GROUP NUMBER: 6442

MScFE 652 RISK MANAGEMENT

Group Work Project # 1

Tasks

Step 1 & Step 2

The problem that the thesis attempts to solve is the problem of underlying factors driving crude oil prices. Apart from predicting prices, it is also necessary to understand how crude oil prices react to hypothetical scenarios like geopolitical tensions or sudden changes in supply. Therefore, the thesis attempts to solve this problem by performing stress tests and evaluating the robustness of the model under extreme conditions.

Bayesian networks are suitable for solving the problem of underlying factors driving crude oil prices because it can combine a lot of variables to find the dependencies between them and successfully extrapolate the data thanks to the learned knowledge. This method applies probabilistic reasoning and can be dynamically adapted towards an ever changing world. Bayesian networks models casual relationships between variables which allows for effective stress testing by simulating the impact of different hypothetical situations on crude oil prices.

The main advantage is that it lets us introduce prior knowledge that could be either expert-based or extracted from other models and put it into the decision process. As compared to traditional time-series models that might overlook the complex interactions like the underlying factors driving crude oil prices, bayesian networks provide more accurate and reliable forecasts.

Step 3 Student A

In [1]:
```
!pip install fredapi
!pip install hmms
```

```
Collecting fredapi
  Downloading fredapi-0.5.2-py3-none-any.whl (11 kB)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from
fredapi) (2.0.3)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dis
t-packages (from pandas->fredapi) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages
(from pandas->fredapi) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packag
es (from pandas->fredapi) (2024.1)
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-package
s (from pandas->fredapi) (1.25.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (fr
om python-dateutil>=2.8.2->pandas->fredapi) (1.16.0)
Installing collected packages: fredapi
Successfully installed fredapi-0.5.2
Collecting hmms
  Downloading hmms-0.2.3.tar.gz (524 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 524.8/524.8 kB 3.6 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: Cython in /usr/local/lib/python3.10/dist-packages (from
hmms) (3.0.10)
Requirement already satisfied: NumPy in /usr/local/lib/python3.10/dist-packages (from
hmms) (1.25.2)
Requirement already satisfied: ipython in /usr/local/lib/python3.10/dist-packages (fro
m hmms) (7.34.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages
(from hmms) (3.7.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from
hmms) (2.0.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from
hmms) (1.11.4)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.10/dist-pack
ages (from ipython->hmms) (67.7.2)
Collecting jedi>=0.16 (from ipython->hmms)
  Downloading jedi-0.19.1-py2.py3-none-any.whl (1.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.6/1.6 MB 24.7 MB/s eta 0:00:00
Requirement already satisfied: decorator in /usr/local/lib/python3.10/dist-packages (f
rom ipython->hmms) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.10/dist-packages
(from ipython->hmms) (0.7.5)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.10/dist-packag
es (from ipython->hmms) (5.7.1)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in /usr/lo
cal/lib/python3.10/dist-packages (from ipython->hmms) (3.0.47)
Requirement already satisfied: pygments in /usr/local/lib/python3.10/dist-packages (fr
om ipython->hmms) (2.16.1)
Requirement already satisfied: backcall in /usr/local/lib/python3.10/dist-packages (fr
om ipython->hmms) (0.2.0)
Requirement already satisfied: matplotlib-inline in /usr/local/lib/python3.10/dist-pac
kages (from ipython->hmms) (0.1.7)
Requirement already satisfied: pexpect>4.3 in /usr/local/lib/python3.10/dist-packages
(from ipython->hmms) (4.9.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-pack
ages (from matplotlib->hmms) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages
```

```
(from matplotlib->hmms) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-pac
kages (from matplotlib->hmms) (4.53.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-pac
kages (from matplotlib->hmms) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packa
ges (from matplotlib->hmms) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-package
s (from matplotlib->hmms) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-pack
ages (from matplotlib->hmms) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->hmms) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages
(from pandas->hmms) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packag
es (from pandas->hmms) (2024.1)
Requirement already satisfied: parso<0.9.0,>=0.8.3 in /usr/local/lib/python3.10/dist-p
ackages (from jedi>=0.16->ipython->hmms) (0.8.4)
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.10/dist-packa
ges (from pexpect>4.3->ipython->hmms) (0.7.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.10/dist-packages (fro
m prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0->ipython->hmms) (0.2.13)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (fr
om python-dateutil>=2.7->matplotlib->hmms) (1.16.0)
Building wheels for collected packages: hmms
  Building wheel for hmms (setup.py) ... done
  Created wheel for hmms: filename=hmms-0.2.3-cp310-cp310-linux_x86_64.whl size=215261
6 sha256=06160f72bea8bab201c598c6c29a64cb06b43c03cb3fe901a7d71824cc25306b
  Stored in directory: /root/.cache/pip/wheels/aa/6f/a4/1dbae244341f24881dce9465aa5337
29d2ae870cff3866070f
Successfully built hmms
Installing collected packages: jedi, hmms
Successfully installed hmms-0.2.3 jedi-0.19.1
```

In [2]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import statsmodels.api as sm
from scipy import stats
from statsmodels.tsa.stattools import kpss, adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.stats.diagnostic import acorr_ljungbox
```

In [3]:

```python
from fredapi import Fred
# FRED API key
fred_key = "f9c22fca078ece81a7a2ac6fba29b8a9";
# Initiates a session with the FRED datacenter to recieve datasets
fred = Fred(api_key=fred_key);
# Retrieve data from FRED API
fred_data = pd.DataFrame(fred.get_series('WTISPLC'), columns=['WTISPLC'])
```

EDA

In [4]:
```
datasets_fred = [
'WTISPLC',    # Spot Crude Oil Price: West Texas Intermediate (WTI) (WTISPLC)
'CPIENGSL', # Consumer Price Index for All Urban Consumers: Energy in U.S. City Avera
'CAPG211S', # Industrial Capacity: Mining: Oil and Gas Extraction (NAICS = 211)
'CAPUTLG211S', #  Capacity Utilization: Mining: Oil and Gas Extraction (NAICS = 211)
'IPG211S', # Industrial Production Index: Mining: Oil and Gas Extraction (NAICS = 211
'INDPRO', #  Industrial Production: Total Index
'IPN213111N', # Industrial Production: Mining: Drilling Oil and Gas Wells
'PCU211211', # Producer Price Index: Mining: Oil and Gas Extraction (NAICS = 211)
                ];

data_frames = []; # List of dataframes to be concatenated

# Adding FRED datasets
for series_id in datasets_fred:
  # Get series from FRED
  df = pd.DataFrame(fred.get_series(series_id), columns=[series_id]);
  data_frames.append(df);

data_merge = pd.concat(data_frames, axis=1)
#data_merge = data_merge[data_merge.index > '2000-01-01']
data_merge.head()
```

Out[4]:

	WTISPLC	CPIENGSL	CAPG211S	CAPUTLG211S	IPG211S	INDPRO	IPN213111N	PC
1919-01-01	NaN	NaN	NaN	NaN	NaN	4.8654	NaN	
1919-02-01	NaN	NaN	NaN	NaN	NaN	4.6504	NaN	
1919-03-01	NaN	NaN	NaN	NaN	NaN	4.5160	NaN	
1919-04-01	NaN	NaN	NaN	NaN	NaN	4.5966	NaN	
1919-05-01	NaN	NaN	NaN	NaN	NaN	4.6235	NaN	

In [5]:
```
data_merge.isnull().sum()
```

Out[5]:
```
WTISPLC        324
CPIENGSL       456
CAPG211S       637
CAPUTLG211S    637
IPG211S        637
INDPRO           1
IPN213111N     637
PCU211211      804
dtype: int64
```

In [6]:
```
data_merge.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	m
WTISPLC	942.0	27.816605	29.284847	1.1700	3.0000	18.3125	39.34000	133.93
CPIENGSL	810.0	114.829889	80.335992	21.3000	31.7500	101.5000	192.18225	331.73
CAPG211S	629.0	81.421457	21.937600	61.4822	66.6233	76.3514	81.75120	149.28
CAPUTLG211S	629.0	93.202929	3.239208	78.6360	91.5201	93.1402	94.95650	101.54
IPG211S	629.0	76.173594	22.164265	48.8141	62.4444	68.5466	78.22200	144.42
INDPRO	1265.0	45.891390	34.813005	3.6827	13.7629	39.1057	84.15640	104.10
IPN213111N	629.0	130.404341	53.132521	47.9947	94.0882	113.9683	156.98800	334.62
PCU211211	462.0	154.771381	83.664228	54.6000	77.3750	138.1500	221.97500	490.40

Step 3 Student C

Identified that the financial data on securities and markets that affect the price of oil are:

1. Canadian dollar to US dollar exchange rate
2. CBOE crude oil futures
3. WTI crude oil futures
4. Brent crude oil futures
5. S&P500

Importing, structuring and graphing the financial data on securities and markets that affect the price of oil.

In [7]:
```
from fredapi import Fred
# FRED API key
fred_key = "f9c22fca078ece81a7a2ac6fba29b8a9";
# Initiates a session with the FRED datacenter to recieve datasets
fred = Fred(api_key=fred_key);
# Retrieve data from FRED API
fred_data = pd.DataFrame(fred.get_series('DEXCAUS'), columns=['DEXCAUS'])
```

In [8]:
```
financial_datasets_fred = [
'DEXCAUS', #Canadian dollar to US dollar exchange rate
'VIXCLS', #CBOE Volatility Index
'DCOILWTICO', #WTI Crude oil futures
'DCOILBRENTEU', #Brent crude oil futures
'SP500', #S&P500 Index
];

finan_data_frames = []; # List of dataframes to be concatenated

# Adding FRED datasets
for series_id in financial_datasets_fred:
  # Get series from FRED
  df = pd.DataFrame(fred.get_series(series_id), columns=[series_id]);
  finan_data_frames.append(df);

fin_data = pd.concat(finan_data_frames, axis=1)
#fin_data = data_merge[fin_data.index > '2000-01-01']
fin_data.head()
```

Out[8]:

	DEXCAUS	VIXCLS	DCOILWTICO	DCOILBRENTEU	SP500
1971-01-04	1.0109	NaN	NaN	NaN	NaN
1971-01-05	1.0102	NaN	NaN	NaN	NaN
1971-01-06	1.0106	NaN	NaN	NaN	NaN
1971-01-07	1.0148	NaN	NaN	NaN	NaN
1971-01-08	1.0154	NaN	NaN	NaN	NaN

In [9]:
```
fin_data.isnull().sum()
```

Out[9]:
```
DEXCAUS           539
VIXCLS           5253
DCOILWTICO       4264
DCOILBRENTEU     4541
SP500           11448
dtype: int64
```

In [51]:
```
fin_data.describe().T
```

Out[51]:

	count	mean	std	min	25%	50%	7!
DEXCAUS	13425.0	1.229735	0.160415	0.9168	1.1035	1.2353	1.34
VIXCLS	8711.0	19.491915	7.879984	9.1400	13.7950	17.6300	22.87
DCOILWTICO	9700.0	47.291728	29.700010	-36.9800	20.1500	39.2800	70.94
DCOILBRENTEU	9423.0	49.936190	32.927056	9.1000	19.2800	42.7200	74.23
SP500	2516.0	3177.629996	979.254402	1829.0800	2268.9750	2890.6550	4090.42

Step 4

Dictionary of Macroeconomic data

In [11]:

```
start_date = data_merge.index.min()
end_date = data_merge.index.max()


macro_data_info = {
    'WTISPLC': {
        'description': 'Oil Price',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'CPIENGSL': {
        'description': 'Consumer Price Index for All Urban Consumers: Energy in U.S.
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'CAPG211S': {
        'description': 'Industrial Capacity: Mining: Oil and Gas Extraction',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'CAPUTLG211S': {
        'description': 'Capacity Utilization: Mining: Oil and Gas Extraction',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'IPG211S': {
        'description': 'Industrial Production Index: Mining: Oil and Gas Extraction',
        'frequency': 'Monthly',
```

```
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'INDPRO': {
        'description': 'Industrial Production: Total Index',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'IPN213111N': {
        'description': 'Industrial Production: Mining: Drilling Oil and Gas Wells',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'PCU211211': {
        'description': 'Producer Price Index: Mining: Oil and Gas Extraction',
        'frequency': 'Monthly',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    }
}

macro_data_info_list = [
    ['WTISPLC', 'Spot Crude Oil Price: West Texas Intermediate (WTI)', 'Monthly', 'FF
    ['CPIENGSL', 'Consumer Price Index for All Urban Consumers: Energy in U.S. City A
    ['CAPG211S', 'Industrial Capacity: Mining: Oil and Gas Extraction', 'Monthly', 'F
    ['CAPUTLG211S', 'Capacity Utilization: Mining: Oil and Gas Extraction', 'Monthly'
    ['IPG211S', 'Industrial Production Index: Mining: Oil and Gas Extraction', 'Month
    ['INDPRO', 'Industrial Production: Total Index', 'Monthly', 'FRED', start_date, e
    ['IPN213111N', 'Industrial Production: Total Index', 'Monthly', 'FRED', start_dat
    ['PCU211211', 'Producer Price Index: Mining: Oil and Gas Extraction', 'Monthly', 
]

macro_data_info = pd.DataFrame(macro_data_info_list, columns=['Ticker',
                                                              'Description',
                                                              'Frequency',
                                                              'Source',
                                                              'Start Date',
                                                              'End Date'])


macro_data_info
```

Out[11]:

	Ticker	Description	Frequency	Source	Start Date	End Date
0	WTISPLC	Spot Crude Oil Price: West Texas Intermediate ...	Monthly	FRED	1919-01-01	2024-06-01
1	CPIENGSL	Consumer Price Index for All Urban Consumers: ...	Monthly	FRED	1919-01-01	2024-06-01
2	CAPG211S	Industrial Capacity: Mining: Oil and Gas Extra...	Monthly	FRED	1919-01-01	2024-06-01
3	CAPUTLG211S	Capacity Utilization: Mining: Oil and Gas Extr...	Monthly	FRED	1919-01-01	2024-06-01
4	IPG211S	Industrial Production Index: Mining: Oil and G...	Monthly	FRED	1919-01-01	2024-06-01
5	INDPRO	Industrial Production: Total Index	Monthly	FRED	1919-01-01	2024-06-01
6	IPN213111N	Industrial Production: Total Index	Monthly	FRED	1919-01-01	2024-06-01
7	PCU211211	Producer Price Index: Mining: Oil and Gas Extr...	Monthly	FRED	1919-01-01	2024-06-01

Dictionary of the financial data:

In [12]:
```
start_date = fin_data.index.min()
end_date = fin_data.index.max()

print("Start Date:", start_date)
print("End Date:", end_date)
```

```
Start Date: 1971-01-04 00:00:00
End Date: 2024-07-11 00:00:00
```

In [13]:
```
data_info = {
    'DEXCAUS': {
        'description': 'Canadian dollar to US dollar exchange rate',
        'frequency': 'Daily',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'VIXCLS': {
        'description': 'CBOE Volatility Index',
        'frequency': 'Daily',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'DCOILWTICO': {
        'description': 'WTI Crude oil futures',
        'frequency': 'Daily',
```

```
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'DCOILBRENTEU': {
        'description': 'Brent crude oil futures',
        'frequency': 'Daily',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'SP500-45': {
        'description': 'S&P 500 Energy sector index',
        'frequency': 'Daily',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    },
    'SP500': {
        'description': 'S&P500 Index',
        'frequency': 'Daily',
        'source': 'FRED',
        'start_date': start_date,
        'end_date': end_date
    }
}

# Print the dictionary
for key, value in data_info.items():
    print(f"{key}: {value}")
```

```
DEXCAUS: {'description': 'Canadian dollar to US dollar exchange rate', 'frequency': 'D
aily', 'source': 'FRED', 'start_date': Timestamp('1971-01-04 00:00:00'), 'end_date': T
imestamp('2024-07-11 00:00:00')}
VIXCLS: {'description': 'CBOE Volatility Index', 'frequency': 'Daily', 'source': 'FRE
D', 'start_date': Timestamp('1971-01-04 00:00:00'), 'end_date': Timestamp('2024-07-11
00:00:00')}
DCOILWTICO: {'description': 'WTI Crude oil futures', 'frequency': 'Daily', 'source':
'FRED', 'start_date': Timestamp('1971-01-04 00:00:00'), 'end_date': Timestamp('2024-07
-11 00:00:00')}
DCOILBRENTEU: {'description': 'Brent crude oil futures', 'frequency': 'Daily', 'sourc
e': 'FRED', 'start_date': Timestamp('1971-01-04 00:00:00'), 'end_date': Timestamp('202
4-07-11 00:00:00')}
SP500-45: {'description': 'S&P 500 Energy sector index', 'frequency': 'Daily', 'sourc
e': 'FRED', 'start_date': Timestamp('1971-01-04 00:00:00'), 'end_date': Timestamp('202
4-07-11 00:00:00')}
SP500: {'description': 'S&P500 Index', 'frequency': 'Daily', 'source': 'FRED', 'start_
date': Timestamp('1971-01-04 00:00:00'), 'end_date': Timestamp('2024-07-11 00:00:00')}
```

Table showing the financial data

In [14]:

```
data_info_list = [
    ['DEXCAUS', 'Canadian dollar to US dollar exchange rate', 'Daily', 'FRED', start_
    ['VIXCLS', 'CBOE Volatility Index', 'Daily', 'FRED', start_date, end_date],
    ['DCOILWTICO', 'WTI Crude oil futures', 'Daily', 'FRED', start_date, end_date],
    ['DCOILBRENTEU', 'Brent crude oil futures', 'Daily', 'FRED', start_date, end_date
```

```
    ['SP500-45', 'S&P 500 Energy sector index', 'Daily', 'FRED', start_date, end_date
    ['SP500', 'S&P500 Index', 'Daily', 'FRED', start_date, end_date]
]

data_info_df = pd.DataFrame(data_info_list, columns=['Ticker', 'Description', 'Freque


data_info_df
```

Out[14]:

	Ticker	Description	Frequency	Source	Start Date	End Date
0	DEXCAUS	Canadian dollar to US dollar exchange rate	Daily	FRED	1971-01-04	2024-07-11
1	VIXCLS	CBOE Volatility Index	Daily	FRED	1971-01-04	2024-07-11
2	DCOILWTICO	WTI Crude oil futures	Daily	FRED	1971-01-04	2024-07-11
3	DCOILBRENTEU	Brent crude oil futures	Daily	FRED	1971-01-04	2024-07-11
4	SP500-45	S&P 500 Energy sector index	Daily	FRED	1971-01-04	2024-07-11
5	SP500	S&P500 Index	Daily	FRED	1971-01-04	2024-07-11

Step 5

Removing Outliers

Macroeconomic Data

In [15]:

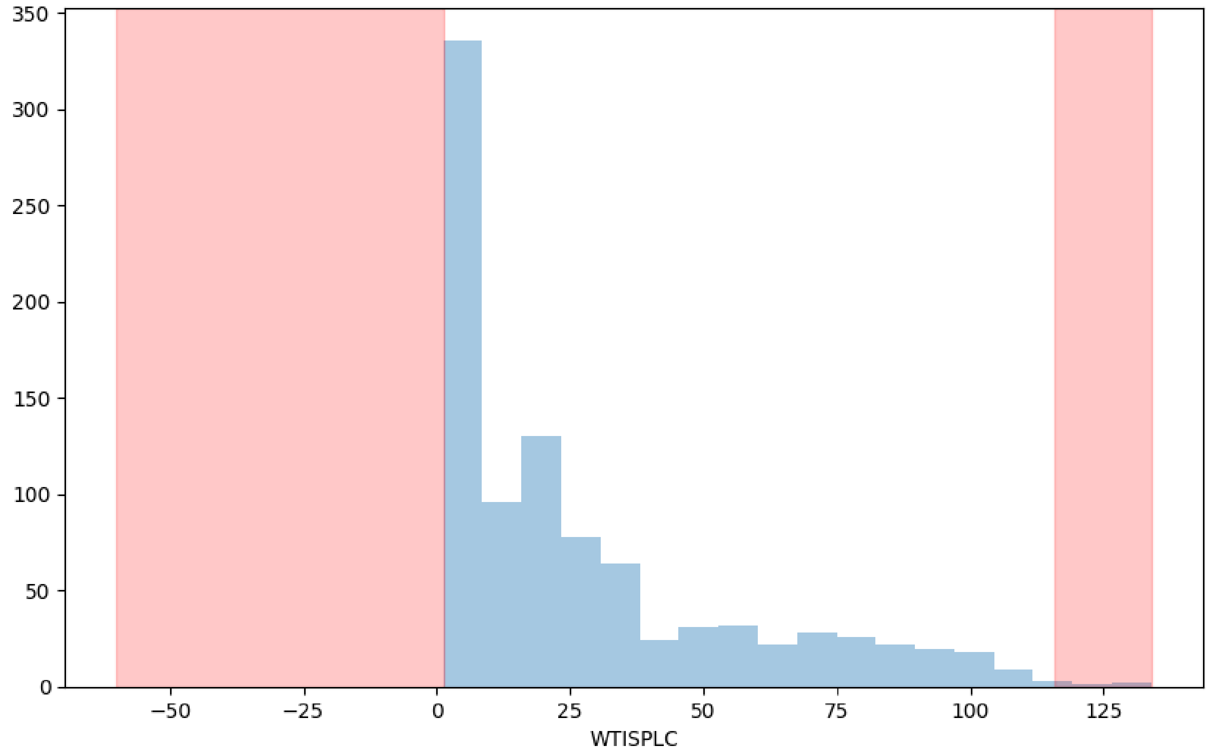
```
def out_std(df, column):
    global lower,upper
    # calculate the mean and standard deviation of the data frame
    data_mean, data_std = df[column].mean(), df[column].std()
    # calculate the cutoff value
    cut_off = data_std * 3
    # calculate the lower and upper bound value
    lower, upper = data_mean - cut_off, data_mean + cut_off
    print('The lower bound value is', lower)
    print('The upper bound value is', upper)
    # Calculate the number of records below and above lower and above bound value res
    df1 = df[df[column] > upper]
    df2 = df[df[column] < lower]
    return print('Total number of outliers are', df1.shape[0]+ df2.shape[0])
```

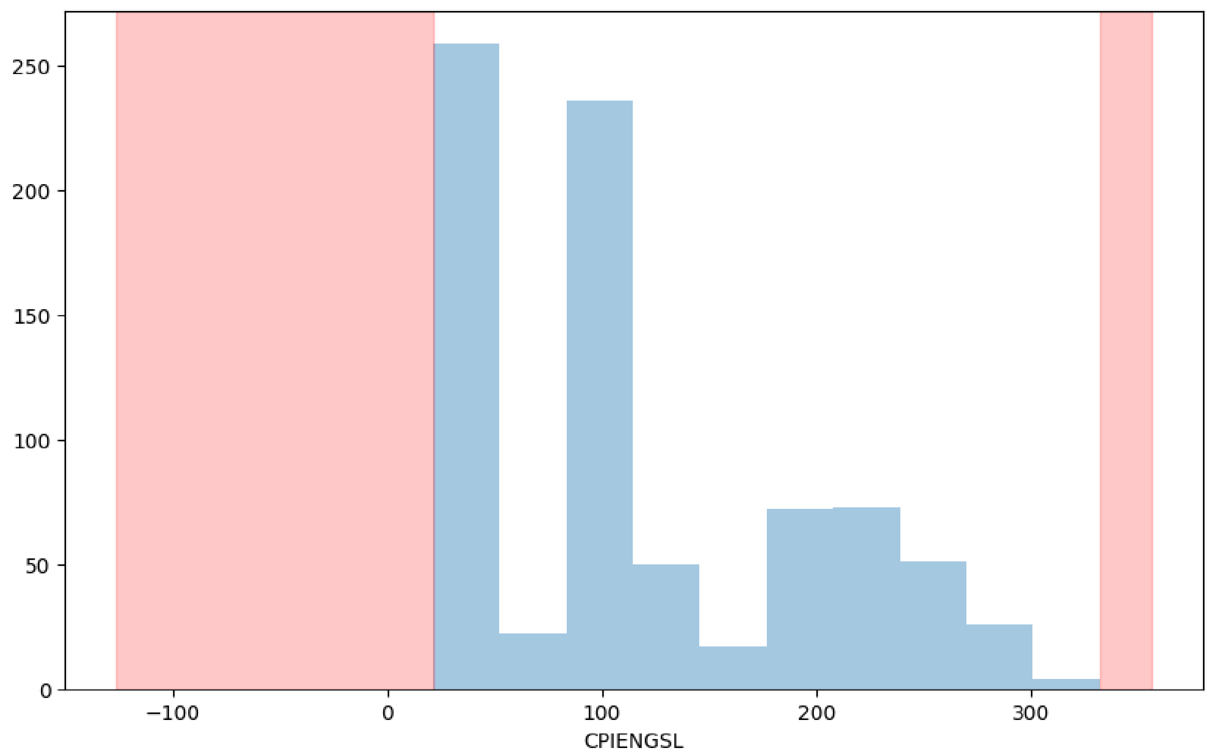
```python
for col in data_merge.columns:
    out_std(data_merge, col)

    plt.figure(figsize = (10,6))
    sns.distplot(data_merge[col], kde=False)
    plt.axvspan(xmin = lower,xmax= data_merge[col].min(),alpha=0.2, color='red')
    plt.axvspan(xmin = upper,xmax= data_merge[col].max(),alpha=0.2, color='red')
```

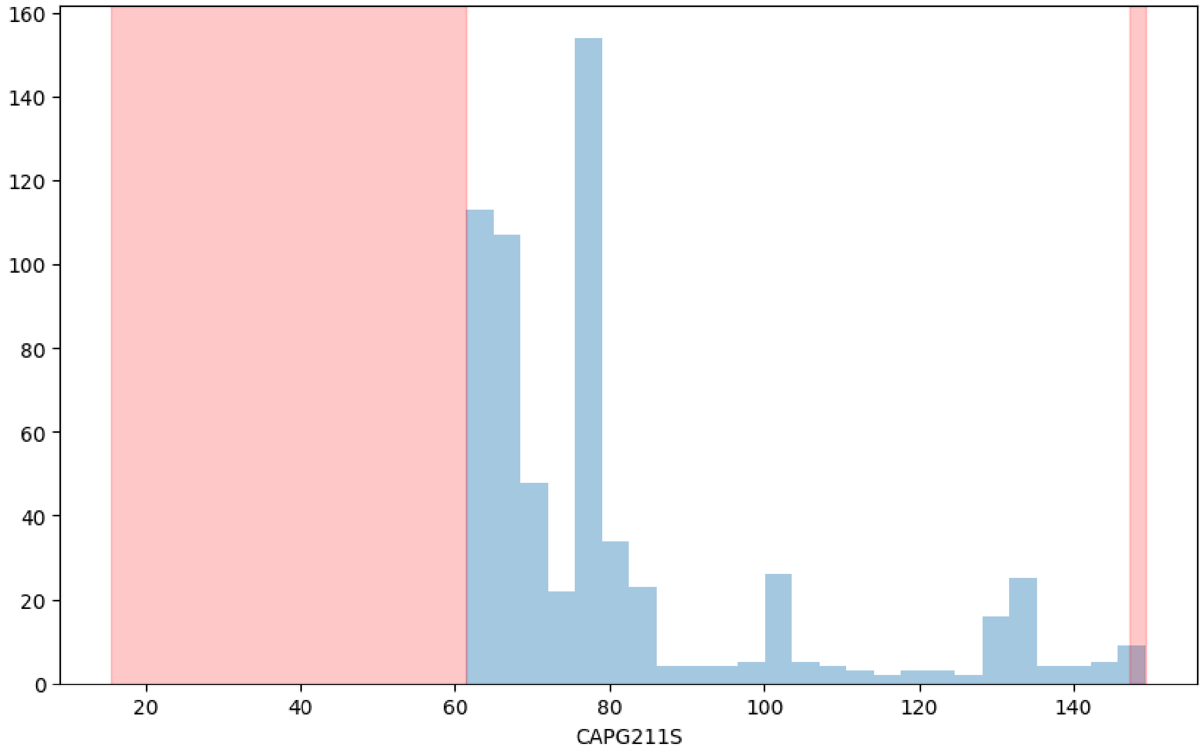
```
The lower bound value is -60.037936242848204
The upper bound value is 115.67114643393101
Total number of outliers are 4
The lower bound value is -126.1780877872839
The upper bound value is 355.83786556506163
Total number of outliers are 0
The lower bound value is 15.608656858545089
The upper bound value is 147.23425697293345
Total number of outliers are 6
```

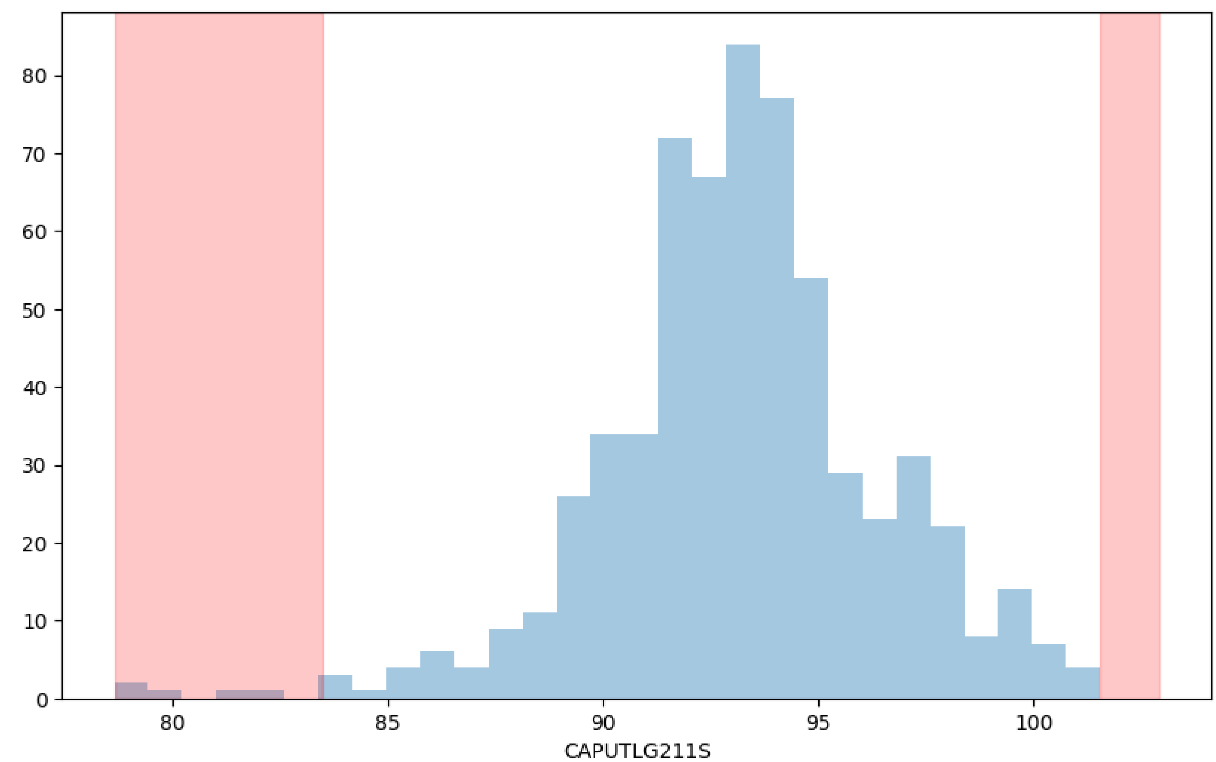
```
<ipython-input-15-238fc34c1aa0>:20: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data_merge[col], kde=False)
```

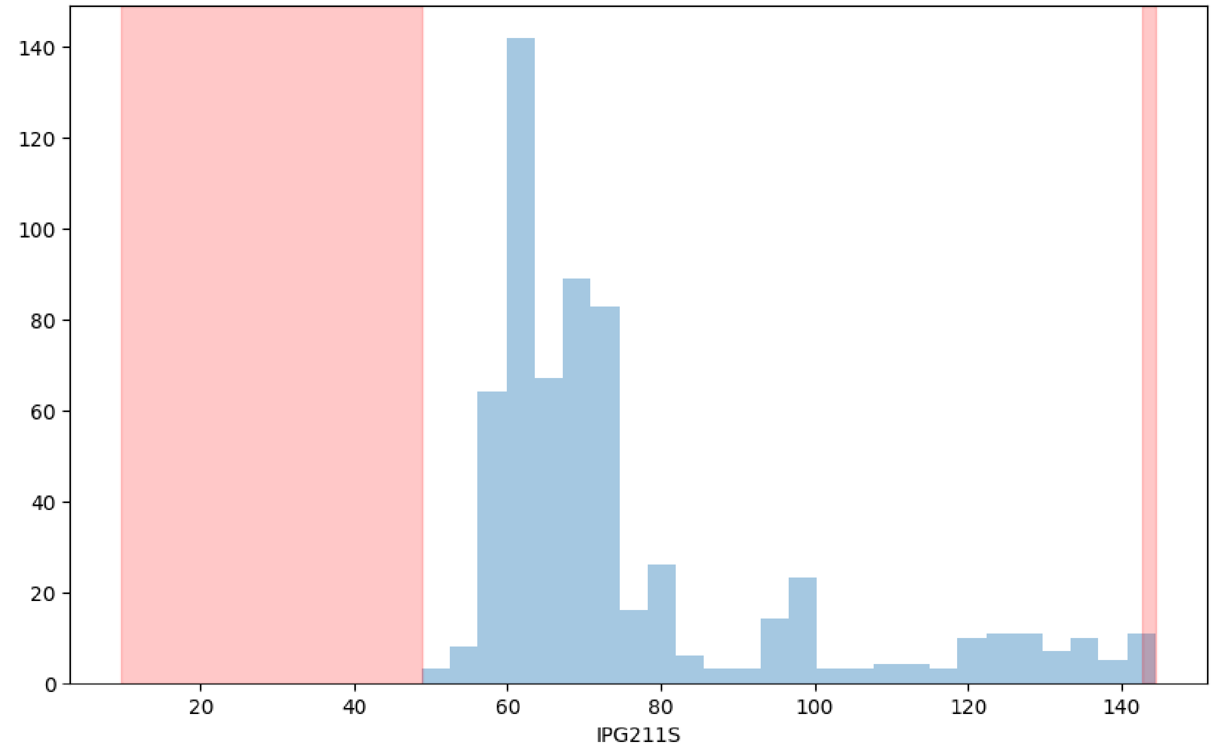
```
The lower bound value is 83.48530555873768
The upper bound value is 102.92055199293165
Total number of outliers are 5
The lower bound value is 9.680800381005028
The upper bound value is 142.6663878542891
Total number of outliers are 9
The lower bound value is -58.54762458917536
The upper bound value is 150.33040419391844
Total number of outliers are 0
The lower bound value is -28.99322264970334
The upper bound value is 289.8019050026445
Total number of outliers are 12
The lower bound value is -96.22130158117326
The upper bound value is 405.76406348593514
Total number of outliers are 3
```


350
300
250
200
150
100
50
0
−50
−25
0
25
50
75
100
125
WTISPLC

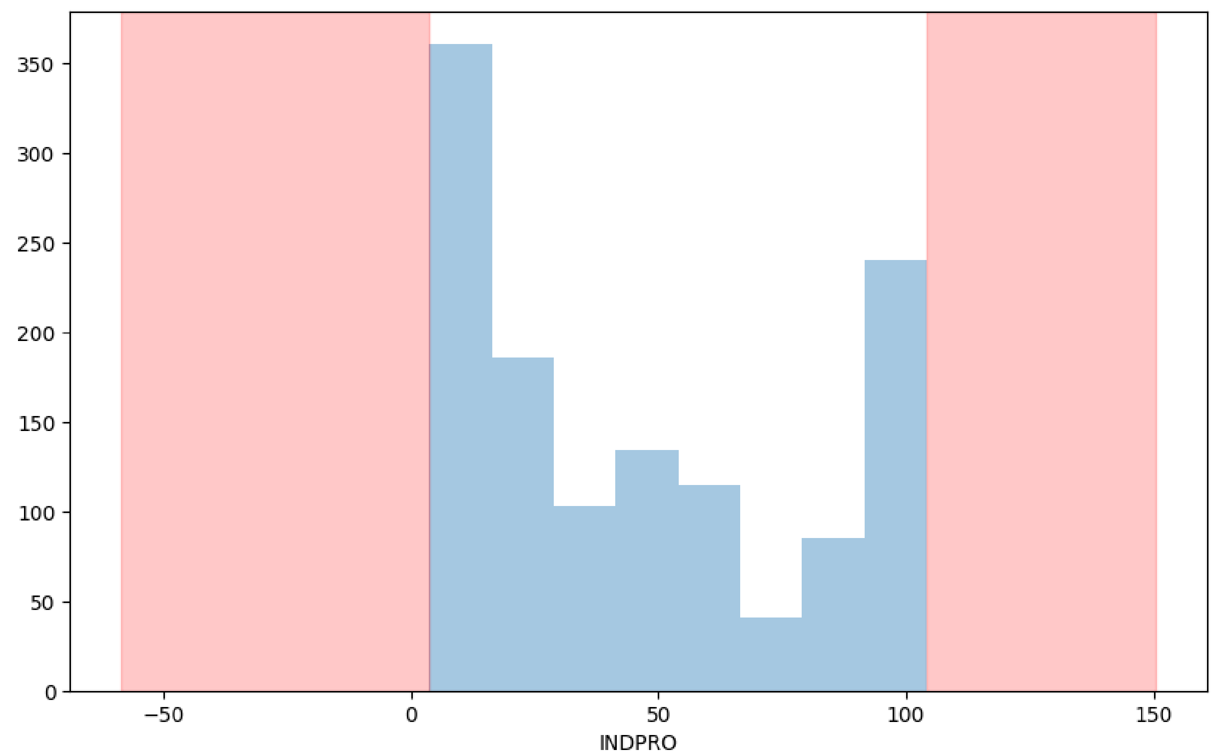

250
200
150
100
50
0
−100
0
100
200
300
CPIENGSL


160
140
120
100
80
60
40
20
0
20
40
60
80
100
120
140
CAPG211S

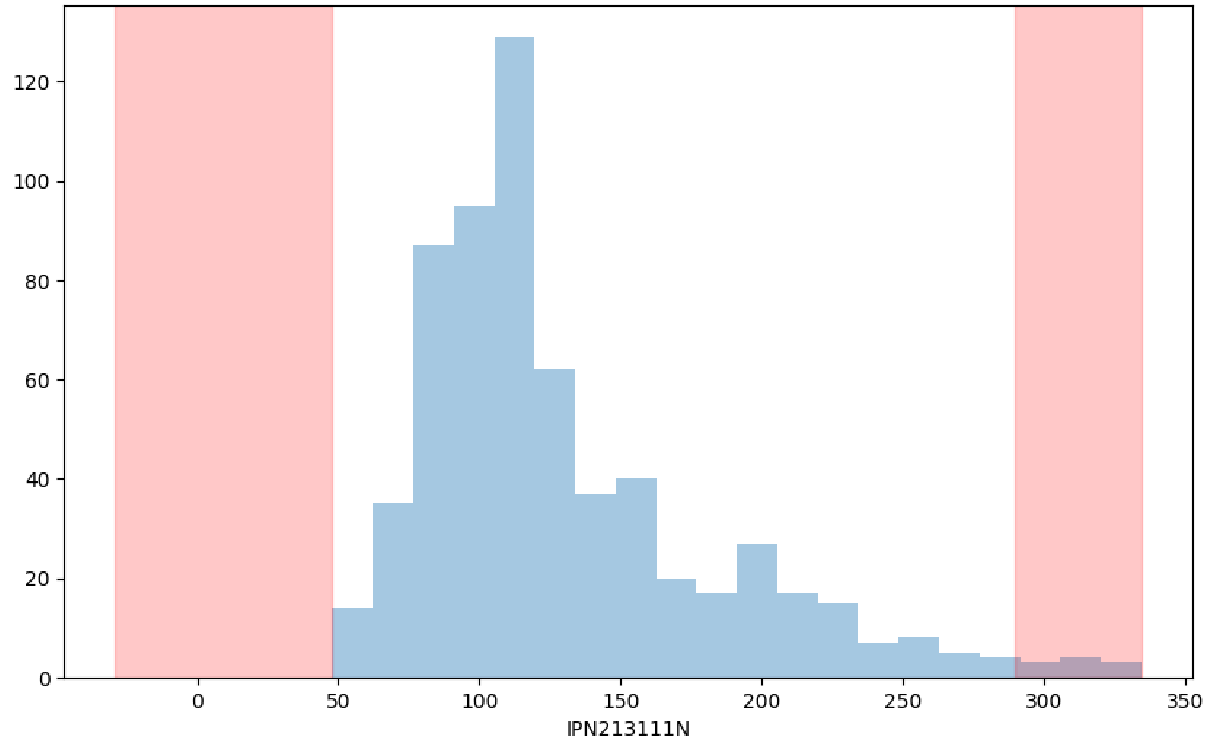

80
70
60
50
40
30
20
10
0
80
85
90
95
100
CAPUTLG211S

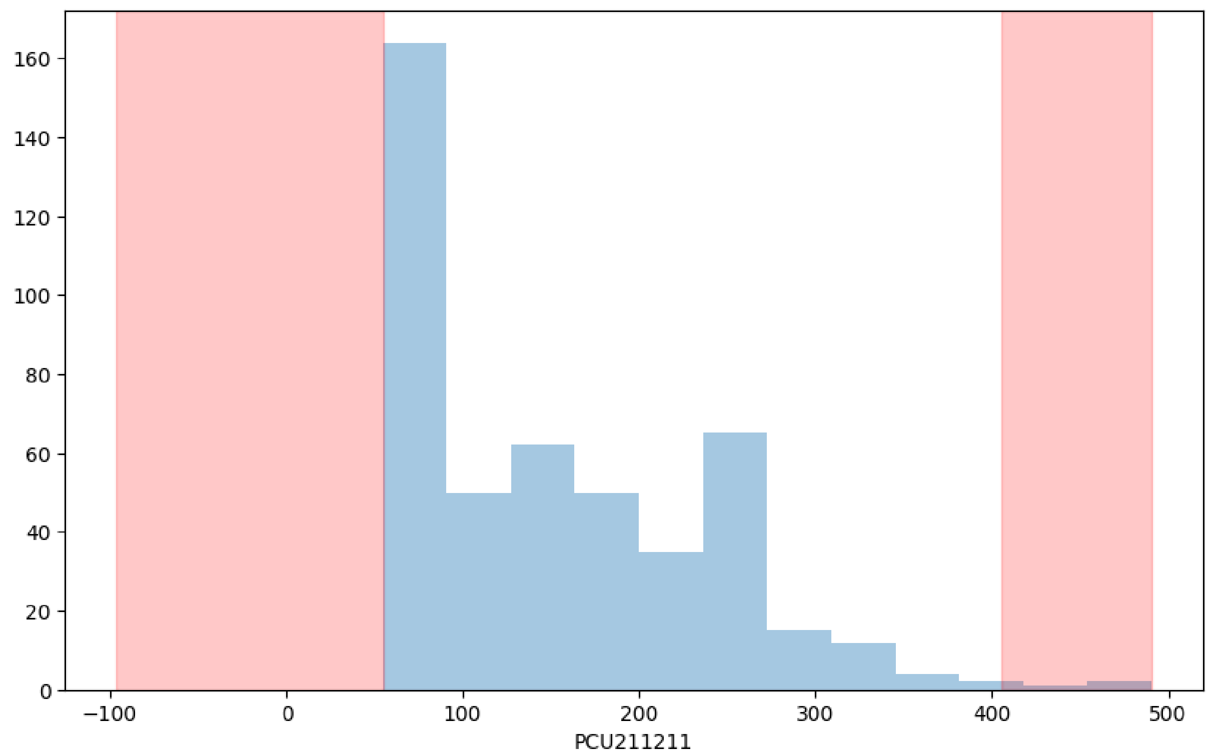


0
20
40
60
80
100
120
140
20
40
60
80
100
120
140
IPG211S



0
50
100
150
200
250
300
350
−50
0
50
100
150
INDPRO





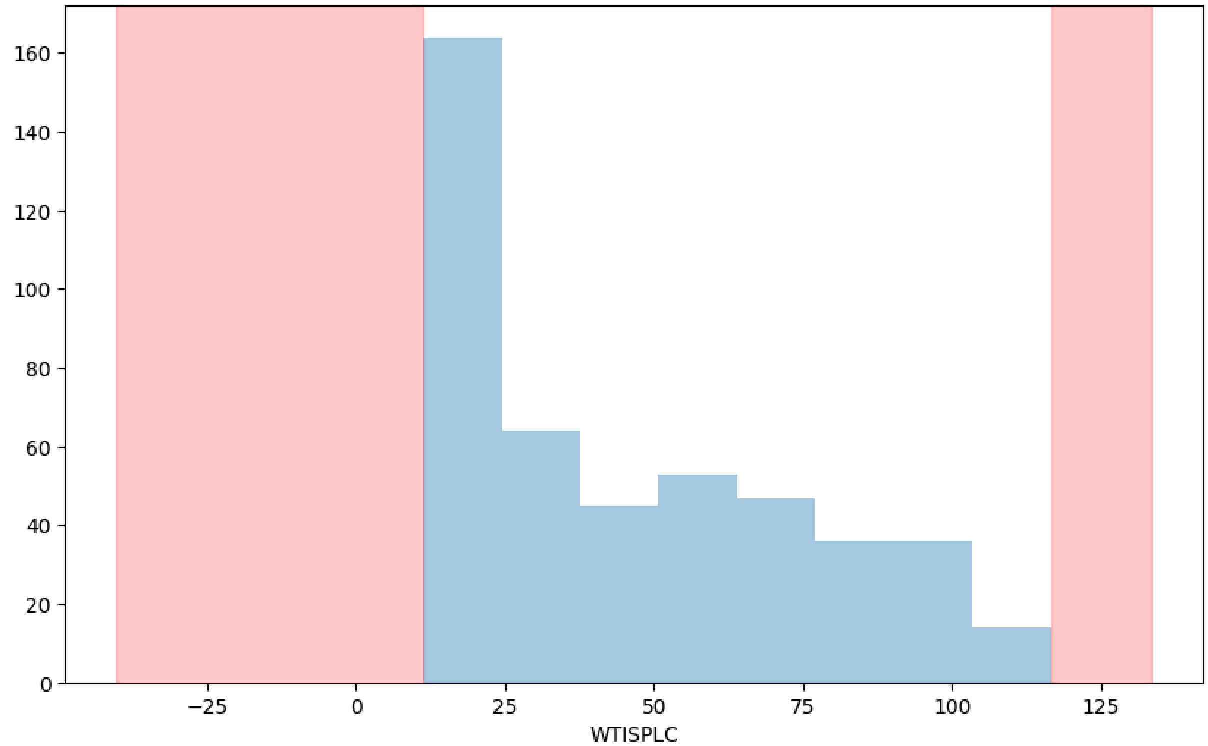
In [16]:
```
df_new = pd.DataFrame()

for col in data_merge.columns:
    #Data Frame without outliers
    df_new = data_merge[(data_merge[col] > lower)  & (data_merge[col] < upper) ]

for col in df_new.columns:
    out_std(df_new, col)
```

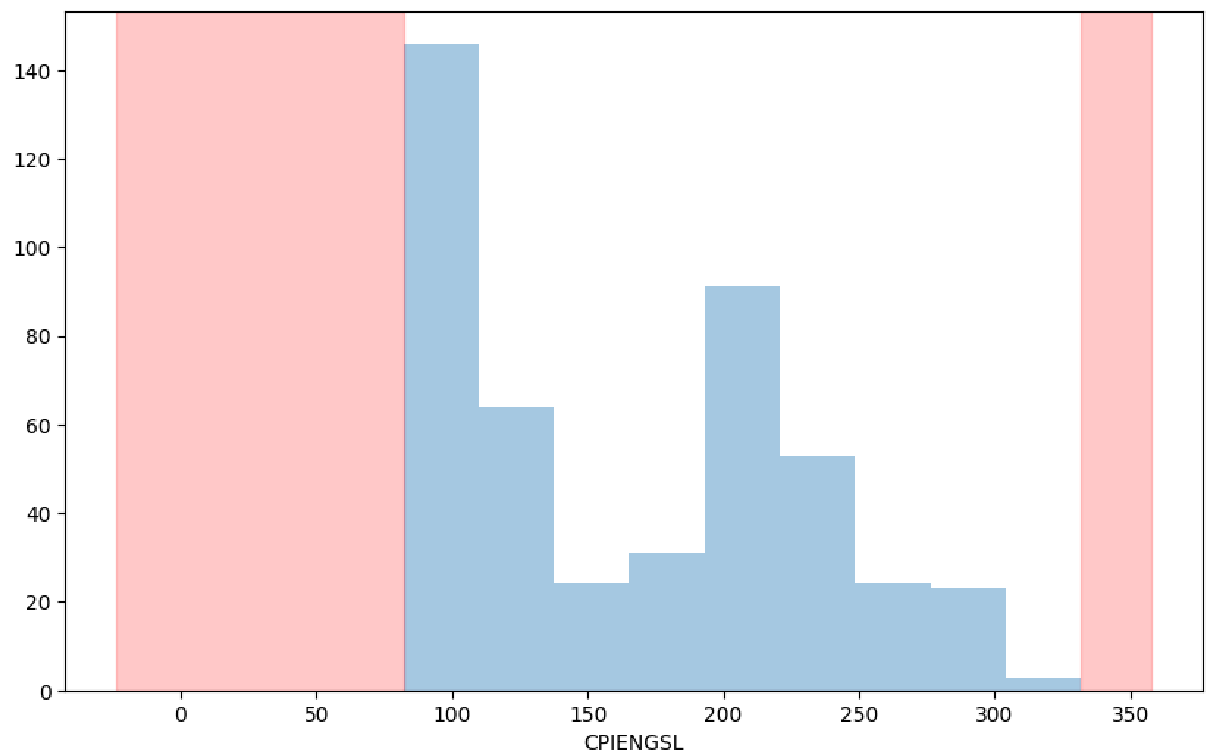
```
    plt.figure(figsize = (10,6))
    sns.distplot(df_new[col], kde=False)
    plt.axvspan(xmin = lower,xmax= df_new[col].min(),alpha=0.2, color='red')
    plt.axvspan(xmin = upper,xmax= df_new[col].max(),alpha=0.2, color='red')
```

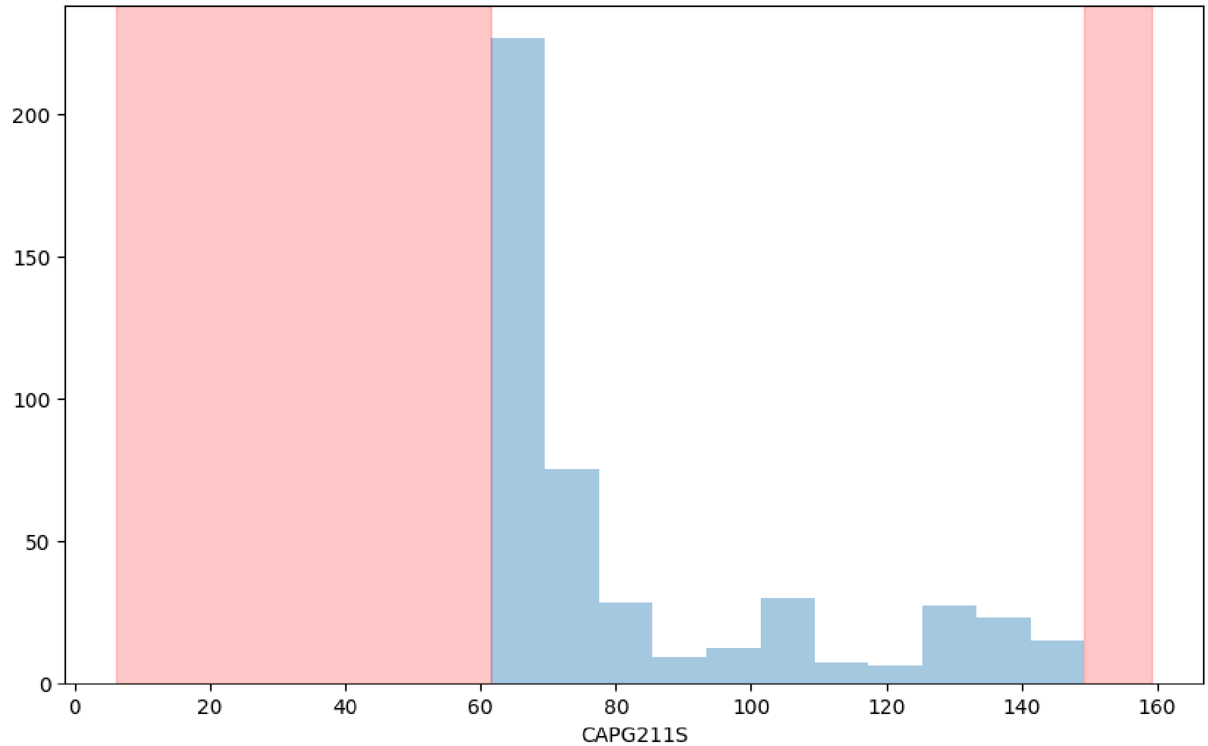
```
The lower bound value is -40.082532829843636
The upper bound value is 133.40170930043186
Total number of outliers are 0
The lower bound value is -23.57509455720819
The upper bound value is 357.58868061385306
Total number of outliers are 0
The lower bound value is 6.15368154560106
The upper bound value is 159.17391540429003
Total number of outliers are 0
The lower bound value is 82.76136514142729
The upper bound value is 104.20412113308254
Total number of outliers are 5
The lower bound value is 0.5550927639357894
The upper bound value is 154.7436218330141
Total number of outliers are 0
```

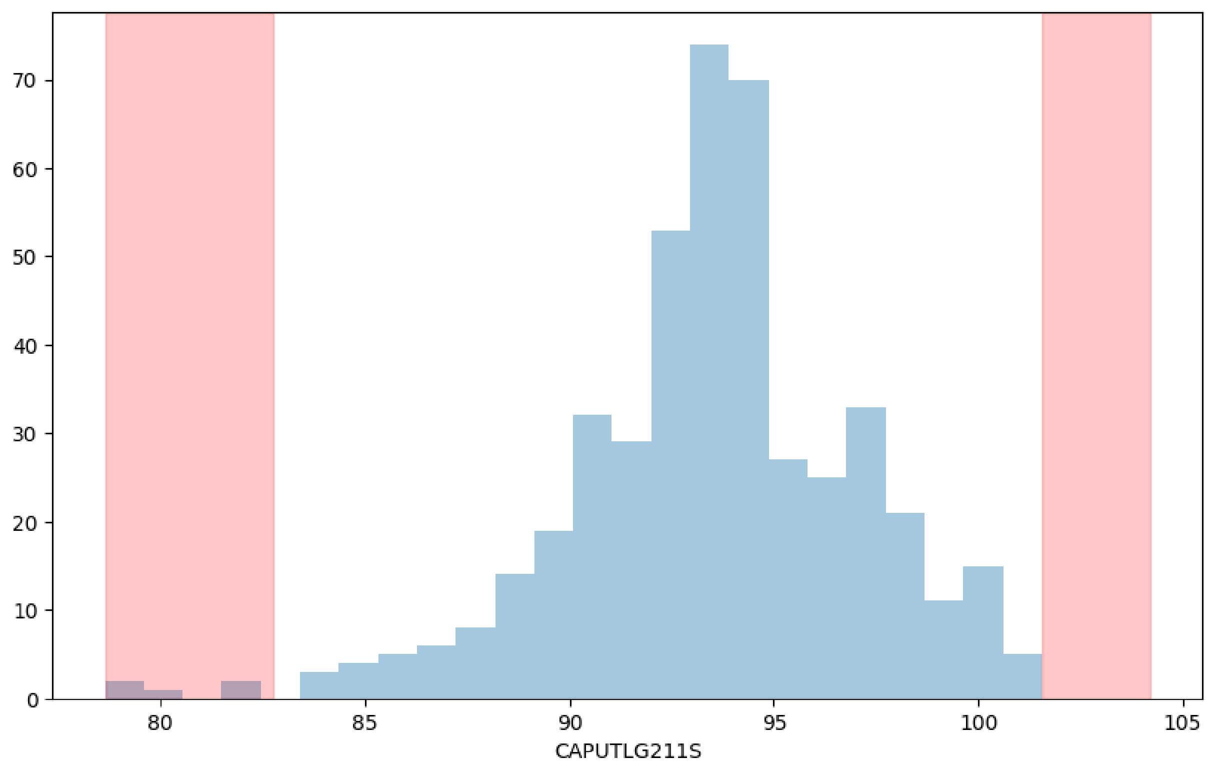
```
<ipython-input-16-d512fc6a9f76>:11: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df_new[col], kde=False)
```

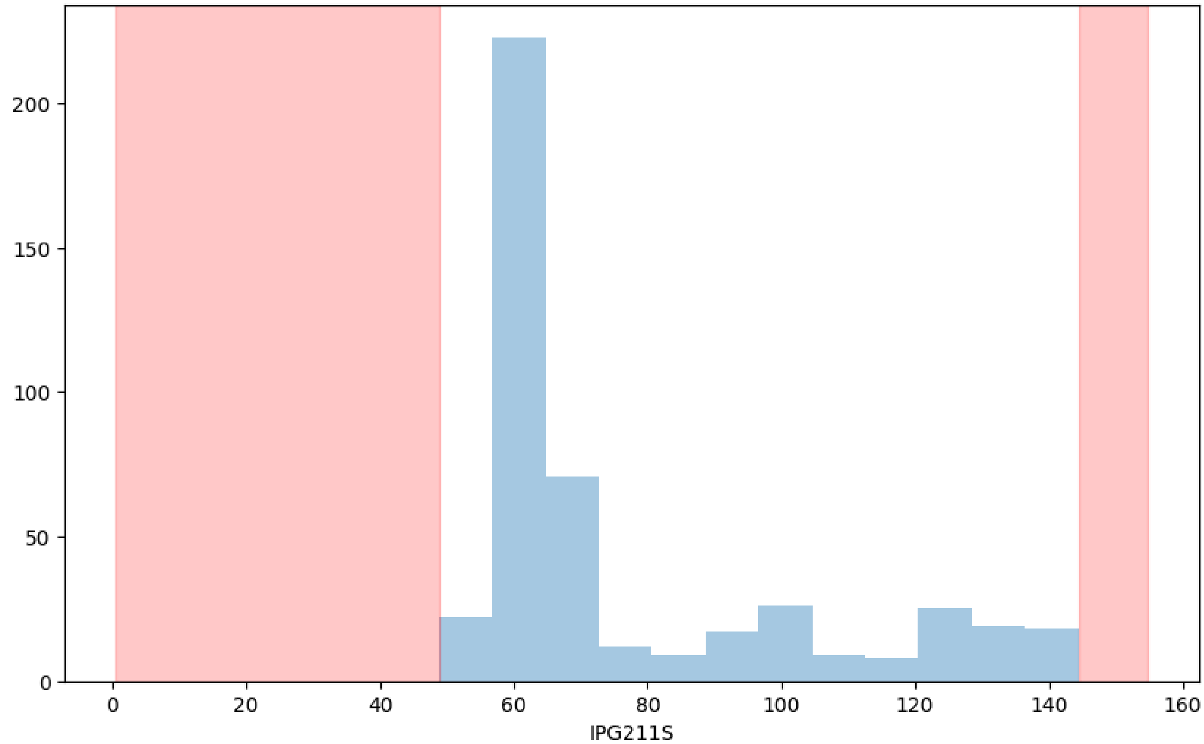
```
The lower bound value is 39.572396006374206
The upper bound value is 133.53064015920313
Total number of outliers are 0
The lower bound value is 23.142984182915242
The upper bound value is 196.66759620924165
Total number of outliers are 0
The lower bound value is -87.6888973772983
The upper bound value is 393.2304137171676
Total number of outliers are 0
```

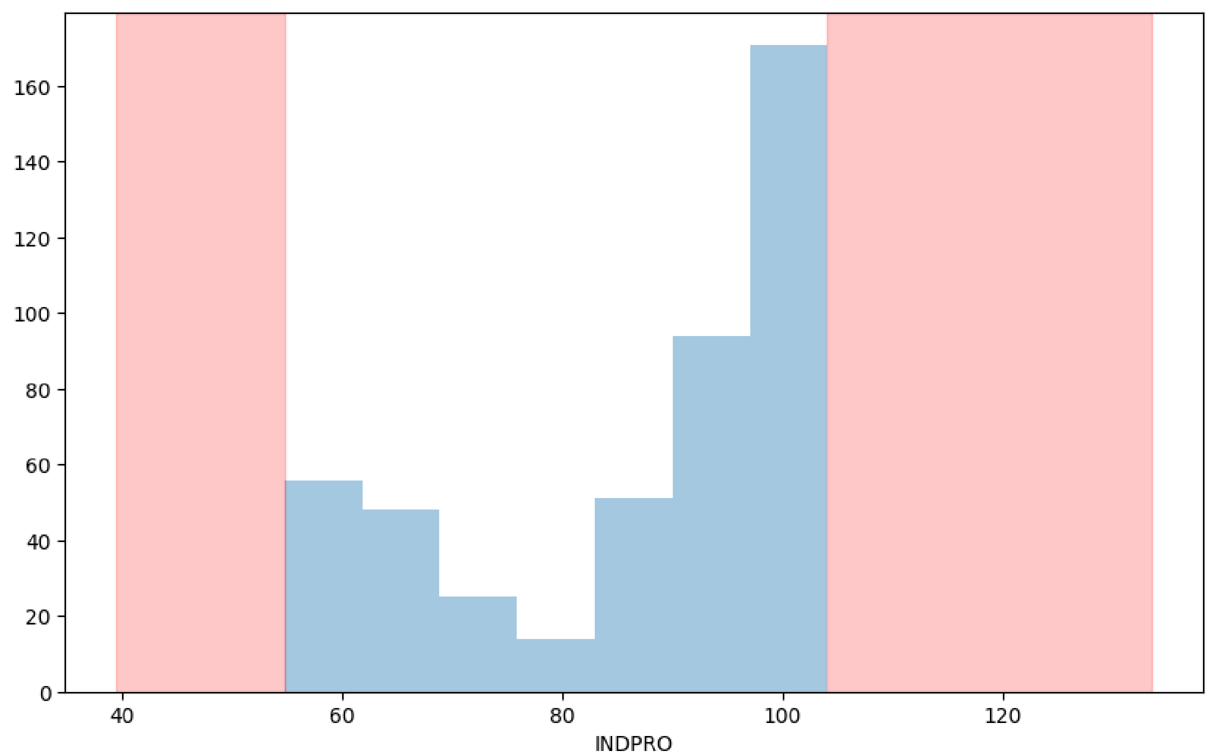

160
140
120
100
80
60
40
20
0
−25
0
25
50
75
100
125
WTISPLC

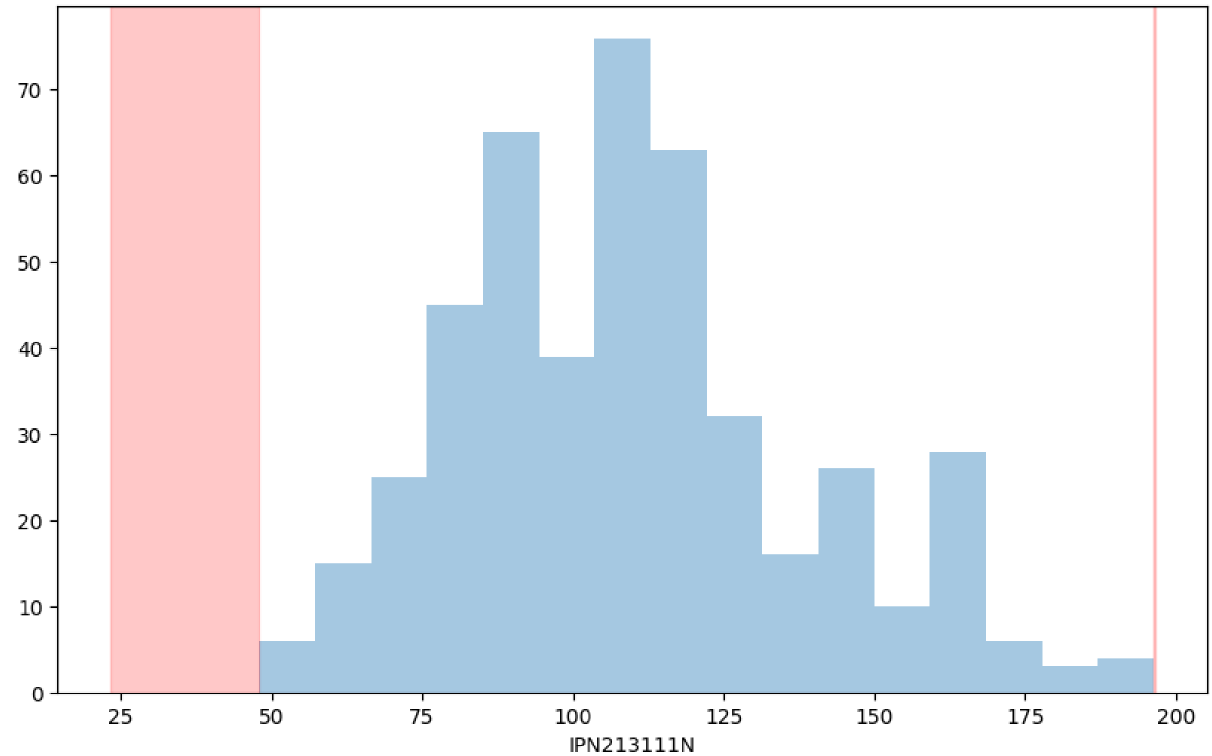

140
120
100
80
60
40
20
0
0
50
100
150
200
250
300
350
CPIENGSL

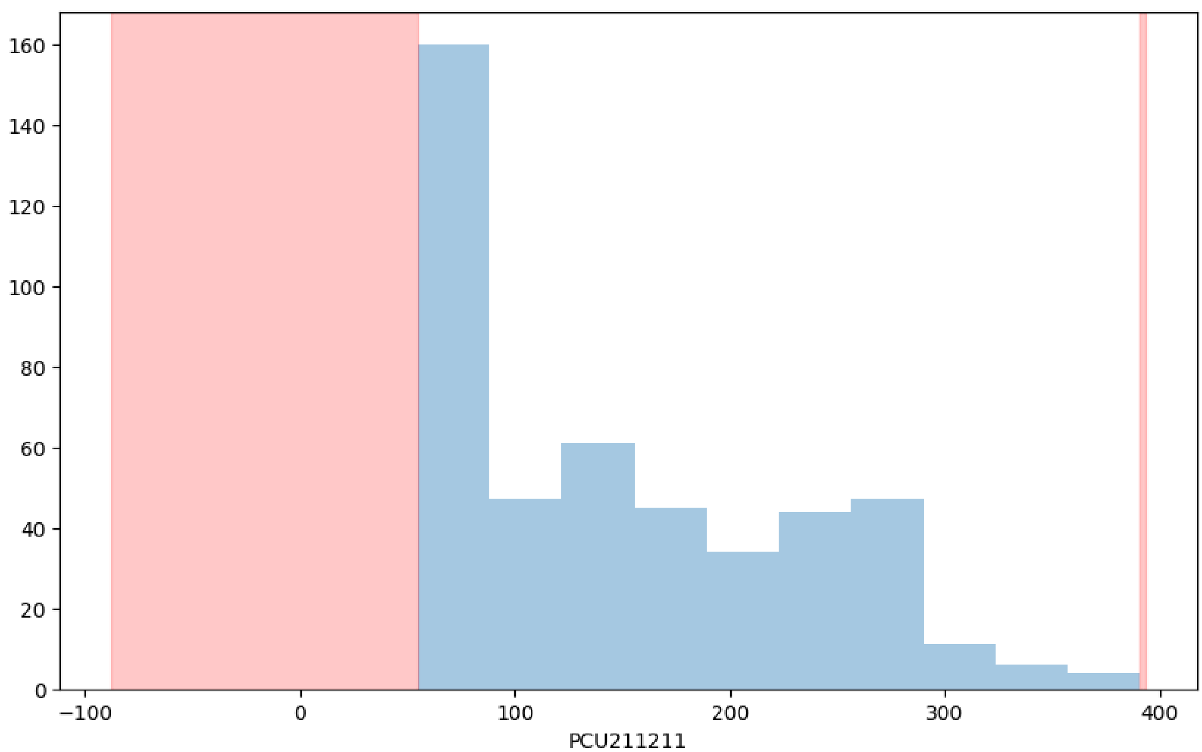

0
50
100
150
200
0
20
40
60
80
100
120
140
160
CAPG211S


0
10
20
30
40
50
60
70
80
85
90
95
100
105
CAPUTLG211S


0
50
100
150
200
0
20
40
60
80
100
120
140
160
IPG211S


0
20
40
60
80
100
120
140
160
40
60
80
100
120
INDPRO





Financial Data

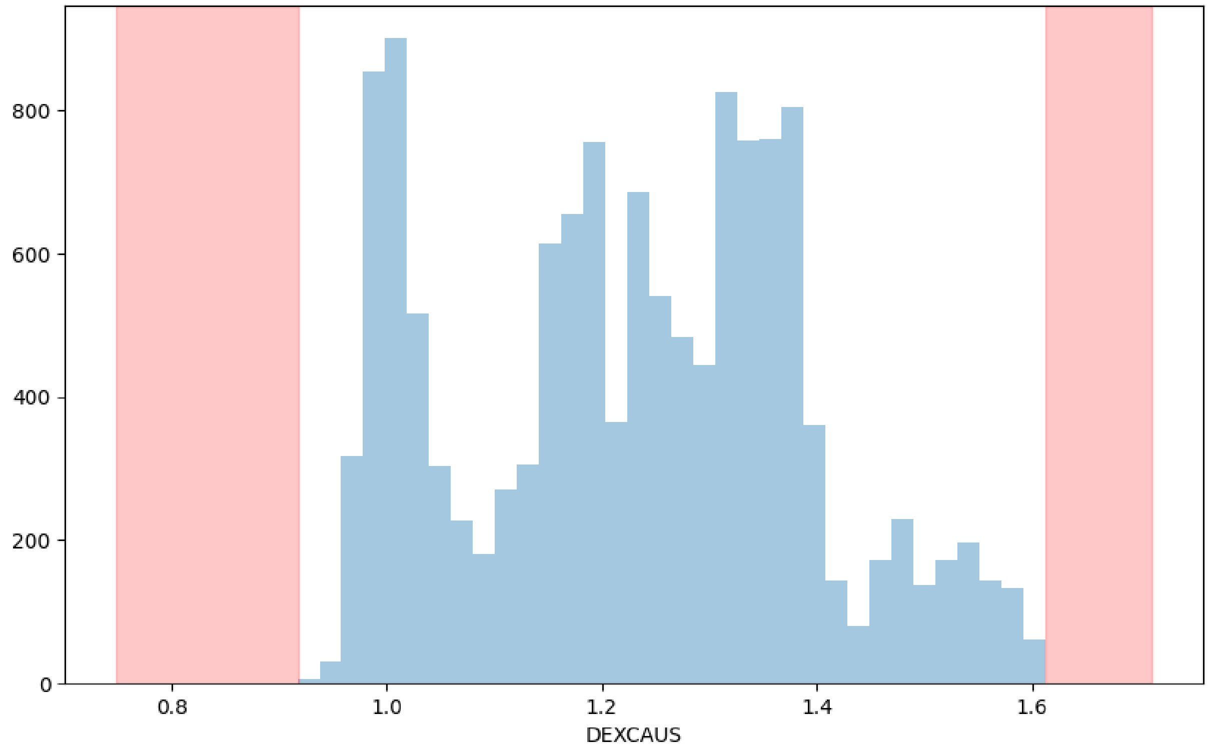
In [17]:
```
def out_std(df, column):
    global lower,upper
    # calculate the mean and standard deviation of the data frame
    data_mean, data_std = df[column].mean(), df[column].std()
    # calculate the cutoff value
    cut_off = data_std * 3
    # calculate the lower and upper bound value
```

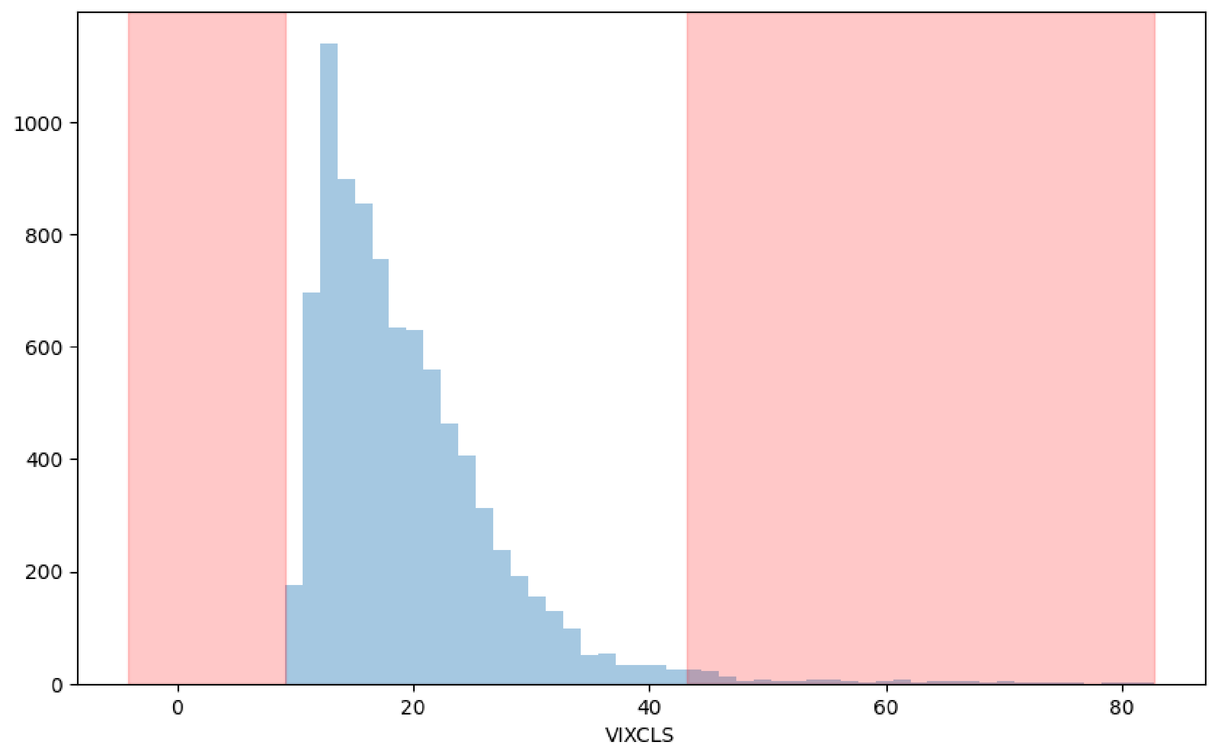
```
    lower, upper = data_mean - cut_off, data_mean + cut_off
    print('The lower bound value is', lower)
    print('The upper bound value is', upper)
    # Calculate the number of records below and above lower and above bound value res
    df1 = df[df[column] > upper]
    df2 = df[df[column] < lower]
    return print('Total number of outliers are', df1.shape[0]+ df2.shape[0])

for col in fin_data.columns:
    out_std(fin_data, col)

    plt.figure(figsize = (10,6))
    sns.distplot(fin_data[col], kde=False)
    plt.axvspan(xmin = lower,xmax= fin_data[col].min(),alpha=0.2, color='red')
    plt.axvspan(xmin = upper,xmax= fin_data[col].max(),alpha=0.2, color='red')
```

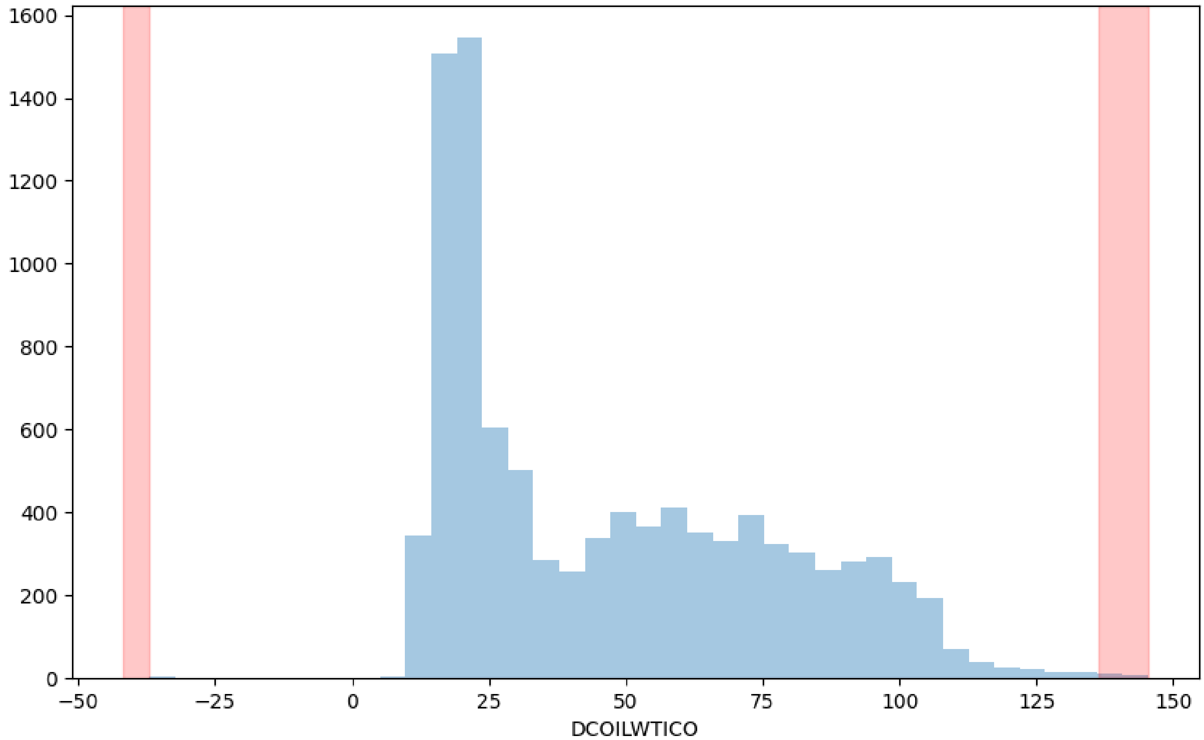
```
The lower bound value is 0.7484901853824507
The upper bound value is 1.7109794459024652
Total number of outliers are 0
The lower bound value is -4.148036317968636
The upper bound value is 43.131865958652824
Total number of outliers are 142
The lower bound value is -41.80830253900812
The upper bound value is 136.3917582091112
Total number of outliers are 16
```

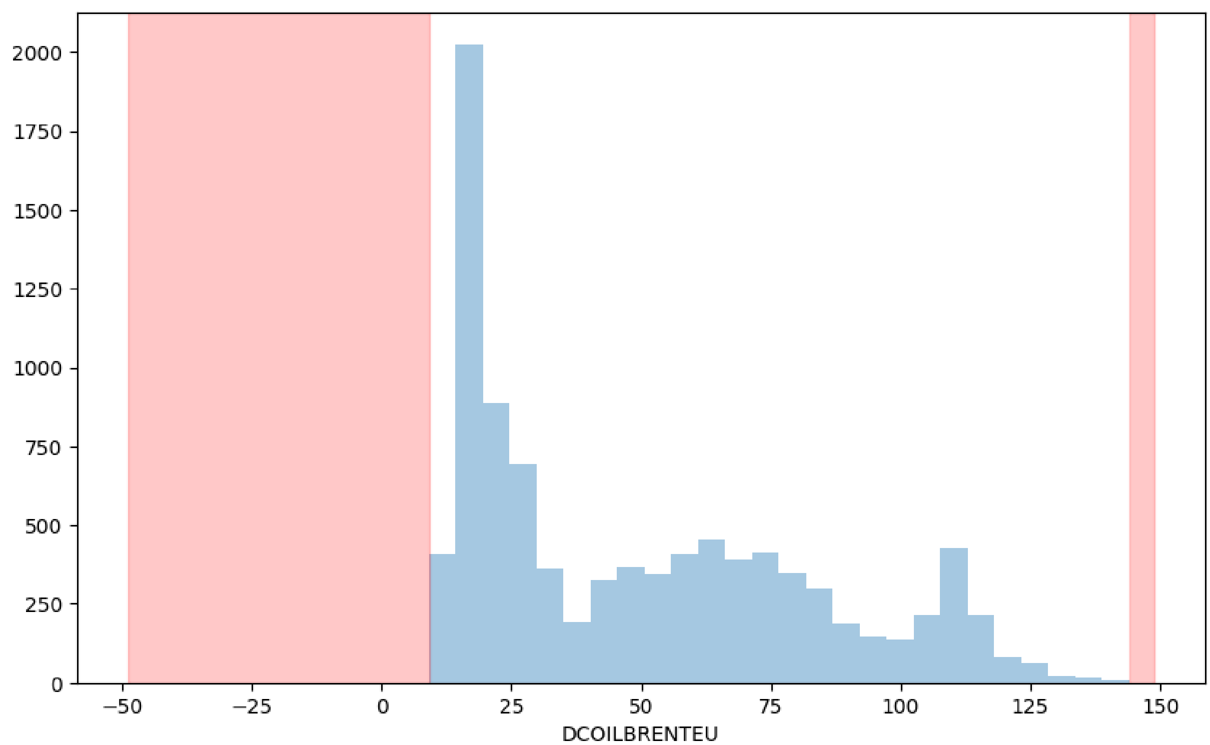
```
<ipython-input-17-a4129b99bc3f>:20: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(fin_data[col], kde=False)
```

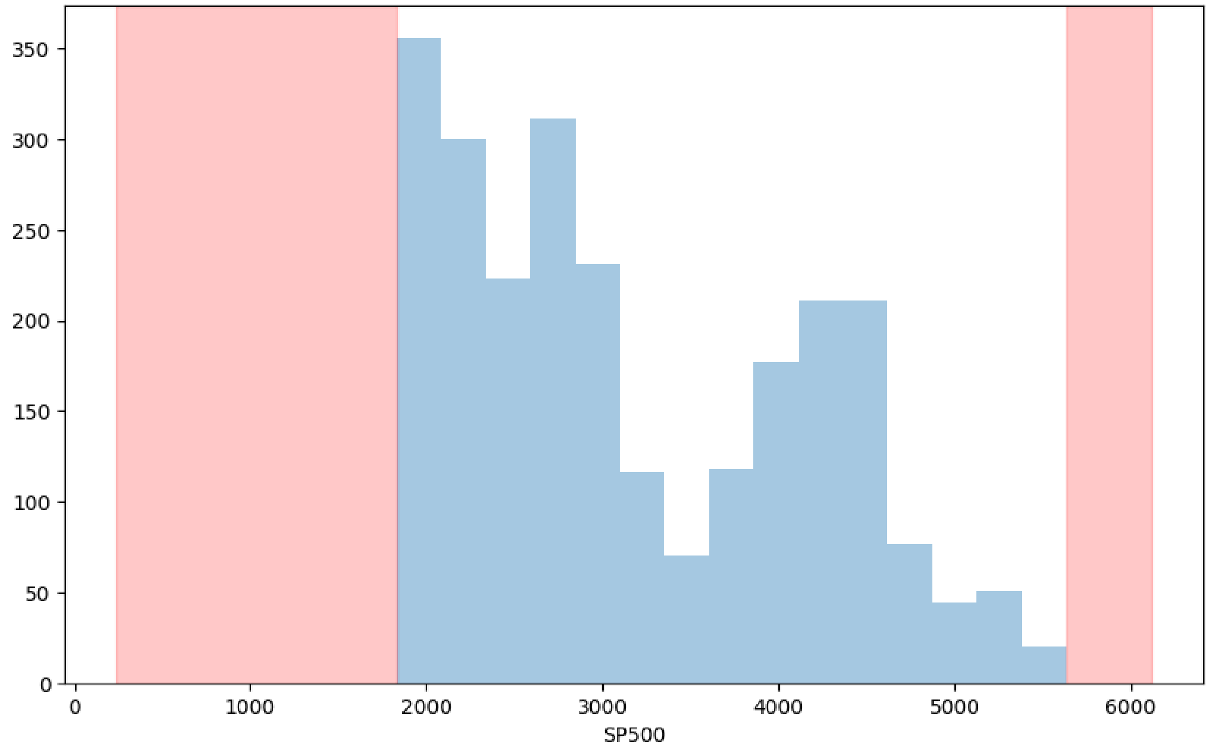
```
The lower bound value is -48.84497754215096
The upper bound value is 148.71735788811296
Total number of outliers are 0
The lower bound value is 239.8667915078745
The upper bound value is 6115.393200543
Total number of outliers are 0
```


800
600
400
200
0
0.8
1.0
1.2
1.4
1.6
DEXCAUS


1000
800
600
400
200
0
0
20
40
60
80
VIXCLS


1600
1400
1200
1000
800
600
400
200
0
−50
−25
0
25
50
75
100
125
150
DCOILWTICO


2000
1750
1500
1250
1000
750
500
250
0
−50
−25
0
25
50
75
100
125
150
DCOILBRENTEU



Handling missing values and Step 6

In [18]:
```
clean_filtered_macrodata = df_new[df_new.index > '2000-01-01']
for col in clean_filtered_macrodata.columns:
    #Data Frame without outliers
    clean_filtered_macrodata = clean_filtered_macrodata[(clean_filtered_macrodata[col
clean_filtered_macrodata.dropna()
```

Out[18]:

WTISPLC	CPIENGSL	CAPG211S	CAPUTLG211S	IPG211S	INDPRO	IPN213111N	PCU2112

In [19]:
```
clean_filtered_fin_data = fin_data[fin_data.index > '2000-01-01']

for col in clean_filtered_fin_data.columns:
    out_std(clean_filtered_fin_data, col)
    clean_filtered_fin_data = clean_filtered_fin_data[(clean_filtered_fin_data[col] >

clean_filtered_fin_data
```

```
The lower bound value is 0.7383116741499283
The upper bound value is 1.754145663956157
Total number of outliers are 0
The lower bound value is -5.619809271550544
The upper bound value is 45.44014309580189
Total number of outliers are 102
The lower bound value is -13.297905292740182
The upper bound value is 140.99957836003023
Total number of outliers are 8
The lower bound value is -20.30716118329657
The upper bound value is 153.93805280642147
Total number of outliers are 0
The lower bound value is 241.3547172663093
The upper bound value is 6106.041783351229
Total number of outliers are 0
```

Out[19]:

	DEXCAUS	VIXCLS	DCOILWTICO	DCOILBRENTEU	SP500
2014-07-14	1.0721	11.82	101.73	104.73	1977.10
2014-07-15	1.0766	11.96	100.56	104.73	1973.28
2014-07-16	1.0749	11.00	101.88	105.41	1981.57
2014-07-17	1.0753	14.54	103.84	106.04	1958.12
2014-07-18	1.0737	12.06	103.83	106.03	1978.22
...	...	...	...	...	...
2024-06-28	1.3684	12.44	82.83	87.26	5460.48
2024-07-01	1.3742	12.22	84.70	86.57	5475.09
2024-07-02	1.3691	12.03	84.09	88.28	5509.01
2024-07-03	1.3624	12.09	85.19	88.25	5537.02
2024-07-05	1.3631	12.48	84.44	88.66	5567.19

2429 rows × 5 columns

In [20]:

```
clean_filtered_fin_data.isnull().sum()
```

Out[20]:

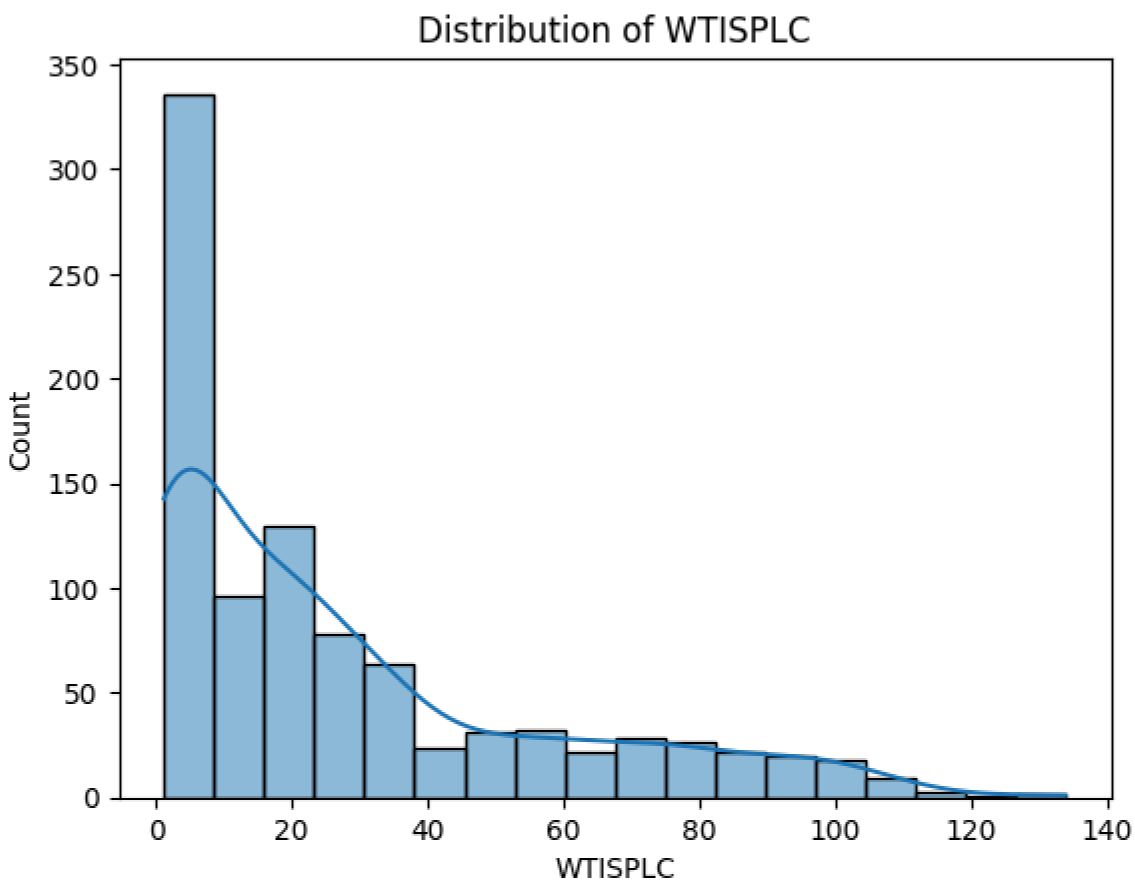
```
DEXCAUS         0
VIXCLS          0
DCOILWTICO      0
DCOILBRENTEU    0
SP500           0
dtype: int64
```

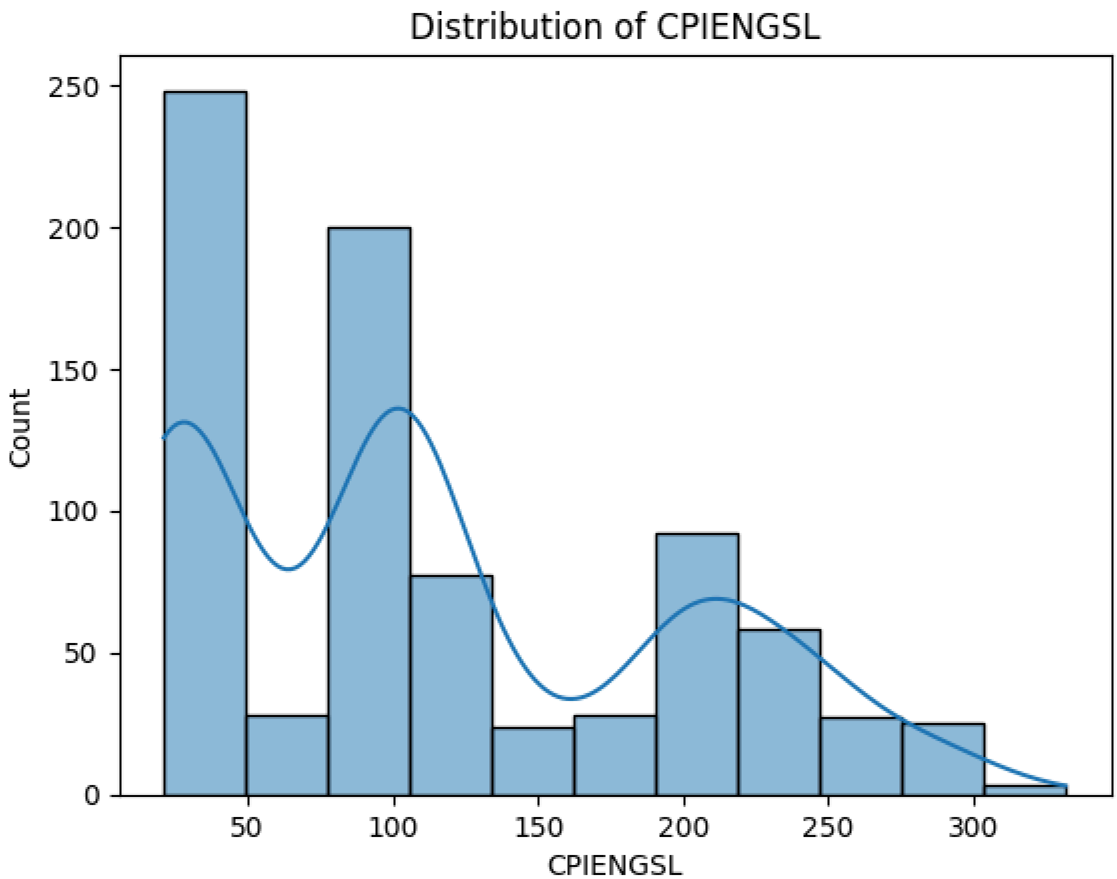
We are filthering all the data before 01.01.2000 and from now on we are going to work with only the data after 2000 because we think that this timeframe is big enough and also this are the most recent 24 years that do have the most and recent important impact over history and the corresponding price action. In order to to get rid of the outliers we are applying the 3 standard deviation outlier detection method and after this we are dropping the data point that are outside of the 3 standard eviation metric. After this we check for null data and we gladly find out that there is not so no further imputation is needed.

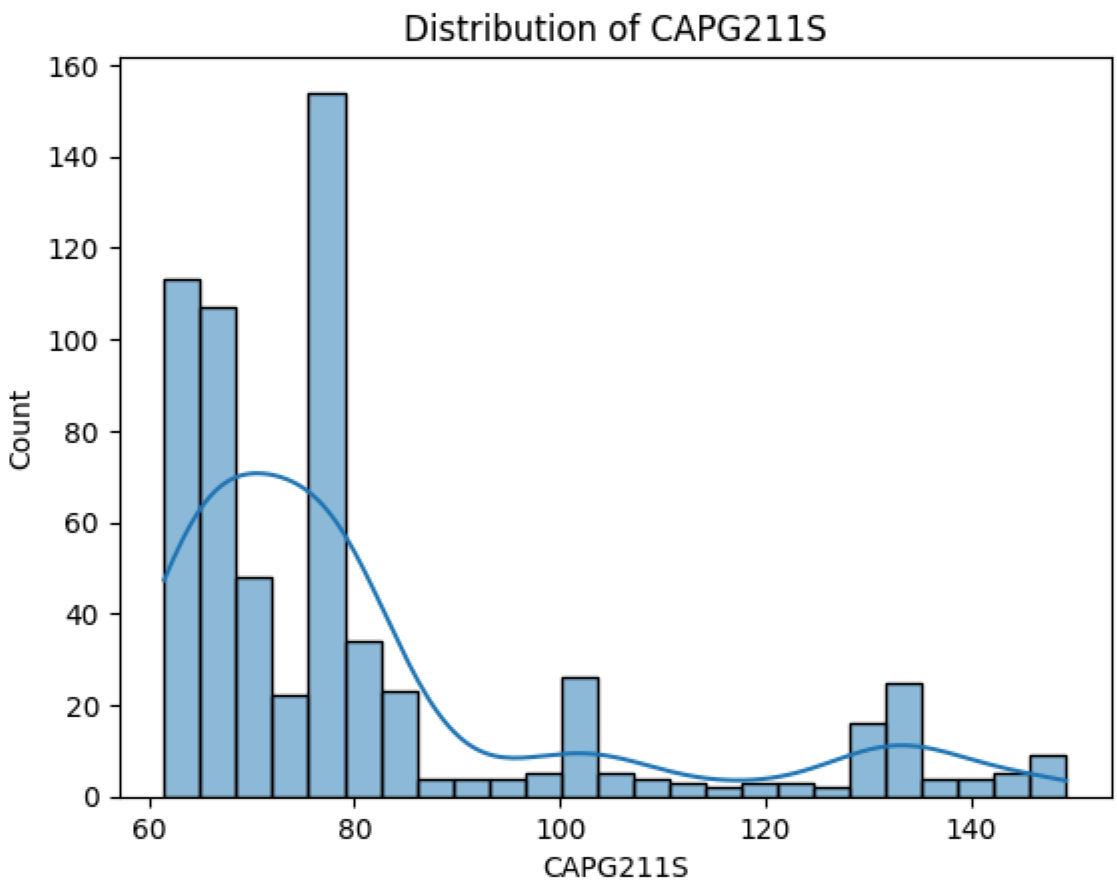
Step 7

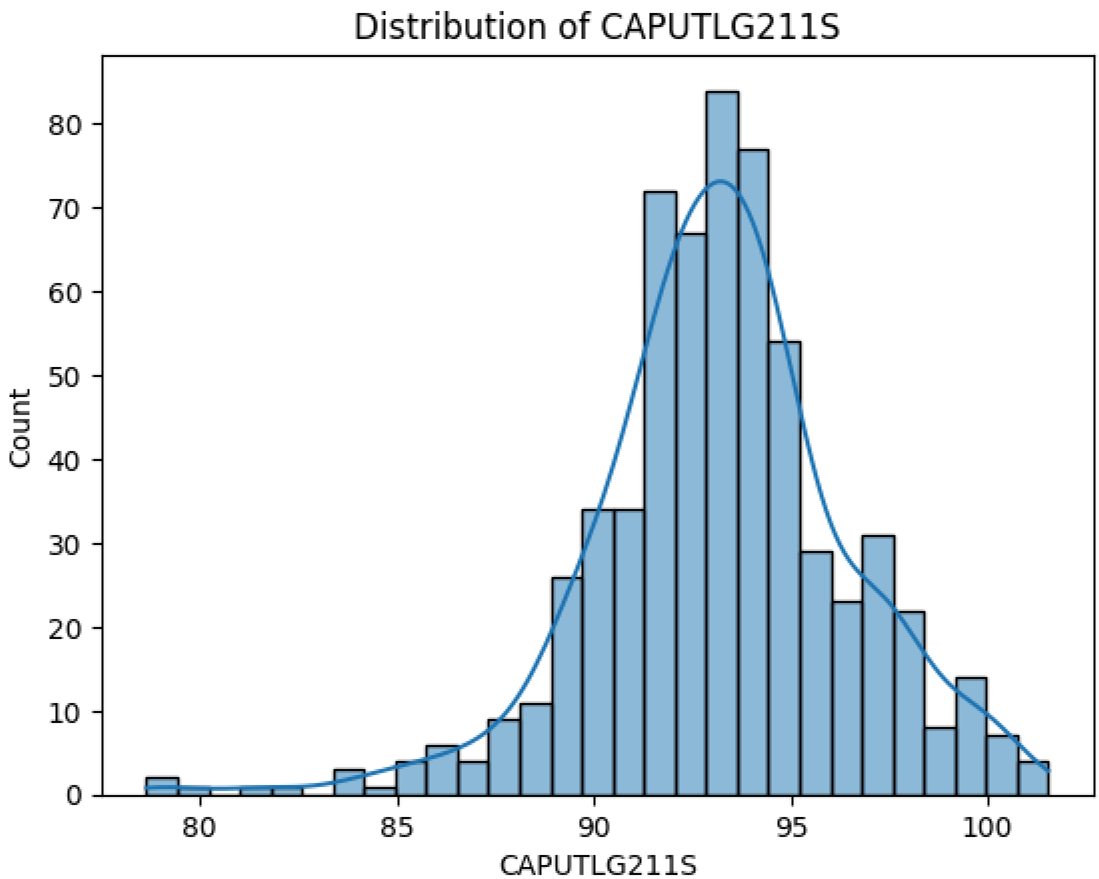
Distributional plots of Macroeconomic Data

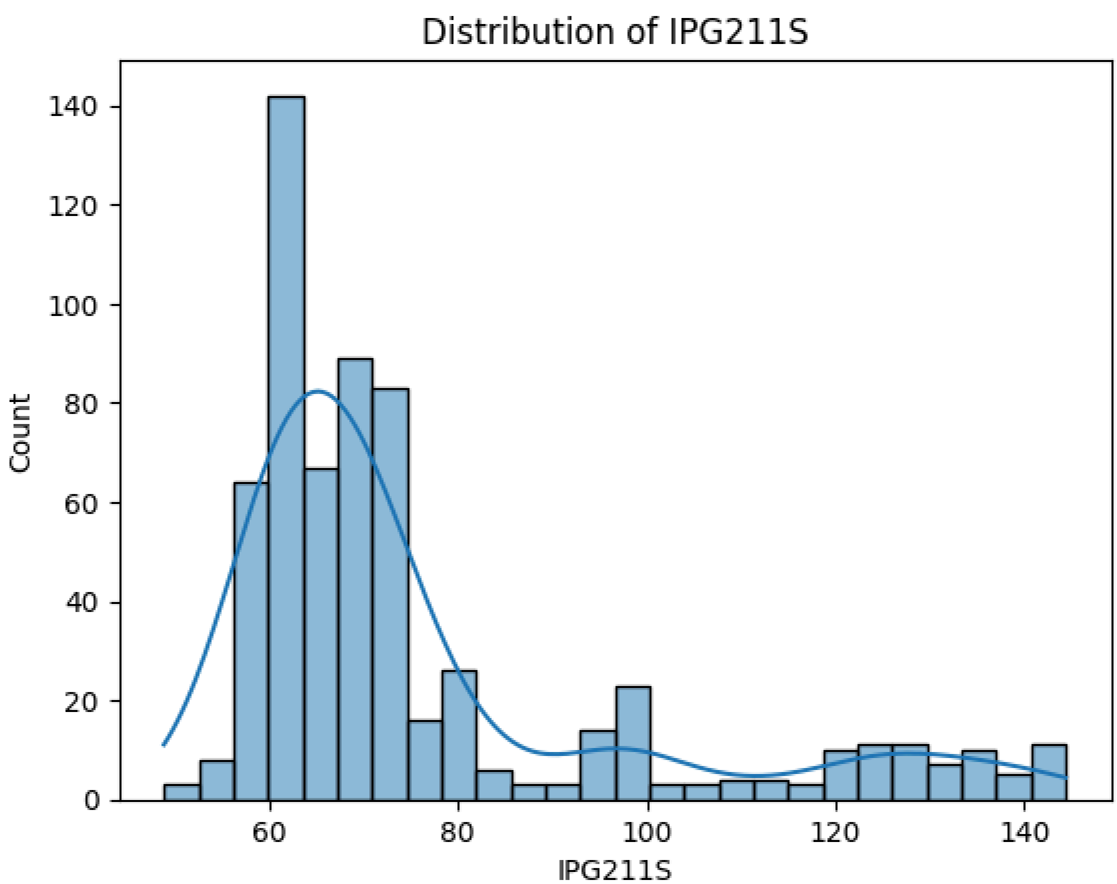
In [21]:
```
# Distribution of each variable
for col in data_merge.columns:
    plt.figure()
    sns.histplot(data_merge[col], kde=True)
    plt.title(f"Distribution of {col}")
    plt.show()
```

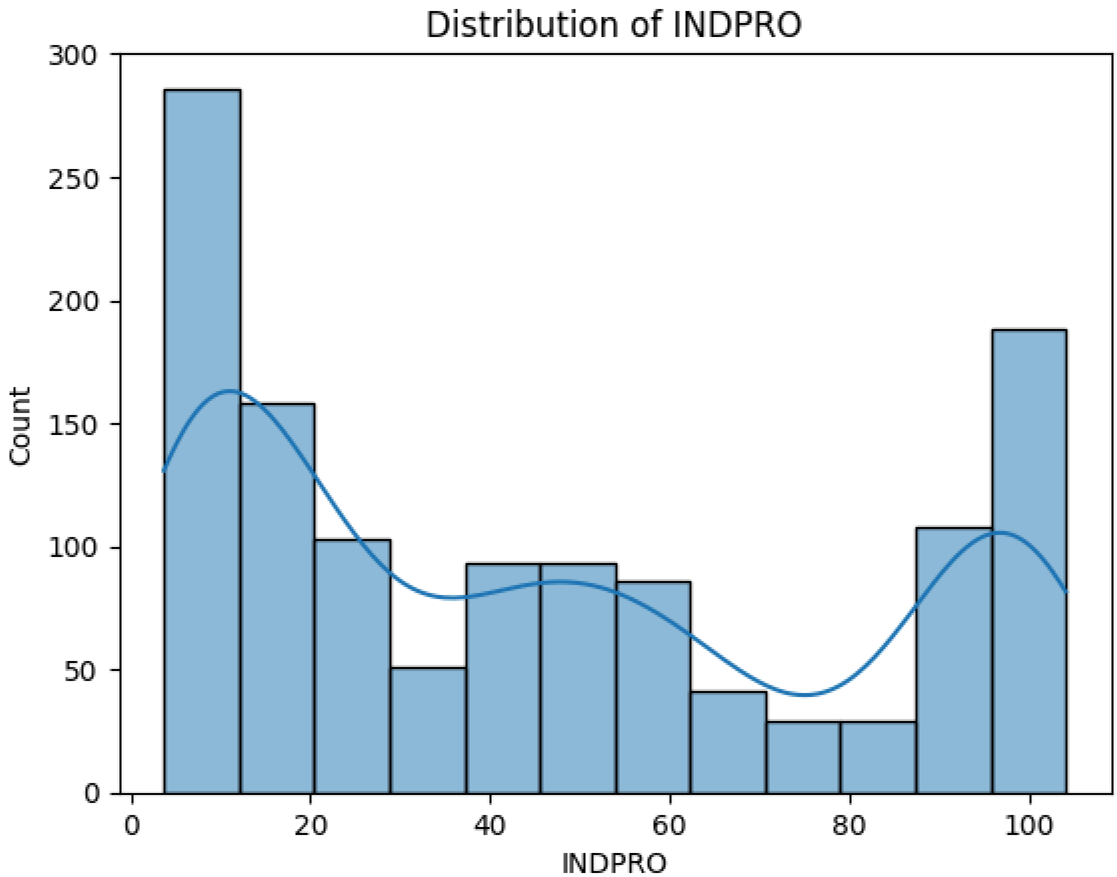


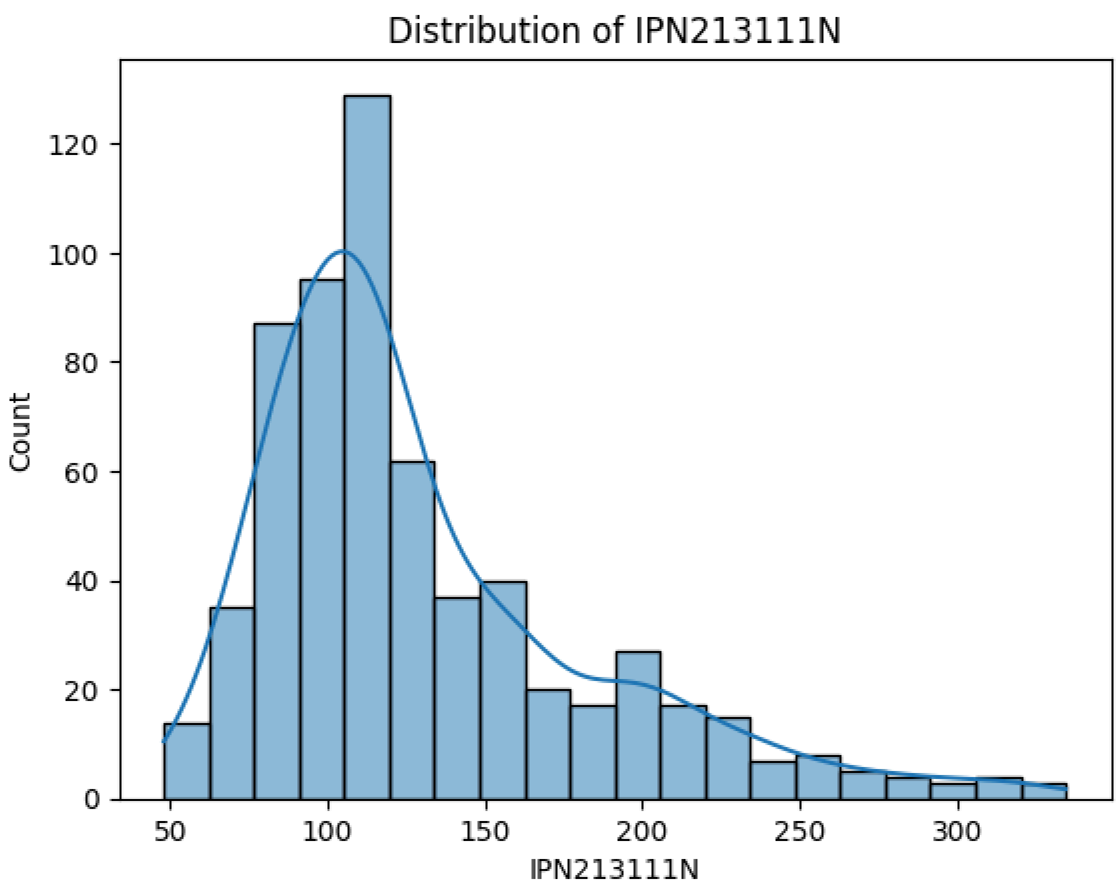

Distribution of CPIENGSL
Count
CPIENGSL
0
50
100
150
200
250
300

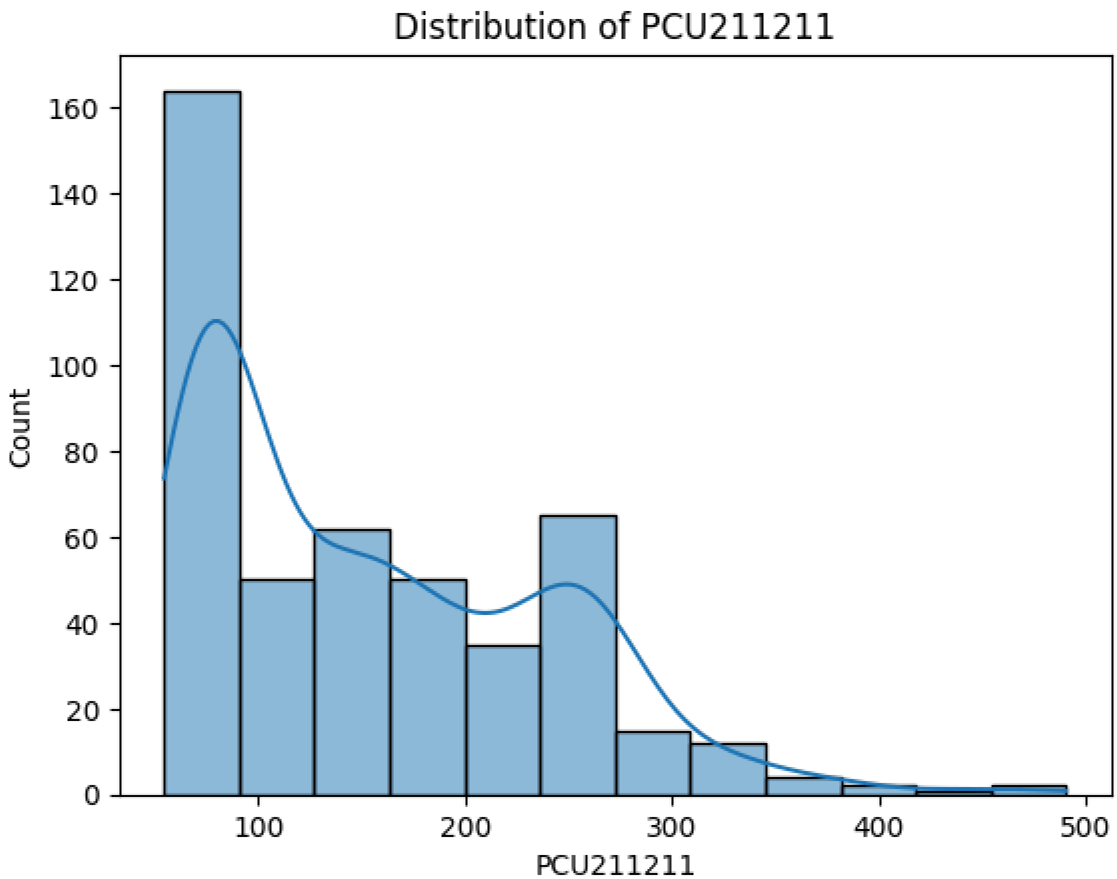

Distribution of CAPG211S
Count
CAPG211S
0
20
40
60
80
100
120
140
160


Distribution of CAPUTLG211S
Count
CAPUTLG211S
0
10
20
30
40
50
60
70
80
80
85
90
95
100

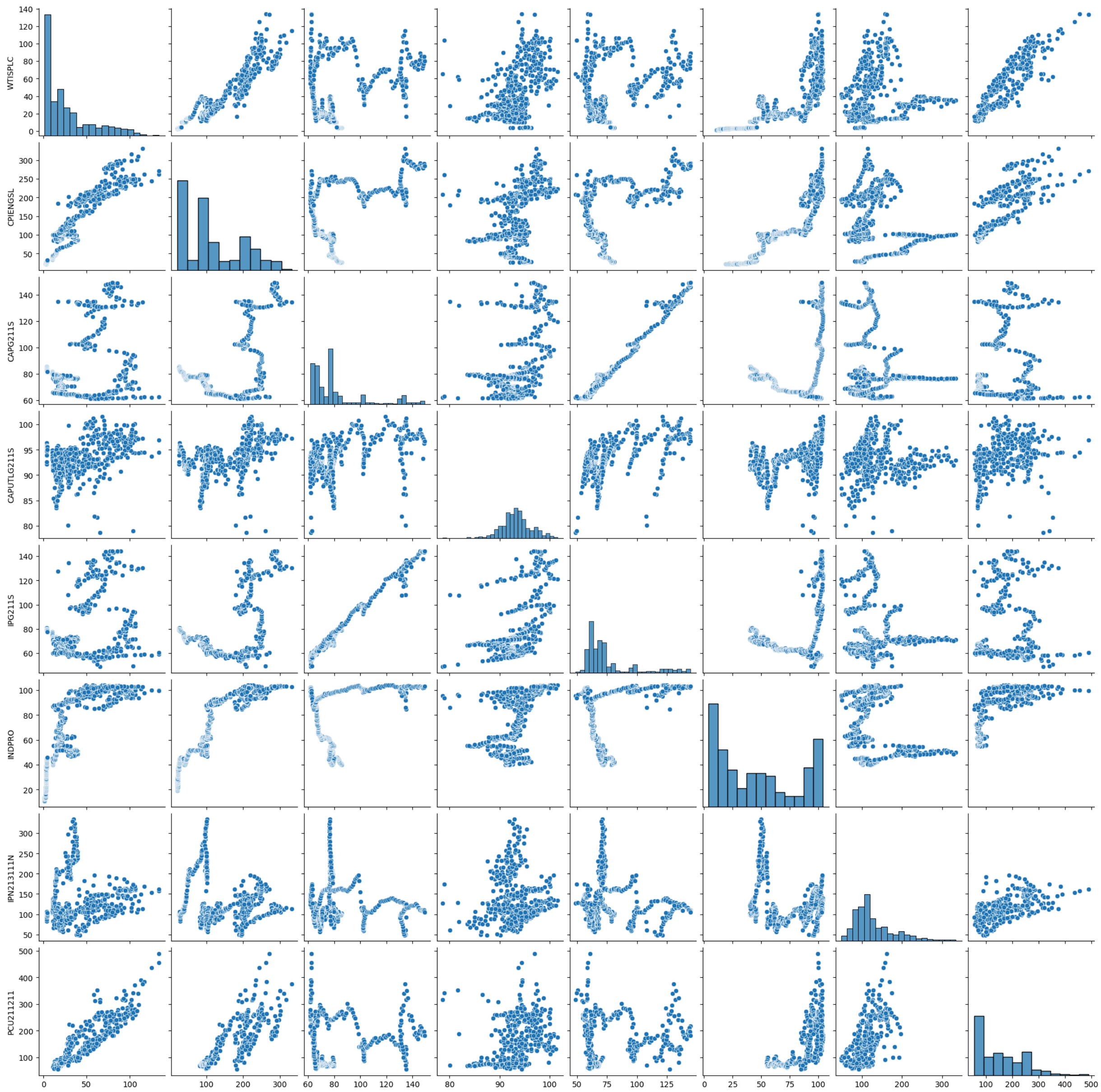

Distribution of IPG211S
Count
IPG211S
0
20
40
60
80
100
120
140
60
80
100
120
140


Distribution of INDPRO
Count
300
250
200
150
100
50
0
0
20
40
60
80
100
INDPRO

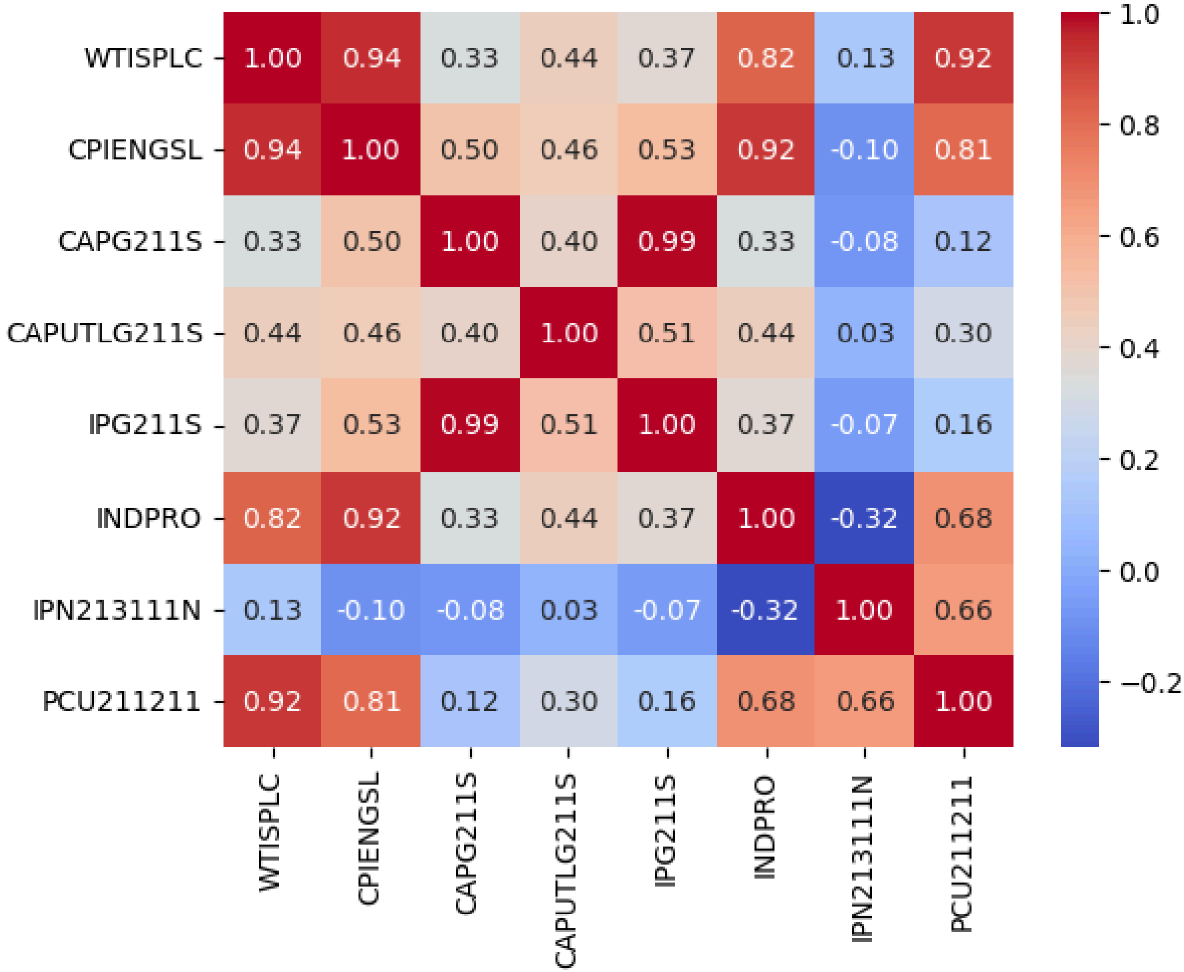

Distribution of IPN213111N
Count
120
100
80
60
40
20
0
50
100
150
200
250
300
IPN213111N



In [22]:
```
# Scatter plot matrix
sns.pairplot(data_merge)
plt.show()
```

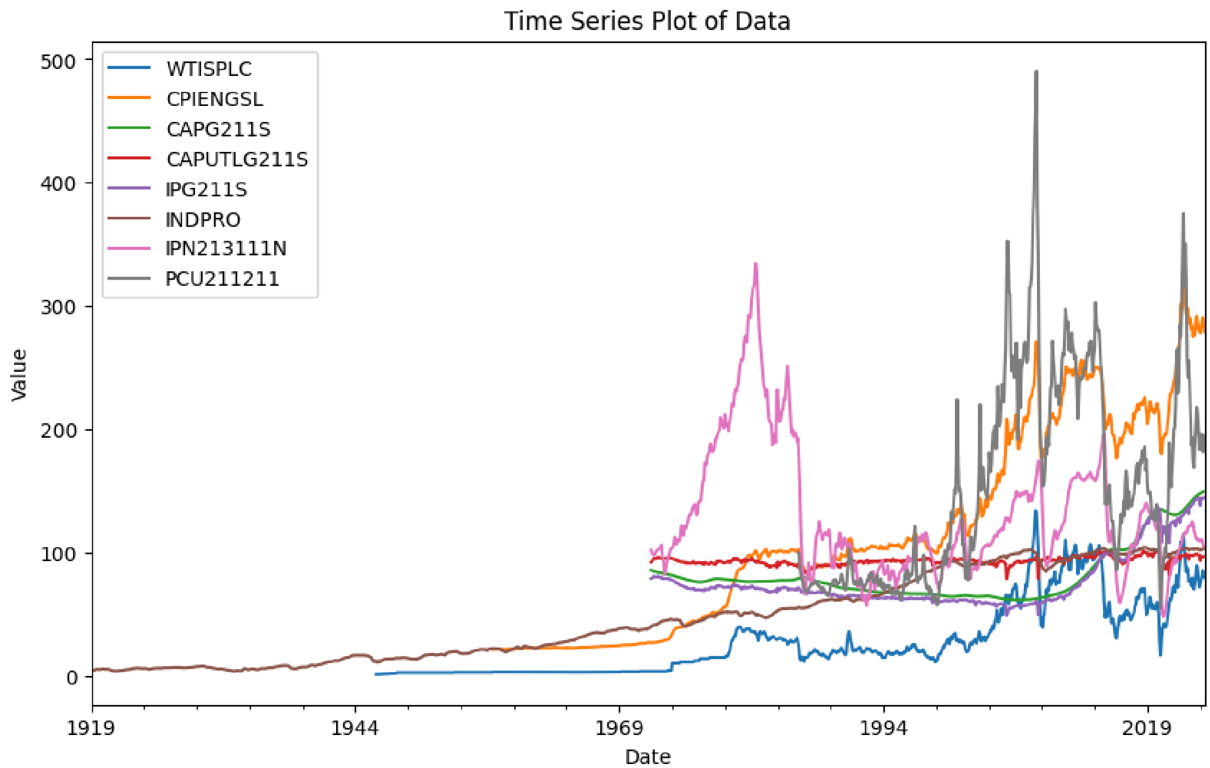


In [23]:
```
# Correlation matrix
corr_matrix = data_merge.corr()
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.show()
```



Time Series plot of Macroeconomic Data

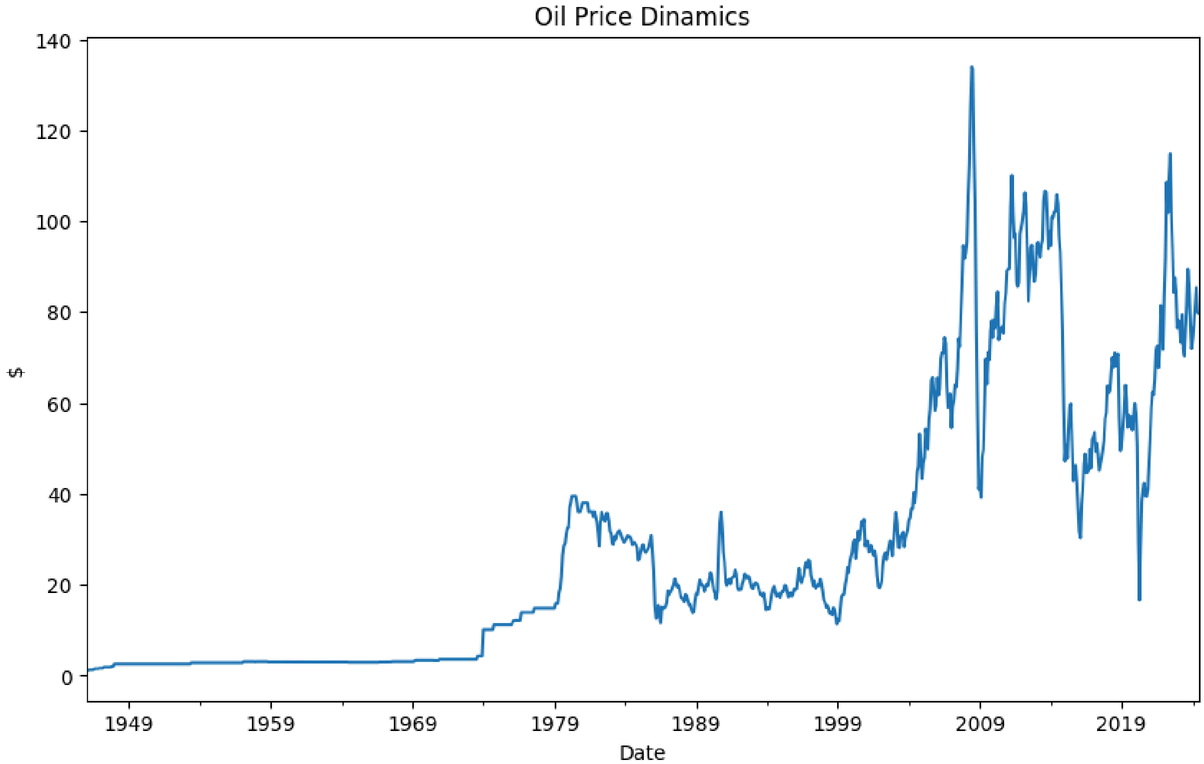
In [24]:
```
# Time series plot
data_merge.plot(figsize=(10, 6))
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("Time Series Plot of Data")
plt.show()
```



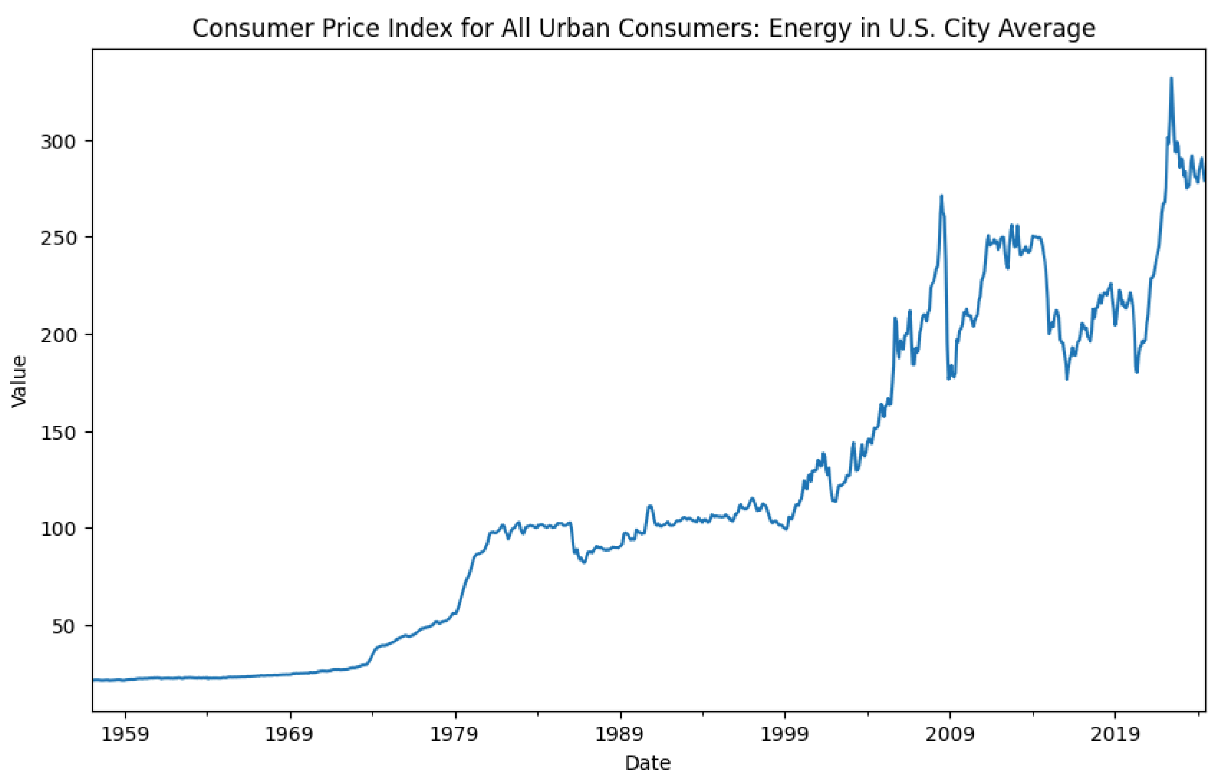
In [25]:
```
'WTISPLC',    # Spot Crude Oil Price: West Texas Intermediate (WTI) (WTISPLC)
'CPIENGSL', # Consumer Price Index for All Urban Consumers: Energy in U.S. City Avera
'CAPG211S', # Industrial Capacity: Mining: Oil and Gas Extraction (NAICS = 211)
'CAPUTLG211S', #  Capacity Utilization: Mining: Oil and Gas Extraction (NAICS = 211)
'IPG211S', # Industrial Production Index: Mining: Oil and Gas Extraction (NAICS = 211
'INDPRO', #  Industrial Production: Total Index
'IPN213111N', # Industrial Production: Mining: Drilling Oil and Gas Wells
'PCU211211', # Producer Price Index: Mining: Oil and Gas Extraction (NAICS = 211)
```

Out[25]: ('PCU211211',)

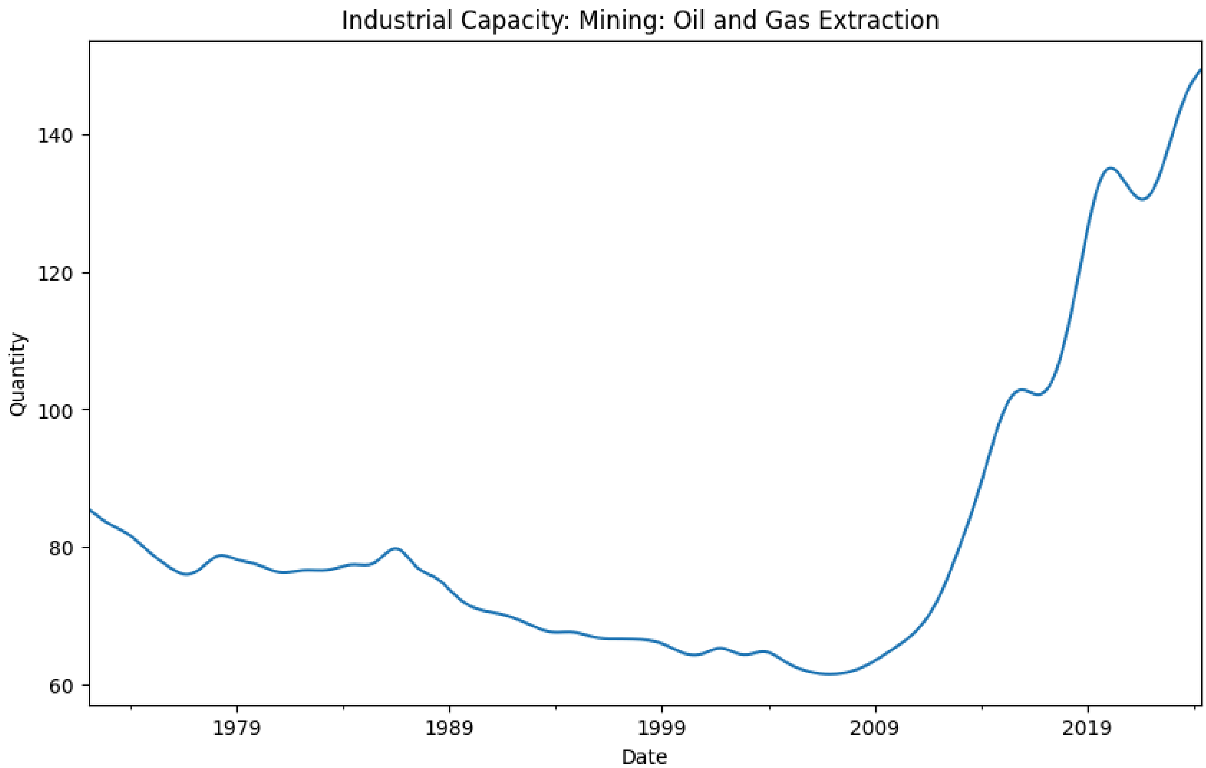
In [26]:
```
# Time series plot
data_merge['WTISPLC'].dropna().plot(figsize=(10, 6))  # Spot Crude Oil Price: West Te
plt.xlabel("Date")
plt.ylabel("$")
plt.title("Oil Price Dinamics")
plt.show()
```



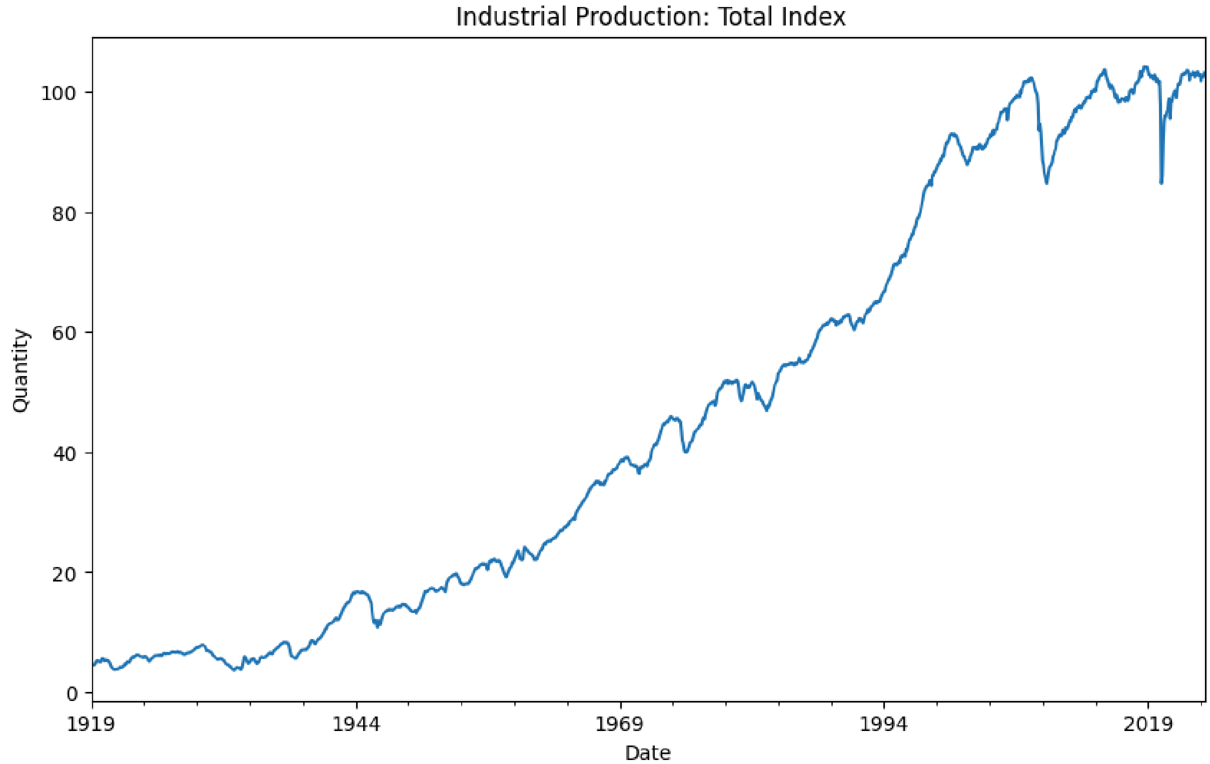
In [27]:
```
# Time series plot
data_merge['CPIENGSL'].dropna().plot(figsize=(10, 6)) # Consumer Price Index for All
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("Consumer Price Index for All Urban Consumers: Energy in U.S. City Average
plt.show()
```



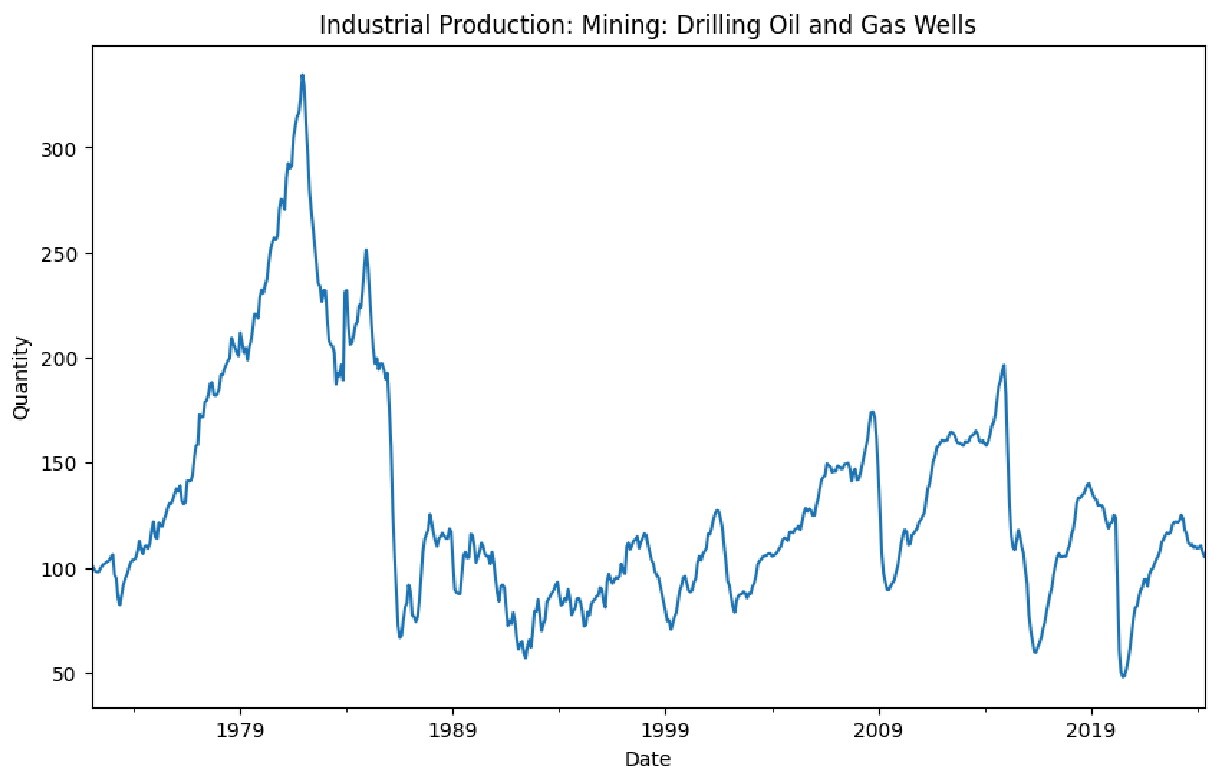
In [28]:
```
# Time series plot
data_merge['CAPG211S'].dropna().plot(figsize=(10, 6)) # Industrial Capacity: Mining:
plt.xlabel("Date")
plt.ylabel("Quantity")
plt.title("Industrial Capacity: Mining: Oil and Gas Extraction ")
plt.show()
```



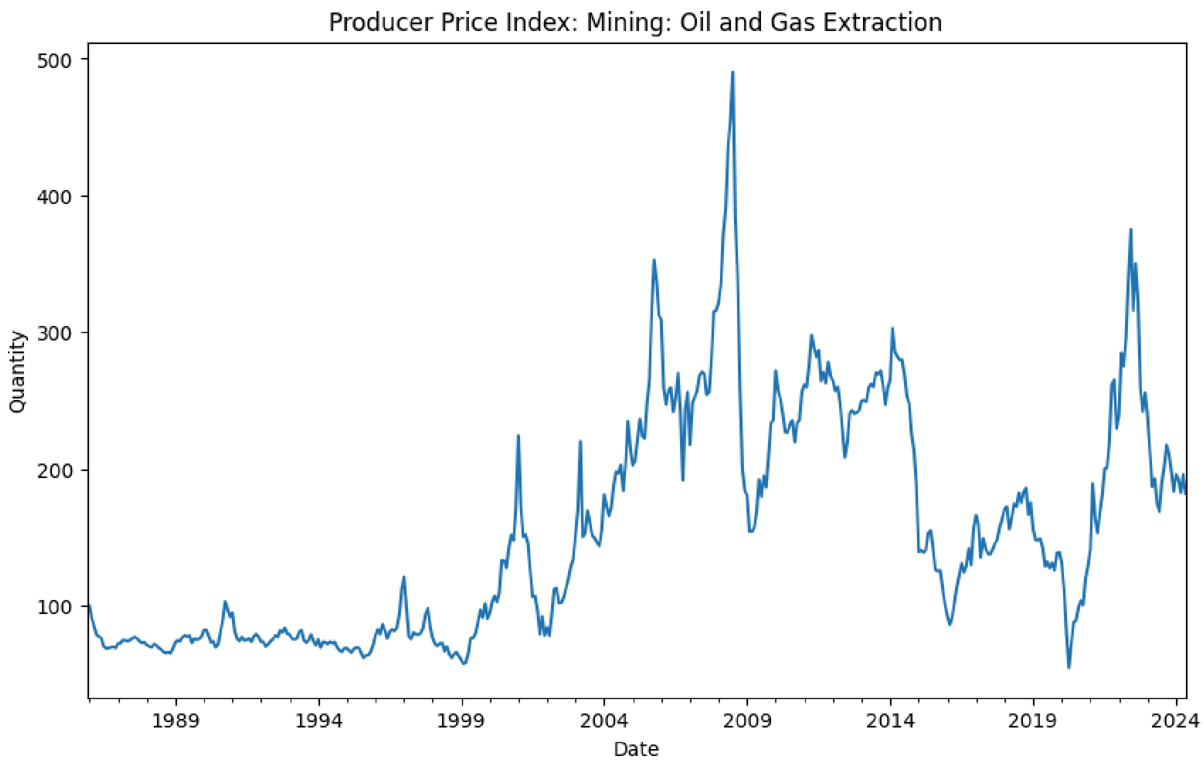
In [29]:
```
# Time series plot
data_merge['INDPRO'].dropna().plot(figsize=(10, 6))  #  Industrial Production: Total
plt.xlabel("Date")
plt.ylabel("Quantity")
plt.title(" Industrial Production: Total Index")
plt.show()
```



In [30]:
```
# Time series plot
data_merge['IPN213111N'].dropna().plot(figsize=(10, 6)) # Industrial Production: Mini
plt.xlabel("Date")
plt.ylabel("Quantity")
plt.title(" Industrial Production: Mining: Drilling Oil and Gas Wells ")
plt.show()
```

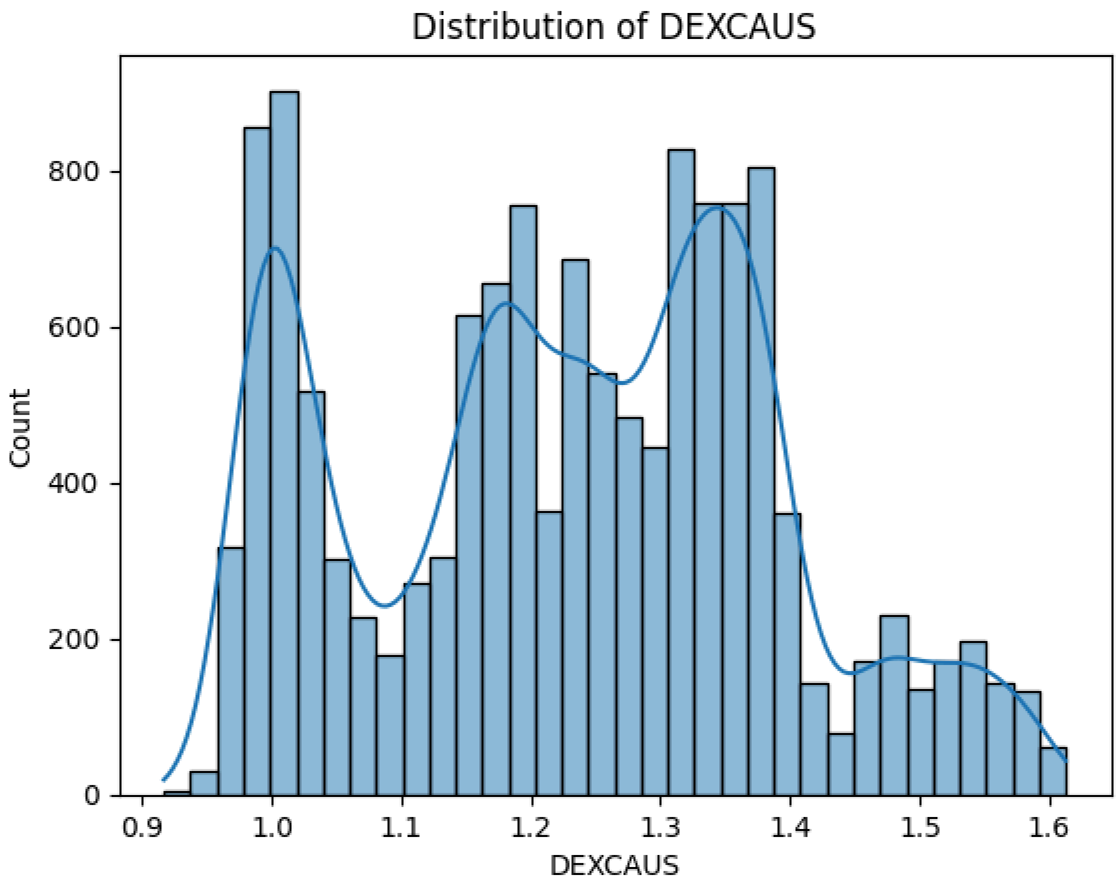


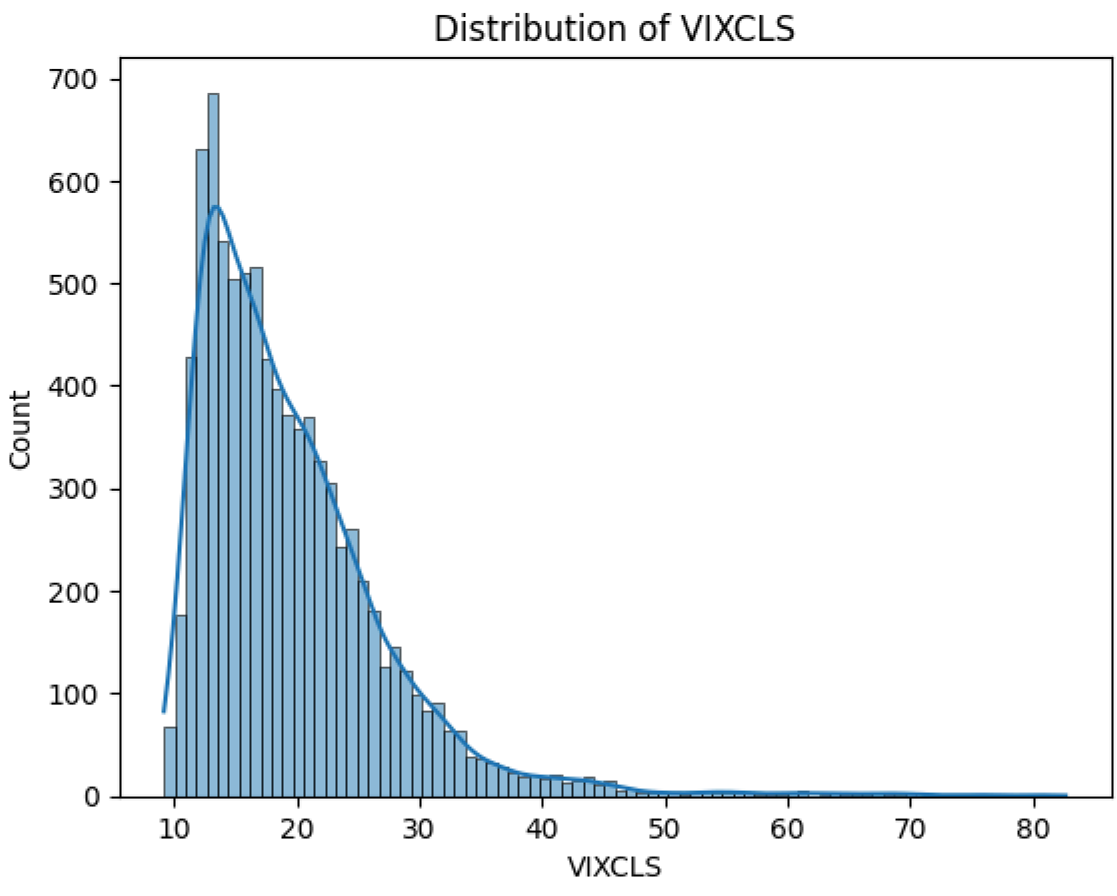
In [31]:
```
# Time series plot
data_merge['PCU211211'].dropna().plot(figsize=(10, 6)) # Producer Price Index: Mining
plt.xlabel("Date")
plt.ylabel("Quantity")
plt.title("Producer Price Index: Mining: Oil and Gas Extraction")
plt.show()
```

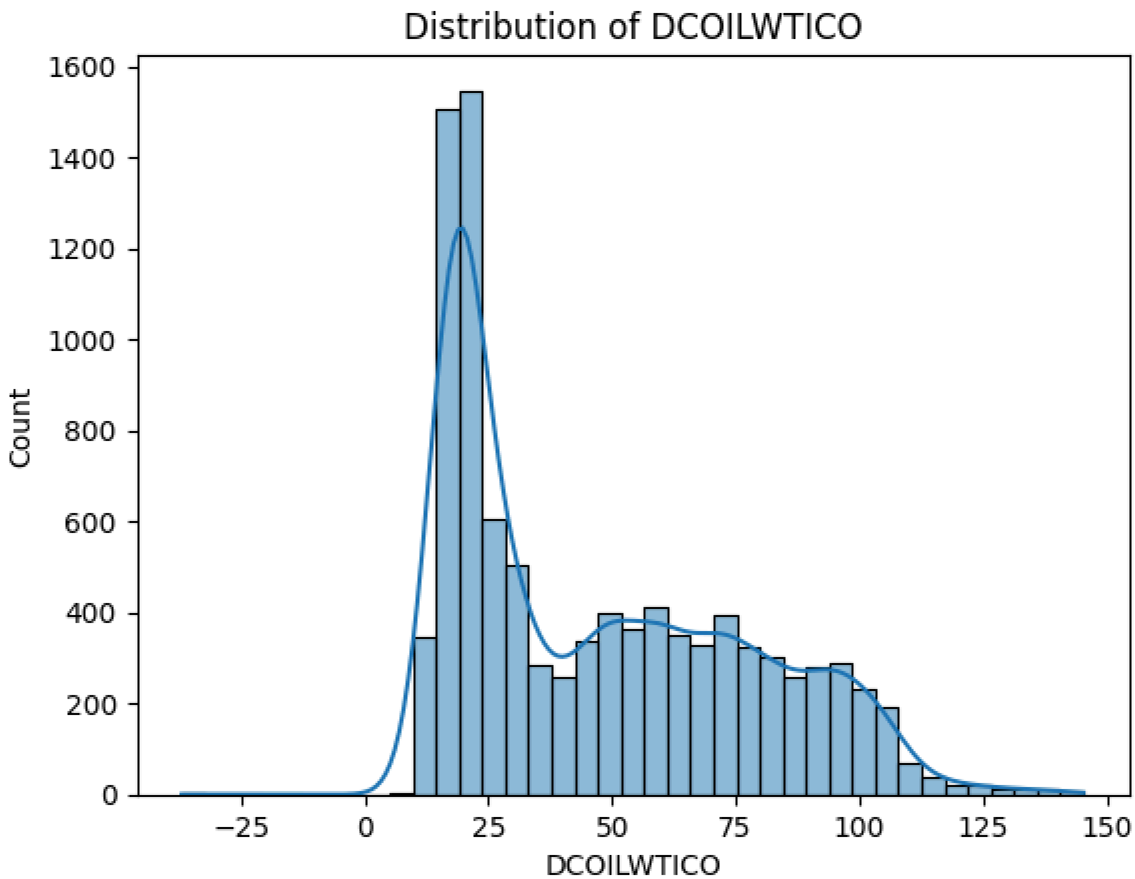


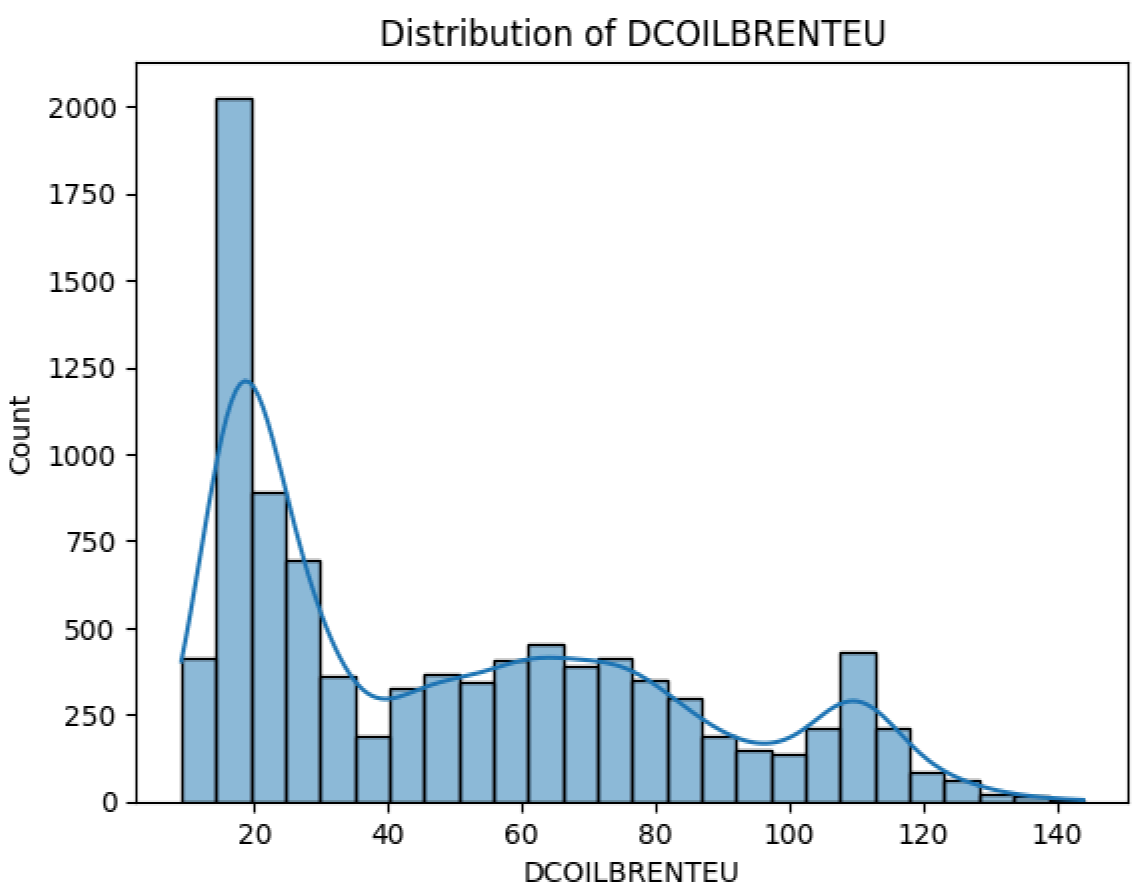
Distributional Plot of Financial Data

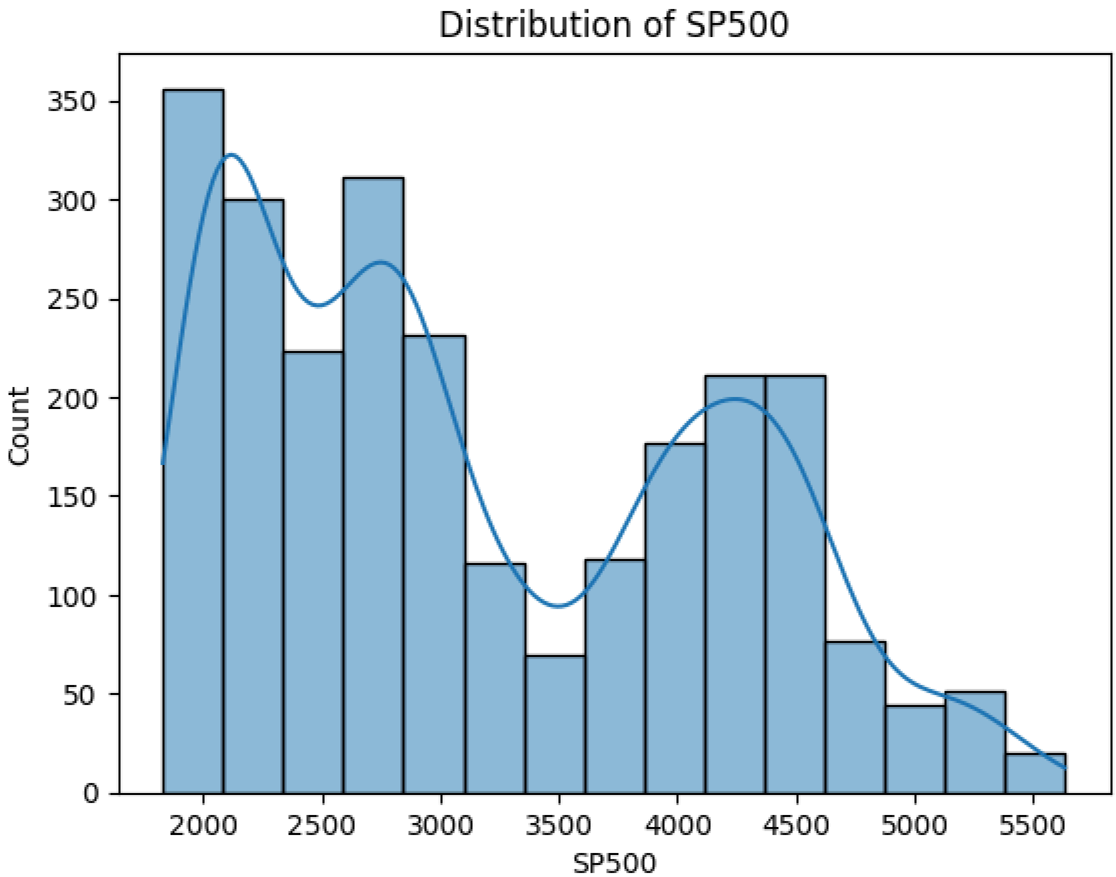
In [32]:
```
# Distribution of each variable
for col in fin_data.columns:
    plt.figure()
    sns.histplot(fin_data[col], kde=True)
    plt.title(f"Distribution of {col}")
    plt.show()
```


Distribution of DEXCAUS
Count
DEXCAUS
0
200
400
600
800
0.9
1.0
1.1
1.2
1.3
1.4
1.5
1.6

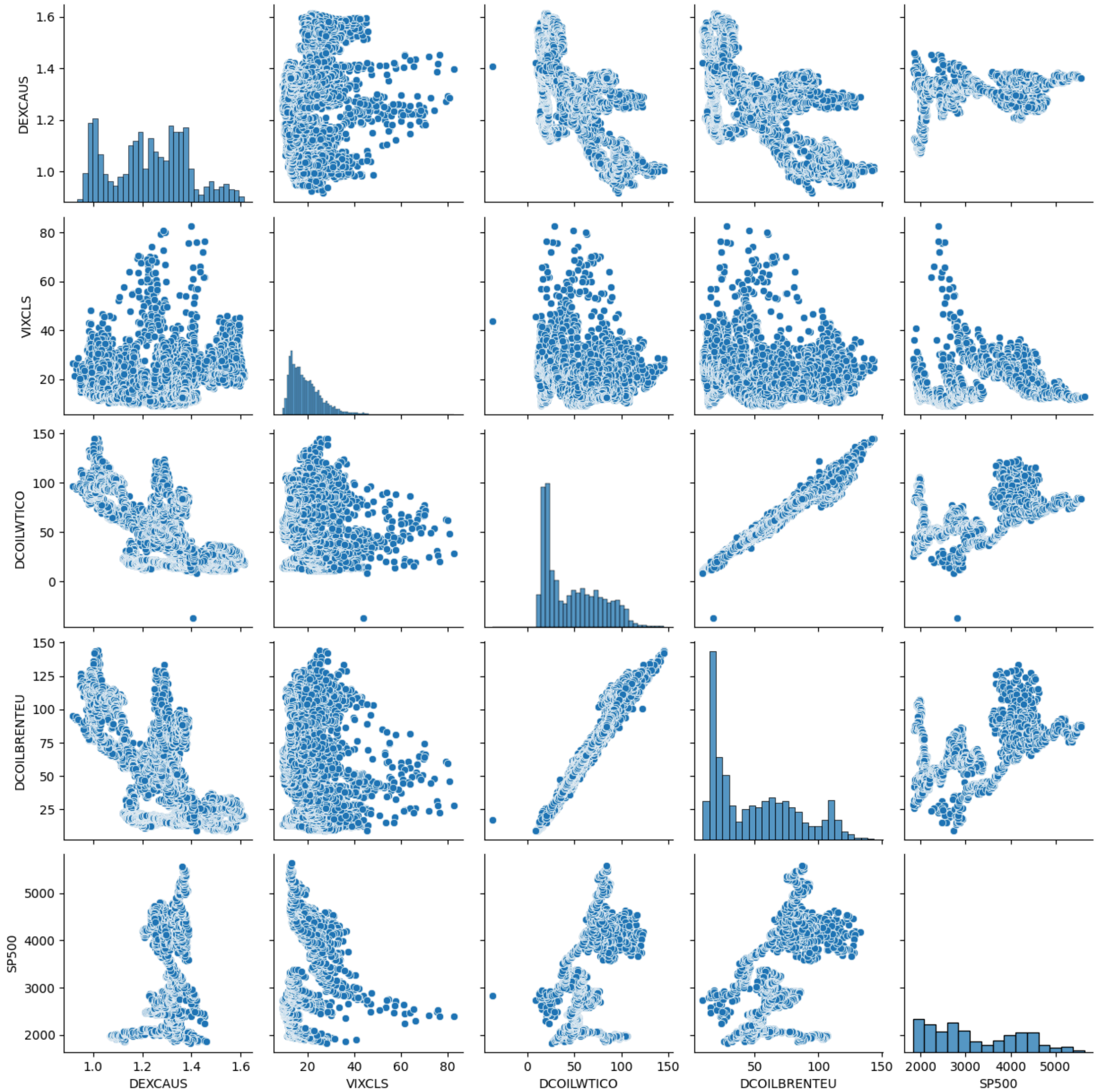

Distribution of VIXCLS
Count
VIXCLS
0
100
200
300
400
500
600
700
10
20
30
40
50
60
70
80


Distribution of DCOILWTICO
Count
0
200
400
600
800
1000
1200
1400
1600
−25
0
25
50
75
100
125
150
DCOILWTICO

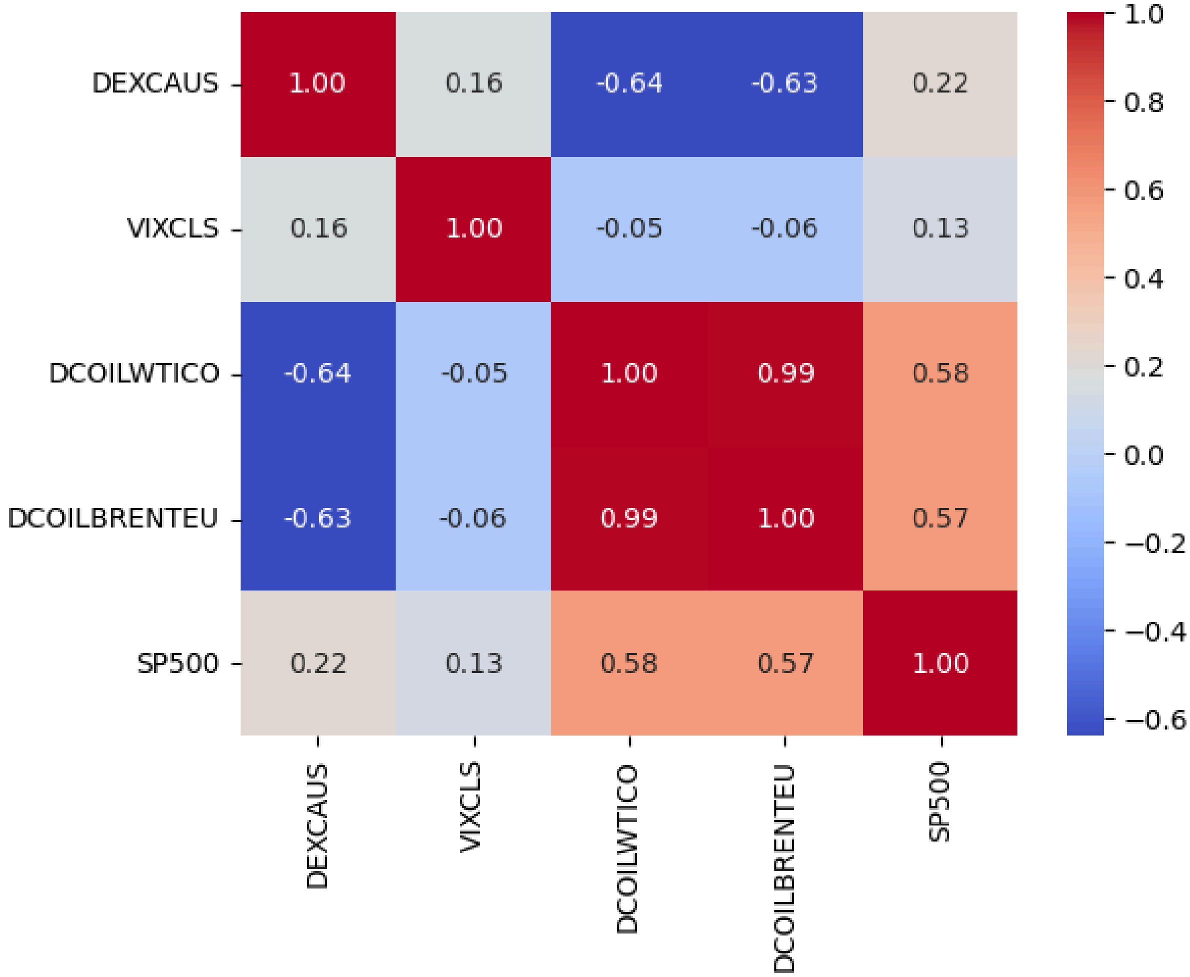

Distribution of DCOILBRENTEU
Count
0
250
500
750
1000
1250
1500
1750
2000
20
40
60
80
100
120
140
DCOILBRENTEU



In [33]:
```
# Scatter plot matrix
sns.pairplot(fin_data)
plt.show()
```

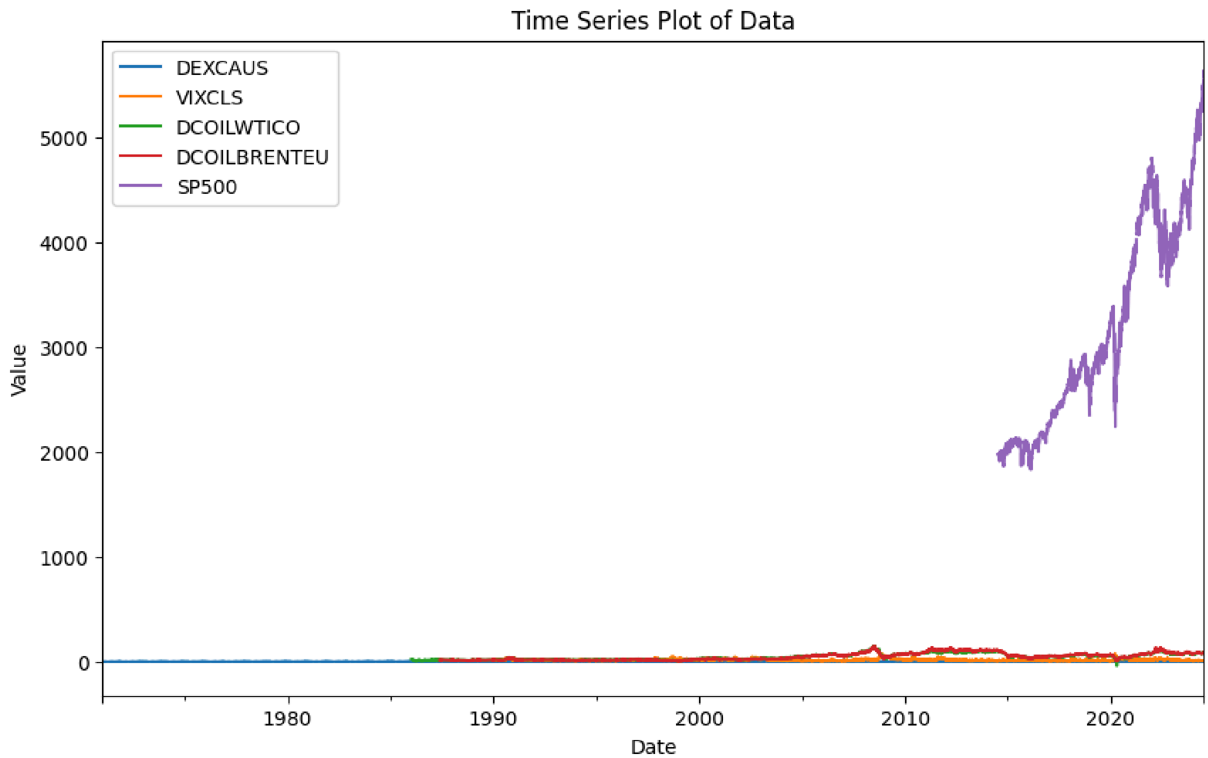


In [34]:
```
# Correlation matrix
corr_matrix = fin_data.corr()
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.show()
```

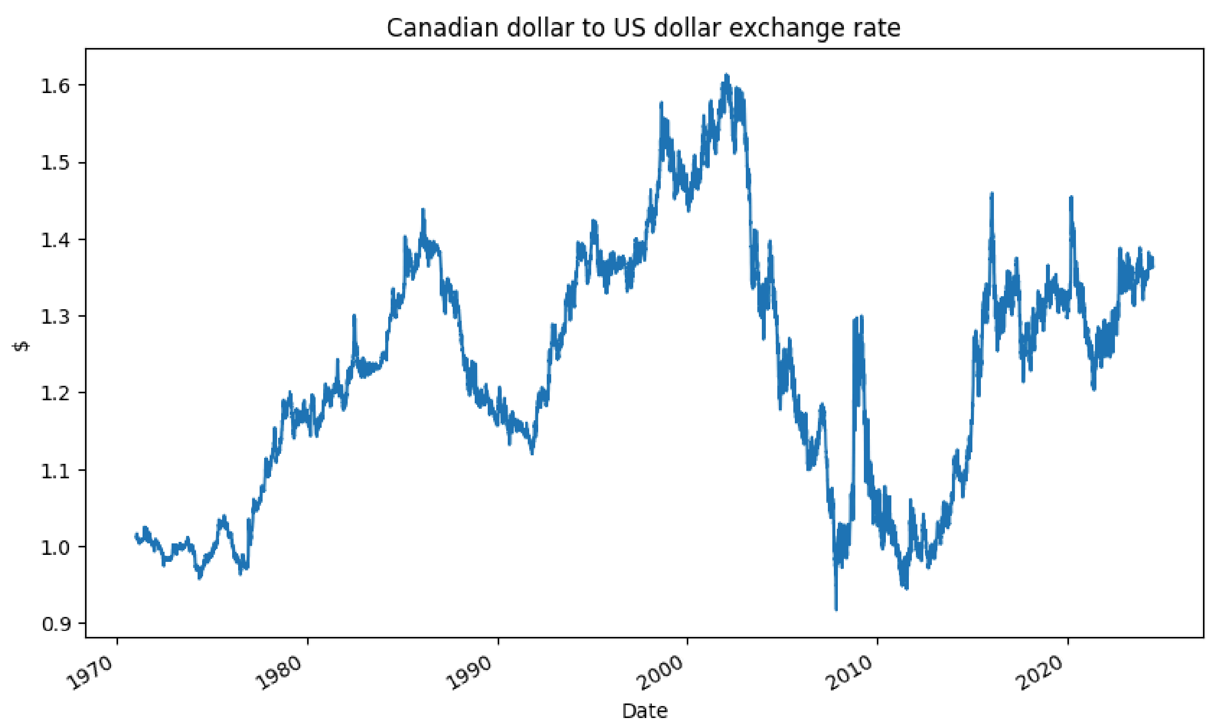


Time Series Plot of Financial Data

In [35]:
```
# Time series plot
fin_data.plot(figsize=(10, 6))
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("Time Series Plot of Data")
plt.show()
```

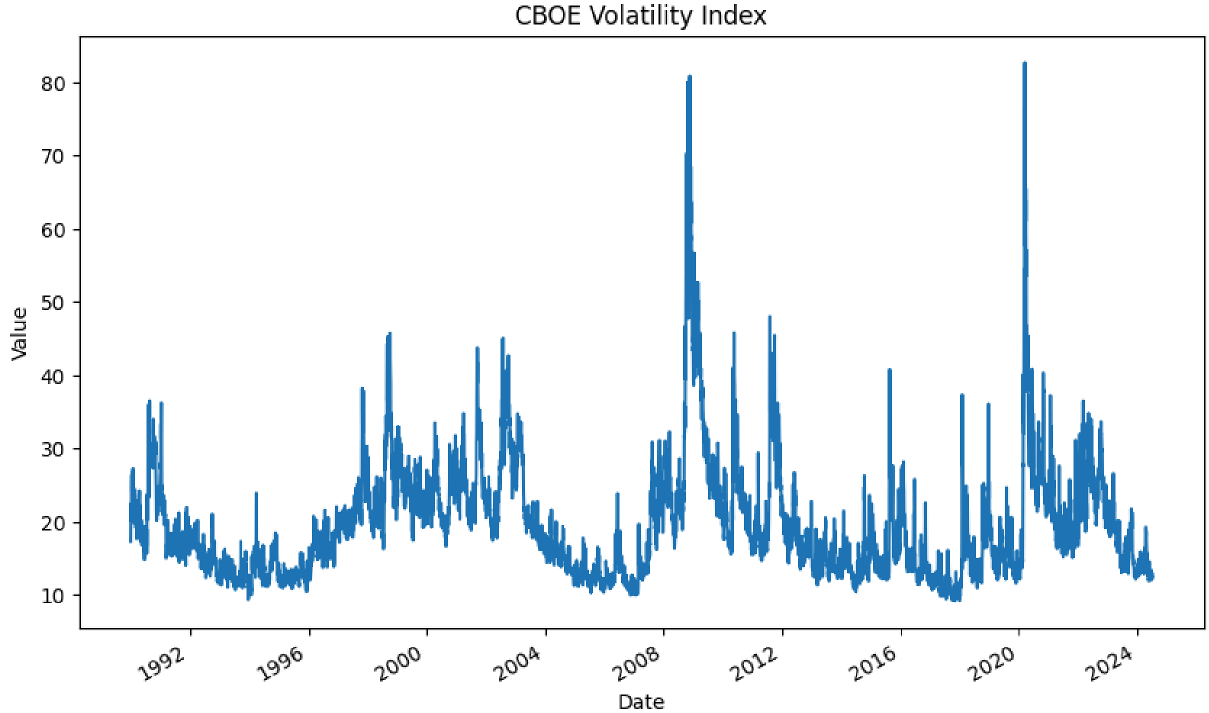


In [36]:
```
# Time series plot
fin_data['DEXCAUS'].dropna().plot(figsize=(10, 6))  # Canadian dollar to US dollar ex
plt.xlabel("Date")
plt.ylabel("$")
plt.title("Canadian dollar to US dollar exchange rate")
plt.show()
```

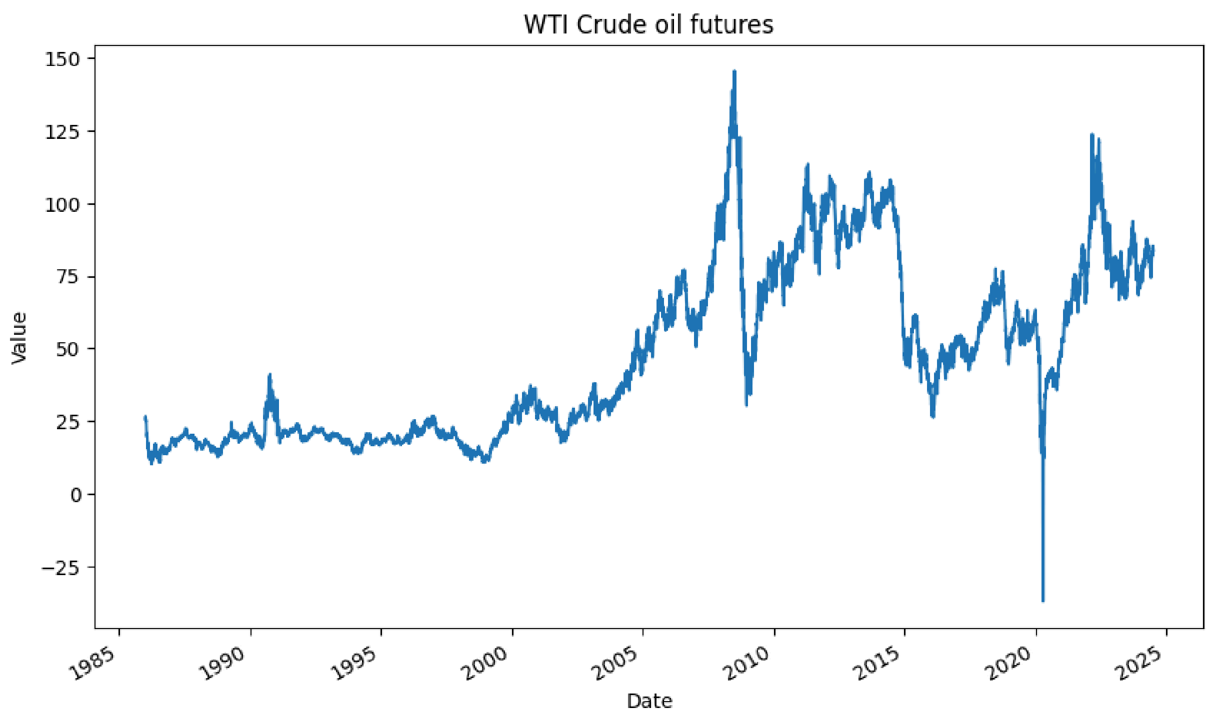


In [37]:
```
# Time series plot
fin_data['VIXCLS'].dropna().plot(figsize=(10, 6))  # CBOE Volatility Index
plt.xlabel("Date")
```

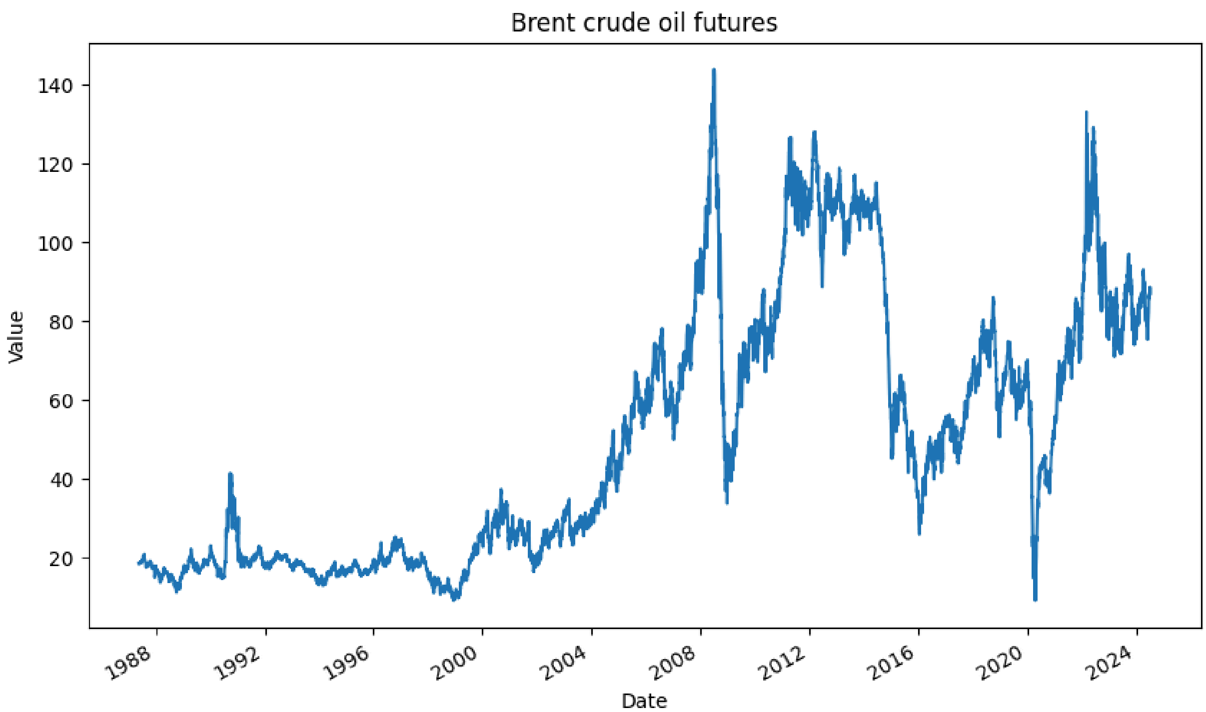
```
plt.ylabel("Value")
plt.title("CBOE Volatility Index")
plt.show()
```



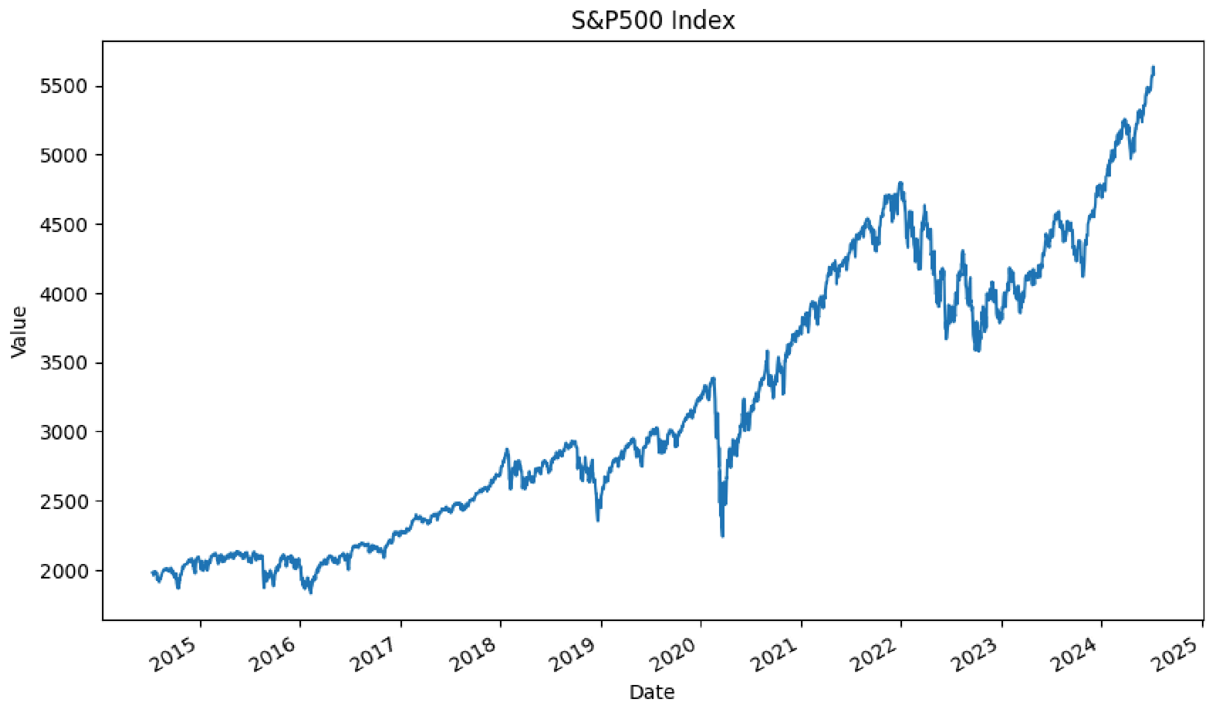
In [38]:
```
# Time series plot
fin_data['DCOILWTICO'].dropna().plot(figsize=(10, 6))  # WTI Crude oil futures
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("WTI Crude oil futures")
plt.show()
```



In [39]:
```
# Time series plot
fin_data['DCOILBRENTEU'].dropna().plot(figsize=(10, 6))  # Brent crude oil futures
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("Brent crude oil futures")
plt.show()
```

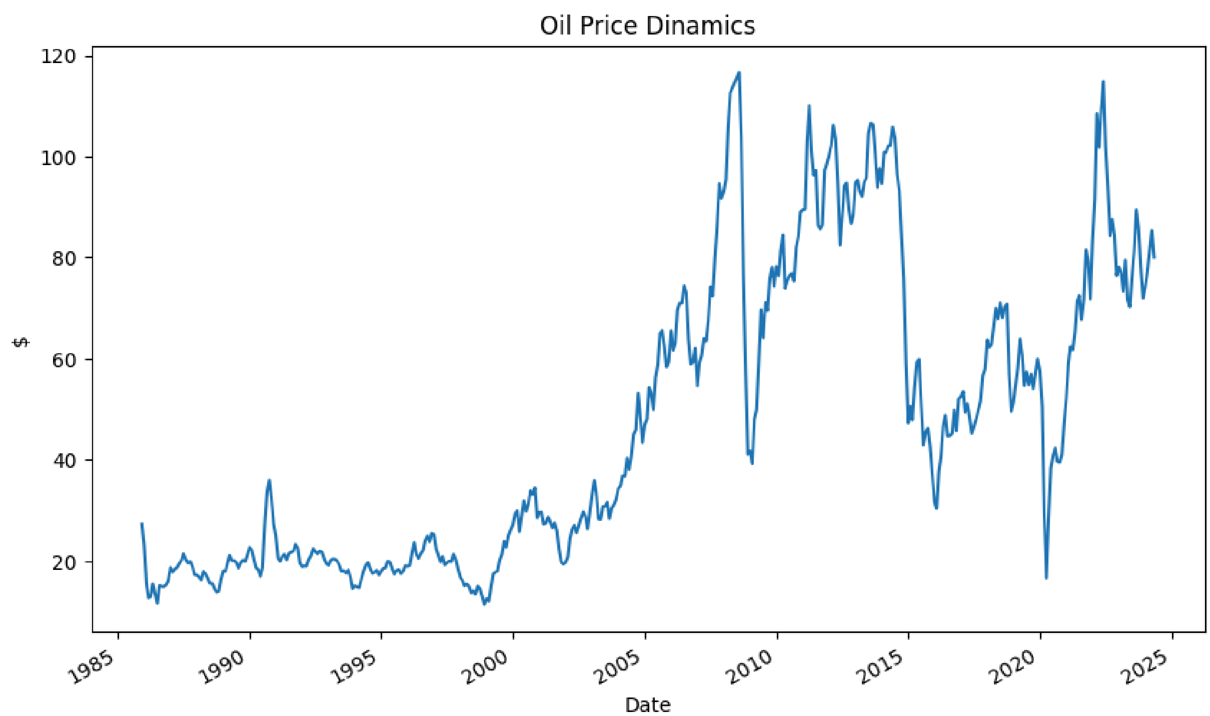


In [40]:
```
# Time series plot
fin_data['SP500'].dropna().plot(figsize=(10, 6))  # S&P500 Index
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("S&P500 Index")
plt.show()
```



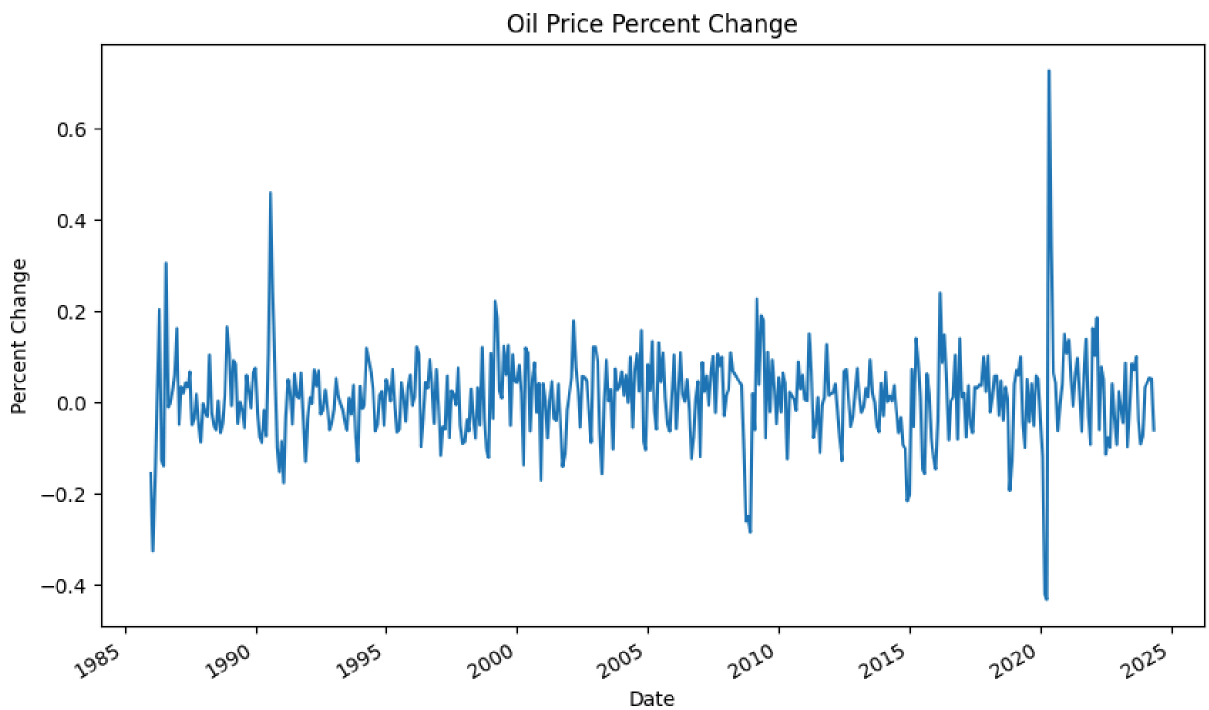
Step 8

In [63]:
```
# Time series plot
df_new['WTISPLC'].plot(figsize=(10, 6))  # Spot Crude Oil Price: West Texas Intermedi
plt.xlabel("Date")
plt.ylabel("$")
plt.title("Oil Price Dinamics")
plt.show()
```



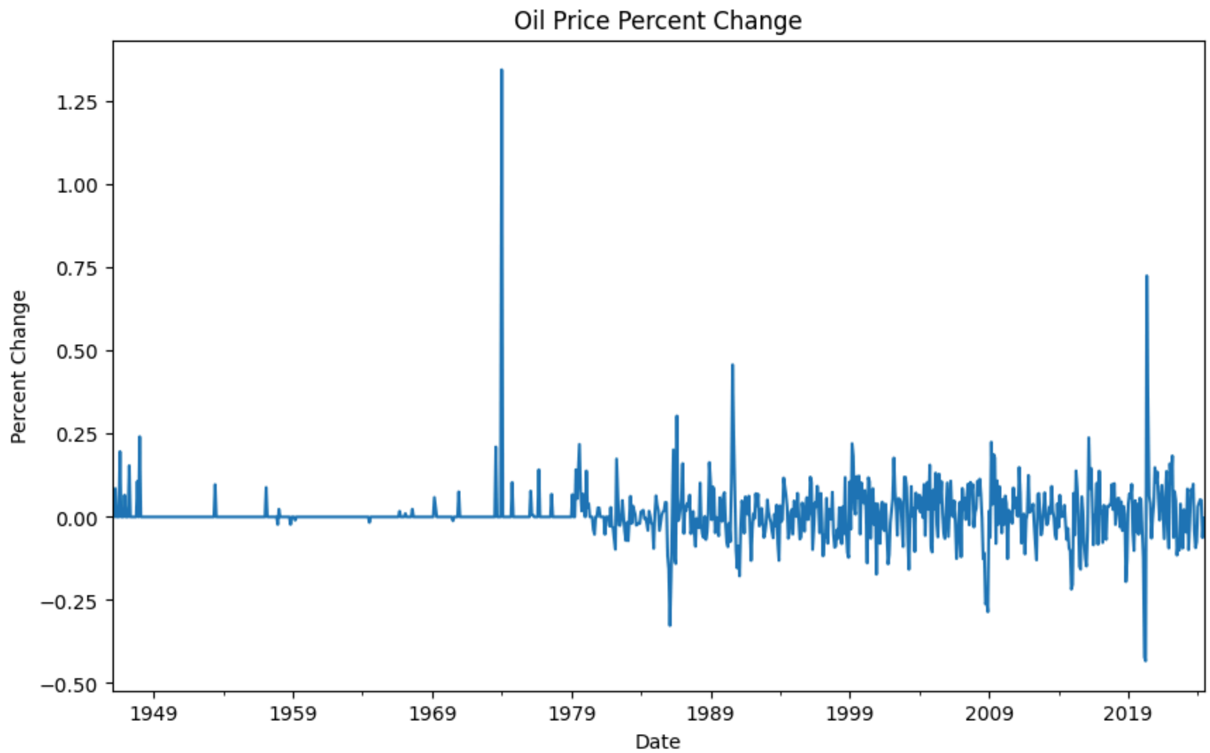
We see that the for the period 2000 - 2024 Oil price is locked in a very big range from $20 till$ 140 with big spikes and steep declines as well. Usually the big spikes are at periods of booming economy and afterwards followed by crisis that are known with low consumption of oil so it is quite normal for prices to normalize and fall down. Such booming economy periods are 2002 - 2008, 2010 - 2012, 2020 - 2023 and they are followoed crisis (2008 - 2009 The Gread Financial Crisis, 2015-2016, 2019-2020 Covid19) and step decline in demand for oil.

In [64]:
```
df_new['WTISPLC'].pct_change().plot(figsize=(10, 6))
plt.xlabel("Date")
plt.ylabel("Percent Change")
plt.title("Oil Price Percent Change")
plt.show()
```



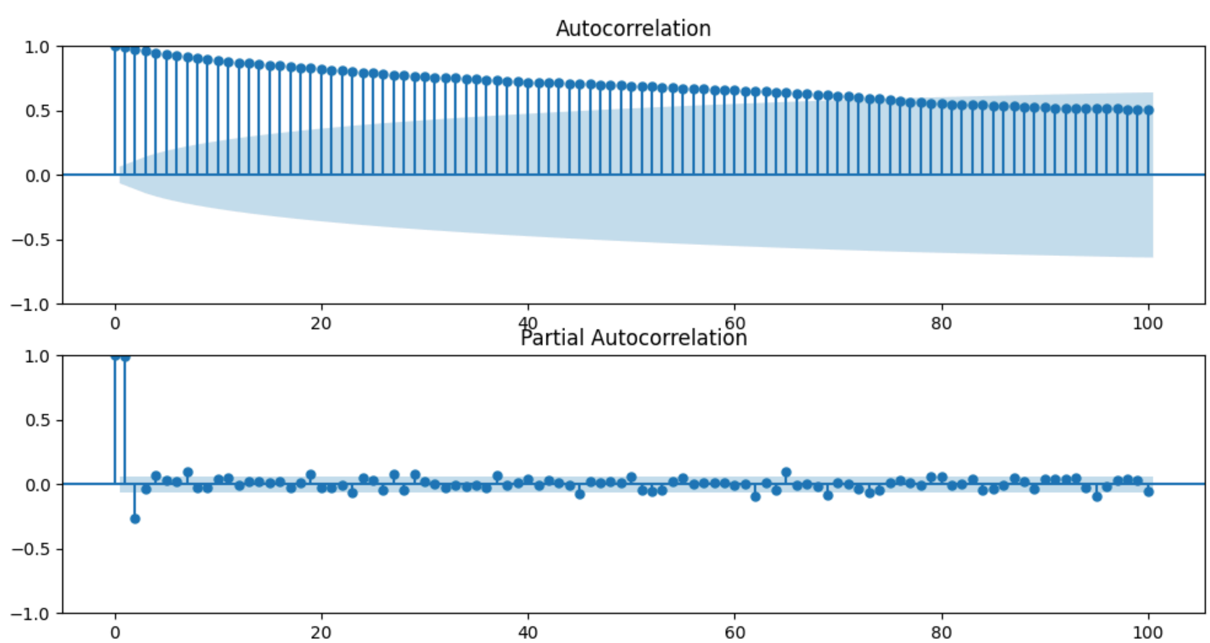
We can say that the plot of Oil prices returns for the period 2000 - 2024 look quite normal (but we have to check it with some statistical methods) with the biggest spike arround Covid19. Lets look at the bigger picture: all the data

In [43]:
```
data_merge['WTISPLC'].dropna().pct_change().plot(figsize=(10, 6))
plt.xlabel("Date")
plt.ylabel("Percent Change")
plt.title("Oil Price Percent Change")
plt.show()
```



The entire Oil returns data show a more ugly picture with a lot more spikes. Lets see the ACF and Pacf plots for more insights

In [44]:
```
# Create the plots
fig, axes = plt.subplots(2, figsize=(12,6))
plot_acf(data_merge['WTISPLC'].dropna(), lags=100, ax=axes[0])
plot_pacf(data_merge['WTISPLC'].dropna(), lags=100, ax=axes[1])
plt.show()
```



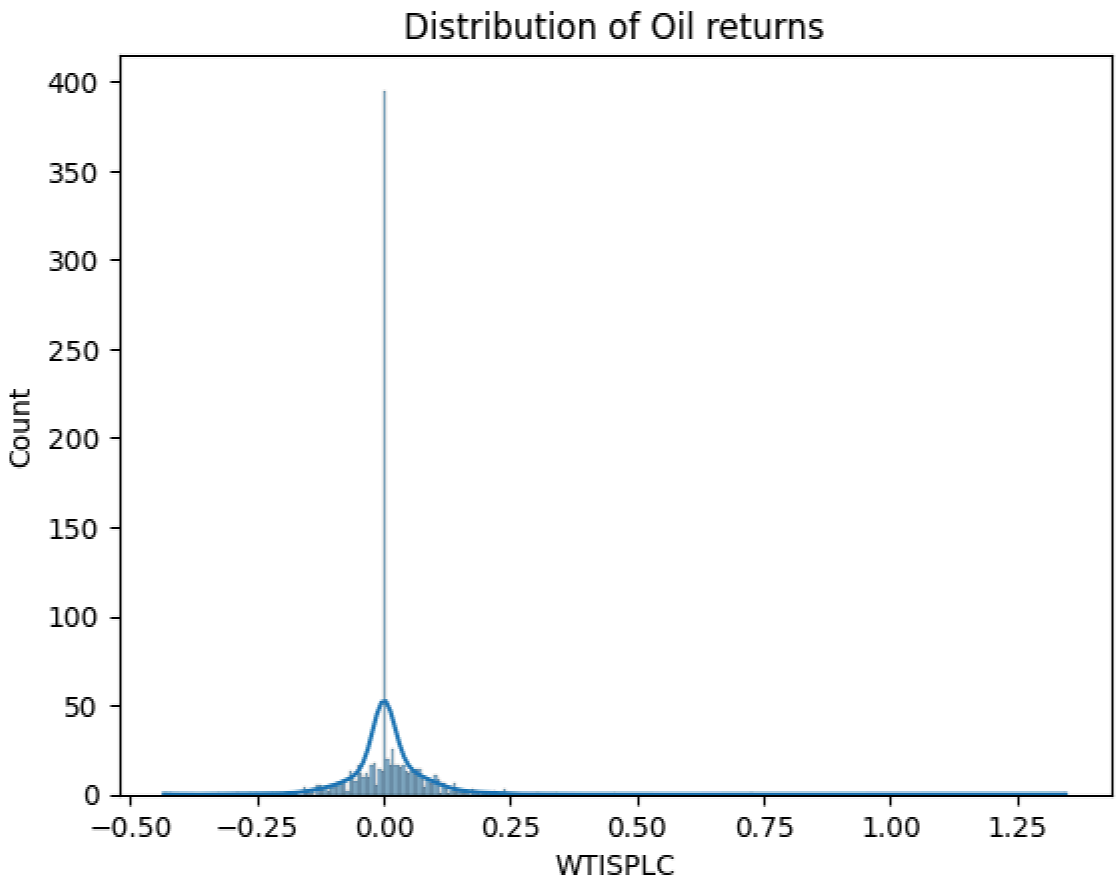
From the ACF plot we can see that there is trend in the Oil price, which is quite normal as everithing with time goes uo thanks to the inflation (a totally normal process). The interesting thing is the PACF where we can see that there is a seasonality pathern where we can see that at the begining of the year there is a downward spike (during the northern globe is winter and since there is most of the population located and the fact that it is winter suggests that there is also a lower demand for Oil) and also during the summer of the year (I am talking about the northern globe seasons) then an upward spike in the Oil consumption because it is summer time and a lot of traweling is happening at this time of the year

In [45]:
```
# Perform ADF test
print('Results of ADF Test:')
# Replace infinite or nan values with finite numbers
data_merge['WTISPLC'] = data_merge['WTISPLC'].replace([np.inf, -np.inf], np.nan).fill
# Calculate percentage change on the shifted series to avoid introducing NaNs
dftest = adfuller(data_merge['WTISPLC'].dropna().shift().pct_change().dropna())
dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','P-value','#Lags Used','Num
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value
print(dfoutput)
```

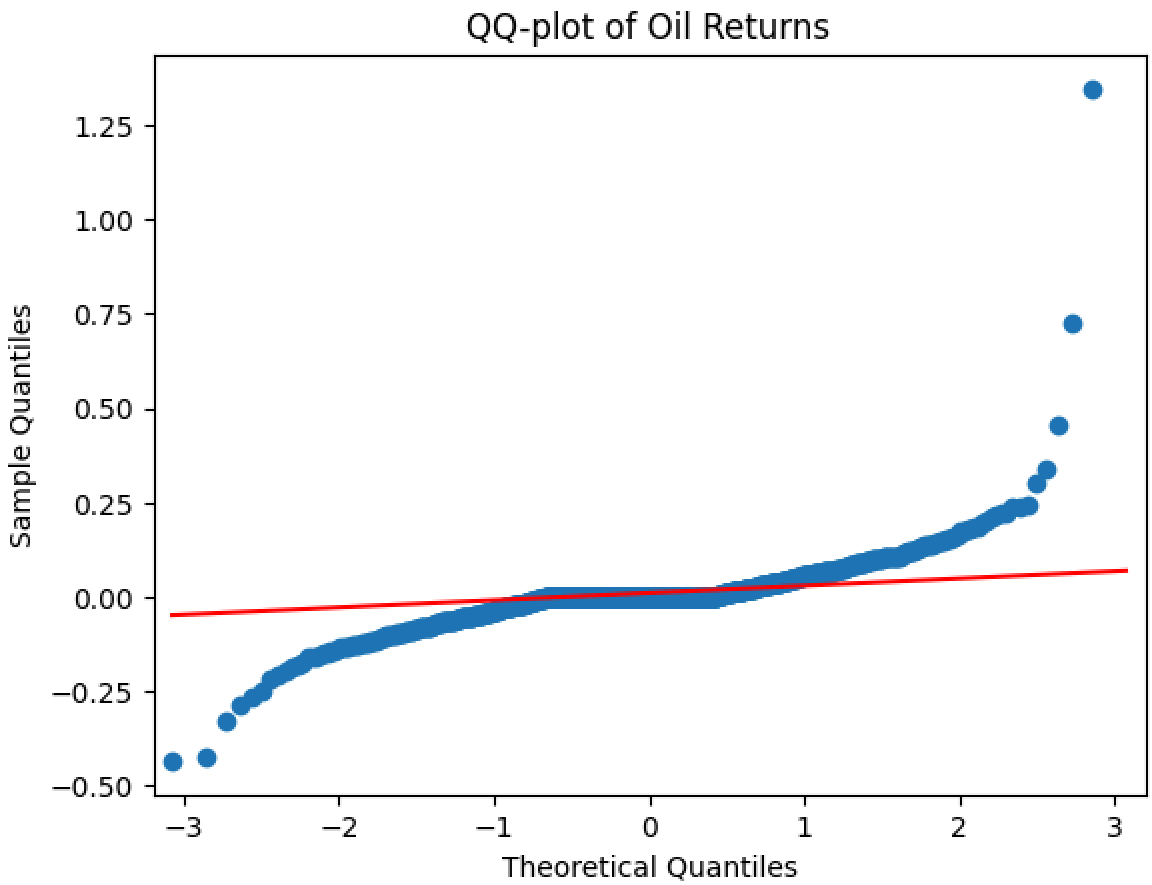
```
Results of ADF Test:
Test Statistic                -1.633727e+01
P-value                        3.020024e-29
#Lags Used                     3.000000e+00
Number of Observations Used    9.360000e+02
Critical Value (1%)           -3.437356e+00
Critical Value (5%)           -2.864633e+00
Critical Value (10%)          -2.568417e+00
dtype: float64
```

Here the ADF test's p-value of 3.020962e-29 proves that the data is it is very unlikely that the data has a unir root so the data is stationary

In [66]:
```
#
plt.figure()
sns.histplot(data_merge['WTISPLC'].dropna().pct_change(), kde=True)
plt.title(f"Distribution of Oil returns")
plt.show()
```



In [65]:
```
fig = sm.qqplot(data_merge['WTISPLC'].dropna().pct_change(), line='q')
plt.title('QQ-plot of Oil Returns')
plt.show()
```



Lets do some exploration about whether the Oil returns data is normally distributed and we are doing this by a QQ-plot that shows that the data has big tails and this suggest that overall the data may look like it is normally distributed by the bell shaped histogram plot. Actually it is not because of the fat tails. For better proove of this hypothesis we will do the statistical test for normallity check called Shapiro-Wilk test for normallity. This will undeniably prove or deny the hipothesis mentioned above

In [48]:
```
# Shapiro-Wilk Test
statistic, p_value = stats.shapiro(data_merge['WTISPLC'].dropna())
print('Shapiro-Wilk Test:')
print('Statistic:', statistic)
print('P-value:', p_value)
```

```
Shapiro-Wilk Test:
Statistic: 0.8222251534461975
P-value: 4.956003613292808e-31
```

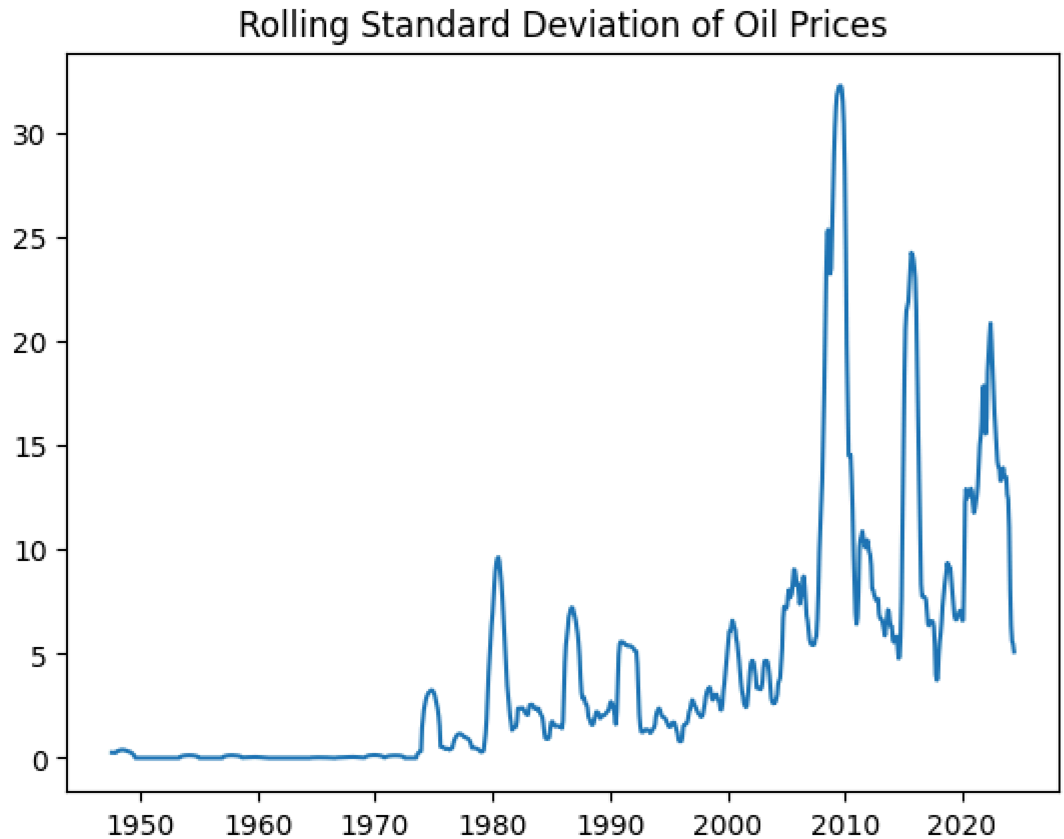
Yet againd a p-value of 4.912296382340533e-31 for Shapiro-Wilk normallity test proves the the data is not normally distributed. With such a small p-value we cannot accept the null hypothesis (which suggests that the data is normally distributed) so in this case we fail to accept it and we can say that we have statistically proved that the data is NOT normally distributed. Something else is very interesting and it is the statistic= 0.822 for simularity to a normal distribution. This suggest that the data is close to a normal distributio (the bell shape) but the fat tails fails this thesis

In [49]:
```
from statsmodels.stats.diagnostic import acorr_ljungbox

# Perform Ljung-Box test up to lag 10
result = acorr_ljungbox(data_merge['WTISPLC'].dropna(), lags=10)

print(result)
```

```
        lb_stat      lb_pvalue
1    928.818987  5.333691e-204
2   1834.309316   0.000000e+00
3   2713.712826   0.000000e+00
4   3568.678890   0.000000e+00
5   4401.499486   0.000000e+00
6   5214.266084   0.000000e+00
7   6010.910499   0.000000e+00
8   6792.604186   0.000000e+00
9   7559.300054   0.000000e+00
10  8311.736911   0.000000e+00
```

With Ljung-Box Test we check for autocorrelation and prove that there is such with lag of 1. (The lag 1 p-value of Ljung-Box Test is: 6.392185e-204 which is a lot lower than 0.05). This is also visible in the PACF plot but it is good to have it statistically proven

In [50]:
```
data = data_merge['WTISPLC'].dropna()

# Calculate and plot rolling standard deviation (e.g., 20-period window)
rolling_std = data.rolling(window=20).std()
plt.plot(rolling_std)
plt.title('Rolling Standard Deviation of Oil Prices')
plt.show()
```



It is quite normal for Oil prices to have big spikes in volatility (expecially in war time periods) but also a big trough are quite normal at time of crisis where the demand and usage of oil is much lower than normally like in the 2008 Financial crisis and the Covid19 as well. So with the plot of the Rolling Standard Deviation of Oil Prices we can see exactly that: volatility clustering arround periods of boom and bust (economy progress and crisis)

```
In [50]:
```