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Bulls or Bears: how does investor sentiment shape energy profit spreads?

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Aim: The purpose of this study is to look into how investor sentiment affected the profit spreads of three significant oil and gas companies from 2014 to 2024: PB PLC, Exxon Mobil, and Chevron. The study investigates the relationship between investor sentiment and market performance, especially during times of global upheaval like the COVID-19 pandemic and the crisis in Russia and Ukraine.

Design / Research methods: The study evaluates the correlation between daily profit spreads and weekly investor sentiment indices using a Mixed Data Sampling (MIDAS) regression framework. Analysis is done on data from January 2014 to May 2024. To assess the MIDAS model's performance and explanatory power, the results are contrasted with those of conventional linear regressions.

Conclusions / findings: The findings show a complicated and firm-specific relationship between profit spreads and investor sentiment. However, there are mixed positive and negative MIDAS regression coefficients for lagged sentiment. Because of its strong mean reversion and emphasis on long-term projects, Chevron exhibits little sensitivity. Although the direction and interpretation are still unclear, Exxon Mobil exhibits some notable sentiment effects. The oil and gas industry's long-term orientation is reflected in PB PLC's inconsistent sentiment effects. In general, it seems that investor sentiment has little effect on daily stock prices, but it might have a more subtle effect on profit spreads.

Originality / value of the article: By integrating high-frequency sentiment data into asset pricing models, this paper adds to the expanding body of research on behavioural finance. In a turbulent decade characterised by pandemics and war, it employs the MIDAS approach in a novel way to evaluate the sentiment-profitability relationships among three multinational oil companies

Keywords: Bulls, Bears, investors' sentiment, profit spread, Impact, MIDAS.
JEL: C32, C58, G11, G12, G14, Q40.

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1. Introduction

The widespread consensus is that underlying firm performance has an impact on stock markets. However, it is also well acknowledged that external variables (such as investor emotion) as well as fundamentals drive markets. Therefore, it is neither reasonable or appropriate for investors to assume that stock prices will reliably and timely reflect a company's fundamental value. The dominance and ubiquity of trading connected to noise in the market additionally create the potential for mood to play a major role, leading to stock market overreactions or underreactions, which can result in severe price distortions. (e.g. Baker, Wurgler 2006; Hirshleifer 2015; Zhou 2018; Narayan et al. 2021; Nyakurukwa, Seetharam 2023; Du et al. 2024). Despite the fact that sentiment is strongly supported by a large body of research and evidence, it is interesting to note that relatively few academic papers have fully explored the complex relationship between sentiment and more conventional measures of stock market valuation, like the profit spread, or have identified the factors that determine sentiment. One important indicator is the profit spread, which is the stock market value divided by the company's book value of equity. It provides important information about how a company is valued overall in the stock market. (Li et al. 2023).

Investors must comprehend the subtleties and complexity of stock market behaviour beyond company performance as the financial markets continue to change and adapt (Goldstein 2023; Sharma, Ranjan 2021). Although fundamentals are unquestionably important, it is important to recognise that markets are complex systems that are impacted by both internal and external causes, such as investor emotion (Goodell et al. 2023).

Aware that a company's stock price is not always correlated with its intrinsic worth, prudent investors need to be cautious and steer clear of oversimplified assumptions. The interaction of sentiment-related trading highlights the possible influence of sentiment, which can cause noticeable over- or underreactions in the market (Goodell et al. 2023; Sattar et al. 2020). It is important to keep in mind that these heightened swings could lead to significant pricing distortions.

It is puzzling that so few academic papers have really examined the factors that influence sentiment or the complex relationship between sentiment and well-known stock market valuation metrics like the profit spread, in spite of the overwhelming evidence and body of research demonstrating the importance of sentiment. A critical metric that compares the stock market value to the company's book value of equity is the profit spread. It provides important information about how a company is valued overall in the volatile stock market environment.

It is nevertheless critical for academics and industry players to identify the underlying causes of sentiment and its far-reaching effects as we negotiate the ups and downs of the financial scene. We can have a more thorough grasp of the delicate dance between sentiment and conventional valuation metrics by disentangling the complex web of influences. The relationship between these components might be the key to deciphering deeper insights into the intricate workings of the always shifting stock market tapestry, which would enable better decision-making and a more obvious route to stock market investment success. Hence, the primary objective of the present paper is to examine the impact of investor sentiment on profit spreads by using a MIDAS regression model and to determine whether sentiment-based trading is an important contributor to valuation distortions in Saudi Arabian stock market.

We build on the work of (Bergström, Svensson 2020) by providing extensive documentation of a deep and compelling relationship between emotion and profit spread that makes use of a direct measure of stock overreaction. This cleverly gets around any possible problems arising from the unique invocation of convergence.

To sum up, our study makes a substantial contribution to our understanding of the dynamics of financial markets. We shed light on the factors behind emotion, stock overreaction, and market behaviour by exploring their complex interplay. Our findings will help investors, regulators, and corporate decision-makers make better investment decisions by pointing them in the direction of enhanced valuation models, more successful risk management plans, and more knowledge. With more research, the intricate relationship between sentiment, stock prices, and market behaviour can be better understood, advancing the field and enabling market players to confidently and clearly negotiate the constantly shifting financial landscape.

The paper is composed of 6 section. The main literature review is presented below (section 2). In section 3, the data and methodology are described, in section 4, the results are described and in section 5 are discussed, and in section 6, conclusions are drawn.

2. Literature review

Investor sentiments have become an important determinant in financial markets in asset pricing, volatility, and investor behavior. Given the strong interaction of psychological bias and wrong informational asymmetries with market imperfections, within the factor and along with macroeconomic events, such is the case. This section will present a critical synthesis of the past literature that relates how stock returns are influenced by investor sentiment, with attention to varying methodologies, geographies, and changes in sentiment measures.

The early studies such as (Fisher, Statman 2000) persuade concerning sentiment from Wall Street strategists, retail investors, and newsletter writers. Their novelty unfolds quite contrarian because high optimism is always repudiated by a subsequent S&P 500 bad performance. In brief, it points out that this kind of sentiment from small-cap shares seems to be better predicted, while strategist sentiment more coincides with that of individual investors in large-cap equities.

Among the countries under consideration, consumer confidence has been taken as a proxy for investor sentiment within 18 developed countries, (Schmeling 2009) Highly elevated sentiment would be expected to spell lower aggregate returns, particularly for countries with the strongest herd behavior and inferior market integrity. Such relationship still holds for different forecasting horizons as well as asset classes, illustrating the behavioral finance fundamental assumption to be that mispricing is created by beliefs rather than by fundamentals.

In emerging markets, by contrast (Corredor et al. 2015) investor sentiment has a much greater influence in Poland, Hungary, and the Czech Republic as compared with the mature European exchanges. Their findings also point to the specific roles played by country factors, showing how stock characteristics such as size and liquidity act as moderators in sentiment sensitivity. In the same line the study of (Shi et al. 2022) reveals that return implications of local investors' emotions on sectors may differ in countries such as China, Brazil, India, Mexico, Indonesia, and Turkey, while the global sentiment alone might not suffice to make predictions (Parveen et al. 2020) analyzed the biases investors exhibited in Pakistan's stock market pegged on heuristics and overconfidence. Using a composite sentiment index consisting of adjusted turnover, buy-sell imbalance, and RSI (Kim, Lee 2022) analyze the markets in Korea. They find that significant sentiment-return relationships exist with regard to KOSDAQ partly due to the dominance of individual investors. The most important factor here is the way mobile trading influences investment rationality shifting from speculation to informed decision-making. At the same time, event-triggered offers also make-analysis of sentiment shift (Cheema et al. 2020) showed, positive moods of investors in China predicted increased price returns during the bubble in the period of 2006-2008, but they seemed to lose their value when the bubble burst. Results of the study by (Sun et al. 2021) show the impact that the COVID-19 pandemic made on the Malaysian market. The study found that the positive effects of policy measures such as Movement Control Orders were much greater in returns, while daily cases and deaths were less influential. Behavioral bases of sentiment are to be further explored by (He et al. 2019) and (Hu et al. 2021), who put up a case for further examination of Investor Risk Compensation (IRC) under flated emotional conditions. Findings indicate that real IRC has a beneficial effect on returns, regardless of emotional field, whereas retrospective IRC exercises an unyielding negative influence across conditioning, suggesting asymmetries in historical valence.

Emerging proxies for sentiment represent attempts to capture the psychological drivers more accurately. Griffith et al. (2020) applied the Thomson Reuters MarketPsych data to show that fear and stress considerably influence volatility and returns. Edmans et al. (2022) develop a music-based global sentiment index developed from listeners' song choices that correlates with stock market returns and volatility in the same week. This unequivocal, real-time indicator generates mood variations based on seasons, weather, and policy events, thus showing robustness across geographies. Recently, social media has become important for studying investor mood. Duz Tan and Tas (2021) focused on sentiment from Twitter and found it to have predictive power for trading volume and returns even after controlling for news sentiment. Guégan and Renault (2021) analyzed over a million StockTwits posts, linking short-term movements in the price of Bitcoin to bursts of sentiment, especially in times marked as market bubbles. In technological integration, further refinements are done on modeling sentiment. Duxbury and Wang (2024) conclude stronger power in explaining the risk-return relationship exists when combining retail sentiment with institutional sentiment. In a later collaboration with Jing et al. (2021) they proposed a hybrid forecasting model consisting of CNN-based sentiment classification and LSTM neural networks that greatly improve stock price prediction on the Shanghai Stock Exchange.

Among the methodological innovations is an investor attention index constructed, (Chen et al. 2022) which they claimed has been built from a wide array of literary proxies. Composite measure is built through partial least squares and scaled principal component analysis. This measure adds strong predictive power for stock market risk premiums, particularly enhancing the prediction for the most volatile equities. Furthermore, the index's strength lay in reversing short-term price distortions, leading to strong in-sample and out-of-sample returns with corresponding implications for asset allocation. This work includes further developments of an Investor Sentiment Index (ISI) developed for KOSPI above Huang et al. (2015) and partial least squares by (Bouteska et al. 2024). Their index surpasses the Baker-Wurgler BM index on the grounds of validity in predicting and explaining further some small-firm effect anomalies disregarded by traditional asset pricing models. The Sentix database has been used to gauge the consumer sentiment toward Bitcoin in the Cryptocurrency markets (Anamika et al. 2023). This is correlated with a strong positive reaction to prices very contrastively influenced by carrying market sentiment measured by VIX and Baker-Wurgler indices. Guégan and Renault (2021) show that social sentiment has induced high-frequency effects on intraday returns, although profit is still restrained by arbitrage limits. To support the empirical framework of this study, the A series of core concepts is being outlined hereafter:

- ✓ Investor Sentiment Index: A composite measure of investor mood deduced from surveys, media content, social media analysis, and trading behavior.

- ✓ Profit Spread: Difference between the stock price at closing and that at opening on a daily basis, adjusted for dividends and splits; it is used to represent the company's performance and volatility.
- ✓ MIDAS Regression (Mixed Data Sampling): An econometric technique permitting the integration of high- and low-frequency variables, well-suited for combining daily financial variables with weekly sentiment scores.

In the above context, these findings offer a broad and comprehensive backdrop for investigating the role of sentiment in the financial markets while offering methodological and behavioral insights that inform the design and hypothesis of this study.

3. Data and method

This section gives the relevant data, methods of collection, empirical framework and hypothesis on which the analysis would be based. The prime objective of the research is to explore the presence of a great aspect of investor sentiment as of whether profit spreads in the leading companies of energy industry are determined by the investor sentiment or not regarding a period of ten years in the global turbulence, with the help of a MIDAS regression model. The paper considers the role of sentiment-based trading in valuation distortions by contrasting between the sensitivity of profit spreads on sentiment indices without controlling other important macroeconomic and financial factors.

3.1. Data description

The dataset runs from January 2014 until May 2024, covering this time of more sensitive markets in the wake of the COVID-19 pandemic and the Russia-Ukraine crisis. Thomson Reuters database has been chosen for the purpose of data extraction as it included a full-out coverage of financial metrics, sentiment analysis, and company fundamentals.

The analyzed subjects are three of the biggest oil and gas companies worldwide: PB PLC (London, UK), Exxon Mobil (Texas, USA), and Chevron (California, USA). These are chosen in consideration of their enormous global operations, coupled with very strong visibility by investors and a diverse strategy approach. Hence, they offer a balanced cross-sectional perspective concerning sentiment analysis.

Investor sentiment data were collected at a weekly frequency based on the American Association of Individual Investors (AAII) sentiment survey and advanced textual analytics applied to news, social media, and related content. Polling was conducted weekly from Thursday 12:01 a.m. to Wednesday 11:59 p.m., yielding forward-looking indicators that reduce hindsight bias and capture investor perceptions in real time.

Profit spreads, on the other hand, were computed daily, difference between the closing and opening stock prices adjusted with dividends and stock splits. Because of this measure, almost real time actionable firm level performance signals are given concerning market conditions.

Table 1. Data description

Variable Name	Description	Unit	Source	Code in dataset
Investor Sentiment Index	Weekly average sentiment derived from investor surveys and text-based sentiment analysis	Index value	AAII	Sent-Index
Profit Spread of three companies	Daily close-open price difference, adjusted for dividends and stock splits	USD	Thomson Reuters	BP-PLC
				Exxon Mobil
				Chevron

Source: author's elaboration.

Table 1 outlines the key variables, their measurement units, sources, and dataset codes, serving as a reference point throughout the empirical analysis.

3.2. Data sources and collection

All financial data were obtained from the Thomson Reuters platform, which includes:

- Historical Stock Prices: Daily opening and closing prices for PB PLC, Exxon Mobil, and Chevron, adjusted for corporate actions.
- Sentiment Scores: Weekly sentiment scores using AAII's proprietary algorithms, integrating multiple text-based sentiment signals from media channels.

This dual-frequency data enables alignment between investor expectations and market behavior at complementary temporal scales.

3.3. Preliminary analytical steps

Before applying MIDAS regression, this study follows a structured approach: stationarity tests confirm the suitability of time series analysis; an initial OLS model provides baseline insights; and wavelet-based variance decomposition highlights multi-scale volatility patterns across firms. These steps ensure the data is stable, the modeling path is justified, and sentiment effects are captured dynamically.

3.4. MIDAS method

Mixed data sampling (MIDAS) regressions are now commonly used to deal with time series data sampled at different frequencies. This paper focuses on single-equation MIDAS regression models involving stationary processes with the dependent variable observed at a lower frequency than the explanatory on (Foroni et al. 2015; Ghysels et al. 2020).

In a baseline MIDAS regression deal with a single low-frequency variable projected onto a high-frequency variable possibly augmented with the lagged-dependent variable. When the difference in sampling frequencies is small, we may treat this as a regular regression problem, now dubbed the unconstrained MIDAS model namely when dealing with, for instance, yearly projected onto quarterly or quarterly projected onto monthly (Foroni et al. 2019).

The linear and quasi-linear MIDAS models given as follow:

$$Y_t = \beta_0 + \beta_1 B\left(L^{\frac{1}{m}}\right) X_{t-1}^{m} + \varepsilon_t^{m}$$

Where y is the dependent variable, x is the regressor, m denotes the frequency.

3.5. Hypotheses development

H_1: Major oil and gas companies' profit spreads are significantly impacted by investor sentiment.

Justification: According to earlier behavioural finance research, investor sentiment may have an impact on pricing irregularities and departures from core values. Lagged sentiment effects on high-frequency profit data can be captured using the MIDAS regression framework. This hypothesis investigates whether changes in profit spreads across BP, Exxon Mobil, and Chevron are influenced by sentiment.

H_2: Due to differences in market sensitivity and strategic orientation, different firms experience different effects of investor sentiment on profit spreads.

Justification: The way sentiment affects profit spreads may be mitigated by firm-specific traits like Exxon Mobil's steady cash flow strategy or Chevron's long-term investment horizon. In line with theories of firm-level financial behaviour under uncertainty, this hypothesis seeks to investigate the variations in sentiment responsiveness amongst businesses.

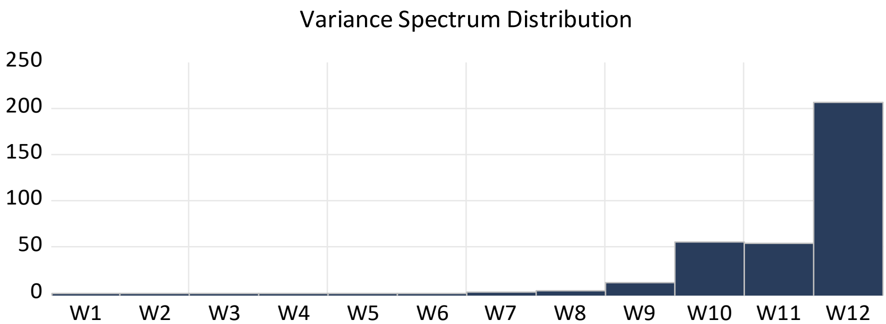
4. Empirical results

This section gives the empirical results of the study starting with graphical representations in order to explain the dynamics of investor sentiment and profit spreads during the sample. These visualizations offer a rough picture of what the patterns and possible relationship between variables are. We then report and interpret the results of the MIDAS regression models and test the hypothesis that investor sentiment is a significant explanation of the changes in profit spreads in the energy sector. The results are explained in the context of the purpose of the study, which sheds some light on the possible contribution of sentiment-based trading to the valuation effects.

4.1. Wavelet analysis

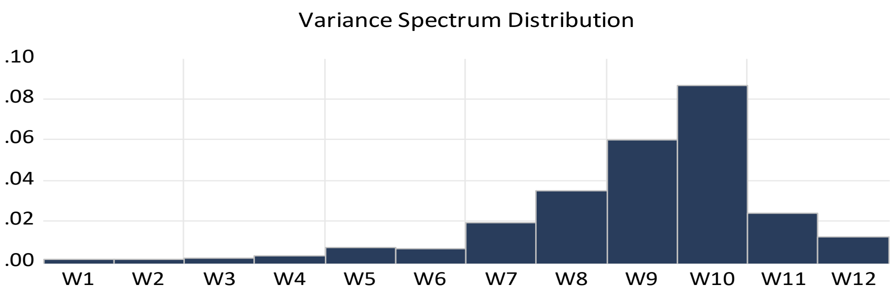
W1-W12 are the scales of the wavelet decomposition where the smallest scales (W1-W4) contain short-term changes in the profit spread, and the large ones (W11-W12) contain long-term changes related to structural forces, including oil price changes, macroeconomics, and geopolitics. The variance decomposition in Figure 1 indicates that 55.24 and 207.35 of the total variability are explained by W11 and W12, respectively, which shows that the profit spread at Exxon Mobil is largely determined by long-term dynamics, and the short-term effects have a comparatively minor influence.

Figure 1. Variance decomposition (Exxon Mobil)



Source: author's elaboration.

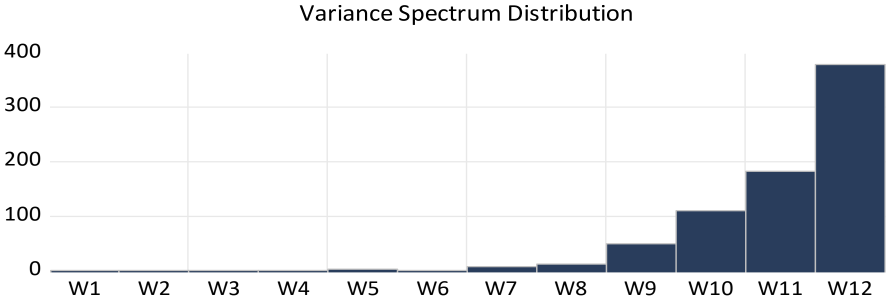
Figure 2. Variance decomposition (BP-PLC)



Source: author's elaboration.

W1-W12 are the scales of Wavelet decomposition with low scales (W1-W4) representing the short-run variations of profit spread, and higher scales (W8-W12) representing long-run structural changes. In Figure 2, it has been indicated that most of the spread variance of the profit of BP PLC is attributed to a limited number of strong components, which are mainly W10, W9, and W8, hence long-run dynamics are the primary source of profitability. Other scales play a minor part each, which explains the relevance of focusing on these major elements when gauging the profit performance of the company and maximizing it.

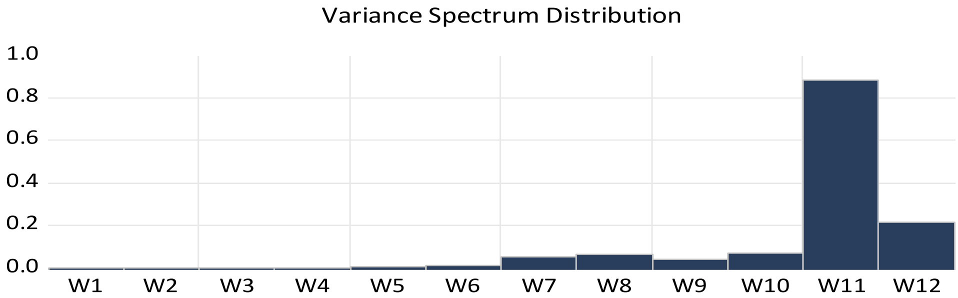
Figure 3. Variance decomposition (Chevron)



Source: author's elaboration.

W1-W12 are the scales of the wavelet decomposition, with smaller scales (W1-W4) capturing short-term oscillations, and larger scales (W8-W12) capturing long-term structural oscillations. The variance decomposition of Chevron (see Figure 3) indicates that the scale (W12) that has the biggest variation in the distribution of profit spreads follows the other two scales W10 and W11. It means that the long-term aspects (such as the macroeconomic conditions, oil price cycles, and strategic investment decisions) are the main determinants of the profitability of Chevron. The lower magnitude of smaller sizes (W1-W8) indicates that the impact of short-term volatility and sentiment on the profit spread of the company is relatively small based on the long-term nature of capital projects and the company cash flows, which Chevron focuses on.

Figure 4. Variance decomposition of Bullish, Bearish, of Sentiment Indices.



Note: BP PLC has a different scale as its returns are more volatile and a daily return data is used on a weekly sentiment data. This difference is factual and not that there is a methodological problem.
Source: author's elaboration.

Figure 4 documents the variance break down of the sentiment index over growing forecast horizons (W1-W12). Over the short term (W1-W4) the decomposition shows that the persistence is largely strong and thus the sentiment index is majorly explained by its own shocks with other variables playing a trivial role. In intermediate horizons (W5-W8) the role of fundamental variables in the contribution, most prominently the profit spread, increases with a modest contribution, which means that the valuation changes have a lagging contribution to investor mood. But at the longest of horizons (W9-W12) there are dominating the innovations of the sentiment index (around three quarters of the forecast-error variance), whereas the returns of oil prices and the dollar index are minor contributors (only a few percent each). These patterns taken together suggest that overall investor sentiment is self-reinforcing in the long-run and, though fundamentals (in particular profit spreads) can have an impact on sentiment, this impact is less immediate and more powerful at intermediate horizons than at the long run.

Table 2. Summary of stationary tests

Method	Statistic	Prob	Cross section	Obs
Levin, Lin & Chu t*	-10.1929	0.0000	3	7782
Im, Pesaran and Shin W-stat	-13.5127	0.0000	3	7782
ADF – Fisher Chi-square	190.949	0.0000	3	7782
PP – Fisher Chi-square	80.4049	0.0000	3	7803

Unit root test results for profit spreads of PB PLC, Exxon Mobil, and Chevron (2014–2024); all tests confirm stationarity at the 1% level (*p < 0.01).
Source: author's elaboration.

As shown in Table 2, these stationarity tests' findings allow us to conclude that PB PLC, ExxonMobil, and Chevron's profit spreads are stationary. This indicates that their statistical characteristics have not changed much over time, which is an essential premise for many time series analysis methods, including the OLS regression-based MIDAS method.

4.2. Midas method results

Table 03 displays from the regression study that the profit spreads of PB PLC, Chevron, ExxonMobil, and Sentiment index AII given on Neutral index have substantial correlations with one another. According to the coefficients, shifts in one company's profit spread are linked to equivalent shifts in investor sentiment. The comparatively low adjusted R-squared values, however, suggest that there may be additional factors, such as geopolitical and economic risks, influencing profit spreads that are not included in our analysis.

Table 3. OLS method

	chevron	**Exxon Mobil**	**PB PLC**
Method	OLS		
Coefficient	-0.3867	0.4369	-0.45057
Std. Error	0.03986	0.0385	0.03824
t-Statistic	-9.6999	11.327	-11.782
P-value	0.0000	0.0000	0.0000
Fit Model			
Adjusted R-squared	0.146714	0.19394	0.205806
Prob(F-statistic)	0.000000	0.00000	0.000000
Schwarz criterion	10.09884	10.1795	10.22538
Hannan-Quinn criter.	10.08428	10.1649	10.21069
Durbin-Watson stat	2.186993	2.21750	2.231667

OLS regression for profit spreads of PB PLC, Exxon Mobil, and Chevron (2014–2024); at the 1% level of significance (*$p < 0.01$).

Source: author's elaboration.

Table 4. MIDAS method based on PDL (Exxon Mobil company)

	PDL01	PDL02	PDL03
Exxon Mobile	MIDAS PDL		
	-0.0271	-0.046397	0.032103
	0.3329	0.301766	0.059327
	-0.0816	-0.153751	0.541126
	0.9350	0.8779	0.5887
Model fit			
Adjusted R-squared	0.230604		
Schwarz criterion	10.17864		

PDL for profit spreads of Exxon Mobil (2014–2024).

Source: author's elaboration.

Table 04 shows the MIDAS-PDL result that lag variables have an impact on ExxonMobil's profit spread; however, the nature of this link varies according on the PDL specification selected. The adjusted R-squared value is relatively low, suggesting that the model may be missing some important components. ExxonMobil's profit spread determinants may be better understood by additional variables or further analysis using alternative PDL specifications.

Table 5. MIDAS method based on PDL (BP-PLC)

	PDL01	PDL02	PDL03
BP-PLC	MIDAS PDL		
	-0.0271	-0.0463	0.0321
	0.3329	0.30176	0.0593
	-0.0816	-0.1537	0.5411
	0.9350	0.8779	0.5887
Model Fit			
Adjusted R-squared	0.230604		
Schwarz criterion	10.21978		

PDL for profit spreads of PB PLC (2014–2024).

Source: author's elaboration.

Based on the table 05, the PB PLC MIDAS PDL analysis indicates that lagged variables have an impact on the company's profit spread; however, the nature of this relationship differs according on the PDL specification selected. The BP profit spread can be affected by lagged variables in both positive and negative ways, and the significance of these impacts varies depending on the specifications, according to the coefficients for PDL01, PDL02, and PDL03. Even while the model only partially explains the fluctuation in the profit spread, as indicated by the adjusted R-squared value of 0.230604, it nevertheless offers insightful information about the possible factors influencing BP's profitability.

Table 6. MIDAS method based on PDL (Chevron)

	PDL01	PDL02	PDL03
Chevron	MIDAS PDL		
	-113.4257	155.9516	-36.76743
	135.0490	128.1874	25.39818
	-0.839886	1.216591	-1.447640
	0.4014	0.2243	0.1483
Model Fit			
Adjusted R-squared	0.230604		
Schwarz criterion	10.21978		

PDL for profit spreads of chevron (2014–2024).

Source: author's elaboration.

Table 6 provides that Chevron's profit spread is also influenced by lagged variables, according to the MIDAS PDL research. On the other hand, BP's PDL specifications' coefficients are much less in magnitude than Chevron's, indicating a weaker correlation between delayed factors and Chevron's profitability. While PDL03's negative coefficient shows the opposite link, the positive coefficients for PDL01 and PDL02 show that rises in the historical values of the independent variables led to increases in Chevron's profit spread. Similar to BP, the modified R-squared value of 0.230604 shows that while the model may not account for all important factors, it does explain some of the fluctuation in Chevron's profit spread.

Table 7. MIDAS method based on steps

Exxon Mobil				
	Coefficient	Std. Error	t-Statistic	P-value
Step 01	-2.844390	15.20956	-0.187013	0.8517
Step 02	-31.48030	41.23640	-0.763410	0.4456
Model Fit				
Adjusted R-squared	0.214320			
Schwarz criterion	10.19678			
BP-PLC				
	Coefficient	Std. Error	t-Statistic	P-value
Step 01	0.039220	0.104097	0.376764	0.7065
Step 02	0.255459	0.139264	1.834360	0.0672
Model Fit				
Adjusted R-squared	0.227609			
Schwarz criterion	10.21156			
Chevron				
	Coefficient	Std. Error	t-Statistic	P-value
Step 01	26.44004	14.29734	1.849297	0.0650
Step 02	-75.35293	38.89295	-1.937444	0.0532
Model Fit				
Adjusted R-squared	0.156605			
Schwarz criterion	10.10485			

MEDAS method based on steps for profit spreads of PB PLC, Exxon Mobil, and Chevron (2014–2024); at the 10% level of significance (*p < 0.1.
Source: author’s elaboration.

Table 7 regroups the coefficients exhibit variability among the three companies between Step 01 and Step 02, suggesting a complicated and potentially variable link between the lagged independent factors and the dependent variable (presumably the profit spread). Lagged variables can have both growing and reducing effects on the profit spread, as indicated by some positive and some negative coefficients.

The statistical significance of the coefficients is indicated by the p-values that correspond with them. At the 5% level, a p-value of less than 0.05 often denotes statistical significance for the coefficient.

5. Discussion

Closer inspection into the outputs of the MIDAS regression indicates that the effect of investor sentiment changes from firm to firm regarding profit spreads, which is guided by the strategic profile and time sensitivity of each firm.

According to MIDAS-PDL results on Exxon Mobil, sentiment-related lag variables have logically significant and structurally ambiguous effects on profit spreads. Variations in coefficient signs from PDL01 to PDL03 with a combination of positive and negative lag responses point to the nonlinear, inconsistent transmission mechanism. Investor mood and profit dynamics within Exxon Mobil, which might be ascribed to many macroeconomic variables such as oil price and geopolitical changes, could be a complicated interplay. Although the adjusted R-squared value remains at low levels, some significant lags provide evidence toward the position that sentiment drives up-through short-run profit fluctuations, even though a rather stable cash flow strategy would substitute it from extreme swings.

For the case of PB PLC, the complexity is revealed by the analysis of MIDAS-PDL, shown through several lag effects that operate above multifaceted sentiment. The coefficients in PDL01, PDL02, and PDL03 show both amphitory and dampening effects, indicating that profit spread in BP is sensitive to changes in the mood of investors but in a temporally fragmented way. BP’s extended operational exposure-from European regulatory pressures to environmental headlines-explains why sentiment impacts profit spread in both persistent and transient forms. Although the adjusted R-squared (≈0.23) suggests that much of the variation is left unexplained, the mixed-lag results show that some sentiment waves that last for several days resonate with BP’s market valuation.

Chevron, on the other hand, exhibits a more insulated relationship with investor sentiment. Although the MIDAS-PDL estimates show that lagged variables do have an effect on Chevron's profit spread, the effects of investor sentiment seem to be weaker in comparison to those of BP and Exxon Mobil. Positive coefficients for PDL01 and PDL02 indicate some responsiveness to historical sentiment values; however, the negative coefficient for PDL03 and the general lack of statistical significance imply that sentiment is not a key driver of Chevron's short-run profitability. This interpretation fits well with the company's strategic focus on long-term capital projects and stable dividend policies that dampen short-term sentiment sensitivity. The adjusted R-squared value also lends credibility to the argument that other structural factors like oil futures, investment cycles, and internal cash-flows management have greater explanatory power in the case of Chevron, just as it has for BP.

The MIDAS results strengthen Hypothesis 2 by demonstrating how investor sentiment interacts differently between firms according to their financial architecture and strategic focus. BP-PLC and Exxon Mobil show greater sensitivity to sentiment through different lag structures, while Chevron's limited reactivity demonstrates its immunity to short-term market noise emanating from an emotional source. These dissimilarities are essential to interpretation from a behavioral finance perspective across various types of firms in the energy sector.

6. Conclusion

The moulding of investor sentiment and behavioral pattern among markets by economic occurrences and crises is a multifaceted event, which has been pointed out in many foundational works (Baker, Wurgler 2006; López-Cabarcos et al. 2020; Li et al. 2023; Du et al. 2024). In traditional theories in finance, the psychological and social bases are often overlooked partly explaining investor actions (Nareswari et al. 2021; Akhtar, Das 2020). This becomes apparent in the aforementioned works (Lerner 1936; Prechter 2016; Shiller 2000; Shleifer 2000; Steelman 2016) as well as Parker and Keynes who understand the point that the dynamic nature of markets is therefore tied up with social cues and, through social narratives, emotional reactions.

While empirical studies (Dhaoui 2015) confirm the strong effects of sentiment on trading volumes and market shocks, isolating individual investor behavior has been consistently cited as a challenge throughout the literature. The main objective of this paper was to examine the significant impact of investor sentiment on profit spreads in the energy industry. The present study addresses this issue by establishing an empirical link between investor sentiment, measured through media signals, and profit spreads for PB PLC, Exxon Mobil, and Chevron firms via MIDAS regression and wavelet decomposition.

The results confirm both hypotheses. Firstly, Hypothesis 1 is supported, in that investor sentiment has a measurable impact on profit spreads of the major oil companies, though the strength and clarity of this impact can alter. Secondly, the characteristics of the firm influence the extent of the sentiment's effect, thus supporting Hypothesis 2: BP is mixed in its responsiveness to sentiment, Exxon Mobil has some statistically significant effects, and Chevron appears to be largely insulated from sentiment due to strategic considerations.

We notice that during economic shocks, high sentiments strengthen the overreaction of the market, which then causes asset valuations to drift away from intrinsic benchmarks. This further confirms the behavioral patterns that bring about investor mispricing, volatility, and distress. The findings carry very important implications for valuation models, investment policy, and risk management: with an understanding of sentiment-based valuations, both investors and regulators would better anticipate the market-response dynamics during crises.

Overall, the results reinforce adding sentiment data to financial models in real time. In the future, research ought to investigate how economic headlines and global uncertainties create emotional narratives that shape investor expectations, asset pricing, and market resilience.

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