

The effect of OPEC Announcements on Oil Prices

Sentiment Analysis on OPEC Monthly Reports

Agenda



OPEC and the Oil Market



Literature Review



Methodology



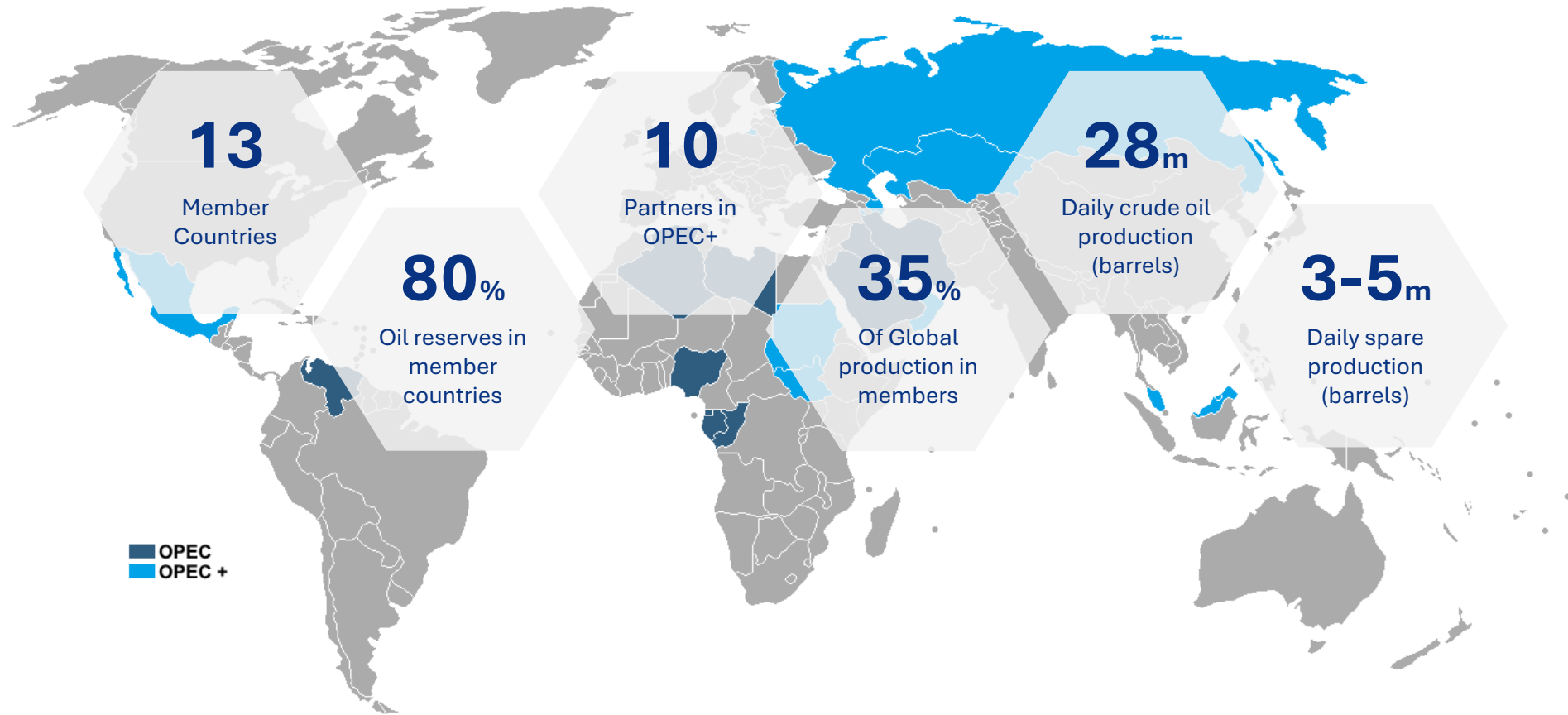
Results



Back-Testing and Discussion



The OPEC

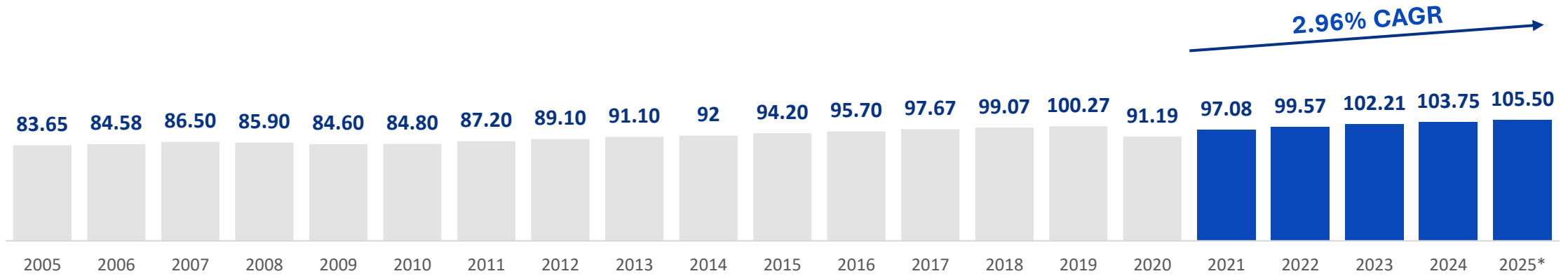


- OPEC releases monthly reports that contain insights on future oil demand and supply, as well as on general developments of the oil market export market
- These reports are released at 12.00 UTC every month

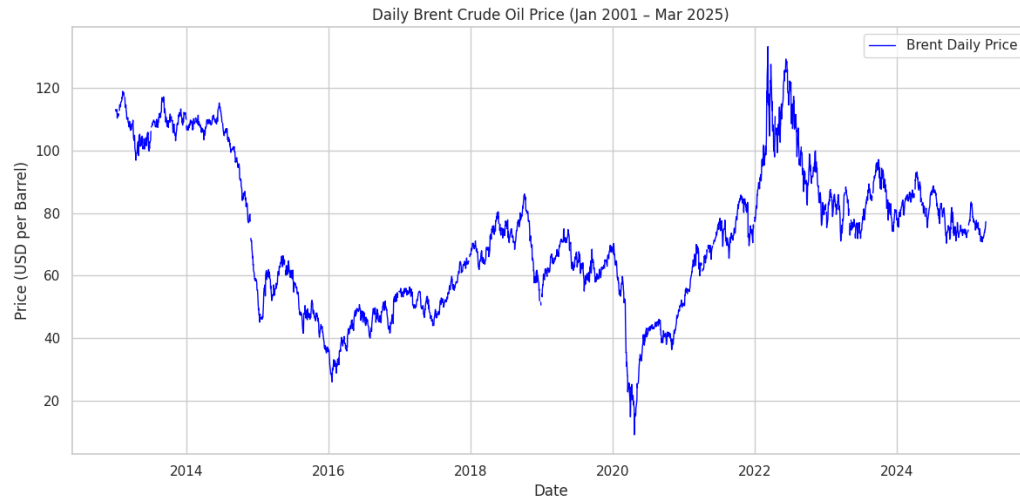


Global oil market overview

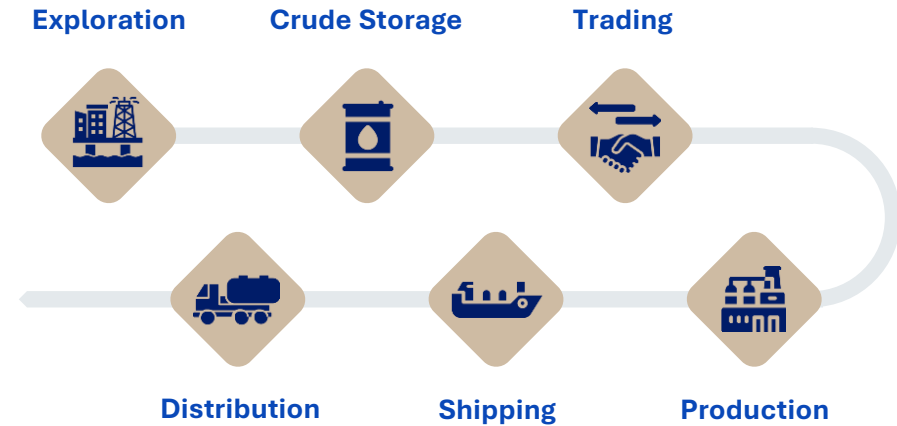
Demand for crude oil worldwide – OPEC Report April 2025 – in barrels per day, 2025 is forecast



Evolution of crude oil price, 2013-2025 - FRED



Oil Supply Chain





Literature Review

Title	Authors & Year	Notes
Energy Organisation Sentiment and Oil Return Forecast	Minhyuk Jeong, Kwangwon Ahn (2025)	This paper investigates the predictive capability of organization sentiment, extracted from OPEC monthly oil reports, on future crude oil price changes, finding that they are related through the oil production channel (whereby reports affect outlook on levels of supply)
Predicting Crude Oil Returns and Trading Position: Evidence from News Sentiment	Hail Jung, Daejin Kim (2024)	This paper investigates the effectiveness of oil market sentiment in newspaper articles on predicting the returns of crude oil futures, finding that supervised ML algorithms outperform conventional dictionary-based methods for this specific source
Do OPEC Policies Help Predict The Oil Price?	Jingjing Li, Zhanjiang Hong, Lean Yu, Chengyuan Zhang, Jiqin Ren (2024)	This paper aims to construct a new sentiment index based on OPEC policy news and evaluate its capacity in predicting crude oil futures price, finding a strong relationship between the two given the index's alignment with production change decisions

Our Research Aim: Investigating the impact of OPEC monthly report on intra-day brent crude oil prices upon release as well as their capability to predict price changes



Methodology

1

Web scraping

Reports have been scraped from the official OPEC website

2

Sentiment Evaluation

Each report has been scored based on its sentiment using both the LM Dictionary and the FinBERT model

3

Regression Analysis

The time series of sentiment scores has been regressed on various price changes evaluated at different time intervals from the publication time

4

Back-Testing

The results of the parameters estimated have been evaluated based on their statistical significance and back-tested



Methodology – LM Dictionary

Word Tokenization

- Every report is broken down into the set of all its words and cleaned up

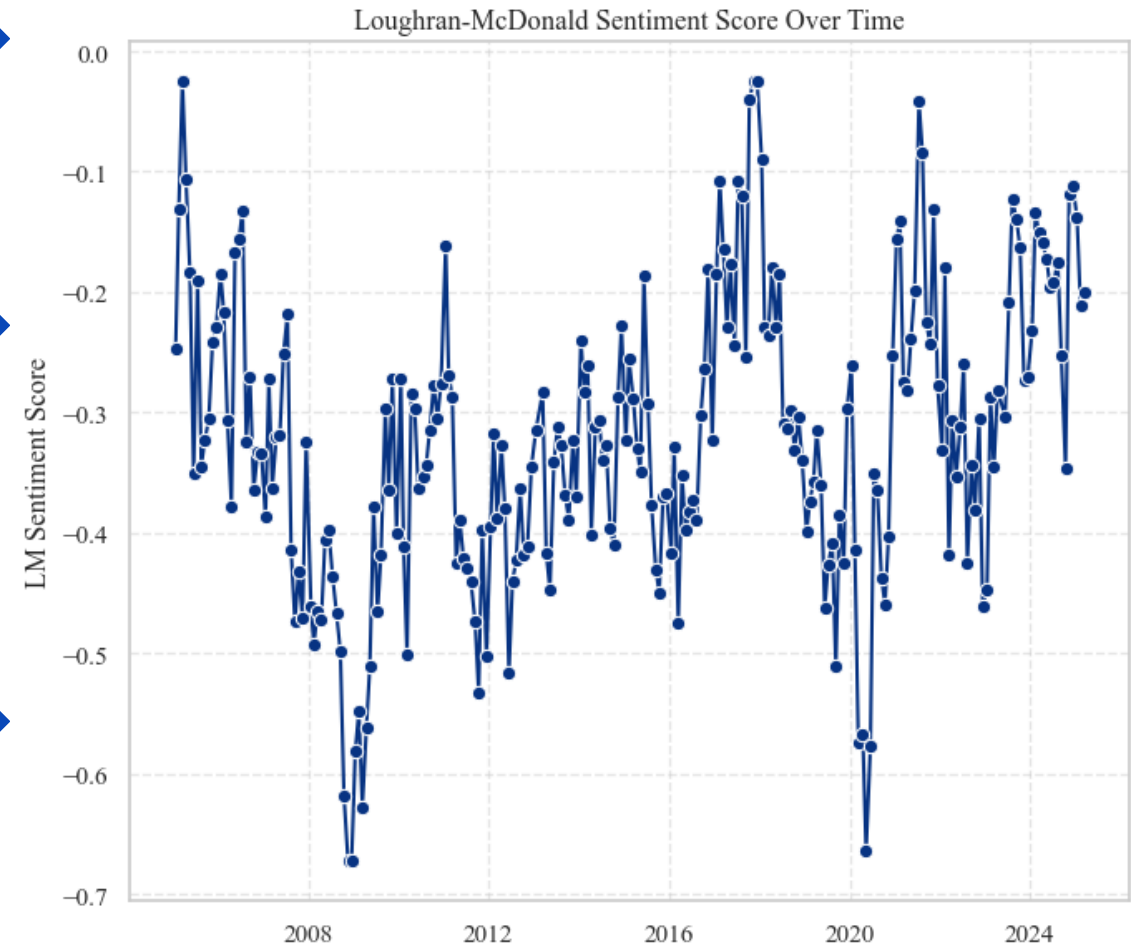
Sentiment Evaluation

- Each word matched in the LM Dictionary is counted as reflecting either Positive or Negative sentiment
- The dictionary classifications are based on empirically derived contextual use, mainly SEC filings

Report Scoring

$$LM\ Score = \frac{\sum_{w \in r} (CountPositive(w) - CountNegative(w))}{\sum_{w \in r} (CountPositive(w) + CountNegative(w))}$$

- The appropriate normalisation then yields a sentiment score between 1 and -1





Methodology – FinBERT Method

Sentence Tokenization

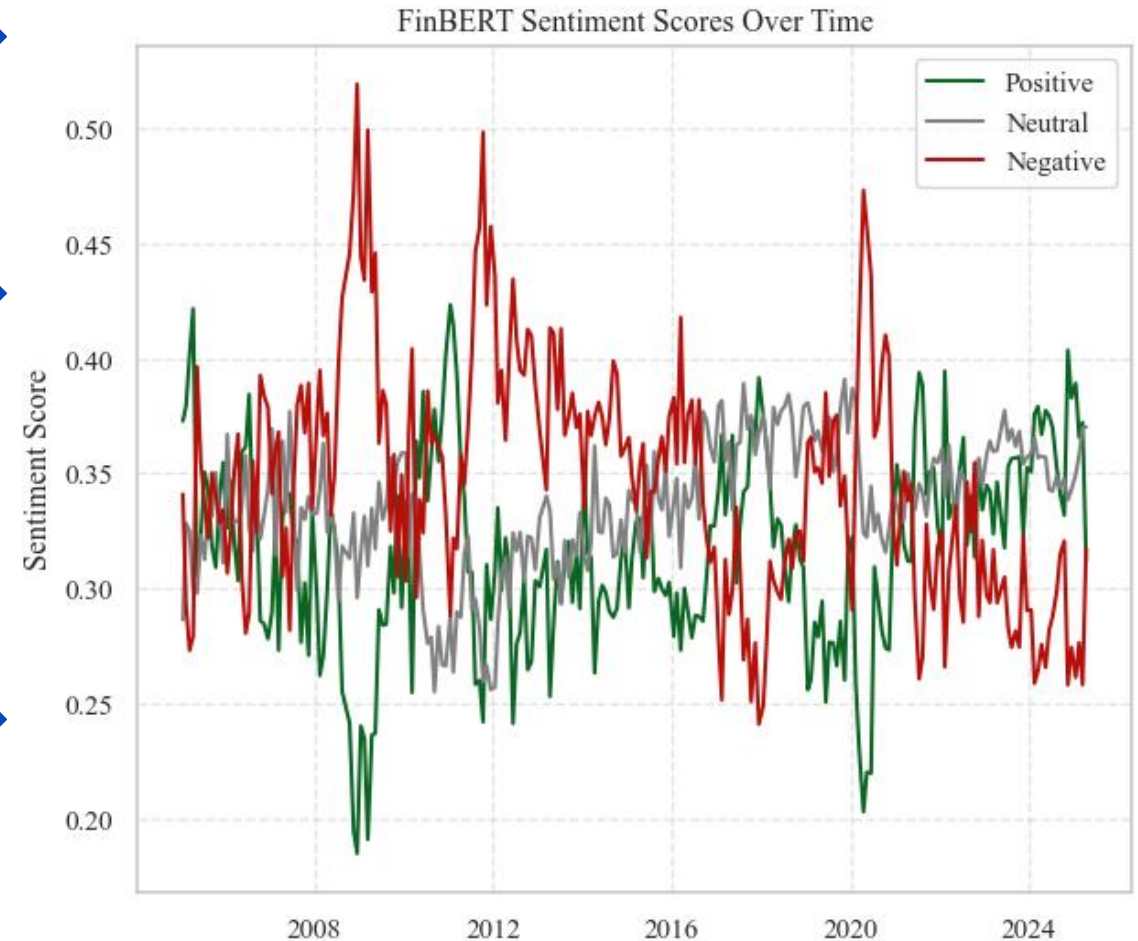
- Every report is broken down into individual sentences

Sentiment Evaluation

- Each sentence is evaluated through the FinBERT model as Positive, Neutral or Negative
- **FinBERT** is a pre-trained financial sentiment analysis model, used to automatically assess the general sentiment of a given text

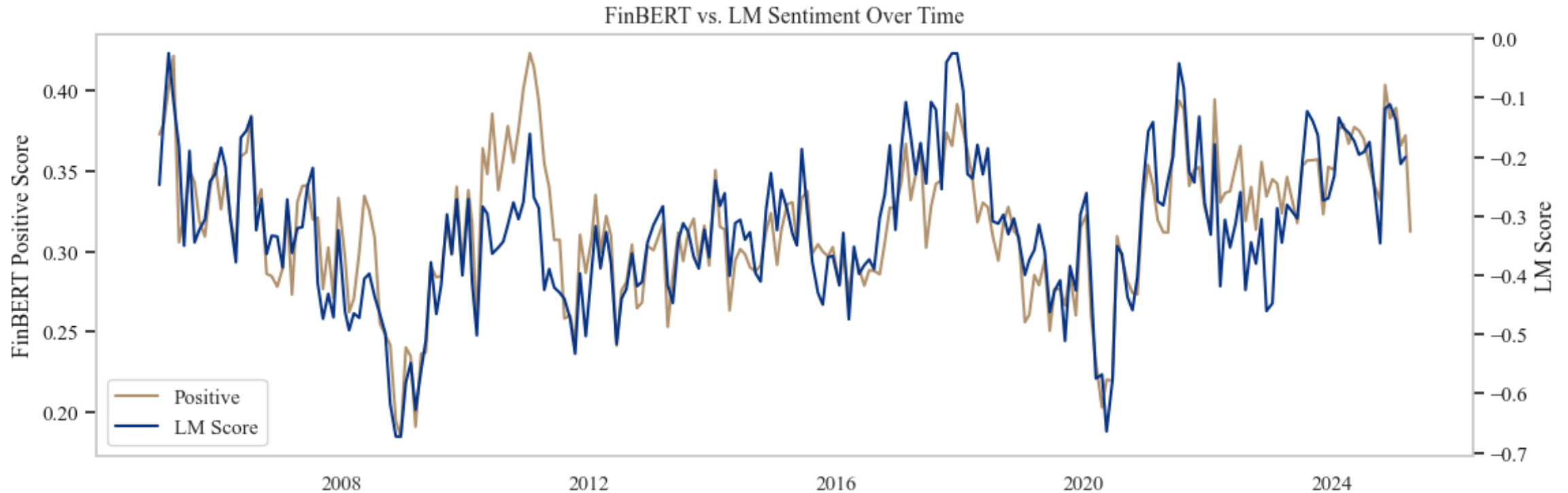
Report Scoring

- The report is then scored through the proportion of Positive, Negative and Neutral sentences
- The outcome are therefore three variables, one for each of the categories





Results – Sentiment Scores Comparison



- The resulting LM and FinBERT Positive scores are quite aligned, and generally agree on their evaluation of reports
- As a result, we should expect further analysis to be quite consistent between the two



Methodology – Linear Regression and Back-Testing

Linear Regression Model

$$1 \quad r_{t+\Delta} = \alpha + \beta SENT_t + \varepsilon_{t+\Delta}, \quad r_{t+\Delta} = \frac{P_{t+\Delta} - P_t}{P_t}$$

- The linear regression model has been chosen to fit the data
- Specifically, the above equation shows the model specification, where P_t is the price of crude oil at time t , $SENT_t$ is the sentiment index of the report published at time t , ε_t the error term
- Δ is the time-period after the publication date over which the price change has been calculated
- To fully eliminate imperfections in the publication time and the effect of noise, P_t has been approximated with the price 10 minutes before the actual publication time

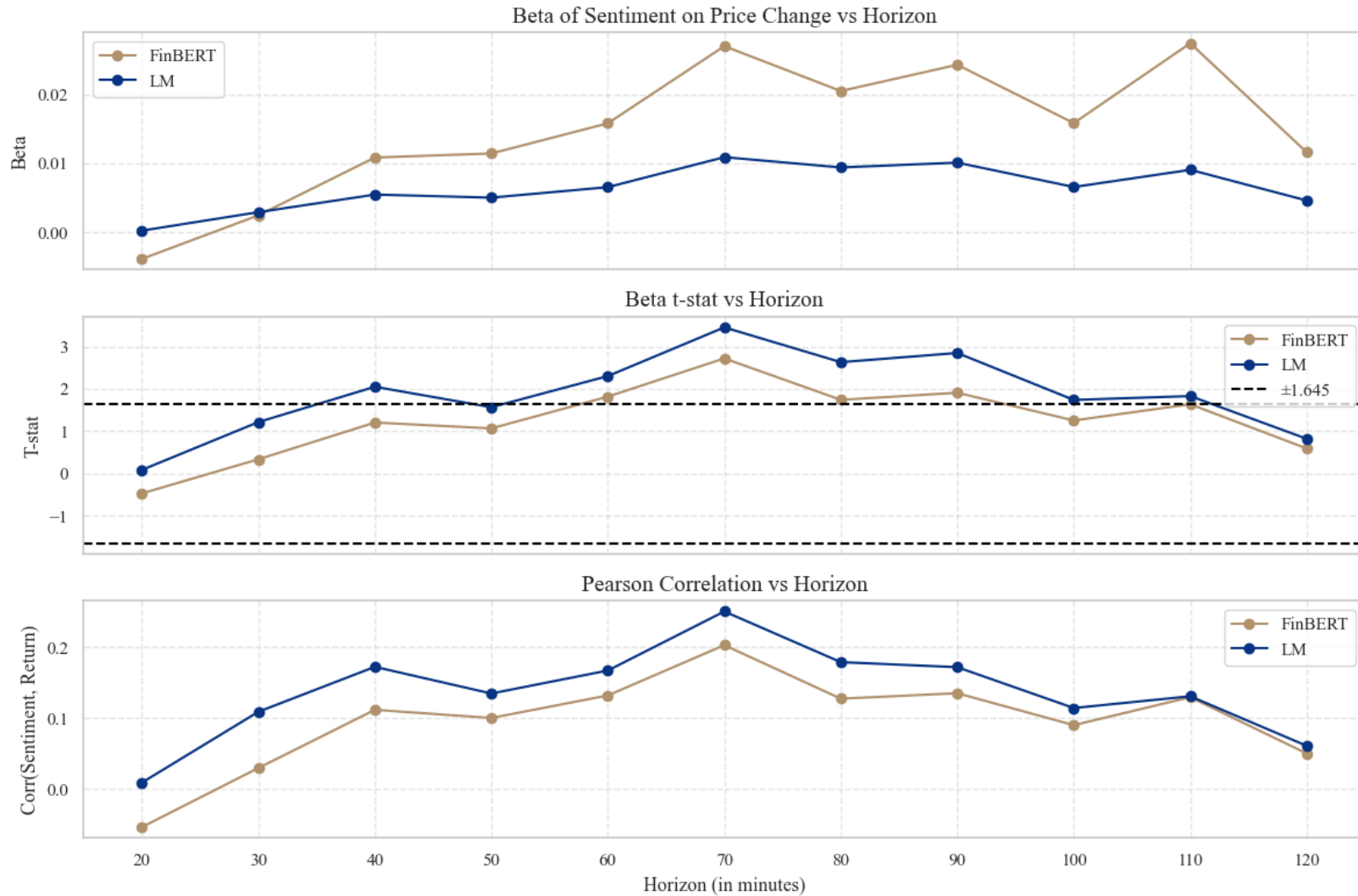
Back-Testing Procedure

$$2 \quad R_{OOS}^2 = 1 - \frac{\sum_{t=\tau}^{T-\Delta} (r_{t+\Delta} - \hat{r}_{t+\Delta|t})^2}{\sum_{t=\tau}^{T-\Delta} (r_{t+\Delta} - \bar{r}_{t+\Delta|t})^2}, \quad \hat{r}_{t+\Delta|t} = \hat{\alpha} + \hat{\beta} SENT_t$$

- The model has been back-tested by evaluating its out-of-sample performance
- Specifically, a rolling regression has been implemented with a fixed window of length w , using observations from $t - w$ to $t - 1$ to predict price change at time t
- The performance of the predictive model has been tested against the naïve historical mean (mean of price changes from $t - w$ to $t - 1$) forecast method by using the out-of-sample R^2 (equation 2)
- A positive R_{OOS}^2 suggests that the implemented model performs relatively better than the historical mean



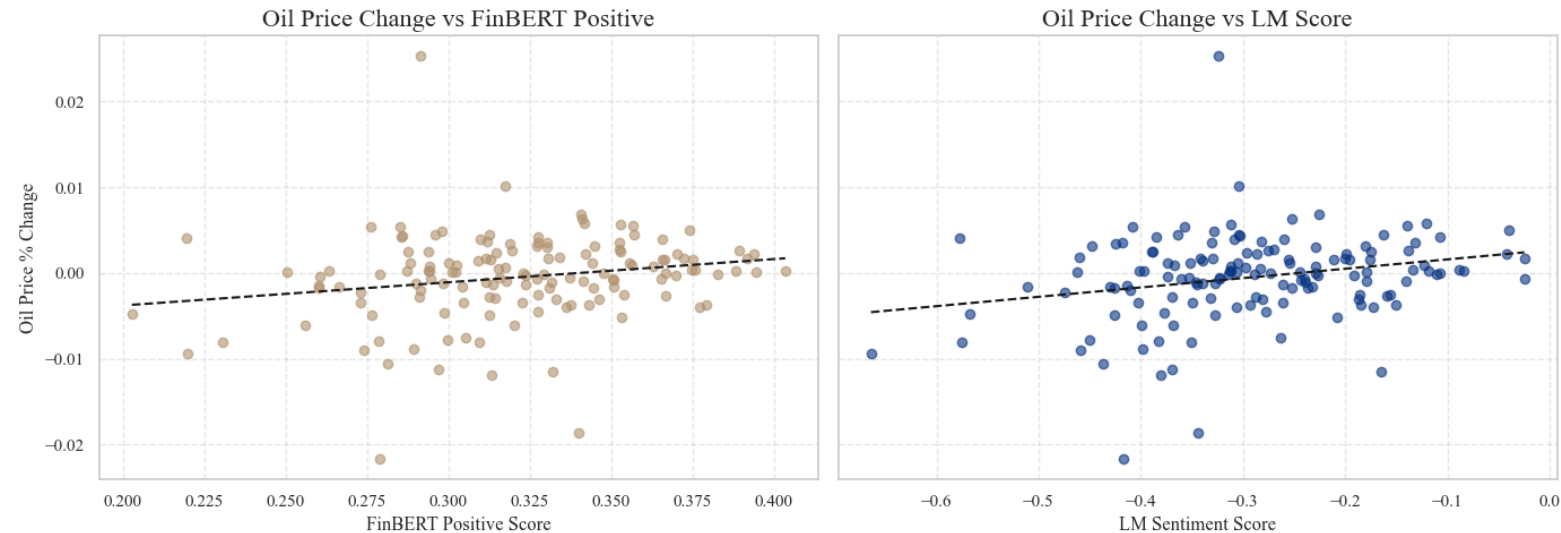
Results – Linear Regression



- The resulting coefficients and correlations between price changes at different time intervals and sentiment score show a relatively better performance for LM method
- The highest-performing time horizon is 70 minutes from 11.50, i.e. one hour from the report publication time
- The movement of prices in the first ten minutes from the publication seems unable to be predicted by the content of the report, as well as the one too far in time



Results – Linear Regression, FinBERT and LM Sentiment, 1-hour interval



	FinBERT Model		LM Model	
	Coefficient	P-value	Coefficient	P-value
Constant	-0.0092 (-2.70)	0.0070***	0.0027 3.22	0.0013***
FinBERT Score	0.0270 2.72	0.0065***	-	-
LM Score	-	-	0.0109 (3.45)	0.0006***
<i>Model Statistics</i>				
Observations	141		141	
R-squared	0.041		0.063	
AIC	-1090.52		-1093.71	

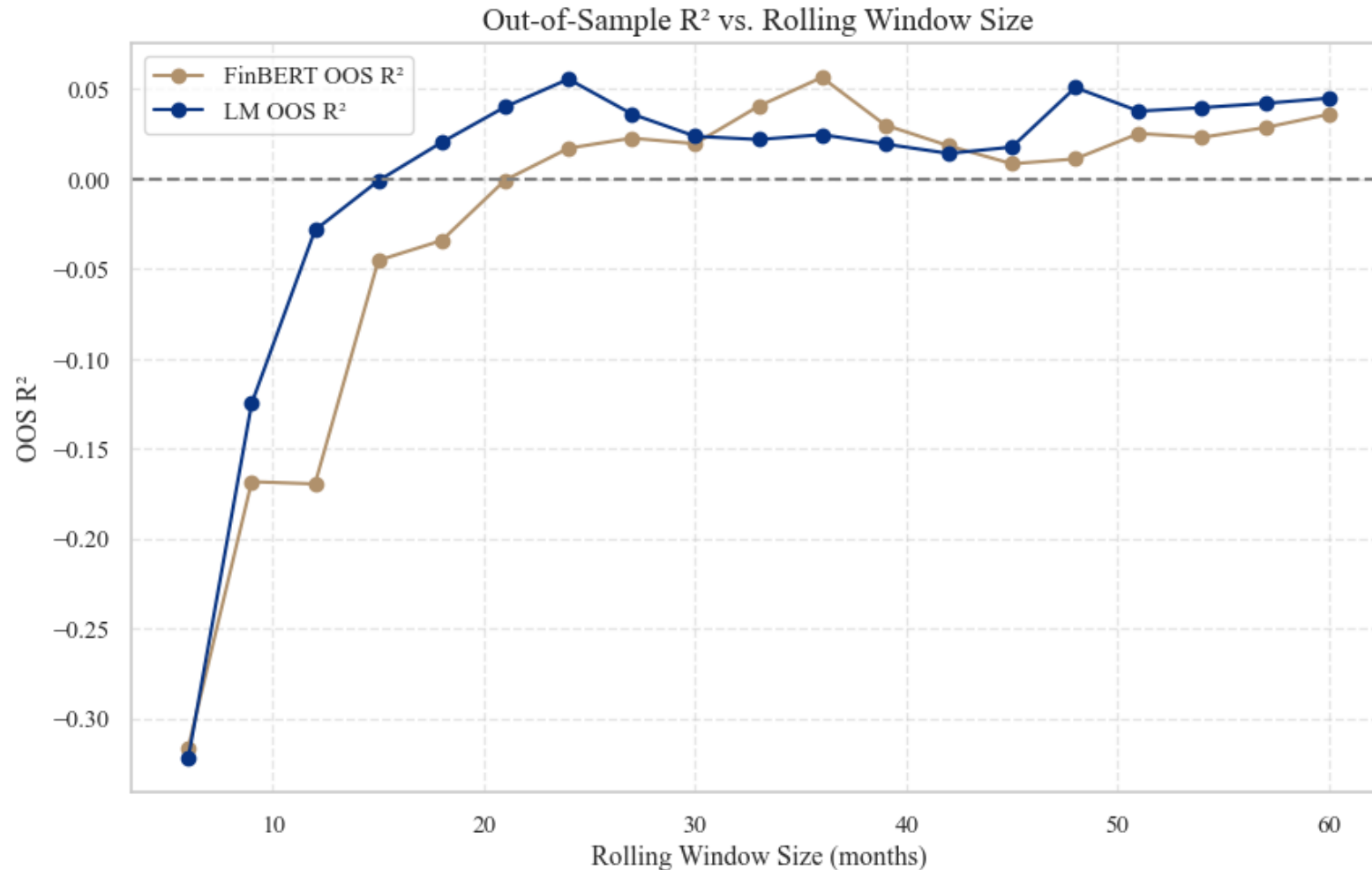
Notes: Robust standard errors used for regressions. T-stats in parenthesis.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

- The regression statistics have been computed for the two sentiment scores using the 1-hour interval, which turned out to be the most significant
- The results show a R2 of 6.3% for the LM score, vs 4.1% for the FinBERT Positive score, confirming that the former performs better as seen before
- In both cases, the results are significant at a 99% confidence interval



Back-Testing – Finding the Optimal Rolling Window

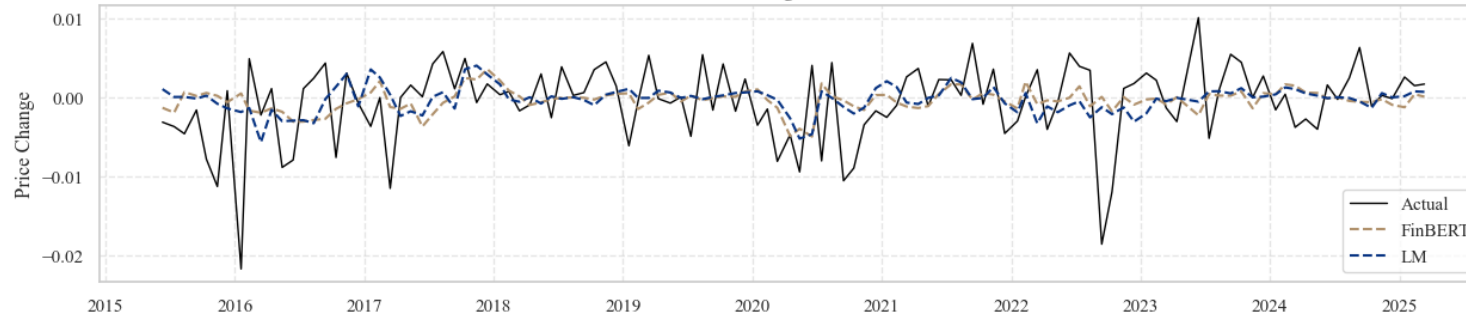


- Here a rolling regression has been used to back-test the predictive performance of the chosen model (1-hour interval)
- For each rolling window from 3 to 60 (approximately 50% of the sample), the out-of-sample R^2 has been recorded, which measures how much the model relatively outperforms the historical mean in predicting price changes
- The R^2 for the LM score peaks at 2 and 4 years, while the one for the FinBERT Positive score peaks at 3 years

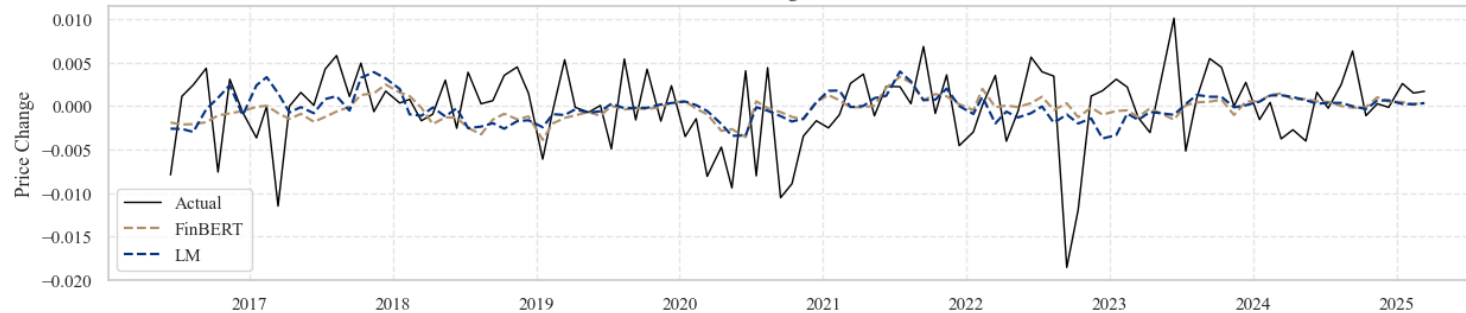


Back-Testing – Predicted vs Actual Price Change

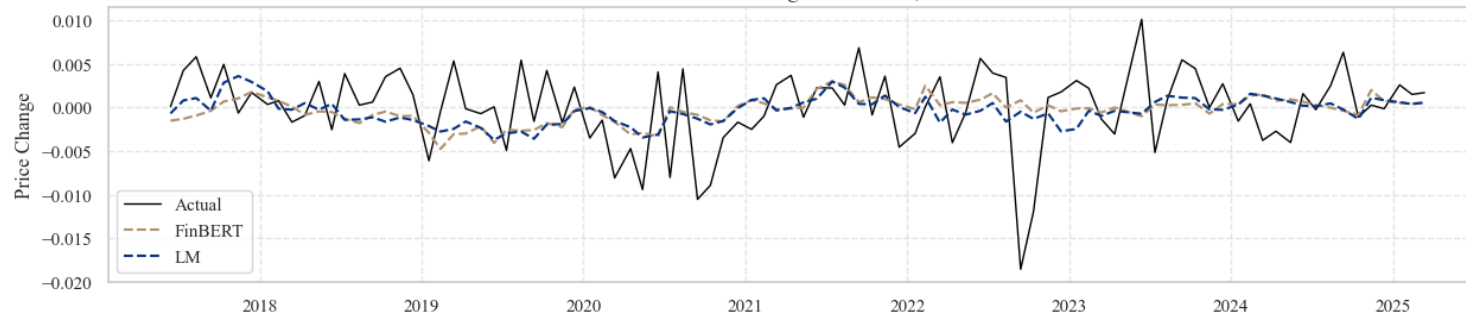
Actual vs Predicted Price Change Over Time, 24-month window



Actual vs Predicted Price Change Over Time, 36-month window



Actual vs Predicted Price Change Over Time, 48-month window



- For each of the three optimal rolling windows, the predicted vs actual price changes have been plotted
- As expected, a lower window allows for more flexibility and is able to predict better when significant variations in sentiment are present
- However, longer windows allow for lower volatility in predictions and in more rigid models, reducing the noise caused by shocks in sentiment
- In general, the three windows chosen have approximately the same out-of-sample performance, showing that the gain in flexibility is compensated by the reduction in noise



Discussion – Why does this matter?

1

Predictability

Sentiment analysis is able to predict and explain around 5% of the price changes from 11:50 to 13:00, suggesting that the oil markets does react to the report publication. At the same time, the fact that there's no excessive movement in prices due to the sentiment of the report supports effective communication

2

Positive Correlation

Prices react positively to high sentiment reports, suggesting either that investors demand lower expected returns being optimist or that they trust the report to be accurate in guiding the future movements in prices

3

Reaction Timings

Markets take on average one hour to incorporate their updated expectations after the report publication time, showing that most of the effect is probably driven by strategic investors as opposed to speculators

4

Importance of OPEC Monthly Reports

The results obtained highlight the key role played by the OPEC, which acts as a guide in the oil market developments and is well-trusted. Given how relevant oil prices are in the global economy, this shows how important its announcements are at a global level



Discussion – Issues and Further Work

1

Omitted Variables

Sentiment index might be correlated with omitted variables that affect oil prices, therefore causing biased coefficients in the linear regression model

Model with Known Independent Variables

The model might be estimated including known variables that affect oil prices, to yield better estimates of the impact of sentiment on price movements

2

Dependent Variable

In this analysis, crude oil prices have been used, but they might not be able to fully isolate changes in investors' expectations from actual supply shocks

Using Futures Prices

In further analyses, oil futures prices might be used as opposed to actual oil prices to isolate the effect of sentiment on investors expectations

3

Generic Sentiment Evaluators

The methods to evaluate report sentiment are quite generic, and might fail to capture specific dynamics in oil market expectations

Tailored Trained Model

A new tailored machine learning model might be trained on specific oil market communications, so that insights on their specific dynamics could be obtained

4

Model Selection

The predictability of price movements has been analysed across different time intervals and rolling windows, risking data mining complications. Also, the true model might be non-linear

Further Testing

The model obtained should be tested with other relevant variables and possibly in other time periods, to further confirm its relevance

Thank You