Does the S&P500 index lead the crude oil dynamics? A complexity-based approach☆

Catherine Kyrtsou[a,b], Christina Mikropoulou[a,*], Angeliki Papana[a]

[a] *Department of Economics - University of Macedonia, 156 Egnatia str., 54006, Thessaloniki, Greece*
[b] *CAC IXXI-ENS Lyon, University of Paris 10 (EconomiX) & University of Strasbourg (BETA)*

Abstract

Taking the complex property of nonlinear feedback connectivity into consideration, the goal of this paper is to apprehend the interdependences between the financial and energy sectors. Our contribution is both theoretical and methodological. We conduct a multivariate analysis employing nonlinear tools, namely the Partial Transfer Entropy and the Asymmetric Mackey-Glass causality test. In particular, we build a system comprising the petroleum complex (crude oil, gasoline and heating oil), the S&P500 index and the 1-month futures-spot spread for crude oil. By adopting a rolling-window approach, we observe a persistent lead-lag relationship between the S&P500 index and the market participants' expectations for crude oil, from 2004 to 2009. Depending on the bubble period in the stock market, it appears that the resulting coupling becomes subject to the deterioration of global economic activity, induced by large common shocks.

Keywords: nonlinear causality, S&P500, petroleum complex, futures-spot price spread, speculation

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*corresponding author

Email addresses: `ckyrtsou@uom.gr` (Catherine Kyrtsou), `cmikro@uom.gr` (Christina Mikropoulou), `angeliki.papana@gmail.com` (Angeliki Papana)

1. Introduction

In the editorial introduction of a recent special issue on Economic Complexity, Kyrtsou and Sornette (2013) pointed out that factors such as portfolio optimization, heterogeneous beliefs or options trading can contribute to the formation of feedbacks throughout various trading processes. The effects that these characteristics and techniques may have on prices, revive the view of financial markets as dynamical systems made of several interacting components with complex feedback loops. In this line of research, Brock et al. (2009) state that, in the presence of heterogeneous investors, the adoption of hedging instruments may destabilize prices.

Indeed, the way that the consequences of the ongoing crisis have been propagated within the global economic system was an unexpected shock for the mainstream economic theory, advocating the stability and efficiency of financial markets. The reaction of economic agents, the exorbitance of the different rating schemes, the regulatory gaps as well as the subsequent pronounced character of the financial disturbances, spreading fast into the real economy, have revealed that markets are not subject to external fluctuations solely, but embody a profound complexity. Their instability gives rise to nonlinear feedback effects. Having said that, the analysis of interdependence between financial and commodity markets gets a novel perspective. As Harmon et al. (2010) show, through the construction of a large economic network including the financial and energy sectors, the presence of nonlinearity affects within- and between-sector correlations under varying economic conditions prior to and during the recent financial crisis.

Taking into consideration the complex property of nonlinear connectivity, and its intertemporal variation, the goal of this paper is to suggest an alternative study of linkages between stock index and energy prices. Our contribution is both theoretical and methodological. We conduct a multivariate analysis employing nonlinear tools, namely the Partial Transfer Entropy and the Asymmetric Mackey-Glass causality test. In particular, we build a system comprising the petroleum complex[1] (crude oil, gasoline and heating oil), the S&P500

[1]As defined in Pindyck (2001). Similarly, Chinn and Coibion (2014) report that "there is significant

index and the 1-month futures-spot spread for crude oil. Following the rationale of Bhar and Malliaris (2011), the inclusion of oil by-products[2] such as gasoline and heating oil, which are influenced by common macroeconomic shocks, adds rich structures to our network. Besides, in the effort to unveil the role of speculation as a key-factor in the build up of the bubble in the price of oil, the futures-spot price spread is introduced in the set of the four aforementioned variables, as indicator of shifts in expectations about future oil-supply shortfalls (Alquist and Arbatli (2010)). Although various econometric settings and agent-based models have included this spread as explanatory variable, so far there has been no empirical study concerning its impact on the dynamics of an economic network.

Our empirical findings underline that none of the widely cited factors determined alone the 2007-2009 oil price evolution. It has been rather triggered by the synergetic, complex interaction between macroeconomic and financial conditions. By adopting a rolling-window approach, we observe a persistent lead-lag relationship between the S&P500 index and the market participants' expectations for crude oil, from 2004 to 2009. Likewise, depending on the bubble period in the stock market, it appears that the resulting coupling becomes subject to the deterioration of global economic activity, induced by large common shocks.

2. Literature Review

Empirically, there is a noticeable number of research papers investigating feedbacks among financial markets, and between the financial system and the real economy. Milani (2009) shows that the changing character of agents' beliefs can explain variations in the impact of oil prices into real activity and inflation. Kyrtsou and Labys (2006) and Kyrtsou and Vorlow (2009) argue that heterogeneity of market participants with boundedly rational expectations, receiving manipulated endogenous information, along with the presence of

comovement among the prices of different commodities, particularly for oil, heating oil and gasoline." (p. 613). The same set of variables has been studied by Serletis (1991), as a fair representation of the energy market.

[2]On these two refined products, the Chicago Mercantile Exchange Group also trades popular contracts (Hull (2015)).

noise, quite often cause price behaviour to deviate from being efficient.

The enigmatic nature of crude oil, either as a commodity or as a financial asset, has been widely discussed in several studies attempting to explore the unexpected "bubbly" phases of the oil market. Since crude oil prices are determined in the futures market, from the aggregate movements of supply-demand forces, certain authors attributed the emergence of turning points to oil-specific incidents (i.e. OPEC's decisions, geopolitical events, refineries). Aside from these structural sources of instability, indicators such as interest rates, industrial production, exchange rates and inflation, can contribute in a crucial manner to the observed volatility of oil prices. More specifically, Bhar and Malliaris (2011) suggest that, prior to 2007-2009, crude oil drove the suppressed value of the U.S. dollar. When these fundamental events are not enough to explain the price discovery process, another pool of factors appears in the frontline, that of the financial sector and more precisely the positions of non-commercial traders. Existing works on the origins of oil market perturbations are fairly extensive and well diversified. Recent thorough surveys have pointed out linkages between oil and other economic variables, as well as their possible implications (Morana (2013); Fattouh et al. (2013); Kaufmann (2011); Hamilton (2008); Hamilton (2009)).

The strand of literature supporting the argument of "oil financialization", relied heavily on the premise that the overall turbulent economic conditions may have led international investors, in the pursuit of a safe-haven, to place wealth and hedge the multiple sources of risk (inflationary, monetary and financial). Sornette et al. (2009), using a log-periodic power law, investigate whether the 2007-2008 oil price run-up can be characterized as an irrational bubble issued from positive feedback trading schemes. They conclude that up to 2006, supply and demand forces contributed substantially to the oil pricing procedure; beyond this time period, agents' speculation hypothesis cannot be ruled out. In the same line, Cifarelli and Paladino (2010) adopt a behavioral ICAPM model which incorporates two types of investors (informed and noise traders) in order to capture the impact of their actions on the variability of oil dynamics. Their findings reveal that oil returns exhibit nonlinear dynamics driven by positive feedback trading and heterogeneous expectations.

In a multivariate framework, Ji (2012) performs a battery of tools and identifies an in-

formation transmission process that links factors able to move crude oil price. He finds that the 2008 financial crisis altered in a significant manner the detected mechanism. Additionally, via a Markov-Switching Error Correction model with two regimes (standard and crisis), Hache and Lantz (2013) investigate spot and futures prices dynamics, transaction volumes and open interests related to the WTI oil market. Their application indicates the existence of a long-term equilibrium, highlighting the contribution of non-commercial traders to the oil-bubble formation process.

On the other hand, Büyüksahin and Harris (2011) test the ability of either commercial or non-commercial trader positions to Granger-cause prices of oil futures contracts, with a focus on the turbulent period of 2004-2009. They demonstrate that the latter group of investors exhibits a trend-chasing behavior, but their impact on oil price variations is quite negligible. Supporting the argument that the market for oil is fundamentally-driven, Kilian and Murphy (2014) construct a Structural VAR allowing for supply, demand and speculative (inventory) shocks. Their results claim that the 2003-2008 crude oil escalation was mainly due to demand forces fueled by the rise of the global business cycle. Finally, Hamilton (2009) and Kilian (2009) agree that the 2007-2008 oil-price episode was a side-effect of the downward course of world production, and that to a smaller extent can be associated with speculative inventories accumulation.

Although the aforementioned works suggest a very interesting spectrum of empirical methodologies, they all converge upon the fact that after 2000s oil market fluctuations cannot be entirely attributed to shifts in supply and demand. But if crude oil does not behave constantly as a simple commodity, which are the factors triggering sudden changes? Via the following methodological scheme, our goal is to bring out possible contributing factors.

3. Methodology

Due to the complex nature of financial and energy data (Papana et al. (2015); Kyrtsou et al. (2009)), it is evident that nonlinear multivariate causality measures, such as the Partial Transfer Entropy, are needed for the investigation of potential interdependences. These

measures proved to be effective for the determination of the information flow in complex systems (e.g. see Blinowska et al. (2004); Kus et al. (2004); Eichler (2012)). Even so, given the specific structure of an economic network, the investigation of asymmetry in the resulting couplings can shed light on behavioral characteristics, able to feed and amplify nonlinearity. In financial markets, the interactions among heterogeneous investors are shown to be at the source of nonlinearity in mean (neglected nonlinearity). Such structures can generate tail dynamics even in the absence of exogenous disturbances (Kyrtsou (2008) and Ashley (2012)), providing a market-based interpretation of commonly observed stylized facts. In the aim to take advantage of the rich properties of the neglected nonlinearity, once connectivity is identified among variables, we proceed with the joint application of the Asymmetric Mackey-Glass test.[3]

3.1. Partial Transfer Entropy (PTE)

Information theory dates back to the seminal work of Shannon (1948) and it is based on probability theory and statistics. The most important quantities of information theory are the entropy and the mutual information. More specifically, the Shannon entropy of a discrete variable X is given as $H(X) = -\sum p(x_i) ln p(x_i)$, where $p(x_i)$ is the probability mass function of X at the value x_i. The mutual information (MI) of two variables X and Y is defined as $I(X,Y) = H(X) + H(Y) - H(X,Y)$.

The transfer entropy (TE) is a bivariate nonlinear information causality measure that quantifies the amount of information explained in X at h steps ahead from the state of Y accounting for the concurrent state of X (Schreiber (2000)). The TE is an expression of conditional MI. It is non-symmetric, since it measures the degree of dependence of the variable Y on X, and not vice versa. Moreover, it takes the dynamics of information transport into account. The main advantages of TE are that it is a model-free technique and able to identify both linear and nonlinear causal effects.

[3]The MATLAB codes for implementing the PTE are available upon request. The code for the Asymmetric Mackey-Glass causality test can be downloaded from https://catherinekyrtsou.wordpress.com/research-publications/.

Let us consider two simultaneously observed time series $\{x_t\}$ and $\{y_t\}$, $t = 1, \ldots, n$, derived from the dynamical systems X and Y, respectively. We set the same free parameters for the reconstruction of the state space of both systems (as found to be the optimal choice in Papana et al. (2011)), where m is the embedding dimension, τ the time delay and h the number of time steps ahead to address the interaction. The reconstructed points (vectors) of X are formulated as $\mathbf{x}_t = (x_t, x_{t-\tau}, \ldots, x_{t-(m-1)\tau})'$, which indicate the states of X at times $t = (m-1)\tau + 1, \ldots, n-h$. Similarly are formed the reconstructed points of Y. The TE from Y to X is defined as the conditional mutual information $I(x_{t+h}, \mathbf{y}_t | \mathbf{x}_t)$ or in terms of probability it is given as

$$\mathrm{TE}_{Y \to X} = \sum p(x_{t+h}, \mathbf{x}_t, \mathbf{y}_t) \log \frac{p(x_{t+h} | \mathbf{x}_t, \mathbf{y}_t)}{p(x_{t+h} | \mathbf{x}_t)}, \tag{1}$$

where $p(x_{t+h}, \mathbf{x}_t, \mathbf{y}_t)$, $p(x_{t+h} | \mathbf{x}_t, \mathbf{y}_t)$, $p(x_{t+h} | \mathbf{x}_t)$ are the joint and conditional probability distributions. TE can also be expressed based on entropy terms as

$$\mathrm{TE}_{Y \to X} = H(\mathbf{y}_t, \mathbf{x}_t) - H(x_{t+h}, \mathbf{y}_t, \mathbf{x}_t) + H(x_{t+h}, \mathbf{x}_t) - H(\mathbf{x}_t). \tag{2}$$

The extension of the TE to account for the presence of confounding variables has been recently introduced, namely the partial TE (PTE), under different estimating schemes, using bins (Verdes (2005)), correlation sums (Vakorin et al. (2009)) and nearest neighbours (Papana et al. (2012)). Applications of the PTE measure in financial and simulated systems can be found in Papana et al. (2013), Papana et al. (2014), Kyrtsou et al. (2014) and Papana et al. (2015), among others.

The PTE quantifies the direct causal effect of Y to X, conditioning on the remaining variables $Z = Z_1, Z_2, \ldots$ of a multivariate system.

$$\mathrm{PTE}_{Y \to X | Z} = \sum p(x_{t+h}, \mathbf{x}_t, \mathbf{y}_t, \mathbf{z}_t) \log \frac{p(x_{t+h} | \mathbf{x}_t, \mathbf{y}_t, \mathbf{z}_t)}{p(x_{t+h} | \mathbf{x}_t, \mathbf{z}_t)}. \tag{3}$$

The joint and conditional probability distributions are estimated here using the k-nearest neighbor's method (Kraskov et al. (2004)) which is found to be stable and not significantly affected by the choice of k (Vlachos and Kugiumtzis (2010)).

A causality measure should get positive values when variables are interrelated, or otherwise be zero. However, due to estimation biases, a significance test is required to infer about

the existence of causality. The statistical significance of PTE is evaluated based on a randomization test since its estimator does not follow a known distribution. In order to examine the null hypothesis H_0: Y does not Granger causes X, or more specifically $\mathrm{PTE}_{Y\to X|Z} = 0$, we generate M appropriate surrogate time series that are consistent with H_0. The procedure of constructing the surrogates, starts by randomly choosing the first d values of the original time series of Y (where d should be less than the time series length n), and then those d values are moved to the end (Quiroga et al. (2002)). These time-shifted surrogates aim to "destroy" the causal effect of Y on X (if any). Finally, we estimate the PTE measure for both the original time series, denoted as q_0, and each of the M time-shifted surrogates as well, defined as $q_1, q_2, \ldots, q_M$. The null hypothesis is rejected if q_0 is at the tail of the empirical distribution of $q_1, q_2, \ldots, q_M$ (two-sided test). Finally, if r_0 is the rank of q_0 in the ordered list of $q_1, q_2, \ldots, q_M$, the p-values[4] are calculated as

$$\text{p-value} = \frac{2(r_0 - 0.326)}{M + 1 + 0.348} \quad \text{if } r_0 < (M+1)/2 \quad \text{or,}$$
$$\text{p-value} = 2\left[1 - \frac{(r_0 - 0.326)}{M + 1 + 0.348}\right] \quad \text{if } r_0 \geq (M+1)/2$$

3.2. Asymmetric Mackey-Glass test

The test of Hristu-Varsakelis and Kyrtsou (2008) is similar to the Granger causality test, except that the model fitted to the series X_t and Y_t is a bivariate noisy Mackey-Glass model (henceforth "M-G") (Kyrtsou and Labys (2006)):

$$\begin{aligned} X_t &= \alpha_{11}\tfrac{X_{t-\tau_1}}{1+X_{t-\tau_1}^{c_1}} - \delta_{11}X_{t-1} + \alpha_{12}\tfrac{Y_{t-\tau_2}}{1+Y_{t-\tau_2}^{c_2}} - \delta_{12}Y_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N(0,\sigma_\varepsilon^2) \\ Y_t &= \alpha_{21}\tfrac{X_{t-\tau_1}}{1+X_{t-\tau_1}^{c_1}} - \delta_{21}X_{t-1} + \alpha_{22}\tfrac{Y_{t-\tau_2}}{1+Y_{t-\tau_2}^{c_2}} - \delta_{22}Y_{t-1} + u_t,\ u_t \sim N(0,\sigma_u^2) \end{aligned} \tag{4}$$

where $t = max(\tau_1, \tau_2), \ldots, n$ and τ_i are integer delays, chosen on the basis of the BIC criterion. The α_{ij} and δ_{ij} are parameters to be estimated. c_i are constants that equal 2 as suggested by Kyrtsou and Terraza (2003), since the resulting dynamics address well-known stylized facts of financial time series.

[4]We apply the correction of Yu and Huang (2001).

We evaluate whether the nonlinear terms in equation (4) offer significant predictive information, for each of the variables X_t and Y_t, by estimating the parameters of a M-G model that best fits the two series, using ordinary least squares. To test for M-G causality from Y_t to X_t, the M-G model is estimated again, under the null hypothesis $\alpha_{12} = 0$. The residuals produced by the unconstrained and constrained best-fit M-G models are then used to compute an F-statistic which, when greater than a specified value, leads us to reject the null hypothesis that Y_t does not cause X_t.

In the so-called "asymmetric" version of the M-G test, we first condition on the causing series being non-negative or non-positive; the best-fit M-G model is then calculated using only those observations that satisfy the appropriate condition on the returns. For example, to test whether non-negative returns in the series Y_t cause the series X_t, an observation (X_t, Y_t) is to be included for regression only if $Y_{t-\tau_2} \geq 0$. The same restricted set of observations is used to compute the model corresponding to the null hypothesis (in this case $\alpha_{12} = 0$). The procedure is then repeated with the order of the series reversed (to investigate whether positive returns in X_t cause Y_t) and with the subset of observations that correspond to non-positive returns.

4. Results and Discussion

The dataset[5] used in this work consists of the S&P500 (X_1), Gasoline (X_4), Heating Oil (X_5), and WTI (X_3) returns series. The spread (X_2) is calculated by subtracting the spot prices from the 1-month futures contract and it is stationary by construction. They expand from 02/03/1986 to 11/12/2012. The way we compute the spread variable adds important information about the reaction of short-term expectations to the changes of other variables. Büyüksahin et al. (2013) report that this crude oil nearby-time spread can also capture the immediacy of the demand for oil in international markets. In addition, Chinn and Coibion (2014) highlight that the futures-spot price spread (in our case called 1-month

[5]Daily data on energy products (Crude Oil, Heating Oil, Gasoline) are obtained from the U.S. Energy Information Administration (EIA). Remaining time series are downloaded from FRED.

basis) is determined by factors such as the storage costs minus the convenience yield, the interest costs, the risk premium and the marking-to-market feature of futures which more or less are linked to either fundamental or behavioral content. As it can be seen in Table 1, the preliminary statistical treatment of the spread and the logarithmic returns of S&P500, Gasoline, Heating Oil and WTI reveals high asymmetry (skewness $\neq 0$) and leptokurtic behavior (kurtosis > 3). Jarque-Bera estimations ($\gg 5.99$) confirm this abnormality.

Table 1: Descriptive Statistics

	S&P500	**WTI spot**	**Gas**	**Heat**	**Spread**
Mean	0.000255	0.000263	0.000250	0.000287	0.017495
Median	0.000304	0.000000	0.000000	0.000000	0.000000
Maximum	0.109557	0.191506	0.235051	0.229538	8.810000
Minimum	-0.228997	-0.406396	-0.300585	-0.470117	-5.450000
Std. Dev.	0.011837	0.024683	0.025968	0.025136	0.378205
Skewness	-1.305612	-0.766625	-0.174989	-1.647379	4.418898
Kurtosis	31.19396	19.53444	9.818261	42.31976	123.2998
Jarque-Bera	231195.4	79516.09	13441.49	448970.7	4196507
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

For the PTE measure, the time horizon h, the embedding dimension m and the time delay τ are set to 1, while the number of neighbor's k equals 10. In the aim to eliminate any linear dependencies and focus on nonlinear causal relationships, we apply the PTE test on the VAR residuals as well. As we can see in Table 2[6], after VAR filtering a few linkages persist indicating a bidirectional nonlinear coupling between the crude oil (X_3) and the spread (X_2) (Figure 1a).

[6]For comparison reasons, we also applied the linear Conditional Granger Causality and Partial Granger Causality Indexes. The resulting couplings are less significant and sporadic confirming Papana et al. (2013) who show that in the case of nonlinear coupled systems the Partial Transfer Entropy outperforms CGC and PGC. The results are available upon request.

Table 2: PTE results on the entire sample[a]

	Returns[b]	**VAR(1) residuals**
PTE	$X_1 \to X_2$, $X_1 \to X_3$, $X_1 \to X_4$	$X_2 \to X_3$
	$X_2 \to X_3$	$X_3 \to X_2$
	$X_3 \to X_1$, $X_3 \to X_2$, $X_3 \to X_4$, $X_3 \to X_5$	
	$X_4 \to X_1$, $X_4 \to X_2$, $X_4 \to X_3$, $X_4 \to X_5$	
	$X_5 \to X_1$, $X_5 \to X_2$, $X_5 \to X_3$, $X_5 \to X_4$	

[a] The table includes only statistically significant couplings.

[b] Where X_1, X_2, X_3, X_4, X_5 denote the S&P500, spread, crude oil, gasoline and heating oil variables respectively.

Figure 1a: Graphical representation of PTE results on the entire sample.

However, as suggested by Bhar and Malliaris (2011), oil price evolution is critically characterized by multiple regimes that depend on the nature of shocks and give rise to the observed imbalances. For this reason, we extend the study by performing sliding (overlapping) windows and recalculating the PTE test. The determination of the window length and the shifting step depends significantly on the research question and the underlying nature of data. In our application, both window and step have to be long enough in order to minimise the impact of noise and capture at least short-term trading respectively. In this line, each sample consists of 1000 observations, i.e. almost 4 years of data, while the step for the time-varying window is set to 250 points[7]. The statistically significant results, based on the VAR(1) residuals, are presented in Table 3.

[Insert Table 3 here]

[7]see also Kyrtsou and Mikropoulou (2014) and Raddant and Wagner (2015)

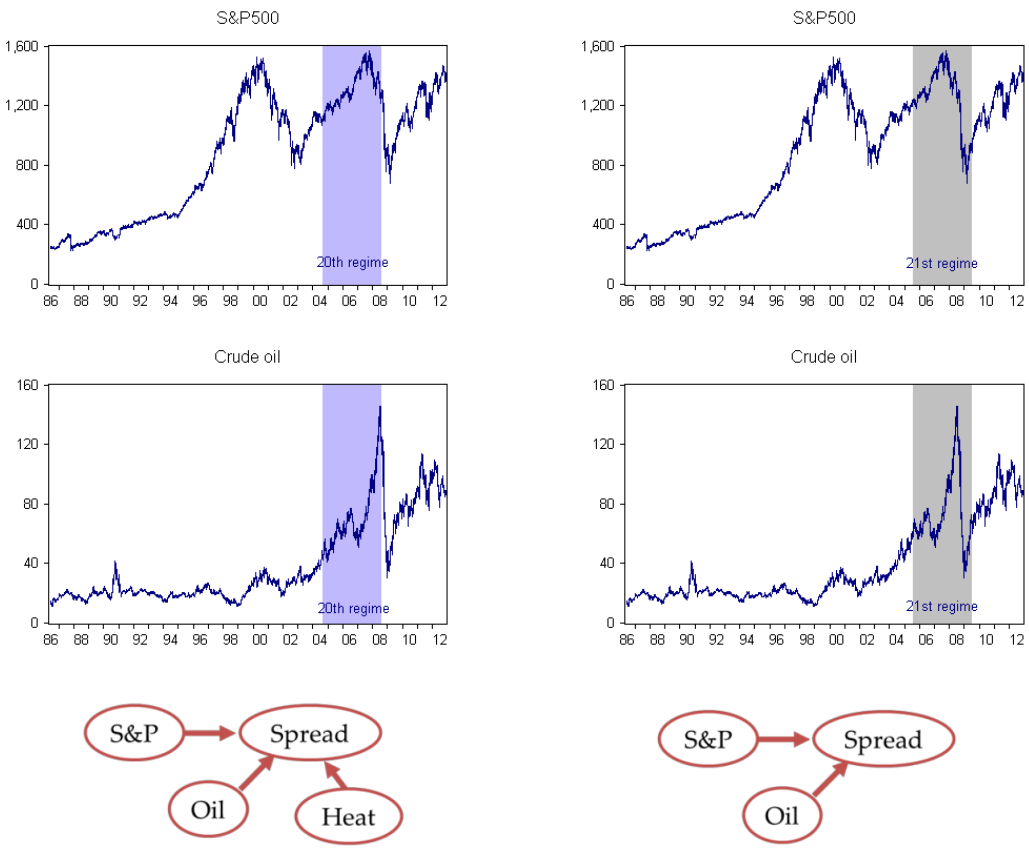

Figure 1b: Graphical representation of PTE results on the subsamples.

For the majority of regimes we detect nonlinear relationships between the energy prices and the spread. The S&P500 intervenes in a consistent manner only during the 20th (17/08/2004-16/06/2008) and the 21st (02/08/2005-01/06/2009) windows. More explicitly, the resulting connectivities in combination with the graphical representation of the relevant periods are given in Figure 1b.

During the 20th regime, which draws information from the pre- and in-bubble periods (left panel-Figure 1b), we observe nonlinear causal relationships going from the S&P500, crude oil and heating oil to the spread[8]. Over the 21st regime, that includes the pre-, in- and post-bubble periods (right panel-Figure 1b), the above findings are concretized to the

[8]When PTE is applied to the original returns series, various linear couplings including gasoline are found to be significant.

nonlinear couplings S&P500 $\rightarrow$ spread and crude oil $\rightarrow$ spread. The former relationship provides convincing evidence that financial shocks contributed to the formation of speculative expectations in the crude oil market. The latter, underscores Lammerding et al. (2013) who argue that speculative activity does not precede oil price changes, but rather reacts to them, because trend-extrapolating chartists dominate the market. In this spirit, Reitz and Slopek (2009) show that the non-linear trading of heterogeneous investors (or speculative "noise trading" - Pindyck (2001)) can be responsible for persistent swings in the oil market and price misalignments from fundamental value.

To analyze further the dynamics between the S&P500 and the crude oil spread, that may emerge during the boom and the burst phases, we then implement the asymmetric test for nonlinear causality of Hristu-Varsakelis and Kyrtsou (2008), for both the 20th and 21st windows. The results of Table 4 bring to light the asymmetric impact of the stock index. Over the 20th window both the positive and negative S&P500 returns cause nonlinearly the spread. Getting a higher value of the test statistic for the coupling S&P500^{+} $\rightarrow$ spread, puts forward the Bhar and Malliaris (2011) conclusion that before crisis euphoric evolution of the U.S. stock market affected crude oil. On the other hand, during the 21st window, where the bubble bust is fully taken into account, only the driving of negative returns is statistically significant. This leverage effect has been extensively studied as one of the key-activating factors of expectations.

[Insert Table 4 here]

In the effort to better understand the asymmetric relationship between the S&P500 returns and the crude oil spread, in the 21st window, we take intuition from the GDP evolution as a proxy for the economic activity, and the St. Louis Financial Stress Index[9] as a variable of reference for investors' expectations. At the end of the marked area (after 2008) in Figure 2, the decreasing S&P500 and crude oil prices coincide with plunging economic

[9]Mirrors increased uncertainty about fundamentals, behavior of other investors and asymmetry of information.

activity and escalating Financial Stress Index, direct signs of the unfolding of the financial crisis. Supportive evidence can be found on the financial dimension of crude oil. More specifically, we refer to Caballero et al. (2008) who point out that: "the asset role of oil suggests a negative correlation between oil prices and the value of assets negatively affected by financial shocks, and a positive association between oil prices and economic growth" (pp. 46-47). During phase A of Figure 2, a decline in stock prices, consistent with their role as leading business cycle indicator, leaves room for a reallocation of assets towards oil. While, in phase B the collapse in growth reduces both financial and oil assets. The swing from a negative to positive correlation can be interpreted in the setting of a general financialization of the oil market. As reported in Kyrtsou et al. (2012), this comovement in the aftermath of the oil bubble decreased the chances of implementing successful diversification strategies.

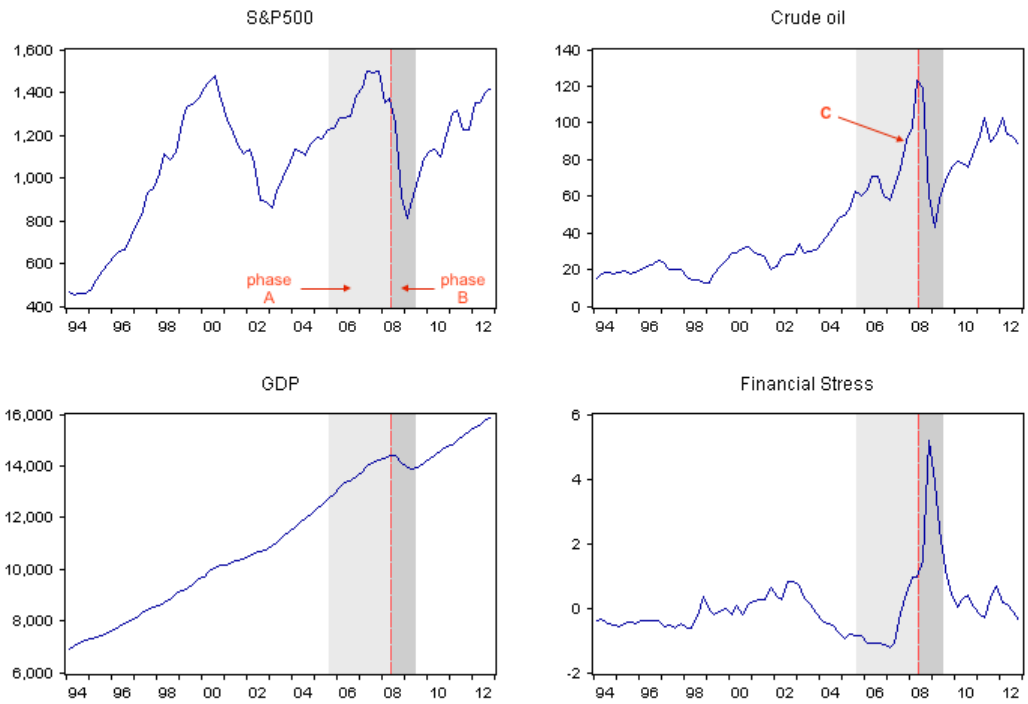

Figure 2: Comparison between S&P500, Crude oil, GDP and Financial Stress Index (21st regime)

Also, over the 21st window the 1-month basis reaches the highest positive values (darken area in Figure 3). Its skewness equals 6.5917 which is greater than its respective values

for the entire sample (4.4188) and the 20th regime (4.8082). Positive skewness implies that the extreme points in the spread time series are located at the right tail of the empirical distribution. These spikes characterize divergences of the futures from the spot prices. According to Krichene (2006), similar out-of-equilibrium fluctuations are linked to a right-skewed behavior, meaning that market participants assign high probabilities to increasing prices above the expected mean, as represented by the futures price. In particular, large capital flow from the equity to the oil market may force oil prices beyond levels determined by market fundamentals (Kolodziej et al. (2014)).

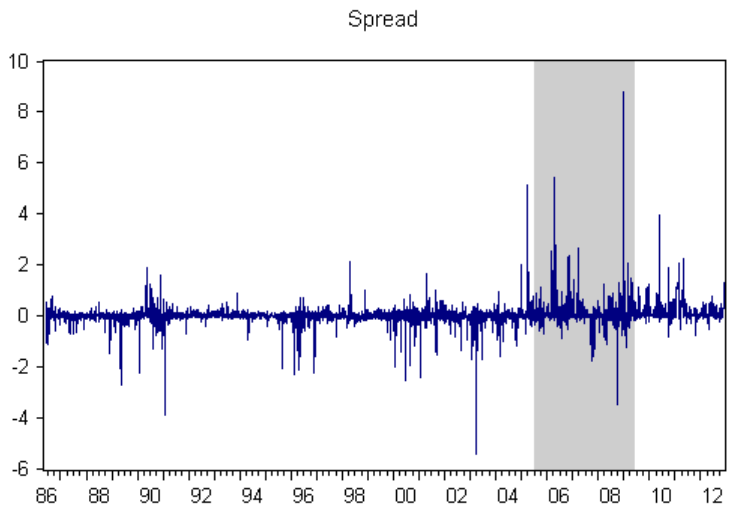

Figure 3: 1-month futures-spot prices spread

The nonlinear structure of the spread, as a result of the break-down in the relationship between spot and far-month futures prices, has been stressed by Abhyankar (1996), Silvapulle and Moosa (1999), Chen and Wuh Lin (2004), Bekiros and Diks (2008) and Huang et al. (2009). Among the main explanations of this nonlinearity, we can mention the nonlinear transaction costs, the noise trading, the market microstructure, and the threshold effects.

5. Conclusion

Prompted by the strong nonlinear interdependence between financial and energy variables, we suggest a multivariate investigation of the dynamic linkages between the S&P500 index and the petroleum complex. In the aim to evaluate whether speculation was a driving factor of the destabilizing behavior in the oil market, we also consider the 1-month futures-spot price spread accounting for short-term expectations. The application of the PTE measure has revealed that, over the entire sample, changes in crude oil cause nonlinearly its spread, and vice versa, giving birth to a feedback mechanism that amplifies received signals. In order to examine the dynamic evolution of these relationships, the methodology is repeated over rolling windows. In this case, the PTE results show that, during the regimes preceding, enclosing and following the oil bubble of 2007-2008, changes in the S&P500 index drive short-term expectations in the oil market as reflected in the spread variable.

The implementation of the Hristu-Varsakelis and Kyrtsou (2008) asymmetric nonlinear causality test emphasizes the presence of nonlinear causal relationship from declining US stock market returns to the crude oil spread over the 21st regime, as a consequence of asset reallocation and the economic uncertainty that came after. The "explosion" of the oil bubble after the critical point C in Figure 2 coincides with the starting phase of the severe decline in stock prices accompanied by significant capital flow from the equity to the oil market. It appears that oil financialization crucially affected the market microstructure, by providing the conditions for the development of behavioral trading activity and the acceleration of a fundamentally-driven momentum. This dynamic mixing was explained by Kaufmann and Ullman (2009) and Kaufmann (2011), who specifically state that misalignment of crude oil prices away from the equilibrium has been triggered by market fundamentals and then exacerbated by speculation. Furthermore, Vansteenkiste (2011) explains the variability of futures oil prices as a result of the heterogeneous investors trading on noise.

The documented contribution of the stock market fluctuations to the spikes in the oil futures-spot spread, together with the fact that futures trading can often provoke destabilizing effects, revive the ongoing debate about the necessity of regulating speculators' activity

during tranquil periods or when global activity is seriously affected by the occurrence of common shocks.

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Table 3: PTE on sliding windows[a]

	Obsvervations	**Nonlinear causal relationships**[b]
Window 1	1:1000	$X_3 \to X_2$
Window 2	251:1250	$X_3 \to X_2$
Window 3	501:1500	$X_2 \to X_3$ $X_2 \to X_5$
Window 4	751:1750	$X_3 \to X_2$
Window 5	1001:2000	$X_2 \to X_5$ $X_3 \to X_2$
Window 6	1251:2250	
Window 7	1501:2500	
Window 8	1751:2750	$X_1 \to X_3$
Window 9	2001:3000	
Window 10	2251:3250	
Window 11	2501:3500	$X_2 \to X_3$ $X_3 \to X_2$
Window 12	2751:3750	$X_3 \to X_2$ $X_3 \to X_5$
Window 13	3001:4000	$X_3 \to X_2$
Window 14	3251:4250	$X_3 \to X_2$ $X_3 \to X_5$
Window 15	3501:4500	
Window 16	3751:4750	$X_3 \to X_2$
Window 17	4001:5000	
Window 18	4251:5250	$X_3 \to X_2$
Window 19	4501:5500	$X_3 \to X_2$
Window 20	4751:5750	$X_1 \to X_2$ $X_3 \to X_2$ $X_5 \to X_2$
Window 21	5001:6000	$X_1 \to X_2$ $X_3 \to X_2$
Window 22	5251:6250	
Window 23	5501:6500	
Window 24	5751:6700	
Window 25	6001:6920	$X_2 \to X_5$

[a] The table includes only statistically significant couplings.

[b] Where X_1, X_2, X_3, X_4, X_5 denote the S&P500, spread, crude oil, gasoline and heating oil variables respectively.

Table 4: Asymmetric Mackey-Glass test for nonlinear Granger causality

	Relationship	**F statistic**	**Probability***	**Lags for M-G**
Window 20	$S\&P500^{+} \rightarrow$ Spread	7.1547	*0.0076*	$\tau_1 = \tau_2 = 1$
	$S\&P500^{-} \rightarrow$ Spread	4.4069	*0.0360*	
	$Spread^{+} \rightarrow$ S&P500	0.2236	0.6364	$c_1 = c_2 = 2$
	$Spread^{-} \rightarrow$ S&P500	0.0868	0.7683	
Window 21	$S\&P500^{+} \rightarrow$ Spread	0.0208	0.8855	$\tau_1 = \tau_2 = 2$
	$S\&P500^{-} \rightarrow$ Spread	5.4573	*0.0197*	
	$Spread^{+} \rightarrow$ S&P500	1.3467	0.2461	$c_1 = c_2 = 2$
	$Spread^{-} \rightarrow$ S&P500	0.0375	0.8465	

* if *prob.* < 0.05, then at 5% we reject the null hypothesis of non-causality. In this case, p-values are given in italics.