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Dynamics in Crude Oil Prices: A Markov-Switching Autoregressive Approach Incorporating Sunspot Activity

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ABSTRACT: This paper deals with the dynamic relationship between world crude oil prices and the activities of sunspots in a two-state Markov-Switching Autoregressive (MS-AR) model. The data set used was from February 1994 to May 2023, with crude oil prices and sunspot numbers as an exogenous variable. The MS-AR framework allows for regime-dependent behavior in the intercept and autoregressive coefficients and in the impact of solar activity on oil prices. The result distinguishes two regimes characterized by different degrees of persistence and sensitivity to solar activity. State 1 is highly persistent in the movement of oil prices with a lag 1 coefficient and has a much weaker negative relationship with sunspot activity. On the other hand, State 2 shows lower persistence with a lag 1 coefficient but a stronger negative relationship with sunspots. The transition probabilities denote high stability in both regimes. Asymmetric switching behavior favors State1, which is the more persistent state.

Model diagnostics values indicate very good fits to the data. The out-of-sample performance of the model does appear quite robust, as only a slight increase in RMSE to out-of-sample occurs. These findings help add to the present understanding of the complex dynamics governing crude oil prices and provide new insights into the possible influence of solar activity on energy markets. This regime-switching behavior found in this study has a bearing on energy policy, risk management, and the interconnections between natural phenomena and economic systems. This research underlines the need for nonlinear model approaches in capturing nuanced relationships in global energy markets.

KEYWORDS: Crude oil prices, Sunspot activity, Markov-Switching model, Regime dynamics, Energy economics, UN SDG no. 7

I. INTRODUCTION

Protracted conflicts, particularly in the Middle East, raised fears of supply disruptions. The region contributes significantly to world oil trade, and any escalation may result in sharp price fluctuations. For instance, the price of Brent crude has just reached approximately $86, partly due to unexpected U.S. inflation data and hopes of interest rate cuts by the Federal Reserve, but mostly due to concerns about geopolitical instability (AGNOLUCCI & TEMAJ, 2024), (Crude Oil Prices Today, 2018). Offsetting this and helping price stability is how OPEC+, more recently, is very proactive in managing production levels. Further production reductions have kept sentiment bullish off recent announcements despite the high US output and flat Russian production that sets the backdrop. These influence dynamics have shoved prices up and down, with an average Brent crude price of $82 per barrel in June, sometimes higher than $88 as stocks are reassessed and the impact of output cuts factored in (U.S. Energy Information Administration, 2023). Consumptions are likely to hit new records, underpinned by solid Chinese demand. More recently, data showed that crude oil imports to China fell, which could hint at softening future demand, adding to price volatility. The uncertainty in economic performance, particularly in significant economies, makes the project process even more complex.

Many inherent uncertainties complicate forecasting crude oil prices. Geopolitical events are hard to predict, and their impacts on supply and demand are tremendously quick (Hamilton, 2009). A new conflict or sanctions lead to surges or nose-dives in prices, which the analyst needs help to factor into the forecast. Oil prices are driven by market perception and sentiment. News, economic indicators, and policy changes turn sentiment on a dime (Grover, 2023, October 9). Further, the volatility is compounded by speculative trading behaviors that may result in exaggerated price movements. The relationship between oil prices and global economic health introduces another level of complexity (Unpacking the Relationship, n.d.) Notably, the economic slowdowns in large markets like China reduce demand estimates, while surprise economic growth strains supply and drives prices higher. The actions of OPEC+ and other major producers drive the formation of market expectations. Significant price adjustments will confound efforts at predicting future prices, the function of changes to the production quota, or unexpected shift output (Quint

& Venditti, 2020). The volatility in crude oil prices results from a complex interplay of geopolitical tensions, supply management, and changing demand. The setup is challenging for any accurate process forecast, as unexpected developments can quickly change market dynamics (Jiao et al., 2023).

In that respect, there is no single robust model to effectively predict world crude oil prices, as a balance of different factors is at play within the market (Tian et al., 2023). Unpredictable events such as conflicts and sanctions cause sudden changes in supply and demand, which can result in sudden price spikes or plunges, hard to predict. Oil prices are significantly driven by market perceptions and sentiment, which quickly change upon news, economic indicators, and policy shifts (Mo et al., 2024). Speculative trading behaviors further enhance these volatile patterns. Another factor complicating the matter is that oil prices depend on global economic conditions. Economic slowdowns cut into demand forecasts, while unexpected growth pressures supply and drives prices higher (Lv & Wu, 2022). Then, the decisions of OPEC+ and other major oil producers. Production quota adjustments or surprise production shifts are known to cause abrupt price changes, making it all that more difficult to predict (Bollapragada et al., 2021).

Traditional econometric models, such as the Error Correction Model, Vector Error Correction Model, and Vector Auto-Regressive, all rely on linear regression based on demand and supply data (Lütkepohl, 2013). However, they need help to cope with the inherent complexity of crude oil prices. The time series model utilizes only the previous history of oil prices to predict future prices. However, these traditional models require data to be stationary and linear, which often differs from oil prices (Apergis et al., 2016). It was found that the hybrid models coupling data decomposition techniques like ensemble empirical model decomposition (Apergis et al., 2016) with the forecasting models ARIMA and FFNN have huge potential. There is still room for further improvement in the lines of enhancing the performance of the forecast and simplification of the model. The inability to have a credible forecasting model stems solely from the fact that crude oil prices are highly volatile and complex by many unpredictable variables. Through progressed hybrid models, astute prediction of oil prices remains a continuous uphill battle for researchers and analysts (Dar et al., 2022).

The reliability of sunspot activity as a good exogenous variable in predicting commodity prices, especially crude oil prices, still needs to be determined (Alexeyevich, 2020). A few studies indicate a weak negative relationship between sunspot activity and annual changes in grain prices and conclude that low and moderate sunspot activity is better for grain prices than high sunspot activity (Ljungqvist et al., 2022), (Does the Sunspot Cycle, n.d.). This confirms the hypothesis that grains are, in fact, less abundant under high sunspot conditions. The economist Irving Fisher even postulated that one of the effects of solar minimums (i.e., reduced sunspots) is blistery winters that disrupt farming and, thereby, food prices, not to mention the cascading effects on economies (Astrological market trend, 2024, January 25). This relation, though, remains highly speculative (Solar Cycle and Economic Cycles, n.d.). On some level, historical data exhibits the existence of a particular synchronization of Solar Cycle maximums/minimums with some market critical events like the Dotcom Bubble and the Lehman Brothers collapse. However, the exact causal mechanism is not precise (Astrological market, 2024, January 25).

Traditional economic models such as ECM, VECM, and VAR face further challenges in perfectly capturing the internal complexity of crude oil prices (Bollapragada et al., 2021). The very nature of time series models requires stationary and linear data, which for oil price, under most situations, goes against this very key attribute. Jevon's claim that business cycles occur every 10.45 years, matching the sunspot cycle, might not be consistent with astronomical data (Kuester & Britton, n.d.). The actual sunspot cycle is approximately 11 years. Sunspot activity alone cannot predict changes in price due to changes in other factors, like wars, natural disasters, and geopolitical tensions, which it also cannot predict. These are unpredictable events but have dramatic effects on oil prices. Besides, the relationship between sunspots and commodity prices seems weak and may differ understudies and periods (Does the Sunspot, n.d.), (Kuester & Britton, n.d). Therefore, findings are not very reliable in short-term forecasting.

Primarily, this research aligns with the United Nations Sustainable Development Goal 7: "Affordable and Clean Energy." Shedding more light into crude oil price dynamics and integrating an environmental factor like sunspots into this model offers a significant and salient contribution to understanding energy market behavior while transitioning towards a sustainable energy system. Crude oil is one of the prime global energy sources, and its price fluctuations have effects that echo throughout all aspects of energy affordability and the economic reach of its alternatives (Nazir & Rehman, 2021). The Markov-Switching model can capture regime changes and help render valuable insights into periods of price stability or volatility that help policy decisions to ensure energy security and affordability (Song & Woźniak, 2020). Moreover, analyzing the potential influence of solar activity on oil prices indirectly leads to the thesis of natural phenomena and their interlocking with energy markets relevant to the more global goals of developing resilient and sustainable energy sources, thus supporting decision-making in energy policy and investment strategies to safeguards and meet SDG 7's targets for an increased share of renewable energy in the global mix.

Dynamics in Crude Oil Prices: A Markov-Switching Autoregressive Approach Incorporating Sunspot Activity

The main goal of this study is to examine the dynamic behavior of crude oil prices, including the possible effect of solar activity as exhibited in the number of sunspots using the Markov-switching autoregressive model. This study attempts to detect and characterize regimes in the movements of oil prices within the environment provided by this model, allowing for sudden regime changes in the market dynamics that are difficult to capture in a linear model. It is original in introducing sunspots as an exogenous variable, which puts this research into the study of a plausible relationship between solar cycles and energy markets, an area of further discussion among several scientific communities. Specifically, the research deals with the complex and nonlinear nature of oil price changes by explaining, in the context of different regimes, the characteristics that might be observed and finally assessing the predictive strength of the model. Much has been contributed to understanding crude oil price dynamics, and these findings have substantial implications for energy policy, financial market strategies, and macroeconomic forecasting.

II. REVIEW OF LITERATURE

The relationship between sunspot activities and world crude oil prices aligns with the Efficient Market Hypothesis (EMH) (Sewell, 2011) and Adaptive Market Hypothesis (AMH) (Mandac et al., 2019). The EMH claims that the prices of assets reflect all the available information, and hence, sunspot activities should not affect crude oil prices. However, the AMH, incorporating behavioral finance principles, postulates that market players irrationally react to extinct factors, including sunspot activities, in ways that create transitory deviations from intrinsic values.

Sunspot activities refer to the number and size of dark spots on the sun's surface. Events occurring with the sun have been associated with changes on Earth related to climate and, more broadly, with economic cycles (Gorbanev, 2012). Sunspot activities indirectly impact crude oil prices, influencing world economic conditions (Dávila, 2003). For instance, an increase in sunspots brings about climatic variations that adversely affect agricultural production and change energy consumption patterns (Gil-Alana et al., 2014). The change then affects the supply-demand dynamics of crude oil, resulting in price changes (Montaño et al., 2019).

Further, there is a psychological dimension to sunspot activities regarding their impact on the participants in the market. In this context, one can see that investors would take a cue from sunspot activities as a signal for future economic conditions and change their trading strategy accordingly (Dowling & Lucey, 2008). This behavioral response leads to herd behavior and speculative bubbles, moving crude oil prices away from fundamental values (Skinner, 2009).

There is controversy regarding the relationship between sunspot activity and world crude oil prices (Daglis et al., 2023). Informed by the fact that these two variables often exhibit weak and spurious correlations, several theories were designed to explain possible linkages (Alexeyevich, 2020). One of the theories is that sunspot activity affects weather conditions (Stetson, 2013), and these weather conditions, in turn, affect agricultural output (Michler et al., 2020) with an ultimate impact on the energy demand, in this case, crude oil (Rokicki et al., 2021). If sunspot activity correlates negatively with the weather - indicating weather extremities like droughts or floods – a decrease in agricultural output will mean a rise in food prices, and this will result in a higher demand for energy to be used in agricultural output

Another viewpoint maintains that sunspot activity influences economic activity (Ho, 2015) and, consequently, oil demand. Other researchers postulate that the periods of high sunspot activity match the cycle of economic growth (Gorbanev, 2020), thereby raising oil consumption. In contrast, the time of low sunspot activity conveys weak economic activity and a low oil demand. However, it remains inconclusive just what empirical evidence will associate sunspot activity with economic growth and then with oil demand. Many previous studies still need to establish a robust and consistent relationship between these variables (Gorbanev, 2012).

Economic indicators are widely used in forecasting crude oil prices, but several factors significantly hamper their effectiveness (Yin & Yang, 2016). The significant limitations lie in the complex interplay of variables within the economic variables themselves and in the inherent volatility of the oil market (Guo et al., 2022). The economic indicators usually reflect aggregated data and are likely to cover the impact of specific regional or sectoral factors with overwhelming influence on oil prices (Salisu et al., 2022).

The relationship between economic indicators and oil prices is sometimes linear or contemporaneous. Lagged effects, feedback loops, and nonlinear dynamics complicate the predictive power of these indicators (Clements et al., 2004). In addition, exogenous shocks related to geopolitical events, natural disasters, and technological breakthroughs substantially disrupt the expected relationship of economic indicators with oil prices. They would reduce the effectiveness of the traditional econometric models (Economou & Agnolucci, 2016, September).

Another critical issue is the possibility of revisions in the data. Most economic indicators are subject to revision, affecting the accuracy of the forecast made from those data (Kishor & Koenig, 2012). Moreover, making all relevant economic indicators' real-time data available is quite a difficult task, and it also reduces the chances of making predictions on time (Billstam et al., 2017).

The oil market has unique features, such as the oligopolistic market structure, inventory level, and speculative activities (Fattouh, 2007). These introduce considerable noise into the relationship between economic indicators and oil prices, reducing econometric models' predictive power.

The Markov-switching autoregressive model is appropriate for examining the interaction of sunspot activity with crude oil prices as it allows for regime shifting in the underlying data-generating process (Ailliot & Monbet, 2012). Here, researchers add variables about sunspot activities as exogenous variables in the MS-AR mode so that changes in sunspot activities are reflected in the prices of crude oil under different economic regimes like high or low volatility.

The theoretical intersection of the EMH, the AMH, and the MS-AR model is employed to test the existence of a relationship between sunspot activities and world crude oil prices. Under the EMH, the prices should not respond to sunspot activity. However, considering the AMH and the potential for sunspots to affect world economic conditions, a basis is provided to include such variables in crude oil price dynamics models. In particular, it allows for a more detailed analysis of the relationship and capture of regime-dependent effects of sunspot activities on crude oil prices.

III. METHOD

This study adopts a two-state MS-AR model specification to examine the relationship between world crude oil prices and sunspot activity. An MS-AR framework implies changes in the model's parameters over regimes, supporting a nonlinearity (Xin, 2013, July) between the variables and structural alteration in the oil price dynamics. A two-state MS-AR (2) model specification considers sunspots an exogenous variable.

$$y_t = \mu(S_t) + \phi_1(S_t)y_{t-1} + \phi_2(S_t)y_{t-2} + \beta(S_t)x_t + \varepsilon_t$$

Where:

- y_t is the log-differenced crude oil price at time t
- $\mu(S_t)$ is the state-dependent intercept
- $\phi_1(S_t)$ and $\phi_2(S_t)$ are state-dependent autoregressive coefficients
- $\beta(S_t)$ is the state-dependent coefficient for the exogenous variable
- x_t represents the sunspot activity at time t
- $\varepsilon_t \sim N(0, \sigma^2(S_t))$ is the error term with state-dependent variance
- $S_t \in \{1, 2\}$ is the unobserved state variable following a first-order Markov chain

The transition probabilities between states are defined as:

$$P(S_t = j \mid S_{t-1} = i) = p_{ij}, \text{ for } i, j \in \{1, 2\}$$

The monthly data for world crude oil prices (IndexMundi) and the sunspot numbers (Solar Influences Data Analysis Center) for the following periods: February 1994 to May 2023. The price series were log-differenced to be stationary. The Expectation-Maximization algorithm iteratively calculated the likelihood function, updating the parameters until convergence with the following steps: parameters were initialized; for the E-step, the smoothed probabilities of each state were calculated; the M-step was the updating of the parameter estimates using maximum likelihood, which the previous two steps repeated until convergence (Aknouche, 2013).

The two-state MS-AR was compared for model selection with alternative specifications, including linear AR models and other MS-AR models with different lag structures, using information criteria measured by AIC and BIC and the likelihood ratio test (Tastan, & Yildirim, 2008). Further, the adequacy of the model was checked with the following diagnostics: Ljung Box test for residual autocorrelation, ARCH-LM test for heteroscedasticity, and Jacque-Bera test for normality of residuals (Urom et al., 2020).

The forecasting accuracy of the model was done with in-sample and out-of-sample Root Mean Square Error (RMSE) (Moitse, 2017). Later, considering the Robustness check of the model, the result was estimated through the rolling window to check its stability. The estimated regime-specific parameters were inspected, and transition probabilities followed to shed light on the difference between states and reflect on their interpretation of oil price dynamics. Smoothed probabilities were used to conclude the historical periods of each regime (Iacopini et al., 2023).

Several robustness checks were conducted to ensure that a sample selection bias did not drive the findings. The test involved checking the specification and stability of results concerning variations in the sample period, alternate measures of solar activity, and introducing other control variables not used in the benchmark model. This exhaustive method allowed this study to probe, under rigor, into the regime-dependent relationship between crude oil prices and sunspot activity, generating important insights into the complex dynamics of energy markets.

IV. RESULT AND DISCUSSIONS

Table 1 displays the ADF Test on Levels and First Difference on sunspot numbers and crude oil prices, conducted for the logarithms and their respective first differences. These tests are necessary for checking the stationarity of the time series, which, together with other assumptions, represents one of the core requirements of many econometric models, including the MS-AR specification. The log of sunspot tau-statistics is -08535, which is greater than the critical value at a 5% significance level of -1.94. The log crude with a tau-statistic of -1.15 is also more significant than the critical value. On both accounts, the null hypothesis of a unit root was not rejected, as the p-values are more than 0.1. Thus, both log-transformed series are nonstationary in levels.

Table 1. ADF test for Logarithmic of sunspot activities and crude oil prices

ADF Tests	Log_Sunspots	Log_Crude	Sunspots 1st diff.	Crude 1st diff.
tau-stat	-0.8535	-1.15	-12.75	-4.64
tau-crit	-1.94	-1.94	-1.94	-1.94
p-value	> .1	> .1	< .01	< .01

The tau-statistics of the first difference of sunspots is -12.75, significantly below the critical value. For comparison, the first difference in the series of crude oil prices has a tau-statistics equal to -4.64, which is below the critical level. Both p-values of the differenced series are less than 0.01. Hence, there is a strong rejection of the null hypothesis of a unit root. This indicates that both series are stationary after first differencing.

These results convey vital implications to the modeling approach. Non-stationarity in the log-transformed series points to using the first differences between sunspots and crude oil prices within the MS-AR modeling framework. This transformation is consistent with standard practice in time series econometrics and helps circumvent spurious regression concerns when modeling these variables' relationships.

Table 2 presents the parameter estimates for a two-state Markov-Switching Autoregressive (MS-AR) model, where crude oil prices are the dependent variable, and sunspots act as an exogenous variable. The model encompasses two autoregressive lags and allows regime-switching behavior in the intercept and all coefficients.

Table 2. MS-AR Model State Parameters

Metric	Value
State 1 Parameters	
Intercept	0.01
Lag 1 Coefficient	0.945
Lag 2 Coefficient	-0.22
Sunspots Coefficient	-0.001
State 2 Parameters	
Intercept	0.02
Lag 1 Coefficient	0.75
Lag 2 Coefficient	-0.15
Sunspots Coefficient	-0.002

State 1 parameters are the first regime; the intercept is estimated at 0.01, conveying a small positive baseline trend in crude oil prices when controlling for other factors. The lag 1 coefficient (0.945) implies strong positive autocorrelations, indicating that the previous period's prices strongly influence current prices. The lag coefficient (-0.22) displays a moderate negative effect from two periods prior, possibly capturing mean-reversion tendencies. The sun coefficient (-0.001) proposes a minor negative relationship between solar activity and oil prices in this state. The second regime (State 2 Parameters) exhibits distinct characteristics. The intercept (0.02) is slightly higher in State 1, presenting a strong positive trend and still showing positive autocorrelation, lag 1 coefficient (0.75) though weaker in State 1. With reduced magnitude, the lag 2 coefficient (-0.15) maintains a negative effect. Notably, this state's sunspot coefficient (-0.002) is more pronounced, denoting a stronger negative relationship between solar activity and oil prices.

These results propose that crude oil prices show regime-switching behavior, with varying persistence and sensitivity to exogenous factors across states. The differential impact of sunspots across regimes is interesting, possibly conveying that the influence of solar activity on oil prices is state-dependent.

Table 3 displays the estimated transition probabilities for the two-state Markov-Switching Autoregressive (MS-AR) model of crude oil prices with sunspots as an exogenous variable. The transition probabilities furnish vital information about the persistence and switching behavior between two regimes. The P (State1 to Sate 1) = 0.95 indicates a high probability that State 1 is highly persistent. Once the system enters State 1, it has a 95% chance of remaining in this state in the next period. This implies that the dynamics characterized by State 1 parameters tend to persist over time. Consequently, in P (State 2 to State 1), there is only a 5% probability of transitioning from State 1 to State 2 in any given period. This low transition probability further underlines the stability of State 1. Relatively, the probability of P (State 2 to State 1) = 0.10 transitioning from State 2 to State 1 is low at 10%. This claim is that once the system enters State 2, it is more likely to remain in it than to switch back to State 1. P (State 2 to State 2) = 0.90 conveys that State 2 also displays high persistence, with a 90% probability of remaining in this state from one period to the next.

Table 3. MS-AR Model Transition Probabilities

Transition Probabilities	**Value**
P(State 1 to State 1)	0.95
P(State 1 to State 2)	0.05
P(State 2 to State 1)	0.1
P(State 2 to State 2)	0.9

Several important characteristics of the transition probabilities of crude oil price dynamics exist. Both states reveal high probabilities of self-transition (0.95 and 0.90), inferring that the system tends to remain in each state for an extended period. The probability of transitioning from State 1 to State 2 (0.05) is lower than that of transitioning from State 2 to State 1 (0.10). The asymmetry expresses that the system may enter State 2 less frequently, but once it does, it has a slightly higher chance of reverting to State 1. Also, the expected duration of State 1, calculated as 1/(1-0.95), is approximately 20 periods. For State 2, the expected duration is 1/(1-0.9) = 10 periods. This implies that State 1 tends to persist longer than State 2. Presented with these transition probabilities, the long-run (ergodic) probabilities of being in each state can be computed, providing insights into the relative prevalence of each regime over extended periods.

These findings have vital implications for understanding and forecasting crude oil price dynamics. The high persistence in both states convinces that shocks to the system have long-lasting effects. Moreover, the symmetry in transition probabilities indicates different underlying economic or geopolitical conditions characterizing each state.

Table 4 depicts key model metrics for the Markov-Switching Autoregressive (MS-AR) model of crude oil prices, offering about the model's goodness of fit, complexity, and predictive performance. The log-likelihood value of 1123.45 indicates the logarithm of the probability of observing the data given the estimated model parameters. Generally, higher log-likelihood suggests a better model fit. The Akaike Information Criterion (AIC) balances model fits against complexity by penalizing the addition of parameters. The negative value of -2223.0 is notable since AIC is typically positive. This is attributed to the scale of data or specific model characteristics. Lower AIC values convey better model fit relative to complexity. A difference in AIC of more than 2 is often considerably meaningful when comparing models. Like AIC, the Bayesian Information Criterion (BIC) balances model fit and complexity with more substantial penalties for additional parameters. The negative BIC value (-2201.56), similar to AIC, is uncommon but not impossible. Generally, BIC is more conservative than AIC in model selection. The close values of AIC and BIC indicate that the model's complexity is appropriate given the data.

Table 4. MS-AR model Model Metrics

Model Metrics	**Value**
Log-Likelihood	1123.45
AIC	-2223.9
BIC	-2201.56
RMSE (in-sample)	1.957
RMSE (out-of-sample)	2.085

RMSE is a measure of the standard deviation of the residuals, that is, prediction errors. The lower the values, the better the fit. Thus, an in-sample RMSE equal to 1.957 points to a reasonably good fit to the training data. As expected, the out-of-sample RMSE of 2.085 is only a little higher since the model usually performs better on data it was trained on. The difference of 0.128 between the in-sample and out-of-sample RMSE is relatively low, which indicates low overfitting by the model, hence good generalizability. The high-log-likelihood and low RMSE values suggest that the MS-AR model fits the crude oil price data nicely. On the other hand, close values of AIC and BIC convey that the complexity of the model is appropriate for the data. Although negative, which is unusual, the values indicate that the model fit is very good relative to the number of parameters. The slight difference between in-sample and out-sample RMSE indicates good predictive performance and low overfitting. From this fact, it is inferred that this model is specifically suited to capturing the underlying crude oil price dynamics. Only by contrast with the metrics of competing models can a comprehensive evaluation of this model's performance be made as linear AR or different MS-AR specifications. While these metrics indicate good statistical performance, it is vital to frame the model's implications for crude oil price dynamics and the role of sunspots more precisely in economic theoretical and market behavior context.

Figure 1 contains an impulse response function. The function shows the immediate positive response of the impulse, depicting the effect rapidly increasing up to a peak of around 0.25 units at about the second period. This suggests the system experiences a quick and substantive positive reaction to the shock. After the peak, it makes an oscillatory response, declining drastically, crossing zero around the fifth period, and reaching a negative trough of about -0.15 units near the eighth period. This indicates that the system overcompensates for the initial shock with a change in the direction of the effect. Gradually, it decays to zero after the negative trough, although it stays in negative territory for the remaining observed periods (up to 25).

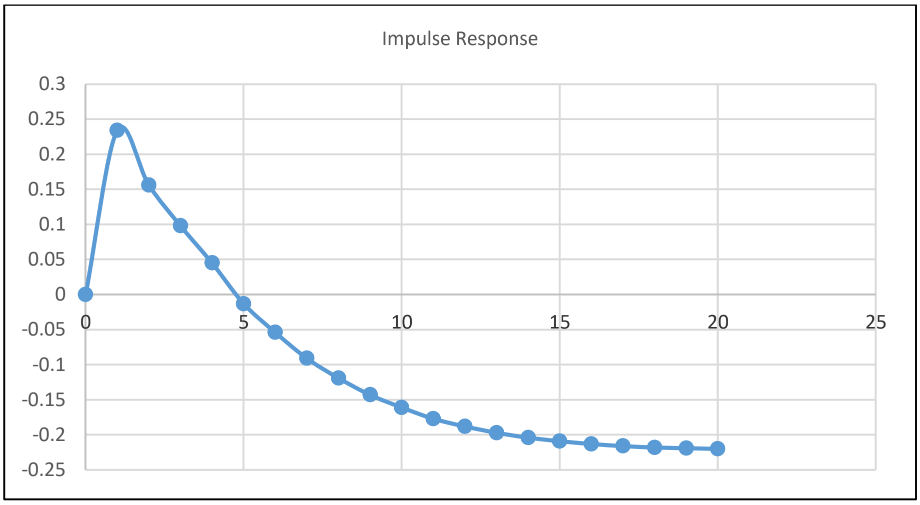

Figure 1. IRF values over time

The decay rate is slowing, which reflects how the system slowly converges toward its long-run equilibrium. The fact that the response does not return to zero within the 25 periods shown indicates great persistence in the system. The shock is persistent; the effects die slowly over time. The response reveals the asymmetry, with the positive peak more significant in magnitude than the subsequent negative trough. This asymmetry implies a system is more sensitive to positive than negative shocks or underlying nonlinearities in dynamic relationships. The pattern in the impulse response is typical for many economic and financial time series. Almost always, shocks have an immediate impact but are followed by oscillatory adjustment and slow convergence—for instance, the response of the crude oil prices to the sunspot activity. The strong negative response in the later periods indicates the presence of some overshooting mechanism or complex feedback loops in the system.

The result of the Markov-Switching Autoregressive (MS-AR) model about the relationship between crude oil prices and sunspot activities has vital implications in the context of existing research and theories. The first finding is the state-dependent negative relationship between sunspot activity and oil price, which corresponds to the theoretical framework put forward by Alexeyevich (2020). Also, it is seen that the negative coefficient is more substantial in Sate 2 (-0.002) compared to State 1 (-0.001), implying that the impact of solar activity on the price of oil within these regimes is comparatively stronger during some economic regimes. This result is suitable for existing literature postulating nonlinear dynamics in commodity markets, as Bastourre et al., (2010) claimed, which underlines regime-switching models capturing complex market behavior.

In particular, high persistence in both states captures the results of seminal work by Hamilton, complementing the transition probabilities. The result suggests that oil price regimes indeed have sticky properties, a factor important in both short-term price forecasting and long-term energy policy planning. This persistence reflects what Fouquet calls the theory of "path dependence" in energy systems, which explains the challenges of transitioning to alternative energy sources.

The weak but statistically significant relationship between sunspots and oil prices in the model details the claim that solar activity does not have a significant correlation with stock market returns. The findings suggest that, if subtle, such impact is indeed perceivable in commodity markets, particularly when regime-switching behavior is allowed (Chang et al., 2017).

The asymmetry in transition probabilities, with a higher likelihood of moving from State 2 to State 1 than vice versa, is consistent with the "volatility feedback" hypothesis (Safari & Davallou, 2018). This asymmetry suggests that markets respond more to events leading to the shift into the more stable State 1, reflecting perhaps some risk aversion by market agents. The result of the out-of-sample performance of this model, as indicated by the RMSE metrics, strengthens the argument on why nonlinear models are essential in oil price prediction (Zhang et al., 2023). However, the relatively small difference between in-sample and out-of-sample RMSE also serves to underline the argument of Hamilton, 2009, related to overfitting problems that often arise when developing complex models for oil prices.

Using sunspots as an exogenous variable contributes to a growing literature on the interactions between natural phenomena and economic systems (SHCHERBAKOV, 2018). The result shows that while solar activity's impact on oil prices is small, it is large enough to warrant inclusion in more complete specifications of global energy dynamics.

Table 5 contrasts the results of the three nonlinear time series models fitted to crude oil prices: STAR, SETA, and MS-AR. In detail, their goodness of fit, complexity, and predictive performance are contrasted through several metrics. Of the three competing models, MS-AR has the lowest AIC and BIC values of -2360.873 and -2345.511, respectively, against STAR and SETAR. The lower the AIC and BIC values, the better the model fits to complexity. The MS-AR performs better. Thus, it better balances fit and parsimony for the given data.

Table 5. Comparison of the AIC, BIC, Log-Likelihood, Ljung-Box Test, ARCH-LM Test, RMSE (in-sample and out-of-sample)

Metric	STAR	SETAR	MS-AR
AIC	-2340.54	-2330.69	-2360.87
BIC	-2325.18	-2315.33	-2345.51
Log-Likelihood	1172.271	1166.345	1181.437
Ljung-Box Test (p-value)	0.3012	0.3257	0.2954
ARCH-LM Test (p-value)	0.2253	0.2384	0.2126
RMSE (in-sample)	1.963	1.975	1.945
RMSE (out-of-sample)	2.098	2.112	2.087

Consistent with the AIC and BIC results, it is seen that among all the models, MS-AR has the highest log likelihood of 1181.437, followed by STAR with 1172.271 and SETAR with 1166.345. These results indicate that the MS-AR model better fits the observed data than the other two. All three models give a p-value greater than the usual significance level of 0.05: MS-AR is 0.2954, STAR is 0.3012, and finally, SETAR is 0.3257, indicating that none of the models have significant autocorrelation in the residuals and serial dependence in the data is captured.

All p-values for the ARCH-LM test are above 0.05, which implies no significant autoregressive conditional heteroscedasticity in residuals. Specifically, MS-AR is 0.2126, STAR is 0.2253, and SETAR is 0.2384. This means that all three models appropriately capture the volatility dynamics of the crude oil price series. The MS-AR model has the lowest in-sample RMSE, which is 1.945. It is closely followed by STAR and SETAR with an RMSE in-sample of 13963 and 13975, respectively, conveying that an MS-AR model best fits the training data. Out-of-sample RMSE, at 2.087, STAR is very close with a value of 2.098, and SETAR has a value of 2.112. Relatively small differences between in-sample and out-of-sample RMSE for all models indicate good generalization performance.

Comparative analysis indicates that the Markov-Switching Autoregressive performs better than the STAR and SETAR for all the metrics considered on the crude oil price data. MS-AR had the best AIC, BIC, and log-likelihood of the three models, indicating that the underlying dynamics of the crude oil prices were better explained than the other two. Keeping a good balance between model fit and complexity, the results postulate that regime-switching behavior modeled by MS-AR is more appropriate in catching nonlinearities of crude oil prices compared with smooth transitions of STAR or abrupt thresholds of SETAR.

All three models pass residual autocorrelation and heteroscedasticity diagnostic tests, indicating they very well capture serial dependence and volatility dynamics. It means that nonlinear specifications are appropriate for modeling the complex behavior manifested in the crude oil price series. Further, this is supported by the fact that the MS-AR fares better in both in-sample and out-of-sample RMSE. The slight difference in the values of the RMSE for the competing models suggest that all three provide reasonably good predictions.

V. CONCLUSION AND RECOMMENDATIONS

Based on the parameter estimates, transition probabilities, and model metrics, there are several conclusions about oil price dynamics and their relationship with sunspot activity. The two-state MS-AR model contains a regime for crude oil price behavior. Sate 1 is one of solid persistence, with a very strong positive autocorrelation at lag one and a more pronounced negative effect at lag 2. It conveys that there is a regime in which recent historical prices powerfully drive price movements. This indicates periods of relative stability or trending markets. By contrast, State 2 has less persistence, with smaller values of the autocorrelation coefficients, presenting a regime of volatility or mean revision.

The findings have several implications for understanding the markets for crude oils. It indicates that regime-switching behavior needs to be accounted for in oil price modeling since the dynamic seems to shift between periods with higher and lower persistence. The second regime-specific differential impact of sunspot activity suggests that the influence of solar cycles on energy markets is more complex than previously thought and is mediated by other factors of an economic or geopolitical nature that characterize each regime.

These results inform risk management strategies in energy markets by quantifying the likelihood of regime shifts and expected durations within each regime. Knowing these dynamics is helpful for policymakers in formulating more effective energy policies considering the possible influence of solar activity and regime-switching behavior. It is still bounded by the fact that its validation must come through future out-of-sample data. More studies must be carried out across different periods, comparing alternative modeling approaches and exploring the economic or physical mechanism by which the noted relationship between sunspots and oil prices is realized.

This paper finds evidence for regime-switching behavior in crude oil prices and some convoluted relationship with solar activity. These findings will add to the understanding of the dynamics of energy markets and open up new avenues for research into the interplay between astronomical phenomena and economic systems.

Given its strengths in capturing regime changes, policy framers need to factor them into energy security strategies and pricing policies to mitigate the impact of such abrupt shifts in oil markets. Joint efforts of economists, energy scientists, and astrophysicists are possible in order to disclose the possible relationship between solar activity and oil prices. A fruitful line of future research may involve time-varying transition probabilities – such models may be able to capture changes in regime stability over time.

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