

An Examination of the Nonlinear Causal Relationship Between Oil Prices and Financial Instability Using the MS-VAR Model

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Abstract:

Objective: This study aims to investigate the nonlinear causal relationship between oil prices and financial instability in the United States. The analysis focuses on identifying regime-dependent dynamics that characterize the interactions between oil price movements and financial instability over time

Methods: The study utilizes monthly data from August 1998 to August 2023 to explore nonlinear dynamics using the Markov Switching Vector Autoregression (MS-VAR) model. This method allows the parameters of the model to change across distinct unobserved regimes (recession vs. boom), providing a flexible approach to analyzing regime-specific relationships. The model is estimated separately for two cases: (1) oil price as the dependent variable, and (2) financial instability index as the dependent variable.

Results: When oil price is the dependent variable, the intercept is negative and statistically significant at the 10% level in the first regime (recession), while it turns positive and significant in the second regime (boom). Conversely, in the model where the financial instability index is the dependent variable, the intercept is positive and significant in the first regime (boom) and negative and significant in the second regime (recession). The regime transition probability matrix indicates that the second regime is more stable and absorptive than the first. Additionally, the results show that during the first regime, there exists a bidirectional nonlinear causal relationship between oil price differences and financial instability. In contrast, the second regime exhibits a unidirectional nonlinear causality from oil prices to financial instability.

Conclusions: The findings underscore the importance of accounting for regime shifts in the relationship between oil prices and financial

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instability. The direction and intensity of causality vary depending on the prevailing economic conditions (boom or recession), highlighting the asymmetric and nonlinear nature of this interaction. Policymakers and investors should consider such regime-dependent dynamics when designing responses to oil market shocks or evaluating financial vulnerability.

1. Introduction

The interdependence between oil prices and financial instability in the United States constitutes a bilateral impact on the global economy. The price of oil, being a fundamental energy source and a fulcrum for global production and consumption, exerts a substantial influence on national economies and financial markets. Financial instability pertains to oscillations in the financial markets, which have the potential to impact fluctuations in oil prices. There are numerous and complex connections between oil prices and financial instability in the United States. These relationships may have both direct and indirect consequences. For instance, financial instability may result in a reduction in oil demand and, consequently, oil prices. Conversely, fluctuations in oil prices exert a direct influence on inflation, interest rates, and exchange rates. In theory, there are two potential channels through which oil price fluctuations could communicate their impact on financial instability: economic activity and investment behavior (Nazlioglu et al. 2015). The economy is negatively impacted by the escalation in oil price volatility due to the investment deferral caused by heightened uncertainty or the costly reallocation of sectoral resources (Rafiq et al. 2009). According to Bernanke (1983), it is preferable for corporations to delay irreversible investment expenditures when they are confronted with greater uncertainty regarding future oil prices. Investment decisions can be influenced by oil price volatility, as increased volatility in oil prices corresponds to heightened uncertainty regarding energy inputs, which subsequently impacts the final product of capital. The adverse consequences of oil price volatility on economic activity could potentially exert strain on credit markets, stock markets, and the finance sector as well (Sheng et al. 2023).

The economic justification for the impact of crude oil price shocks on the dynamics of the stock market is widely documented in the academic literature. Crude oil is by far the most strategic commodity on the planet and has become a significant component in determining geopolitical risks, macroeconomic trends, consumer sentiment, and corporate profitability. It is widely acknowledged that developments in the oil market exert a substantial influence on the worldwide economy and financial markets (Hamilton, 2009). In a theoretical sense, stock valuations may be influenced by oil price fluctuations via the following mechanisms: 1. through anticipated future cash flows since oil price shocks have the potential to exert strain on production expenses and induce unfavorable variations in consumer demand for goods; 2. via discount rates as increase in the

price of oil, frequently accompanied by inflationary pressures, which ultimately result in a higher discount rate and a subsequent decline in stock prices. Furthermore, economic growth concerns have contributed to the increased degree of co-movement between the oil and stock markets in recent years (Bernanke, 2016). Weak global demand has also contributed to the decline in oil prices and stock markets (Baumeister and Kilian, 2016). Based on the aforementioned factors, one could posit that variations in oil prices are partially indicative of investors' perceptions of forthcoming economic circumstances, which are subsequently mirrored in the risk premiums incorporated within the required rate of return (Demirer et al. 2020).

2. Literature Review

The response of financial stress to the shock of oil price fluctuations can provide insights into the impact of oil price fluctuations on financial markets in related studies, because financial stress is derived from various sources: 1. Financial markets (i.e., stockholders, bonds, money, foreign exchange, and hedging (derivatives)); 2. Financial intermediaries (i.e., banks, insurance, etc.); 3. Financial infrastructure (i.e., payment systems and settlement systems). The extant body of scholarly work concerning the Global Financial Crisis (GFC) designates it as a phase characterized by profound systemic financial stress, wherein financial system instability permeated the tangible economy and precipitated the Great Depression of 2007-2009 (Duprey et al. 2017). There is broad consensus that the Great Depression was precipitated in part by the severe stress in global financial markets that resulted from the global financial crisis and permeated the actual economy. Many economists deemed the Great Depression, which occurred prior to the global economic recession caused by the 2020 COVID-19 outbreak (COVID-19 Recession), to be the most grievous global economic crisis since the 1930s. Nonetheless, it is important to note that the economic crises triggered by COVID-19 and the global financial crisis differ significantly. As Harvey (2020) explains, COVID-19 is more accurately characterized as a “natural disaster” than a “global financial crisis” (where firms under financial stress are not mismanaged and there is no extensive structural damage to the economy), since it is in stark contrast to the global financial crisis, which ensued from the collapse of sizable financial institutions and inflicted substantial harm upon the financial system. Consequently, since the data sample in this paper encompasses both recession periods, it is intriguing to determine whether there are any potential differences in the impacts of oil volatility on financial stress between the Great Recession and the COVID-19 recession.

Limited research has been conducted on the impact of market volatility in non-financial sectors, specifically the influence of crude price uncertainty on financial stability. The transition of oil price uncertainty financial stress can be traced via two channels: the macro channel, which impacts economic activity, and the

micro channel, which influences investment and investment behavior. An oil price shock has the potential to exacerbate macroeconomic conditions and activity, as well as undermine macrofinancial stability via the banking system. Gkillas et al. (2020) investigated the relationship between financial stress and oil price fluctuations, focusing on the repercussions of financial stress. Additionally, the transmission of fluctuations between oil prices and financial stress was investigated by Nazlioglu et al. (2015). They advocated for a reciprocal risk transfer mechanism, whereby financial stress influenced oil price fluctuations and vice versa, prior to and following the crisis. They further posited that the volatility of the financial sector could impact investor sentiment and market movements by means of its influence on economic activities and investor behavior. Additionally, they argued that volatility in the energy market contributes to fluctuations in financial stress. An examination of the impact of oil price shocks on China's financial stress was conducted by Liu et al. (2021). Results indicated that, depending on the regime of fluctuations, oil shocks had a substantial impact on China's financial stress.

Production, inflation, and interest rates all contribute to the relationship between oil prices and financial markets. An increase in oil prices typically results in a decrease in anticipated economic growth and an escalation in inflation expectations for shorter time periods. As a result, a decline in economic growth prospects influences stock prices downward by reducing the income expectations of corporations. A shock in oil prices may impact development via the channel of consumption and disposable income, which is industry demand, or it may result in a surge in production costs and a reduction in industry supply (Edelstein and Kilian, 2009). As a consequence, a decline in aggregate demand will impact stock prices negatively through a reduction in the anticipated cash flows of companies. For an oil-exporting country, if the income effect of an increase in oil prices surpasses the increase in production costs, it will result in a positive income effect, higher aggregate demand, increased production, and elevated stock prices. In addition, investments and financial returns are impacted by the rise in short-term interest rates that ensues as a consequence of the escalation in oil prices-induced inflation. Lastly, oil price shocks have the potential to influence monetary policy, which in turn affects output, by influencing inflation (Montoro, 2012; Apostolakis et al. 2021).

According to Nguyen et al. (2018), lower oil prices are detrimental to riskier assets, such as stocks and high-yield bonds, but advantageous to secure assets, such as US long-term assets. In an investigation, Jarrett et al. (2019) demonstrate that superior financial institutions do, in fact, mitigate output volatility and reduce its adverse impact on growth during an ongoing period of low oil prices. Furthermore, Demiret et al. (2020) assert that the impact of oil price shocks extends beyond bond markets and not just stock market returns, even when discount rate shocks and the effects of the entire capital market are controlled for.

In contrast to stock markets, the impact on government bonds is comparatively variable in terms of magnitude and direction, with demand-related shocks constituting the primary catalyst.

Apostolakis et al. (2021) demonstrate that spillovers increased substantially during the COVID-19 outbreak, but did not surpass the magnitudes of the global financial crises of 2007. In conclusion, they assert that oil price uncertainty correlates with increased financial stress in certain G7 countries, whereas it does not correlate with economic policy uncertainty. Moreover, according to Gau et al. (2022), a rise in option-implied oil uncertainty is also associated with a forecast of a decline in the present and forthcoming rates of expansion for production, consumption, investment, and employment. Furthermore, they discovered that periods of elevated oil uncertainty are accompanied by a decline in stock market prices. Another study by Dagher and Hasanov (2023) demonstrates that the financial markets are extremely responsive to the source of oil price shocks (supply or demand). Less stress is experienced by financial markets when oil prices increase due to oil-specific demand shocks. Yet, as a consequence of oil-specific supply shocks, financial markets are subjected to greater stress. Additionally, Sheng et al. (2023) indicate that oil price fluctuations have a positive and stable effect on financial stress. Nevertheless, the magnitude and durability of the impacts of oil price volatility on financial stress throughout the Great Depression were considerably more pronounced in comparison to the COVID-19 recession.

According to the review of studies, the majority of prior research has examined the relationship between oil price and financial instability using either a steady state model with constant time or a linear causal relationship. Nevertheless, the examination of the nonlinear causal relationship in two distinct models has not been conducted. By analyzing the nonlinear causal relationship between financial instability and oil price volatility in two time-varying models using the MS-VAR model, this study contributes to the existing body of knowledge. MS-VAR models are utilized to capture discrete changes in the recent COVID-19 crisis. Also, in this study, according to Park et al. (2014), the financial instability index for the United States is computed through 5 primary components.¹ Hence, this research employs the Markov Switching Vector Autoregression (MS-VAR) model to examine the two-way nonlinear causal relationship between the oil price index and financial instability in the United States across two distinct models from 1998: to 2023:8.

3. Data

Utilizing the Markov Regime Switching Vector Autoregression (MSVAR) model, this study's objective is to examine the nonlinear causal relationship

¹. Data source: <https://aric.adb.org/database/fsi>

between financial instability and oil prices in the United States. MSVAR is based on the traditional VAR model and adds a Markov regime transition model, provides a more accurate description of the nonlinear time-varying attributes exhibited by financial time series. In addition, it is capable of autonomously segmenting the data into distinct regions in accordance with predetermined criteria and analyzing the interregional influence processes. The model under investigation is delineated as follows, following Dagher and Hasanov (2023):

$$X = (FSI, DLOIL) \quad (1)$$

The financial stress index (FSI) is a metric evaluated in accordance with the research of Park et al. (2014). It is composed of five primary components.¹

$$FSI = \beta + Stockreturns + Stockvolatility + Debtsreads + EMPI \quad (2)$$

1) Banking Sector (β)

The banking sector's risk relative to other economic sectors is evaluated using the beta coefficient, where r_m and r_b are the returns to the banking sector stock price index and the overall stock price index, respectively. A higher value indicates a higher stress level in the banking sector. This beta coefficient is

$$\text{expressed as } \beta = \frac{cov(r_m, r_b)}{var r_m}.$$

2) Equity Market Returns (Stock Returns)

$$r_t = \ln(y_t) - \ln(y_{t-1}) \quad (3)$$

Where r_t is the equity return in the current period, and r_{t-1} is the equity return in the previous period. A lower value indicates a higher stress level in the equity market.

3) Equity Market Volatility (Stock Volatility)

The volatility follows a GARCH (1,1) process and is given by equation 4:

$$\sigma_t^2 = \omega + \phi_1 \varepsilon_{t-1}^2 + \phi_2 \sigma_{t-1}^2 \quad (4)$$

Where σ^2 refers to the variance, and ε represents the error term in the regression is given by:

$$r_t = a_{i,t} + \beta r_{t-1} + \varepsilon_{i,t} \quad (5)$$

See definition of r_t and r_{t-1} in component 2. A higher value indicates a higher stress level in the equity market.

4) Sovereign Debt Spreads (Debt Spreads)

Sovereign debt spreads serve as an indicator of the level of government debt stress. With the information at hand, the data pertains to the yield disparity between short-term (2-year) local government bonds and long-term (10-year) local government bonds. A wider spread indicates a higher stress level in the debt market.

5) Stock Market Pressure Index (EMPI)

$$EMPI_{i,t} = \frac{(\Delta \varepsilon_{i,t} - \mu_{i,\Delta \varepsilon})}{\sigma_{i,\Delta \varepsilon}} - \frac{(\Delta RES_{i,t} - \mu_{i,\Delta RES})}{\sigma_{i,\Delta RES}} \quad (6)$$

¹. Data source: <https://aric.adb.org/database/fsi>

Where EMPI represents foreign exchange reserves and the depreciation of the local currency against the United States dollar. An elevated value signifies an increased degree of stress within the currency market.

Δe and ΔRES denote the monthly percentage fluctuations, respectively, in the foreign exchange rate of the domestic currency relative to the US dollar and foreign currency reserves; whereas σ and μ represent, respectively, the mean and standard deviation.

Figure 1 illustrates the level of financial instability in the USA from 1995:1 to 2023:8 using monthly data.

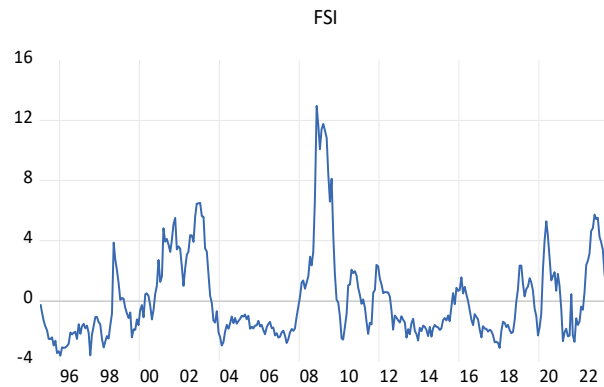


Figure 1. The financial instability of the USA from 1995:1 to 2023:8

Source: Asia Regional Integration Center

DLOIL is the difference in oil prices. The monthly crude oil price index of the first domestic purchase (in dollars per barrel), as published by the US Energy Information Administration (Source: <https://www.eia.gov/totalenergy/data/monthly/index.php>), is utilized to calculate this index.

Figures 2 and 3 illustrate the logarithm of the crude oil price and its difference from 1995:1 to 2023:8 as measured by the monthly data.

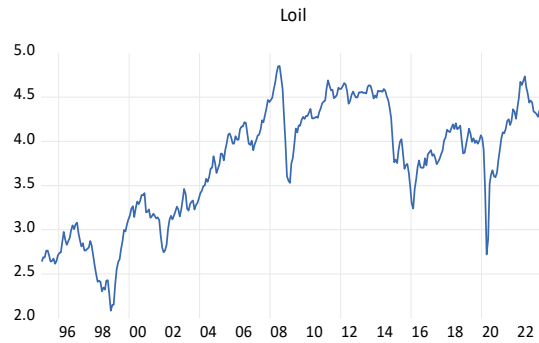


Figure 2. The value of the crude oil prices logarithm index in the United States from 1995:1 to 2023:8

Source: US Energy Information Administration

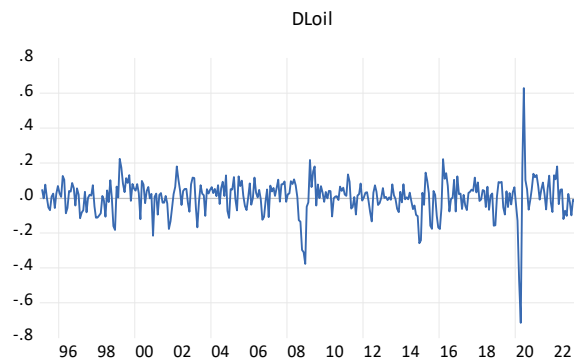


Figure 3. The value of the crude oil price difference in the United States from 1995:1 to 2023:8

Source: US Energy Information Administration

4. Research Methodology

To investigate the nonlinear relationship between crude oil prices and financial instability in the United States, this study employs the Markov Switching Vector Autoregressive (MS-VAR) model. The MS-VAR framework allows the model parameters—including intercepts, variances, and lag coefficients—to vary across unobservable regimes, typically interpreted as different phases of the economic cycle (e.g., recession vs. expansion). This flexibility enables a more accurate representation of the structural changes and regime-dependent dynamics that often characterize macro-financial time series.

The MS-VAR model assumes that regime shifts follow a first-order Markov process, making it well-suited for capturing structural breaks and non-linearities

in economic relationships. In what follows, the general specification of the MS-VAR(P) model with lag order p is introduced.

Equation 7 describes the MS-VAR(P) with lag p :

$$y_t = v(s_t) + A_1(s_t)(y_{t-1}) + \dots + A_p(s_t)(y_{t-p}) + u_t \quad (7)$$

$$u_t \sim i.i.d.N(0, \Sigma^{(s_t)})$$

Where s_t is the unobservable regime. The probability of switching from regime i to regime j is as follows:

$$p_{ij} = Pr(s_{t+1} = j | s_t = i), \quad \sum_{i=1}^m p_{ij} = 1, \quad \forall i, j \in \{1, 2, \dots, m\} \quad (8)$$

In which m represents the number of regimes. Assuming $m = 2$, the probability transformation matrix corresponding to the given value of m for regimes is as follows:

$$p = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

For every $i \in \{1, 2\}$, $p_{i1} + p_{i2} = 1$.

Assuming that the mean, variance, intercept, and coefficients of the equation can be changed, various innovative MS-VAR models can be obtained. For the two-regime system, the mean and variance of the adjusted innovative MSMH (2)-VAR (P) model with lag p order can be written as:

$$y_t - u(s_t) = A_1(y_{t-1} - u(s_{t-1})) + \dots + A_p(y_{t-p} - u(s_{t-p})) + u_t \quad (9)$$

Where $u(s_t)$ denotes the mean value under different regimes. $u_t \sim NID(0, \Sigma^{(s_t)})$. If $s_t = 1$, $u(s_t) = u_1$, and if $s_t = 2$, $u(s_t) = u_2$.

As indicated by Equation 9, a mean value increase will result from a regime switching. Possibly a more precise assumption is that the mean value attains a fresh level subsequent to the switch from regime i to regime j . Equation 10 represents the intercept and variance-adjusted innovative MSIH(2)-VAR(P) model for two-regime lag p -order:

$$y_t = v(s_t) + A_1(y_{t-1}) + \dots + A_p(y_{t-p}) + u_t \quad (10)$$

In which $v(s_t)$ denotes the intercept in each regime, $u_t \sim NID(0, \Sigma^{(s_t)})$. If $s_t = 1$, $v(s_t) = v_1$ and if $s_t = 2$, $v(s_t) = v_2$.

In order to confirm the validity of the MS(q)-VAR(q) model's conclusion, which incorporates regime q lag p , the method of multiple linear regression is applied to the relationship between oil prices and financial instability. With respect to the primary objective of this study, which is to investigate the two-way nonlinear causal relationship between the financial stress index (FSI) and the crude oil price difference index (DLOIL), both are included as dependent variables in the regression equation. Given that the financial stress index (FSI) consists of five indicators, the regression equation does not incorporate any additional control variables.

5. Model estimation and results

5.1. Examining the Variables' Stationarity

Prior to estimating the model, it is essential to verify the stationarity of the research variables in time series analysis. Given that all variables utilized in the nonlinear vector autoregression approach of MS-VAR must be stationary, so if the variable is non-stationary, its difference should be used in modeling. The results of the Augmented Dickey-Fuller (ADF) unit root test, which was conducted to assess the stationarity of the variables, are presented in Table 1.

Table 1. The results of the stationarity test of the variables

Variable	With intercept in the level	
	T-statistic	P-value
FSI	-3.7391	0.0040
LOIL	-2.0318	0.2732
DLOIL	-12.4342	0.0000

Source: Research calculations and findings

The findings from the unit root test indicate that the FSI variable is stationary at the level, but the LOIL becomes stationary in I (1). Consequently, the model incorporates two stationary variables, namely financial stress index (FSI) and the crude oil price difference (DLOIL). Due to the fact that the logarithm of crude oil price is not stationary at level and is stationary in I (1), it is necessary to conduct Johansen's cointegration test in order to examine the long-term.

5.2. Johansen-Juselius Cointegration Test

Due to the fact that one of the variables in the model becomes stationary in I (1), the Johansen-Juselius cointegration test can be used to determine the cointegration vectors. By selecting the optimal lag value of 4 for the vector autoregression model, the trace matrix and maximum eigenvalue tests were utilized to ascertain the number of cointegration vectors. The results of the two experiments conducted in the model to ascertain the quantity of co-integration vectors are presented in Table 2.

According to Table 4, consistent with the results of the trace matrix and maximum eigen value tests, a cointegration vector has been detected among the model's variables.

Table 2. Test of the number of cointegration vectors

Effect test					
H0	Alternative hypothesis	Eigenvector	Statistic	Critical value at the 5% level	P-value at the 5% level
$r = 0$	$r \geq 1$	0.057321	23.267	15.494	0.002
$r \leq 1$	$r \geq 2$	0.009560	3.2563	3.8414	0.071
Test of maximum eigenvalues					
H0	Alternative hypothesis	Eigenvector	Statistic	Critical value at the 5% level	P-value at the 5% level
$r = 0$	$r = 1$	0.057321	20.011	14.264	0.005
$r \leq 1$	$r = 2$	0.009560	3.2563	3.8414	0.07

Source: Research calculations and findings

5.3. MS-VAR Model Estimation

Prior to specifying the MS-VAR model, the optimal model is utilized to ascertain the regime and lag. The model exhibiting the lowest Akaike criterion yields the most significant results. The intercept and autoregression coefficients of this model depend on the regime. Furthermore, lag 4 is deemed the optimal lag for the intended model, as the stability of the regime and the significance of the variables could not be confirmed by the other lags. The findings pertaining to the selection of the optimal regime in accordance with the Akaike criterion are displayed in Table 3.

Table 3. Akaike statistic to determine the optimal lag

Akaike criterion (AIC)	Number of lags
0.51193	1
0.49367	2
0.51755	3
0.42236*	4

Source: Research calculations and findings

Based on the findings presented in Table 3, the optimal lag is identified as lag 4 that possesses the smallest Akaike value.

Table 4. Estimation results of MS (2)-VAR (4) model

Model 1: Dependent variable: crude oil price difference (DLOIL)					
Regime 1			Regime 2		
Variable	Coefficient	T-statistic	Variable	Coefficient	T-statistic
<i>Constant(0)</i>	-0.0256	-1.79	<i>Constant(1)</i>	0.0261	5.20
<i>DLOIL_1(0)</i>	1.0073	8.60	<i>DLOIL_1(1)</i>	0.0159	0.287
<i>DLOIL_2(0)</i>	-0.3302	-2.18	<i>DLOIL_2(1)</i>	0.0020	0.036
<i>DLOIL_3(0)</i>	-0.2464	-1.45	<i>DLOIL_3(1)</i>	-0.0698	-1.43
<i>DLOIL_4(0)</i>	-0.2046	-1.08	<i>DLOIL_4(1)</i>	-0.0351	-0.74
<i>FSI_1(0)</i>	-0.0222	-2.35	<i>FSI_1(1)</i>	0.0053	0.790
<i>FSI_2(0)</i>	0.0300	0.354	<i>FSI_2(1)</i>	0.0033	2.29
<i>FSI_3(0)</i>	-0.0252	-1.78	<i>FSI_3(1)</i>	-0.0080	-0.35
<i>FSI_4(0)</i>	0.0242	2.25	<i>FSI_4(1)</i>	-0.0008	-0.13

Model 2: Dependent variable: financial instability index (FSI)					
Regime 1			Regime 2		
Variable	Coefficient	T-statistic	Variable	Coefficient	T-statistic
<i>Constant</i> (0)	0.3214	1.72	<i>Constant</i> (1)	-0.0936	-2.00
<i>DLOIL_1</i> (0)	-3.7497	-2.56	<i>DLOIL_1</i> (1)	-0.1723	-0.33
<i>DLOIL_2</i> (0)	4.3217	2.27	<i>DLOIL_2</i> (1)	-0.6684	-1.22
<i>DLOIL_3</i> (0)	-6.7483	-3.06	<i>DLOIL_3</i> (1)	1.0152	2.14
<i>DLOIL_4</i> (0)	2.787	1.27	<i>DLOIL_4</i> (1)	0.8058	1.82
<i>FSI_1</i> (0)	1.0953	8.71	<i>FSI_1</i> (1)	1.0134	15.2
<i>FSI_2</i> (0)	-0.4363	-2.46	<i>FSI_2</i> (1)	0.108	1.14
<i>FSI_3</i> (0)	0.4319	2.24	<i>FSI_3</i> (1)	-0.1550	1.79
<i>FSI_4</i> (0)	-0.2173	-1.55	<i>FSI_4</i> (1)	-0.0561	-1.02
Linearity LR – test $\chi^2(20) = 248.95 [0.0000] **$					
approximate upperbound: [0.000] **					

* indicates the optimal lag and variable used.

Source: Research calculations and findings

Based on the data presented in Table 4, it is evident that the first stage yielded a probability value of less than 1% for the χ^2 test. Consequently, this value provides confirmation that the relationship between the variables is nonlinear. According to Hamilton (1994), a recession regime is denoted by a negative intercept, while a boom regime is indicated by a positive intercept. In the first regime, the intercept (*Constant*) in the model where the dependent variable is oil price is negative and statistically significant at the 10% level. However, in the second regime, it becomes positive and statistically significant. As a result, the first regime in this first model corresponds to the recession regime, while the second regime represents the boom regime. Furthermore, in the first regime, the impact of financial instability (*FSI_4*) featuring lag 4 (optimal lag) on the crude oil price difference is positive and statistically significant, resulting in an increase in crude oil prices. During the first regime (recession), this effect can be described as follows: A rise in financial instability has engendered a decline in investor confidence, and this precarious confidence may subsequently curtail investment in the crude oil sector, thereby resulting in a reduction in crude oil supply on the market and a subsequent escalation in price. Additionally, financial instability during a recession may reduce crude oil demand due to a decline in industrial production and transportation. The reduction in demand for crude oil results in a corresponding decrease in supply and an increase in its price. However, financial instability (*FSI_4*) with lag 4 (optimal lag) on crude oil price difference is negative and insignificant under the second regime. The obtained outcomes align with the anticipated theoretical expectations.

Furthermore, the findings indicate that the impact of the fourth lag (optimal lag) of the price of the crude oil on the crude oil price difference (*DLOIL_4*) is negative and insignificant in both regimes. This effect can be represented as follows: a previous increase in the price of crude oil results in a subsequent

decrease in its quantity during the current period. Yet, due to its insignificance in the 4th lag, this effect warrants cautious analysis.

Furthermore, in the first regime, the intercept (*Constant*) in the model where the dependent variable is the financial instability index is positive and statistically significant at the 10% level. However, in the second regime, it becomes negative and statistically significant. As a result, the first regime in this second model corresponds to the boom regime, while the second regime represents recession. Furthermore, the financial instability index is positively impacted by the crude oil price difference (*DLOIL_4*) with lag 4 (optimal lag) in both boom and recession regimes. This effect contributes to an increase in financial instability, which is insignificant in the first regime but significant in the second at the 10% level (It is statistically significant in the preceding lags as well). This effect can be represented as follows: fuel and petroleum product prices are directly impacted by the price increase of crude oil. The production and transportation expenses for these products increase as a result of the price increase. Consequences include increased prices for fuel and petroleum products for final consumers. Indeed, rising crude oil price differences reduce economic activity, may put pressure on credit markets, and adversely affect stock markets and the banking system, all of which contribute to heightened financial instability. The findings of this research align with those of Dagher and Hasanov (2023) and Sheng et al. (2023).

Moreover, the results indicate that the effect of the fourth lag (optimal lag) of the financial instability index (*FSI_4*) on the financial instability index itself is negative and insignificant in both regimes, but in the preceding lags this effect is significant. This effect can be expressed by a reduction in current financial volatility that can be observed as a consequence of a previous escalation in such instability.

Table 5. Likelihood of regime switching

Regime	<i>Regime 0, t</i> (first regime)	<i>Regime 1, t</i> (second regime)
<i>Regime 0, t + 1</i> (first regime)	0.63586	0.13734
<i>Regime 1, t + 1</i> (second regime)	0.36414	0.86266

Source: Research calculations and findings

Based on the information presented in Table 5, the probability matrix indicates that in regime 1 during period t (the current period), the likelihood of remaining in regime 1 (*Regime 0* denoting the recession regime for the crude oil price difference and the boom regime for the financial instability index) is 0.63586. Additionally, the probability of switching to the second regime (*Regime 1*, representing the recession regime for the financial instability index and the boom regime for the crude oil price difference) is 0.36414. Furthermore, the findings indicate that with a probability of 0.13734, individuals remaining in regime 2 at

time t will move to regime 1, while the probability of remaining in regime 2 is 0.86266. Hence, based on the findings, it can be concluded that regime 2 exhibits greater stability in comparison to regime 1. Specifically, the likelihood of remaining in regime 1 is 0.63586, while the likelihood of remaining in regime 2 is 0.86266. Consequently, the second regime possesses a greater absorptive than the first regime.

The estimated model error terms for two variables—crude oil price difference (*DLOIL*) and financial stress index (*FSI*)—are normalized in Figure 4. Normalization is achieved through dividing the actual value of the error terms by the standard deviation of the error terms in the regime containing the desired observation. Normalization is performed so that there is no distinction between the first error terms of the regression and the normalized error terms when the standard deviation or variance of the error terms is not dependent on the regime. In essence, the standard deviation of the error terms is calculated by dividing each value of the error terms by a constant number, namely the error terms' standard deviation. The distinction emerges when we consider it as a function of the regime. As a result of dividing each value of the error terms by the standard deviation of the regime in which it is situated, a distinction arises between the first regression error terms and the normalized error terms in this particular instance. Normalization is performed to enable comparisons of errors across various regimes.



Figure 4. Normalization of the estimated model error terms using the MS (2)-VAR (4) model estimation results

Source: Research calculations and findings

Figure 5 depicts the Actual values, the fitted values, 1-step prediction and observations assigned to regime 1. In this figure, the red line represents the actual values of the Financial Stress Index (FSI) and crude oil price difference (*DLOIL*), which are the dependent variables. The fitted value or explained value of the model is represented by the blue line. When the line representing the fitted values aligns with the actual values, it indicates that the model possesses sufficient

explanatory capability. Errors terms signify the disparity that arises when the fitted values deviate from the actual values. 1-step prediction, which also refers to forecasting the subsequent period, utilizes all the information available up to period $t-1$ to derive the observed value of period t . One distinction between the fitted values and the predicted values of a subsequent period (1-step prediction) is that the fitted values are computed using the complete set of information contained in the sample or the observations. For the computation of forecast values for a period following observations, values from 1 to $t-1$ are utilized.

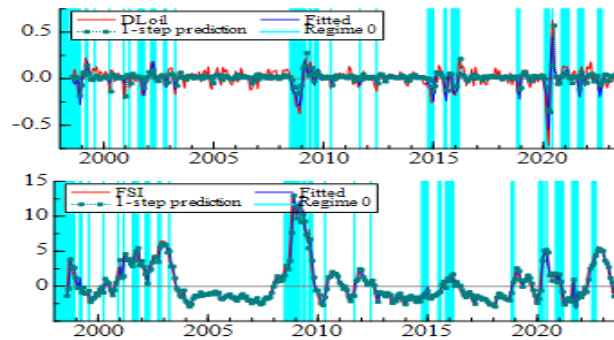


Figure 5. Actual values, fitted values, 1-step prediction, and observations assigned to regime 1 in accordance with the estimation results of the MS (2)-VAR (4) model

Source: Research calculations and findings

Figures 6 and 7 illustrate the smoothed probabilities and distribution of observations in regimes 1 and 2, respectively. The Markov switching model utilizes smoothed probabilities to partition observations between regimes. Considering the increased probability that observation t could be in any of the regimes, it is accordingly designated to that regime. Contrary to structural failure models, which define the war period as an exogenous variable, the Markov switching model partitions regimes endogenously through the utilization of probabilities and the data's structure.

Figure 6 illustrates the observations belonging to regime 1, denoted as **Regime 0**, which corresponds to the boom regime of the financial instability index and the recession regime of the crude oil price difference. Conversely, Figure 7 presents the observations belonging to regime 2, denoted as **Regime 1**, signifies the recession regime of the financial instability index and the boom regime of the crude oil price difference. In these figures, the red lines correspond to the smoothed probabilities. To facilitate comprehension of the smoothed probabilities associated with the first observation, Figure 6 indicates that it is situated in regime 1 with a 0.64073 probability and in regime 2 with a 0.35927 probability. It is evident that the sum of these probabilities should equal one; the

reason for that is clear, the observations can either be in regime 1 or regime 2. Thus, the overall probability of being in either of these two regimes is one. As was previously stated, the observation will be attributed to the regime with the greater calculated probabilities. Given that the probability of being assigned to regime 1 is 0.64073, the first observation of the sample will inevitably be assigned to regime 1. The presence of blue areas delineating the first observation and subsequent observations encompassed within this regime is visually represented. As depicted in Figure 7, the grey color signifies observations that are within regime 2.

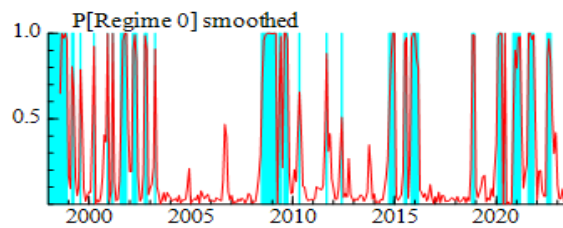


Figure 6. The years associated with the probability of being in the first regime as estimated by the MS (2)-VAR (4) model

Source: Research calculations and findings

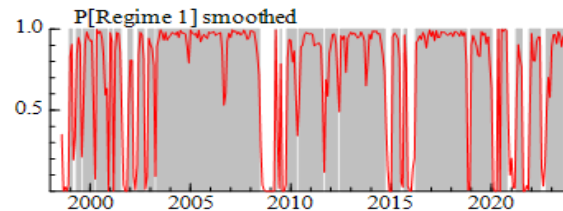


Figure 7. The years associated with the probability of being in the second regime as estimated by the MS (2)-VAR (4) model

Source: Research calculations and findings

Table 6. The results of the causal relationship between the statistic value (χ^2) and the probability value

Independent variable Dependent variable	Regime 1		Regime 2	
	DLOIL	FSI	DLOIL	FSI
DLCOMM	96.5828 (0.0000)	12.3803 (0.0147)	3.93557 (0.4148)	4.60155 (0.3307)
FSI	14.7556 (0.0052)	368.929 (0.0000)	16.8912 (0.0020)	2089.01 (0.0000)

The numbers in parentheses indicate the probability value.

Source: Research calculations and findings

The two-way nonlinear causal relationship between crude oil price difference (DLOIL) and financial stress index (FSI) in the first regime is illustrated in Table 6. These two factors may contribute to an explanation for the reciprocal causal

relationship between crude oil price difference and financial instability in the United States. This relationship demonstrates that fluctuations in crude oil price difference can significantly affect financial instability in the United States. Conversely, an upsurge in crude oil price difference has the opposite effect, diminishing economic activity and potentially exerting strain on credit markets, stocks, and banking systems, all of which contribute to financial instability. Indeed, periods of severe financial stress result in a deceleration of economic activity, which subsequently curbs energy demand and reduces crude oil price difference. Crude oil markets are regarded by investors as alternative investment sectors to financial markets. The reactions of investors to fluctuations in energy prices will have an impact on the valuation of financial assets. However, escalating financial stress also induces investors to modify their portfolios, which has an impact on the crude oil markets. Financial stress exerts an influence on economic activity via the bank lending channel by diminishing the quantity of accessible credit, as well as via financial leverage by means of alterations in the creditworthiness of borrower enterprises. Consistent with the findings of the investigation by Nazlioglu et al. (2015) is this result. However, within the second regime, a one-way nonlinear causal relationship exists between the price of crude oil and financial instability. It is also possible to contend that as the price of crude oil rises, the expenses associated with production and transportation for businesses operating in the oil industry will also escalate. The escalation in expenses may precipitate a decline in corporate profitability and, consequently, financial instability. This may result in financial instability due to factors including a decline in investment, an increase in debt, and a reduction in competitiveness. Additionally, a crude oil price difference increase may have significant repercussions for the national economy. The United States, being a major consumer and importer of crude oil globally, is susceptible to the effects of crude oil price difference fluctuations on inflation, economic growth, and productivity rates. Energy costs will increase for both producers and consumers in the event of a crude oil price difference increase. This can diminish both the purchasing power of individuals and the profitability of businesses. Financial instability and rising interest rates may ensue as a consequence. The findings of this research align with those of Dagher and Hasanov (2023) and Sheng et al. (2023).

In conclusion, the crude oil price difference index (DLOIL) is the Grangerian causality of the crude oil price difference variable in the first regime of the preceding interruptions; however, this relationship is not demonstrated in the second regime. Furthermore, the findings indicate that the previous lags of the financial stress index (FSI) serve as the Granger causality for the FSI variable in both regimes, and that the financial stress index (FSI) and the previous lags have a two-way causal relationship in both regimes. Therefore, it can be stated that the

variables under investigation exhibit nonlinear Grangerian causality within the context of the United States.

6. Conclusion and Recommendations

Using monthly data from 1998:8 to 2023:8, this study aimed to investigate the nonlinear causal relationship between crude oil price and financial instability in the United States. In order to examine the nonlinear causal relationship, the nonlinear Markov Switching Vector Autoregression (MS-VAR) model was employed. In the first regime, the results indicate that the intercept in the model where oil price is the dependent variable is negative and statistically significant at the 10% level. However, in the second regime, the intercept is positive and statistically significant. As a result, the first regime in this first model corresponds to the recession regime, while the second regime represents the boom regime. Additionally, in the first regime, the first intercept in the model where the dependent variable is the financial instability index is positive and statistically significant at the 10% level. However, in the second regime, it becomes negative and statistically significant. As a result, the first regime within this second model represents boom, whereas the subsequent regime represents recession. Furthermore, the probability matrix results indicate that the second regime is more stable and absorptive than the first regime. In accordance with the findings of Nazlioglu et al. (2015), the results of the nonlinear causal relationship indicate that the oil price and the financial instability index have a two-way nonlinear causal relationship in the first regime. However, under the second regime, a one-way nonlinear causal relationship exists between oil price fluctuations and financial instability. This effect can be stated as follows: a rise in crude oil price may result in higher energy expenses for both consumers and producers in the United States. Consequently, this may decrease the purchasing power of individuals and the profitability of businesses, ultimately contributing to financial instability and economic apprehensions. The findings of this research align with those of Dagher and Hasanov (2023) and Sheng et al. (2023).

Given that financial instability affects crude oil prices in the United States, prudent monetary and financial policies, as well as regulation and strict oversight of financial markets, are necessary to control financial instability and its effects on the global financial markets. Additionally, economic policies and legal frameworks that are suitable can aid in mitigating the impact of financial instability on crude oil price. Furthermore, given the correlation between escalating crude oil price and financial instability in the United States, it is advisable to diversify economic sectors and foster the growth of new industries—both of which are critical in mitigating reliance on crude oil and financial instability—in order to mitigate this effect.

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بررسی رابطه علی غیرخطی میان قیمت نفت و بی ثباتی مالی در ایالات متحده با استفاده از مدل MS-VAR

هدف: هدف این مطالعه بررسی رابطه علی غیرخطی میان قیمت نفت و بی ثباتی مالی در ایالات متحده است. این تحلیل بر شناسایی پویایی‌های وابسته به رژیم تمرکز دارد؛ پویایی‌هایی که ویژگی‌های متقابل میان نوسانات قیمت نفت و بی ثباتی مالی را در گذر زمان تبیین می‌کنند.

روش‌شناسی: این مطالعه با استفاده از داده‌های ماهانه طی بازه زمانی آگوست ۱۹۹۸ تا آگوست ۲۰۲۳، به بررسی پویایی‌های غیرخطی می‌پردازد. مدل مورد استفاده، مدل خودرگرسیون برداری با تغییر رژیم مارکوف (MS-VAR) است که به مدل اجازه می‌دهد پارامترهای خود را در رژیم‌های پنهان مختلف (مانند رکود یا رونق) تغییر دهد. این مدل به صورت جداگانه برای دو حالت تخمین زده شده است: (۱) زمانی که قیمت نفت متغیر وابسته است و (۲) زمانی که شاخص بی ثباتی مالی متغیر وابسته است.

یافته‌ها: زمانی که قیمت نفت به عنوان متغیر وابسته در نظر گرفته می‌شود، عرض از مبدأ در رژیم اول (رکود) منفی و در سطح ۱۰ درصد معنادار است، در حالی که در رژیم دوم (رونق) مثبت و معنادار است. در مقابل، زمانی که شاخص بی ثباتی مالی متغیر وابسته باشد، عرض از مبدأ در رژیم اول (رونق) مثبت و معنادار و در رژیم دوم (رکود) منفی و معنادار است. ماتریس احتمال گذار میان رژیم‌ها نشان می‌دهد که رژیم دوم پایدارتر و جذب‌کننده‌تر از رژیم اول است. همچنین، نتایج نشان می‌دهند که در رژیم اول، یک رابطه علی غیرخطی دوطرفه میان تفاوت قیمت نفت و شاخص بی ثباتی مالی وجود دارد، در حالی که در رژیم دوم، رابطه علی غیرخطی یک‌طرفه از قیمت نفت به بی ثباتی مالی برقرار است.

نتیجه‌گیری: یافته‌های این تحقیق بر ضرورت در نظر گرفتن تغییر رژیم‌ها در تحلیل روابط بین قیمت نفت و بی ثباتی مالی تأکید دارند. جهت و شدت رابطه علی میان این متغیرها بسته به شرایط اقتصادی (رونق یا رکود) متفاوت است و این مسأله نشان‌دهنده ماهیت نامتقارن و غیرخطی این تعامل است. سیاست‌گذاران و سرمایه‌گذاران باید چنین پویایی‌های وابسته به رژیم را در طراحی واکنش به شوک‌های بازار نفت و ارزیابی آسیب‌پذیری مالی مدنظر قرار دهند.

واژگان کلیدی: بی ثباتی مالی، قیمت نفت، رابطه علی غیرخطی، مدل MS-VAR، ایالات متحده آمریکا.

طبقه‌بندی JEL: G01، Q43