



## Regime Switching Mechanism during Energy Futures' Price Bubbles

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### ABSTRACT

In the last 20 years, many huge ups and downs have been seen in not only oil prices but also in other spot and derivative' energy prices too. This study has two main purposes. The main purpose of the study is to detect bubbles and their beginning and ending dates in energy derivatives futures prices. Crude oil WTI, natural gas, and heating oil monthly prices are analyzed for the period beginning from 1990 to 2018. Following detecting bubbles, Markov Regime Switching Autoregressive (MSAR) models and Markov Regime Switching Vector Autoregressive (MSVAR) models are used to analyze the movement of the regime-switching mechanism between the bubble dates. The general evidence indicates that the switching mechanism during bubble periods has some mutual similarities as generally their direction is to regime 1 as recession with low/negative returns and high volatility. Following positive return periods in energy prices, mostly after the high return/high volatility periods, the market actors might face bubble collapses.

**Keywords:** Energy Futures, Bubble, Generalized Sup Augmented Dickey-Fuller, Markov Switching

**JEL Classifications:** G12, G13, G14, Q41

### 1. INTRODUCTION

Energy prices have undergone major changes since the 1990s. Oil prices, which tended to decline for political and economic reasons in the 1990s, fell to as low as 12 US dollars after the Asian Crisis and soon they began to rise again in 2002. The highest price has been seen for oil prices is 140 US dollars on 1 June 2008. Similar rises have been seen in other energy prices as natural gas and heating oil too. Especially natural gas prices have been in many huge ups and downs. The natural gas prices exceeding 12 US dollars in 2005 and 2008 are under 3 US dollars in 2019. As well as other energy prices, the heating oil prices exceeding 3.90 US dollars are around 1.96 in 2019. Analyzing those 2-4 times price differences have got increasing importance for researchers.

Huge price increases and speculative attacks are easily seen in financial markets many times. The behavior and expectations of investors may cause many different anomalies. Information

coming to the market may cause a needed major price change or any price change from any information may cause the following investor attack. Those movements are generally explained by herding behavior. The size of the globalized financial markets, and the power to influence the spot market, are also on the academicians' agenda. Speculative movements and return expectations cause price bubbles in many different financial markets. The spot and derivative energy markets, which have an important transaction volume, may also have been affected by the herding behavior of investors.

Knowing price bubbles are the separations of financial assets from the random walking process, they are also explained as becoming distant from their real value. In his 1985 study, Tirole describes the main actors causing the price bubbles as durability, scarcity, and common beliefs associated with behavioral finance. In the following study, De Long et al. (1988; 1990) explain bubbles related to some non-rational behavior with the noise traders'

misperceive expected returns. There are also other authors explain that behavior with simple feedback rule and the dynamics of the financial markets (Day and Huang, 1990; Chiarella 1992). As mentioned in many studies, psychological factors cause investors to invest systematically in the same direction. Beginning with the first known price bubble tulipmania in the 1630s, those behavior cause bubbles in many types of commodity markets as precious metals (Baur and Glover, 2012), agriculture (Diesteldorf et al., 2016) or oil products (Su et al., 2017).

On the other hand, when the subject of price bubbles is considered in terms of commodity-based derivative instruments, reasons specific to that commodity, especially supply and demand, are the first reasons analyzed. However, the studies carry evidence that supply and demand partially explain the price changes. According to Arezki and Blanchard (2014), the low demand in 2014 only explains 20-35% of the price decrease. In another study using Structural Vector Autoregressive (SVAR) model, oil supply shocks and global oil demand shocks are found as the explanatory variables for 50 and 35% of oil price fluctuations (Caldara et al., 2016).

It is aimed in this study to model the prominent ups and downs in energy prices, especially the oil contract, and to correlate these ups and downs with both the regime structure of the market and the bubbles. We try to find the answer if the returns and volatility in the energy markets give preliminary information to the market actors about the formation of a bubble. During the bubble periods, the market can be in different regimes as it might be in a recession regime, a moderate growth regime, or a growth regime. Therefore, Markov Regime Switching (MRS) models, which distinguish these regimes according to their return and volatility characteristics and connect the transition between regimes to a Markov process, will help to find the real answer to our question. For the three energy products futures contracts *crude oil WTI*, *natural gas*, and *heating oil*, the bubbles are also detected by Sup Augmented Dickey-Fuller (SADF) and Generalized Sup Augmented Dickey-Fuller (GSADF) tests. Significantly, these tests are successful at investigating the bubble dates, however, these results are not enough to analyze the general price behavior. Following detecting bubbles, with the help of MSAR models, the movement of the regime-switching mechanism between the bubble dates is shown. Moreover, the results are expanded with the MSVAR model, which analyzes the mutual switching mechanism of all energy derivative variables together.

## 2. LITERATURE REVIEW

As in the other studies in the field of finance (Koy, 2018; Su et al., 2020; Zeren and Ergüzel, 2015), there is widening literature on examining the price discovery on energy products by nonlinear models (Vo, 2009; Kordnoori et al., 2013; and Zlatcu et al., 2015) and widening literature on detecting bubbles on energy prices either. For instance, with data sampled from 1985 to 2010, Shi and Arora (2012) estimate three different models of speculative behavior using oil price data during 2008. Their estimations also show that an increase in the probability of being in a bubble surviving regime can come before or during the collapsing

Figure 1: GSADF for crude oil

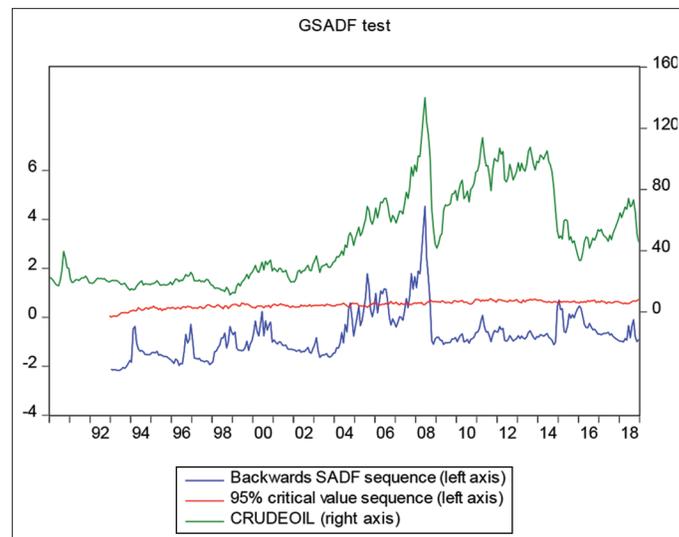
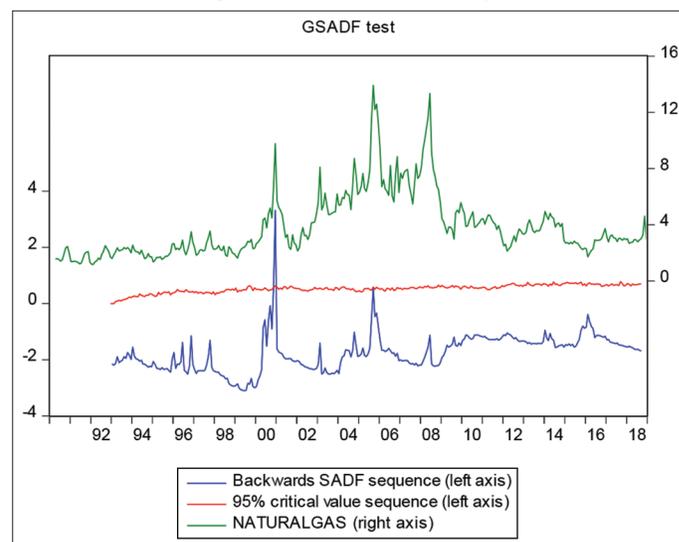


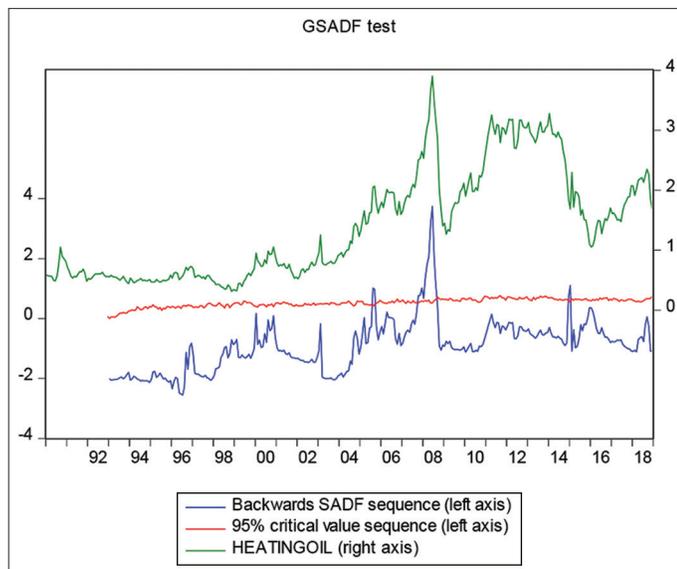
Figure 2: GSADF for natural gas



regime of the bubble. In another study, by expressing the standard present-value model in the state-space form, Lammerding et al. (2012) divide the fundamental part of the oil price from the bubble component. They also use a Bayesian Markov-switching state-space approach with two regimes as stable and explosive phases to detect bubbles.

GSADF test which we also used in this study is a new model developed by Philips et al. in 2015. Using GSADF, Su et al. (2017) find six bubbles in oil in 21 years period ending in 2016. The dates of the bubbles are dated to specific events as in the other studies on oil bubbles. Likewise, examining the 1876-2014 period Caspi et al. (2018) finds 13 bubbles. In the study combining the real oil price and the nominal price-supply they also apply GSADF tests to price-supply ratios for the period 1920-2014.

Sharma and Escobari (2018) identify bubble periods for three energy sector indices for crude oil, heating oil, and natural gas, and they analyze five energy sector spot prices for West Texas

**Figure 3:** GSADF for heating oil

Intermediate (WTI) Brent, heating oil, natural gas, and jet fuel with the help of SADF and GSADF tests. Similarly, bubble tests are also used for detecting bubbles in renewable energy industries include wind, solar, and hydro (Wang et al., 2019). Applying the GSADF test, the evidence shows multiple bubbles in both three sectors for the period 2005-2019 in China. Herrera and Tourinho (2019) find multi-bubbles in Brent but not in WTI for a longer period in a weekly range between 1990 and 2019. They also analyze the fundamental value calculated from the arbitrage condition between the spot oil market and the futures oil market. In a similar period from 2001 to 2020, employing GSADF test, Khan et al. (2021) finds three bubbles for different data ranges as week and quarter for Brent oil.

Apart from bubble studies, there are many studies analyzing energy prices with nonlinear models. Moreover, different types of Markov Switching (MS) models are used in some of the studies. In Fong and See (2002), the effect of volatility in daily returns on crude oil futures are examined using the main types and regime-switching types of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Vo (2009) explains the behavior of oil prices to forecast their volatility by the Bayesian Markov Chain Monte Carlo methodology with the regime-switching mechanism. In another hybrid model, Kordnoori et al. (2013) model the fluctuations of Brent oil prices by integrating the limit probability distribution of a Markov chain and Gumbel Max distribution according to short term, middle and long term periods.

Zhang and Zhang (2015) analyze Brent and WTI crude oil prices before and after the 2008 financial crisis with MS models. Their findings show that markets for crude oil have got three regimes before and after the crisis. Comparing the MS Multifractal volatility model to the other GARCH type models, Wang et al. (2016) indicate that MS volatility models perform better in forecasting for crude oil. Fantazzini (2016) has got a similar perspective to our study that identifies the bubble periods with the GSADF test in the first step, and he applies the log-periodic power law (LPPL) model in the following step. In a similar perspective, examining the

intrinsic time of price volatility and metric of volatility horizons, Garcia-Carranco et al. (2016) find that price volatility dynamics are characterized by two different universal metrics of volatility horizons during the bubble and non-bubble periods.

The causality of geopolitical risk on oil prices and financial liquidity is studied by Su et al. (2019) by wavelet analysis in Saudi Arabia for the period 1998-2018. The findings indicate that oil price and financial liquidity are related in the time domain when GPR is high. They also detect both short-term and medium-term relations among oil price, financial liquidity and geopolitical risk in different frequencies. Applying the time-varying parameter-stochastic volatility-vector autoregression model, Su et al. (2020) investigate the contributions of partisan conflicts, the dollar index and U.S. oil production on the oil price for the period 1990-2018. As consistent with the literature, the impact of the partisan conflicts is found less than that of the dollar index, and the negative effect of the dollar index was strengthened after the global economic crisis.

### 3. METHODOLOGY AND DATA

We use monthly closing prices of crude oil WTI futures contracts, natural gas futures contracts, and heating oil futures contracts for the period beginning from 1990 to 2018. Due to the fact that the high price movements have been observed especially since 1990 and have increased gradually in the last 20 years, the entire period is taken as the sample period. The empirical analysis in the study is composed of three steps. In the first step, the bubble in prices is analyzed by the Generalized Sup Augmented Dickey-Fuller Test (GSADF) using E-views program. Following detecting bubbles, MSAR models are used to analyze the switching mechanism between different regimes among the bubble dates. In the third step, with the help of the MSVAR model, the mutual switching mechanism of all energy derivative variables is analyzed using OxMetrics. While the bubbles are detected in the levels of the variables, the MRS models need to test in the stationary series. The logarithmic or logarithmic differences of the variables that are stationary are investigated using the augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests.

#### 3.1. Sup Augmented Dickey-Fuller Test

Philips et al. (2011) developed the SADF test which is one of the right-tailed unit root tests. The analysis allowed for a null random walk process with an asymptotically negligible drift.

$$y_t = dT^{-k} + \phi y_{t-1} + \mu_t, \mu_t \sim^{iid} N(0, \tilde{\sigma}^2), \phi = 1 \quad (1)$$

$d = \text{constant}$ ,

$T = \text{sample size}$ ,

$\eta > 1/2$

The empirical regression model in formula (1) includes an intercept but it does not include a trend. When we suppose a regression sample starts from the  $r_1^{\text{th}}$  fraction of the total sample and ends

at the  $r_1^{\text{th}}$  fraction of the sample, while  $r_2 = r_1 + r_w$  and  $r_w$  is the (fractional) window size of the regression, the model is:

$$\Delta y_t = \alpha_{r_1 r_2} + \beta_{r_1 r_2} y_{t-1} + \sum_{i=1}^k \phi_{r_1 r_2}^i \Delta y_{t-i} + \mu_t$$

$k = \text{lag order}$ ,

$$\varepsilon_t \sim \text{iid } N(0, \alpha_{r_1 r_2}^2)$$

$T_w = \lfloor Tr_w \rfloor = \text{Number of the observations in the regression}$

ADF statistic (t ratio) based on this regression is signified by  $ADF_{r_1}^{r_2}$ .

This right-tailed unit root test estimates the Augmented Dickey-Fuller (ADF) model repeatedly on a forward expanding sample sequence conducts a hypothesis test based on the sup value of the corresponding ADF statistic sequence.

$r_w = \text{window size}$

window size expands from  $r_0$  to 1.

The ending point of each sample  $r_2$  is equal to  $r_w$ .

The ADF statistic for a sample that runs from 0 to  $r_2$  is denoted by  $ADF_0^{r_2}$ . The SADF statistic is defined as  $\sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}$  and is denoted by SADF ( $r_0$ ).

### 3.2. Generalized Sup Augmented Dickey-Fuller Test

The GSADF test based on the idea of repeatedly running the ADF test on a sample sequence. GSADF test allows the starting point  $r_1$  to change within a feasible range. This range is from 0 to  $r_2 - r_0$ . Moreover, the GSADF test can be defined as the largest ADF statistic over the feasible ranges for  $r_1$  and  $r_2$  (Philips et al., 2012; 2015(a); 2015 (b)).

$$GSADF(r_0) = \sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0, 1]}} \left\{ ADF_{r_1}^{r_2} \right\} \quad (3)$$

After including an intercept into the model and the null hypothesis is a random walk without drift (i.e.  $dT^n$  with  $n > 1/2$  and constant  $d$ ), GSADF test statistic's limit distribution is:

$$\sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0, 1]}} \left\{ \frac{\frac{1}{2} r_w \left[ W(r_2)^2 - W(r_1)^2 - r_w \right] - \int_{r_1}^{r_2} W(r) dr \left[ W(r_2) - W(r_1) \right]}{r_w^2 \left\{ r_w \int_{r_1}^{r_2} W(r)^2 dr - \left[ \int_{r_1}^{r_2} W(r) dr \right]^2 \right\}^{1/2}} \right\} \quad (4)$$

$r_w = r_2 - r_1$  and  $W$  is a standard Wiener process.

If the total number of observations ( $T$ ) in GSADF is small (large),  $r_0$  needs to be large (smaller).  $r_0$  should be enough to ensure there are enough observations for adequate initial estimation. If  $T$  is large, a smaller  $r_0$  is needed, then the test does not miss any opportunity to detect an early explosive episode (Phillips et al. (2011)). Thus the random and explosive processes are successfully distinguished from each other in a GSADF test.

### 3.3. Markov Switching Autoregressive Model

In MRS models the regime-generating process is an ergodic Markov chain with a finite number of states defined by the transition probabilities (Krolzig, 2000).

$$p_{ij} = P_r(s_{t+1} = j | s_t = i); \sum_{j=1}^m P_{ij} = 1; i, j = \{1, \dots, m\} \quad (5)$$

$s_t$  follows an ergodic  $M$ -state Markov process with an irreducible transition matrix.  $P(s_{t+1} = 1 | s_t = 2) = p_{12}$  is the transition probability from state 1 to state 2:

$$P = \begin{bmatrix} p_{11} & \dots & p_{1m} & \dots & \dots & \dots & p_{m1} & \dots & p_{mm} \end{bmatrix} \quad (6)$$

The probability of which regime is in operation at time  $t$  conditional on the information at time  $t = -1$  only depends only on the statistical inference on  $s_{t-1}$

$$\Pr(s_t | Y_{t-1}; X_t; S_{t-1}) = \Pr(s_t | s_{t-1}) \quad (7)$$

The probability of any observation being in any state is called the ergodic probability. The ergodic probabilities for a two-state model are given as (Bildirici, 2010):

$$P_r(s_t = 1) = \frac{1 - p_{22}}{1 - p_{11} - p_{22}}, \quad P_r(s_t = 2) = \frac{1 - p_{11}}{1 - p_{11} - p_{22}} \quad (8)$$

Hamilton (1989) first implemented the MRS model to analyze business cycles. One of the main types of MRS models is the Markov Switching Model of Conditional Mean (MSM) where the regime switches according to the conditional mean ( $\mu_t$ ), and the other model is Markov Switching Intercept (MSI) model where the regime switches according to the constant ( $c_t$ ). The Markov Switching Intercept and Heteroscedasticity (MSIH) model is a third model that has proven to be strong in explaining financial time series is. The models can be written as:

$$\text{MSM Model: } y_t - \mu_t = \phi(y_{t-1} - \mu_{t-1}) + u_t \quad (9)$$

$$\text{MSI Model: } y_t - c_{st} = \phi y_{t-1} + u_t \quad (10)$$

$$\text{MSIH Model: } y_t - c_{st} = \phi y_{t-1} + u_t + \Omega^{1/2} \quad (11)$$

$\phi$  is an  $n \times n$  matrix of regime-dependent autoregressive coefficients.

$u_t$  is an  $(n \times 1)$  unobservable zero-mean white noise vector process.

$y_{t-1}$  is the lagged values of the dependent variable.

Matrix  $\Omega^{1/2}$  represents the factor applicable to state  $s_t$  in a state-dependent Cholesky factorization of the variance-covariance matrix of the variable ( $y$ )  $\Omega s_t$ .

$$\Omega_{s_t} = \text{Var} [y_t | \mathcal{X}_{t-1}, s_t]; \quad (12)$$

$\mathcal{X}_{t-1}$ : denotes time t-1 information of all past observations and states.

A two-state bivariate Matrix  $\Omega^{1/2}$  is (Guidolin, 2016):

$$\Omega_{st} = \begin{vmatrix} \sigma_{1,s_t}^2 & \sigma_{12,s_t}^2 & \sigma_{12,s_t}^2 & \sigma_{2,s_t}^2 \\ \sigma_{12,s_t}^2 & \sigma_{2,s_t}^2 & \sigma_{12,s_t}^2 & \sigma_{1,s_t}^2 \end{vmatrix} \quad (13)$$

### 4. EMPIRICAL RESULTS

In this section, the empirical results are given in three parts. The first part gives the results on detecting bubbles with the help of GSADF tests. In the second part, the results of MS models are given. And finally, the third part explains the switching mechanism between bubble dates with the help of two different methodologies as GSADF tests and MS models.

#### 4.1. Detecting Bubbles with GSADF Tests

The results of GSADF tests are given in Table 1. The statistics are compared with the critical values obtained from the Monte Carlo simulation with 1000 replications for each observation. It is concluded that multiple bubbles are found in all three energy derivative contracts during the sampling period for the probability of 99%.

Figures 1 to 3 include GSADF tests' results as images. The green lines in the figures are the futures prices, the green lines are critical

values of the test and the calculated sequences are shown in blue. Generally, the areas above the red critical values of the blue line, indicate bubble possibilities.

With the help of the GSADF test, three bubble periods have been found for crude oil. As seen in Figure 1 the first and second bubble dates are very close to each other. The first one occurs between June 2005 and October 2005. The following second bubble begins in December 2005 and ends by September 2006. After 9 months, the last bubble in the observation period occurs. It begins in June 2007 and ends by October 2008.

In Figure 2, the blue line exceeds over redline online 1 time. This bubble period is beginning from November 2000 ends in January 2001. This is the first bubble that occurs in the sample period includes the prices for all three contracts.

The possibility of price bubbles for heating oil is seen 3 times in the sample period in Figure 3. The first one is seen from July 2005 to October 2005. These dates are also in the first bubble period for crude oil (crude oil: June 2005-October 2005). After 2 years, in September 2007 another bubble occurs. This bubble appears following the last crude oil price bubble begins in June 2007, and it lasts 1 month before the crude oil bubble, in September 2008 (crude oil: October 2008). Finally, the last bubble for heating oil and also for the whole three commodities occurred between November 2014 and January 2015.

The bubble periods found in GSADF tests are shown in Table 2. According to the evidence, both crude oil and heating oil have got three bubble periods, however, natural gas has got only one bubble period.

**Table 1: Test statistics for GSADF**

Test stat.	Finite sample critical values		
	90%	95%	99%
Crude Oil WTI Window size: 37 4.531674 (0.0000)	2.910424	2.231080	1.982021
Natural Gas Window size: 37 3.314644 (0.0010)	2.931459	2.235399	1.973033
Heating Oil Window size: 37 3.738451 (0.0000)	2.910424	2.231080	1.982021

#### 4.2. Unit Root Tests

To obtain reliable results in MRS models, the stationary series should be used. ADF, PP and KPSS tests are used to the natural logarithms of series. The unit root tests' results in Table 3 show that, when we take differences to the natural logarithms, all

**Table 2: Bubble periods**

	1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>
Crude Oil	June 2005-October 2005	December 2005-September 2006	June 2007-October 2008
Natural Gas	November 2000-January 2001		
Heating Oil	July 2005-October 2005	September 2007-September 2008	November 2014-January 2015

**Table 3: Unit root tests**

	ADF			Philips Perron			KPSS	
	T-stat.	Prob.	Lag	Bandwidth	Adj. T-stat.	Prob.	Bandwidth	L-M Stat.
Crude Oil								
I (0)	-1.7532	0.4036	1	10	-1.4817	0.5419	15	1.7794
I (1)	-5.7538	0.000***	1	15	-15.1669	0.000***	11	0.0972
Natural Gas								
I (0)	-2.2488	0.1896	11	3	-2.7113	0.0731	15	0.8910
I (1)	-8.6697	0.000***	8	9	-18.7256	0.000***	9	0.0917
Heating Oil								
I (0)	-1.4406	0.5626	0	2	-1.4697	0.5480	15	1.8448
I (1)	-17.9463	0.000***	0	4	-17.9368	0.000***	4	0.0670

I (0): Natural logarithm and I (1): Natural logarithmic differences. Lag length is determined according to the Akaike information criterion. Maximum lags are determined "2". \*, \*\* and \*\*\* respectively, 0.10, 0.05, and 0.01 indicates the level of statistical significance

variables become stationary. According to the results, the first differences of the natural logarithmic variables should be used in the next steps.

### 4.3. Markov Switching Models and Cycle Dates

In the second step, autoregressive models with different numbers of regimes (2 or 3) and different lags are applied to time series data for crude oil, natural gas, and heating oil. Taking linearity as our null hypothesis, and following Davies' (1987), a  $P < 0.05$  considered a statistically significant rejection of the null hypothesis. In several models that have been found, the model that best explains the nonlinear relationship is the MSIH model with three regimes which are specified by the intercept (I) and volatility/heteroscedasticity (H). The estimation procedure implemented in the "Ox Metrics program" identifies regime 1 as the recession regime, regime 2 as the moderate growth regime, and lastly regime 3 as the expansion regime of the model.

Table 4 gives the information criterions for the selected Markov Switching Models. The selected model for crude oil is the MSIH (3) AR (3) model. It has three regimes and three lags. The models describing the switching mechanism for natural gas and heating

oil are MSIH (3) AR (5) with three regimes and five lags. Lastly, the MSVAR model with three variables has got three regimes too.

Transition probability represents the likelihood that the indexes will stay in the original regime or switch to another regime. Table 5 presents the transition probabilities. It is a remarkable finding that the transition from the first regime to the third regime is relatively high for crude oil (0.3412) and heating oil (0.2016). A similar situation is also noticeable in the MSVAR (model 4) model, which examines the mutual switching mechanism (0.3427). Similarly, the transition from regime 1 to regime 3 is higher than other transition possibilities for natural gas (0.2206) and model 4 (0.3081). When the transitions from the second regime, which has lower volatility than other regimes, to other regimes are examined, the direction of the regime for natural gas and heating oil dominated towards the first regime.

Regime properties are exhibited in Table 6. The moderate growth regime with the lowest volatility is the most observed in all four models. The second regime of the crude oil model has the highest duration value with 53 days. This value shows that, if the oil price enters the moderate growth regime, it can remain on this regime for an average

**Table 4: Information criterions for markov switching models**

Model	Variables	Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES (5%)
1	Crude Oil	MSIH (3) AR (3)	152.07	-1.9770	-1.9098	-1.8084	43.91	0.00
2	Natural Gas	MSIH (3) AR (5)	188.28	-1.0105	-0.9340	-0.8186	42.99	0.00
3	Heating Oil	MSIH (3) AR (5)	341.36	-1.9136	-1.8371	-1.7217	51.73	0.00
4	Crude Oil Natural Gas Heating Oil	MSIH (3) VAR (1)	1116.92	-6.2678	-6.0806	-5.7978	179.04	0.00

**Table 5: Transition probabilities**

Model	Variable	Model	Regime 1	Regime 2	Regime 3
Model 1	Crude Oil	MSIH (3) AR (3)	Regime 1	0.6587	4.541e-005
			Regime 2	0.0188	0.9811
			Regime 3	0.0000	0.08327
Model 2	Natural Gas	MSIH (3) AR (5)	Regime 1	0.6176	<b>0.2231</b>
			Regime 2	0.0922	0.7477
			Regime 3	<b>0.2206</b>	0.0959
Model 3	Heating Oil	MSIH (3) AR (5)	Regime 1	0.5650	<b>0.2335</b>
			Regime 2	0.0392	0.9177
			Regime 3	0.1422	0.0157
Model 4	Crude Oil Natural Gas Heating Oil	MSIH (3) VAR (1)	Regime 1	0.5734	0.0840
			Regime 2	0.0577	0.8993
			Regime 3	<b>0.3081</b>	<b>0.2935</b>

**Table 6: Regime properties**

Model	Variable	Model	Regime	Number of Observation	Probability	Duration
Model 1	Crude Oil	MSIH (3) AR (3)	Regime 1	14	0.0430	2.93
			Regime 2	<b>266.9</b>	<b>0.7803</b>	<b>53.02</b>
			Regime 3	60.2	0.1767	12.01
Model 2	Natural Gas	MSIH (3) AR (5)	Regime 1	96	0.2850	2.61
			Regime 2	<b>128.5</b>	<b>0.3796</b>	<b>3.96</b>
			Regime 3	<b>114.5</b>	<b>0.3355</b>	<b>3.16</b>
Model 3	Heating Oil	MSIH (3) AR (5)	Regime 1	52.7	0.1559	2.30
			Regime 2	<b>171.4</b>	<b>0.5069</b>	<b>12.16</b>
			Regime 3	114.9	0.3372	6.33
Model 4	Crude Oil Natural Gas Heating Oil	MSIH (3) VAR (1)	Regime 1	68.6	0.2022	2.34
			Regime 2	<b>219.7</b>	<b>0.6370</b>	<b>9.93</b>
			Regime 3	54.7	0.1608	1.66

of 53 days. It takes attention in the natural gas model that the number of the observation (129-115), probability (0.38-0.34) and duration (3.96-3.16) of regime 2 and regime 3 are very close to each other.

### 4.3. The Relation between Bubble Dates and Cycle Dates

The cycle dates are given in Tables 7-10. The cycle dates which are between bubble dates are signed with grey and bold in Tables. The switching is possible from any regime

**Table 7: Cycle dates of crude oil**

CRUDE OIL – MSIH (3) AR (3)		
Regime 1	Regime 2	Regime 3
1998:10-1998:11 [0.5231]	1991:3-1998:9 [0.9711]	1990:8-1991:2 [0.9467]
<b>2008:9-2008:12</b> [0.9228]	<b>2001:2-2008:8</b> [0.9193]	1998:12-2001:1 [0.9392]
2014:10-2015:1 [0.7886]	2009:6-2014:9 [0.9672]	2009:1-2009:5 [0.8898]
2018:10-2018:12 [0.7788]	2016:5-2018:9 [0.9465]	2015:2-2016:4 [0.7993]

to another one (regime 1 to regime 2, regime 1 to regime 3, regime 2 to regime 1, regime 2 to regime 3, regime 3 to regime 1, regime 3 to regime 2), however, the results show that the switching mechanism during bubble periods have some mutual similarities.

Among the 4 models, it is seen that oil changed fewer regimes than others. Three consecutive bubbles in crude oil have hardly ever switched in the regime. It is an important finding that all three bubbles take place in the second regime with low volatility and positive returns between 2005 and 2008. Only a regime change took place at the end of the third bubble in 2008. The one switching for crude oil is from regime 2 to regime 1. Next, natural gas switches 1 time during its only bubble period from regime 3 to regime 1 in 2001.

In the first bubble period in 2005, heating oil switches from regime 3 to regime 1. In the following 2007-2008 bubble, the regime switches from regime 2 to regime 3, then it switches to regime 1. Finally, the last bubble occurs in the first regime in 2014-2015.

**Table 8: Cycle dates of natural gas**

NATURAL GAS – MSIH (3) AR (5)		
Regime 1	Regime 2	Regime 3
1990:12-1991:4 [0.8989]	1991:5-1991:7 [0.6858]	1990:10-1990:11 [0.9970]
1991:12-1992:2 [0.9954]	1992:3-1992:4 [0.6633]	1991:8-1991:11 [0.9942]
1992:11-1993:1 [0.7742]	1993:2-1993:2 [0.5331]	1992:5-1992:10 [0.8832]
1993:12-1993:12 [0.4121]	1993:5-1993:11 [0.8518]	1993:3-1993:4 [0.8644]
1994:2-1994:2 [0.7129]	1994:3-1994:6 [0.7127]	1994:1-1994:1 [0.9609]
1994:7-1994:8 [0.9079]	1994:9-1994:9 [0.4867]	1994:10-1994:10 [0.7008]
1994:11-1995:1 [0.7281]	1995:2-1995:9 [0.9175]	1995:10-1996:1 [0.8258]
1996:7-1996:8 [0.9810]	1996:2-1996:5 [0.7159]	1996:6-1996:6 [0.9806]
1996:12-1997:3 [0.7707]	1997:4-1997:7 [0.8226]	1996:9-1996:11 [0.9165]
1997:11-1998:1 [0.9333]	1998:2-1998:5 [0.8324]	1997:8-1997:10 [0.9993]
1998:7-1998:8 [0.9307]	1998:12-1998:12 [0.4535]	1998:6-1998:6 [0.5500]
1998:11-1998:11 [0.6500]	1999:12-2000:2 [0.7189]	1998:9-1998:10 [0.6939]
1999:1-1999:2 [0.8602]	2002:5-2002:7 [0.5437]	1999:3-1999:10 [0.9270]
1999:11-1999:11 [0.9829]	2003:8-2003:11 [0.8615]	<b>2000:3-2000:12 [0.8816]</b>
<b>2001:1-2001:9</b> [0.9760]	2004:1-2004:7 [0.8038]	2001:10-2001:10 [0.9977]
2001:11-2002:1 [0.8602]	2005:1-2005:6 [0.7992]	2002:2-2002:4 [0.8566]
2003:3-2003:3 [0.9896]	2007:2-2007:5 [0.6953]	2002:8-2003:2 [0.9162]
2003:6-2003:7 [0.9326]	2009:5-2009:7 [0.7849]	2003:4-2003:5 [0.5465]
2004:8-2004:8 [0.8946]	2010:4-2010:6 [0.7143]	2003:12-2003:12 [0.9967]
2004:12-2004:12 [0.8592]	2010:9-2011:8 [0.9101]	2004:9-2004:11 [0.8304]
2005:12-2006:6 [0.8799]	2011:10-2011:10 [0.5015]	2005:7-2005:11 [0.9387]
2006:8-2006:9 [0.7901]	2012:4-2012:5 [0.6993]	2006:7-2006:7 [0.9994]
2006:12-2006:12 [0.9699]	2012:11-2013:2 [0.8054]	2006:10-2006:11 [0.9988]
2007:6-2007:8 [0.9724]	2013:5-2013:10 [0.8271]	2007:1-2007:1 [0.9698]
2008:7-2009:4 [0.9978]	2014:2-2014:6 [0.7929]	2007:9-2008:6 [0.9159]
2009:8-2009:8 [0.9235]	2014:8-2014:11 [0.8530]	2009:9-2010:1 [0.9064]
2010:2-2010:3 [0.8913]	2015:4-2016:1 [0.8296]	2010:7-2010:7 [0.5741]
2010:8-2010:8 [0.9197]	2016:3-2016:4 [0.6009]	2012:6-2012:10 [0.9395]
2011:9-2011:9 [0.6271]	2017:3-2018:9 [0.9353]	2013:3-2013:4 [0.6855]
2011:11-2012:3 [0.9444]		2013:11-2014:1 [0.8569]
2014:7-2014:7 [0.6712]		2016:5-2016:12 [0.7874]
2014:12-2015:3 [0.8323]		2018:10-2018:11 [0.8305]
2016:2-2016:2 [0.9962]		
2017:1-2017:2 [0.7713]		
2018:12-2018:12 [0.9964]		

**Table 9: Cycle dates of heating oil**

HEATING OIL-MSIH (3) AR (5)		
Regime 1	Regime 2	Regime 3
1990:10-1991:4 [0.6971]	1991:5-1991:10 [0.6278]	1993:10-1994:2 [0.5578]
1991:11-1991:12 [0.8044]	1992:1-1993:9 [0.9119]	1995:12-1996:12 [0.7160]
1994:3-1994:3 [0.5405]	1994:4-1995:11 [0.9172]	1998:3-1998:10 [0.5882]
1997:1-1997:2 [0.6838]	1997:3-1997:11 [0.6614]	1998:12-2000:11 [0.8933]
1997:12-1998:2 [0.3881]	2001:3-2001:5 [0.4862]	2001:6-2001:8 [0.5332]
1998:11-1998:11 [0.5074]	2003:5-2004:6 [0.8529]	2001:12-2003:2 [0.8116]
2000:12-2001:2 [0.6142]	2005:12-2006:8 [0.7650]	2004:7- <b>2005:9 [0.8896]</b>
2001:9-2001:11 [0.5939]	2007:1- <b>2008:1 [0.8150]</b>	2006:10-2006:11 [0.4967]
2003:3-2003:4 [0.7245]	2009:8-2010:4 [0.6047]	<b>2008:2-2008:7 [0.6559]</b>
<b>2005:10-2005:11 [0.6523]</b>	2010:6-2012:4 [0.9204]	2009:3-2009:7 [0.7067]
2006:9-2006:9 [0.5927]	2012:6-2014:9 [0.9291]	2015:2-2015:6 [0.7654]
2006:12-2006:12 [0.6015]	2016:8-2018:10 [0.9025]	2015:8-2015:8 [0.6010]
<b>2008:8-2009:2 [0.7770]</b>		2016:1-2016:6 [0.7449]
2010:5-2010:5 [0.4773]		
2012:5-2012:5 [0.6692]		
2014:10- <b>2015:1 [0.6306]</b>		
2015:7-2015:7 [0.5263]		
2015:9-2015:12 [0.5973]		
2016:7-2016:7 [0.6397]		
2018:11-2018:12 [0.7872]		

**Table 10: Cycle dates of model 4**

MODEL 4-MSIH (3) VAR (1)		
Regime 1	Regime 2	Regime 3
1990:6-1990:6 [0.4688]	1991:5-1991:11 [0.8835]	1990:7-1990:9 [0.8667]
1990:10-1991:2 [0.9192]	1992:1-1993:12 [0.9312]	1991:3-1991:4 [0.9951]
1994:2-1994:2 [0.6799]	1994:5-1994:12 [0.8124]	1991:12-1991:12 [0.9988]
1996:7-1996:8 [0.6723]	1995:2-1996:4 [0.8669]	1994:1-1994:1 [0.9849]
1996:10-1996:10 [0.6836]	1997:3-1998:5 [0.9035]	1994:3-1994:4 [0.9403]
1996:12-1997:1 [0.6277]	1999:7-1999:9 [0.7929]	1995:1-1995:1 [0.7516]
1998:6-1998:6 [0.4953]	2001:3-2001:4 [0.4239]	1996:5-1996:6 [0.6857]
1998:8-1998:8 [0.6514]	2001:12-2003:1 [0.8975]	1996:9-1996:9 [0.4954]
1998:10-1998:11 [0.9096]	2003:6-2004:8 [0.8919]	1996:11-1996:11 [0.4285]
1999:2-1999:2 [0.5494]	2004:10- <b>2005:7 [0.8936]</b>	1997:2-1997:2 [0.6919]
1999:5-1999:5 [0.6282]	2005:12-2005:12 [0.4166]	1998:7-1998:7 [0.4305]
1999:10-1999:12 [0.6363]	2006:3-2006:6 [0.8275]	1998:9-1998:9 [0.8374]
2000:3-2000:4 [0.7859]	2007:1- <b>2008:6 [0.9245]</b>	1998:12-1999:1 [0.4391]
2000:7-2000:7 [0.9173]	2009:6-2009:7 [0.7256]	1999:3-1999:4 [0.8871]
2000:9-2000:10 [0.6089]	2009:10-2014:9 [0.9015]	1999:6-1999:6 [0.7593]
2000:12-2000:12 [0.9971]	2015:5-2015:6 [0.5111]	2000:1-2000:2 [0.9996]
2001:5-2001:11 [0.6941]	2015:8-2015:10 [0.5091]	2000:5-2000:6 [0.6826]
2003:4-2003:4 [0.9359]	2016:3-2018:9 [0.9355]	2000:8-2000:8 [0.9861]
<b>2005:9-2005:11 [0.4525]</b>		<b>2000:11-2000:11 [0.5932]</b>
2006:1-2006:2 [0.4844]		<b>2001:1-2001:2 [0.6801]</b>
2006:7-2006:10 [0.8396]		2003:2-2003:3 [1.0000]
<b>2008:7-2009:1 [0.8944]</b>		2003:5-2003:5 [0.9633]
2009:8-2009:9 [0.6028]		2004:9-2004:9 [0.7692]
2014:10-2015:1 [0.8652]		<b>2005:8-2005:8 [0.9553]</b>
2015:7-2015:7 [0.7617]		2006:11-2006:12 [0.8278]
2015:11-2015:11 [0.6708]		2009:2-2009:5 [0.7351]
2016:1-2016:2 [0.4996]		2015:2-2015:4 [0.9945]
2018:10-2018:12 [0.8781]		2015:12-2015:12 [0.4729]

In the last table, the dates of the cycle of Model 4 are given. Model 4, shows the mutual switching mechanism with all three variables in an MSVAR model. When we examine all the bubble dates of the three variables within the scope of the common regime change, it is seen that the direction of the regime-switching is predominantly towards the second regime and the third regime.

While the first bubble between all (natural gas) begins in November 2000, the regime is in high growth. In the next month, it switches to the recession, then it comes back to Regime 3. The next bubble shown in crude oil prices and heating oil prices begins in June 2005 in a moderate growth regime. In 2 months the regime switches to the recession. A few months later another bubble begins in December 2005 in the moderate growth regime. In this bubble

period, the regime switches 3 times between moderate growth and recession. The third bubble for crude oil includes the second bubble of heating oil at the same time. The bubbles begin and stay in regime 2 for a year, then regime switches to 1.

Finally, the last bubble period occurs in the recession regime and it does not switch to another one.

## 5. CONCLUSION

Considering energy prices have undergone major changes since the 1990s, this study focuses on two main purposes. While detecting bubbles' beginning and ending dates in energy derivatives futures prices, the switching mechanism during bubble dates are determined. Supply and demand are the first reasons analyzed for the huge price changes in commodity futures. Depending on the growth in the global economy after 2002, the increase in demand led to a rapid increase in oil prices. Although this increasing process continued until the 2008 crisis, it is observed that there were different bubbles in oil prices before the crisis. Moreover, the evidence in the studies notes that the supply and the demand partially explain the price changes. Under these conditions, analyzing the price behavior between bubble dates in a model that explains the regime of the economy as recession or growth should be explanatory.

In the study, we use monthly closing prices of crude oil WTI futures contracts, natural gas futures contracts, and heating oil futures contracts for the period beginning from 1990 to 2018. According to GSADF tests, which are successful at detecting bubbles, while natural gas has got one bubble period, others have got their different bubble periods. These estimations provide support for the findings of Caspi et al. (2018), Su et al. (2017), and Sharma and Escobari (2018).

While the switching is possible from any regime to another one, the results show that the switching mechanism during bubble periods has some mutual similarities as generally their direction is to regime 1 as recession with negative/low returns and high volatility. The findings show that during the bubble periods of crude oil, only one regime change from regime 2 to regime 1 is seen at the end of the third bubble in 2008. Moreover, all three bubbles take place in the second regime, which is a regime with low volatility and positive returns. It is interesting to note that periods where volatility is relatively low (as regime 2-moderate growth) and price changes are not very high can end with bubble collapses.

In the only bubble period of natural gas, the regime switches from 3 to 1. Next, for heating oil regime switches from 3 to 1 in 2005, switches 2 to 3, then it switches to regime 1 in the following 2007-2008 bubble, and finally, the last bubble occurs in the first regime in 2014-2015.

The most switching between bubble periods for the whole four models is seen from regime 3 which is the regime with high volatility and positive returns to regime 1 with high volatility and low/negative returns. Following the positive return periods

in energy prices, bubble collapses may appear. If the volatility increases while the returns continue to be positive, market actors should be cautious. The fact that sometimes the asset bubbles have already taken place in low volatility regimes before moving on to high volatility periods (going to collapse), installing warning alert systems is difficult. Nevertheless, according to evidence, we can say that high volatility periods with high returns mean that investors and policymakers should be careful about bubble collapses.

## REFERENCES

- Arezki, R., Blanchard, O. (2014), Seven Questions about the Recent Oil Price Slump. IMFdirect-The IMF Blog, No. 22. Available from: <https://blogs.imf.org/2014/12/22/seven-questions-about-the-recent-oil-price-slump>
- Baur, D.G., Glover, K.J. (2012), A Gold Bubble? University of Technology Sydney. Finance Discipline Group Working Paper, No. 175.
- Bildirici, M.E., Alp, E.A., Ersin, Ö.Ö., Bozoklu, Ü. (2010), İktisatta Kullanılan Doğrusal Olmayan Zaman Serisi Yöntemleri. Türkmen Kitabevi.
- Caldara, D., Cavallo, M., Iacoviello, M. (2016), Oil Price Elasticities and Oil Price Fluctuations. International Finance Discussion Papers, No. 1173.
- Caspi, I., Katzke, N., Gupta, R. (2018), Date stamping historical periods of oil price explosivity: 1876-2014. Energy Economics, 70, 582-587.
- Chiarella, C. (1992), The dynamics of speculative behaviour. Annals of Operations Research, 37(1), 101-123.
- Day, R.H., Huang, W. (1990), Bulls, bears and market sheep. Journal of Economic Behavior and Organization, 14(3), 299-329.
- De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J. (1988), The Survival of Noise Traders in Financial Markets (No. w2715). National Bureau of Economic Research. Available from: [https://www.nber.org/system/files/working\\_papers/w2715/w2715.pdf](https://www.nber.org/system/files/working_papers/w2715/w2715.pdf)
- De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J. (1990), Noise trader risk in financial markets. Journal of Political Economy, 98(4), 703-738.
- Diesteldorf, J., Meyer, S., Voelzke, J. (2016), New Evidence for Explosive Behavior of Commodity Prices. Center of Quantitative Economics, University of Muenster, 50/2016.
- Fantazzini, D. (2016), The oil price crash in 2014/15: Was there a (negative) financial bubble? Energy Policy, 96, 383-396.
- Fong, W.M., See, K.H. (2002), A Markov switching model of the conditional volatility of crude oil futures prices. Energy Economics, 24(1), 71-95.
- García-Carranco, S.M., Bory-Reyes, J., Balankin, A.S. (2016), The crude oil price bubbling and universal scaling dynamics of price volatility. Physica A: Statistical Mechanics and its Applications, 452, 60-68.
- Guidolin, M. (2016), Modelling, Estimating and Forecasting Financial Data under Regime (Markov) Switching. Lecture 7. Department of Finance. Bocconi University. Available from: [http://didattica.unibocconi.it/mypage/download.php?nomefile=Lecture\\_7\\_-\\_Markov\\_Switching\\_Models20130520235704.pdf](http://didattica.unibocconi.it/mypage/download.php?nomefile=Lecture_7_-_Markov_Switching_Models20130520235704.pdf) [Last accessed on 2016 Mar 30].
- Hamilton, J.D. (1989), A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57(2), 357-384.
- Herrera, C.J.J., Tourinho, O.A. (2019), Multiple Bubbles in Crude Oil Prices 1990-2019: SADF and GSADF Tests. Available from: [https://sistemas.colmex.mx/Reportes/LACEALAMES/LACEALAMES2019\\_paper\\_676.pdf](https://sistemas.colmex.mx/Reportes/LACEALAMES/LACEALAMES2019_paper_676.pdf)
- Khan, K., Su, C.W., Umar, M., Yue, X.G. (2021), Do crude oil price

- bubbles occur? *Resources Policy*, 71, 101936.
- Kordnoori, S., Mostafaei, H., Ostadrahimi, M. (2013), Modelling the fluctuations of Brent oil prices by a probabilistic Markov chain. *African Journal of Business Management*, 7(17), 1648-1654.
- Koy, A. (2018), Multibubbles in emerging stock markets. *Finans Politik and Ekonomik Yorumlar*, 55(637), 95-109.
- Krolzig, H.M. (2000), Predicting Markov-Switching Vector Autoregressive Processes. Oxford University Working Paper, No. 2000W31.
- Lammerding, M., Stephan, P., Trede, M., Wilfling, B. (2013), Speculative bubbles in recent oil price dynamics: Evidence from a Bayesian Markov-switching state-space approach. *Energy Economics*, 36, 491-502.
- Phillips, P.C., Shi, S., Yu, J. (2015), Testing for multiple bubbles: Limit theory of real-time detectors. *International Economic Review*, 56, 1079-1134.
- Phillips, P.C.B., Shi, S., Yu, J. (2015), Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56, 1043-1078.
- Phillips, P.C.B., Shi, S.P., Yu, J. (2011), Testing for Multiple Bubbles. Cowles Foundation Discussion Paper No. 1843.
- Sharma, S., Escobari, D. (2018), Identifying price bubble periods in the energy sector. *Energy Economics*, 69, 418-429.
- Shi, S., Arora, V. (2012), An application of models of speculative behavior to oil prices. *Economics Letters*, 115(3), 469-472.
- Su, C.W., Khan, K., Tao, R., Nicoleta-Claudia, M. (2019), Does geopolitical risk strengthen or depress oil prices and financial liquidity? Evidence from Saudi Arabia. *Energy*, 187, 116003.
- Su, C.W., Li, Z.Z., Chang, H.L., Lobonț, O.R. (2017), When will occur the crude oil bubbles? *Energy Policy*, 102, 1-6.
- Su, C.W., Qin, M., Tao, R., Moldovan, N.C., Lobonț, O.R. (2020), Factors driving oil price from the perspective of United States. *Energy*, 197, 117219.
- Su, C.W., Wang, X.Q., Zhu, H., Tao, R., Moldovan, N.C., Lobonț, O.R. (2020), Testing for multiple bubbles in the copper price: Periodically collapsing behavior. *Resources Policy*, 65, 101587.
- Tirole, J. (1985), Asset bubbles and overlapping generations. *Econometrica*, 53(5), 1071-1100.
- Vo, M.T. (2009), Regime-switching stochastic volatility: Evidence from the crude oil market. *Energy Economics*, 31(5), 779-788.
- Wang, Y., Wu, C., Yang, L. (2016), Forecasting crude oil market volatility: A Markov switching multifractal volatility approach. *International Journal of Forecasting*, 32(1), 1-9.
- Zeren, F., Ergüzel, O.S. (2015), Testing for bubbles in the housing market: Further evidence from Turkey. *Financial Studies*, 19(1), 40-52.
- Zhang, Y.J., Zhang, L. (2015), Interpreting the crude oil price movements: Evidence from the Markov regime switching model. *Applied Energy*, 143, 96-109.
- Zlatcu, I., Kubinschi, M., Barnea, D. (2015), Fuel price volatility and asymmetric transmission of crude oil price changes to fuel prices. *Theoretical and Applied Economics*, 22(4), 33-44.