

# ***Oil Price Formation Revisited: The Increasing Role of the Non-Commercials***

***By***

***Doulos Dimitris,***

*Dept.of Economics*

*Deree College, ddoulos@acg.edu*

***Katsaitis Odysseas,***

*Dept.of Economics*

*Deree College, katsa@acg.edu*

***Margaritis Kostas,***

*BA Economics*

*Deree College, K.Margaritis@acg.edu*

***Merika Anna***

*Dept.of Economics*

*Deree College, merikas@acg.edu*

## ***Abstract***

We study the role of commercial versus non-commercial traders in the oil market. We find that over the period 1993-2016 the impact of non-commercials increased drastically while that of the commercials nearly faded out. Trying to investigate further we run quantile regression under heteroscedasticity and found that even though the impact of non-commercials on oil price formation is stronger and remains consistent as we move to higher quantiles over the 2008-2016 period, it is the commercials that primarily influence and explain oil price volatility in a positive manner. Further, non-commercials at the higher quantile of 0.9 are found to have a significant but reducing impact on volatility. This finding impinges directly upon the nature of this commodity and illustrates the impact that unexpected geopolitical events can have on the price of oil. It seems that non-commercials have a stabilizing effect on the market and commercials account for the price volatility. Our results have important implications for all stakeholders involved.

**Keywords:** Commercial oil traders, Non-commercial oil traders, oil market, quantile regression analysis.

## ***1. Introduction***

The sharp increase in oil prices in the late 2000s and the subsequent recent decline has drawn the attention of academics, market participants and policy makers with subsequent research to focus on the underlying market dynamics. The exploration of oil price formation not only helps to explain the causes of this recent price volatility but it may also have important policy implications. More specifically, if speculation is found to be a significant contributor in the recent ups and downs in oil markets, this could be a reason for stricter regulation and supervision in derivative markets. If, on the other hand, it is fundamentals that primarily affect oil prices, then the arena is set for policy makers to act accordingly.

There is no doubt that oil markets underwent significant structural changes in the last two decades. Fan and Hu (2011) argue that oil markets became more globalized during this period, mainly due to the increase in international trade and advances in technology. Furthermore, they are increasingly related to other financial markets as well as macroeconomic developments. In other words, prices are no longer determined primarily by demand and supply forces but they are more and more affected by developments in other financial markets such as currency, stock and futures markets.

There has been an extensive debate over whether the recent fluctuations in the price of crude oil are due to changes in macroeconomic fundamentals or to increasing speculation in oil futures and other financial markets activity. Liu et. al. (2016) break down the effects of fundamental and derivative market speculative shocks on oil prices. Using a structural VAR with sign restrictions they found that speculative shocks explain only 10% of the oil price variance whereas US and China demand shocks explain almost 70%, with the effect from China being significantly stronger. Hamilton (2009a) confirmed the conventional view that oil price shocks before the 2000s were due to significant disruptions in oil production caused by geopolitical events whereas the recent run up in oil prices before the financial crisis was caused by demand conditions. In Hamilton (2009b), the author argued that strong growth in demand for oil by newly industrialized countries and the failure of global production to increase have triggered significant commodity speculation. Fan and Hu (2011) explored the main factors that caused oil price fluctuations during the 2000-2009 period considering both fundamentals and financial markets. Using an endogenously determined break test they identified three sub-periods: 2000-2004, 2004-2008 and 2008-2009. They found that

speculation and strong demand drove oil prices before the financial crisis and supply/demand fundamentals right after the crisis. They conclude that the effects of non-fundamentals have increased over the period examined. Finally, the existence of oil price bubbles was investigated by Zhang and Yao (2016) for the 2001-2015 period. They identified positive bubbles in Brent and WTI during the 2000-08 period concluding that these bubbles were responsible for the overshooting of oil prices before the financial crisis.

Oil markets have been increasingly financialized as more and more different types of investors (hedge funds, speculators, portfolio managers) participate using several different financial tools such as futures, options, index funds etc. The growing impact on oil prices from trading activity in other financial markets, mainly stock and derivative markets, has recently been extensively investigated. Aloni and Aissa (2016) explored the dynamic relationship between oil price movements, the US stock market and the dollar exchange rate and found that an increase in oil prices is associated with the dollar depreciation and an increase in stock prices. Ewing and Malik (2016) found a direct and indirect transmission of volatility between the oil and the stock market for the 1996-2013 period. The interdependence between oil and stock markets has also been confirmed by Mensi et. al. (2017) and Bouri et. al. (2017).

The rapid development of markets for derivative securities, especially for oil futures, has been a very important factor in oil markets, primarily for two reasons: the transfer of risk and the contribution to price discovery. The role of futures trading in affecting oil prices and their volatility has recently attracted significant research interest. Conventionally, trading oil futures is conducted by two groups: Companies or states for the purpose of hedging risk exposure (the so called *commercial traders*) and speculators, such as traders and hedge funds (the so called *non-commercial traders*). The focus of this study is on the contribution of these traders on price discovery process in the oil spot market and their attributed role in explaining oil price volatility.

More specifically we show, using monthly data over the period 1993-2016, through robust least squares, that both commercials and non-commercials impact significantly and positively oil price formation. Other factors like the Baltic Dry Index, used as a proxy to economic growth and the SP500 have also a positive and significant impact on the price of oil. Consequently we split our sample into three periods: 1993-

2003, 2004-2016, and 2008-2016. It became apparent that during the 2004-2016, the so called China factor period, the impact of non-commercials increased drastically while that of the commercials nearly faded out. The same pattern was observed clearly during 2008-2016. Trying to investigate further we run quantile regression under heteroscedasticity and found that even though the impact of non-commercials on oil price formation is stronger and remains consistent as we move to higher quantiles over the 2008-2016 period, it is the commercials that primarily influence and explain oil price volatility in a positive manner. Further, non-commercials at the higher quantile of 0.9 are found to have a significant but reducing impact on volatility. This finding impinges directly upon the nature of this commodity and illustrates the impact that unexpected geopolitical events can have on the price of oil.

Silverio and Szklo (2012) measured the degree of contribution of financial markets to the price discovery process in the oil markets. Using a cointegration model with error correction, they found an increasing contribution of futures markets to price discovery. Li et. al (2015) concluded that speculative and hedging trades have a dominant role in the oil markets during the last two decades. Specifically, speculative trades dominated during 2006-2011 period and hedging before and after this period. Li et. al. (2016) found that hedgers and speculators trading activity contributed to the oil price bubble of 2008. These results confirmed previous findings by Ding et. al. (2014) who had argued that it was excessive financial speculation in the oil futures market that destabilized crude oil spot prices and contributed to the “speculative bubble” in the oil futures market.

Excessive speculation in oil futures has also been blamed for the high volatility in oil prices. Kaufmann & Ullman (2009) examined the links between spot and futures oil prices. Using a two-step DOLS error correction model and a full information maximum likelihood estimate for a VECM they found that after September 2004 market fundamentals initiated a long-term increase in oil prices that was exacerbated by speculators who recognized an increase in the probability that oil prices would rise over time. Shanker (2017) argued that volatility in crude oil futures market decreases with adequate speculation and increases with excess speculation. On the other hand, Manera et. al. (2016) examined the role of financial speculation in modeling the volatility in commodity futures prices and concluded that speculation doesn't destabilize crude oil prices.

The following section presents the data characteristics in the oil market and the third section discusses the methodology used. The fourth section presents and discusses our empirical findings. The final section concludes this study.

## 2. Data Characteristics

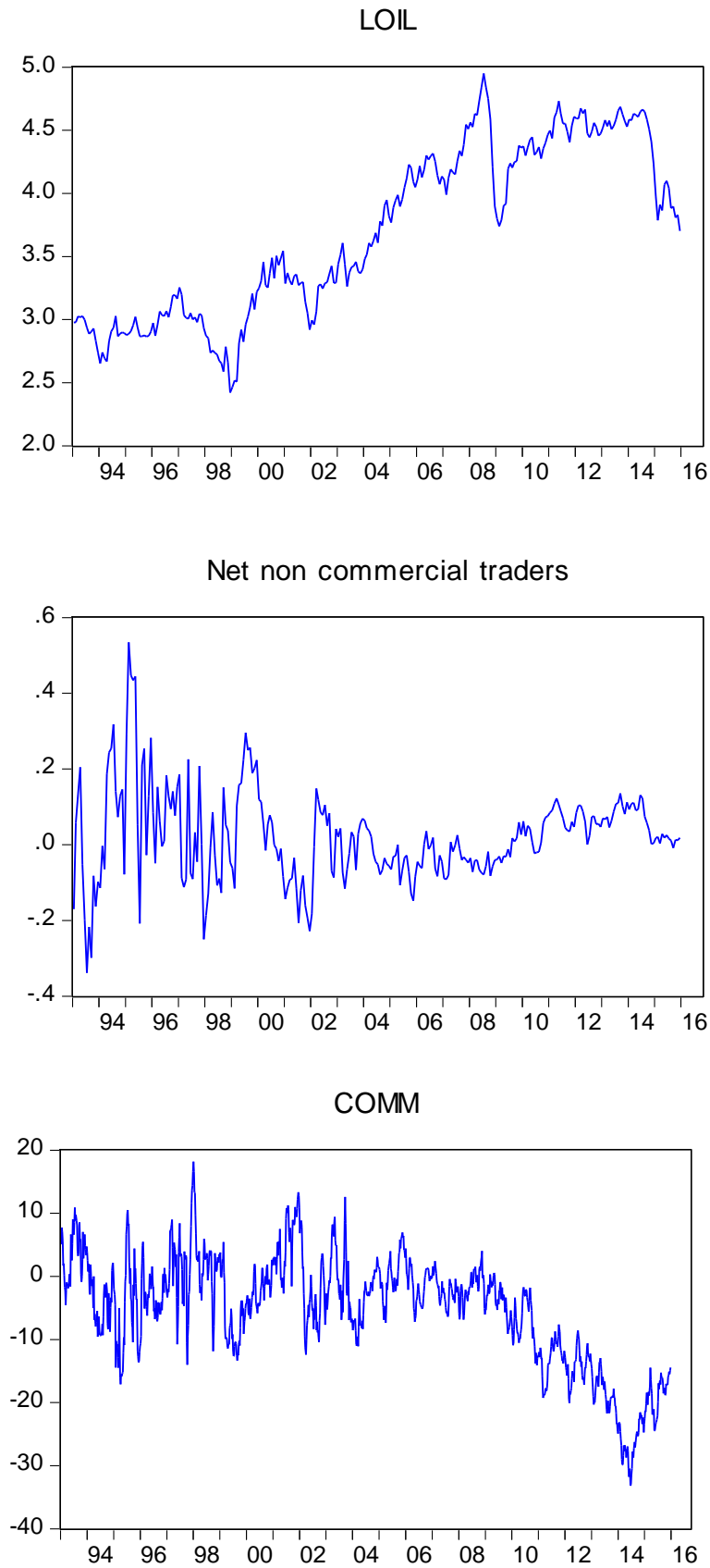
The data employed in this paper is derived from the OECD database and Clarksons, a shipping database and consulting company based in the UK. Our dataset includes 276 monthly observations over 1993-2016 for the price of crude oil, the net non-commercial position, the net-commercial position and the effective rate of interest. The Baltic Dry Index is taken from Clarksons.

Table 1 provides the description and summary statistics of the full dataset.

**TABLE 1: Data description**

<i>Panel A: Definition of variables</i>						
<i>LOIL</i>	Natural Logarithm of the price of crude oil.					
<i>NONCOM</i>	$(\text{Long non-commercial position} - \text{short non-commercial position}) / (\text{Long} + \text{short} + 2 * \text{spread})$					
<i>COMM</i>	$(\text{Long commercial} - \text{short commercial}) / (\text{Long} + \text{short})$					
<i>FR</i>	Federal Funds Effective Rate of Interest					
<i>LBDI</i>	Natural Logarithm of the Dry Bulk Index as a proxy to economic growth.					
<i>LSP</i>	Natural Logarithm of the SP500.					
<i>Panel B: Descriptive statistics</i>						
	LOIL	NONCOM	COMM	LBDI	LSP	FR
Mean	3.696146	0.075018	-5.312171	7.472291	6.953415	0.028017
Median	3.655359	0.081116	-3.566103	7.290966	7.045546	0.029600
Maximum	4.949185	0.593781	18.20051	9.237372	7.653205	0.065400
Minimum	2.422144	-0.462716	-32.96261	6.251904	6.035003	0.000700
Std. Dev.	0.678052	0.158108	8.895635	0.646262	0.406117	0.022863

**Figure 1: The Price of Oil, Non-Commercial Traders and Commercials over 1993-2016**



### 3. Methodology

In the presence of outliers, the sensitivity of ordinary least squares estimators might result in coefficient estimates which do not accurately reflect the underlying statistical relationship.

Robust least squares refers to a number of regression methods designed to be robust, or less sensitive, to outliers. S-estimation (Rousseeuw and Yohai (1984), is a computationally intensive procedure that focuses on outliers in the regressor variables.

Let  $\hat{\beta}_\zeta = \min_\beta \hat{\sigma}_\zeta(e_1, e_2, \dots, e_n)$  be the S-estimator that satisfies

$$\min \sum_{i=1}^n \rho\left(\frac{y_i - \sum_{j=1}^k x_{ij}\beta}{\hat{\sigma}_\zeta}\right) \text{ where } \hat{\sigma}_\zeta = \sqrt{\frac{1}{nk} \sum_{i=1}^n w_i e_i^2} \quad (1)$$

$k=0.199$ ,  $w_i = w_\sigma(u_i) = \frac{\rho u_i}{u_i^2}$  and the initial estimate is

$$\hat{\sigma}_\zeta = \frac{\text{median}|e_i - \text{median}(e_i)|}{0.6745}$$

The solution is obtained by differentiating (1) w.r.t  $\beta$ , so that

$$\sum_{i=1}^n x_{ij} \psi\left(\frac{y_i - \sum_{j=0}^k x_{ij}\beta}{\hat{\sigma}_\zeta}\right) = 0, j = 0, 1, \dots, k \quad (2)$$

$\Psi$  is the derivative of  $\rho$ .

$$\psi(u_i) = \rho'(u_i) = \begin{cases} u_i \left[ 1 - \left(\frac{u_i}{c}\right)^2 \right]^2 & |u_i| \leq c \\ 0 & |u_i| > c \end{cases}$$

$$\text{or } \psi(u_i) = \rho'(u_i) = 0, |u_i| > c$$

In our case, the chosen set of regressors is  $x = (\text{NONCOM}, \text{COMM}, \text{D(FR)}, \text{LBDI}, \text{LSP})$  with a distinct outliers presence in COMM.

We run initially a regression over the whole sample period and then we divided our sample into two sub periods. One between 1993-2003 where the market even though volatile (Figure 1) did not experience any strong uprising trend and one between

2004-2016 where the market was dominated by the so called China factor effect and also the sharp fall due to the 2008 crisis.

To further investigate the impact of NONCOM as well as COMM on the oil price formation and its volatility, we resorted to quantile regression, in order to describe the relationship between our dependent variable and the regressors at different points of the distribution of the price of oil. The quantile regression estimator for a quantile  $q$  minimizes the objective function

$$Q(\beta_q) = \sum_{i: y_i \geq x_i' \beta} q |y_i - x_i' \beta_q| + \sum_{i: y_i < x_i' \beta} (1-q) |y_i - x_i' \beta_q| \quad (3)$$

This non differentiable function is minimized through the simplex method which yields a solution after a finite number of iterations. The main advantages of the quantile regression is its robustness to non-normal errors and outliers while it also allows us to consider the impact of our covariates on the entire distribution of the dependent variable and not only on its conditional mean.

## 4. Empirical Results and Discussion

### 4.1 Robust Least Squares

**Table 2**

Regression on the determinants of oil price formation over the period 1993-2016. The table presents the results of the Robust least squares regression analysis for D(LOIL), the first difference of the price of oil, for stationarity. The symbols \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are Huber Sandwich S.Es. No denotes the number of observations.

	Dep Var. D(LOIL) 1993-2016	Dep Var. D(LOIL) 2008-2016
Const	-0.680*** (0.128)	-0.021 (0.388)
NONCOM	0.226*** (0.057)	1.444*** (0.522)
COMM	0.003*** (0.001)	0.007* 0.004
D(FR)	0.647* (0.364)	1.024* (0.638)
LBDI	0.026*** (0.009)	0.053*** (0.016)
LSP	0.073*** (0.017)	-0.062 (0.048)
R <sup>2</sup>	0.15	R <sup>2</sup> 0.17
No	276	No. 96



From Table 2 above it appears that over the whole period under examination 1993-2016 both groups commercials and non-commercials together with economic growth and the financial markets significantly influence and in a positive manner oil price formation. The 2008 crisis though reveals a changing role in the two trading groups, commercials and non-commercials. We observe from the same Table 2 that the impact of non-commercials has drastically risen over 2008-2016, while the commercials have nearly become insignificant. A plausible explanation for this might be found in the quantitative easing of the FED. The non-commercials may act based on fundamentals like the commercials but quite important for them is also the rate of interest. So we have a drastic reduction in the importance of commercials due to the low economic activity and at the same time a rise in the non-commercials both proportionally and in terms of significance due to the low interest rate.

**Table 3**

Regression on the determinants of oil price formation over the period 1993-2003 and 2004-2016.

The table presents the results of the Robust least squares regression analysis for D(LOIL), the first difference of the price of oil, for stationarity. The symbols \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are Huber Sandwich S.Es. No denotes the number of observations.

	Dep Var. D(LOIL) 1993-2003	Dep Var. D(LOIL) 2004-2016
Const	-0.909*** (0.289)	0.004 (0.322)
NONCOM	0.208*** (0.071)	0.652*** (0.271)
COMM	0.003 (0.002)	0.002* (0.003)
D(FR)	0.254 (0.486)	0.801* (0.473)
LBDI	0.049* (0.030)	0.042*** (0.013)
LSP	0.083*** (0.020)	-0.057 (0.042)
R <sup>2</sup>	0.23	R <sup>2</sup> 0.15
No	129	No 144

Table 3 above confirms the rising importance of the non-commercials since the beginning of the China factor effect in 2004. The various events until the financial crisis of 2008 did not affect the continuation of the rising importance of non-commercials in the oil market. The first drastic reduction in the price of oil occurs with the drop in the international trade and the fear over the Chinese economy slowdown, around 2013. Since then the price has never really recovered. We at the same time experienced gradual escalation of geopolitical sources of tension which threatened market stability and this also did not allow the price of oil to resume. We then proceed to run a quantile regression over the period 2008-2016 in order to investigate further the changing roles of the commercials and non-commercial traders on the oil price formation and its volatility.

#### 4.2 Quantile Regression

**Table 4**

Regression on the determinants of oil price formation over the period 2008-2016. The table presents the results of the quantile regression analysis ( $\tau=0.5$ ) for  $D(\text{LOIL})$ , the first difference of the price of oil, for stationarity and the variance of the error. The symbols \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are Huber Sandwich S.Es. No denotes the number of observations.

	Dep Var. $D(\text{LOIL})$	Dep Var. $\text{Var}(\text{Error})$
Const	0.203 (0.727)	-0.060*** (0.003)
NONCOM	1.417** (0.708)	0.010 (0.009)
COMM	0.006 (0.006)	0.002*** (0.0002)
$D(\text{FR})$	0.754 (0.787)	0.630 (7.132)
LBDI	0.047* (0.003)	0.001 (0.001)
LSP	-0.089 (0.083)	0.007*** (0.0009)
Pseudo $R^2$	0.14	Pseudo $R^2$ 0.07
No	96	No 96

**Table 5**

Regression on the determinants of oil price formation over the period 2008-2016.

The table presents the results of the quantile regression analysis ( $\tau=0.75$ ) for  $D(\text{LOIL})$ , the first difference of the price of oil, for stationarity and the variance of the error. The symbols \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are Huber Sandwich S.Es. No denotes the number of observations.

	Dep Var. $D(\text{LOIL})$	Dep Var. Var(Error)
Const	-0.467 (0.394)	-0.271*** (0.003)
NONCOM	1.376*** (0.612)	0.005* (0.003)
COMM	0.009** (0.005)	0.002*** (0.0002)
D(FR)	1.366** (0.586)	0.310 (0.864)
LBDI	0.047** (0.002)	0.002 (0.001)
LSP	0.017 (0.056)	0.039*** (0.001)
Pseudo $R^2$	0.14	Pseudo $R^2$ 0.11
No	96	No 96

**Table 6**

Regression on the determinants of oil price formation over the period 2008-2016.

The table presents the results of the quantile regression analysis ( $\tau=0.90$ ) for  $D(\text{LOIL})$ , the first difference of the price of oil, for stationarity and the variance of the error. The symbols \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are Huber Sandwich S.Es. No denotes the number of observations.

	Dep Var. $D(\text{LOIL})$	Dep Var. Var(Error)
Const	-0.004 (0.379)	-0.158 (0.050)
NONCOM	1.246*** (0.546)	-0.226*** (0.072)
COMM	0.009** (0.004)	0.001** (0.0007)
$D(\text{FR})$	1.446** (0.638)	-0.002 (14.608)
LBDI	0.028 (0.023)	-0.022** (0.009)
LSP	-0.021 (0.051)	0.057*** (0.005)
Pseudo $R^2$	0.09	Pseudo $R^2$ 0.29
No	96	No 96

Tables 4-6 above reveal that the non-commercial traders even though their significance and importance remains strong and consistent as we move across to higher quantiles of the distribution of oil price they exert at the same time a stabilizing effect on the market, at high oil prices, 0.9 quantile they negatively impact on volatility. The commercials on the other hand maintain a low but significant impact and account positively for the oil price volatility.

It appears that interest rate policy by the FED has not managed to shift out of the oil market the non-commercial traders despite the recent hike while its volatile nature is substantially supported by the interest of the commercial traders.

## 5. **Concluding Remarks.**

We have explored oil price formation from the point of view of the changing roles for the commercial and non-commercial traders. We discovered a rising importance in the impact of non-commercial traders and a diminishing impact for the commercial traders. This development might be combined with a transfer of wealth from the financial sector into the oil market internationally. The vehicle for this transfer of wealth are hedge funds, private large speculators even states which undertake an increasing role in the happenings of the oil market. These findings bear important implications for investors who pick oil stocks on the basis of risk, return and efficient capital asset allocation in the oil industry. Moreover, oil market regulators and capital-market participants can employ our results in order to rearrange or rethink policies in the international oil market and not restricted to, in the direction of reducing geopolitical conflicts, thereby protecting all providers of capital and fostering growth in the international economy.

While this research has spotted and explored significant regularities in the changing role of agents in the oil market, more work is needed in order to shed light to organizational structures and shifts within the international industry which are entangled with geopolitical strategies and developments. Moreover, our quantitative approach can be complemented with qualitative research: in-depth interviews with both commercial and non-commercial traders can help us discover the tacit aspects of their changing roles in an ever changing environment.

## References

- Aloui, R., Aissa M.S.B. 2016. Relationship between oil, stock prices and exchange rates: A vine copula GARCH method. *North American Journal of Economics and Finance* 37, 458-471.
- Bouri E., Chen, Q., Lien, D., Lv, X. 2017. Causality between oil prices and the stock market in China: The relevance of the reformed oil product pricing mechanism. *International Review of Economics and Finance* 48, 34-48.
- Ding, H., Kim, H., Park, S., 2014. Do net positions in the futures market cause spot prices of crude oil? *Economic Modelling* 41, 177-190.
- Ewing, B., Malik, F., 2016. Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal* 29, 12-23.
- Fan, Y., Xu, J.H., 2011. What has driven oil prices since 2000? A structural change perspective. *Energy Economics* 33, 1082-1094.
- Hamilton, J. 2009a. Causes and consequences of the oil shock of 2007-08. *Brookings Papers of Economics Activity*, 2009 (1), 215-261.
- Hamilton, J. 2009b. Understanding crude oil prices. *Energy Journal* 30, no. 2, 179-206.
- Kaufmann, R., Ullman, B., 2009. Oil Prices, speculation, and fundamentals: Interpreting causal relations among spot and futures prices. *Energy Economics* 31, 550-558.
- Li, H., Kim, M. J., Park, S.Y. 2016. Non-linear relationship between crude oil price and net futures positions: A dynamic conditional distribution approach. *International Review of Financial Analysis* 44, 217-225.
- Li, H., Kim, H., Park, S.Y. 2015. The role of financial speculation in the energy future markets: A new time-varying coefficient approach. *Economic Modelling* 51, 112-122.
- Liu, L., Wang, Y., Wu, C., Wu, W. 2016. Disentangling the determinants of real oil prices. *Energy Economics* 56, 363-373.
- Manera, M., Nicolini, M., Vignati, I., 2016. Modelling futures price volatility in energy markets: Is there a role for financial speculation? *Energy Economics* 53, 220-229.
- Mensi, W., Hammoudeh, S., Sahsad, S., Shahbaz, M. 2017. Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking and Finance* 75, 258-279.
- Shanker, L., 2017. New indices of adequate and excess speculation and their relationship with volatility in the crude oil futures market. *Journal of Commodity Markets*. (Article in press).
- Silverio, R., Szklo, A. 2012. The effect of the financial sector on the evolution of oil prices: Analysis of the contribution of futures market to the price discovery process in the WTI spot market. *Energy Economics* 34, 1799-1808.

