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Markov Switching Autoregressive Model for WTI Crude Oil Price

Nilgün Çil[1] **Çiğdem Yılmaz**[2]

Abstract

In this study, we aimed to test the nonlinear structure of crude oil prices with Markov Regime Switching Autoregressive Models. In the study of weekly prices covering the period from May 06, 1990 to April 11, 2018, a two-regime Markov switching model was applied. In the case of two regimes, we proved the that the probability the process will be in regime 1 or 2 is given by steady-state probabilities. As a result, it can be seen that the predictions made by the Markov switching autoregressive model were succesful.

Keywords

Regime change • Markov Switching Autoregressive Models • Crude Oil

Jel Classification

C01 • C2 • C24 • N7

WTI (West Texas Intermediate) Ham Petrol Fiyatları için Markov Rejim Değişim Otoregresif Modeli

Öz

Bu araştırma ile ham petrol fiyatının doğrusal olmayan yapısını Markov Rejim Değişim Otoregresif Modelleriyle test etmek amaçlanmıştır. 06 Mayıs 1990'dan 11 Nisan 2018'e kadar olan dönemi kapsayan, haftalık fiyatların kullanıldığı çalışmada, iki rejimli Markov Switching Modeli uygulanmıştır. İki rejim durumunda sürecin rejim 1 veya rejim 2'de olacağı kararlı yapı olasılıkları ile kanıtlanmıştır. Sonuç olarak ise, Markov Rejim Değişim Modeli ile yapılan öngörünün başarılı sonuçlar verdiği görülmüştür.

Anahtar Kelimeler

Rejim değişim · Markov Rejim Değişim Otoregresif Modelleri · Ham petrol · Lineer-olmayan · Durağanlık durumu

Jel Sınıflandırması

C01 • C2 • C24 • N7

1 Nilgün Çil (Prof.). Department of Econometrics, Institution of Social Sciences, İstanbul University, Fatih 34116 İstanbul, Turkey. Email: nilgun.cil@istanbul.edu.tr

2 **Correspondence to:** Çiğdem Yılmaz (PhD.) Department of Econometrics, Institution of Social Sciences, İstanbul University, Fatih 34116 İstanbul, Turkey. Email: cigdem_yilmazz@hotmail.com

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Markov Switching Autoregressive Model for WTI Crude Oil Price

Many economic activities are directly or indirectly dependent on energy. The extent of petroleum use as an energy resource is emphasizing the oil market (Solak, 2012, p. 117). The main reasons for the fluctuating nature of the oil market are the increasing dependence of demand and supply on the political and economic stability of countries, and production is heavily related to external factors such as military conflicts, natural disasters, the presence of speculators (Barunik&Malinska, 2015, p. 2).

The fact that oil price changes is affected by many social, political and economic events in the world and can affect the price of crude oil both negatively and positively (King, Deng & Metz, 2012). Because of the "American Civil War" crude oil prices increased in middle of the 1800s, and at the end of the 1800s, prices fell sharply due to the great recession. In the 1990s, prices rose mainly because of the Iran-Iraq War - oil exports from the Middle East region have been interrupted significantly. As a result of a slowdown in economic growth in Asian countries, a significant drop was seen in the period 1997-1999. In 2000**,** the price of crude oil become more stable. The attack on the World Trade Center on September 11th2001, and the Global financial crisis in 2008 crude oil prices became more volatile again. In 2011, crude oil price also affected both The "Arab Spring" and the "Libyan Civil War". OPEC's decisions also affected market prices in 2015 (Ural, 2016). Following these issues, there were many serious fluctuations in crude oil prices and it has therefore become necessary to investigate this (Karahan, 2014, p. 2).

Researchers are developing various time series models to analyze and estimate the behavior of economic and financial variables such as oil prices. Linear time series models such as autoregressive (AR) models, moving average (MA) models, and mixed ARMA models(which are mostly used in literature on account of their ease of application) have become very popular. Although these models are very successful in many applications, they cannot represent many nonlinear dynamic models (Ahdikari & Agrawal, 2013, p. 18).

Hamilton's (1989) Markov Switching Regime Shift model, also known as the, is one of the nonlinear time series models that has been used widely in literature. This model includes multiple equations, so that time series behavior can be characterized in different regimes. In the MS regime shift model, it is possible to capture more complex dynamic patterns by allowing the transition between equations or structures. The Markov switching model is different from the structural change models. While the first permits frequent changes at random time points, the latter only accepts external changes (Kuan, 2002, pp. 1-2).

In this study, we aim to test the nonlinear structure of crude oils price with Markov Regime Change Autoregressive Models. Secondly, we look at the literature on crude oil prices and the Markov switching method. Thirdly, the data, methods and applications used in the study are given and the findings are discussed. In the last part, the main findings in the study are summarized.

Literature

Literature on Oil Prices

Hamilton (1983), investigated the sudden rise in crude oil prices and recessions in the U.S. during World War II. According to Hamilton, the reasons behind fluctuations in oil shocks are mainly supply and demand supply, political events and geopolitical events.

Hamilton (2009), aimed to identify the many reasons for the changes in oil prices. As a result of his study, he showed that physical disruptions in supply were the main cause of the previous oil price crashes.

Chen (2014), used 1984:10 - 2012:8 periods of the monthly data to show the share price indices of oil prices in the energy sector. Short-term nominal and real crude oil prices have strong foresee. This study reflects both market information on time and is ready to predict the spot oil price.

Huang (2017), examined the world economy, oil inventories, futures markets and political stability in the Middle East in terms of fluctuations in oil prices over multiple time periods. As a result of the study, these factors were observed to have some effect on the volatility of oil prices over one or more time periods.

Wong and El (2017), investigated the relation between oil price changes and Gulf Cooperation Council stock markets during the period 2005 - 2015. In this study, they used Granger causality and impulse response function as an econometric model. They found that oil prices are the basis for the stock markets in GCC except Oman.

In the study of Yin, Peng and Tang (2018), they tried to estimate oil prices using a number of estimating variables with a time varying weight combination approach to determine better behavior of a time series. In doing so, the former, they used five different models to predict crude oil prices one by one. The latter, each special model was given a changing weight over time with the new combination approach. They calculated estimated figures for oil prices. According to their calculations, the method gives better and more reliable results than random walk.

Literature on Markov Switching Models

Hamilton (1989), presents an overview of the life cycle of an operator with the Markov Switching Autoregressive Process model, which can be used with various fields such as finance or economy.

Middendorf and Schmidt (2004) modeled the then U.S. current account deficit, (which had continued at a high level for a long time) with three regimes in their study: the rate of increase in current account deficit was high, the rate of increase in current account deficit was low, and the remediation regime. The result was that the current account deficit displayed an asymmetrical structure. In other words the rate of increase in current account deficit is high and the regime lasts long, whereas the correction regime is short-lived, whereas the correction regime is shorter.

Pasaradakis and Spagnolo (2003), investigated the performance of different approaches for Markov Switching AR modes. They used ARMA representation as the selection method and applied Monte Carlo simulation analysis. Eventually they found that TPM and AIC information criteria are more successful than BIC and HQC.

Stale, Kayhan and Koçyiğit (2013), examined the asymmetric behavior of Turkey's unemployment rate for the period 1923-2011. In doing so, they applied linear unit root tests and the Markov regime switching model. Based on the results of the unit root tests, the unemployment rate was not stable at the level of the series but it is at the first differences. As a result of the application of the Markov regime switching model, it was seen that unemployment continued to exhibit asymmetric behavior during the period 1923-1950. According to this, the unemployment rate has a non-linear structure at this period and there are transitions between the two regimes

Econometric Method

Markov Switching Autoregressive Regression Model (MS - AR)

An MS-AR process is the generalized form of the Hidden Markov Model (HMM) and AR models. This process is characterized by two components: S_t and Y_t. S_t represents the latent state at time t and Y_t represents the observable states at time t. Suppose here that the latent air stream follows the Markov Chain process in the first place. Consequently, an MS (m) -AR (p) model means that the model contains an autoregressive process at the p-th order, and the Markov chain process with the m-state. The conditional distribution of S_t is the Markov chain process in m state and rank 1, and depends on the value of S_{t-1}. The conditional distribution of Y_t over S_t is the autoregressive process at the p-th order. The value of Y_t depends on the value of Y_{t-1}, Y_{t-2}, Y_{t-3} … Y_{t-} and S_t. In this case Y_t is explained as follows.

$$Y_t = a_0^{S_t} + \sum_{i=1}^{p} a_i^{S_t} Y_{t-i} + \delta^{S_t} \varepsilon_t$$

Where a_1^{s}, a_2^{st}, a_3^{st} … $a_{t-p}^{st}$are the coefficients of the autoregressive process in the case of S_t. a_o^{st} constant, ε_t error term series, δ^{st} is the standard deviation of the sequence of error terms. In the model of MS (m)-AR (0), There is m regime in Markov chain and the observable regimes depend only on concealed regimes within the same range, which is equivalent to HMM. When considered for the MS (2) -AR (1) model, there are two regimes in the Markov chain and the results observed at time t. Y_t is defined by both the concealed regime in the same period and the observed results at time t-1, Y_{t-1} (Ailliot veMonbet: 2012, 96). This relation can be expressed using an equation similar to the following equation: $Y_t = a_0^{S_t} + a_1^{S_t} Y_{t-1} + \delta^{S_t} \varepsilon_t$

The flow chart in Figure 1 illustrates this process:

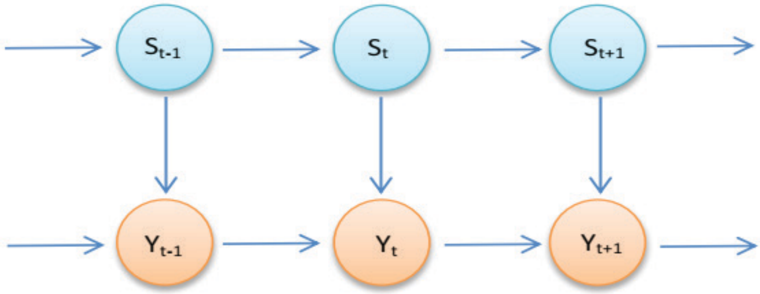

Figure 1. Process of MS(1)-AR (1).

AR(1) model is simply written as follows and it supposes an average and volatility shift in the difference between the regimes

$$Y_t = \mu S_t + \varphi(Y_{t-1} - \mu s_{t-1}) + u_t, \qquad ut \sim NID(0, \sigma^2 St),$$

Here while $\mu S_t = \mu 0(1 - S_t) + \mu_1 S_t$, $\sigma^2 S_t$ is as described above. If S_t, t = 1, ..., T is known in advance, then the problem is about a conventional dummy variable autoregression. However, the appropriate regime is usually not directly observable. Then;

$$P(S_t = j|S_{t-1} = i) = p_{ij}, \qquad (i, j = 0, 1),$$

They are called transition probabilities with $p_{i0} + p_{i1} = 1$, i = 0, 1. The Markov process is a type of processing, in which the current regime depends only on the previous regime and is called a mean and variance Markov Switching model. The probabilities in the Markov process can be presented in matrix form as follows:

$$\begin{pmatrix} P(S_t = 0) \\ P(S_t = 1) \end{pmatrix} = \begin{pmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{pmatrix} \begin{pmatrix} P(S_{t-1} = 0) \\ P(S_{t-1} = 1) \end{pmatrix}$$

Transition probabilities (p_{ij}) are generally estimated with maximum likelihood method (http://lipas.uwasa.fi/~bepa/Markov.pdf).

Data and Empiric Results

The weekly crude oil price was used in the study. The data was obtained from the “imf.org” website and consisted of 1449 observations covering the period from May

06, 1990 to April 11, 2018. The logarithmic state of the crude oil price series was taken and converted from price series to return series with the help of the following formula. The E-views 9.0 program was used to analyze the crude oil price data.

$$y_t = 100\text{x}[\ln(\text{r}_\text{t}) - \ln(\text{r}_{\text{t}-1})]$$

In this paper, it would be more accurate to proceed without seasonal adjustments because each adjustment would affect the results of the analysis to be made, the regression would lead to deterioration at the turning points, and in this case the regime would be distorted (Skalin&Terasvirta, 2000; Fattouh, 2005; Mir, Osborn & Lombardi, 2005).

Graphs of crude oil price (crude) and return (Y) series are given in Figures 2 and 3, respectively.

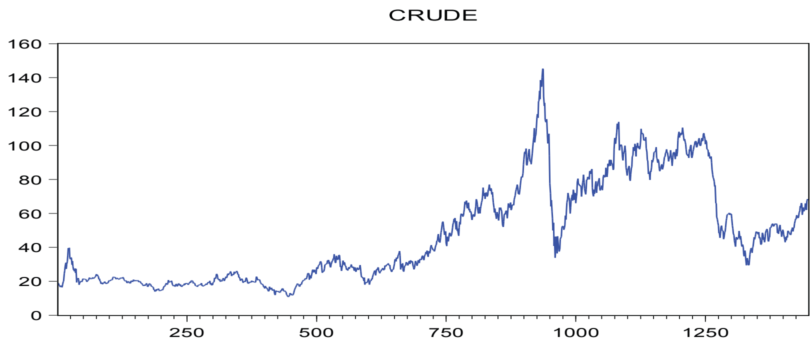

Figure 2. Crude oil price series graph.

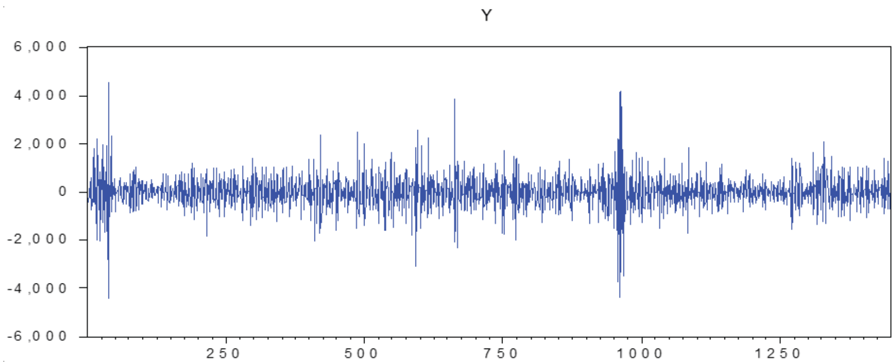

Figure 3. Crude oil return series graph.

As can be seen from Figure 2 and 3, it is clear that rather than a simple random walk, the time series of both up and down trends occur at different time periods. Some test statistics of the crude oil return series are given in Table 1.

Table 1
Descriptive Statistics

Mean	0.082
Median	-11.19507
Max.	4525.5
Min.	-4406.618
Std. Dev.	728.6541
Skewness	0.125772
Kurtosis	9.130907
Jarque-Bera	2270.059
Prob.	0.000000

According to the statistics obtained in Table 1, the series are skewed and kurtosis due to the residuals. According to the JB test statistic value of Jarque and Bera (1980), the error terms of the series do not show normal distribution. Analysis of the stability of the series was made by ADF test.

Table 2
ADF Stationary Test

		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-12.98038	0.0000
Test critical values:	1% level	-3.964507	
	5% level	-3.412971	
	10% level	-3.128482	

*MacKinnon (1996) one-sided p-values.

In Table 2, ADF test statistic showed that the series was stationary at a significance level of 0.05. After this the most appropriate delay length was determined using information criteria and the estimated results of the predicted LSM method are given in Table 3.

Table 3
Least Square Test Result

Parameters	**Estimates**	**SE**	**t-stat.**	**Prob.**
C	0.39	16.33	0.024316	0.9806
Y(-1)	-0.524	0.02	-23.37676	0.0000
F stat.	546.4729			0.0000
R^2	0.27			
D.W.	2.372			

(Y is dependent variable)

As a result of the LSM test, the lagged variable is statistically significant at the 5% significance level. Since time series are more suitable for nonlinear models than linear models, the linearity must be tested before modeling the series that is found to be stationary. The linearity of the series was tested with the Brock Dechert Scheinkman (BDS) Test. The BDS test was developed by Brock, Dechert and Scheinkman (1987). The test is intended to test for nonlinear dependence. In this test, we are investigating whether there is white noise as a null hypothesis (Çinko, 2006). In the BDS test, if the number of observations in the series is more than 500, then the value of m is less than 6 and the value of ε is chosen between 0.5 and 2 times the standard deviation of the data set in terms of accuracy of the results (Sümer&Hepsağ, 2007, p. 11).

Table 4
BDS Linearity Test

	m			
ε	**2**	**3**	**4**	**5**
0.5	0.006395* (0.000)	0.008145* (0.000)	0.005580* (0.000)	0.003366* (0.000)
1	0.015887* (0.000)	0.033254* (0.000)	0.037585* (0.000)	0.035721* (0.000)
1.5	0.018273* (0.000)	0.046109* (0.000)	0.065055* (0.000)	0.075904* (0.000)
2	0.015842* (0.000)	0.041453* (0.000)	0.063587* (0.000)	0.082142* (0.000)

* The hypothesis that the error terms have no similar distribution with respect to the level of 5% significance is accepted

According to the BDS test results applied to the error terms, the hypothesis that the error terms do not have similar distribution as a result of comparing the values calculated at all ε values and m dimensions (at the 5% significance level) with 1.96 values is accepted. According to these results, it is accepted that the models show a nonlinear structure. In this case, a Markov Switching model such as the following can be introduced.

Table 5
Estimating the model from weekly with sample period 1990 to 2018.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-1.902433	13.77044	-0.138153	0.8901
Y(-1)	-0.481434	0.025750	-18.69661	0.0000
LOG(SIGMA)	6.156700	0.026283	234.2457	0.0000
		Regime 2		
C	13.19119	77.32557	0.170593	0.8645
Y(-1)	-0.564815	0.058224	-9.700672	0.0000
LOG(SIGMA)	7.030000	0.064303	109.3262	0.0000
		Transition Matrix Parameters		
P11-C	4.253587	0.343635	12.37822	0.0000
P21-C	-2.467277	0.356959	-6.911943	0.0000
There is mean dependent.	0.375443	There is S.D. dependent.		728.8205
S.E. of regression	620.5122	Sum squared residual		5.54E+08
Durbin-Watson stat	2.375889	Log likelihood		-11211.21
Akaike info criterion	15.51759	Schwarz criterion		15.54678
Hannan-Quinn criter.	15.52848			

In Table 5, it is seen that Markov regime change model coefficients are statistically significant at 5% significance level. Based on these findings, it is decided that the series exhibits a two-phase nonlinear structure. Table 6 shows transition probabilities from Regime 1 to Regime 2 and Regime 1 to Regime 2 respectively. According to these results, regime 1 is quite permanent. When the process is in regime 1, the probability of transition into regime 2 is very low.

Table 6

Transition Probabilities

Constant transition probabilities:		
$P(i, k) = P(s(t) = k \mid s(t-1) = i)$		
(row = i / column = j)		
	1	2
1	0.985986	0.014014
2	0.078184	0.921816
Constant expected durations:		
	1	2
	71.35734	12.79030

The estimated average waiting period of the oil price in regime 1 is 1 / (1 - 0.985986) = 71.35734 weeks, and the estimated average waiting period in regime 2 is 1 / (1 - 0.921816) = 12.79030 weeks, which is an indication of the stability of the regimes. When predicted results are interpreted; it is seen that crude oil prices have a probability of passing the 2nd regime (P_{12}) of 0.014, while the probability of passing the first regime (P_{21}) of 0.078 is the same in the second regime.

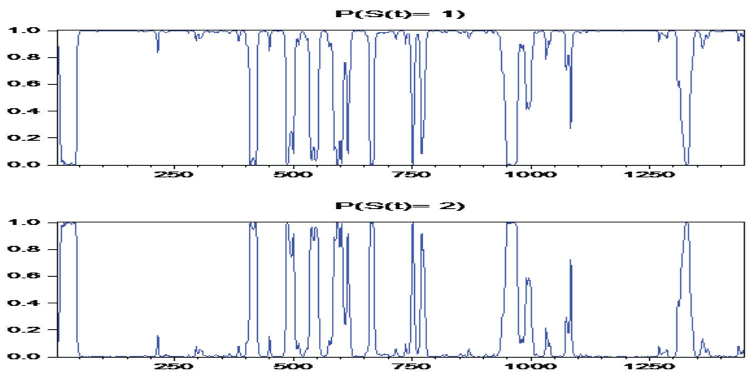

Figure 4. Smoothed regime transition probabilities.

Figure 4 shows the probability of staying in the regime 1 or regime 2 at any given time. When we look at the graph in Figure 4, which shows the probability of transition, the process takes place in regime 1 when there are few fluctuations, while regime 2 takes place when there are more fluctuations.

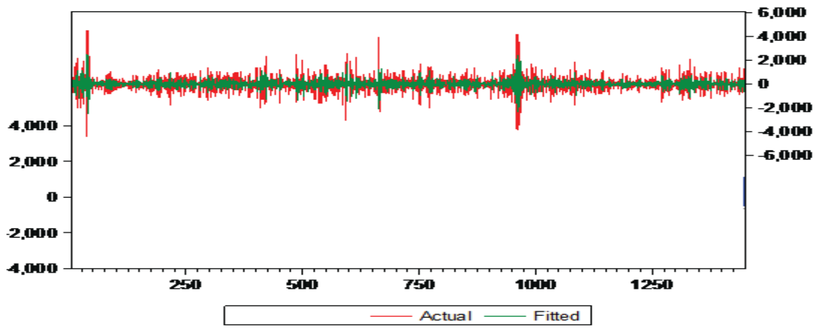

*Figure 5.*Estimated Values with Observed and 2 Regimes Markov Switching Models.

When examining Figure 5 with the aim of observing whether the Markov switching model is well fitted to the observed values, it is seen that the Markov switching model created with 2 regimes matches the observational values well and catches all the turning points.

Conclusion

This article focuses on the fluctuations in crude oil prices. Some jumps occur in the crude oil price fluctuations. If the jumps in the time series comes up, the regimes of the Markov Switching Regime Change models will also change. For this reason, the MS-AR model will be useful for modeling the movements in the crude oil price data.

The price of crude oil for the period from May 06, 1990 to April 11, 2018 was used in the study. The stationarity of the series was determined by the ADF unit root test. The BDS test was used to show that the error terms of the series (which were stable and not seasonally adjusted), were nonlinear. It is seen that the prediction made by the Markov regime change model is successful, and the model catches all return points of the series at close to one hundred percent.

References

Ahdikari, R. & Agrawal, R. K. (2013). *An introductory study on time series modeling and forecasting*. Lambert Academic Publishing. Retrieved from: https://arxiv.org/ftp/arxiv/papers/1302/1302.6613.pdf

Ailliot, P. & Monbet, V. (2012). Markov-switching autoregressive models for wind time series. *Environmental Modelling and Software*, *30*, 92–101. https://doi.org/10.1016/j.envsoft.2011.10.011

Barunik J. & Malinska, B. (2015). Forecasting the term structure of crude oil futures price with neural networks. E*lsevie*r, 2–26. Retrieved from: https://arxiv.org/pdf/1504.04819.pdf

Bayat, T., Kayhan, S. ve Koçyiğit, A. (2013). Türkiye'de işsizliğin asimetrik davranışının Rejim Değişim Modeliyle incelenmesi. *Business and Economics Research Journal*, *4*(2), 79–90. http://docplayer.biz.tr/5976565-Turkiye-de-issizligin-asimetrik-davranisinin-rejim-degisim-modeliyle-incelenmesi.html adresinden edinilmiştir.

Chen, S. S. (2014). Forecasting crude oil price movements with oil - sensitive stocks. *Economic Inquiry*, *52*(2), 830–844. https://doi.org/10.1111/ecin.12053

Çinko, M. (2006). İstanbul Menkul Kıymetler Borsası 100 Endeksinin doğrusallık testi. *Ekonometri ve* İstatistik *e-Dergisi*, *3*, 23–31. http://eidergisi.istanbul.edu.tr/sayi3/iueis3m2.pdf adresinden edinilmiştir.

Engel, C. & Rogers, J. H. (2006). The U.S. current account deficit and the expected share of world output. *Journal of Monetary Economics*, *53*(5), 1063–1093. Retrieved from: https://www.ssc.wisc.edu/~cengel/PublishedPapers/CarnegieRochesterCAcct.pdf

Fattouh, B. (2005). Capital mobility and sustainability evidence from U.S. current account data. *Empirical Economics*, *30*(1), 245–253. https://doi.org/10.1007/s00181-004-0232-6

Hamilton, J. D. (1983). Oil and the macro economy since World War II. *The Journal of Political Economy*, *91*(2), 228–248. http://www.jstor.org/stable/1832055

Hamilton, J. D. (1989). A new approach to the economic analysis of non-stationary time series and the business cycle. *Econometrica*, *57*(2), 357–384. https://doi.org/10.2307/1912559

Hamilton, J. D. (2005). Regime Switching Models. Retrieved from: http://econweb.ucsd.edu/~jhamilton/palgrav1.pdf

Hamilton, J. D. (2009). Causes and consequences of the oil shock of 2007–08. *The National Bureau of Economic Research*, *40*(1), 215–283. https://doi.org/10.3386/w15002

http://lipas.uwasa.fi/~bepa/Markov.pdf

Huang, S., An, H., Wen, S. & An, F. (2017). Revisiting driving factors of oil price shocks across time scales. *Energy*, *139*(C), 617–629. https://dx.doi.org/10.1016/j.energy.2017.07.158

Karahan H. (2014). Petrol piyasalarında neler oluyor? *SETA Perspektif, 79*. https://paperzz.com/doc/5060375/petrol-piyasalar%C4%B1nda-neler-oluyor%3F

King K., Deng A. & Metz D. (2012). *An econometric analysis of oil price movements: the role of political events and economic news, financial trading, and market fundamentals*. Bates White Economic Consulting. Retrieved from: https://www.bateswhite.com/assets/htmldocuments/media.768.pdf

Kuan, C. M. (2002). Lecture on the Markov Switching Model. Retrieved from: http://homepage.ntu.edu.tw/~ckuan/pdf/Lec-Markov_note.pdf

Middendorf, T. & Schmidt, T. (2004). Characterizing movements of the U.S. current account deficit. *RWI Discussion Paper*, *24*. http://dx.doi.org/10.2139/ssrn.628461

Mir, A. M., Osborn, D. R. & Lombardi, M. J. (2005). The effects of seasonal adjustment on the properties of business cycle regimes. *Journal of Applied Econometrics*, *23*(2), 257–278. https://doi.org/10.1002/jae.980

Pape, B. (2005). Regime switching models. *Lecture Notes*, 31–43. Retrieved from: http://lipas.uwasa.fi/~bepa/Markov.pdf

Psaradakis, Z. & Spagnolo, N. (2003). On the determination of the number of regimes in Markov-Switching Autoregressive Models. *Journal of Time Series Analysis*, *24*(2), 237–252. https://doi.org/10.1111/1467-9892.00305

Skalin, J. & Trasvirta, T. (2000). Modelling asymmetries and moving equilibria in unemployment rates. *Macroeconomics Dynamics*, *6*(2), 202–241. https://doi.org/10.1017/S1365100502031024

Solak, A. O. (2012). Petrol fiyatlarını belirleyici faktörler. *International Journal of Alanya Faculty of Business*, *4*(2), 117–124. http://dergipark.gov.tr/download/article-file/201632

Sümer, K. ve Hepsağ, A. (2007). Finansal varlık modelleri çerçevesinde piyasa risklerinin hesaplanması: parametrik olmayan yaklaşım, *Bankacılar Dergisi*, *62*, 3–24. https://www.tbb.org.tr/Dosyalar/Arastirma_ve_Raporlar/finansalvarlik.pdf adresinden edinilmiştir.

Ural, M. (2016). The impact of the global financial crisis on crude oil price volatility. *Yönetim ve Ekonomi Araştırmaları Dergisi, 14*(2), 64–76. http://dx.doi.org/10.11611/JMER810

Wong, V. S. & El Massah, S. (2017). Recent evidence on the oil price shocks on gulf corporation council stock markets. *International Journal of the Economics of Business*, 1–16, https://doi.org/10.1080/13571516.2017.1379216

Yin, X., Peng, J. & Tang, T. (2018). Improving the forecasting accuracy of crude oil prices. *Sustainability*, *10*(2), 454. https://doi.org/10.3390/su10020454