The Dynamic Impact of Oil Prices on Investor Behavior: Evidence from US states

BOUHAF IBTIHAL, university ghardaia, (Algeria), bouhafs.ibtihal@univ-ghardaia.edu.dz

NAAS SALAH EDDINE[*]*, university ghardaia, (Algeria), naas.salaheddine@univ-ghardaia.edu.dz*

Received: 08/01/2025 *Accepted: 28/03/2025* *Published:30/03/2025*

Abstract:

This research aims to study the dynamic correlation correlation between oil prices and US investor sentiment, the study applied GARCH models and DCC-GARCH models to Weekly data during the period from January 2010 to July 2023. The results concluded that oil price fluctuation appositively affect the fluctuations of US investor sentiment, and there is a dynamic conditional correlation over time between the tow variables.

Keywords: Investor sentiment; oil price; volatility; DCC-GARCH Model.

Jel Classification Codes: C15, E44, E37, G10.

[*] *Corresponding author*

1. INTRODUCTION

Oil has long been recognized as the lifeblood of industry, serving as the primary rawmaterial for industrial production. Crudeoil is a vital resource and plays a fundamental role in economic activitiesworldwide. Its markets are characterized by rapid and unpredictable changes and developments, as its prices are frequentlysubject to sharp and sudden fluctuations. These fluctuations significantly impact the economies and stability of oil-exporting and oil-importing countries. Recently, these markets have witnessedunprecedented disruptions due to the widespreadoutbreak of the COVID-19 pandemic. Furthermore, complex and profound economic and political shifts, such as the war between Russia and Ukraine and the political tensions between China and India, have escalated global political and economic uncertainty. Consequently, these factors have led to a significant increase in crude oil price volatility, adversely affecting market sentiment at both regional and global levels.

In recent years, investor sentiment has evolved into a newly emerging concept in the crudeoil market. Investor sentiment is, in fact, one of the most critical factors influencing financial markets. Studies have indicated that oil price shocks can delay or alter key decisions related to production and consumption, which, in turn, can impact market sentiment. Accordingly, the central focus of this research is to explore the potential effects of oil price volatility on the sentiment of American investors, using Weekly data spanning the period from 2010 to 2023.Building on the above, this research is based on the following hypothesis:

- *H_1: there is a dynamic conditional correlation between global oil prices and the behavior of American investors during the study period.*

2. Theoretical Framework and Literature Review

2.1 The Concept of Investor Behavior

Behavioral finance theory has sought to study and understand the behavior of individual investors in financial markets and the extent to which their actions influence investment decisions. Emerging initially as a

conceptualideain 1841, behavioral finance successfullycaptured the attention and interest of researchers, prompting studies on the key factors that significantly affect investment decisions and, consequently, market performance.

Numerous studies have concluded that investor behavior plays a crucial role in understanding market fluctuations and instability. This is primarily due to psychologicalerrors made by investors, which in turn influence their decision-making behavior. Behavioral finance has provided insights into how investors make their investment decisions and why these decisions are not always consistent. This inconsistency is attributed to the emergence of behavioral biases that lead to irrationality in decision-making.

Many researchers consider investor sentiment bias among the most influential behavioral biases affecting investment decisions. According to Hung and Ho (2009), investor sentiment is defined as “a state reflecting their beliefs about the current market condition and their expectations for its future state”.Similarly, Ling et al. (2010) described it as “the irrational components of investors' expectations”.

As noted by Loewenstein and Rick (2008), sentiment plays a significant role in investment decision-making, oftendriving investor behavior in various directions. They argued that sentiment arises from factors unrelated to decision-making processes but ultimatelyexertsconsiderable influence on them.

Lo and Repin (2002) explored whether sentiment plays an essential role in decision-making. They gathered data on physiological characteristics associated with emotionalresponses and found that significant economic events (such as heightened price volatility) could amplify investor emotions. They stated that the ability to make quick decisions influenced by psychological states is critical to derivingsuccess as an investor. However, their study did not confirm whether heightenedemotionalresponses are associated with positive or negative investor performance (BOUHAFS, 2024).

2.2The Evolution of Crude Oil Prices

The crude oil market is characterized by periods of fluctuation,

alternating between phases of rising demand coupled with limited supply, resulting in an increase in crudeoil prices. This leads to higher revenues for oil-exporting countries, whileenergytaxburdensrise for consuming countries. Conversely, there are periods of declining demand accompanied by an oversupply, causing a drop in revenues for exporting countries and a reduction in energytaxburdens for consuming countries. These fluctuations can sometimes be moderate and steady, while at other times, they manifest as severe and intense. In economic literature, such significant variations are referred to as "oil shocks" by consumer nations, whileproducer nations describe them as "oil price adjustments" (Al-Salhi, 2016).

Given the critical importance of oil to the global economy, its fluctuations have been a major concern for economistssince the pioneering work of Hamilton (1983). Undoubtedly, in economiesheavily reliant on oil, significant changes in oil prices are likely to trigger both psychological and tangible effects in the stock market through two interconnectedyet distinct transmission channels: one through the public sector and the other through the private sector (Jadwa Investment, 2015). The oil markets have experiencednumerous price fluctuations from 1973 to the present. These fluctuations were driven by various factors, including changes in OPEC policies (supply and demand), global economic recessions, geopolitical factors, or global financial crises. More recently, global oil markets have facedunprecedented disruptions, includingclimate change events, the COVID-19 pandemic, and Russia’s recent operations in Ukraine. These disruptions have led to a significant increase in crudeoil price volatility, compounded by geopolitical complexities, inflationary pressures, and disturbances in traditional supply chains. The global oil market has sincereturned to a state of normalcy, experiencing a strong rebound after enduring a challenging economic yearin 2020, as indicated by severalindicators. This recovery is attributed to increased demand coupled with constrained production.

2.3 The Relationship Between Oil Price Volatility and Investor Sentiment

Numerous studies have examined the impact of oil price volatility on

economic variables, yetfewer have specifically focused on the relationship between oil markets and changes in investor sentiment. Using the SVAR model, (Ding, Liu, Zhang, & Long, 2017) demonstrated that oil price volatility negatively affects investor sentiment in the Chinese stock market. Their findings also revealed the presence of investor sentiment contagion triggered by fluctuations in international crude oil prices.

In a related study, (He & Zhou, 2018) investigated the correlation between oil prices and market sentiment through causality tests, the TVP-VAR model, and the NARDL model. Their results indicated that changes in oil prices cause both linear and nonlinear shifts in investor behavior. Furthermore, the study highlighted that oil shocks influence sentiment over time.

(Apergis, Cooray, & Rehman, 2018) aimed to explore whether energy prices (crudeoil and naturalgas prices) affect the sentiment of American investors. Using the quantile regression methodology, their results revealed a statistically significant relationship between crudeoil and naturalgas prices and investor sentiment.

Similarly (Yıldırım, Erdoğan, & Çevik, 2018) examined the responsiveness of BRICS stock markets to oil price shocks. Employing the MS-VAR model (impulse response functions) on monthly data spanning from January 1995 to December 2016, the study found that stock markets in all BRICS countries, except China, exhibited a positive and statistically significant response to unexpectedoil price shocks.

Finally,(Ji, Li, & Sun, 2019) analyzed the correlation between West Texas Intermediate (WTI) crudeoil prices and investor sentiment indices. Their findings indicated a strong correlation between sentiment—categorized by trader type—and WTI returns. Additionally, the study concluded that the influence of investor sentiment becomes significantly more pronounced during periods of decliningoil prices.

Using the TVP-SVAR and NARDL models, the study by (He, Zhou, & et al, 2019)found a bidirectional linear relationship between oil prices and individual investor sentiment, with the interaction evolving over time. The study also concluded that oil prices generally have a negative impact

on individual investor sentiment and that the short- and long-term effects of oil prices on individual investor sentiment are asymmetric. However, the impact of individual investor sentiment on oil prices was found to be symmetric.

In contrast, the study by(Li & Ouyang, 2021), based on an investor sentiment index derived from the monthlysurvey conducted by the China Securities Investor Protection Fund Corporation, used a Bayesian Structural Vector Autoregression (SVAR) model to examine the effects of structural shocks in oil prices on sentiment. Their findings revealed the opposite: supply and consumer demand shocks have a positive effect on Chinese investor sentiment. The impact primarily operates by influencing investor confidence in China's economic fundamentals and the international economic environment.

The study by (Ye, Hu, & et al, 2020)constructed an investor sentiment index by decomposingcrudeoil prices into three types of shocks using the SVAR model. It examined the dynamic relationship between investor sentiment and oil price shocks comprehensivelyacross time and frequencydomains through waveletcoherence analysis. The results indicated a co-movement between crudeoil prices and investor sentiment and demonstrated that the co-movement patterns between oil price shocks and investor sentiment vary over time and frequency.

Finally, the study by(Li, Huang, & Failler, 2022)sought to explore the dynamic relationship between crudeoil price shocks and investor sentiment during the period 2013–2021. The researchersconstructed a Chinese investor confidence index using textual data and employed the SVAR and WTC models to analyze the dynamic correlation between crudeoil prices and investor sentiment across time and frequencydomains. The findings revealed heterogeneous dynamic correlations and laggedrelationships between crudeoil prices and investor sentiment. Furthermore, the study concluded that there are asymmetric and lagged dynamic relationships between crudeoil prices and investor sentiment under different price trends.

3. Methodology and Tools

3.1 Data Sources

The study utilized Weekly data for the U.S. investor sentiment index, specifically the bullish and bearish sentiment indicators, obtained from the website aaii.com. Additionally, a monthly series of oil price volatility (OVX) was retrieved from investing.com. The data covers the period from January 2010 to July 2023.

3.2 Model Used

To achieve the study's objectives, we employed univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models as well as multivariate Dynamic Conditional Correlation (DCC-GARCH) models.

This model was developed by Engle (2002) to detect potential changes in conditional correlations over time. This model assumes that the time series follows a normal distribution with a mean equal to zero and a conditional variance H_t. It operates in two steps: first, estimating the GARCH model, and then estimating the conditional correlations as follows (Naas, Bensania, & Bendob, 2019):

$$\boldsymbol{r_t = \mu_t + \varepsilon_t \text{‘} \frac{\varepsilon_t}{\Omega_{t-1}} \rightarrow N(0, H_t)}$$

$$\boldsymbol{H_t = D_t R_t D_t}$$

Where r_t represents a matrix of order (K ×1), ε_t are the residuals and represent a matrix of order (K ×1), Ω_{t-1} represents a matrix of all information available up to time t, $H_t$is the conditional covariance matrix, D_t is a diagonal matrix of order (K×K) for the time-varying standard deviations derived from the GARCH model, and R_t represents the time-varying conditional correlation matrix (K×K). The matrices D_t and $R_t$are determined as follows:

$$\boldsymbol{D_t = diag\left(\sqrt{\sigma_{ii,t}}, \ldots\ldots, \sqrt{\sigma_{kk,t}}\right)}$$

$$\boldsymbol{R_t = \left(diag(\, Q_t)\right)^{-\frac{1}{2}} Q_t \left(diag(\, Q_t)\right)^{-\frac{1}{2}}}$$

$Q_t = (q_{ij,t})$ represents a symmetric and positive-definite conditional covariance matrix of order (K×K) and is expressed as follows:

$$\boldsymbol{Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\mu_{t-1}\mu'_{t-1}) + \beta Q_{t-1}}$$

μ_{t-1}represents the standardizedresiduals, while$\overline{Q} = E(\mu_{t-1}\mu'_{t-1})$represents the unconditional covariance matrix of the errors μ_{it} of order (K×K). αandβ are the unknownparameters to be estimated in the model. For the conditional covariance matrix to be positive definite, it must hold that $\alpha > 0$; $\beta \geq 0$; and $\beta + \alpha < 1$. If $\beta + \alpha$ is close to 1, it indicates the persistence of volatility in the conditional variance.

$(Q_t)^{-\frac{1}{2}}$represents a diagonal matrix composed of the square roots of the inverses of the diagonal elements of Q_t:

$$(\boldsymbol{diag}(\boldsymbol{Q_t}))^{-\frac{1}{2}} = \boldsymbol{diag}\left(\frac{\mathbf{1}}{\sqrt{\boldsymbol{q_{ii,t}}}} \ldots\ldots \frac{\mathbf{1}}{\sqrt{\boldsymbol{q_{mn,t}}}}\right)$$

As for the dynamic conditional correlation coefficient, it is given as follows:

$$\boldsymbol{p_{ij,t}} = \frac{\boldsymbol{q_{ij,t}}}{\sqrt{\boldsymbol{q_{ii,t}}}}, \quad \boldsymbol{i,j = 1,2,\ldots.n}, \quad \boldsymbol{/\, i \neq j}$$

$$\boldsymbol{p_{12,t}} = \frac{(\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta})\overline{\boldsymbol{q}}_{\mathbf{12}} + \boldsymbol{\alpha\mu_{1t-1}\mu_{2,t-1}} + \boldsymbol{\beta q_{12,t-1}}}{\sqrt{[(\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta})\overline{\boldsymbol{q}}_{\mathbf{12}} + \boldsymbol{\alpha\mu_{1t-1}\mu_{2,t-1}} + \boldsymbol{\beta q_{12,t-1}}]}\sqrt{[(\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta})\overline{\boldsymbol{q}}_{\mathbf{12}} + \boldsymbol{\alpha\mu_{1t-1}\mu_{2,t-1}} + \boldsymbol{\beta q_{12,t-1}}]}}$$

4. Results and Discussion

4.1 Descriptive Statistics

The results in Table 1 indicate a lack of symmetry in the distribution of the investor sentiment variable, which is skewed to the right. Additionally, the data exhibit higher kurtosis, suggesting a leptokurtic distribution with fat tails. These findings are supported by the results of the Jarque-Bera test.

From the table, it is evident that the kurtosis coefficient for the OVX index exceedsthree, which is consistent with a non-normal distribution, indicating the presence of fat tails. Furthermore, the standard deviation of the OVX index is notably high, reflecting significant risks and elevated volatility in the oil market during the study period.

The data reveal a sharp and rare decline in oil prices in 2020, driven by two main factors. On the one hand, there was a dramatic collapse in global demand due to government-imposedlockdownmeasures. On the other hand, a price war led to an oversupply of oil in the market.

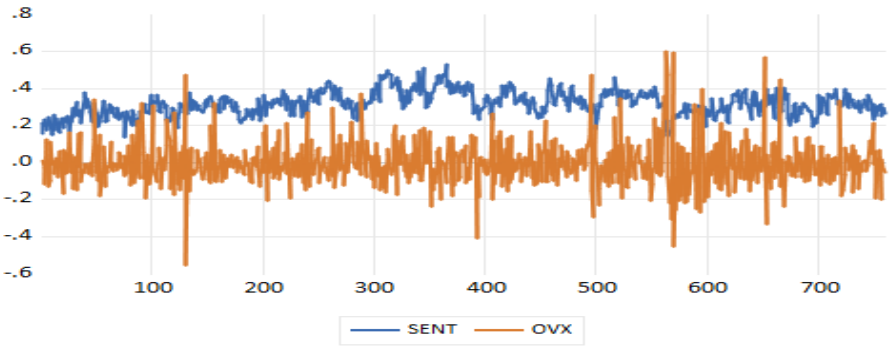
Table 1. Descriptive Statistical Properties of the Variables Studied During the

Research Period

Variables	Mean	Max	Min	Std.Dev	Skewness	Kurtosis	JarqueP-Bera
Sent	0.318078	0.52860	0.13950	0.06453	0.14455	3.0575	2.7484
OVX	-0.000399	0.60004	-0.55197	0.1165	0.86360	7.6185	768.93

Source: Prepared by the researchers based on the study data.

Fig.1. Trends of the Variables Studied During the Research Period



Source: Prepared by the researchers based on the study data.

4.2 Testing the Stationarity of Time Series

The results of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests indicate that the time series data for the study variables are stationary at the level and do not contain a unit root. The table belowpresents the findings:

Table 2. Results of the Stationarity Tests of the Study Data

Variables	ADF Test with Constant and Trend		PP Test with Constant and Trend		KPSS Test with Constant and Trend	
	t-Statistic	Critical Values at 5%	t-Statistic	Critical Values at 5%	t-Statistic	Critical Values at 5%
At Level						
Sent	-5.2481	-3.4157	-10.458	-3.4157	0.0552	0.14600
OVX	-31.254	-3.4157	-31.834	-3.4157	0.0218	0.14600

Source: Based on EViews 12 outputs.

4.3 Granger Causality Test

To determine whether there is a unidirectional or bidirectional causal relationship between the study variables in the short term, the results of the Granger causality test are presented in the table below:

Table 3.Causality Analysis Between the Indicators and Investor Sentiment

Null Hypothesis:	Obs	F-Statistic	Prob.
OVX does not Granger Cause SENT	759	3.45204	0.0321
SENT does not Granger Cause OVX		0.00885	0.9252

Source: Based on EViews 12 outputs.

The causality results indicate that the Oil Volatility Index (OVX) Granger-causes investor sentiment, as evidenced by the statistical significance of the two indicators.

4.4 Regression Analysis Between the Oil Volatility Index and Investor Sentiment

The results of estimating the relationship between oil price volatility and investor sentiment, as shown in Table 4, reveal a statistically significant negative relationship between the Oil Volatility Index and investor sentiment. The coefficient of -0.318 indicates that a one-unit change in the Oil Volatility Index leads to a negative change in investor sentiment by 0.318 units.

Moreover, the regression results suggest that the model is not statistically significant, as indicated by the p-value associated with the Fisher statistic, which exceeds the 5% significance level.

Table 4. Multiple regression results using least squares method

variable	Coefficient	t-Statistic	Prob
c	0.0229	1.1417	0.2539
ovx	-0.3180	-35.8068	0.0000
R-s= 0.17	**F** =1.30	**Prob (F)**=0.2539	

Source: Based on EViews 12 outputs.

One of the conditions for accepting the model is the presence of homogeneity in the error variance. By conducting the ARCH test to discover whether or not the error variance is stable, it was found that there is a problem of heteroscedasticity, which means that this model is not suitable for explaining the relationship. To solve this problem, the GARCH model should be applied.

Table 5: ARCH effect

F-statistic	418.67
Prob. F	0.0000
Obs*R-squared	270.1626
Prob. Chi-Square(1)	0.0000

Source: Based on EViews 12 outputs.

It appears through the GARCH model (1.1) -in which the OVX index is included in the contrast equation, that the majority of the capabilities are acceptable and moral, and the results show that the oil price fluctuations index has a positive impact on conditional contrast, meaning that an increase in these laboratories will lead to an increase in the value of the contrast, This means that the upscale (declining) trend in oil leads to high (low) fluctuations in the index Morality.

Table 6. Results of Multiple Regression Using the OLS Method

Dependent Variable: SENT
Method: ML ARCH - Normal distribution (BFGS / Marquardtsteps)
Sample: 1759
Included observations: 759
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1) + C(5)*OVX

Mean equation	**C**	0.312960 (0.0000)
Variance Equation	**ω(Constant)**	0.001026 (0.0000)
	α(ARCH effect)	0.515661 (0.0000)
	β(GARCH effect)	0.216774 (0.0086)
	Ovx	0.001161 (0.0060)
	α+β	0.7323
Log likelihood		1113.891
ARCH Test		0,6431
Probability		0,4226

Source: Based on EViews 12 outputs.

Considering the sum of a1 and β1, it is found to be less than one but

relatively high. This indicates the persistence of the effects of previous fluctuations, shocks, and variances on current and future variance.

The conditional correlations between oil price volatility (OVX) and investor sentiment were examined for the period 2009–2023 using the DCC-GARCH model. The results show that there are dynamic conditional correlations over time, which are statistically significant and differ from zero. Specifically, the correlation between oil price volatility and investor sentiment volatility is negative. This indicates that investor sentiment is sensitive to changes in oil price volatility in a dynamic manner over time, with an average sensitivity of approximately 8%.

4.5 Results of the DCC-GARCH Model Estimation

The conditional correlations between oil price volatility (OVX) and investor sentiment were examined for the period 2009–2023 using the DCC-GARCH model. The results show that there are dynamic conditional correlations over time, which are statistically significant and differ from zero. Specifically, the correlation between oil price volatility and investor sentiment volatility is negative. This indicates that investor sentiment is sensitive to changes in oil price volatility in a dynamic manner over time, with an average sensitivity of approximately 8%.

Table 7. Estimation Results of the DCC(E)-GARCH (1,1) Model

```
  *************
 ** SERIES  **
*************
#1: sent
#2: ovx

 ********************************
 ** MG@RCH( 1) SPECIFICATIONS **
 ********************************
Conditional Variance : Dynamic Correlation Model (Engle)
Multivariate Normal distribution.

Strong convergence using numerical derivatives
Log-likelihood = 1946.9
Please wait : Computing the Std Errors ...

 Robust Standard Errors (Sandwich formula)
                Coefficient  Std.Error  t-value  t-prob
rho_21           -0.083120   0.036864   -2.255  0.0244
alpha             0.054342   0.025937    2.095  0.0365
beta              0.332443    0.19608    1.695  0.0904
No. Observations :       759  No. Parameters  :        11
No. Series       :         2  Log Likelihood  :  1946.896
Elapsed Time : 0.04 seconds (or 0.000666667 minutes).
```

Source: Based on OxMetrics6 outputs.

The table abovereveals that the sum of the coefficients alpha andbeta

is estimated at 0.3867, indicating the persistence of correlations between oil price volatility and sentiment volatility over the long term. Additionally, as shown in Table 8, the p-values associated with the Hosking and Li-McLeod statistics are greater than the 5% significance level. This implies the absence of autocorrelation in the squared residuals at lag periods of 5 and 10.

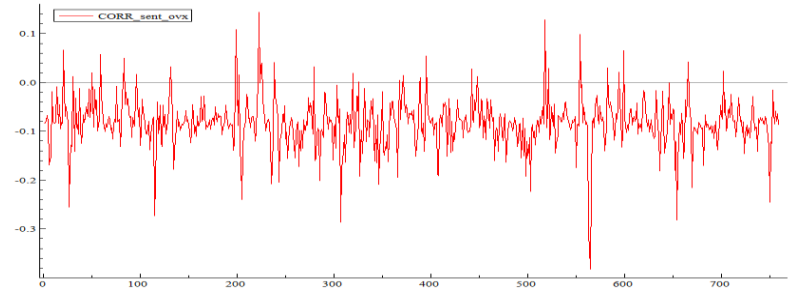
Table 8. Results of Hosking and Li-McLeod Tests

Hosking	Li-McLeod
(5):34.8409	(5):34.7909
(0.0100)	(0.0100)
(10): 47.4077	(10): 47.4214
(0.1409)	(0.1406)

Source: Based on OxMetrics6 outputs.

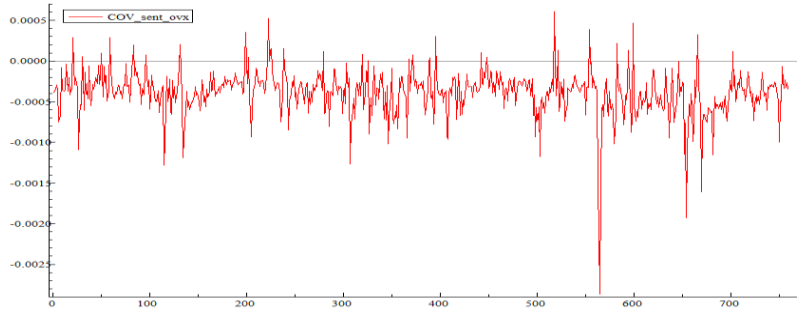
The following figure highlights the dynamic conditional correlations between investor sentiment and oil prices during the studiedperiod:

Fig.2. Dynamic Conditional Correlations (E) Between the Study Variables



Source: Based on OxMetrics6 outputs.

Fig.3.further confirms the high and shared volatility between the two variables



Source: Based on OxMetrics6 outputs.

4.6 Interpretation and Discussion of Results

The transmission of oil price volatility (OVX) to investor sentiment can be attributed to the commodification of global oil markets, transformingcrudeoil into an asset that complements other assets in market participants' portfolios. Consequently, crudeoil prices can exert significant influences on investment and financing decisions, and thereby on investor sentiment.

Moreover, crudeoil is among the most vital resourcesglobally, with its price volatility havingprofound effects on economic development, citizens' lives, and investor expectations acrossvarious countries and regions. This is particularly evident in the United States, which is one of the largest exporters and importers of crude oil.

The relationship between oil price volatility (OVX) and sentiment can also be explained by the fact that substantial fluctuations in oil prices and uncertainty in the oil market lead to heightened tensions, investor panic, and increased risk aversion. This anxiety triggers significant macroeconomic changes, including inflation and stock price fluctuations, which in turndiminish investor confidence and market sentiment.

These findings align with the studies by He, Zhou, Xia, Wen, & Huang (2019) and Zhenghui Li, Huang, &Failler (2022), whilecontradicting the conclusions of Li & Ouyang (2021).

5. CONCLUSION

This study examined the impact of oil price volatility on the behavior of American investors during the period 2010–2023, utilizing the DCC-GARCH model. The study yieldedseveral findings, summarized as follows:

- **Impact on Conditional Variance:** The oil price volatility index significantly affects the conditional variance, meaning that an increase in this index leads to a rise in variance. This indicates that upward (downward) trends in oil price volatility result in decreased (increased) fluctuations in investor sentiment.
- **Dynamic Conditional Correlations:**There are time-varying dynamic conditional correlations between oil price volatility and sentiment fluctuations, which are statistically significant and negative.

Based on these findings, it is recommended that investors diversify

their portfolios by spreadinginvestmentsacrossvarious assets and sectors. This strategy can help mitigate the risks associated with oil price volatility on their investment portfolios.

6.Bibliography list

1. **Al-Salhi, I. (2016).** Oil Shock Between Growing Consumption and Declining Production of Crude Oil During the Period 1990-2014. Iraqi Journal of Economic Sciences(48).
2. **Apergis, N., Cooray, A., & Rehman, M. (2018).** Do Energy Prices Affect U.S. Investor Sentiment? Journal of Behavioral Finance, 19(2).
3. **BOUHAFS, I. (2024).** The Impact of Investors' Behavioral Biases on Stock Returns: An Empirical Study. Faculty of Economic, Commercial, and Management Sciences, Algeria: University of Ghardaia.
4. **Ding, Z., Liu, Z., Zhang, Y., & Long, R. (2017).** The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. Applied energy, 187, pp. 27-36.
5. **He, Z., & Zhou, F. (2018).** Time-varying and asymmetric effects of the oil-specific demand shock on investor sentiment. PloS one, 13(8).
6. **He, Z., Zhou, F., & et al. (2019).** Interaction between Oil Price and Investor Sentiment: Nonlinear Causality, Time- Varying Influence, and Asymmetric Effect. Emerging Markets Finance and Trade, 55(12), pp. 2756-2773.
7. **Jadwa Investment. (2015).** The Relationship Between Oil Prices and the Saudi Financial Market "Tadawul". The Kingdom of Saudi Arabia.
8. **Ji, Q., Li, J., & Sun, X. (2019).** Measuring the interdependence between investor sentiment and crude oil returns: New evidence from the CFTC's disaggregated reports. Finance Research Letters, 30, pp. 420-425.
9. **Li, P., & Ouyang, Y. (2021).** How oil price shocks affect investor sentiment: new evidence from China. Applied Economics Letters, 29(7), pp. 584-592.

10. **Li, Z., Huang, Z., & Failler, P. (2022).** Dynamic Correlation between Crude Oil Price and Investor Sentiment in China: Heterogeneous and Asymmetric Effect. Energies, 15(3).
11. **Ye, Z., Hu, C., & et al. (2020).** The Dynamic Time-frequency Relationship between International Oil Prices and Investor Sentiment in China: A Wavelet Coherence Analysis. The Energy Journal, 41(5), pp. 251-270.
12. **Yıldırım, D., Erdoğan, S., & Çevik, E. (2018).** Regime-Dependent Effect of Crude Oil Price on BRICS Stock Markets. merging Markets Finance and Trade, 54(8).