Results

3.1. Data and descriptive statistics

The data comprise weekly[3] total indices calculated by "datastream" for markets of developed countries. We consider the oil price WTI (West Texas Intermediate grade) spot oil prices and Brent to represent respectively the U.S and European energy markets. We have chosen banking sectors BPI, AIB and BAS respectively for Portugal, Greece and Spain. Finally, concerned stock markets we have chosen the IBEX and ISEQ stock markets respectively for Spain and Ireland. The sample starts from January 2004 and ends June 2012, yielding 408 observations for each series.

Table 1 presents a wide range of descriptive statistics for the seven series under investigation during the period (2004-2012)[4]. The null hypothesis of no ARCH effects is rejected at 1% significance level. This suggests that GARCH parameterization might be appropriate for the conditional variance processes.

Table 1. Summary of descriptive statistics

	Oil prices		Banking sectors			Stock markets	
	WTI	Brent	BPI	AIB	BAS	IBEX	ISEQ
T	408	408	408	408	408	408	408
moy	53.94	71.49	3.81	30.16	15.42	11982	5672
var	459.15	626.40	3.87	511.06	14.97	4602475	69601
skew	0.96	0.58	0.20	-0.10	-0.55	-0.08	0.06
kurt	0.23	-0.29	-1.70	-1.72	-0.36	-0.88	-1.60
J-B	38.17	24.44	30.93	30.44	13.63	8.04	26.08
ARCH	38.79*	18.65*	8.14**	13.85*	26.62*	9.36**	8.23**

Notes :* and ** indicate the significance level at 5% and 10%. The value between (.) indicate the P-value.

3.2. Long memory dependency and the American financial crisis

Firstly, the LW estimators of the long memory parameters for the periods as reported in Table 2 are lower than 0.5 for the full indices. This result indicates that the long memory dependency in the period is important. This may be due to the shocks and the breaks that occurred in the developed financial market during the subprime crisis. A possible explanation is that the invasive occurrences in the oil prices, banking sectors and stock markets during the financial crisis lasted for extended periods and increased the long memory property as the mean process responded to the shocks and the breaks asymmetrically and gradually as pointed out by Andersen et al (2002).

Table 2. Estimation of the long memory parameters returns for all periods

	Oil prices		Banking sectors			Stock markets	
	WTI	Brent	BPI	AIB	BAS	IBEX	ISEQ
LW	0.477	0.465	0.396	0.428	0.347	0.448	0.335
Std Error	0.75	0.78	0.89	0.56	0.54	0.53	0.66

Notes: Std Error indicate the standard error of the parameter estimate.

Table 2 indicates that the long memory property in the series appears to be slightly lower than that 0.5. This may be due to the more asymmetric stock market volatility in these series. It can be seen

[3] We use weekly data here to get meaningful statistical generalizations and obtain a better picture of the movements of oil price and stock market indices.

[4] 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 favour of the alternative hypothesis (even at 5% critical value).

that the volatility is highly persistent in all series during the full period. We note that the highest values for oil prices (0.477 and 0.456 respectively for WTI and Brent), indicating the persistence of shocks of oil prices that of the banking courses and stock markets.

Table 3 reports the structural breaks of series and their emergence dates. The ICSS algorithm detects more than structural breaks in the unconditional variance for all series except AIB and ISEQ that has one structural break. The oil prices WTI and Brent are the first that are affected by the break points indicates that these two markets are the origins of the recent financial crisis. The structural breaks in 2007 for all market studied can possibly be due to some of the major crisis events during 2007-2011 period.

Table 3. The structural breaks and their emergence dates

	WTI	Brent	BPI	AIB	BAS	IBEX	ISEQ
1	29-05-06	11-03-05	24-12-07	29-10-07	11-09-06	11-09-06	02-01-06
2	16-10-06	13-01-06	22-09-08	-	18-05-09	27-01-08	-
3	12-03-07	14-04-06	13-09-10	-	04-07-11	26-05-08	-
4	02-07-07	22-09-06	-	-	-	23-06-08	-
5	05-11-07	28-09-07	-	-	-	29-09-08	-
6	23-06-08	15-10-10	-	-	-	13-10-08	-
7	-	21-01-11	-	-	-	11-05-09	-
8	-	-	-	-	-	04-07-11	-

The subprime financial crisis was marked by two phases. The first phase 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 for bankruptcy. In June 2007 two Bear Stearns funds sold $4 billion of assets to cover redemptions and expected margin calls arising from subprime losses. On July 10th, 2007 Standard & Poor's said it might cut ratings on some $12 billion of subprime debts (we see a structural change on WTI in July 2007). A week later Bear Stearns said two hedge funds with subprime exposure had a very little value and credit spreads soared. On the 20th 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 purchases country wide financial in all-stock transaction.). We see a structural change on WTI in June 2008 (table 3). We based in the structural change (see table 3), we determine the pre-crisis period which spreads from January 2004 to February 15, 2007 and the crisis period which spreads from February 16, 2007 to June 15, 2012.

The analysis of the dynamics between oil prices and future prices which is the subject of a vast literature faces many difficulties when we take an approach in terms of co-integration. The statistical analysis of chronic price can highlight changes in volatility that can be found through tests of volatility changes on the balance of long-term (Test-ARCH Autoregressive Conditional heteroskedasticity) and tests break ICSS algorithm in the studied period. Also an estimate GARCH model with break points allows us to consider two regimes of the oil prices, banking sectors and stock markets dynamics characterized by volatilities and restoring forces separate. The first tests on WTI and Brent oil prices give conclusive results in this direction. It is then necessary to estimate a model explaining the probability of being in one of the schemes based on indicators on open positions, transaction volumes or inventory changes to characterize each system and highlight behaviour of agents. For this part of econometric analysis of weekly data will be used.

The objective of this paragraph is to test the presence of Granger causality in a bivariate VAR model between different indicators (oil prices, banking sectors and stock markets) on the market sovereign debt. More precisely, we want to analyze the evolution of causality between the periods of crisis: the crisis period (February 16, 2007 to June 15, 2012). In order to evaluate the existence of causality relationships between the oil prices and the stock markets, the causality concept, originally, proposed by Granger (1969) is used. In the prosecution of the causality tests, for each pair of variables, the Fisher test statistic is applied.

According to the results presented above in Table 4 and what concerns to crisis period, none of the variables can be considered as totally exogenous, since at least one causality relationship is detected for each variable, and given the significance of the coefficient that is associated with the error correction terms. The indexes that accomplish the adjustment mechanism in relation to the deviations that are observed in the equilibrium relationships between oil prices, banking sectors and stock markets are WTI and Brent. In what respects to the causality tests, a joint causality of the variables: for example BPI-BAS, BPI-IBEX, AIB-BAS, at a significance level of 5%, is detected. This fact ratifies the importance of the inclusion of this set of variables in the specification of the model that is used here. The existence of feedback relationships between the oil price and stock markets must be stressed. From this, we only detect the existence of unidirectional causalities for example between WTI and BPI, AIB-BPI. In this ambit, it is of noticing the importance of the WTI and Brent oil prices, which is the origin of the causality for all market studied, at a significance level of 5%. It is also detected that, for this period, the WTI and Brent are the origin of two causality relationship banking sectors and stock markets; nevertheless, it is explained by the past values of the oil prices considered.

Table 4. Granger standard causality test

Sour / of c	WTI	Brent	BPI	AIB	BAS	IBEX	ISEQ
WTI	-	*	*	-	*	-	*
Brent	*	-	*	*	*	*	*
BPI	*	*	-	*	*	*	-
AIB	*	*	-	-	*	*	-
BAS	*	*	*	*	-	-	*
IBEX	*	*	*	-	*	-	*
ISEQ	*	*	-	-	*	*	-

Notes: sour of c indicate that the market in line is the source of contagion in the market of column* indicate the significance level at 5%.

An important element of specifying a VAR process is to determine the optimal lag of the explanatory variables. Different criteria can be used. In the empirical literature most frequently used are: SIC (Schwarz Information Criterion) and AIC (Akaike Information Criterion). On this foundation, we use SIC criterion to select the optimal lag length of the VAR model. Results of the optimal lag (equal to one) selection are presented in Table 4. We see the significance of the explanatory variables that the important relationship between WTI and Brent on the one hand and banking sectors and stock markets on the other.

After checking the stationarity of variables, we construct a VAR (Vector Auto Regressive) model. These models analyze the effects of one variable on another through simulations of random shocks. What interests us in fact; it is the assessment of the propagation mechanisms of shocks on different variables. To do this we will begin by presenting the means of analysis chosen to evaluate the mechanisms of transmission of shocks before proceeding to the analysis of empirical results for series. We consider in table 6, WTI and Brent oil prices the source of contagion, because the two markets are the relationships with all markets studied (see Table 5).

Table 5. Estimation of VAR (p) process

	WTI	Brent	BPI	AIB	BAS	IBEX	ISEQ
WTI	-	0.42**	0.15*	-	7.10^{-3**}	-	0.21*
Brent	0.56*	-	0.11*	0.63*	0.74*	0.09*	0.12*
BPI	0.23*	0.17*	-	0.39*	0.19*	84.83*	-
AIB	0.35	0.28*	-	-	-0.01**	1.47	-
BAS	0.18	0.25*	-0.003	-0.06**	-	-	-2.13
IBEX	0.52	0.08*	-10^{-5}	-	$-3.\ 10^{-5}$	-	-0.003
ISEQ	0.05*	0.37*	-	-	-10^{-6}	-0.03	-

The results in table 6 show that there is evidence of contagion in several cases of oil price (WTI and Brent) and stock market examined using the crisis period with DCC coefficients, whereas the short period will indicate the propagation of crisis of WTI to all markets except banking sector AIB and stock market IBEX. Table 6 shows that the propagation of crisis of Brent oil prices to all markets studied.

Table 6. Tests of contagious effects

	WTI source of contagion				Brent source of contagion			
	$\overline{C}_{ij}^{pre-crisis}$	$\overline{C}_{ij}^{crisis}$	t	No-con	$\overline{C}_{ij}^{pre-crisis}$	$\overline{C}_{ij}^{crisis}$	t	No-con
Oil	0.12	0.45	8.36*	No	0.17	0.60	7.39*	No
BPI	0.11	0.32	7.36*	No	0.12	0.75	9.12*	No
AIB	0.32	0.14	1.78	Yes	0.10	0.63	8.96*	No
BAS	0.13	0.45	7.12*	No	0.08	0.86	9.12*	No
IBEX	0.35	0.20	2.14	Yes	0.11	0.14	097*	No
ISEQ	0.20	0.23	7.39*	No	0.09	0.12	8.67*	No

The results reported in Table 6 show the increase in correlations between the banking sectors and the stock markets, which in turn is strongly correlated with the oil prices market crisis. These two markets are highly correlated with the series of all markets (banking sectors and stock markets). Series at the two variables (WTI and Brent) are highly correlated with their towers variations in banking courses. Finally, the series in the Brent oil price and WTI crude oil are highly correlated with series of banking sectors.

Table 5 summarizes the results of the estimation of the VAR model for crisis period. This allows us to determine if there is a significant difference in the relationship between oil prices, stock market and banking sectors during the crisis. These results show that the movements of the Brent and WTI prices are sensitive to changes in equity returns during the crisis period with a continuing decline. The coefficient is positive and significant indicating that a negative shock to the stock market leads to the yielding down of banking sectors and stock markets. This result is coherent with the Quan and Titman (1999) who found significant positive relationships between real estate values and stock returns. The oil market is strongly aligned with the level of inflation.

Our results also show a positive and a significant dependence on oil prices and the banking courses in times of crisis. Oil prices have increased inflationary pressures in the economy, which reduces real household income and thus results in a reduction in demand for real estate. This result is consistent with the findings of Hamilton (1996) and Hooker (2002) who showed that the increase in oil prices can affect the national economy through the production and domestic price levels which give rise to reduced consumer demand for goods.

Indeed, inflation is positively sensitive to changes at the level of industrial production, stock returns and oil price changes. However, the price of crude oil has doubled from (74 barrel) in July 2007 (145 barrel) in July 2008, which raised expectations of inflation, where the value of shares decreased. The expectation of rising inflation could force the Fed to raise interest rates during a period of economic weakness, which affects stock market advantage already in trouble. These results show a clear trend of contagion between European markets.

4. Conclusion

Our paper has examined the international transmission of the subprime financial crisis. As a starting point we have employed Local Whittle method to analyze the effects of this crisis in the developed countries. There is the long memory dependency on the volatility process of the oil prices, stock markets and banking sectors. The estimation results show that the long memory dependency on the volatility process is more significant especially in oil prices markets which experienced significant shocks and breaks associated with the crisis. We have adopted the VAR-MGARCH-DCC model whose estimated parameters that enable us to distinguish between turbulent and ordinary regimes.

Then, we have analyzed the contagion effect of subprime financial crisis using a DCC multivariate GARCH model according to two periods: the pre-crisis period and the crisis period. Volatility spillovers are found only during the crisis period. For the oil prices, highly significant, increasing correlation has been observed during the crisis period, which is a clear evidence of crisis contagion.

The recent financial crisis provides us with an ideal opportunity to properly study the contagion. The subprime crisis, the oil prices (WTI and Brent) crash and high oil prices are factors that have played a complex role in the recent financial crisis and recession. Motivated by the definition of contagion frequently adopted in the literature and proposed by Forbes and Rigobon (2000), we adopted a VAR model to test changes in the international market linkages. We tested a scale model macroeconomic purpose of considering the links among oil price on the one hand and the links with banking sectors and stock markets on the other. The main contribution of this model lies in the study of inter-markets links increase in attendance of domestic and global factors, an issue that has not been addressed in the literature so far. The main conclusions of our work are as follows;

Our results provide strong evidence of an increase in cross-market linkages. Before the recent financial crisis, yielding estimated variables contain little useful information for forecasting yields in other major markets. In times of crisis the variations observed in oil prices have become highly predictive for banking sectors and stock markets. In many cases, the key indicators of the U.S. economy are able to predict oil yields, stock returns and changes in foreign banking sectors and stock markets.

Finally, using a VAR-MGARCH-DCC bivariate, we have estimated six pair-wise models. During the crisis, the Brent, BPI, BAS and ISEQ markets were affected by a strong contagion coming directly from the US market (WTI oil price). For the Brent oil price, we consider the propagation to all markets. This indicates that the European market was partially integrated into the world market.

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