CRUDE OIL PRICE FLUCTUATIONS: AN ARIMA-GARCH AND HAR ANALYSIS OF ITS IMPACT ON STOCK VOLATILITY

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1. Introduction

The purpose of our research is to investigate the effects of West Texas Intermediate (WTI) crude oil prices on three US energy companies, ExxonMobil (XOM), Chevron Corporation (CVX) and NextEra Energy (NEE).

Energy prices play a crucial role in our lives and in several key industries, so we thought it would be relevant to investigate the effects crude oil prices have on a few major energy companies. Our criteria to select the three companies were; US based, listed on the stock market a few years before COVID, have a large market capitalization and to have other revenue sources other than crude oil.

Our initial hypothesis is that WTI prices will have a visible effect on the volatility of the chosen companies. Additionally, we are expecting these effects to be larger in the case of ExxonMobil and Chevron, since they are more exposed to crude oil prices, while NextEra has a strong focus on wind, solar and nuclear power. Since our focus is on volatility and not price movements, we expect crude oil prices to have a strong effect on the volatility of NextEra as well, albeit with a negative correlation on the stock price.

Our aim is to answer the question whether crude oil prices have any effect on the volatilities of our selected companies.

To date, several studies have explored the relationship between crude oil futures and oil company returns, albeit with mixed findings. Some studies have suggested that increased trading activity in crude oil futures markets leads to heightened volatility in oil company stock prices, as investors react to new information and adjust their expectations regarding future oil prices (Gjolberg & Johnsen, 1999). Other research has proposed that the presence of crude oil futures markets serves as a stabilization mechanism, dampening the volatility of oil company returns by providing a platform for hedging and price discovery (Beckmann & Czudaj, 2017),(Sadorsky, 2006).

In the literature, various methodologies have been employed to investigate this relationship. Some studies have relied on econometric models such as vector autoregression (VAR) and GARCH models to analyze the volatility spillover effects between crude oil futures and oil company returns. Others have employed event study methodologies to examine the impact of specific events or announcements in the futures markets on oil company volatility.

To find the answers to our research question we used several time-series analysis methods, such as four different ARIMA-GARCH models, with structural breaks and crude oil as an exogenous variable, multivariate GARCH models and HAR models.

In the next chapter we will talk about our dataset after which we will go into more detail regarding our time-series models.

2. Dataset

Our dataset contains the daily closing prices of WTI, XOM, CVX and NEE between 2016.01.04 and 2023.05.12 as well as intraday data for the three stock prices with one-minute intervals for the same duration. The time-interval was chosen to capture a few years before and after the COVID price crash of crude oil. This will allow us to introduce structural breaks to our models to further improve the results of our investigations and capture information before and after the COVID period.

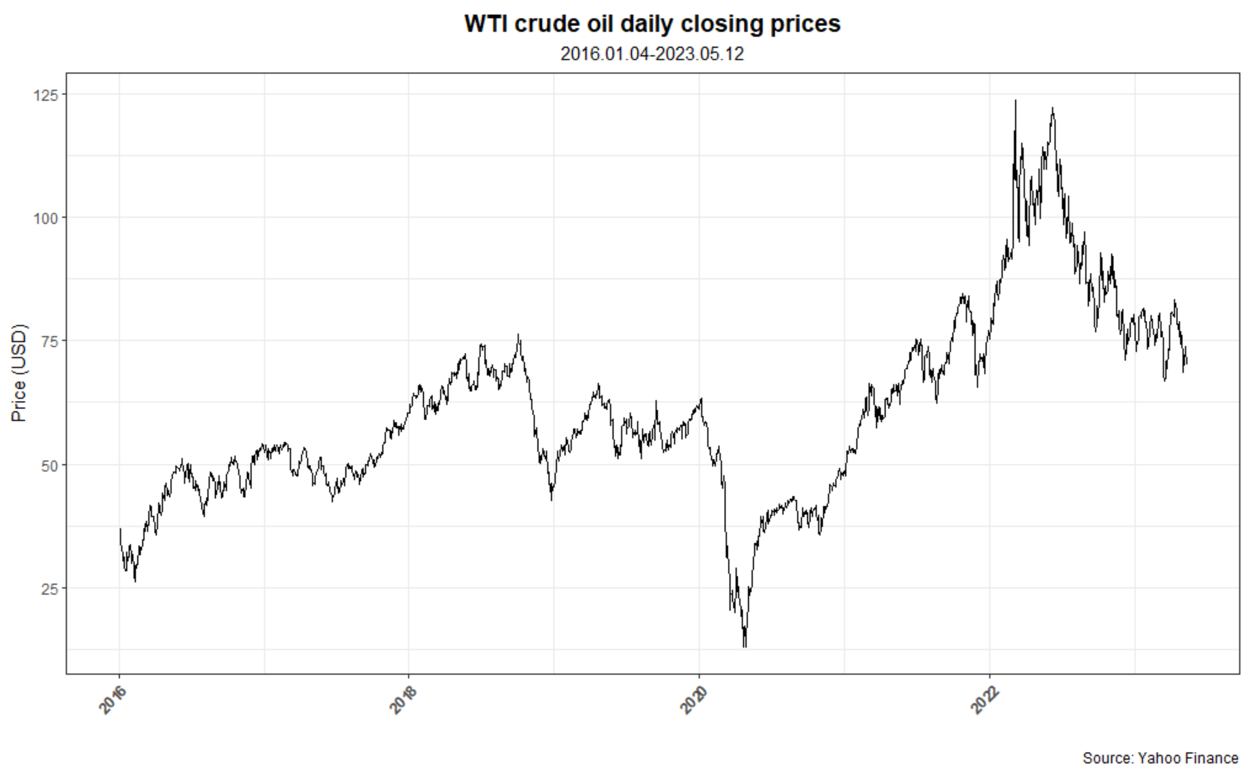

Figure 1: Daily closing prices of WTI

On Figure 1 we can see the daily closing prices of WTI for the given time-period. The price between 2016 and 2019 was showing a slowly increasing trend, which was interrupted by lower demands in 2019. After a year of relative stability, the prices crashed when the COVID outbreak caused mass-lockdowns worldwide. After this we can see the clear structural break with an almost exponential increase in prices.

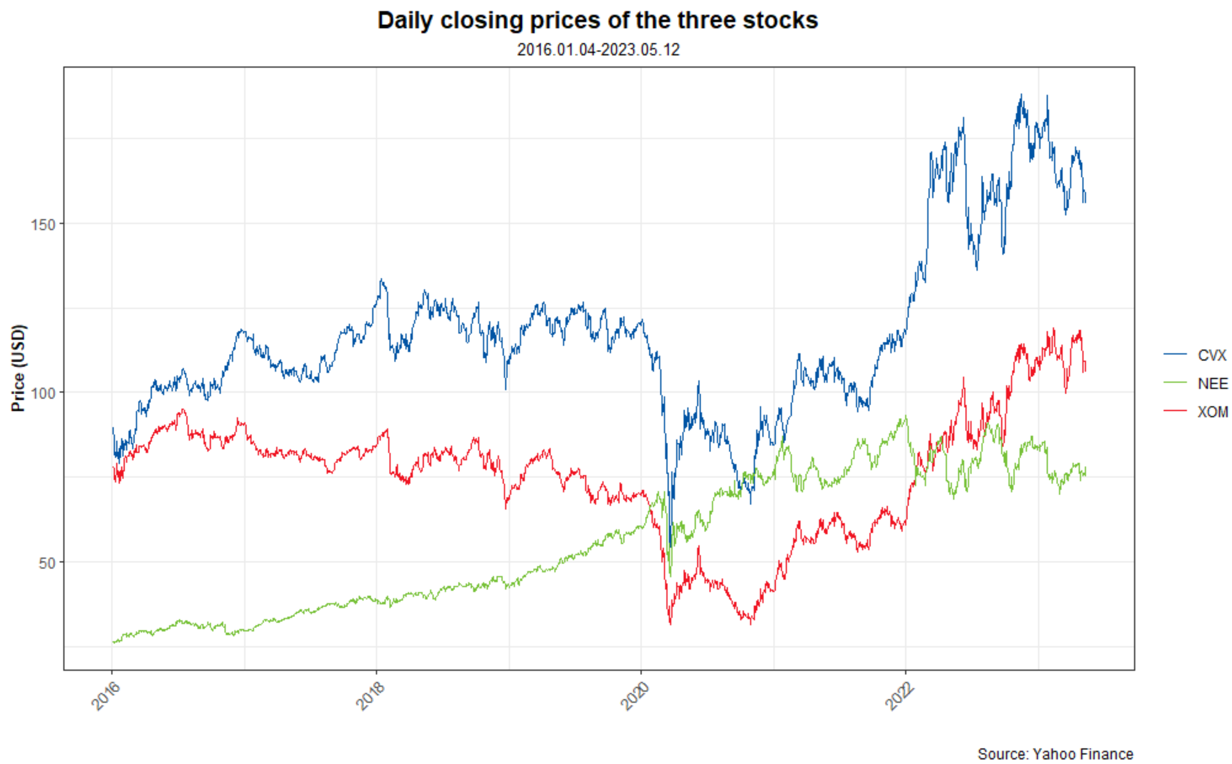

Figure 2: Daily closing prices of the three stocks

Figure 2 shows us the daily closing prices of our chosen companies. We can see XOM and CVX following a similar trajectory to the crude oil prices prior to COVID, while NEE was steadily climbing upwards. The crash of crude oil prices severely affected XOM and CVX, however due to a general market decline NEE also experienced a slight drop in price. The three years after COVID favored the energy sector, as we can see that NEE kept increasing in price until hitting a stagnating period, while both XOM and CVX reached levels higher than before COVID.

We can see that none of the time-series data that we are working with demonstrates stationarity, which is a crucial property to have, because most statistical forecasting methods assume that the underlying data is stationary. Therefore, in the next chapter we will try to address these issues by implementing four different ARIMA-GARCH models with the goal of removing the non-stationarity properties from our data.

3. ARIMA-GARCH models

The first step to make time-series data stationary is to transform the daily closing prices into logarithmic returns the following way:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

Where P_t and P_{t-1} represent the closing prices of a given and a previous day respectively.

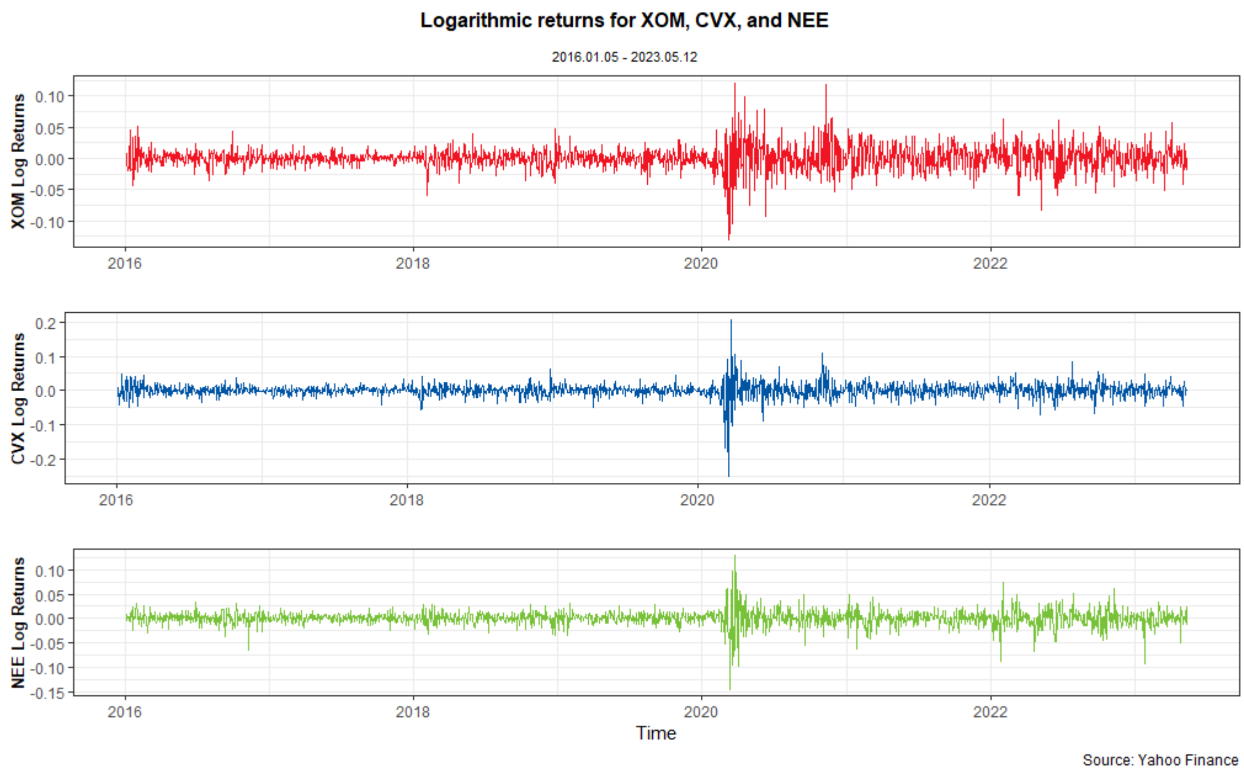

Figure 3: Logarithmic returns of XOM, CVX and NEE.

On figure 3 we can see all three of the logarithmic returns having an expected value of 0, however the variance does seem to be affected by time, which indicates that ARIMA might be required. Furthermore, we can see volatility clustering around the starting period of COVID and see a potential structural break as well since the following period is more volatile.

To test the stationarity of the returns we used Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Shin (KPSS) tests. The null hypothesis of ADF is that a unit root is present in the time-series sample, it assumes non-stationarity. The null hypothesis of the KPSS test on the other hand assumes the data to be stationary. Using both tests reduce Type I and Type II errors, so we can be more confident in our results. According to both tests the returns of XOM are stationary, while CVX and NEE are still not stationary, therefore we will further develop our ARIMA models for these two stocks -since the logarithmic returns are already an ARIMA (0,1,0) by definition-. The results are further confirmed by our visual investigation of the autocorrelation and partial autocorrelation functions (ACF, PACF).

We also tested the three returns for autocorrelation with the Ljung-Box test. The null hypothesis states that the data is independently distributed, so it assumes that there is no autocorrelation, which means that the data is a white-noise process. According to the test XOM is white noise, with no autocorrelation, while CVX and NEE are not. A significance level of 5% was used for all our tests.

To determine the optimal ARIMA models we investigated the ACF and PACF plots, and selected the models based on the best Bayesian Information Criterion (BIC) out of the ones that were the Ljung-Box test showed no autocorrelation. For CVX the best model was an ARIMA (5,1,2), while for NEE an ARIMA (3,1,3) was selected -and an ARIMA (0,1,0) for XOM-.

The ARIMA models were not able to capture the volatility clustering, so the next step was to determine the optimal GARCH models for our data.

We decided to use four different GARCH models for our data; Standard GARCH (SGARCH), Threshold GARCH (TGARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) and Exponential GARCH (EGARCH). Our chosen distribution model was the skewed Student-t distribution. The reason for these choices partly come from a research paper mentioning 11 stylized facts for financial assets, titled *Empirical properties of asset returns: stylized facts and statistical issues* written by Rama Cont in 2000.

Some of the stylized facts that are relevant to our case:

(2) Heavy tails (distributions): The distribution of the returns of financial instruments is wider on the tails and sharper compared to a normal distribution. This means that extreme

events are more likely to happen and due to the sharper form less observations are around the expected value.

(3) Gain/loss asymmetry: Larger and more frequent downward movements can be observed in stock prices and index values, but equally large upward movements are not as common. This property does not apply to currency exchange rates where a higher symmetry can be observed). (Rama Cont, 2001, p. 224)

We also looked at the kurtosis and skewness of our data as well as the Shapiro-Wilkins test. All three of the stock returns showed a negative skew and high kurtosis, which align with the 3. Stylized fact, stating that negative news is more common/has a stronger effect compared to positive news. Our returns are also leptokurtic, which means a heavier tail and sharper peak compared to the normal distribution, further proven by the Shapiro-Wilkins test, where we rejected the null-hypothesis for all three returns, which states that the data is normally distributed.

These tests and theoretical facts resulted in our choice of skewed Student-t distribution over the normal student-t distribution, and the four GARCH model types that are most commonly used to model financial data.

These four models were used for all three return series, additionally we tested these models with the stationary return series of WTI as an exogenous variable, with a structural break as a dummy variable and with both the WTI as an exogenous variable and the structural break. This resulted in us having 16 models for each stock.

Additionally, we forecasted the volatility with the models for 252 days, with a rolling window estimation, re-adjusted after every day. The training data included the time-period of 2016-01-05 until 2022-05-11, and the test data was the last 252 days.

To check the performance of the models we used BIC and likelihood for in-sample results and mean squared errors (MSE) for the out of sample performance. Based on these metrics, the best model for each stock is the following

XOM: ARIMA (0,1,0) - GJR-GARCH (1,1) with WTI as an exogenous variable.

CVX: ARIMA (5,1,2) – EGARCH (1,1) with WTI as an exogenous variable and a structural break.

NEE: ARIMA (3,1,3) – EGARCH (1,1) with WTI as an exogenous variable and a structural break.

The results of all 48 models can be found in the appendix.

In the case of XOM and CVX adding the structural break did not improve the likelihood and BIC of the models substantially, however adding WTI did. While combining WTI with the structural break did produce the best in-sample results for all three stocks, it did perform worse out of sample in the case of XOM, which is why the best model for this stock only included the WTI.

Some of the results were also tested with a Diebold-Mariano test, where the null hypothesis states the forecast errors from the models having the same variance. The results of the test showed that there is a difference in the predictive models (MSE).

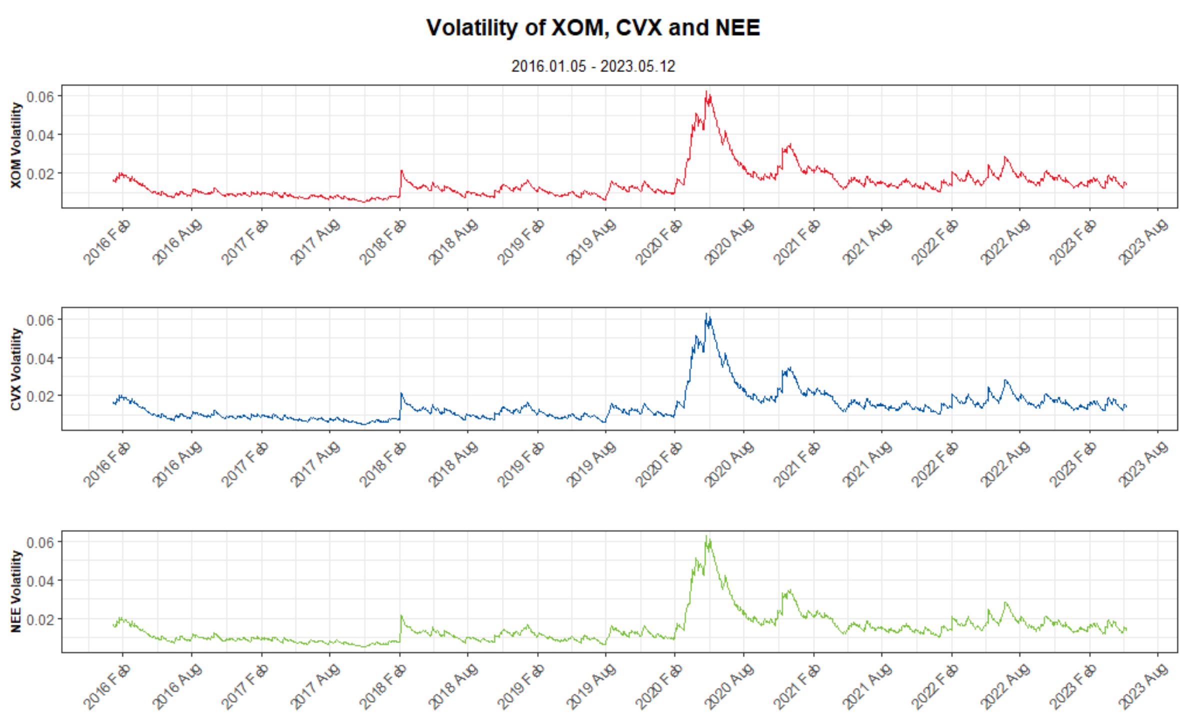

Figure 4: Volatility of the three stocks after the GARCH models

On figure 4 we can see the final volatility output of the GARCH models. The data is smoothed out except for the COVID crash, which could be due to it being a structural break, so there were no past values for the model to train for this scenario. GARCH models also assume stationary conditions, such as the underlying conditions staying constant over time, however this is rarely the case in reality.

In the next section we will examine multivariate GARCH models.

4. DCC-GARCH models

In the following passage we estimated a dynamic conditional correlation GARCH model (DCC-GARCH) for each stock joint with WTI futures to capture the possible spillover effect that crude oil volatility has on stock price's volatility. For this purpose, we utilized daily closing prices for both the companies' stocks and WTI future index.

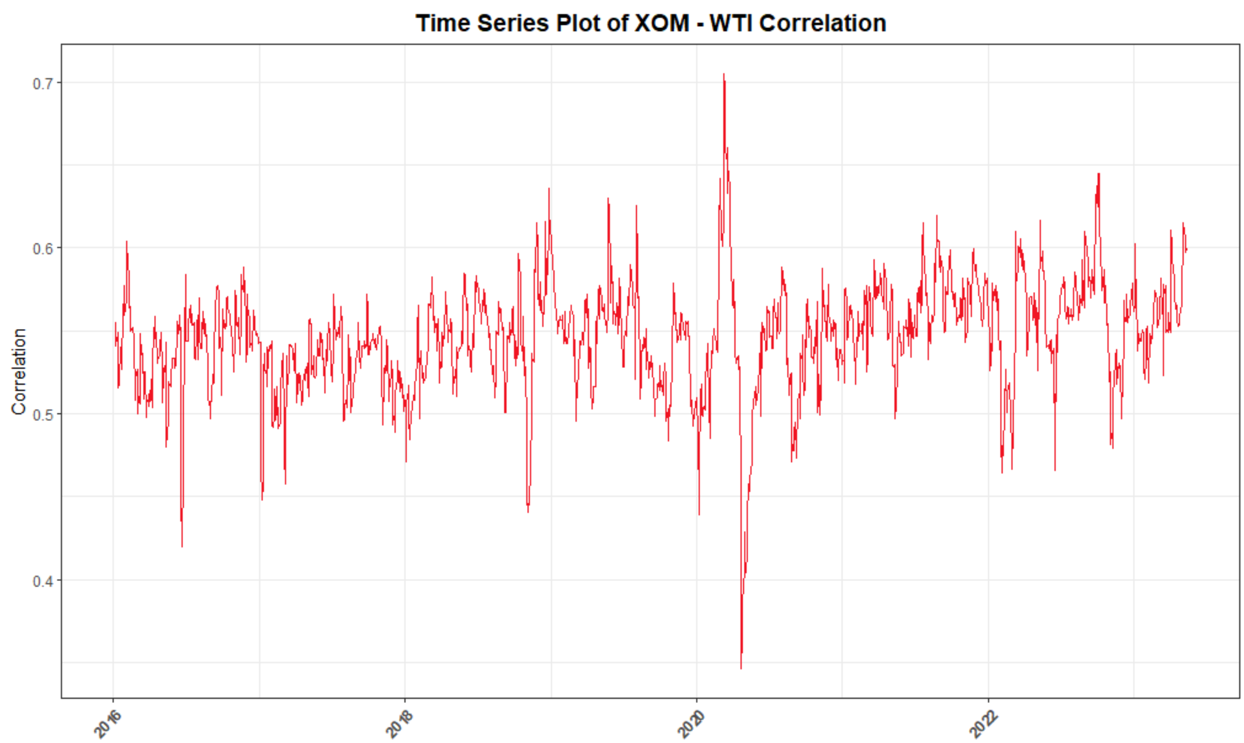

Figure 5: Correlation plot of XOM and WTI

We firstly estimated the XOM – WTI DCC (1,1) model with multivariate normal distribution with the intention to investigate if GARCH (1,1) specification is appropriate for this time series. In this way, we look at "alpha1" and "beta1" coefficients, which are all significant, so we can conclude that this model seems to make sense. Additionally, to test the appropriateness of the chosen model (DCC -GARCH), we test the joint significance of its coefficients. Therefore, failing this test would imply that the model is not appropriate for our analysis. In the case in which the conditional correlations are constant, we would expect "dcca1" to be approximately 0 (insignificantly different from 0) and “dccb1” to be approximately 1 (insignificantly different from 1, but significantly different from 0). In our model estimate, we have that “dcca1” coefficient is close to zero and is not significant at 10% level and “dccb1” coefficient is highly significant with an estimate of 0.88. “dcca1” provides the contribution of the realized correlation matrix from last period while “dccb1” provides the contribution of a "long-run" correlation matrix that is due to all previous periods. By knowing this, we can conclude that WTI has no short-term spillover effect on XOM, but a strong long-run spillover effect. In fact, as we can note from the time series correlation plot below, and by looking at dynamic conditional correlations’ parameter estimates, the correlation is quite strong and close to 60%.

	WTI	**XOM**
WTI	1	0.599791
XOM	0.599791	1

As it is possible to note from the above plot, we see a large spike in correlation, corresponding to the Covid outbreak, suggesting that XOM stock price volatility was highly correlated with WTI index futures volatility, especially in that specific time.

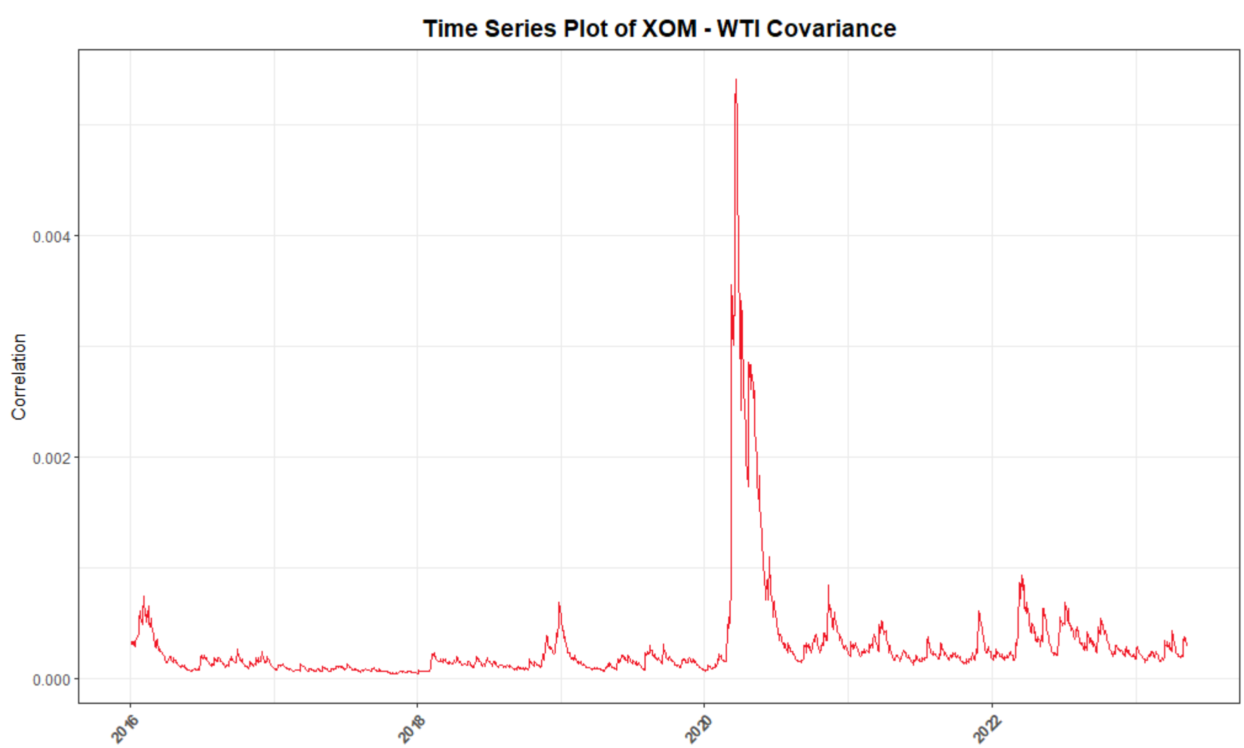

Figure 6: Covariance plot of XOM and WTI

Model XOM	# par.	Likelihood	AIC	BIC	MSE
DCC	15	9732.34	-10.49389	-10.44915	0.00103280391011859

We secondly estimated the CVX – WTI DCC (1,1) model, applying the same methodology as in the XOM – WTI DCC (1,1) MODEL. In this case, we have that "dcca1" coefficient is quite small (0.056) but significant at 10% level and "dccb1" coefficient is significant at 10% level with an estimate of 0.5. In this way, we can conclude that WTI has both short-term and long-run spillover effect. In fact, as we can note from the time series correlation plot below, and by looking at dynamic conditional correlations' parameter estimates, the correlation is strong a slightly lower if compared to XOM – WTI.

	WTI	CVX
WTI	1	0.5495657
CVX	0.5495657	1

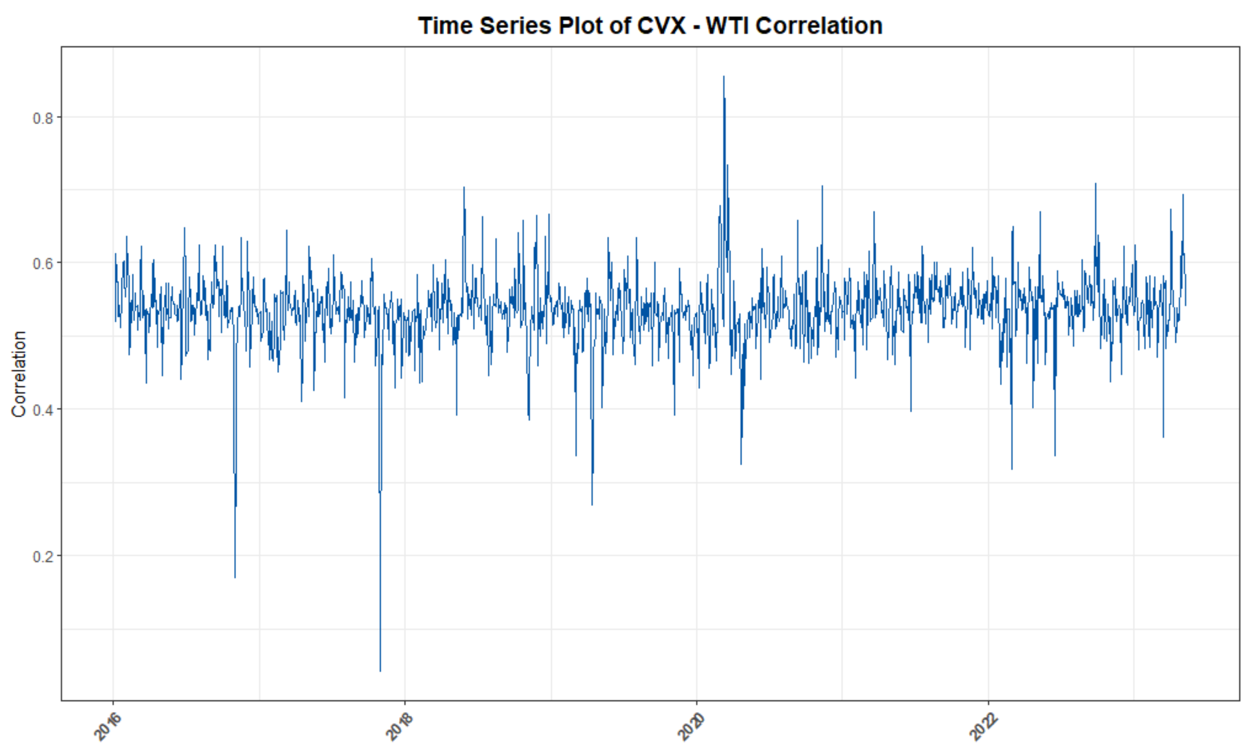

Figure 7: Correlation plot of CVX and WTI

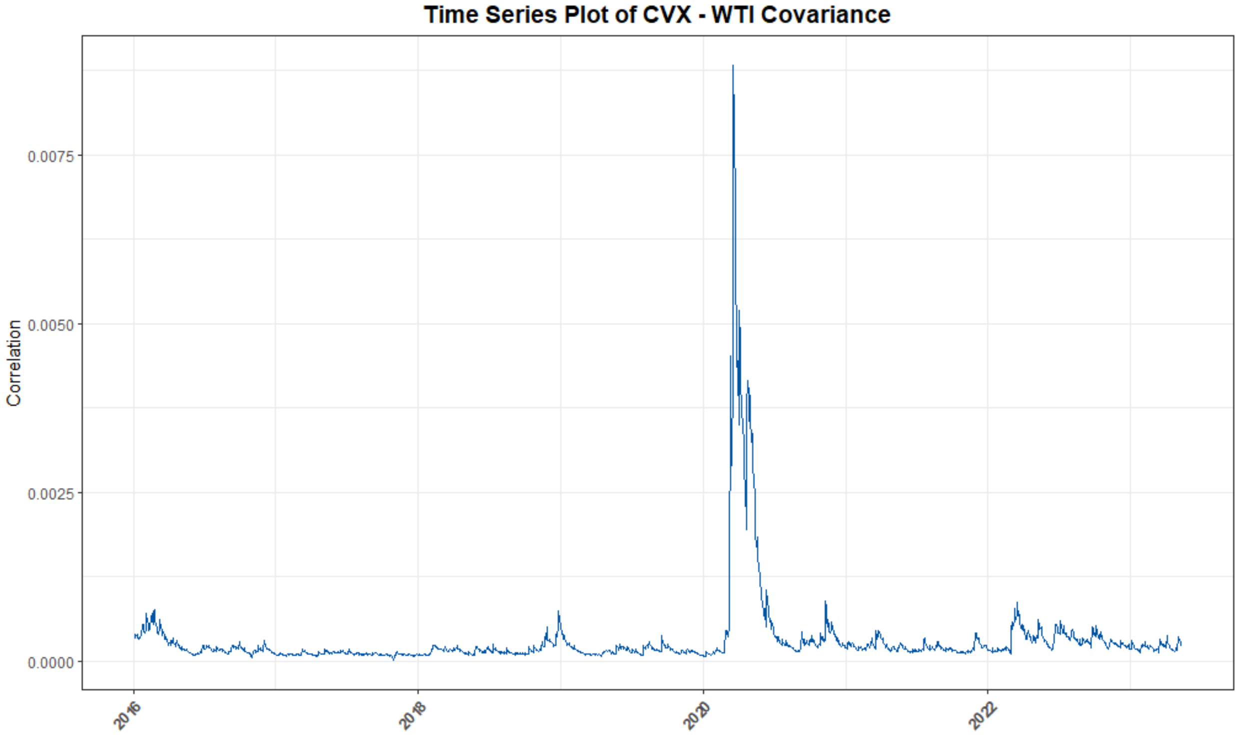

Figure 8: Covariance plot of CVX and WTI

As it is possible to note from the above plot, if we compare it to XOM – WTI, we see some discrepancies, in fact, apart from the large spike in correlation during Covid outbreak, CVX experienced low correlations in other two moments.

Model CVX	# par.	Likelihood	AIC	BIC	MSE
DCC	29	9651.013	-10.391	-10.304	0.000827510136266476

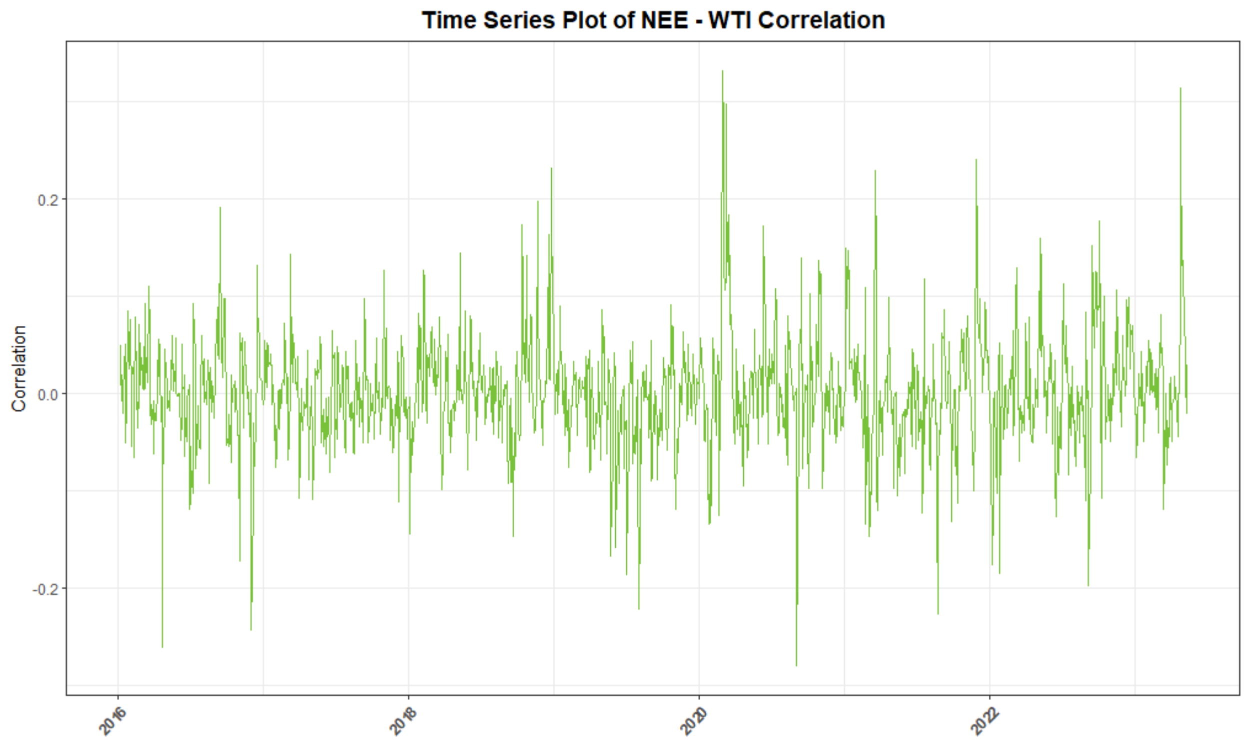

Figure 9: Correlation plot of NEE and WTI

Then, we estimated NEE – WTI DCC (1,1) model. By checking "alpha1" and "beta1" coefficients, which are all significant, we can conclude that this model seems to be appropriate. On the other hand, both "dcca1" and "dccb1" coefficients are not significant at any level, thus indicating that WTI has no spillover effect, neither in the short-term, nor in the long run. Consequently, we can affirm that WTI volatility has almost no correlation with NEE volatility, as we can see both from the correlation matrix and from the correlation plot.

	WTI	**NEE**
WTI	1	0.03244572
NEE	0.03244572	1

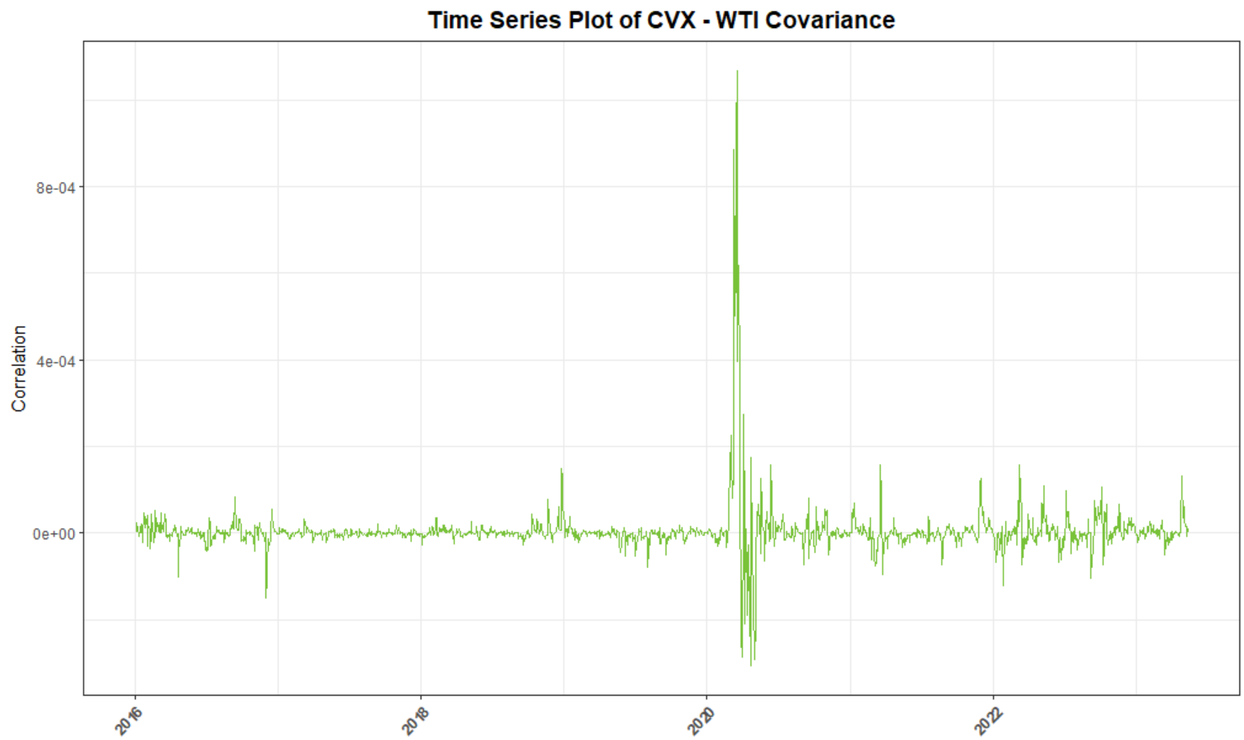

Figure 10: Covariance plot of NEE and WTI

As it is possible to note from the above plot, the correlation of NEE and WTI is "less stable" if compared to the correlations of the other two companies and on average it is equal to zero. This can be explained by the fact that approximately 41% of NextEra Energy's generating capacity was from fossil fuels and non-renewables as of 2020, in contrast to the way higher dependency on fossil fuels (as crude oil) of both Exxon Mobil and Chevron Corporation. This lower dependency can partially explain the correlation between NEE and WTI compared to the other two stocks analyzed. In addition, by looking at the covariance plot, we notice, as in the other stocks' covariance plots, the spike in covariance, which coincides to the Covid outbreak.

Model NEE	**# par.**	**Likelihood**	**AIC**	**BIC**	**MSE**
DCC	27	9755.854	-10.506	-10.426	0.000949456010449329

5. HAR model

In the following passage, an estimation of the Heterogeneous Autoregressive (HAR) model is conducted to explore the relationship between crude oil futures and daily volatility of oil companies. For that purpose, we will estimate HAR model without additional covariates and HAR model with additional covariates related to crude oil future for every oil company on a rolling basis. Then we will make a one-day conditional prediction for each model, and in the end we will calculate prediction accuracies and loss functions of models with different sets of covariates and conduct statistical tests to determine, whether there is a significance difference between the calculated statistics.

The HAR model is a popular econometric framework that incorporates different frequencies of volatility to capture the dynamic behavior of financial assets. Firstly, we need to estimate optimal intraday frequencies for calculating realized daily volatility for each oil company. For that purpose, we build a Volatility Signature Plot for each Oil company.

We iterate over the range of intraday frequencies from 1 to 60 minutes. Then for each frequency we estimate daily realized volatilities for the period of 1 year, calculate the average value of these volatilities, and then depict all average realized volatilities for each intraday frequency on a single plot. Daily realized volatility is estimated using following formula:

$$\sigma_{RV} = \sqrt{\frac{n}{n-1} \times scaling\_factor \times \sum_{i=1}^{n} r_i^2}$$

$$scaling\_factor = \frac{390}{390 - 390\% frequency}$$

$$n = \left\lfloor \frac{390}{frequency} \right\rfloor$$

$$r_i = \log\left(P_{end-(i-1)\times frequency}\right) - \log\left(P_{end-i\times frequency}\right)$$

$$where\ P_{end}\ is\ the\ asset's\ price\ at\ its\ closing\ minute\ and\ P_k\ is\ price\ of\ the\ asset\ at\ minute\ k\ of\ the\ trading\ day$$

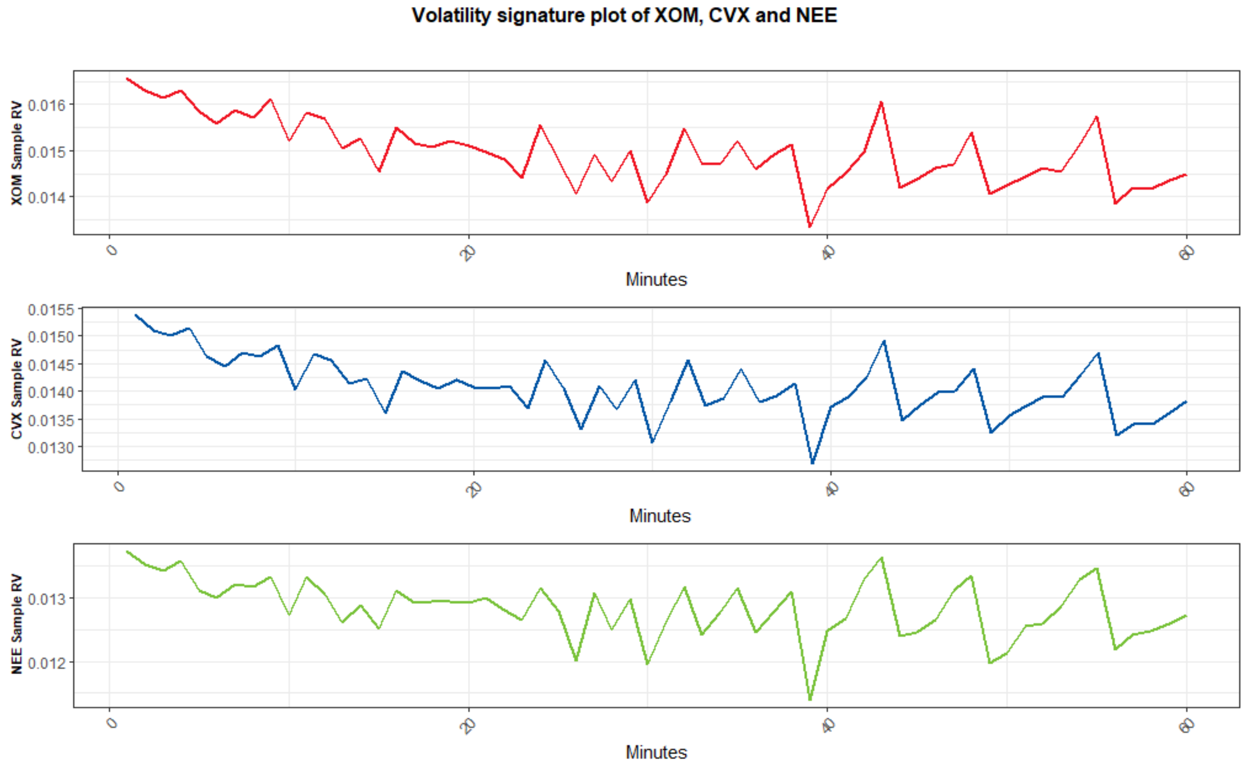

Figure 11: Volatility signature plot of the three stocks

The shapes of Volatility Signature Plots are quite unusual. From frequencies 1 to 20 we have a decreasing trend, then after intraday frequency of 20 trend becomes more or less constant, but fluctuations of average daily realized volatilities become higher. Our possible explanation for such effect is following: We can notice that larger changes in the average daily realized volatilities happen, when the value of $\left\lfloor \frac{390}{frequency} \right\rfloor$ $changes$. For example, $\left\lfloor \frac{390}{55} \right\rfloor = 7$ and $\left\lfloor \frac{390}{56} \right\rfloor = 6$. And we can notice a significant drop in average daily realized volatility from 55 frequency to 56. Similarly, $\left\lfloor \frac{390}{48} \right\rfloor = 8$ and $\left\lfloor \frac{390}{49} \right\rfloor = 7$. And we can notice a significant drop in average daily realized volatility from 48 frequency to 49. Most likely, we observe such effect, because for example for frequency 48 we cover all most the whole trading day with 48 minutes intraday periods (only 6 minutes are left uncovered), while for frequency 49 minutes we have 47 minutes of trading day uncovered. In our algorithm we started from the end of the trading day and then iteratively subtracted daily frequency and calculated log-returns at each intraday interval. We also could have started from the beginning of the trading day and then add daily frequency and calculate log-returns at each intraday interval. But in both strategies, for example for frequency 49, we don't cover either the first 47 minutes of the trading day or the last 47 minutes of the trading day. And is spite of the fact that we use a scaling factor, start and end of the trading day have structural differences from the rest of the day, usually traders trade more actively at these periods, and volatility is higher. Thus, simply multiplying by scaling factor doesn't completely help us.

Potential solutions are:

1. Calculate squared log return on the remainder of the trading day using different frequency. For example, for 49 minutes frequency use 47 minutes frequency to calculate squared log return on the remainder of 47 minutes
2. Consider only frequencies, which have a small remainder of the trading day not accounted. For example, impose $390\%frequency \leq 10$
3. We might also move the start/end of our iteration inside the trading day. For example, for 49 minutes frequency we might start from the 23th minute of the trading day, then iteratively add 49 minutes and finish at 24 minutes before the end of the trading day.

All the methods above have certain drawbacks (For method 1 we are inconsistent with frequencies. And it's not clear, why fitting 27 frequency into the remainder is better than fitting 23 and 24 frequency, and in general we overcomplicate our model. For method 2 we ignore some of the frequencies, which might potentially provide a better approximation. And in method 3 we still don't account for the edges of trading day and thus might underestimate the intraday volatility). But the effect of the remainder is less, when we observe less frequencies and we can also notice that from the plots. Thus, it will be reasonable to select a relatively low intraday frequency, where Volatility Signature plot becomes more stable. We decided to select **20 minutes** as intraday frequency for calculation of daily realized volatilities.

Another interesting observation is that Volatility Signature Plots of NEE, XOM and CVX are very similar. And though they have different ranges, and magnitudes and sometimes even directions of fluctuations differ, in general they have very similar pattern. That might be explained by high correlation of the log returns of all 3 oil companies' stocks.

Based on the 20 minutes intraday frequency we calculated daily realized volatilities for each Oil company and each day available in our datasets (2016-02-05 - 2023-05-11). And then estimated HAR model on a rolling basis (rolling window = 252 days) for each oil company:

$$RV(t+1,1) = \beta_0 + \beta_D \times RV(t,1) + \beta_W \times RV(t,5) + \beta_M \times RV(t,21) + \varepsilon_{t+1}$$

Then we predict daily realized volatility for the next day using the estimated model. Model is reestimated every 7 days in order not to spend too much computational power. The approach of reestimating model every 252 days allows us to account for structural breaks (we decrease bias of the model) , but at the same time it increases variance of our model, because coefficients depend upon less observations (than if we increased the size of rolling window, or at each period estimated a model, using all the data available) and therefore is less stable. Thus, we face the problem of bias-variance tradeoff here. We could have done grid search over various values of rolling window and then compare them by several statistics (MSE or Likelihood) and choose the best one. But using such approach we may experience overfitting problem, that's why we decided to choose fixed rolling window of 252 days, what is equal to 1 trading year.

Then we estimate the second model with additional covariate: lagged squared log return of WTI

$$RV(t+1,1) = \beta_0 + \beta_D \times RV(t,1) + \beta_W \times RV(t,5) + \beta_M \times RV(t,21) + \beta_{WTI} \times r^2_{WTI,t} + \varepsilon_{t+1}$$

And calculate all the necessary statistics and compare them to the ones calculated for model with no WTI covariate.

	NEE		**XOM**		**CVX**	
Model	HAR	HAR+WTI	HAR	HAR+WTI	HAR	HAR+WTI
MSE	1.9735e-05	2.0172e-05	2.4569e-05	2.4511e-05	3.1538e-05	3.1053e-05
DMW	-1.8885		0.041254		0.10751	
p-value	0.05914		0.9671		0.9144	

6. Conclusion

The goal of our research was to investigate whether WTI crude oil prices have any effect on our three selected energy companies (XOM, CVX, NEE). Our initial hypothesis stated that WTI will influence the selected companies. We expected stronger effects on XOM and CVX, and additionally expected inverse effects on NEE.

To achieve a conclusion first we transformed our data to be stationary and white noise so we could perform further analysis on it, for this we used log-returns and ARIMA models. Afterwards we investigated the effects of WTI on the selected companies with several univariate GARCH, multivariate DCC-GARCH and high frequency HAR models.

Our results align with our initial hypothesis. For XOM and CVX we see improvements in the GARCH models when adding WTI as an exogenous variable, while in the case of NEE these improvements are not too noticeable. The correlation between the time series of XOM – WTI and CVX – WTI is also strong positive, while it is 0 for the case of NEE – WTI.

In the case of the HAR models as well, NEE was the only stock where adding WTI as an exogenous variable decreased the models performance.

Our results could suggest that there is value in using crude oil to model the price of energy companies, additionally this could also be extended to other sectors that have high dependency on raw materials. Our research could be expanded by increasing the pool of companies, investigate other industries and fine-tune our models by increasing the type of GARCH models or using additional exogenous parameters and input variables in the multivariate GARCH models.

Some limitations we faced or could face with these methods is computational power, these models use a vast number of variables and could potentially require cloud computing methods.

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Appendix

GARCH MODELS FOR THE VOLATILITY OF XOM								
	Log-returns				WTI as exogenous variable			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.542826	-5.54572	-5.5422	-5.546783	-5.827779	-5.821145	-5.823875	-5.823444
Likelihood (in sample):	5155.229	5161.441	5158.412	5162.655	5422.858	5420.476	5423.004	5422.605
MSE (out of sample):	0.000418583	0.000418667	0.000418694	0.000418639	0.000418967	0.000419046	0.000419016	0.00041907
	Structural break dummy				WTI and structural break			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.539165	-5.542534	-5.539054	-5.543808	-5.824285	-5.818048	-5.820494	-5.820338
Likelihood (in sample):	5155.601	5162.483	5159.26	5163.662	5423.384	5421.37	5423.635	5423.491
MSE (out of sample):	0.000418625	0.000418864	0.000418826	0.000418822	0.000419025	0.000419233	0.000419107	0.00041925

A1: Table for all the GARCH models for XOM. Each Model is ARIMA (0,1,0) – GARCH (1,1)

GARCH MODELS FOR THE VOLATILITY OF CVX								
	Log-returns				WTI as exogenous variable			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.499425	-5.493585	-5.497779	-5.499213	-5.825757	-5.817782	-5.822093	-5.823671
Likelihood (in sample):	5141.373	5139.728	5143.612	5144.939	5447.319	5443.696	5447.688	5449.15
MSE (out of sample):	0.000370785	0.000370579	0.000370665	0.000370598	0.000370617	0.000370507	0.000370559	0.000370511
	Structural break dummy				WTI and structural break			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.494683	-5.490969	-5.494503	-5.496451	-5.822054	-5.814916	-5.82085	-5.820754
Likelihood (in sample):	5140.744	5141.068	5144.34	5146.143	5447.652	5444.804	5450.3	5450.21
MSE (out of sample):	0.000370554	0.000370388	0.000370434	0.000370397	0.000370459	0.000370375	0.000370383	0.000370366

A2: Table for all the GARCH models for CVX. Each Model is ARIMA (5,1,2) – GARCH (1,1)

GARCH MODELS FOR THE VOLATILITY OF NEE								
	Log-returns				WTI as exogenous variable			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.962372	-5.963061	-5.959696	-5.961555	-5.959378	-5.960253	-5.958383	-5.960903
Likelihood (in sample):	5566.301	5570.701	5567.585	5569.306	5567.29	5571.862	5570.131	5572.464
MSE (out of sample):	0.000314944	0.000314784	0.00031481	0.00031479	0.000314952	0.000314758	0.00031481	0.000314759
	Structural break dummy				WTI and structural break			
	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH	S-GARCH	T-GARCH	GJR-GARCH	E-GARCH
BIC (in sample):	-5.959503	-5.959165	-5.95633	-5.960144	-5.956486	-5.95914	-5.953427	-5.960718
Likelihood (in sample):	5567.405	5570.855	5568.229	5571.761	5568.374	5574.593	5569.303	5576.055
MSE (out of sample):	0.00031499	0.000314707	0.00031478	0.00031474	0.000314995	0.000314684	0.00031478	0.000314717

A3: Table for all the GARCH models for NEE. Each Model is ARIMA (3,1,3) – GARCH (1,1)