Volatility Spillover Analysis between Oil Prices and Financial Stress

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Abstract
The volatility transmission between oil prices and financial stress has been recently investigated. Hovewer, there exist a small number of studies that explore this relationship by considering the spillover effect of oil prices on financial stress index or vice versa since financial stress index is a new concept. In this study, we explore the volatility spillover between oil prices and financial stress index by employing DCC-GARCH and VAR models. We use weekly WTI crude oil prices and St. Louis financial stress index for the period 1994-2015 and we split it into three sub-periods: pre-crisis, crisis and post-crisis periods. Besides, the causality tests are employed in oder to determine the risk transfers from oil prices to financial stress and from financial stress to oil prices in the pre-crisis, crisis and post-crisis periods.

Keywords: Volatility Transmission, Oil Prices, Financial Stress Index
JEL Classification: C32, C58, Q43.

1. Introduction and Literature Review

The relationship between oil price shocks and economic activity has been investigated by several studies in the literature and the adverse effect of oil price shocks on economic activity was obtained in some of them. Killian (2008) develops a measure of aggregate exogenous production shortfall across all OPEC countries for the period 1973-2006 and it employs a new method in order to determine the dynamic effects on macroeconomic aggeragates and on the price of oil. The study suggests that exogenous oil production shortfalls can describe only a small part of oil price movements and oil prices occurred in 1973, 1979, and 2004/05. Lescaroux and Mignon (2008) investigate the relationships between oil prices and financial and macroeconomic variables (GDP, CPI, household consumption expenditures, unemployment rate and share prices) for a sample of countries. The results of the study indicate that there exists a strong Granger-causality running from oil to share prices, especially for oil-exporting countries and it is is negative and always runs from oil prices to stock markets. The effect of oil price shocks on growth rate of output of a subset of developed countries (Canada, France, Germany, Italy, Japan, United Kingdom and United States) is estimated and specified by using different Markov-Switching (M-S) regime autoregressive models for the data period 1970q1-2005q1 in another study developed by Cologni and Manera (2009). It is argued that three-regimes MS models outperform than two regime specifications in describing the business cycle features for each country in G-7 and the models that include exogenous oil variables usually outperform than the models which exclude oil, oil price shocks tend to be asymmetric.

Some studies examine the effects of oil price shocks by directly focusing on it's impacts on stock prices returns. Park and Ratti (2008) analyse the impact of oil price shocks on real stock returns contemporaneously and/or within the following month in the U.S. and 13 European countries from 1986:1 to 2005:12. The results of the study demonstrate that oil price shocks have a statistically significant impact on real stock returns in the same month or within one month for U.S. and 12 European countries, while on the contrary the effect of oil price shocks on real stock return is positive for Norway as an oil exporter and this effect vary between countries dependent to being an outlier representing the major outcome among countries. The time varying correlation between oil prices and stock market prices is examined by Filis et al. (2011) by splitting countries in accordance with exporting/importing oil. The findings of the study indicate that time varying correlation doesn't differ for oil-exporting and oil-importing countries and it increases positively (negatively) in respond to important aggregate demand-side oil price shocks. Jammazi (2012) investigates the effect of crude oil price shocks on stock market returns for five developed countries (USA, UK, Japan, Germany and Canada) by focusing on transmission of oil shocks to stock markets returns. It is argued in the study that there is a close link between equity and crude oil high volatility state, higher real crude oil price shocks come from non-European countries for an oil importing country and the responses of the stock market to an oil shock are connected to the geographic area for the main source of supply apart from UK and Japanese. The effects of oil price shocks on stock market are investigated in (Aloui et al., 2012) by differentiating these effects on bullish and bearish periods. The study uses 25 emerging countries' data from September 29, 1997 to November 2, 2007 for a total of 2,512 daily observations (daily closing index prices on individual emerging markets and daily closing prices of West Texas Intermediate (WTI) crude oil futures contract) and the results of it suggest that oil price risk is an important determinant for pricing of market stocks and the oil sensitivity of stock returns is asymmetric and there exist a significant relationship between market returns and global market betas during bullish periods, while this relationship become negative in bearish periods. Killian and Park (2013) examine the bi-directional relationship between oil prices and stock returns by considering stock returns to measure of demand and supply shocks in the global crude oil market. The findings of the study indicate that i) Unanticipated disruptions of crude oil production do not have a significant effect on cumulative U.S. stock returns, while an unexpected rise in the global demand for industrial commodities will cause a sustained increase in U.S. stock returns and it is partially statistically significant for the first 7 months. ii) An increase in the demand for oil would cause negative persistent effect on U.S. stock returns. iii) Crude oil production shocks are less important in understanding changes in stock prices than aggregate demand shocks or oil demand shocks. The impact of oil price shocks on stock returns for 12 oil importing countries is analyzed in (Cunado and Gracia, 2014) and the results of the study indicate that oil price changes have a significant and negative impact on stock market returns in most of the countries, oil supply shocks tend to have a greater negative impact on stock market returns than oil demand shocks and oil price increase due to a supply has more negative effect on stock returns than oil price increase due to a demand shock.

Some recent studies directly focus on the spillover effect of oil price shocks on financial stress index while the number of them is few since financial stress concept is new. Chen et al.

(2014) examine the effect of an exogenous shock arisen from fluctuations in financial market conditions and the effect of oil price changes to macroeconomic conditions by taking the Kansas City Financial Stress Index (KCFSI) as a proxy for global financial market conditions. The results of the study demonstrate that a positive financial shock results to a statistically significant decline in oil prices and it has a relatively high explanatory power for oil price fluctuations. The transmission of volatility between oil prices and financial stress is examined in (Nazlioglu et al., 2015) by focusing on the volatility spillovers between daily WTI crude oil prices and Cleveland financial stress index (CFSI) from 25.09.1991 to January 02.01.2014 and the sample is splitted into pre-crisis, crisis and post-crisis. The results of the study show that oil prices and the financial stress index are dominated by the long-run volatility, there exists a causality from oil prices to financial stress after the crisis and there exists a causality from financial stress to oil prices in the crisis.

2. Methodology

2.1. Data Description

Daily observation of oil prices and weekly observation of financial stress measure are used in our study. We use the West Texas Intermediate (WTI) spot crude oil prices, downloaded from Quandl Financial and Economic Database and we convert it to weekly by the help of R program. As a financial stress measure, we decide to use St. Louis financial stress index, obtained by FRED database of St. Louis Federal Reserve Bank. Stlfsi measures financial stress in the markets and it includes 18 weekly data series: Seven interest rate series, six yield spreads and five other financial series starting from December 1993.

The data set covers oil prices and financial stress index between January 1994 and October 2015 in which both of variables are available and it is splitted into three sub periods: Pre-crisis (01.14.1994-26.02.2007), Crisis (27.02.2007-31.08.2010) and Post-crisis (01.09.2010-09.10.2015). The selection of these sub periods are based on the crisis timeline of Federal Reserve Bank of St. Louis.

2.2. Dynamic Conditional Correlation (DCC)

Engle (2002) proposes Dynamic Conditional Correlation (DCC) estimations which are observed from a new multivariate GARCH model. This new method can be viewed as generalization of constant correlation estimators that are developed by Bollersev (1990).

He set up the multivariate return series as follows:

$r_t|\varphi_{t-1} \sim N(0, H_t)$ where $H_t = D_t R_t D_t$ and $D_t = diag\{\sqrt{H_{i,t}}\}$

$h_{i,t} = E_{t-1}(r_{i,t}^2)$, $r_{i,t} = \sqrt{h_{i,t}}\varepsilon_{i,t}$, $i = 1,2$

R_t remains the time varying correlation matrix which is obtained by covariance matrix Q_t as follows:

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$$

The log likelihood estimator is given as follows by this estimation:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + 2log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t'\varepsilon_t + log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t)$$

2.3. Causality in Mean Test

Toda and Yamomoto (1995) propose that the levels of VAR can be estimated and the general restrictions on the parameters can be tested even if the processes may be integrated or cointegrated of an arbitrary order. The lag selection precedure is done for a possibly integrated or cointegrated VAR in the first place. In addition to the selection of lag length k, $(k + d_{max})$ th-order VAR is estimated in which d_{max} is the maximal order of integration that might occur in the process. The coofficient matrices of the last d_{max} in the model are ignored and the linear or non-linear restictions on the first k coefficient matrices are tested.

2.4 Causality in Variance Test

Nakanati and Ter$\ddot{a}$svirta (2009) propose an LM test for detecting the presence of volatility interactions or transmission in the CCC-GARCH framework. The null hypothesis of the test is the Constant Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (CCC-GARCH) model in which volatility of an asset is described only through lagged squared innovations and volatility of its own with an alternative hypothesis of an extension of that model in which volatility is modelled as a linear combination not only of its own lagged squared innovations and volatility but also of those in the other equations while keeping the conditional correlation structure constant.

In the first step they construct the vector $ECCC - GARCH(p, q)$ process of ε_t which is defined as follows:

$$h_t = \left[h_{1,t}, \dots, h_{N,t}\right]' = a_0 + \sum_{i=1}^{q} A_i \varepsilon_{t-i}^{(2)} + \sum_{j=1}^{p} B_j h_{t-j}$$

$$y_t = \mu + \varepsilon_t$$

$$\varepsilon_t = D_t z_t$$

where y_t is a stochastic $(N\times1)$ vector, μ is an $(N\times1)$ intercept vector and $D_t = diag\left(\sqrt{h_{1,t}}, \dots, \sqrt{h_{N,t}}\right)$ is a diagonal matrix of conditional standard deviations of ε_t. The sequence $\{z_t\}$ of independent and identically distributed variables with mean 0.

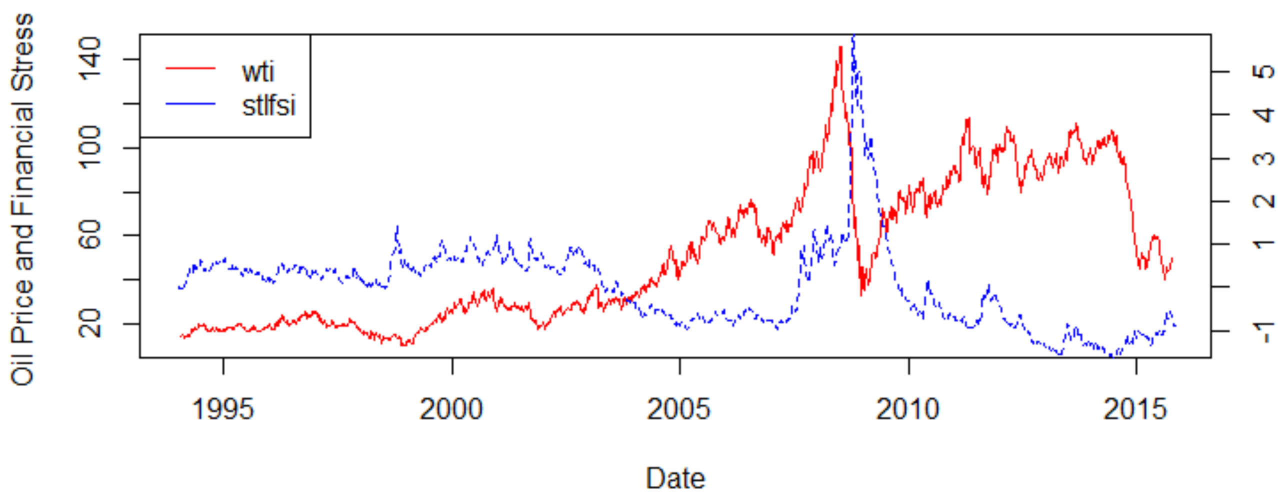
Afterwards, they set up a test for testing the hypothesis that A_1 and B_1 are diagonal matrices. The quasi-log-likelihood function for observation t is given by:

$$l_i(\theta) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2} ln|D_t P D_t| - \frac{1}{2}\varepsilon_t' D_t^{-1} P^{-1} D_t^{-1} \varepsilon_t$$

3. Empirical Findings

Before the econometric analysis, we first visualize the WTI and Stlfsi data between the period January 1994 and October 2015.

Fig. 1: Oil price and Financial Stress



It can be seen from Fig. 1, that the oil price and financial stress tend to move closely during the crisis period while they move away during the post-crisis period.

3.1.Unit Root Tests

The unit root tests ADF, Dickey and Fuller (1979) and KPSS, Kwiatkowski et al. (1992) tests are employed in order to determine the stationarity of the series. Results can be seen in Table 1.

	Financial Stress				Oil Price			
	Full Sample	Pre-Crisis	Crisis	Post-Crisis	Full Sample	Pre-Crisis	Crisis	Post-Crisis
	1994/01/14 2015/10/09	1994/01/14 2007/02/26	2007/02/27 2010/08/31	2010/09/01 2015/10/09	1994/01/14 2015/10/09	1994/01/14 2007/02/26	2007/02/27 2010/08/31	2010/09/01 2015/10/09
ADF	-2,93 ***	-2,11 ***	-1,50 ***	-1,30 ***	-3,54	-1,79 **	-1,89 ***	-2,14 ***
KPSS	3,14 ***	5,12 ***	0,90 ***	3,19 ***	11,8 ***	7,52 ***	0,63 ***	2,28 ***

Table 1: Unit Root Tests Results

Notes: *, ** and ** show significance level at 10, 5 and 1 percent levels.

ADF and KPSS unit root tests indicate that oil prices and financial stress have unit roots except for oil price in full sample.

3.2. Summary Statistics

We report summary statistics for the financial stress and oil prices in Table 2.

Table 2: Descriptive Statistics

	Financial Stress				**Oil Price**			
	Full Sample	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Full Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
	1994/01/14 2015/10/09	1994/01/14 2007/02/26	2007/02/27 2010/08/31	2010/09/01 2015/10/09	1994/01/14 2015/10/09	1994/01/14 2007/02/26	2007/02/27 2010/08/31	2010/09/01 2015/10/09
Min. :	-1.619000	-0.9770	-0.8230	-1.6190	10.86	10.86	33.17	40.45
1st Qu.:	-0.744000	-0.3400	-0.3311	-1.3290	22.23	18.94	65.87	83.87
Median :	0.098000	0.3380	0.6310	-1.0830	42.45	25.83	75.41	93.32
Mean :	0.002731	0.1602	0.8880	-1.0330	51.42	30.30	79.17	87.78
Std. Dev. :	0.994308	0.5555	1.5386	0.3753	31.84	15.70	23.44	18.07
3rd Qu.:	0.520000	0.5370	1.2910	-0.9205	78.71	34.51	90.46	99.97

Max. :	5.861000	1.4240	5.8610	0.0750	145.3	76.80	145.3	110.6
Kurtosis :	8.861158	2.1594	4.0167	3.6473	2.744	3.487	3.504	3.362
Skewness :	1.568592	-0.5401	1.2603	1.0839	0.546	1.227	0.749	-1.099
Jarq.-Bera:	2182.1	56.277	58.791	46.706	104.4	188.1	19.92	44.40

As expected the financial stress index has the highest standart deviation and the highest mean during the crisis period. Similarly, oil price has the highest standart deviation during the crisis period, while it has the highest mean during post-crisis period. This is probably due to increasing trend of oil prices during post-crisis period. Skewness values of financial stress indicate that the series is right tailed during crisis and post-crisis periods, while it is left tailed during pre-crisis period. As for oil price, it is right tailed during pre-crisis and crisis periods, while it is left tailed during post-crisis period. Jarque Bera test statistics reject the null hypothesis of normality for financial stress and oil price series. Kurtosis value of financial stress indicate that it is less peaked during the crisis period as compared to pre-crisis and post-crisis periods.

DCC-GARCH (1,1) with arma order (1,1) model is employed to the series in the next step and dynamic condional corelations are obtained in pre-crisis, crisis and post-crisis periods. Results of the model can be seen in Table 3:

Table 3: DCC-GARCH(1,1) Results

	Full sample	**Pre-crisis**	**Crisis**	**Post-Crisis**
	1994/01/14	1994/01/14	2007/02/27	2010/09/01
	2015/10/09	2007/02/26	2010/08/31	2015/10/09
[wti].mu	14.94130	14.88679	63.14682	74.431392
[wti].omega	0.020860	0.025370	0.963728	0.284851
[wti].alpha1	0.094232	0.109381	0.128426	0.030093
[wti].beta1	0.904768	0.887521	0.823747	0.939557
[stlfsi].mu	-0.158418	-0.047614	0.128217	-0.345742
[stlfsi].omega	0.000754	0.000830	0.003286	0.002024
[stlfsi].alpha1	0.427537	0.209758	0.661199	0.371654
[stlfsi].beta1	0.554194	0.596944	0.337801	0.235224
[Joint]dcca1	0.000000	0.000000	0.004847	0.000000
[Joint]dccb1	0.948088	0.907773	0.974646	0.936223

It can be seen Table 3 that, the ARCH parameter α for oil price in the model has the highest value in crisis period and it is comperable higher than those that belong to other periods. The ARCH parameter α for financial stress is the highest in crisis period as expected. As for the GARCH estimators;oil price has the highest β value during post-crisis period and it is probably due to fluctuations of oil price in that period. Financial stress has the highest β value during pre-crisis period and it has slightly smaller β value in post-crisisperiod than in pre-crisis and crisis periods.

Figure 2, Figure 3 and Figure 4 illustrate Dynamic Conditional Correlations (DCCR) between oil price and financial stress during pre-crisis, crisis and post-crisis periods respectively.

Fig. 2: DCCR of Oil Price and Financial Stress in Pre-Crisis

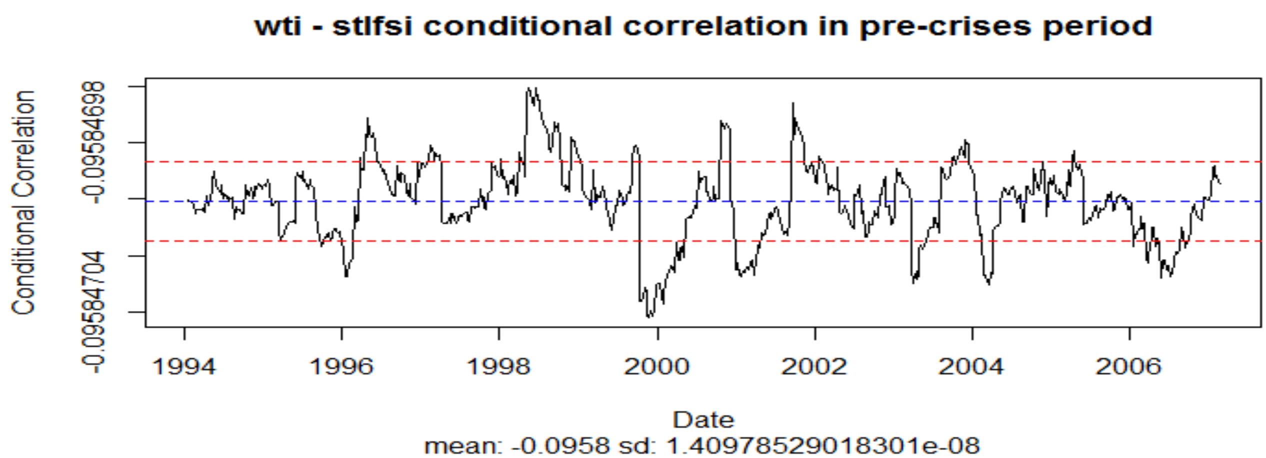


Fig. 3: DCCR of Oil Price and Financial Stress in Crisis

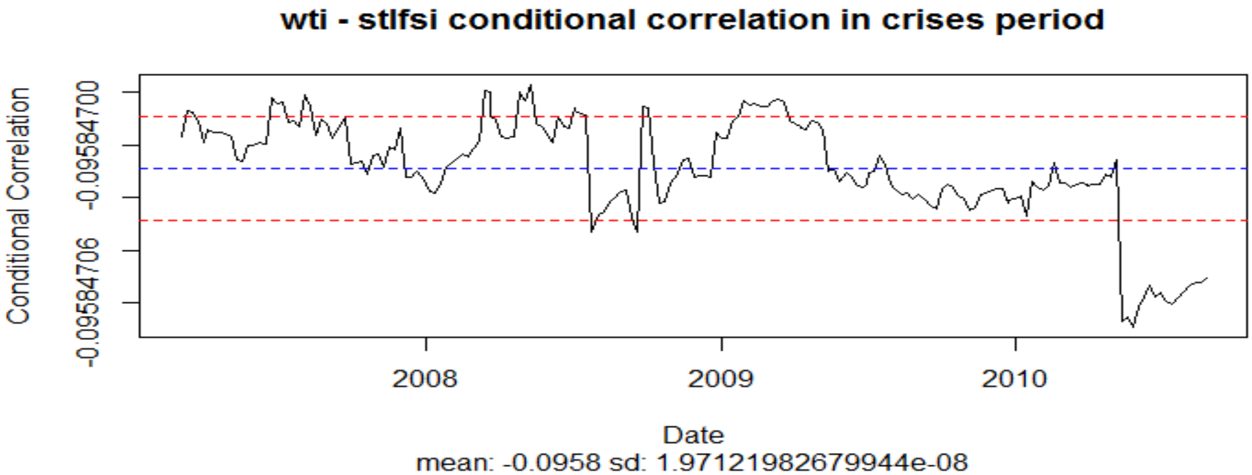
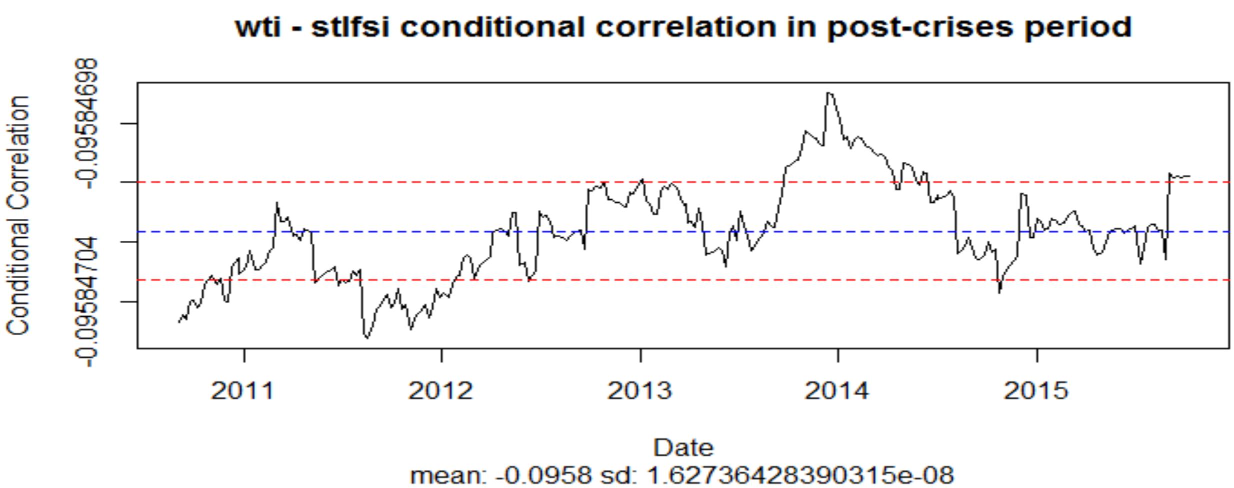


Fig. 4: DCCR of Oil Price and Financial Stress in Post-Crisis



It can be concluded that, DCCR between oil price and financial stress in crisis period are slightly higher than in pre-crisis and post-crisis periods. Especially, it is considerable high at the peak level of the global financial crisis. During post-crisis period DCCR generally fluctuate between lower values except the dates from the middle of 2013 to the end of 2014. Besides, the standart deviation of DCCR is higher during crisis period.

We employ Granger causality test suggested by Toda and Yamomoto (1995) since this method doesn't require co-integration and there doesn't need to transform original series in order to use their stationarity forms. In order to test the causality, the Wald test is implemented. The results of Toda-Yamomoto causality test can be seen in Table 4.

Table 4: Toda-Yamomoto Causality Test Results

	Full sample 1994/01/14 2015/10/09	**Pre-crisis** 1994/01/14 2007/02/26	**Crisis** 2007/02/27 2010/08/31	**Post-Crisis** 2010/09/01 2015/10/09
Causality from oil price to fin. stress (p value)	2E-07	0.05	0.0015	0.05
Causality from fin. stress to oil price (p value)	6.8E-05	0.05	0.021	0.00062

It can be concluded from Table 4 that financial stress Granger causes oil prices significantly at %1 and %5 levels, while it is not significant at %10 level during pre-crisis period. Similarly, oil price Granger causes financial stress significantly at %1 and %5 levels, while it is not significant at %10 level during pre-crisis period. During crisis and post-crisis periods financial stress and oil price Granger causes each other at %1, %5 and %10 significantly. This causality relationship is also valid for the full sample. As a consequence, it can be concluded that oil price and financial stress are strongly linked.

Table 5 shows the results of variance spillover test proposed by Nakanati and Terӓsvirta (2009). It is employed to DCC-GARCH (1,1) models for pre-crisis, crisis and post-crisis periods.

Table 5. Nakanati and Terӓsvirta Test Results

Full sample		Pre-crisis		Crisis		Post-Crisis	
1994/01/14		1994/01/14		2007/02/27		2010/09/01	
2015/10/09		2007/02/26		2010/08/31		2015/10/09	
p value	test stat.	p value	test stat.	p value	test stat.	p value	test stat.
0.3759	4.2289	0.2478	5.4090	0.2747	5.1244	0.8587	1.3156

It seems in Table 5 that the LM test statistics in pre-crisis and crisis periods are higher than those in post-crisis and full sample periods. This is probably due to high volatility transmission between oil price and financial stress during these periods.

In order to catch bi-directional short run temporary shocks between oil price and financial stress, we employ VAR analysis and the impulse-response functions during different periods can be seen in Figure 5, Figure 6, Figure 7 and Figure 8.

Fig. 5: Impulse Response Functions for the Full-Sample

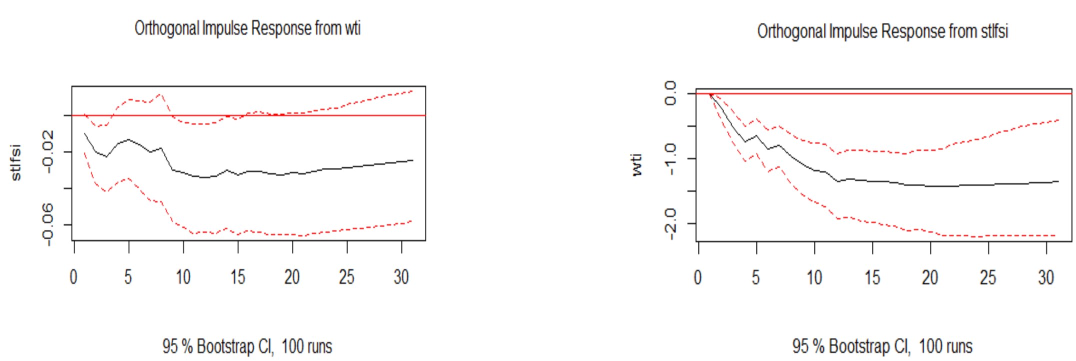


Fig. 6: Impulse Response Functions for the Pre-Crisis Period

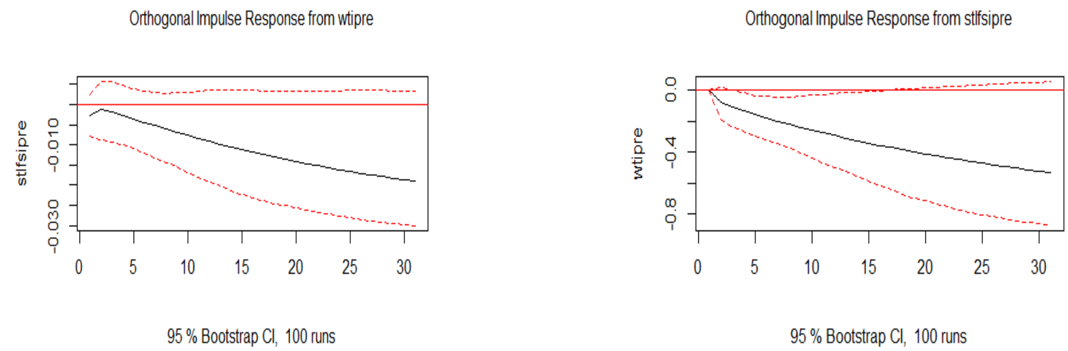


Fig. 7: Impulse Response Functions for the Crisis Period

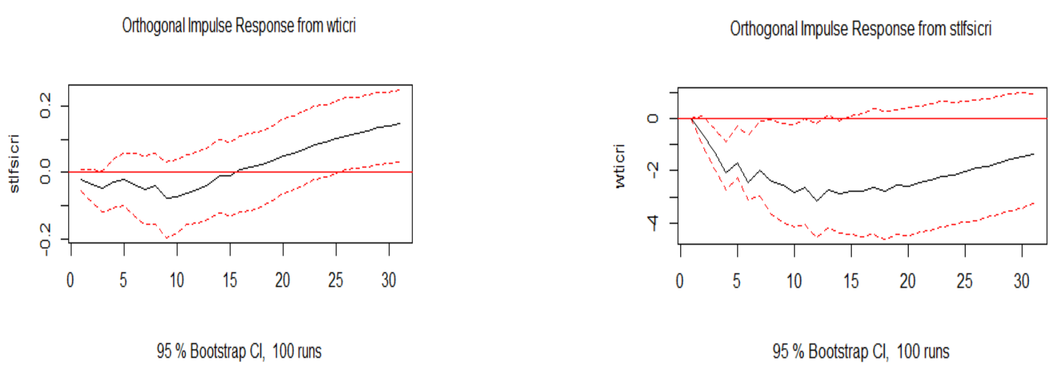
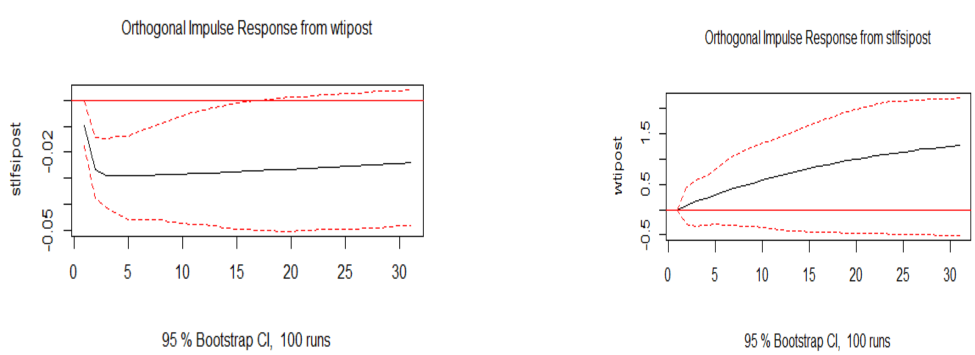


Fig. 8: Impulse Response Functions for the Post-Crisis Period



The generalized impulse response functions are based on VAR models (Toda-Yamomoto causality test's estimations). It can be seen in the figures that, the impulse response functions behave differently during different periods. Before the crisis, the impulse responses are negative initially and they are getting smaller and persistent. At the beginning of the crisis, impulse response from oil price to financial stress is negative, short-lived and it becomes positive and it gets larger in the crisis. As for the reverse side, impulse response from financial stress to oil price is negative at the beginning and it is getting a while smaller in the crisis. After the crisis period, impulse response from oil price to financial stress is negative, short lived and it becomes stable by time. As for the reverse side, impulse response from financial stress to oil price is positive at the beginning and it is getting larger and persistent after the crisis period.

4. Conclusion

In this study, we investigate the volatility and mean transmission between oil prices and financal stress before, during and after the global financial crisis occurred between February 2007 and August 2010. We analyze the volatility spillover mechanism between the oil prices and financial stess by employing the LM test proposed by Nakanati and Teräsvirta (2009). The Dynamic Conditional Correlations (DCCR) proposed by Engle (2002) between financial stress and oil prices are also examined during pre-crisis, crisis and post-crisis periods in order to investigate the conditional correlation between the series in different periods. Besides, the causality tests suggested by Toda and Yamomoto (1995) are employed in order to catch mean spillover between the series and VAR analysis are implemented in order to determine impulse responses between oil prices and financial stress.

The results of this study indicate that there exist volatility and mean spillover between oil prices and financial stress in pre-crises, crises and post-crises periods, while the significance levels are somehow differed. Existence of considerable higher DCCR during crisis period is coherent to financial crisis' stylized facts. Due to the evidence of strong linkage of oil price and financial stress especially observed in crisis period, as a possible trigger of financial crisis it is important to determine possible break fragility points of financial systems resulted by energy price shocks. While the generalized impulse response functions of VAR tests behave differently during different periods, the initially negative impulse-responses between the series strengthen the role of energy price shocks on financial crisis as a possible determinant.

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