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A comprehensive analysis of Brent Crude oil forecasting methods combining machine learning and quantitative models with application

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Supervisor:

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Content

Abstract

This study utilizes time series analysis and machine learning techniques to forecast Brent Crude oil prices. The forecasting models include an ARIMAX model, three machine learning models (GRU, LSTM, CNN) and an ARIMAX model augmented with LASSO regularization.

The findings indicate that the ARIMAX model exhibits the best forecasting performance; however, it is prone to overfitting. To address this issue, LASSO regularization is applied to the ARIMAX model to penalize complexity. Surprisingly, incorporating LASSO regularization results in reduced forecasting performance compared to the initial ARIMAX model.

Among the basic machine learning models, the GRU model demonstrates highest predictive accuracy, followed by the LSTM model, while the CNN model exhibits lower predictive accuracy. When adding a dropout term, we find that the ranking order changes, and the CNN exhibits highest predictive accuracy. Further, when generalizing the models using cross-validation, we find that LSTM exhibits the best overall forecasting performance among the machine learning models.

As an extension of our main research, we seek to use machine learning models to predict out-of-sample Brent Crude oil price and evaluate its impact on the valuation of Aker BP and Vår Energi. When applying the forecasted Brent Crude oil prices obtained from the Prophet model, the findings reveal that both companies are undervalued relative to their current market values.

These results underscore the significance of accurate forecasting models in informing investment decisions and highlight the potential undervaluation of the companies analyzed.

Acknowledgement

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Lastly, we would like to acknowledge the contributions of all the researchers, authors, and professionals whose work and insights have formed the foundation of our thesis. Their dedication to advancing knowledge in the field of finance has been a source of inspiration for our own research.

To all those who have played a part, no matter how big or small, in our journey towards completing this master's thesis, we offer our heartfelt appreciation and gratitude. Your support and encouragement have made this achievement possible, and we are truly grateful.

List of Abbreviations

ARIMAX – Autoregressive Integrated Moving Average Model with Exogenous Variable

ARIMA – Autoregressive Integrated Moving Average Model

ML – Machine Learning

AR – Autoregressive Model

RNN – Recurring Neural Network

GRU – Gated Recurrent Unit

LSTM – Long Short-Term Memory

CNN – Convolutional Neural Network

NN – Neural Network

MAE – Mean Absolute Error

MSE – Mean Squared Error

RMSE – Root Mean Squared Error

AIC – Akaike Information Criterion

DCF – Discounted Cash flow Model

EVA – Economic Value-added Model

WACC – Weighted Average Cost of Capital

CAPM – Capital Asset Pricing Model

BOEPD – Barrel of Oil Equivalent per day

MMBTU – One Million British Thermal Units

MCF – One Thousand Cubic Feet

$\boldsymbol{R^2}$ – Goodness of fit

$\boldsymbol{R^2_{adj}}$ – Corrected goodness of fit

$\boldsymbol{r_e}$ – Cost of Equity

$\boldsymbol{r_d}$ – Cost of Debt

$\boldsymbol{r_f}$ – Risk-free rate

$\boldsymbol{\beta}$ – Beta

1. Introduction

1.1 Purpose

The main objective of this thesis is to explore methods for forecasting the price of Brent Crude oil using quantitative models and machine learning techniques. Additionally, we aim to assess the impact of the Prophet model forecast on the fundamental values of Norwegian oil and gas companies.

To achieve this, we will first develop an oil price forecast by employing various statistical forecasting models and utilizing machine learning algorithms. These approaches will help us generate reliable predictions for the future price of oil. Subsequently, we will conduct a comprehensive valuation analysis of the selected oil and gas companies. This analysis will involve the application of two present value methods, as well as an option pricing model. By incorporating our oil price forecast into these valuation models, we can obtain forward estimates for key factors that contribute to the fundamental value of oil and gas companies.

Furthermore, we acknowledge that the selected companies have a significant presence in the gas sector. Therefore, we will incorporate the gas price based on the forward curve and expert estimates provided by macroeconomists and gas analysts. This will enable us to capture the dynamics of the gas market and its influence on the overall valuation of the companies.

In summary, the primary objective of this thesis is to examine forecasting models for Brent Crude oil. Furthermore, we seek to obtain a forward estimate on the Brent Crude oil using machine learning and evaluate its impact on the fundamental values of Norwegian oil and gas companies. By doing so, we aim to enhance our understanding of these industries and contribute to the existing body of knowledge in the field.

1.2 Motivation

The motivation behind this thesis stems from the current global energy crisis, characterized by high energy prices, increasing living costs and increased volatility in energy prices. While the invasion of Ukraine by Russia has contributed to the surge in energy prices, we believe that there are other underlying issues impacting global energy prices. We seek to gain an understanding of which underlying variables that affect energy prices.

To gain a deeper understanding of the market dynamics that govern energy prices worldwide, we aim to investigate how these factors impact the fundamental values of Norwegian oil and gas companies. Given the candidates' interest in the oil market and its critical role in the global energy mix, we find it compelling to explore forecasting methods and their influence on the valuation of the selected companies.

Furthermore, our objective is to acquire insights into accurate and efficient forecasting techniques and methodologies, particularly in the context of commodity markets. We aspire to develop a framework that leverages machine learning and quantitative models to forecast the price of Brent Crude oil.

By conducting this research, we aim to contribute to the development of effective forecasting approaches, understanding of variables that impact energy prices, and valuation of oil and gas companies. Ultimately, our goal is to provide valuable insights and tools that can assist in making informed decisions in the energy sector and mitigate the challenges posed by volatile energy prices.

1.3 Research Question

Our research question is:

"How well do machine learning models perform on forecasting Brent Crude oil relative to traditional multivariate time series forecasting models?"

With the following research sub-question:

"What is the fundamental value of Aker BP and Vår Energi when applying the Brent Crude oil price forecasted by the Prophet model, and how does it compare to their current market values?"

2. Literature review

2.1 Forecasting oil price

Early research on oil price forecasting was conducted by Wang, Yu, and Lai (2005) who compared ARIMA models and neural networks. They proposed a new methodology to predict Crude oil prices. They compared an ARIMA model to an ANN model. Their findings suggest that for the full period, the ANN outperformed ARIMA by just 0.2% based on RMSE. An important factor that Wang, Yu and Lai highlights in their paper is that the models have very little practical use.

Wang, Yu and Lai (2008) continued their work with comparing ARIMA to an empirical mode decomposition (EMD) for world Crude oil spot price forecasting. In this paper, they use a three-layer feed-forward neural network (FNN) and compared it to ARIMA. In this paper, ARIMA was the worst performer and achieved an RMSE significantly higher than the neural networks, which is interesting when compared to their previous work. They highlight that the bad performance can be attributed to the weaknesses of individual models, and that hybrid models tend to perform better.

Ahmed and Shabri (2014) forecasted daily WTI Crude prices using ARIMA and comparing them to SVM and GARCH respectively. The study shows that ARIMA has strong predicting power but was outperformed by SVM. However, the study points out that ARIMA had higher predicting capabilities than GARCH.

Zhao and Wang (2014) created an ARIMA model with Crude oil prices from 1970 to 2006 to forecast annual Crude oil prices. They propose an ARIMA model and shows that ARIMA possesses high predicting power, but notes that forecasting oil prices is an uncertain and arbitrary process. Forecasting of Crude oil prices is influenced by a lot of factors and is complex. Xiang and Zhuang (2013) focused on a short-term forecast, and therefore created a short-term prediction of international Crude oil prices with an ARIMA model application on a one-year basis, with data from November 2012 until April 2013. They found that an ARIMA (1,1,1) possessed good prediction effects. They concluded that on a short-term basis ARIMA is a good model when forecasting international Crude oil prices.

More recent studies performed using ARIMA is Gasper and Mbwambo (2023) who researched how forecasting using ARIMA has been affected post Covid-19 and war in Ukraine. The study points to the fact that considering these crises where we experienced high volatility in the energy markets, ARIMA models are still able to forecast Crude oil prices with high accuracy. They point to the fact that ARIMA achieves the highest predicting capabilities in the short term.

Employing machine learning models for forecasting Crude oil prices has become a popular technique. Gupta and Pandey (2018) constructed an LSTM neural network to predict Crude oil prices. Their study focused on implementing different LSTM tuning with different epochs, lookbacks, and other tuning techniques and finds that LSTM possesses high predictive accuracy. However, their research suggests that increasing lookbacks did not increase predictive accuracy, but they conclude that the implementation of LSTM is promising.

Wu, Wu, and Zhu (2019) continued using LSTM combining it with an ensemble empirical mode decomposition (EEMD) to forecast Crude oil prices. They experienced that traditional ensemble models broke down during training, but when LSTM was introduced, the model was able to accurately forecast WTI Crude oil.

This work was extended by Assaad and Fayek (2021) where they also introduced CNN as a neural network used to forecast Crude oil prices. They implemented a hybrid model consisting of CNN and LSTM and compared this model to a regular LSTM and a Deep neural network (DNN). The model was based on fluctuations in US stocks, and they used these fluctuations to check whether this could help predict Crude prices. Based on their findings, the research suggests that LSTM was the best model to predict Crude oil prices.

Nasir, Aamir, Haq, Khan, Amin & Naeem (2023) compared different ARIMA and LSTM setups and compared their forecasting performance on WTI. Their models are a novel hybrid prediction technique that depends on local mean decomposition. Their findings suggest that a hybrid model between LMD-SD-ARIMA-LSTM performed best. More interesting was the fact that their basic ARIMA model performed better than a basic LSTM model, where their ARIMA model achieved an RMSE of 1.461.

Through our research we aim to contribute to the existing body of knowledge, and investigate the performance of the LSTM, CNN and GRU in forecasting Brent Crude oil prices, compared to the ARIMAX model.

2.2 Valuation

Enterprise DCF remains a favorite of practitioners and academics because it relies on the flow of cash in and out of the company, rather than on accounting-based earnings. For its part, the discounted economic-profit valuation model can be quite insightful because of its close link to economic theory and competitive strategy. Economic profit highlights whether a company is earning its cost of capital and quantifies the amount of value created each year. Koller, Goedhart and Wessels recommend creating both enterprise DCF and economic-profit models when valuing a company. Both the enterprise DCF and economic-profit models rely on the weighted average cost of capital (WACC). WACC-based models work best when a company maintains a stable debt-to-value ratio. The authors highlight that the discounted cash flow analysis delivers the best results.

Professor Aswath Damodaran (2012) argues in his book *Tools and techniques for determining the value of any asset* that in general terms there are three approaches to valuation. The first, discounted cash flow (DCF) valuation, relates to the value of an asset to the present value (PV) of expected future cash flows on that asset. The second, relative valuation, estimates the value of an asset by looking at the pricing of comparable assets relative to a common variable such as earnings, cash flows, book values or sales. The third, contingent claim valuation, uses option pricing models to measure the value of assets that share option characteristics. Damodaran highlights the research on valuation in his paper *Approaches and Metrics: A Survey of the Theory and Evidence* (Damodaran, A., 2006). The valuation theory and framework used in this thesis is commonly regarded as the best literature on valuation and widely used in universities and among professionals, and will rely on the following literature: Koller, T., Goedhart, M., & Wessels, D. (2020), Damodaran, A. (2006), Damodaran, A. (2012) and Petersen C., Plenborg T., & Kinserdal F. (2017).

3. Research Methodology

Throughout the chapter we will explain the methodology behind the forecasting and the valuation models.

3.1 Time Series Analysis

The selection of ARIMAX over ARMA models is predicated on the assumption that the data is non-stationary. The ADF test is used to examine the stationarity of the data. We are 95% certain that no unit root exists based on the test results. Therefore, we can say that the data is not stationary, and a level of integration is required. Exogenous variables that will be used for forecasting are represented by the X in the ARIMA model.

3.1.1 The Autoregressive model (AR)

The AR model shows that the current value of the series X_t can be explained as a function of p past values, $x_{t-1}, x_{t-2}, \dots, x_{t-p}$, where p determines the number of steps into the past needed to forecast the current value (Shumway, R. H., & Stoffer, D. S. 2011) and is abbreviated as $AR(p)$. An example of an autoregressive model of order p may be expressed as:

$$X_t = c + \sum_{i=1}^{p} \phi_i x_{t-1} + \epsilon_t$$

Where X_t is stationary and $\phi_1, \phi_2, \dots, \phi_p$ are constants and where we assume ϵ_t is a Gaussian white noise series with mean zero and variance σ_ϵ^2. Moving average models work as an alternative to autoregressive models where X_t is assumed to be combined linearly. The moving average of order q, abbreviated as $MA(q)$, assumes the white noise ϵ_t on the right-hand side of the defining equation are combined linearly to form the observed data. An example of a $MA(q)$ can be expressed as:

$$X_t = \mu + \sum_{i=1}^{q} \theta_i \, \epsilon_{t-1} + \epsilon$$

Where there are q lags in the moving average and $\theta_1, \theta_2, \dots, \theta_q$ $(\theta_q \neq 0)$ are parameters. We assume that ϵ_t is a Gaussian white noise series with mean zero and variance σ_w^2 unless otherwise stated.

3.1.2 The ARIMAX model

The Autoregressive Integrated Moving Average (ARIMA) model is an extension of the Autoregressive Moving Average (ARMA) model that incorporates an integration component to account for the non-stationarity of the variable of interest. The X is an extension of the ARIMA model where the X represents the exogenous variables making it a multivariate time series model. The integration component of the ARIMA model enables the representation of trends or patterns in the variable that may not be directly attributable to its previous values, but rather to other underlying factors. In order to eliminate potential trends or seasonality, the procedure of integrating the variable involves differentiating the time series data. The order of integration, designated by "d," indicates the number of times the data has been differentiated to eliminate these components. By taking differences, the ARIMA model attempts to transform the original time series into a stationary series, making it possible to analyze and model the underlying stochastic process.

To determine which model that will be utilized in this study, we apply the Akaike information criterion (AIC). AIC is a statistical measure used for comparing and selecting models. It provides a trade-off between the model's fit and its complexity, with the objective of identifying the model that best balances these two factors. AIC is founded on the principles of information theory and considers the likelihood of the data given the model and the number of parameters. The lower the AIC value, the more desirable the model (Akaike, 1974). The AIC may be expressed as:

$$AIC = -2ln(L) + 2k$$

3.2 Machine learning

In this thesis we use three different machine learning models. All the different machine learning models use the *Adam algorithm*. The models utilized in this study is the Long Short-Term Memory (LSTM), 1D Convolutional Neural Network (1D CNN), and Gated Recurrent Unit (GRU). The models use different input parameters, and the complexity of the models are different. When comparing the models, we are able to assess model performance through accuracy and computational efficiency.

3.2.1 Recurring Neural Network (RNN)

RNN is an artificial neural network that employs sequential or time series data. Typically, these deep learning algorithms are applied to ordinal or temporal problems, such as language translation, natural language processing (nlp), speech recognition, and time series analysis (*What Are Recurrent Neural Networks? | IBM*, n.d.). The output from the nodes can influence subsequent input to the same nodes in an RNN, a family of artificial neural networks where connections between nodes can establish a loop. All neural networks is built to minimize the RMSE.

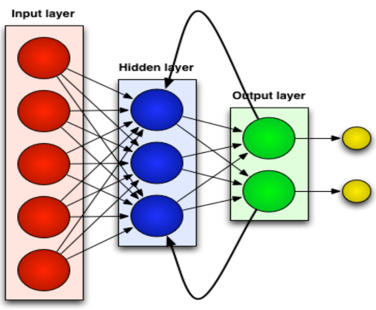

Figure 1. RNN. (Roell. 2017)

Jason Roell (2017) describes RNNs as the prominent neural network in regard to time series analysis because of the use of memory. A typical feedforward neural network uses no memory, and therefore will not remember the datapoint at $t-1$ when assessing t (Roell. 2017). The use of memory is the big advantage of RNN.

Adam optimization is a stochastic gradient descent method that is based on adaptive estimation of first order and second-order moments. According to Kingma and Ba (2014) the algorithm is straightforward to implement, is computationally efficient, has little memory requirements, is invariant to diagonal rescaling of the gradients, and is well suited for problems that are large in terms of data and/or parameters. The algorithm is also appropriate for non-stationary objectives and problems with very noisy and/or sparse gradients. This makes it a good algorithm to implement in regard to forecasting oil prices, since we already have proved that historical data of oil price is non-stationary. The algorithm is set to find a set of internal model parameters that perform well against some performance measure such as logarithmic loss or root mean squared error as in our case.

3.2.2 Long Short-Term Memory (LSTM)

LSTM is an artificial deep learning neural network that is a more complex subtype of Recurring Neural Network (RNN). It is employed to spot patterns in data sequences, like those found in sensor data, stock prices, or spoken language. RNNs are able to achieve this because, in addition to including the actual value in the prediction, they also include the location of the value in the sequence (Lang, 2022). LSTM learns and remembers long-term dependencies in the data dynamically, enabling it to capture context and make accurate predictions. Based on learned patterns and contextual information, the model transforms input data, performs internal calculations, and generates output predictions.

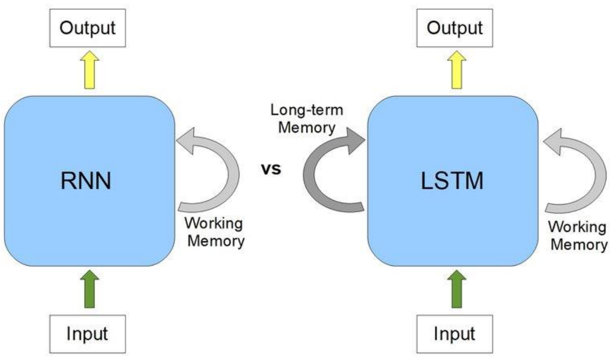

Figure 2. Difference between RNN and the subtype LSTM. Bag, S. (2022)

3.2.3 Convolutional Neural Network (CNN)

CNN is a class of artificial NN that has become prevalent in a variety of computer vision tasks and is gaining interest in a wide range of fields, including time series analysis. CNN is designed to learn spatial hierarchies of features automatically and adaptively via backpropagation by employing multiple building blocks, including convolution layers, pooling layers, and fully connected layers (Yamashita, Nishio, Kinh Gian Do & Togashi, 2018).

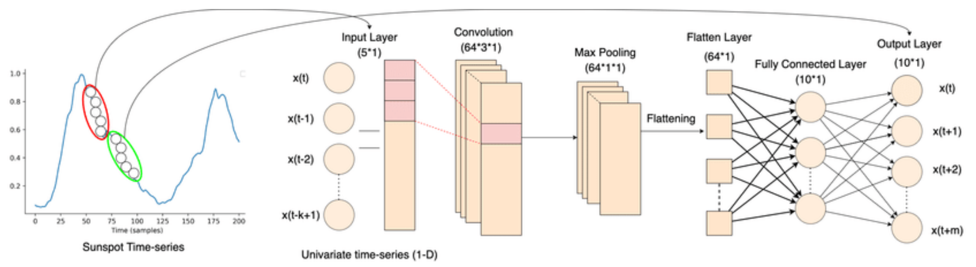

Figure 3. Time series 1d CNN. Chandra, R., Goyal, S., & Gupta, R. (2021)

3.2.4 Gated Recurrent Unit (GRU)

GRU is part of a specific model of recurrent neural network that intends to use connections through a sequence of nodes to perform machine learning tasks associated with memory and clustering, for instance, in time series analysis. Gated recurrent units aid in adjusting neural network input weights to solve the common issue of vanishing gradients in recurrent neural networks (Techopedia.com, 2018). Compared to conventional RNNs, GRUs offer a number of benefits. GRUs selectively update their internal state via gating techniques, which enables them to recall long-term dependencies without experiencing vanishing gradient problems.

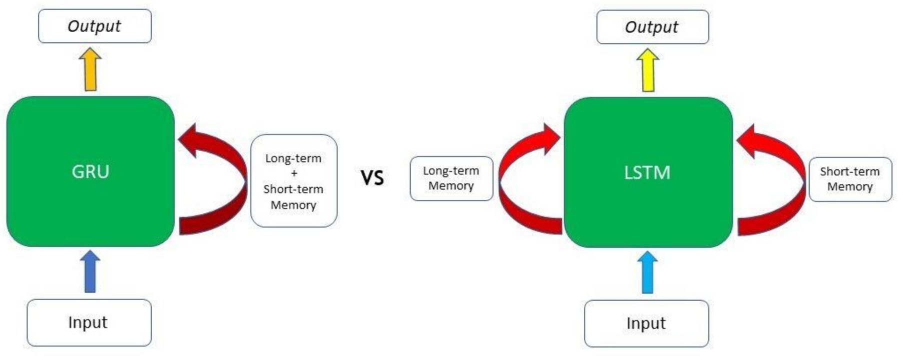

Figure 4. Difference between GRU and LSTM. Loye, G. (2023)

3.3 *Forecast performance*

To assess the forecast performance, we use five evaluation metrics. The first evaluation metric employed is the Mean Squared Error (MSE), which calculates the average squared difference between actual value and the predicted value. MSE is calculated by:

$$MSE = \frac{1}{N} \times \sum (y_i - \hat{y})^2$$

The second evaluation metric employed is the Root Mean Squared Error (RMSE), which is the squared value of the MSE, representing the standard deviation of the residuals. RMSE is calculated by:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \times \sum (y_i - \hat{y})^2}$$

The third evaluation metric employed is the Mean Absolute Error (MAE), which is the average absolute error between the actual and the predicted value. The MAE is calculated by:

$$MAE = \frac{1}{N} \sum |y_i - \hat{y}|$$

The fourth evaluation metric employed is the Goodness of fit (R^2), which measures how well the regression line fits the actual data. The R^2 is calculated by:

$$R^2 = 1 - \frac{\Sigma (y_i - \hat{y})^2}{\Sigma (y_i - \bar{y})^2}$$

The fifth metric employed is the corrected Goodness of fit (R^2_{adj}), which is similar to R^2 but adjust for the number of terms in the model. The R^2_{adj} is calculated by:

$$R^2_{adj} = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$$

3.4 Valuation Methods

To value the selected oil and gas companies, we will use two present value models, in addition to an option pricing model. We will use the DCF model, the EVA model, and the Black-Scholes model as an option pricing model to value the companies as of March 31, 2023.

3.4.1 Present Value Methods

<u>*Discounted Cash Flow model (DCF)*</u>

The discounted cash flow model can be specified in two ways, one estimates the enterprise value, and one estimates the equity value. Our research employs the enterprise value model. To obtain the market value of equity we extract the net interest-bearing from the enterprise value (Petersen et al., 2017). According to the model, only the free cash flows and WACC affect the market value of the company.

$$EV_0 = \sum_{t=1}^{n} \frac{FCFF_t}{(1 + WACC)^t} + \frac{FCFF_{n+1}}{(WACC - g)} \times \frac{1}{(1 + WACC)^n}$$

Equation 1. The Discounted Cash Flow Model

<u>*Economic Value-added model (EVA):*</u>

EVA is a measure of the dollar surplus value created by an investment. It is computed as the product of the excess return made on an investment and the capital invested (Damodaran, A. 2012). In this thesis, we have employed the two-stage model for valuation purposes. According to the EVA model, the value of a company is derived by considering the original invested capital, which comprises the book value of equity plus net interest-bearing debt. In addition to the invested capital, the EVA model incorporates the present value of all future EVAs to determine the enterprise value.

$$EV_0 = \sum_{t=1}^{n} \frac{EVA_t}{(1 + WACC)^t} + \frac{EVA_{n+1}}{(WACC - g)} \times \frac{1}{(1 + WACC)^n}$$

Equation 2. The Economic Value-added model

3.4.2 Black-Scholes model

In most publicly traded firms, equity has two features. The first is that the equity investors run the firm and can choose to liquidate its assets and pay off other claim holders at any time. The second is that the liability of equity investors in some private firms and all publicly traded firms is restricted to their equity investments in these firms. This combination of the option to liquidate and limited liability allows equity to have the features of a call option (Damodaran, A. 2006). The equity in a firm is a residual claim; that is, equity holders lay claim to all cash flows left after other financial claim holders have been satisfied. If a firm is liquidated, equity investors receive the cash that is left in the firm after all outstanding debt and financial claims have been paid off (Damodaran, A. 2006).

$$European\ call: C_0 = S_0 e^{-\delta T} N(d_1) - e^{-rT} K N(d_2)$$

where:

$$d_1 = \frac{ln\left(\frac{S_0}{K}\right) + \left(r - \delta + \frac{\sigma^2}{\sigma}\right)T}{\sigma\sqrt{T}}$$

and:

$$d_2 = d_1 - \sigma\sqrt{T}$$

A visualization of the payoff structure is attached in (Appendix 1), and a detailed Black-Scholes formula is attached in (Equation 8).

Relative Valuation

Valuation based on multiples is a widely used method due to its low level of complexity and efficiency. A valuation based on multiples is dependent on the relative pricing of comparable companies. Which multiples are most appropriate depends on the type of company, whether it is asset heavy or asset light and whether the company is in a steady state or not (Petersen et al., 2017). Multiples as P/E and P/B estimates the value of equity. The idea behind using multiples for valuation is that similar assets should sell for similar prices (Koller et al., 2020).

4. Data Collection

The research conducted in this thesis is based on data between January 1, 2000, and March 31, 2023. To guarantee that the input data used in the models is sufficient and representative for Brent Crude oil forecasting, data on all variables used are collected from Refinitiv.

Data has been collected at both daily and monthly intervals to provide a thorough and accurate study, and to examine whether the models perform best on daily or monthly data. As the machine learning models require a lot of data to learn trends and patterns in the data, we found it important to use an extended dataset of the oil price, containing many learning parameters. The data collected on daily Brent Crude oil prices corresponds to the daily closing prices. Data APIs that offered real-time and historical market data were used to access financial platforms, primarily DataStream through Refinitiv, to retrieve data. DataStream retrieves all the selected variables within the predetermined time frame and converts the data into a structured spreadsheet. The daily variables are presented below.

Variables
WTI Crude Spot
S&P 500 commodities total return
Gold spot
Natural Gas spot
US 10Y

Table 1. Daily input variables

To assess whether the machine learning models performed best on daily or monthly data, data on the Brent Crude oil were collected with monthly closing price observations. A comprehensive validation and cleaning process was used to guarantee the accuracy of the data that was obtained. To keep the dataset's integrity, missing values, outliers, and other inconsistencies were carefully discovered and dealt with using the proper approaches, including data interpolation or data imputation. The acquired data was organized and prepared for time series analysis.

Ethical considerations were followed throughout the data collection process. To ensure the ethical use of the obtained data, data usage rights, privacy rules, and related policies were followed. During the data collection, we discovered limitations with the availability of daily data for daily exogenous variables in contrast to monthly exogenous variables. Most of the macroeconomic variables are published on a monthly or quarterly basis. Based on the significant daily variables presented, we were able to generate a comprehensive dataset that captured the fundamental temporal patterns and trends in Brent Crude oil prices.

Financial data is collected from reputable sources such as Refinitiv, annual reports, quarterly reports, and the capital market day reports from the selected companies. For this thesis, the analysis is based on annual reports from 2015 to 2022, providing a comprehensive view of the companies' financial performance during this period. However, it is worth noting that the historical financial data presented in the thesis covers the time limit from 2017 to 2022. This limitation arises due to the availability of publicly accessible data, particularly for Vår Energi, which does not have data beyond that period.

To estimate the regression betas, monthly return data from the Oslo Børs Benchmark Index (OSEBX), Aker BP, and Vår Energi has been collected. It is important to mention that Vår Energi's inclusion in the OSEBX commenced on February 16, 2022. Consequently, return data from industry peers were gathered to estimate the average peer beta. The market risk premium utilized in this study is consistent with the risk premium Damodaran, A. (2023) finds for the US stock market. We highlight that the risk premium is also consistent with the one calculated for the Norwegian stock market published in PwC's report, "Risk premium in the Norwegian market." Furthermore, the risk-free rate employed in the thesis is the annual average of the 10-year government bond rate for 2022, as officially released by the Federal Reserve.

It is important to note that the data collection limit for this thesis concludes on March 31, 2023, ensuring the relevance and accuracy of the analysis within the specified time limit.

4.1 Preprocessing and splitting the data

4.1.1 Preprocessing of the data

We begin by preprocessing the data and standardizing all variables due to the differences between the variables. We normalize it by generating z values. This process will reduce the likelihood of multicollinearity by decreasing the correlation between predictor variables. The standardization process produces a dataset with a mean of zero and a standard deviation of one.

4.1.2 Splitting the data

When forecasting the data, it is important that the model is correctly separated between learning and testing set. The concept is that the model evaluation is based on how well the model is able to forecast unseen data using the training set as a training model. In general, the original dataset is divided into two subsets: the training set and the testing set. The ARIMA model's parameters are estimated using the training set, and the model's forecasting precision is assessed using the testing set. In the ARIMAX example, we use an 80:20 ratio, where 80% of the dataset is used for training and 20% of the dataset is used for testing. In the machine learning example, we use an 80% split in training set, 11% validation set, and a 9% testing set.

We also include a validation set, that is separate from the training set. This set is then used to validate the model's performance during the training. We can describe this validation set as a way for the model to tell us if the training set is moving in the right direction or not. This is done to prevent overfitting, and the validation is run simultaneously as the training set.

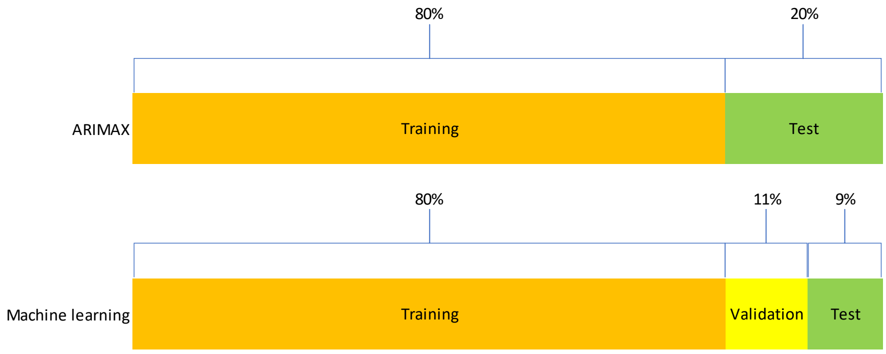

Figure 5. Model Procedures

The training set is utilized somewhat differently in the machine learning models than in the ARIMAX model, with the ML model running through 100 epochs, also known as a hypermeter, which specifies the number of times the learning algorithm will traverse the entire training set. Each sample in the training set has the opportunity to revise the internal model parameters during one epoch. An epoch consists of 152 batches in the models.

4.2 Accounting data

In this section we will present accounting quality and data structuring.

4.2.1.1 Accounting quality

The Financial Accounting Standards Board (FASB) defines accounting quality as "the accuracy, completeness, reliability, and transparency of the financial information reported by a company. High accounting quality implies that the financial statements present a true and fair view of a company's financial performance and position. It involves the application of appropriate accounting policies, adherence to accounting standards, proper measurement and disclosure of financial data, and effective internal controls to prevent errors or fraud".

Aker BP and Vår Energi are two oil and gas companies listed on the OSEBX. They follow IFRS accounting standards and regulatory requirements. Their adherence to these standards suggests a commitment to transparent and reliable financial reporting, enhancing investor confidence. The use of IFRS promotes standardized reporting, comparability, transparency, and reliability of financial information. However, it is important to highlight that within IFRS, there is still some flexibility, for instance, as the lifespan of a specific asset varies based on its usage, maintenance, and the policy regarding the level of updates required for a company's assets (Petersen et al., 2017).

4.2.1.2 Data and analytical reformulation

We started our research by collecting accounting data from Refinitiv on both Aker BP and Vår Energi. We obtained data from the income statement, the balance sheet and the cash flow statement between 2015 and 2022. In order to ascertain the integrity of the data acquired from Refinitiv, we conducted thorough cross-referencing by utilizing the official websites of the relevant companies and cross-verified the information against the corresponding annual reports published during the identical time frame.

Further, to organize the data for financial analysis and valuation, it was necessary to reformulate the income statement, balance sheet, and the cash flow statement. The first step involves classifying the items on the balance sheet as either operating or financing activities. The second step is to reformulate the balance sheet into a Net Operating Assets (NOA) format, which distinguishes between items belonging to net working capital (NWC) and items belonging to net operating non-current assets (NONCA). NWC is calculated as the difference between operating current assets and operating current liabilities, while net operating non-current assets are calculated as the difference between operating non-current assets and operating non-current liabilities. These items constitute the NOA (invested capital).

On the other side of the balance sheet, we divide into total equity and net interest-bearing debt (NIBD). Through the reformulation, we obtain the net working capital and the change in net operating non-current assets, which are important components in the calculation of free cash flow. Finally, the net interest-bearing debt obtained from the other side of the balance sheet is used to derive the market value of equity (MVE). To arrive at MVE, we subtract NIBD from the enterprise value (EV).

To examine our findings related to Aker BP please see (Appendix 3) for the reformulated historical income statement, (Appendix 4) for the reformulated historical balance sheet, and (Appendix 5) for the reformulated historical cash flow statement. Furthermore, to examine our findings related to Vår Energi please see (Appendix 6) for the reformulated historical income statement, (Appendix 7) for the reformulated historical balance sheet, and (Appendix 8) for the reformulated historical cash flow statement.

4.3 Assumptions and limitations

Historical data on Brent Crude oil and WTI oil are collected from Refinitiv. The research conducted is based on data between 2000 and March 31, 2023.

Furthermore, in this research we have used the 10-year US government bond as the risk-free interest rate. The rate is measured at 2.95% as an annual average for 2022, according to the Federal Reserve. The market risk premium used is 5.90%.

The models we have employed in this thesis is the ARIMAX model, in addition to three machine learning models (LSTM, CNN, and GRU). In addition to the models mentioned, we will construct a future forecast of the Brent Crude oil using the Prophet model for application purposes. For simplicity and due to the limitations of TensorFlow-based models in forecasting beyond the provided dataset, we have opted to utilize the

Prophet model. Furthermore, our analysis reveals that Prophet yields notably better results when applied to monthly data, a critical aspect considering the prevailing challenging macroeconomic environment and the lack of daily macroeconomic data. In the valuation chapter, we focus on two present value models: the Discounted Cash Flow model (DCF) and the Economic Value-Added model (EVA). The final estimate of the fundamental value will rely on the DCF model, based on Koller, Goedhart and Wessels research who argue that DCF valuation yields the best results. Additionally, we have utilized the Black-Scholes model to value the equity of the selected companies as a call option.

Regarding the selection of oil and gas companies, we have eliminated based on specific criteria. The companies must be listed on the Oslo Stock Exchange, have a similar product portfolio, possess significant producing assets on the Norwegian continental shelf, have available option prices, operate within the same industry, and exhibit similar growth prospects. Based on these criteria, we have chosen Aker BP and Vår Energi among the Norwegian oil and gas companies.

5. Model selection

5.1 ARIMAX

The optimal ARIMAX model was found by minimizing the AIC, corresponding to an ARIMA (1,1,2) model. We obtained an AIC of -1120. The following equation shows the selected ARIMAX model, which exhibits a level of integration one. The equation is presented as:

$$y_t = y_{t-1} + \phi_1(y_{t-1} - y_{t-2}) + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \sum \beta X_i$$

Equation 3. ARIMAX model

where $\sum \beta X_i$ is the sum of exogenous variables. The exogenous variables were chosen on the background of testing. We examined fifteen independent variables and ran the ARIMAX model. Further, we excluded all insignificant variables which we believe can cause noise in the model. The variables were chosen based on their impact on Brent Crude oil. Each variable's direct impact will be discussed and presented in "results and analysis".

5.2 Machine learning

The machine learning models are grounded in the same principles, albeit employing different methods depending on the type of machine learning model used. This approach is adopted to facilitate a precise comparison of error measurements among the models. By utilizing consistent underlying principles while employing different techniques, we can assess and compare the model errors in a meaningful manner.

We construct a matrix consisting of five consecutive inputs. The objective is to utilize the five preceding inputs to predict the sixth variable. Subsequently, the model incorporates the input variables [2,3,4,5] and the predicted sixth variable to generate a seventh variable. This process is a rolling window method, using five lags to predict the next value. We use five lags to capture momentum and patterns in the time series. Hence, the model examines patterns and potential influence of oil prices from input one to five on the price observed on output six. The model procedure is presented below.

Input	Output
[1,2,3,4,5]	[6]
[2,3,4,5,6]	[7]
[3,4,5,6,7]	[8]

Table 2. Machine learning models procedure

For all the machine learning models, we divide the data as described in the chapter "Splitting the Data". This means that the training set matrix has the following dimensions: 4837 prices in the first dimension, 6 variables in the second dimension, and a window of 5 prices in the third dimension. Therefore, we create a 4837x6x5 matrix used as the training set for the neural network. The validation set is a matrix with dimensions of 544x6x5, while the testing set is a matrix with dimensions of 660x6x5. These matrices maintain the same structure as the training set, allowing for proper evaluation and testing of the machine learning models.

5.2.1 LSTM

The model is a sequential neural network, meaning that the model starts with inputs, then goes through different layers sequentially (A. D'Agostino, 2022). Furthermore, we incorporated additionally layers called "dense" into the machine learning model. These dense layers are added to enhance the complexity and capability of the model to learn intricate patterns and relationships within the data.

We use two types of dense layers in the model: relu and linear. The relu dense layer consists of 8 layers with the rectified linear unit activation function, while the linear dense layer has 1 layer with linear activation. These layers form a structure, allowing the model to learn complex patterns and relationships within the data. The layers in a sequential model are visualized through the table presented below.

Sequential model
Input
↓
Layer 1
↓
Layer 2
↓
Layer...
↓
Layer n
↓
Output

Table 3. Visualization of the sequential model

The LSTM model has a total of 18,449 parameters. These parameters enable the model to learn and generate predictions for Brent Crude oil prices.

Layer (type)	Output shape	Parameters
LSTM	(None, 64)	17,920
Dense	(None, 8)	520
Dense_1	(None, 1)	9
Total Parameters		18,449

Table 4. LSTM model parameters

The neural network is configured with specified parameters. This involves identifying the learning rate, the error function for training, and the algorithm to be implemented (Adam). In addition, we use the same number of epochs and error metric for all models, while adjusting the learning rate proportionately. Our research settles on a learning rate of 0.001 for the LSTM model. While it is typically recommended to increase the number of epochs when lowering the learning rate (Jason Brownlee, 2020), we decided to maintain 100 epochs to conserve data usage, given that the available data was already depleted.

5.2.2 CNN

CNN operates differently from LSTM, as explained in the methodology section. While the data splitting process remains similar to LSTM and GRU, the parameter tuning differs. We use a one-dimensional CNN, with a kernel size of two. The model takes on two values, called windows, and combines them into one value. The model repeats this process 64 times. To keep the model one-dimensional, we include a flatten command that converts the output into a one-dimensional vector.

We add relu and linear layers, similar to LSTM and GRU, resulting in a total of 2,769 parameters. Weytjens, H., & De Weerdt, J. (2020) found that CNNs are typically faster than LSTM, which aligns with our research. CNN requires less parameters, therefore less computational power.

Layer (type)	Output shape	Parameters
CNN	(None, 4, 64)	704
Flatten	(None, 256)	0
Dense_2	(None, 8)	2056
Dense_3	(None, 1)	9
Total Parameters		2,769

Table 5. CNN model parameters

The parameter tuning of the CNN model is similar to LSTM. During the parameter tuning of CNN, we found that the model did not require as low learning rate as the LSTM to achieve satisfactory results. Therefore, we increased the learning rate to 0.01.

5.2.3 GRU

GRU shares similar parameter tuning to LSTM, utilizing the same input layers as LSTM. For the GRU model we had to incorporate additional relu layers into the model. Specifically, we had to reduce the learning rate to achieve satisfactory results. Consequently, the model contains 24 relu layers with a learning rate of 0.0001. The model consists of 15,217 parameters. The increased number of relu layers and lowered learning rate indicate that the GRU model is more complex compared to other NN models in this thesis.

Layer (type)	Output shape	Parameters
GRU	(None, 64)	13,632
Dense_10	(None, 24)	1,560
Dense_11	(None, 1)	25
Total Parameters		15,217

Table 6. GRU model parameters

6. Results and analysis

In this analysis we will present the overall results. All models examined use the exogenous variables presented in (Table 1). Firstly, a visualization of the model performance will be presented. Secondly, a visualization of the model performance with restrictions will be presented and discussed. Thirdly, a summary of the overall performance will be presented as a table. Lastly, our findings related to the cost of capital will be presented.

6.1.1 ARIMAX

The regular ARIMAX (1,1,2) exhibit the best overall performance during our research. We find that commodities such as gas and gold have a significant effect on the daily Brent Crude oil price. Further, the S&P 500 commodity index yields a significant effect, in addition to the US10 Year government bond, indicating that the global economic activity plays a role in daily volatility. One could argue that high interest rates can lead to lower economic activity, in turn affecting the global oil demand. However, reduced investments in the global oil and gas sector can lead to reduced supply. All the exogenous variables (Table 1) are significantly different from zero.

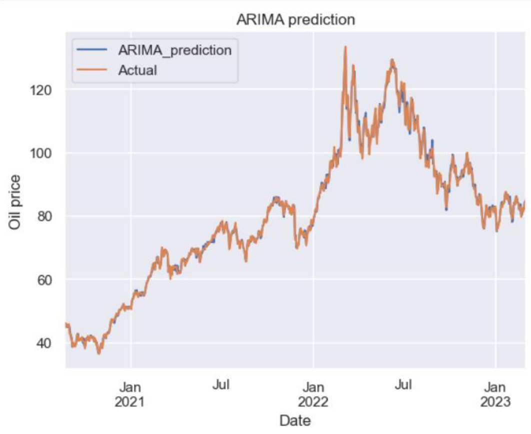

Figure 7. ARIMAX visualization of results

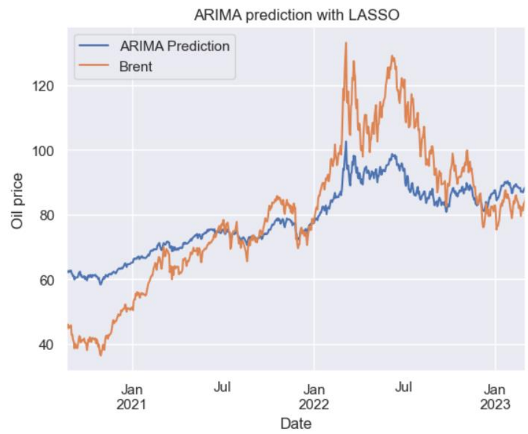

Figure 6. ARIMAX visualization w. LASSO

From the ARIMAX model we obtain an AIC of 13274. The coefficient estimates and their significance are attached in (Appendix 44). The model describes how one autoregressive and two moving average variables together with the exogenous variables are able to forecast the Brent Crude price with high accuracy. However, we find it appropriate to penalize the coefficients as the model appears to overfit. This can be done with "Least Absolute Shrinkage and Selection Operator" (LASSO) which adds a penalty term to the models' coefficients. This procedure helps to reduce complexity and mitigate overfitting.

After adding the LASSO, we observe that the model exhibits lower forecasting performance opposite to the original ARIMAX model. The model does not seem to overfit, and we observe that the model is able to forecast trends, but not as accurately as the original model. To define whether the ARIMAX model was adequate, we examined the residuals of the model and ran an ACF test to check for autocorrelation. The model shows that all residuals are insignificant until lag 20. We do observe a few significant lagged residuals, but at an acceptable level (Appendix 2).

6.1.2 Machine learning

To forecast Brent Crude oil prices, we have employed three machine learning models: LSTM, CNN, and GRU. These models were chosen based on their ability to detect connections and patterns in time series data. Additionally, we will present two additional techniques to adjust for overfitting and noise. Firstly, to adjust for overfitting we readjust all models with a dropout term. Secondly, we resample all the model's using cross-validation.

Basic test

Figure 9. LSTM visualization of results

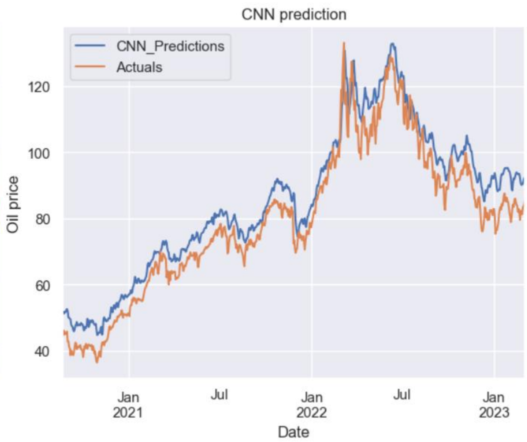

Figure 8. CNN visualization of results

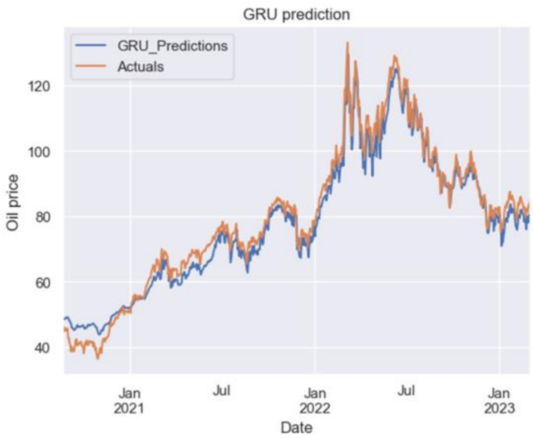

Figure 10. GRU visualization of results

In the table below we present the ranking order and the respective RMSE.

Neural Network models	Rank	RMSE
GRU	1	3.9109
LSTM	2	5.8482
CNN	3	6.7168

Table 7. Machine learning model comparison

The analysis shows that GRU exhibit the best forecasting performance when comparing the basic machine learning models. We achieved an RMSE of 3.9109 which was 33.13% lower than LSTM and 41.77% lower than CNN. The results are intriguing given that the machine learning models are provided with the same variables as the regular ARIMAX model but perform worse throughout our analysis. All the ML models exhibit high explanatory power which indicates that the exogenous variables are significantly different from zero, with an impact on the Brent Crude oil price.

Based on our findings we assume that all the models suffer from overfitting. Previous research suggest that all ML models are prone to overfitting, and therefore cross-validation techniques and out of sample testing should be used to examine the generalizability and robustness of the models in order to provide a more accurate assessment on their predicting capabilities. The model visualizations show how the model differs in overshooting or undershooting. Both GRU and LSTM undershoot in its predictions, while CNN overshoots. It is expected that GRU and LSTM will perform and operate similarly since they are built using the same framework, while CNN is built using a different framework.

Dropout test

To minimize overfitting, we add a dropout layer to the models in order to test the neural network. Dropout is a tool used to arbitrarily remove units and their connections from the training set in order to prevent co-adaptation (Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014)). The desired result is that the model will be less sensitive to the specific weights of various neurons, making it more generalizable and less vulnerable to overfitting (Brownlee, 2022). We also add more complexity to the models with more model layers in order to prevent overfitting together with the dropout layers. In the analysis we find that a dropout term changes the ranking order based on RMSE.

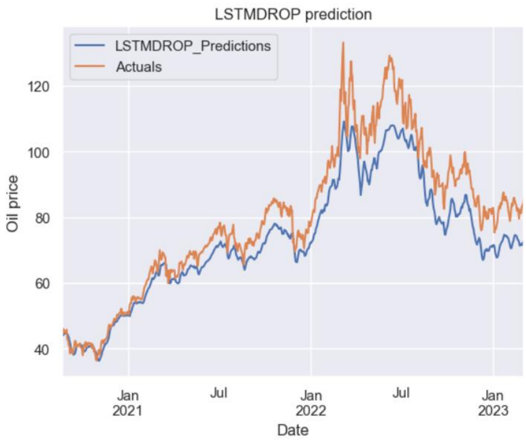

Figure 11. LSTM visualization w. dropout

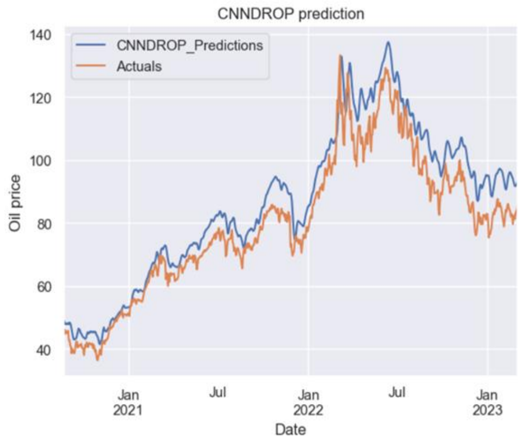

Figure 12. CNN visualization w. dropout

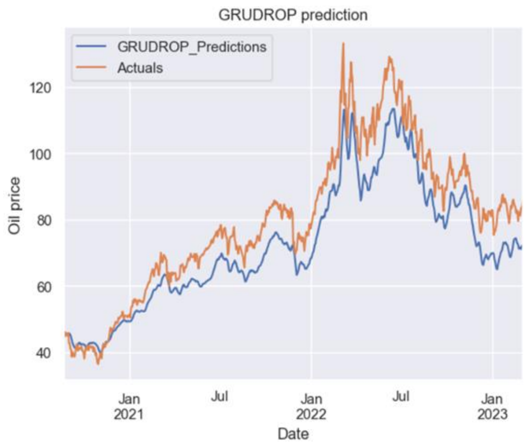

Figure 13. GRU visualization w. dropout

In the table below we present the ranking order and the respective RMSE.

Neural Network models	Rank	RMSE
CNN w. dropout	1	8.1098
LSTM w. dropout	2	8.6632
GRU w. dropout	3	9.4230

Table 8. ML model comparison w. dropout

In the basic NN models, GRU performed best with lowest RMSE and highest predicting power. After adding a dropout layer GRU was the worst performing model with an RMSE of 9.4120, which is 140.94% higher than the original model. CNN was the best performing model with an RMSE of 8.1098 which is 20.74% higher than original, and LSTM performed 48.13% higher with an RMSE of 8.6632. These results indicate that the basic models have been prone to overfitting, and that adding a layer of dropout can prevent overfitting.

K-fold cross-validation test

We apply a second method in order to overcome overfitting and test the models with Cross-Validation (CV). This is a resampling technique that fits a model k times. This technique involves randomly dividing the set of observations into k groups or folds of roughly equal size. The first fold is regarded as a validation set, and the method is fit to the remaining k-1 folds. On the observations in the held-out crease, the RMSE is then computed. This procedure is repeated k times, with a new group of observations serving as the validation set each time. These values are averaged to derive the k-fold CV estimate (James, Witten, Hastie & Tibshirani, 2014, p. 178-183). We apply k = 5 in the model. After examining the model, the results did not change when adjusting for k. An improperly selected value for k can lead to a misrepresentation of the model's accuracy, such as a score with high variance (Brownlee, 2020).

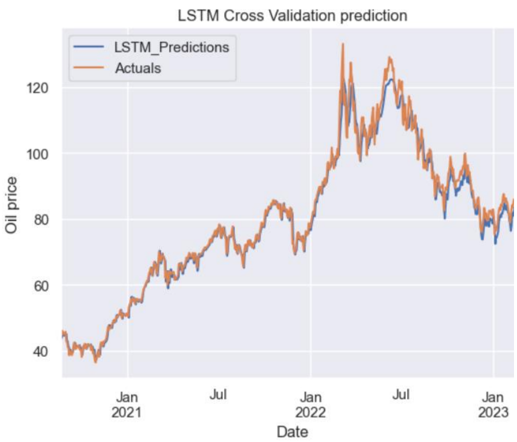

Figure 15. LSTM visualization w. cross-validation

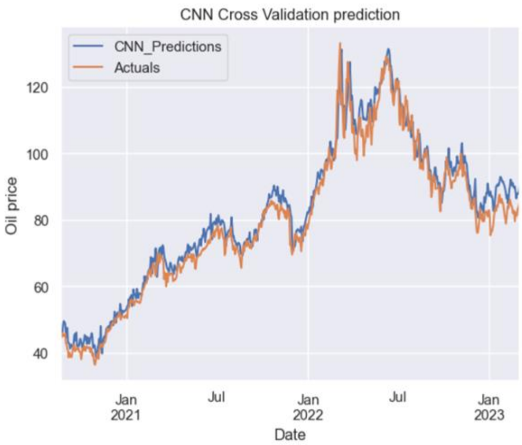

Figure 14. CNN visualization w. cross-validation

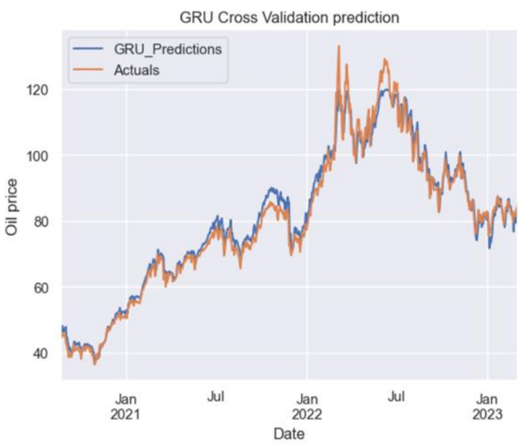

Figure 16. GRU visualization w. cross-validation

In the table below we present the ranking order and the respective RMSE.

Neural Network models	Rank	RMSE
LSTM w. cross-validation	1	2.8655
GRU w. cross-validation	2	3.1410
CNN w. cross-validation	3	4.1637

Table 9. ML model comparison w. cross-validation

The analysis done on NN with cross-validation shows that the models perform better with lower RMSE than the original models. We find that the predicting power is higher, and that LSTM was the best performer with an RMSE of 2.8655, 51% lower than the original model and 66.92% lower than LSTM with dropout. GRU is the second-best performer with an RMSE of 3.1410, 19.69% lower than originally and 66.67% lower than GRU with dropout. CNN is the worst performer of the models with an RMSE of 4.1637 which is 38.01% lower than originally and 48.66% lower than CNN.

Discussion of results

A possible explanation to why the ARIMAX model may outperform the ML models is that it may be more effective at capturing the stochastic components of the time series data. When data exhibits substantial stochasticity, ARIMAX models can capture and predict these random fluctuations effectively. The models are able to estimate the parameters that best characterize the stochastic process and use them to generate forecasts.

As explained in the data collection chapter, the time period we selected is done on the background of price volatility. We believe that due to the temporal structure of the time series, seasonality, and potential autocorrelation between the variables, the ARIMAX model may be the most accurate forecasting technique on our dataset. Our findings are in line with research conducted by Nasir, Aamir, Haq, Khan, Amin & Naeem (2023) who demonstrated that the ARIMAX model outperformed the basic ML models.

Furthermore, we highlight that the errors obtained from the ARIMAX model closely resemble those reported by Nasir, Aamir, Haq, Khan, Amin & Naeem in their research on WTI. None of the other papers we have highlighted has introduced cross-validation and dropout to the basic ML models for comparison reasons. However, Assad and Fayek (2021) found that LSTM performed better than CNN on forecasting Crude oil prices. This is in line with our findings, where LSTM exhibits the best forecasting performance, followed by the CNN model both in the basic models and the models with cross-validation. The LSTM model underperforms relatively to the CNN model when introducing dropout. The introduction of dropout reduced the forecast performance for all our models, which can be attributed to several reasons. By incorporating noise, dropout regularizes the model and encourages it to learn more robust representations. Still, if the model's capacity is insufficient to encompass the complexity of the underlying data, dropout may impede the model's ability to discover important patterns.

The introduction of K-fold cross-validation proved to be highly successful, delivering the most accurate forecasting performance. Cross-validation gives a more precise estimate of a model's performance than a simple split between train and test set. By dividing the data into multiple folds and executing multiple iterations, the model's generalization performance can be evaluated with greater precision. This provides a more accurate estimate of the model performance on unobserved data by reducing the bias introduced by a single train-test split.

As we emphasized in the data collection, ML models require a lot of data to learn pattern and trends. To enhance the performance of the ML models, one could examine additional significant variables, better parameter tuning or extended datasets. However, we found that when adding more variables, our models performed worse. These findings can be attributed to noise, and the relevancy of the variables used.

Based on our research, we find that the ARIMAX and classical time series analysis perform well when forecasting financial time series. These time-tested methods have demonstrated their dependability and usefulness over the years. It is however worth noting that when adding the LASSO penalization term, the model performance is the worst among all models examined in this thesis.

Among the basic ML models analyzed we find that GRU exhibits the best forecasting performance. When adding the dropout term, the ranking order changes, and the CNN exhibits the best forecasting performance, however, weaker performance in regard to the basic ML models. Further, we find that cross-validation enhances the overall ML performance, and the LSTM model provided us with an RMSE of 2.8655.

We find evidence that Machine Learning and Neural Network has a place in forecasting Brent Crude oil. We have shown sufficient evidence and reasoning to say that machine learning and time series analysis are good tools for forecasting Brent Crude oil on a daily dataset.

6.1.3 Model performance

In this section we will present all the errors that we have measured. We evaluated each model's forecasting performance using the RMSE statistic. In addition, we will highlight the MSE, MAE, R^2 and the adjusted R^2. We obtain the following results from the models:

	MAE	MSE	RMSE	R^2	R^2adj
ARIMAX	0.6820	1.3662	1.1688	0.99720	0.99719
ARIMAX w. LASSO	9.5656	158.6860	12.5971	0.67530	0.67395
GRU	3.2889	15.2950	3.9109	0.96908	0.96884
LSTM	4.4378	34.2017	5.8482	0.93086	0.93033
CNN	6.0334	45.1147	6.7168	0.90880	0.90810
GRU w. dropout	8.1923	88.7932	9.4230	0.82050	0.81910
CNN w. dropout	6.9442	65.7687	8.1098	0.86700	0.86600
LSTM w. dropout	7.0513	75.0514	8.6632	0.84830	0.84710
GRU w. cross-validation	2.4019	9.8660	3.1410	0.98005	0.97990
CNN w. cross-validation	3.2689	17.3362	4.1637	0.96495	0.96469
LSTM w. cross-validation	2.0048	8.2108	2.8655	0.98340	0.98327

Table 10. Summary of model performance

From the summary of model performance, we observe that the ARIMAX model exhibits the best overall performance. When we add the LASSO penalization term, we observe that the ARIMAX model exhibits the worst forecasting performance. Among the basic machine learning models, we observe that GRU exhibits the best forecasting performance. However, when resampling the model using cross-validation, we observe that the LSTM model exhibits the best overall ML forecasting performance.

6.2 Cost of capital

The cost of capital represents the minimum rate of return a company must generate to add value (Damodaran, A. 2012). Cost of capital, further referred to as WACC, is employed as the discount rate in both the DCF and the EVA model. The cost of capital plays an important role in the valuation of Aker BP and Vår Energi.

6.2.1 The equity cost of capital (CAPM)

The CAPM (Equation 4) postulates that the expected rate of return on any security equals the risk-free rate plus the security's beta times the market risk premium (Koller et al., 2020). In the CAPM, the risk-free rate and the market risk premium, which is defined as the difference between r_m and r_f , are common to all companies; only beta varies across companies.

6.2.1.1 Risk-free rate

The risk-free rate explains the alternative return an investor can get without taking on any risk and is therefore referred to as risk-free. We have chosen the 10-year government bond as the risk-free rate, as the 30-year government bond often include a significant liquidity premium that affects the interest rate. To ensure the applicability of the 10-year government bond as the risk-free rate, we have applied the government bond denominated in the same currency as the cash flows of the selected companies. According to data from the Federal Reserve, the average yield on the 10-year government bond for 2022 was 2.95%.

6.2.1.2 Beta estimation

Beta represents a stock's incremental risk to a diversified investor, where risk is defined as the extent to which the stock moves up and down in conjunction with the aggregate stock market (Koller et al., 2020). The betas are estimated through a regression analysis based on historical returns from the OSEBX and the selected stocks over a period of 8 years. This approach has been applied because measurement periods for raw regressions should include a minimum of 60 data points, and raw regressions should be based on monthly returns. Using more frequent return periods, such as daily and weekly returns, leads to systematic biases (Koller et al., 2020).

6.2.1.3 Blume's adjusted beta

In this section we seek to adjust the beta closer to the mean of all companies. This process aims to reduce beta estimation error and is based on Marshall Blume's research (Equation 5), which suggests that betas are mean reverting (Koller et al., 2020). Our findings is presented in the table below.

	Aker BP	Vår Energi
Raw beta	1.92	1.48
Blumes adj. Beta	1.62	1.39

Table 7. Beta calculations

6.2.1.4 Market risk premium

The market risk premium is the premium demanded by investors for investing in the market portfolio, which includes all the risky assets in the market, instead of investing in a riskless asset (Damodaran, A. 2012). In this thesis, a market risk premium of 5.90% is utilized.

6.2.2 Cost of debt

The cost of debt (Equation 6) measures the current cost to the firm of borrowing funds to finance projects (Damodaran, 2012). When estimating the cost of debt, there are several approaches available. One can analyze the interest expense in relation to the interest-bearing debt, calculate the cost of debt based on the riskless rate and the default spread, or consider the credit rating and the associated default spread. In this thesis we have utilized the average long-term cost of debt, assuming that the companies will maintain its historical borrowing cost.

6.2.3 *Weighted average cost of capital (WACC)*

Estimating the WACC (Equation 7), we have assumed a target debt-to-equity ratio (D/E) of 22.5% for both Aker BP and Vår Energi. This assumption is justified by (Koller et al., 2020) who argue that "the cost of capital should rely on a forecast of target weights, rather than current weights, because at any point a company's current capital structure may not reflect the level expected to prevail over the life of the business". We obtain the following results based on our research.

	Aker BP	Vår Energi
WACC	10.44%	9.38%
Re	12.49%	11.14%
Rd	4.60%	5.50%
Tax rate	71.78%	71.51%

Table 8. WACC calculations

7. Future forecast

The future forecast is derived from historical accounting data spanning from 2015 to 2022, company guidance, and a modeled forecast of the Brent Crude oil price. When creating the future forecast, we consider historical ratios between balance sheet items and the income statement. Specifically, we consider and incorporate balance sheet items that fluctuate with revenues in the forecast.

7.1 The length of the future forecast

The length of the future forecast is five years. We have projected accounting data five years into the future, with a corresponding terminal year in 2028 for all the analyzed companies. The Prophet model projects Brent Crude oil prices five years into the future, with the terminal year 2028 representing the average oil price in the period 2000 to March 31, 2023.

7.2 Forecast of the oil price

The limits of TensorFlow-based models like LSTM, CNN, and GRU in forecasting beyond the given dataset need the investigation of alternate methodologies. In this case, using the Prophet algorithm proposed by Taylor and Letham (2017) is a convincing option. Prophet offers a number of features that make it a viable model for predicting and forecasting future Brent Crude oil prices. Please see (Appendix 42) for the significant variables.

Prophet detects underlying patterns and trends in Brent Crude oil price time series data using ML techniques. By designating the required number of future periods, we create a data frame that represents the future time span for price forecasts. By incorporating this expanded data frame into its modeling process, Prophet can generate forecasts. Prophet's adaptability to various time series patterns, such as seasonality and non-linear trends in Brent Crude oil prices, adds to its viability for this forecasting assignment. The daily back test provided us with errors presented in (Appendix 43).

In conclusion, when compared to TensorFlow packages for forecasting future Brent Crude oil prices beyond the given dataset, Prophet emerges as a compelling alternative. We argue that the given macroeconomic conditions and the restricted supply/demand balance in the market needs to be accounted for. During our research we found that the Prophet model produced significantly better results when using monthly variables. In addition to the beyond dataset limitations of the TensorFlow-based models presented, Prophet allowed us to account for the monthly variables. In order to facilitate a comparison between the forecast and the forward curve on Brent Crude, we will present a discounted forecast using a risk-free asset. This is necessary as the ML algorithms do not incorporate trading, emotions, or risk-based discounts. In contrast, a forward curve on Brent Crude is a tradable instrument that accounts for time risk over the long-term horizon. The forecasted values are presented below.

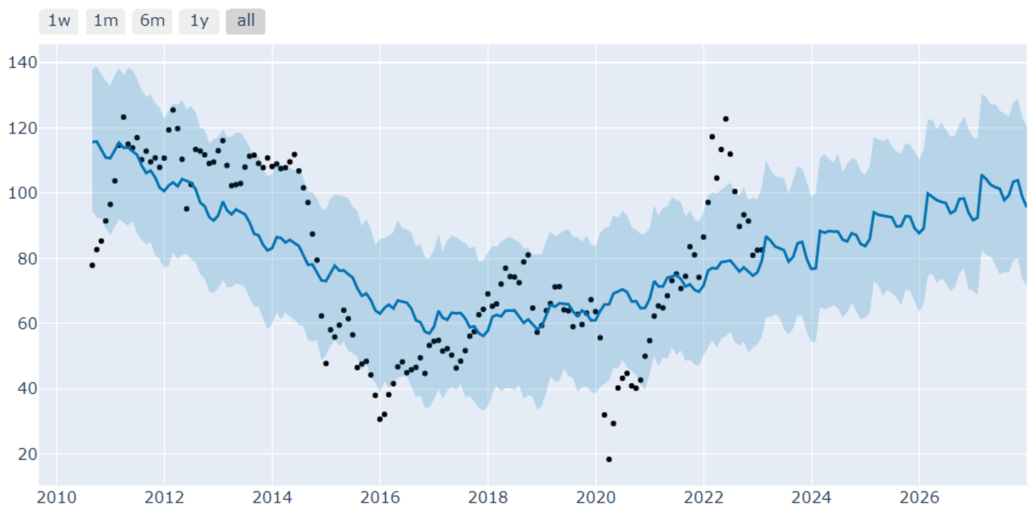

Figure 17. Prophet model Brent Crude oil forecast

Forecasted values	2023	2024	2025	2026	2027	2028T
Brent Crude oil ($/bbl)	81.69	85.97	91.16	95.86	100.57	65.00
Discounted values	79.35	81.11	83.54	85.34	86.96	65.00

Table 9. Forecasted and discounted Brent values

7.3 Forecast of the income statement

The projected income statement is influenced by various factors, including value drivers (Appendix 9) and (Appendix 10), key performance indicators, historical trends, company guidance (Appendix 11) and (Appendix 12), forward curves, external estimates, and our proprietary model. Specifically important is the net operating profit after tax (NOPAT) and depreciation & amortization (D&A) when estimating the free cash flow. For income related to gas, we have utilized the natural gas price forward curve and external estimates. The assumptions for oil and gas prices are presented in the table below.

Price assumptions	2023	2024	2025	2026	2027	2028T
Brent Crude oil ($/bbl)	81.69	85.97	91.16	95.86	100.57	65.00
Natural gas ($/mcf)	15.00	20.00	15.00	12.50	12.50	10.00

Table 10. Oil and gas price assumptions

Furthermore, the operational expense (OPEX) are derived from the companies' guidance on OPEX per barrel during the explicit period, while the tax rate is based on the historical tax rate. We do not possess actual data for future tax expenses, our best estimate is therefore to utilize the average historical tax rate. The USD/NOK exchange rate used in the thesis is 10.47 NOK, representing the exchange rate on March 31, 2023.

The projected income statement and our findings related to Aker BP is attached in (Appendix 13). Furthermore, the projected income statement and our findings related to Vår Energi is attached in (Appendix 14).

7.4 Forecast of the balance sheet

The projected balance sheet utilizes balance sheet ratios, primarily linked to revenues (Appendix 15) and (Appendix 16). In order to highlight the key items, we have included a condensed version of the balance sheet. Of particular importance is the growth in invested capital (NOA), which exhibits a consistent increase in the explicit period for Aker BP, and a steady increase until the end of 2025 followed by a decline for Vår Energi. This trend is primarily attributed to Vår Energi's capital expenditure (CAPEX) program aimed at achieving the guided production of approximately 350 kboepd at the end of 2025. Conversely, Aker BP maintains a high level of CAPEX until 2028 to attain the targeted production of approximately 525 kboepd.

The projected balance statement and our findings related to Aker BP are attached in (Appendix 17). Further, the projected balance sheet statement and our findings related to Vår Energi are attached in (Appendix 18).

7.5 Forecast of the cash flow statement

The projected cash flow statement is derived from the information obtained in the income statement and the balance sheet. The change in NONCA reflects the cash flow from investing activities, while the disparity between free cash flow to the firm and free cash flow to equity holders represents the cash flow from financing activities. To support our findings and ensure the accuracy of the cash flows, we have included a cash flow control (Appendix 19) and (Appendix 20), which demonstrates that the cash flows aligns with the NOPAT +/- the change in invested capital.

The projected cash flow statement and our findings related to Aker BP are attached in (Appendix 21). Further, the projected cash flow statement and our findings related to Vår Energi are attached in (Appendix 22).

8. Valuation

In Chapter 8, we will present the results obtained from the present value models. Additionally, we will highlight the outcomes derived from the Black-Scholes model.

8.1 Discounted cash flow model (DCF)

To determine the MVE, we have discounted the estimated cash flows using the appropriate WACC. We incorporated a mid-year adjustment for the discount factor to consider the continuous flow of cash throughout the year.

8.1.1 Aker BP

The results provided from the DCF model are presented in the table below.

		2023	2024	2025	2026	2027	Terminal	
DCF				Forecast horizon				WACC
Period	0	1	2	3	4	5	6	10 %
FCF		2 795	1 304	815	1 105	3 661	2 992	
Discount factor		0,91	0,82	0,74	0,67	0,61		
Midyear adj.		0,95	0,86	0,78	0,71	0,64		
PV FCFF		2 660	1 124	636	781	2 342		
PV term x.x.6						28 671		
PV term x.x.0						18 342		
EV	25 884							
NIBD	2 658							
MVE	243 182							
Fundamental Value (NOK)	**385**							

Figure 18. Aker BP DCF valuation

8.1.2 Vår Energi

The results provided from the DCF model are presented in the table below.

		2023	2024	2025	2026	2027	Terminal	
DCF				Forecast horizon				WACC
Period	0	1	2	3	4	5	7	9 %
FCF		327	1 310	1 652	3 287	2 122	1 266	
Discount factor		0,91	0,84	0,76	0,70	0,64		
Midyear adj.		0,96	0,87	0,80	0,73	0,67		
PV FCFF		312	1 145	1 320	2 401	1 418		
PV term x.x.6						13 499		
PV term x.x.0						9 017		
EV	15 613							
NIBD	2 720							
MVE	134 997							
Fundamental Value (NOK)	**54**							

Figure 19. Vår Energi DCF valuation

Furthermore, we have assumed a zero percent terminal growth rate due to the finite nature of oil and gas resources. Additionally, in the terminal period, we have modeled CAPEX higher than D&A, assuming that the companies will continue to invest, justifying non-negative terminal growth.

8.2 *Economic value-added model (EVA)*

We discount the EVAs at the appropriate discount rate, with the same assumptions for the terminal growth rate.

8.2.1 Aker BP

The results provided from the EVA model are presented in the table below.

		2023	2024	2025	2026	2027	Terminal	
EVA	Forecast horizon							WACC
Period	0	1	2	3	4	5	6	10 %
NOA	15 086	15 068	16 907	19 118	21 000	20 969	20 379	
NOPAT		2 778	3 143	3 026	2 987	3 630	2 403	
WACC x NOA_t-1		1 574	1 573	1 765	1 995	2 192	2 188	
EVA		1 203	1 571	1 261	992	1 438	214	
PV term x.x.6						2 055		
Discount factor		0,91	0,82	0,74	0,67	0,61		
PV term x.x.0	1 251							
PV EVA		1 090	1 288	936	667	876		
Sum EVA x.x.0	6 107							
MV EVA x.x.0	21 193							
NIBD	2 658							
MVE	194 066							
Fundamental Value	**307**							

Figure 20. Aker BP EVA valuation

8.2.2 Vår Energi

The results provided from the EVA model are presented in the table below.

		2023	2024	2025	2026	2027	Terminal	
EVA	Forecast horizon							WACC
Period	0	1	2	3	4	5	6	9 %
NOA	4 201	4 842	4 931	5 021	4 259	4 620	4 811	
NOPAT		967	1 399	1 741	2 524	2 484	1 457	
WACC x NOA_t-1		394	454	463	471	399	433	
EVA		573	945	1 279	2 053	2 084	1 023	
PV term x.x.6						10 907		
Discount factor		0,91	0,84	0,76	0,70	0,64		
PV term x.x.0	6 966							
PV EVA		524	790	977	1 435	1 331		
Sum EVA x.x.0	12 023							
MV EVA x.x.0	16 225							
NIBD	2 720							
MVE	141 397							
Fundamental Value	**57**							

Figure 21. Vår Energi EVA valuation

8.3 Black-Scholes Model

In this section the equity is treated as a call option on the firm, where exercising the option requires that the firm will be liquidated and the face value of the debt (which corresponds to the exercise price) is paid off. In addition to the Black-Scholes model we have utilized the Heston model. The Heston model incorporates stochastic volatility, which better captures market dynamics than the Black-Scholes model, which assumes constant volatility.

The Heston model offers a more complex method of pricing options by considering the correlation between the asset and its volatility. From the Black-Scholes model we obtain a share price of NOK 268 for Aker BP and NOK 43.6 for Vår Energi. From the Heston model we obtain a share price of NOK 281 and NOK 44, respectively. Please see (Appendix 23) and (Appendix 39) for calculations. Furthermore, the Monte Carlo simulations is attached in (Appendix 40) and (Appendix 41)

8.4 Multiples approach

In this section we have forecasted a set of forward multiples based on our estimates. We find that Aker BP trades higher on the P/E multiple, while Vår Energi trades higher on the P/B multiple. Furthermore, Aker BP trades higher on both the EV/EBITDA and EV/EBIT multiple. When comparing the forward multiples to the average forward multiple among peers, our findings indicates an upside of 74% and 30% for Vår Energi and Aker BP.

8.4.1 Aker BP

We have examined the forward estimates on the selected peer group and find that the average P/E-multiple among analysts is 6.89 for the peer group. When applying the P/E-multiple on our forward estimates, our research suggests that the company's fair value spans from NOK 311 to 410 in the explicit period.

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
Valuation (USDm)						
Share price (USD end)	24,5	24,5	24,5	24,5	24,5	24,5
Nr shares fully diluted	632	632	632	632	632	631,8
NIBD	1414	1898	2471	2405	127	-1500
Enterprise value	**16880**	**17365**	**17938**	**17871**	**15594**	**13966**
EV/sales	1,3	1,2	1,3	1,3	1,0	1,1
EV/EBITDA	1,4	1,3	1,4	1,4	1,0	1,5
EV/EBIT	1,7	1,6	1,7	1,7	1,2	1,6
P/E	5,7	5,0	5,2	5,2	4,3	6,5
P/B	1,1	1,0	0,9	0,8	0,7	0,7

Figure 22. Aker BP multiple valuation

8.4.2 Vår Energi

When applying the same P/E multiple to Vår Energi's forward estimates, we find that the company's fair value spans from NOK 27 to 71 in the explicit period.

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
Valuation (USDm)						
Share price (USD end)	2,4	2,4	2,4	2,4	2,4	2,4
Nr shares fully diluted	2496	2496	2496	2496	2496	2496
NIBD	2939	2602	1994	242	-363	-772
Enterprise value	**9024**	**8687**	**8079**	**6327**	**5722**	**5313**
EV/sales	1,3	1,0	0,7	0,5	0,5	0,7
EV/EBITDA	1,9	1,3	1,0	0,6	0,5	0,9
EV/EBIT	2,6	1,8	1,3	0,7	0,7	1,0
P/E	6,6	4,5	3,6	2,4	2,5	4,2
P/B	3,2	2,6	2,0	1,5	1,2	1,1

Figure 23. Vår Energi multiple valuation

9. Uncertainty considerations

In this analysis we will perform sensitivity analysis, scenario analysis and variable flexing.

9.1 Sensitivity analysis

In this section we want to capture the uncertainty related to the input variables. Sensitivity analysis helps to bound the valuation range when there is uncertainty about the inputs (Koller et al., 2020).

9.1.1 Aker BP

From the sensitivity analysis of the DCF model, we have found that Aker BP's fair value spans from 300 NOK to 537 NOK. This range analyze sensitivities on WACC and terminal growth assumptions

		WACC				
		9,4 %	9,9 %	10,4 %	10,9 %	11,4 %
rg	-2,0 %	367	348	331	315	300
	-1,0 %	397	375	356	337	321
	0,0 %	434	408	385	364	345
	1,0 %	479	448	420	396	373
	2,0 %	537	498	464	434	408

Figure 24. Aker BP DCF sensitivity analysis

From the sensitivity analysis of the EVA model, we have determined that Aker BP's fair value spans from 276 NOK to 355 NOK (Appendix 33).

9.1.2 Vår Energi

From the sensitivity analysis of the DCF model, we have determined that Vår Energi's fair value spans from 43 NOK to 75 NOK.

		WACC				
		8,4 %	8,9 %	9,4 %	9,9 %	10,4 %
rg	-2,0 %	53	50	47	45	43
	-1,0 %	56	53	50	48	45
	0,0 %	61	57	54	51	48
	1,0 %	67	63	59	55	52
	2,0 %	75	69	64	60	56

Figure 25. Vår Energi DCF sensitivity analysis

From the sensitivity analysis of the EVA model, we have determined that Vår Energi's fair value spans from 48 NOK to 73 NOK (Appendix 34). A sensitivity analysis of the P/E ratio is attached in (Appendix 24) and (Appendix 25), where we flex Brent Crude price on the X-axis and natural gas price on the Y-axis for all years in the explicit period. As our research suggests, should the Brent Crude oil and natural gas estimates come true, we see significant upside from current valuation. Higher energy prices may lead to lower WACC due to increased financial robustness and higher operability, reducing the risk related to lending and lowering the required return on capital. However, inflation may lead to higher required return on capital. In addition to the analysis on the P/E ratio and the Brent Crude oil price, we modeled a sensitivity analysis on the peer group P/E ratio and the USD/NOK exchange rate. The sensitivity analysis for the explicit period is attached in (Appendix 26) and (Appendix 27). As our research show, should the companies earn a high P/E ratio and should the USD/NOK remain at elevated levels, the upside in both companies is significant.

9.2 Scenario analysis

When applying the forward curve for the Brent Crude oil on the DCF model, we find that the fair value of Aker BP and Vår Energi is 267 NOK and 35 NOK, respectively. Please see (Appendix 28) and (Appendix 29) for detailed estimates. Our findings show that the market valuates Aker BP close to the forward curve on the Brent crude, using our estimates for the forward gas price. Vår Energi is underpriced using the same assumptions. This is consistent with our findings from the multiple valuation, where Vår Energi is underpriced relatively to Aker BP on forward estimates. The forward curve on Brent Crude used for comparison are presented in (Appendix 32).

9.3 Monte Carlo simulation

In this section we perform a Monte Carlo analysis with 50,000 simulations. In the sensitivity analysis we analyzed the valuation impact by flexing

WACC and terminal growth. In the Monte Carlo simulation, we seek to incorporate revenue growth, gross margin, OPEX, CAPEX, working capital and NONCA to capture the uncertainty in the underlying estimates.

9.3.1 Aker BP

The research conducted show that the mean value is NOK 397. We obtain a value of NOK 336 for the 25th percentile, a value of NOK 386 for the 50th percentile and a value of NOK 445 for the 75th percentile.

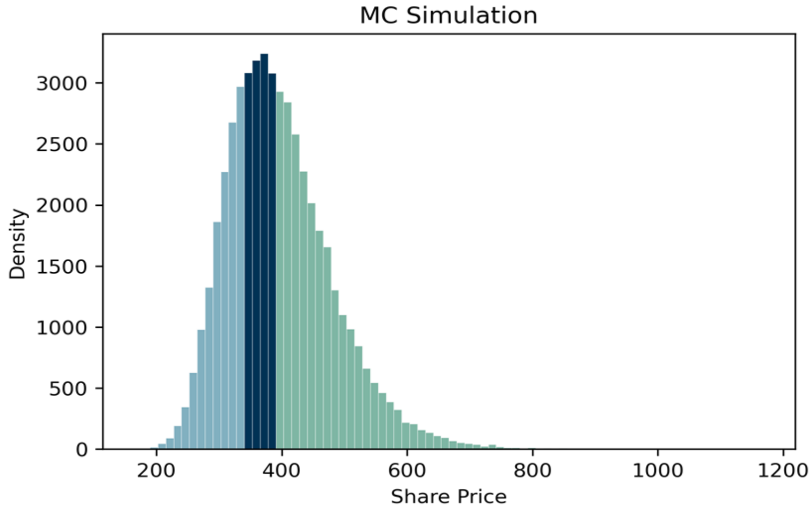

Figure 26. Aker BP MC simulation

9.3.2 Vår Energi

The mean value is NOK 56. We obtain a value of NOK 44 for the 25th percentile, a value of NOK 55 for the 50th percentile and a value of NOK 67 for the 75th percentile.

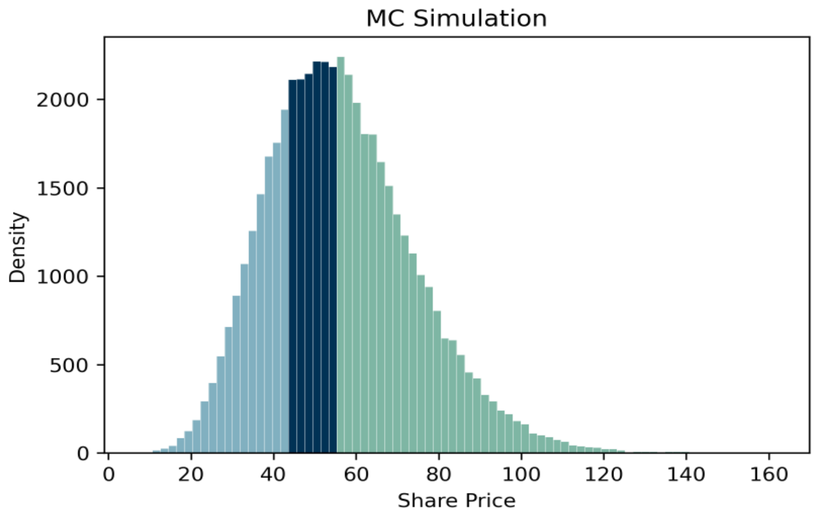

Figure 27. Vår Energi MC simulation

10. Discussion

All the models examined in this thesis is highly dependent on computational power. Hence, the results may be hard to replicate. This is an important shortfall with machine learning models. During our research, we tested the ML model both on daily and monthly data. We experienced that the ML models broke down during the test phase on monthly data. We believe this is attributed to the lack of data, and the fact that ML models require a lot of data to learn pattern and trends.

During our research we find that the machine learning models exhibit different forecasting performance when we add a dropout term and generalize our model using cross-validation. While adding a dropout term changes the ranking order and significantly reduces the overall forecasting performance, generalizing the models using cross-validation significantly increases the overall forecasting performance and change the ranking order. These results are intriguing, and the overall best results was obtained from the LSTM model, contrary to our findings on the basic ML models. These findings aligns with Assaad and Fayek (2021) who found that the LSTM exhibits the best forecasting performance compared to CNN. The difference in RMSE between basic, dropout and cross-validated models, suggests that the models is sensitive to noise, and therefore needs to be interpreted with caution.

We emphasize that our estimates are highly uncertain and depend on a set of assumptions that may not be best estimates. The estimates obtained from our present value models depend on a constant WACC estimated during our research. This WACC may not represent the true weighted average cost of capital. Furthermore, our assumptions for the terminal growth rate may be incorrect. Assumptions related to the cash flow from investing activities are based on the companies' guidance, and the assumptions related to the working capital are our own best estimates. We emphasize that our assumptions related to the net working capital might be wrong and, therefore, provide us with incorrect estimates for the fundamental values.

The revenue projections are based on the companies' guided production and our forward estimate for Brent Crude oil. We have also incorporated the gas-related revenues, for which we have used external estimates. We emphasize that the model provides us with an uncertain Brent Crude oil estimate, the external estimates on natural gas might be wrong, and the guided production might not be achieved, which, in turn, results in incorrect fundamental values. We think it is important to highlight these factors and the uncertainty in our estimates.

Furthermore, we observe that the different valuation methods provide us with different estimates, although all models and methods indicate an upside from the current valuation. The fact that different models and methods provide us with different values highlights the uncertainty in our calculations. To deal with the uncertainty, we have used uncertainty analysis through sensitivity analysis and Monte Carlo analysis, flexing different input variables that play an important role in calculating the fundamental value of the selected companies. We also observe that the selected companies trade on different multiples both today and in the explicit period. The reasons behind pricing differences are not something we investigate in this research, but we leave this open for others to investigate. Furthermore, in the course of our research, we have solely examined three ML models and one ARIMAX model. We leave the investigation of additional ML and time series models, as well as the investigation of existing models with enhanced computing power, open for others to research.

We believe that forward estimates are highly uncertain, and all forward estimates presented in this thesis should be interpreted with caution.

11. Conclusion

Based on the analysis conducted in this master's thesis, it can be concluded that the ARIMAX model outperformed the machine learning models in terms of accuracy, as evidenced by its lower MAE, MSE, and RMSE values, as well as its higher R^2 and adjusted R^2 values. However, there are concerns regarding overfitting in the ARIMAX model, which suggests that its performance on unseen data might not be as reliable. Attempts to mitigate overfitting through the implementation of LASSO resulted in a significant deterioration in model performance.

Among the basic machine learning models examined, the GRU model exhibits the best forecasting performance. It achieved lower MAE, MSE, and RMSE values compared to the LSTM and the CNN model. When generalizing our models with cross-validation the LSTM model exhibits the best overall ML forecasting performance.

The output from the Prophet model on Brent Crude oil prices was tested against the fundamental values of Aker BP and Vår Energi using a DCF model. The analysis yielded a fair value of NOK 385 for Aker BP and NOK 54 for Vår Energi, corresponding to an upside of 50% and 112% from their current market values.

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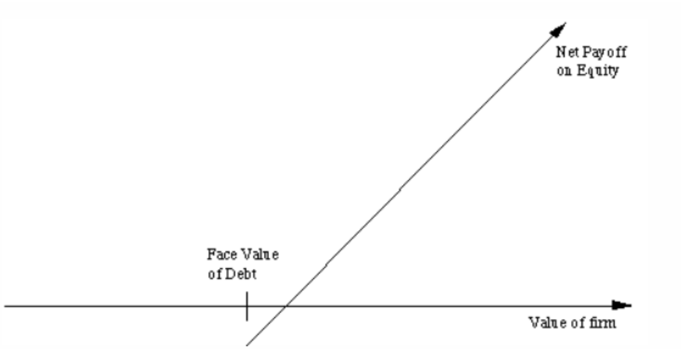
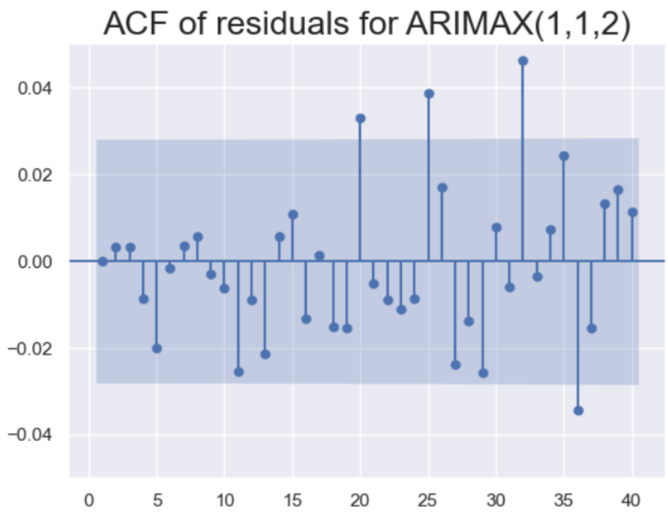
Appendix

Appendix 1. Black-Scholes model graphical pay-off structure



Appendix 2. ACF of residuals ARIMAX (1,1,2)



Appendix 3. Aker BP reformulated historical income statement

Aker BP	2017	2018	2019	2020	2021	2022
P&L in USD						
Revenues	**2 562,9**	**3 742,9**	**3 379,0**	**2 925,7**	**5 693,6**	**13 010,0**
Cost of Revenues	1250,1	1446	1532,2	1749,8	1709,4	2718,5
D&A	726,7	752,5	811,9	1121,9	964,1	1785,7
Gross Profit	**1 312,9**	**2 296,9**	**1 846,8**	**1 175,9**	**3 984,2**	**10 291,0**
SG&A	225,7	295,9	305,5	174,1	353,0	242,2
Other Operating Expense	27,6	17,0	35,3	49,5	29,3	52,6
Operating Expense	**1 503,4**	**1 759,0**	**1 873,0**	**1 973,4**	**2 091,7**	**3 013,3**
Operating Profit before non-rec.	**1059,6**	**1984,0**	**1505,9**	**952,3**	**3601,9**	**9996,6**
Non-Recurring Income/(Expense)	-48,1	-34,9	-169,3	-500,3	-312,6	-1 032,2
EBITDA	**1 738,2**	**2 701,6**	**2 148,5**	**1 573,9**	**4 253,4**	**10 750,1**
EBIT	**1011,5**	**1949,1**	**1336,6**	**452,0**	**3289,3**	**8964,4**
NOPAT	**344,5**	**459,3**	**239,8**	**290,9**	**935,1**	**1653,3**
Net Financial items	-209,4	-226,7	-204,1	-234,7	-201,3	-187,6
Income before Taxes	**811,1**	**1802,0**	**1084,3**	**163,7**	**3072,8**	**8776,9**
Income Taxes	536,3	1 326,2	943,2	119,0	2 222,1	7 173,9
Net Income	**274,8**	**475,8**	**141,1**	**44,7**	**850,7**	**1 602,9**

Appendix 4. Aker BP reformulated historical balance sheet

Aker BP - (NOA-FORMAT)	2017	2018	2019	2020	2021	2022
Balance sheet in USD						
NONCA	5237,6	5753,6	6627,0	5868,9	5505,1	19192,5
NWC	907,5	-803,7	-766,4	-235,1	-1421,1	-4106,9
NOA (invested capital)	**6145,1**	**4950,0**	**5860,6**	**5633,8**	**4084,0**	**15085,6**
Total Equity	2988,6	2976,5	2367,6	1987,3	2341,9	12428,0
NIBD	3156,5	1973,5	3493,0	3646,5	1742,1	2657,6
Total E + NIBD	**6145,1**	**4950,0**	**5860,6**	**5633,8**	**4084,0**	**15085,6**

Appendix 5. Aker BP reformulated historical cash flow statement

Aker BP	2017	2018	2019	2020	2021	2022
Cash flow in USD						
NOPAT	344,5	459,3	239,8	290,9	935,1	1 653,3
+D&A	683,7	713,7	891,1	1 524,1	1 199,2	2 817,9
-increase in NWC	- 729,2	1 711,2	- 37,3	- 531,3	1 185,9	2 685,9
-ΔNONCA	- 1 225,1	- 1 229,7	- 1 764,5	- 766,0	- 835,3	- 16 505,4
FCFF	**- 926,1**	**1 654,4**	**- 670,8**	**517,7**	**2 484,9**	**- 9 348,3**
-inc. NIBD w.o cash	856,3	- 1 369,6	1 581,7	584,2	- 471,3	1 700,6
NFI after tax	- 69,7	16,5	- 98,7	- 246,2	- 84,4	- 50,4
FCFE	**- 139,5**	**301,3**	**812,2**	**855,7**	**1 929,2**	**- 7 698,1**
dividends and Δequity buybacks	264,6	- 487,9	- 750,0	- 425,0	- 496,1	8 483,2
Cash surplus	**125,1**	**- 186,6**	**62,2**	**430,7**	**1 433,1**	**785,1**
Cash at the beginning of period	106,4	231,5	44,9	107,1	537,8	1 970,9
+/- cash surplus	125,1	- 186,6	62,2	430,7	1 433,1	785,1
= Cash at the end of period	**231,5**	**44,9**	**107,1**	**537,8**	**1 970,9**	**2 756,0**

Appendix 6. Vår Energi reformulated historical income statement

Vår Energi	2017	2018	2019	2020	2021	2022
P&L in USD						
Revenues	**1 910,1**	**2 716,3**	**2 855,7**	**2 893,8**	**6 072,7**	**9 827,6**
Cost of Revenues	1 247,4	1 490,3	1 862,1	2 764,0	2 994,5	2 591,1
D&A	792,0	985,3	1023,9	1706,7	1704,6	1448,0
Gross Profit	**662,7**	**1226,0**	**993,6**	**129,9**	**3078,2**	**7236,5**
SG&A	113,7	39,4	125,4	102,6	115,8	125,8
Other Operating Expense	183,1	173,3	218,6	158,0	146,5	-57,7
Operating Expense	**1 544,3**	**1 702,9**	**2 206,1**	**3 024,5**	**3 256,9**	**2 659,2**
Operating Profit before non-rec.	**365,9**	**1013,4**	**649,7**	**-130,7**	**2815,8**	**7168,4**
Non-Recurring Income/(Expense)	265,7	0,0	49,5	-2196,7	-1,0	-893,8
EBITDA	**1 423,6**	**1 998,7**	**1 723,1**	**-620,7**	**4 519,4**	**7 722,6**
EBIT	**631,6**	**1013,4**	**699,2**	**-2327,4**	**2814,8**	**6274,6**
NOPAT	**175,8**	**297,3**	**261,4**	**-1717,7**	**700,6**	**1049,9**
Net Financial items	-49,2	-17,3	73,8	123,3	-317,1	-418,7
Income before Taxes	**582,4**	**996,1**	**772,9**	**-2204,0**	**2497,7**	**5855,9**
Income Taxes	420,3	703,9	487,5	-577,4	1876,1	4919,5
Net Income	**162,1**	**292,2**	**285,4**	**-1626,6**	**621,6**	**936,4**

Appendix 7. Vår Energi reformulated historical balance sheet

Vår Energi - (NOA-FORMAT)	2017	2018	2019	2020	2021	2022
Balance sheet in USD						
NONCA	692,5	3952,7	8206,6	7012,5	7019,3	5635,8
NWC	-26,8	-1821,7	-1078,8	317,3	-589,2	-1434,4
NOA (invested capital)	**665,7**	**2 131,0**	**7 127,8**	**7 329,7**	**6 430,1**	**4 201,4**
Total Equity	688,1	2494,7	2518,8	1854,9	1502,9	1481,6
NIBD	-22,5	-363,7	4609,0	5474,8	4927,2	2719,8
Total E + NIBD	**665,7**	**2131,0**	**7127,8**	**7329,7**	**6430,1**	**4201,4**

Appendix 8. Vår Energi reformulated historical cash flow statement

Vår Energi	2017	2018	2019	2020	2021	2022
Cash flow in USD						
NOPAT	175,8	297,3	261,4	- 1 717,7	700,6	1 049,9
+D&A	526,3	985,3	974,5	3 903,4	1 705,6	2 341,8
-increase in NWC	n.a.	1 794,9	- 742,9	- 1 396,0	906,5	845,1
-ΔNONCA	n.a.	- 4 245,5	- 5 228,4	- 2 709,3	- 1 712,4	- 958,3
FCFF	**n.a.**	**- 1 168,0**	**- 4 735,5**	**- 1 919,6**	**1 600,3**	**3 278,6**
-inc. NIBD w.o cash	n.a.	646,1	4 165,9	932,7	- 801,1	- 1 782,1
NFI after tax	n.a.	- 5,1	24,0	91,1	- 79,0	- 113,5
FCFE	**n.a.**	**- 527,0**	**- 545,5**	**- 895,8**	**720,2**	**1 382,9**
dividends and Δequity buybacks	-	1 514,4	- 261,3	962,7	- 973,6	- 957,7
Cash surplus	n.a.	**987,4**	**- 806,8**	**66,9**	**- 253,4**	**425,2**
Cash at the beginning of period	n.a.	15,4	1 002,8	196,0	262,9	9,5
+/- cash surplus	n.a.	987,4	- 806,8	66,9	- 253,4	425,2
= Cash at the end of period	**15,4**	**1 002,8**	**196,0**	**262,9**	**9,5**	**434,7**

Appendix 9. Aker BP income statement drivers

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
Ratios (Income statement)						
Sales growth	2,9 %	8,7 %	-6,1 %	-2,0 %	20,0 %	-24,4 %
Sales growth reversion rate	-125,6 %	5,8 %	-14,8 %	4,2 %	22,0 %	-44,4 %
Gross profit margin	76,0 %	77,5 %	79,5 %	80,0 %	80,9 %	72,0 %
Operating expense/sales	2,5 %	1,0 %	1,0 %	1,0 %	0,9 %	2,0 %
Depreciation/Gross prior-year PP&E	13,2 %	10,0 %	10,0 %	9,0 %	8,1 %	3,0 %
Interest income/Prior-year cash	2,4 %	2,4 %	2,4 %	2,4 %	2,4 %	2,4 %
Interest expense/Prior-year IBD	4,6 %	4,6 %	4,6 %	4,6 %	4,6 %	4,6 %
Income tax expense/pretax income	71,8 %	71,8 %	71,8 %	71,8 %	71,8 %	71,8 %

Appendix 10. Vår Energi income statement drivers

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
Ratios (Income statement)						
Sales growth	-32,0 %	31,8 %	25,6 %	6,8 %	-3,9 %	-30,4 %
Sales growth reversion rate	-93,8 %	63,7 %	-6,2 %	-18,7 %	-10,8 %	-26,5 %
Gross profit margin	65,0 %	70,0 %	70,0 %	76,0 %	78,0 %	70,0 %
Operating expense/Sales	14,0 %	14,0 %	14,5 %	0,7 %	0,9 %	5,0 %
Depreciation/Gross prior-year PP&E	9,3 %	9,3 %	9,3 %	9,0 %	9,0 %	4,0 %
Interest income/Prior-year cash	2,5 %	2,5 %	2,5 %	2,5 %	2,5 %	2,5 %
Interest expense/Prior-year IBD	5,5 %	5,5 %	5,5 %	5,5 %	5,5 %	5,5 %
Income tax expense/pretax income	71,6 %	71,6 %	71,6 %	71,6 %	71,6 %	71,6 %

Appendix 11. Aker BP revenue and cost drivers

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
Production (mboepd)	449	445	417	400	460	525
Total production (mboe)	163 768	162 597	152 143	146 000	167 900	191 625
Oil (%)	*85 %*	*85 %*	*85 %*	*85 %*	*85 %*	*85 %*
Gas (%)	*15 %*	*15 %*	*15 %*	*15 %*	*15 %*	*15 %*
USD/mcf	15,00	20,00	15,00	12,50	12,50	10,00
USD/mmbtu	14,46	19,29	14,46	12,05	12,05	9,64
USD/boe (5,69 mmbtu = 1boe)	82,30	109,74	82,30	68,59	68,59	54,87
Price per bbl (oil)	81,69	85,97	91,16	95,86	100,57	65,00
Combined realized price per barrel	81,78	89,54	89,83	91,77	95,77	63,48
Revenues	13 393,33	14 558,15	13 667,26	13 398,29	16 080,22	12 164,45
OPEX/boe	7,91	7,67	7,06	7,03	6,99	6,95

Appendix 12. Vår Energi revenue and cost drivers

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
Production (mboepd)	224	261	338	355	326	341
Total production (mboe)	81 640	95 367	123 523	129 575	118 990	124 465
Oil (%)	*66 %*	*73 %*	*82 %*	*83 %*	*84 %*	*85 %*
Gas (%)	*34 %*	*27 %*	*18 %*	*17 %*	*16 %*	*15 %*
USD/mcf	15,00	20,00	15,00	12,50	12,50	10,00
USD/mmbtu	14,46	19,29	14,46	12,05	12,05	9,64
USD/boe (5,69 mmbtu = 1boe)	82,30	109,74	82,30	68,59	68,59	54,87
Price per bbl (oil)	81,69	85,97	91,16	95,86	100,57	65,00
Combined realized price per barrel	81,90	92,39	89,57	91,22	95,45	63,48
Revenues	6 686,20	8 810,77	11 063,49	11 820,30	11 357,92	7 901,10
OPEX/boe	14,65	14,84	14,55	8,22	7,98	8,11

Appendix 13. Aker BP Income statement explicit period

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
P&L in USD						
Revenues	**13 393,3**	**14 558,2**	**13 667,3**	**13 398,3**	**16 080,2**	**12 164,4**
Cost of Revenues	3214,4	3272,7	2807,5	2679,7	3071,3	3406,0
D&A	2112,4	1820,5	2257,2	2339,0	2419,9	930,0
Gross Profit	**10 178,9**	**11 285,5**	**10 859,7**	**10 718,6**	**13 008,9**	**8 758,4**
SG&A	275,1	119,6	112,3	110,1	118,9	199,9
Other Operating Expense	59,7	26,0	24,4	23,9	25,8	43,4
Operating Expense	**3 549,2**	**3 418,3**	**2 944,2**	**2 813,6**	**3 216,0**	**3 649,3**
Operating Profit before non-rec.	**9844,1**	**11139,9**	**10723,1**	**10584,6**	**12864,2**	**8515,1**
Non-Recurring Income/(Expense)	-	-	-	-	-	-
EBITDA	**11 956,5**	**12 960,4**	**12 980,3**	**12 923,7**	**15 284,0**	**9 445,1**
EBIT	**9844,1**	**11139,9**	**10723,1**	**10584,6**	**12864,2**	**8515,1**
NOPAT	**2777,8**	**3143,5**	**3025,9**	**2986,8**	**3630,0**	**2402,8**
Net Financial items	-182,5	-137,8	-135,6	-135,5	-120,0	-51,1
Income before Taxes	**9661,6**	**11002,1**	**10587,5**	**10449,2**	**12744,2**	**8464,0**
Income Taxes	6 935,3	7 897,5	7 599,9	7 500,6	9 148,0	6 075,6
Net Income	**2 726,3**	**3 104,6**	**2 987,6**	**2 948,6**	**3 596,2**	**2 388,4**

Appendix 14. Vår Energi Income statement explicit period

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
P&L in USD						
Revenues	**6 686,2**	**8 810,8**	**11 063,5**	**11 820,3**	**11 357,9**	**7 901,1**
Cost of Revenues	2 340,2	2 643,2	3 319,0	2 836,9	2 498,7	2 370,3
D&A	1377,9	1659,2	1807,5	1988,8	2010,1	902,5
Gross Profit	**4346,0**	**6167,5**	**7744,4**	**8983,4**	**8859,2**	**5530,8**
SG&A	413,3	544,6	708,3	36,5	45,1	174,4
Other Operating Expense	522,8	688,9	895,9	46,2	57,1	220,6
Operating Expense	**3 276,2**	**3 876,7**	**4 923,3**	**2 919,6**	**2 601,0**	**2 765,4**
Operating Profit before non-rec.	**3410,0**	**4934,0**	**6140,2**	**8900,7**	**8757,0**	**5135,7**
Non-Recurring Income/(Expense)	0,0	0,0	0,0	0,0	0,0	0,0
EBITDA	**4 787,9**	**6 593,2**	**7 947,7**	**10 889,5**	**10 767,1**	**6 038,2**
EBIT	**3410,0**	**4934,0**	**6140,2**	**8900,7**	**8757,0**	**5135,7**
NOPAT	**967,1**	**1399,4**	**1741,5**	**2524,4**	**2483,6**	**1456,6**
Net Financial items	-163,2	-169,0	-154,7	-121,7	-59,9	-26,8
Income before Taxes	**3246,7**	**4765,1**	**5985,5**	**8779,0**	**8697,0**	**5108,9**
Income Taxes	2325,9	3413,6	4287,9	6289,1	6230,4	3659,9
Net Income	**920,8**	**1351,5**	**1697,6**	**2489,9**	**2466,6**	**1449,0**

Appendix 15. Aker BP balance sheet drivers

Ratios (Balance sheet)	2023E	2024E	2025E	2026E	2027E	2028T
Account receivable turnover rate	7,43	7,43	7,25	7,25	6,00	8,95
Inventory turnover rate	42,37	42,82	48,08	48,84	48,84	46,84
Deferred tax/PP&E	39,4 %	41,1 %	46,3 %	45,3 %	43,5 %	42,0 %
Account payable turnover rate	36,72	36,72	36,72	36,72	50,00	32,44
Tax payable/Tax expense	70,9 %	70,9 %	70,9 %	70,9 %	70,9 %	85,0 %
Dividends (in millions)	1500	1750	1350	1000	1350	1350
Dividend ratio (Dividend/Net income)	55 %	56 %	45 %	34 %	38 %	57 %
PPE (CAPEX)	2 207	4 367	3 417	3 886	1 126	1 642
CAPEX/Sales	16 %	30 %	25 %	29 %	7 %	14 %
Installments interest-bearing debt	- 636,30	- 636,30	- 636,30	- 636,30	- 636,30	-
NWC	- 4 259,71	- 4 682,64	- 5 131,01	- 5 473,86	- 5 612,29	- 6 263,26
Change in NWC	- 152,78	- 422,94	- 448,37	- 342,85	- 138,43	- 650,97
Intangibles/sales	116,3 %	100,0 %	118,0 %	125,0 %	99,0 %	118 %
Other non-current assets/sales	0,6 %	0,6 %	0,6 %	0,6 %	0,6 %	0,5 %
Prepaid expense/sales	1,5 %	1,5 %	1,5 %	1,5 %	1,5 %	1,2 %
Other non-current liabilities/sales	56,2 %	44,9 %	44,3 %	51,0 %	44,3 %	56,2 %
Derivative Instruments - Short term	0,6 %	0,6 %	0,6 %	0,6 %	0,6 %	0,3 %
Other Current Liabilities/sales	9,9 %	8,5 %	13,0 %	16,0 %	13,0 %	20,5 %
Receivables & Loans - Long term	1,3 %	1,5 %	1,2 %	1,2 %	1,2 %	1,2 %
Derivative Liabilities - Short term	0,3 %	0,3 %	0,3 %	0,3 %	0,3 %	0,3 %

Appendix 16. Vår Energi balance sheet drivers

Ratios (Balance sheet)	2023E	2024E	2025E	2026E	2027E	2028T
Account receivable turnover rate	8,50	11,20	14,06	15,03	14,44	9,18
Inventory turnover rate	29,25	32,18	35,39	36,10	36,82	37,00
Deferred tax/PP&E	60,0 %	60,0 %	58,0 %	58,0 %	58,0 %	58,4 %
Account payable turnover rate	14,50	15,94	23,44	23,44	26,44	14,00
Tax payable/Tax expense	45,0 %	39,4 %	39,4 %	39,4 %	33,0 %	43,0 %
Dividends (in millions)	500	925	1000	1500	1500	850
Dividend ratio (Dividend/Net income)	54,3 %	68,4 %	58,9 %	60,2 %	60,8 %	58,7 %
PPE (CAPEX)	3 008,79	1 585,94	2 765,87	236,41	227,16	316,04
CAPEX/Sales	45 %	18 %	25 %	2 %	2 %	4 %
Installments interest-bearing debt	-	- 200,00	- 600,00	- 600,00	- 600,00	0
NWC	- 1 624,42	- 1 491,25	- 1 883,57	- 2 746,21	- 2 232,33	- 2 170,59
Change in NWC	- 190,06	133,17	- 392,32	- 862,64	513,88	61,73
Intangibles/sales	25,8 %	23,2 %	23,2 %	18,0 %	15,0 %	23,8 %
Other non-current assets/sales	0,1 %	0,1 %	0,1 %	0,1 %	0,1 %	0,1 %
Prepaid expense/sales	0,3 %	0,3 %	0,3 %	0,3 %	0,3 %	0,2 %
Other non-current liabilities/sales	35,4 %	38,2 %	44,8 %	38,2 %	38,2 %	56,0 %
Derivative Instruments - Short term	0,2 %	0,2 %	0,2 %	0,2 %	0,2 %	0,2 %
Other Current Liabilities/sales	17,0 %	7,5 %	7,5 %	7,5 %	7,5 %	14,0 %
Derivative Liabilities - Short term	0,4 %	0,4 %	0,4 %	0,4 %	0,4 %	0,4 %
Other current assets/sales	0,3 %	0,3 %	0,3 %	0,3 %	0,3 %	0,3 %

Appendix 17. Aker BP compressed balance sheet explicit period

Aker BP - (NOA-FORMAT)	2023E	2024E	2025E	2026E	2027E	2028T
Balance sheet in USD						
NONCA	19327,9	21590,0	24248,7	26473,5	26581,1	26642,7
NWC	-4259,7	-4682,6	-5131,0	-5473,9	-5612,3	-6263,3
NOA (invested capital)	**15068,2**	**16907,3**	**19117,7**	**20999,7**	**20968,8**	**20379,4**
Total Equity	13654,3	15009,0	16646,6	18595,1	20841,3	21879,7
NIBD	1413,9	1898,4	2471,2	2404,5	127,4	-1500,3
Total E + NIBD	**15068,2**	**16907,3**	**19117,7**	**20999,7**	**20968,8**	**20379,4**

Appendix 18. Vår Energi compressed balance sheet explicit period

Vår Energi - (NOA-FORMAT)	2023E	2024E	2025E	2026E	2027E	2028T
Balance sheet in USD						
NONCA	6466,2	6422,5	6904,4	7004,9	6852,5	6981,1
NWC	-1624,4	-1491,3	-1883,6	-2746,2	-2232,3	-2170,6
NOA (invested capital)	**4 841,7**	**4 931,3**	**5 020,8**	**4 258,7**	**4 620,2**	**4 810,5**
Total Equity	1902,4	2328,9	3026,5	4016,4	4983,0	5582,0
NIBD	2939,3	2602,4	1994,3	242,3	-362,8	-771,5
Total E + NIBD	**4841,7**	**4931,3**	**5020,8**	**4258,7**	**4620,2**	**4810,5**

Appendix 19. Aker BP cash flow control

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
Cash flow control in USD						
NOPAT	2 777,83	3 143,49	3 025,86	2 986,81	3 630,05	2 402,82
+/- ΔNOA	17,40	- 1 839,14	- 2 210,38	- 1 881,95	30,91	589,36
FCFF	**2 795,23**	**1 304,34**	**815,49**	**1 104,86**	**3 660,96**	**2 992,18**

Appendix 20. Vår Energi cash flow control

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
Cash flow control in USD						
NOPAT	967,13	1 399,39	1 741,49	2 524,41	2 483,64	1 456,59
+/- ΔNOA	- 640,32	- 89,51	- 89,55	762,10	- 361,48	- 190,32
FCFF	**326,81**	**1 309,87**	**1 651,94**	**3 286,50**	**2 122,17**	**1 266,27**

Appendix 21. Aker BP cash flow statement explicit period

Aker BP	2023E	2024E	2025E	2026E	2027E	2028T
Cash flow in USD						
NOPAT	2 777,8	3 143,5	3 025,9	2 986,8	3 630,0	2 402,8
+D&A	2 112,4	1 820,5	2 257,2	2 339,0	2 419,9	930,0
-increase in NWC	152,8	422,9	448,4	342,9	138,4	651,0
-ΔNONCA	- 2 247,8	- 4 082,6	- 4 916,0	- 4 563,8	- 2 527,4	- 991,6
FCFF	**2 795,2**	**1 304,3**	**815,5**	**1 104,9**	**3 661,0**	**2 992,2**
-inc. NIBD w.o cash	- 672,6	- 636,3	- 636,3	- 636,3	- 636,3	- 636,3
NFI after tax	- 51,5	- 38,9	- 38,3	- 38,2	- 33,8	- 14,4
FCFE	**2 071,1**	**629,2**	**140,9**	**430,3**	**2 990,8**	**2 341,5**
dividends and Δequity buybacks	- 1 500,0	- 1 750,0	- 1 350,0	- 1 000,0	- 1 350,0	- 1 350,0
Cash surplus	**571,1**	**- 1 120,8**	**- 1 209,1**	**569,7**	**1 640,8**	**991,5**
Cash at the beginning of period	2 756,0	3 327,1	2 206,3	997,2	427,6	2 068,4
+/- cash surplus	571,1	- 1 120,8	- 1 209,1	569,7	1 640,8	991,5
= Cash at the end of period	**3 327,1**	**2 206,3**	**997,2**	**427,6**	**2 068,4**	**3 059,8**

Appendix 22. Vår Energi cash flow statement explicit period

Vår Energi	2023E	2024E	2025E	2026E	2027E	2028T
Cash flow in USD						
NOPAT	967,1	1 399,4	1 741,5	2 524,4	2 483,6	1 456,6
+D&A	1 377,9	1 659,2	1 807,5	1 988,8	2 010,1	902,5
-increase in NWC	190,1	-133,2	392,3	862,6	-513,9	-61,7
-ΔNONCA	-2 208,3	-1 615,6	-2 289,4	-2 089,4	-1 857,7	-1 031,1
FCFF	**326,8**	**1 309,9**	**1 651,9**	**3 286,5**	**2 122,2**	**1 266,3**
-inc. NIBD w.o cash	-10,8	-206,6	-607,0	-602,3	-598,6	10,7
NFI after tax	-46,3	-47,9	-43,9	-34,5	-17,0	-7,6
FCFE	**269,7**	**1 055,4**	**1 001,1**	**2 649,6**	**1 506,6**	**1 269,4**
dividends and Δequity buybacks	-500,0	-925,0	-1 000,0	-1 500,0	-1 500,0	-850,0
Cash surplus	**-230,3**	**130,4**	**1,1**	**1 149,6**	**6,6**	**419,4**
Cash at the beginning of period	434,7	204,4	334,8	335,8	1 485,5	1 492,1
+/- cash surplus	-230,3	130,4	1,1	1 149,6	6,6	419,4
= Cash at the end of period	**204,4**	**334,8**	**335,8**	**1 485,5**	**1 492,1**	**1 911,5**

Appendix 23. Black-Scholes model valuation

	EV	FV debt	t	Value call	Value debt	Pay off	P/Share
Aker BP	25 884,18	5 569,00	4,64	21 027,72	4 856,46	16 171,26	268,0
Vår Energi	15 613,49	3 046,00	5,33	13 010,54	2 602,95	10 407,59	43,6

Appendix 24. Aker BP P/E sensitivity 2023

P/E 23e	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	10,1x	8,5x	7,3x	6,4x	5,8x	5,2x	4,7x
USD/mcf 10	9,3x	7,9x	6,9x	6,1x	5,5x	5,0x	4,5x
USD/mcf 15	8,5x	7,4x	6,5x	5,8x	5,2x	4,8x	4,4x
USD/mcf 20	7,9x	6,9x	6,1x	5,5x	5,0x	4,6x	4,2x
USD/mcf 30	6,9x	6,1x	5,5x	5,0x	4,6x	4,2x	3,9x
USD/mcf 40	6,2x	5,5x	5,0x	4,6x	4,2x	3,9x	3,6x
USD/mcf 50	5,5x	5,0x	4,6x	4,2x	3,9x	3,7x	3,4x

Aker BP P/E sensitivity 2024

P/E 24e	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	9,7x	8,2x	7,0x	6,2x	5,5x	5,0x	4,6x
USD/mcf 10	8,9x	7,6x	6,6x	5,9x	5,3x	4,8x	4,4x
USD/mcf 15	8,2x	7,1x	6,2x	5,6x	5,0x	4,6x	4,2x
USD/mcf 20	7,6x	6,6x	5,9x	5,3x	4,8x	4,4x	4,0x
USD/mcf 30	6,7x	5,9x	5,3x	4,8x	4,4x	4,1x	3,8x
USD/mcf 40	5,9x	5,3x	4,8x	4,4x	4,1x	3,8x	3,5x
USD/mcf 50	5,3x	4,8x	4,4x	4,1x	3,8x	3,5x	3,3x

Aker BP P/E sensitivity 2025

	P/E 25e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	10,1x	8,5x	7,3x	6,5x	5,8x	5,2x	4,8x
USD/mcf 10	9,3x	7,9x	6,9x	6,1x	5,5x	5,0x	4,6x
USD/mcf 15	8,5x	7,4x	6,5x	5,8x	5,2x	4,8x	4,4x
USD/mcf 20	7,9x	6,9x	6,1x	5,5x	5,0x	4,6x	4,2x
USD/mcf 30	7,0x	6,2x	5,5x	5,0x	4,6x	4,2x	3,9x
USD/mcf 40	6,2x	5,5x	5,0x	4,6x	4,2x	3,9x	3,7x
USD/mcf 50	5,6x	5,0x	4,6x	4,3x	3,9x	3,7x	3,4x

Aker BP P/E sensitivity 2026

	P/E 26e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	10,5x	8,8x	7,6x	6,7x	6,0x	5,4x	4,9x
USD/mcf 10	9,6x	8,2x	7,1x	6,3x	5,7x	5,2x	4,7x
USD/mcf 15	8,9x	7,6x	6,7x	6,0x	5,4x	4,9x	4,5x
USD/mcf 20	8,2x	7,2x	6,4x	5,7x	5,2x	4,7x	4,4x
USD/mcf 30	7,2x	6,4x	5,7x	5,2x	4,8x	4,4x	4,1x
USD/mcf 40	6,4x	5,7x	5,2x	4,8x	4,4x	4,1x	3,8x
USD/mcf 50	5,8x	5,2x	4,8x	4,4x	4,1x	3,8x	3,6x

Aker BP P/E sensitivity 2027

	P/E 27e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	8,9x	7,5x	6,5x	5,7x	5,1x	4,6x	4,2x
USD/mcf 10	8,2x	7,0x	6,1x	5,4x	4,9x	4,4x	4,0x
USD/mcf 15	7,6x	6,5x	5,8x	5,1x	4,6x	4,2x	3,9x
USD/mcf 20	7,0x	6,1x	5,4x	4,9x	4,4x	4,1x	3,7x
USD/mcf 30	6,2x	5,5x	4,9x	4,4x	4,1x	3,8x	3,5x
USD/mcf 40	5,5x	4,9x	4,5x	4,1x	3,8x	3,5x	3,3x
USD/mcf 50	4,9x	4,5x	4,1x	3,8x	3,5x	3,3x	3,1x

Appendix 25. Vår Energi P/E sensitivity 2023

	P/E 23e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	13,4x	11,4x	10,0x	8,9x	8,0x	7,2x	6,6x
USD/mcf 10	10,8x	9,5x	8,5x	7,6x	7,0x	6,4x	5,9x
USD/mcf 15	9,0x	8,1x	7,3x	6,7x	6,2x	5,7x	5,3x
USD/mcf 20	7,8x	7,1x	6,5x	6,0x	5,6x	5,2x	4,9x
USD/mcf 30	6,1x	5,6x	5,2x	4,9x	4,6x	4,4x	4,1x
USD/mcf 40	5,0x	4,7x	4,4x	4,2x	4,0x	3,8x	3,6x
USD/mcf 50	4,2x	4,0x	3,8x	3,6x	3,5x	3,3x	3,2x

Vår Energi P/E sensitivity 2024

	P/E 24e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	9,9x	8,4x	7,3x	6,4x	5,7x	5,2x	4,8x
USD/mcf 10	8,3x	7,2x	6,4x	5,7x	5,2x	4,7x	4,4x
USD/mcf 15	7,2x	6,4x	5,7x	5,2x	4,7x	4,4x	4,0x
USD/mcf 20	6,4x	5,7x	5,2x	4,7x	4,4x	4,0x	3,8x
USD/mcf 30	5,2x	4,7x	4,3x	4,0x	3,8x	3,5x	3,3x
USD/mcf 40	4,3x	4,0x	3,7x	3,5x	3,3x	3,1x	2,9x
USD/mcf 50	3,7x	3,5x	3,3x	3,1x	2,9x	2,8x	2,7x

Vår Energi P/E sensitivity 2025

	P/E 25e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	7,2x	6,0x	5,2x	4,6x	4,1x	3,7x	3,4x
USD/mcf 10	6,4x	5,5x	4,8x	4,3x	3,8x	3,5x	3,2x
USD/mcf 15	5,8x	5,1x	4,5x	4,0x	3,6x	3,3x	3,0x
USD/mcf 20	5,3x	4,7x	4,2x	3,8x	3,4x	3,1x	2,9x
USD/mcf 30	4,6x	4,1x	3,7x	3,4x	3,1x	2,9x	2,7x
USD/mcf 40	4,0x	3,6x	3,3x	3,0x	2,8x	2,6x	2,5x
USD/mcf 50	3,6x	3,2x	3,0x	2,8x	2,6x	2,4x	2,3x

Vår Energi P/E sensitivity 2026

	P/E 26e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	4,9x	4,1x	3,6x	3,1x	2,8x	2,5x	2,3x
USD/mcf 10	4,4x	3,8x	3,3x	3,0x	2,7x	2,4x	2,2x
USD/mcf 15	4,1x	3,5x	3,1x	2,8x	2,5x	2,3x	2,1x
USD/mcf 20	3,7x	3,3x	2,9x	2,6x	2,4x	2,2x	2,0x
USD/mcf 30	3,2x	2,9x	2,6x	2,4x	2,2x	2,0x	1,9x
USD/mcf 40	2,8x	2,6x	2,3x	2,1x	2,0x	1,8x	1,7x
USD/mcf 50	2,5x	2,3x	2,1x	2,0x	1,8x	1,7x	1,6x

Vår Energi P/E sensitivity 2027

	P/E 27e						
	USD/bbl 50	USD/bbl 60	USD/bbl 70	USD/bbl 80	USD/bbl 90	USD/bbl 100	USD/bbl 110
USD/mcf 5	5,1x	4,3x	3,7x	3,3x	2,9x	2,7x	2,4x
USD/mcf 10	4,7x	4,0x	3,5x	3,1x	2,8x	2,5x	2,3x
USD/mcf 15	4,3x	3,7x	3,3x	2,9x	2,7x	2,4x	2,2x
USD/mcf 20	4,0x	3,5x	3,1x	2,8x	2,5x	2,3x	2,1x
USD/mcf 30	3,5x	3,1x	2,8x	2,5x	2,3x	2,1x	2,0x
USD/mcf 40	3,1x	2,8x	2,5x	2,3x	2,1x	2,0x	1,8x
USD/mcf 50	2,7x	2,5x	2,3x	2,1x	2,0x	1,8x	1,7x

Appendix 26. Aker BP P/E multiple and USD/NOK sensitivity 2023

	P/E multiple 23e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	103,5	142,2	180,9	219,6	258,3	297,0	335,7
9,5	109,2	150,1	191,0	231,8	272,7	313,5	354,4
10,0	115,0	158,0	201,0	244,1	287,1	330,1	373,1
10,5	120,8	165,9	211,1	256,3	301,5	346,7	391,8
11,0	126,5	173,9	221,2	268,5	315,9	363,2	410,6
11,5	132,3	181,8	231,3	280,8	330,3	379,8	429,3
12,0	138,1	189,7	241,4	293,0	344,7	396,3	448,0

Aker BP P/E multiple and USD/NOK sensitivity 2024

	P/E multiple 24e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	117,8	161,9	206,0	250,0	294,1	338,2	382,3
9,5	124,4	170,9	217,5	264,0	310,5	357,1	403,6
10,0	131,0	179,9	228,9	277,9	326,9	375,9	424,9
10,5	137,5	189,0	240,4	291,9	343,3	394,8	446,2
11,0	144,1	198,0	251,9	305,8	359,7	413,6	467,5
11,5	150,7	207,0	263,4	319,7	376,1	432,5	488,8
12,0	157,2	216,0	274,9	333,7	392,5	451,3	510,1

Aker BP P/E multiple and USD/NOK sensitivity 2025

	P/E multiple 25e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	113,4	155,8	198,2	240,6	283,0	325,5	367,9
9,5	119,7	164,5	209,3	254,0	298,8	343,6	388,4
10,0	126,0	173,2	220,3	267,4	314,6	361,7	408,9
10,5	132,3	181,8	231,4	280,9	330,4	379,9	429,4
11,0	138,7	190,5	242,4	294,3	346,1	398,0	449,9
11,5	145,0	199,2	253,4	307,7	361,9	416,2	470,4
12,0	151,3	207,9	264,5	321,1	377,7	434,3	490,9

Aker BP P/E multiple and USD/NOK sensitivity 2026

	P/E multiple 26e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	111,9	153,8	195,6	237,5	279,3	321,2	363,1
9,5	118,1	162,3	206,5	250,7	294,9	339,1	383,3
10,0	124,4	170,9	217,4	264,0	310,5	357,0	403,5
10,5	130,6	179,5	228,3	277,2	326,1	374,9	423,8
11,0	136,8	188,0	239,2	290,4	341,6	392,8	444,0
11,5	143,1	196,6	250,1	303,7	357,2	410,7	464,3
12,0	149,3	205,2	261,0	316,9	372,8	428,6	484,5

Aker BP P/E multiple and USD/NOK sensitivity 2027

	P/E multiple 27e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	136,5	187,5	238,6	289,6	340,7	391,8	442,8
9,5	144,1	198,0	251,9	305,8	359,7	413,6	467,5
10,0	151,7	208,4	265,2	321,9	378,7	435,4	492,2
10,5	159,3	218,9	278,5	338,1	397,7	457,3	516,9
11,0	166,9	229,3	291,8	354,2	416,7	479,1	541,5
11,5	174,5	239,8	305,1	370,4	435,7	500,9	566,2
12,0	182,1	250,2	318,4	386,5	454,6	522,8	590,9

Appendix 27. Vår Energi P/E multiple and USD/NOK sensitivity 2023

	P/E multiple 23e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	8,8	12,2	15,5	18,8	22,1	25,4	28,7
9,5	9,3	12,8	16,3	19,8	23,3	26,8	30,3
10,0	9,8	13,5	17,2	20,9	24,5	28,2	31,9
10,5	10,3	14,2	18,0	21,9	25,8	29,6	33,5
11,0	10,8	14,9	18,9	23,0	27,0	31,0	35,1
11,5	11,3	15,5	19,8	24,0	28,2	32,5	36,7
12,0	11,8	16,2	20,6	25,0	29,5	33,9	38,3

Vår Energi P/E multiple and USD/NOK sensitivity 2024

	P/E multiple 24e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	13,0	17,8	22,7	27,5	32,4	37,3	42,1
9,5	13,7	18,8	24,0	29,1	34,2	39,3	44,5
10,0	14,4	19,8	25,2	30,6	36,0	41,4	46,8
10,5	15,2	20,8	26,5	32,2	37,8	43,5	49,2
11,0	15,9	21,8	27,8	33,7	39,6	45,6	51,5
11,5	16,6	22,8	29,0	35,2	41,4	47,6	53,9
12,0	17,3	23,8	30,3	36,8	43,2	49,7	56,2

Vår Energi P/E multiple and USD/NOK sensitivity 2025

	P/E multiple 25e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	16,3	22,4	28,5	34,6	40,7	46,8	52,9
9,5	17,2	23,7	30,1	36,5	43,0	49,4	55,9
10,0	18,1	24,9	31,7	38,5	45,2	52,0	58,8
10,5	19,0	26,2	33,3	40,4	47,5	54,6	61,7
11,0	19,9	27,4	34,9	42,3	49,8	57,2	64,7
11,5	20,8	28,6	36,4	44,2	52,0	59,8	67,6
12,0	21,8	29,9	38,0	46,2	54,3	62,5	70,6

Vår Energi P/E multiple and USD/NOK sensitivity 2026

	P/E multiple 26e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	23,9	32,9	41,8	50,8	59,7	68,6	77,6
9,5	25,2	34,7	44,1	53,6	63,0	72,5	81,9
10,0	26,6	36,5	46,5	56,4	66,4	76,3	86,2
10,5	27,9	38,4	48,8	59,2	69,7	80,1	90,6
11,0	29,2	40,2	51,1	62,1	73,0	84,0	94,9
11,5	30,6	42,0	53,5	64,9	76,3	87,8	99,2
12,0	31,9	43,9	55,8	67,7	79,7	91,6	103,5

Vår Energi P/E multiple and USD/NOK sensitivity 2027

	P/E multiple 27e						
	2,7	3,7	4,7	5,7	6,7	7,7	8,7
9,0	23,7	32,6	41,4	50,3	59,1	68,0	76,9
9,5	25,0	34,4	43,7	53,1	62,4	71,8	81,2
10,0	26,3	36,2	46,0	55,9	65,7	75,6	85,4
10,5	27,7	38,0	48,3	58,7	69,0	79,4	89,7
11,0	29,0	39,8	50,7	61,5	72,3	83,2	94,0
11,5	30,3	41,6	53,0	64,3	75,6	87,0	98,3
12,0	31,6	43,4	55,3	67,1	78,9	90,7	102,6

Appendix 28. Aker BP DCF valuation applying forward curve

		2023	**2024**	**2025**	**2026**	**2027**	**Terminal**	
DCF				Forecast horizon				WACC
Period	0	1	2	3	4	5	6	10 %
FCF		2 880	152	- 484	470	1 723	2 420	
Discount factor		0,91	0,82	0,74	0,67	0,61		
Midyear adj.		0,95	0,86	0,78	0,71	0,64		
PV FCFF		2 740	131	- 378	332	1 102		
PV term x.x.6						23 189		
PV term x.x.0						14 835		
EV	18 762							
NIBD	2 658							
MVE	168 615							
Fundamental Value (NOK)	**267**							

Appendix 29. Vår Energi DCF valuation applying forward curve

		2023	2024	2025	2026	2027	Terminal	
DCF				Forecast horizon				WACC
Period	0	1	2	3	4	5	7	9 %
FCF		369	1 146	1 086	1 206	1 067	1 011	
Discount factor		0,91	0,84	0,76	0,70	0,64		
Midyear adj.		0,96	0,87	0,80	0,73	0,67		
PV FCFF		352	1 002	868	881	713		
PV term x.x.6						10 782		
PV term x.x.0						7 202		
EV	11 018							
NIBD	2 720							
MVE	86 885							
Fundamental Value (NOK)	**35**							

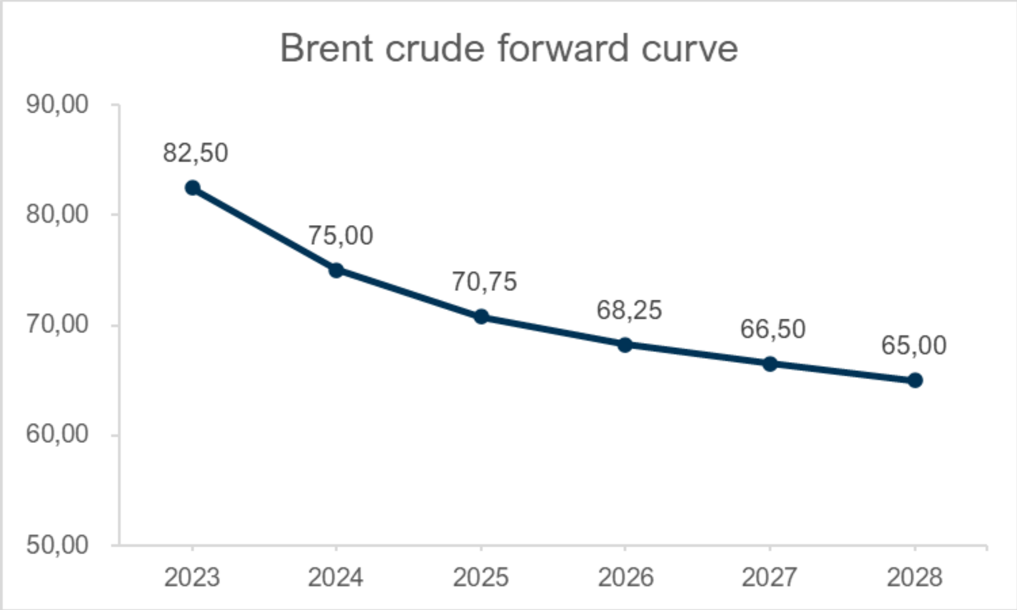
Appendix 30. Aker BP EVA valuation applying forward curve

		2023	2024	2025	2026	2027	Terminal	
EVA				Forecast horizon				WACC
Period	0	1	2	3	4	5	6	10 %
NOA	15 086	15 016	17 580	20 345	21 895	22 432	22 414	
NOPAT		2 810	2 716	2 281	2 020	2 259	2 403	
WACC x NOA_t-1		1 574	1 567	1 835	2 123	2 285	2 341	
EVA		1 236	1 149	446	- 103	- 26	62	
PV term x.x.6						592		
Discount factor		0,91	0,82	0,74	0,67	0,61		
PV term x.x.0	360							
PV EVA		1 119	942	331	- 69	- 16		
Sum EVA x.x.0	2 667							
MV EVA x.x.0	17 753							
NIBD	2 658							
MVE	158 048							
Fundamental Value	**250**							

Appendix 31. Vår Energi EVA valuation applying forward curve

		2023	2024	2025	2026	2027	Terminal	
EVA				Forecast horizon				WACC
Period	0	1	2	3	4	5	6	9 %
NOA	4 201	4 818	4 861	4 939	5 414	5 863	6 308	
NOPAT		985	1 189	1 163	1 682	1 516	1 457	
WACC x NOA_t-1		394	452	456	463	508	550	
EVA		591	737	707	1 219	1 008	907	
PV term x.x.6						9 664		
Discount factor		0,91	0,84	0,76	0,70	0,64		
PV term x.x.0	6 173							
PV EVA		540	616	541	851	644		
Sum EVA x.x.0	9 365							
MV EVA x.x.0	13 566							
NIBD	2 720							
MVE	113 559							
Fundamental Value	**45**							

Appendix 32. Brent Crude forward curve



Appendix 33. Aker BP EVA sensitivity analysis

		WACC				
		9,4 %	9,9 %	10,4 %	10,9 %	11,4 %
rg	-2,0 %	334	319	304	290	276
	-1,0 %	338	321	305	290	276
	0,0 %	342	324	307	291	276
	1,0 %	348	328	309	292	276
	2,0 %	355	332	312	293	276

Figure 28. Aker BP EVA sensitivity analysis

Appendix 34. Vår Energi EVA sensitivity analysis

		WACC				
		8,4 %	8,9 %	9,4 %	9,9 %	10,4 %
rg	-2,0 %	56	54	52	50	48
	-1,0 %	59	56	54	52	50
	0,0 %	62	59	57	54	52
	1,0 %	67	63	60	57	55
	2,0 %	73	69	65	61	58

Figure 29. Vår Energi EVA sensitivity analysis

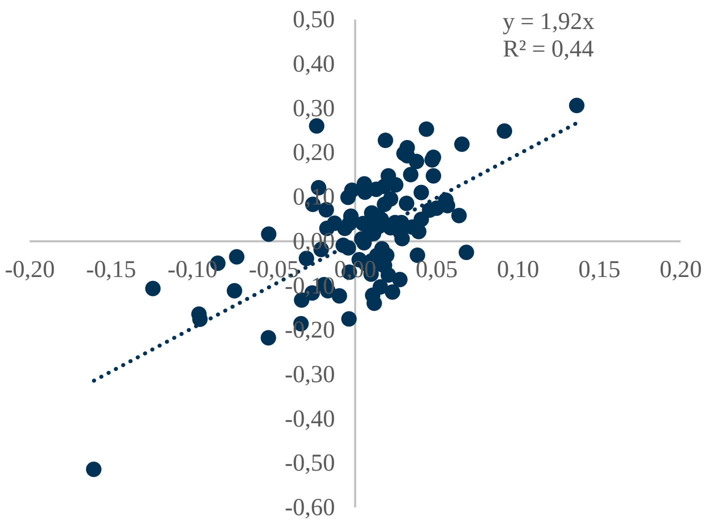
Appendix 35. Machine learning model summary results

	MAE	MSE	RMSE	R2	R2adj
GRU	3.288863	15.295035	3.910887	0.969079	0.968843
LSTM	4.437811	34.201696	5.848222	0.930858	0.930329
CNN	6.033358	45.114730	6.716750	0.908796	0.908099

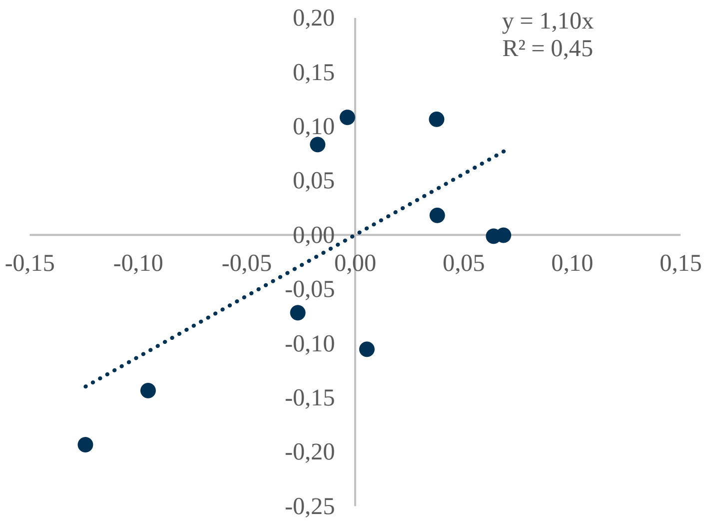
Appendix 36. ARIMAX model summary results

	MAE	MSE	RMSE	R2	R2adj
ARIMAX	0.681994	1.366161	1.168829	0.997205	0.997193

Appendix 37. Aker BP beta visualization



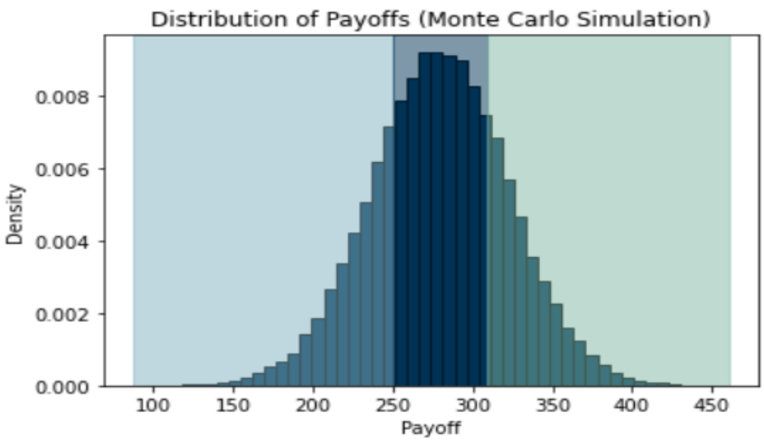
Appendix 38. Vår Energi beta visualization



Appendix 39. *Heston model calculations*

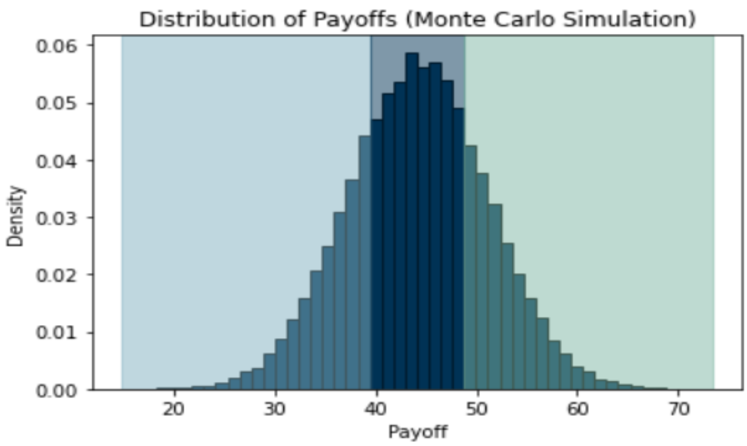
	Aker BP	Vår Energi
S	25884.18	15613.94
K	4856.46	3046.00
T	4.64	5.33
Rf	2.95%	2.95%
Sigma	12.47%	10.57%
Value call	21807.92	13099.99
Share price	281	44

Appendix 40. *Aker BP Heston model MC simulations*




```
Average Payoff: 279.2760703274306
25% Interval: 250.28871387362233
50% Interval: 279.3455313765446
75% Interval: 308.3550347926572
```

Appendix 41. *Vår Energi Heston model MC simulations*




```
Average Payoff: 44.14015554338368
25% Interval: 39.441350718810035
50% Interval: 44.16537257425305
75% Interval: 48.80212415511066
```

Appendix 42. Monthly significant variables

Variables
WTI Crude Spot
S&P 500 commodities total return
Gold spot
Natural Gas spot
US 10Y
US CPI
China total import

Appendix 43. Prophet daily errors

	MAE	MSE	RMSE	R^2	$R^2 adj$
Prophet daily	4.3481	29.1692	5.4008	0.94031	0.94027

Appendix 44. Coefficients and significance level

Variables	Coefficients	z	P>|z|
WTI Crude Spot	0.1963	14.898	0.000
S&P 500 commodities total return	0.0102	36.156	0.000
Gold spot	0.0095	10.507	0.000
Natural Gas spot	-1.0419	-15.252	0.000
US 10Y	1.1826	5.533	0.000

Equations

Equation 4: Capital Asset pricing model:

$$r_e = r_f + \beta \times (r_m - r_f)$$

where;

$r_e \; = \; Equity\ cost\ of\ capital$

$r_f \; = \; Risk - free\ rate$

$\beta \; = \; Asset\ beta$

$(r_m - r_f) \; = \; Market\ risk\ premium$

Equation 5: Blume's adjusted beta:

$$\hat{\beta} = \beta \times (1 - P) + P$$

where;

$\beta \; = \; raw\ beta$

$P \; = \; adjustment\ factor \; = \; 0.33$

$(1 - P) \; = estimation\ error$

Equation 6: Cost of debt:

$$Cost\ of\ debt \; = \frac{Interest\ expenese}{Interest - bearing\ debt}$$

Equation 7: Average Cost of Capital:

$$\mathrm{WACC} = \mathrm{r}_e \times \frac{\mathrm{E}}{(\mathrm{E} + \mathrm{D})} + \mathrm{r}_d \times \frac{\mathrm{D}}{(\mathrm{E} + \mathrm{D})} \times \; (1 - \mathrm{s})$$

where;

$r_e \; = \; Cost\ of\ equity$

$r_d \; = \; Cost\ of\ debt$

$s \; = \; Tax\ rate$

$E \; = \; Equity$

$D \; = \; Debt$

Equation 8. Black-Scholes formula:

$$European\ call: C_0 = S_0 e^{-\delta T} N(d_1) - e^{-rT} K N(d_2)$$

where:

$$d_1 = \frac{ln\left(\frac{S_0}{K}\right) + \left(r - \delta + \frac{\sigma^2}{\sigma}\right)T}{\sigma\sqrt{T}}$$

and:

$$d_2 = d_1 - \sigma\sqrt{T}$$

payoff:

$$Payoff = S - K\ if\ S > K$$

V = Liquidation value of the firm and

D = Face value of the outstanding debt and other external claims

S = Value of the underlying assets = Value of the firm

K = Exercise price = Face value of outstanding debt

T = Life of the option = Life of zero-coupon debt

σ^2 = Variance in the value of the underlying asset = Variance in firm value

r = Riskless rate = Treasury bond rate corresponding to option life

Payoff to equity investors = $V - D\ if\ V > D$

Mean Squared Error (MSE)

$$MSE = \frac{1}{N} \times \sum (y_i - \hat{y})^2$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum |y_i - \hat{y}|$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \times \sum (y_i - \hat{y})^2}$$

Akaike Information Criterion (AIC)

$$AIC = -2ln(L) + 2k$$

where;

k = number of model parameters

L = maximum value of the likelihood function of the model

Goodness of fit (R^2):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

where;

$\hat{y}$ – predicted value of y

$\bar{y}$ – mean of value of y

Corrected goodness of fit (R^2_{adj}):

$$R^2_{adj} = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$$

where;

R^2 = Sample R-squared

N = Total Sample Site

p = Number of independent variables

Dickey-Fuller test:

$$DF_t = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$