In [1]:
```
import os
import datetime as dt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas_datareader.data as web
from scipy import stats
import statsmodels.api as sm
import seaborn as sns
data_dir = "./data/oil_price_analysis"
os.makedirs(data_dir, exist_ok=True)
```

#Crude Oil Prices: West Texas Intermediate (WTI) — Cushing, Oklahoma (DCOILWTICO) #WTI is one of the leading oil price indices due to the large volume of transactions and market participants. #We will download the data for the entire period available and use it for analysis.

In [2]:
```
start = dt.datetime(1950, 1, 1)
end = dt.datetime(2022, 5, 21)
wti_oil_price = web.DataReader('DCOILWTICO', 'fred', start, end)
# save the data
file_path = f"{data_dir}/DCOILWTICO.csv"
wti_oil_price.to_csv(file_path)
wti_oil_price
```

Out[2]:

	DCOILWTICO
DATE	
1986-01-02	25.56
1986-01-03	26.00
1986-01-06	26.53
1986-01-07	25.85
1986-01-08	25.87
...	...
2022-05-16	114.07
2022-05-17	112.31
2022-05-18	109.67
2022-05-19	112.21
2022-05-20	112.63

9492 rows × 1 columns

In [3]:
```
wti_oil_price = pd.read_csv(file_path, index_col="DATE", parse_dates=True)
print(wti_oil_price.shape)
wti_oil_price.tail(3)
wti_oil_price
```

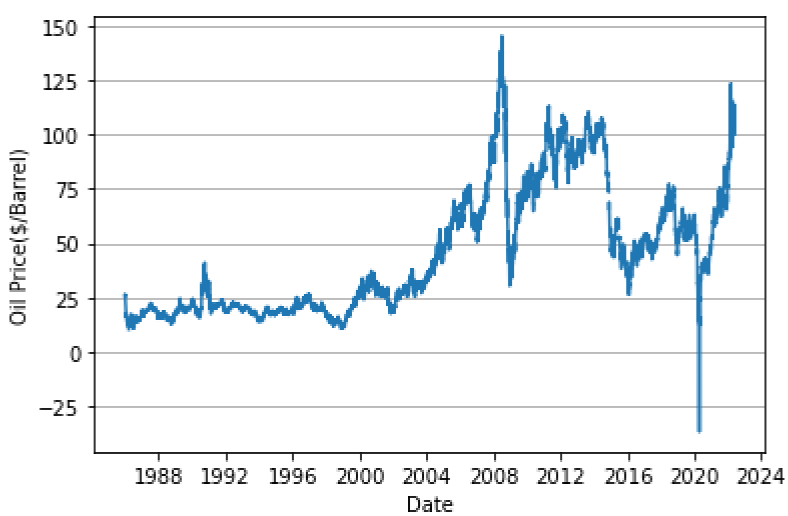
```
(9492, 1)
```

Out[3]:

	DCOILWTICO
DATE	
1986-01-02	25.56
1986-01-03	26.00
1986-01-06	26.53
1986-01-07	25.85
1986-01-08	25.87
...	...
2022-05-16	114.07
2022-05-17	112.31
2022-05-18	109.67
2022-05-19	112.21
2022-05-20	112.63

9492 rows × 1 columns

In [4]:
```
plt.plot(wti_oil_price)
plt.grid(axis="y")
plt.xlabel("Date")
plt.ylabel("Oil Price($/Barrel)")
plt.show()
```



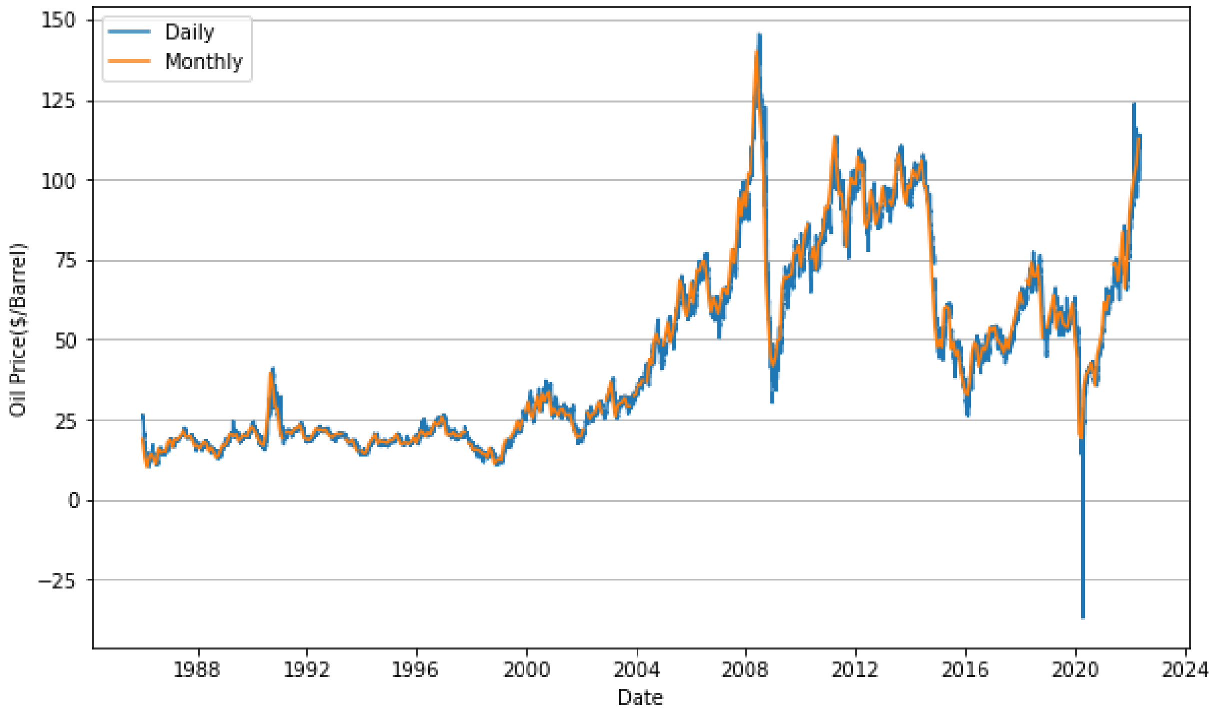
In [6]:
```
# Resampling: The data now is daily data, but data is not available every day. Al
```

In [7]:
```
monthly_data_list = []
year_list = wti_oil_price.index.year.unique()
month_list = sorted(wti_oil_price.index.month.unique())
for year in year_list:
    for month in month_list:
        last_day_data = wti_oil_price[(wti_oil_price.index.year == year) &
                                       (wti_oil_price.index.month == month)].tail(1)
        monthly_data_list.append(last_day_data)
wti_oil_price_monthly = pd.concat(monthly_data_list)
wti_oil_price_monthly.index = pd.to_datetime(
    wti_oil_price_monthly.index.strftime("%Y-%m"))  # reset index to YYYY-01-01
wti_oil_price_monthly.tail()
```

Out[7]:

	DCOILWTICO
DATE	
2022-01-01	89.16
2022-02-01	96.13
2022-03-01	100.53
2022-04-01	104.59
2022-05-01	112.63

In [9]:
```
plt.figure(figsize=(10,6))
plt.plot(wti_oil_price, label="Daily")
plt.plot(wti_oil_price_monthly ,label="Monthly")
plt.grid(axis="y")
plt.xlabel("Date")
plt.ylabel("Oil Price($/Barrel)")
plt.legend(loc="upper left")
plt.show()
```



Draw a graph to confirm that although the number of data has decreased significantly, the trend of the time-series data has not changed.

Moving Average Moving averages are also useful for capturing broad trends. Moving averages calculate the average of the n most recent data, rather than the average of all data. By moving the window in which the average is calculated, the time-series data can be smoothed out.

Moving averages can be calculated using the pandas rolling method.

Here we will calculate and plot the 50-day and 200-day moving averages.

In [11]:
```
# moving average
# moving average
wti_oil_price_moving_average_50 = wti_oil_price.rolling(50).mean()
wti_oil_price_moving_average_200 = wti_oil_price.rolling(200).mean()
```

In [13]:
```
wti_oil_price_moving_average_50
```

Out[13]:

	DCOILWTICO
DATE	
1986-01-02	NaN
1986-01-03	NaN
1986-01-06	NaN
1986-01-07	NaN
1986-01-08	NaN
...	...
2022-05-16	NaN
2022-05-17	NaN
2022-05-18	NaN
2022-05-19	NaN
2022-05-20	NaN

9492 rows × 1 columns

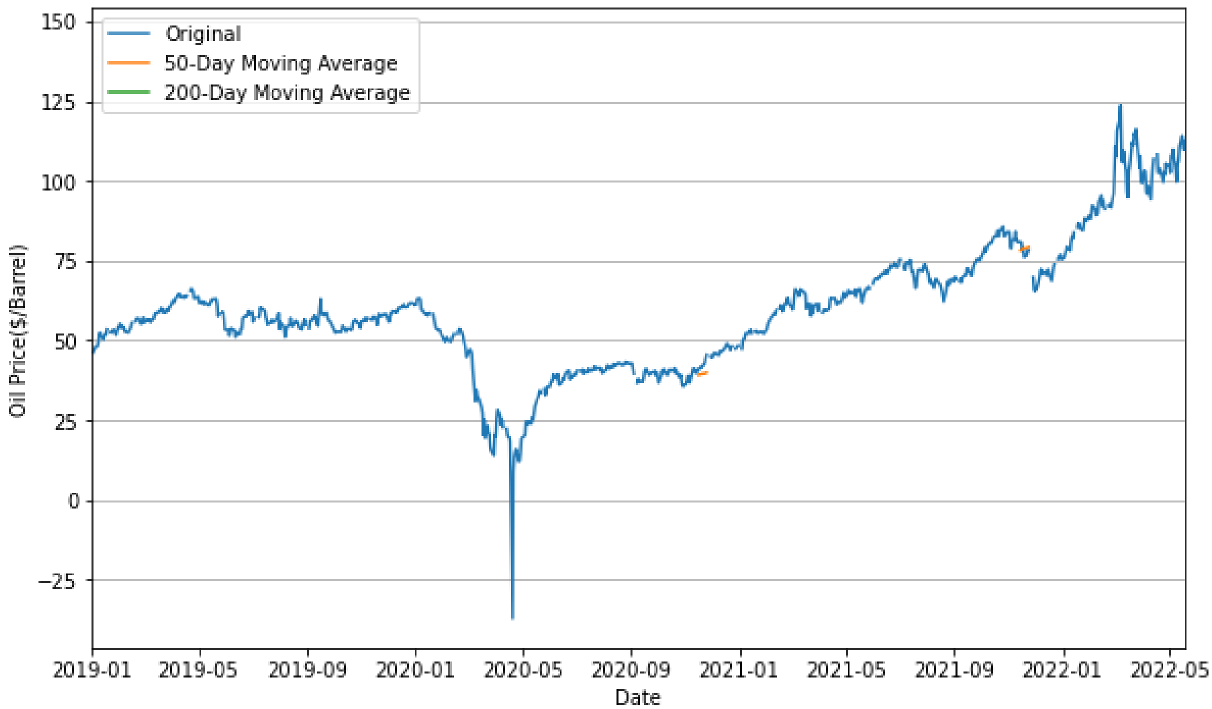
In [15]:
```
wti_oil_price_moving_average_200
```

Out[15]:

	DCOILWTICO
DATE	
1986-01-02	NaN
1986-01-03	NaN
1986-01-06	NaN
1986-01-07	NaN
1986-01-08	NaN
...	...
2022-05-16	NaN
2022-05-17	NaN
2022-05-18	NaN
2022-05-19	NaN
2022-05-20	NaN

9492 rows × 1 columns

In [16]:
```
plt.figure(figsize=(10,6))
plt.plot(wti_oil_price, label="Original")
plt.plot(wti_oil_price_moving_average_50, label="50-Day Moving Average")
plt.plot(wti_oil_price_moving_average_200, label="200-Day Moving Average")
plt.grid(axis="y")
plt.xlabel("Date")
plt.ylabel("Oil Price($/Barrel)")
plt.legend(loc="upper left")
plt.xlim((dt.datetime(2019, 1, 1), max(wti_oil_price.index)))
plt.show()
```



In [63]:
```
# Setting our API key
quandl.ApiConfig.api_key = "C6Qgn_A4j5h8viyhc1b8"

# Importing our data
data = quandl.get("FRED/DCOILBRENTEU", start_date="2000-01-01", end_date="2022-05
```

In [64]:
```
data_new = quandl.get("FRED/DCOILWTICO", start_date="2000-01-01", end_date="2022-
```

In [21]:
```
import sklearn
import matplotlib
import quandl
```

In [20]:
```
!pip install quandl
```

```
Collecting quandl

WARNING: Ignoring invalid distribution -tatsmodels (c:\users\hp\anaconda3\lib\s
ite-packages)
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ite-packages)


  Downloading Quandl-3.7.0-py2.py3-none-any.whl (26 kB)
Requirement already satisfied: numpy>=1.8 in c:\users\hp\anaconda3\lib\site-pac
kages (from quandl) (1.20.3)
Requirement already satisfied: python-dateutil in c:\users\hp\anaconda3\lib\sit
e-packages (from quandl) (2.8.2)
Requirement already satisfied: six in c:\users\hp\anaconda3\lib\site-packages
(from quandl) (1.16.0)
Requirement already satisfied: requests>=2.7.0 in c:\users\hp\anaconda3\lib\sit
e-packages (from quandl) (2.26.0)
Requirement already satisfied: pandas>=0.14 in c:\users\hp\anaconda3\lib\site-p
ackages (from quandl) (1.3.4)
Requirement already satisfied: more-itertools in c:\users\hp\anaconda3\lib\site
-packages (from quandl) (8.10.0)
Requirement already satisfied: inflection>=0.3.1 in c:\users\hp\anaconda3\lib\s
ite-packages (from quandl) (0.5.1)
Requirement already satisfied: pytz>=2017.3 in c:\users\hp\anaconda3\lib\site-p
ackages (from pandas>=0.14->quandl) (2021.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in c:\users\hp\anacond
a3\lib\site-packages (from requests>=2.7.0->quandl) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\hp\anaconda3\lib\site-p
ackages (from requests>=2.7.0->quandl) (3.2)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\hp\anaconda3\lib
\site-packages (from requests>=2.7.0->quandl) (2021.10.8)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\hp\anaconda3\l
ib\site-packages (from requests>=2.7.0->quandl) (1.26.7)
Installing collected packages: quandl
Successfully installed quandl-3.7.0
```

In [24]:

```
# A machine learning library used for linear regression
from sklearn.linear_model import LinearRegression
# numpy and pandas will be used for data manipulation
import numpy as np
import pandas as pd
# matplotlib will be used for visually representing our data
import matplotlib.pyplot as plt
# Quandl will be used for importing historical oil prices
import quandl
```

In [25]:

```
data
```

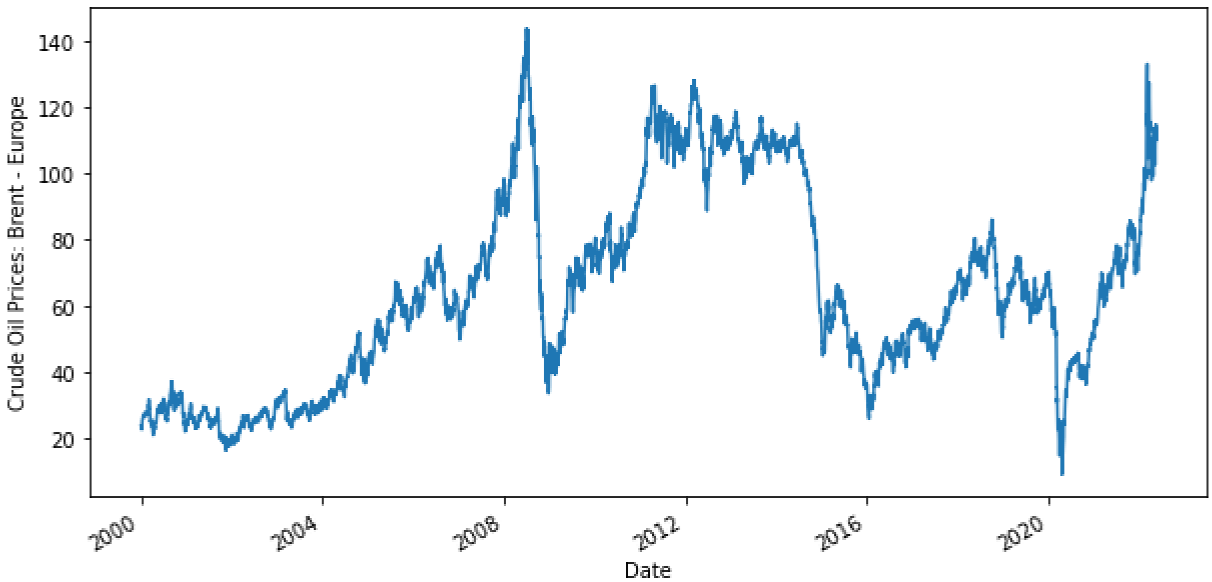
Out[25]:

	Value
Date	
2000-01-04	23.95
2000-01-05	23.72
2000-01-06	23.55
2000-01-07	23.35
2000-01-10	22.77
...	...
2022-05-16	114.86
2022-05-17	112.89
2022-05-18	110.04
2022-05-19	113.22
2022-05-20	113.63

5686 rows × 1 columns

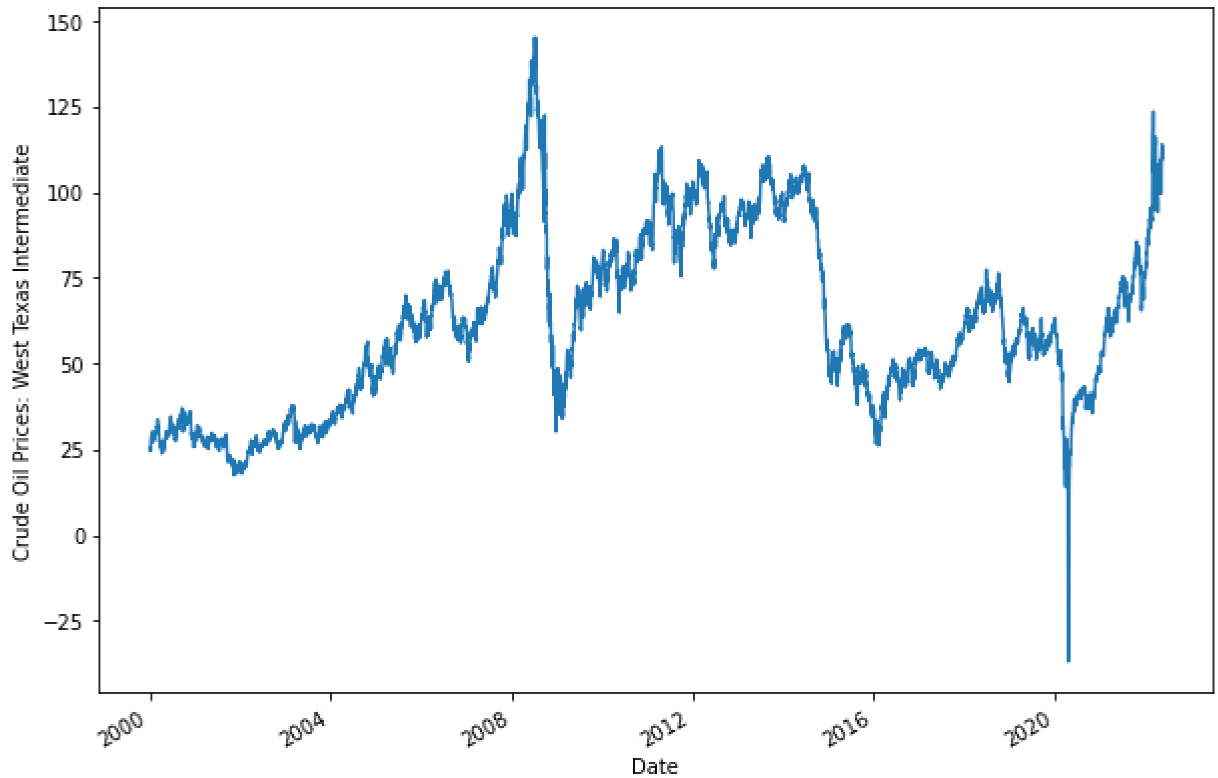
In [26]:
```python
# Setting the text on the Y-axis
plt.ylabel("Crude Oil Prices: Brent - Europe")

# Setting the size of our graph
data.Value.plot(figsize=(10,5))
```

Out[26]: <AxesSubplot:xlabel='Date', ylabel='Crude Oil Prices: Brent - Europe'>



In [66]:
```python
# Setting the text on the Y-axis
plt.ylabel("Crude Oil Prices: West Texas Intermediate")

# Setting the size of our graph
data_new.Value.plot(figsize=(10,7))
```

Out[66]: <AxesSubplot:xlabel='Date', ylabel='Crude Oil Prices: West Texas Intermediate'>



Now that we have properly visualized our data, we are going to define our explanatory variables — the features we are going to use to predict the price of oil. The variables we will be using at this stage, are the moving averages for the past three and nine days.

In [27]:
```python
data['MA3'] = data['Value'].shift(1).rolling(window=3).mean()
data['MA9']= data['Value'].shift(1).rolling(window=9).mean()
```

In [67]:
```python
data_new['MA3'] = data['Value'].shift(1).rolling(window=3).mean()
data_new['MA9']= data['Value'].shift(1).rolling(window=9).mean()
```

In [28]:
```python
# Dropping the NaN values
data = data.dropna()

# Initialising X and assigning the two feature variables
X = data[['MA3','MA9']]

# Getting the head of the data
X.head()
```

Out[28]:

Date	MA3	MA9
2000-01-17	25.006667	24.032222
2000-01-18	25.463333	24.258889
2000-01-19	25.933333	24.546667
2000-01-20	26.156667	24.837778
2000-01-21	26.246667	25.161111

In [68]:
```python
# Dropping the NaN values
data_new = data_new.dropna()

# Initialising X and assigning the two feature variables
X = data_new[['MA3','MA9']]

# Getting the head of the data
X.tail()
```

Out[68]:

Date	MA3	MA9
2022-05-16	109.293333	108.733333
2022-05-17	111.680000	109.835556
2022-05-18	113.290000	110.097778
2022-05-19	112.596667	109.867778
2022-05-20	112.050000	109.796667

In [29]:
```python
# Setting-up the dependent variable
y = data['Value']

# Getting the head of the data
y.head()
```

Out[29]:
```
Date
2000-01-17    25.99
2000-01-18    26.31
2000-01-19    26.17
2000-01-20    26.26
2000-01-21    27.18
Name: Value, dtype: float64
```

In [69]:
```
# Setting-up the dependent variable
y = data_new['Value']

# Getting the head of the data
y.head()
```

Out[69]:
```
Date
2000-01-18    28.98
2000-01-19    29.11
2000-01-20    29.67
2000-01-21    29.71
2000-01-24    29.25
Name: Value, dtype: float64
```

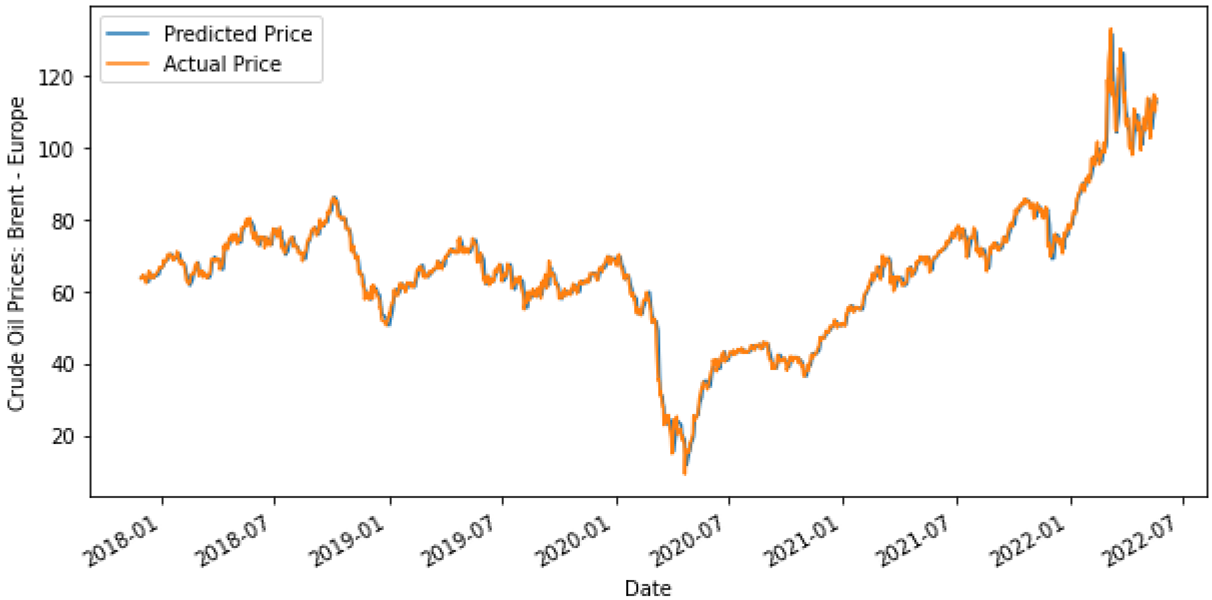
Training Now that everything is set-up, we are going to split our dataset into two distinct parts. We are going to assign 80% of our data into a training set, responsible for training the model. The rest 20% will be assigned to a testing set, used to estimate the accuracy of the model. This way, by connecting the input from the training set with the expected result from the testing set, we create a linear regression model.

In [70]:
```
# Setting the training set to 80% of the data
training = 0.8
t = int(training*len(data_new))

# Training dataset
X_train = X[:t]
y_train = y[:t]

# Testing dataset
X_test = X[t:]
y_test = y[t:]
```

In [31]:
```
# Generate the coefficient and constant for the regression
model = LinearRegression().fit(X_train,y_train)
```

In [71]:
```
# Generate the coefficient and constant for the regression
model = LinearRegression().fit(X_train,y_train)
```

In [32]:
```
predicted_price = model.predict(X_test)
predicted_price = pd.DataFrame(predicted_price,index=y_test.index,columns = ['pri
predicted_price.plot(figsize=(10,5))
y_test.plot()
plt.legend(['Predicted Price','Actual Price'])
plt.ylabel("Crude Oil Prices: Brent - Europe")
plt.show()
```



In [72]:
```
predicted_price = model.predict(X_test)
predicted_price = pd.DataFrame(predicted_price,index=y_test.index,columns = ['pri
predicted_price.plot(figsize=(10,5))
y_test.plot()
plt.legend(['Predicted Price','Actual Price'])
plt.ylabel("Crude Oil Prices: West Texas Intermediate (WTI)")
plt.show()
```

In [60]:
```
# Computing the accuracy of our model
R_squared_score = model.score(X[t:],y[t:])*100
accuracy = ("{0:.2f}".format(R_squared_score))
print ("The model has a " + accuracy + "% accuracy.")
```

```
The model has a 99.73% accuracy.
```

In [73]:
```
# Computing the accuracy of our model
R_squared_score = model.score(X[t:],y[t:])*100
accuracy = ("{0:.2f}".format(R_squared_score))
print ("The model has a " + accuracy + "% accuracy.")
```

```
The model has a 92.91% accuracy.
```

In [56]:
```
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
```

In [34]:
```
# A machine learning library used for linear regression
from sklearn.linear_model import LinearRegression
```

In [40]:
```
# A machine learning library used for linear regression
from sklearn.linear_model import LinearRegression
# numpy and pandas will be used for data manipulation
import numpy as np
import pandas as pd
# matplotlib will be used for visually representing our data
import matplotlib.pyplot as plt
```

In [41]:
```
# Importing our data
data = quandl.get("FRED/DCOILBRENTEU", start_date="1987-05-20", end_date="2020-01
data.head()
```

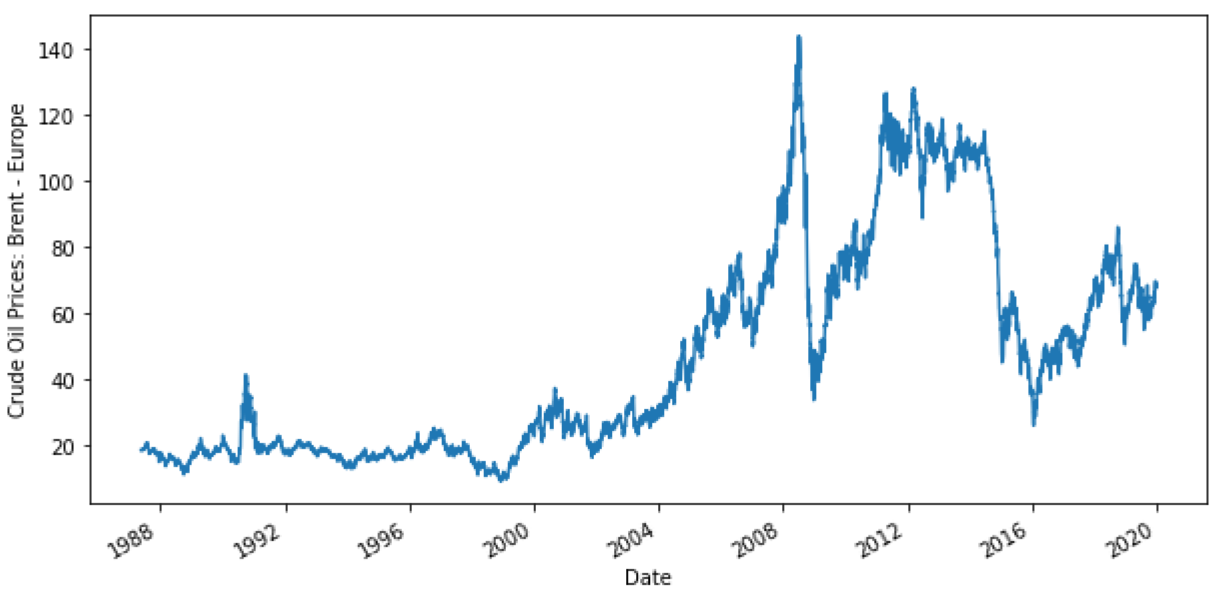
Out[41]:

	Value
Date	
1987-05-20	18.63
1987-05-21	18.45
1987-05-22	18.55
1987-05-25	18.60
1987-05-26	18.63

In [42]:
```python
# Setting the text on the Y-axis
plt.ylabel("Crude Oil Prices: Brent - Europe")

# Setting the size of our graph
data.Value.plot(figsize=(10,5))

data['MA3'] = data['Value'].shift(1).rolling(window=1).mean()
data['MA9']= data['Value'].shift(1).rolling(window=2).mean()

# Dropping the NaN values
data = data.dropna()

# Initialising X and assigning the two feature variables
X = data[['MA3','MA9']]

# Getting the head of the data
X.head()
```

Out[42]:

Date	MA3	MA9
1987-05-22	18.45	18.540
1987-05-25	18.55	18.500
1987-05-26	18.60	18.575
1987-05-27	18.63	18.615
1987-05-28	18.60	18.615

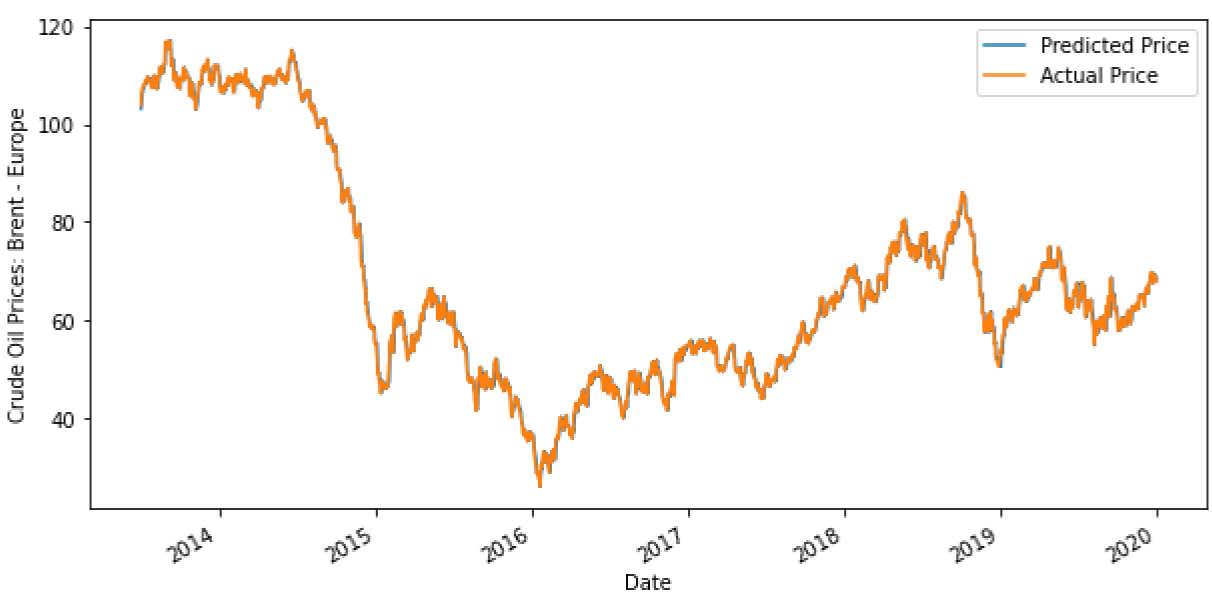


In [43]:
```
# Setting-up the dependent variable
y = data['Value']

# Getting the head of the data
y.head()
```

Out[43]:
```
Date
1987-05-22    18.55
1987-05-25    18.60
1987-05-26    18.63
1987-05-27    18.60
1987-05-28    18.60
Name: Value, dtype: float64
```

In [44]:
```
# Setting the training set to 80% of the data
training = 0.8
t = int(training*len(data))

# Training dataset
X_train = X[:t]
y_train = y[:t]

# Testing dataset
X_test = X[t:]
y_test = y[t:]

# Generate the coefficient and constant for the regression
model = LinearRegression().fit(X_train,y_train)
#linear = LinearRegression().fit(X_train,y_train)
```

In [45]:
```
predicted_price = model.predict(X_test)
predicted_price = pd.DataFrame(predicted_price,index=y_test.index,columns = ['pri
predicted_price.plot(figsize=(10,5))
y_test.plot()
plt.legend(['Predicted Price','Actual Price'])
plt.ylabel("Crude Oil Prices: Brent - Europe")
plt.show()
```



In [59]:
```
R_squared_score = model.score(X[t:],y[t:])*100
accuracy = ("{0:.2f}".format(R_squared_score))
print ("The model has a " + accuracy + "% accuracy.")
```

```
The model has a 99.73% accuracy.
```

In [50]:
```
import numpy
from sklearn.metrics import r2_score
```

In [55]:
```
# LinearRegression is a machine learning library for linear regression
from sklearn.linear_model import LinearRegression
# pandas and numpy are used for data manipulation
import pandas as pd
import numpy as np
```

In [ ]:
```
```