In [ ]:
```
!pip install patool
```

```
Collecting patool
  Downloading patool-2.1.1-py2.py3-none-any.whl (94 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 94.6/94.6 kB 3.2 MB/s eta 0:00:00
Installing collected packages: patool
Successfully installed patool-2.1.1
```

In [ ]:
```
import patoolib
```

In [ ]:
```
patoolib.extract_archive('/content/hmda_2017_ny_all-records_labels.zip')
```

```
INFO patool: Extracting /content/hmda_2017_ny_all-records_labels.zip ...
INFO:patool:Extracting /content/hmda_2017_ny_all-records_labels.zip ...
INFO patool: running /usr/bin/7z x -o./Unpack_bez28goz -- /content/hmda_2017_ny_al
l-records_labels.zip
INFO:patool:running /usr/bin/7z x -o./Unpack_bez28goz -- /content/hmda_2017_ny_all
-records_labels.zip
INFO patool:     with input=''
INFO:patool:    with input=''
INFO patool: ... /content/hmda_2017_ny_all-records_labels.zip extracted to `hmda_2
017_ny_all-records_labels.csv'.
INFO:patool:... /content/hmda_2017_ny_all-records_labels.zip extracted to `hmda_20
17_ny_all-records_labels.csv'.
```

Out[ ]:
```
'hmda_2017_ny_all-records_labels.csv'
```

In [ ]:
```
patoolib.extract_archive('/content/hmda_2007_ny_all-records_labels.zip')
```

```
INFO patool: Extracting /content/hmda_2007_ny_all-records_labels.zip ...
INFO:patool:Extracting /content/hmda_2007_ny_all-records_labels.zip ...
INFO patool: running /usr/bin/7z x -o./Unpack_vkzwyw48 -- /content/hmda_2007_ny_al
l-records_labels.zip
INFO:patool:running /usr/bin/7z x -o./Unpack_vkzwyw48 -- /content/hmda_2007_ny_all
-records_labels.zip
INFO patool:     with input=''
INFO:patool:    with input=''
INFO patool: ... /content/hmda_2007_ny_all-records_labels.zip extracted to `hmda_2
007_ny_all-records_labels.csv'.
INFO:patool:... /content/hmda_2007_ny_all-records_labels.zip extracted to `hmda_20
07_ny_all-records_labels.csv'.
```

Out[ ]:
```
'hmda_2007_ny_all-records_labels.csv'
```

In [18]:
```
import datetime

import numpy as np
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import yfinance as yfin
from scipy import stats


yfin.pdr_override()
```

Money at a floating rate for a secured purchase.

For this task, we use the large-scale real-world mortgage dataset HMDA dataset from https://www.consumerfinance.gov/data-research/hmda/historic-data/?geo=ny&records=all-records&field_descriptions=labels. We take the data from 2 different years, specificlly 2007 and 2017.

In [ ]:
```
hmda_file_2017 = "/content/hmda_2017_ny_all-records_labels.csv"
hmda_data_2017 = pd.read_csv(hmda_file_2017)
```

```
<ipython-input-3-94233b771cbc>:2: DtypeWarning: Columns (34,36,38,44,46,48) have m
ixed types. Specify dtype option on import or set low_memory=False.
  hmda_data_2017 = pd.read_csv(hmda_file_2017)
```

In [ ]:
```
hmda_file_2007 = "/content/hmda_2007_ny_all-records_labels.csv"
hmda_data_2007 = pd.read_csv(hmda_file_2007)
```

```
<ipython-input-4-9f2893ce7a73>:2: DtypeWarning: Columns (34,36,38,42,44,46,48) hav
e mixed types. Specify dtype option on import or set low_memory=False.
  hmda_data_2007 = pd.read_csv(hmda_file_2007)
```

In [ ]:
```
hmda_data_2017['action_taken_name'].unique()
```

Out[ ]:
```
array(['Loan originated', 'Application denied by financial institution',
       'Application approved but not accepted',
       'Loan purchased by the institution',
       'Application withdrawn by applicant',
       'File closed for incompleteness',
       'Preapproval request approved but not accepted',
       'Preapproval request denied by financial institution'],
      dtype=object)
```

In [ ]:
```
approved_set = ['Loan originated', 'Application approved but not accepted', 'Preapp
denined_set = ['Application denied by financial institution', 'Preapproval request
```

In [ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.svm import SVC

def process_df(hmda_data_2017):
  # Simplify the model by selecting a subset of features
  selected_features = ["applicant_income_000s", "applicant_race_name_1", "applicant

  # Preparing the dataset
  hmda_data_2017['loan_approved'] = hmda_data_2017['action_taken_name'].apply(lambd
  hmda_data_2017.dropna(subset=['loan_approved'], inplace=True)
  hmda_data_2017 = hmda_data_2017[selected_features + ['loan_approved']]
  X = hmda_data_2017.drop('loan_approved', axis=1)
  y = hmda_data_2017['loan_approved']

  # Convert categorical columns to strings to avoid type issues
  categorical_cols = X.select_dtypes(include=['object', 'category']).columns
  X[categorical_cols] = X[categorical_cols].astype(str)

  return X, y, categorical_cols
```

In [ ]:
```
X, y, categorical_cols = process_df(hmda_data_2007)
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Preprocessing for numerical data
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())])

# Preprocessing for categorical data
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])

# Bundle preprocessing for numerical and categorical data
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, X.select_dtypes(include=['int64', 'float64']).
        ('cat', categorical_transformer, categorical_cols)])

# Define the model
model = RandomForestClassifier(random_state=42)
#model = SVC(kernel="linear", C=0.025, random_state=42)

# Bundle preprocessing and modeling code in a pipeline
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('model', model)])

# Preprocessing of training data, fit model
pipeline.fit(X_train, y_train)

# Preprocessing of validation data, get predictions
preds = pipeline.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, preds)
```

```
classification_rep = classification_report(y_test, preds)

print("Model Accuracy:", accuracy)
print("Classification Report:\n", classification_rep)
```

```
Model Accuracy: 0.6733522451718342
Classification Report:
               precision    recall  f1-score   support

         0.0       0.55      0.44      0.49     53185
         1.0       0.72      0.80      0.76     97338

    accuracy                           0.67    150523
   macro avg       0.64      0.62      0.62    150523
weighted avg       0.66      0.67      0.66    150523
```

In [ ]:

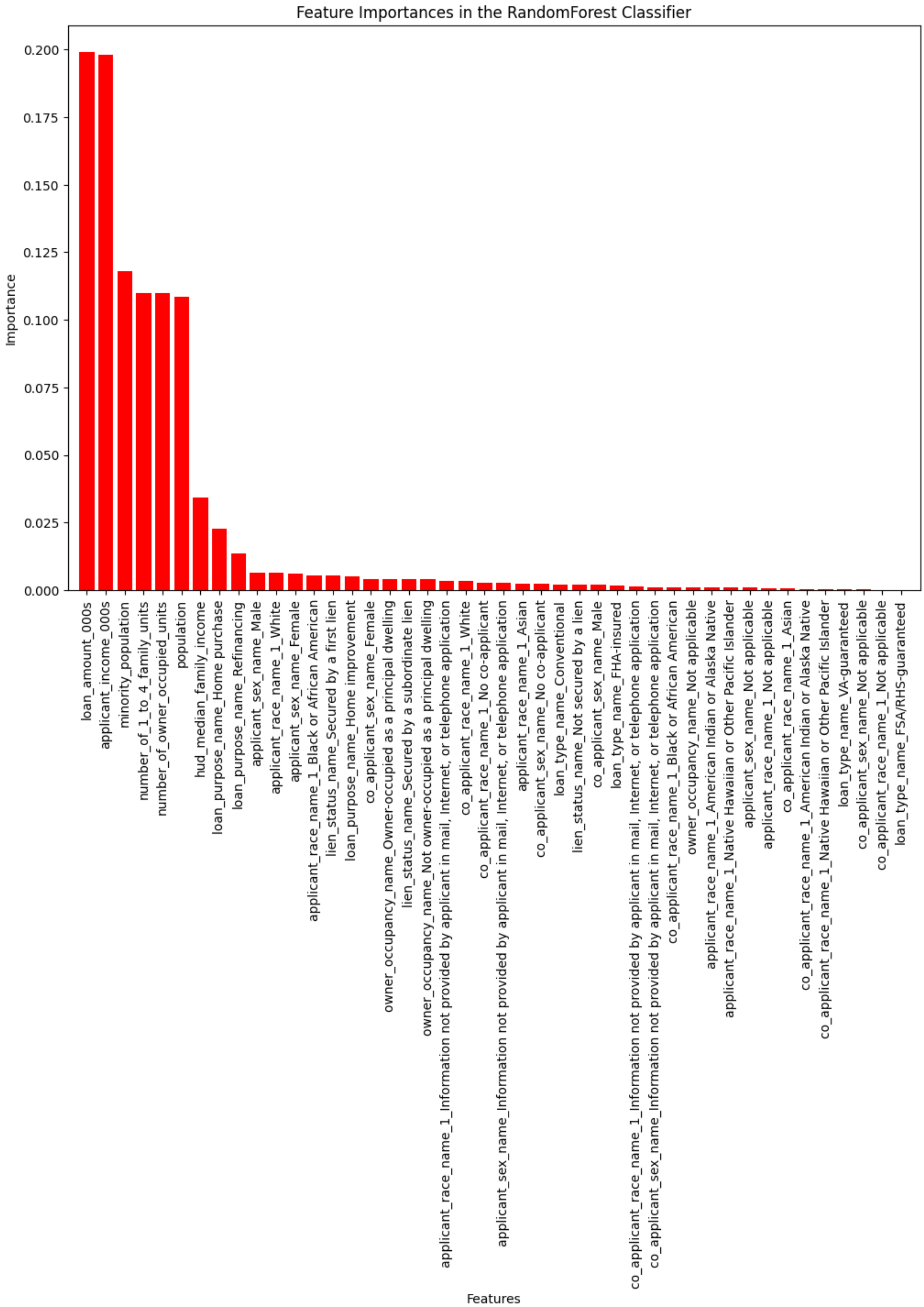
```
X_future, y_future, _ = process_df(hmda_data_2017)
preds = pipeline.predict(X_future)
# Evaluate the model
accuracy = accuracy_score(y_future, preds)
classification_rep = classification_report(y_future, preds)

print("Model Accuracy (Future):", accuracy)
print("Classification Report (Future):\n", classification_rep)
```

```
Model Accuracy (Future): 0.7695051729787932
Classification Report (Future):
               precision    recall  f1-score   support

           0       0.44      0.28      0.34     68266
           1       0.82      0.90      0.86    252149

    accuracy                           0.77    320415
   macro avg       0.63      0.59      0.60    320415
weighted avg       0.74      0.77      0.75    320415
```

In [ ]:

```
import matplotlib.pyplot as plt
import numpy as np

# Retrieve the feature importances from the trained RandomForestClassifier
feature_importances = pipeline.named_steps['model'].feature_importances_

# Get the feature names after one-hot encoding
feature_names_transformed = pipeline.named_steps['preprocessor'].transformers_[1][1
    .named_steps['onehot'].get_feature_names_out(input_features=categorical_cols)

# Combine with numeric feature names
feature_names = np.concatenate([X.select_dtypes(include=['int64', 'float64']).colum

# Sort the features by importance
indices = np.argsort(feature_importances)[::-1]

# Visualize the feature importances
plt.figure(figsize=(12, 8))
plt.title("Feature Importances in the RandomForest Classifier")
plt.bar(range(len(feature_importances)), feature_importances[indices], color="r", a
plt.xticks(range(len(feature_importances)), feature_names[indices], rotation=90)
plt.xlim([-1, len(feature_importances)])
plt.ylabel('Importance')
plt.xlabel('Features')
plt.tight_layout()  # Adjust layout to make room for the rotated x-axis labels
plt.show()
```

```
<ipython-input-11-0507a6c53b1e>:25: UserWarning: Tight layout not applied. The bot
tom and top margins cannot be made large enough to accommodate all axes decoration
s.
  plt.tight_layout()  # Adjust layout to make room for the rotated x-axis labels
```



Publicly traded Equity (e.g. common stock) – that is, securities lending of a stock.

NVIDIA Stock Analysis

In [2]:
```
#To analyze a publicly traded stock I have used 5 years of NVIDIA data using yahoo
```

In [3]:
```
#Downloading the data using yahoo Finance
import datetime
start = datetime.date(2019, 1, 1)
end = datetime.date(2023, 12, 31)
df = web.DataReader(["NVDA"], start, end)
```

```
[*********************100%%**********************]  1 of 1 completed
```

In [4]:
```
df_VIXN = web.DataReader(["^VIX"], start, end)["Adj Close"]
```

```
[*********************100%%**********************]  1 of 1 completed
```

In [5]:
```
#Merging the VIX index data with our NVDIA dataset
df = df.merge(df_VIXN, on="Date", how="outer")
df.rename(columns={'Adj Close_y': 'VIX index'}, inplace=True)
df.describe()
```

Out[5]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX inde
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.00000
mean	177.352243	180.632174	173.983038	177.463569	177.238880	4.626251e+07	21.36791
std	124.757333	126.716487	122.525187	124.675773	124.722888	1.998936e+07	8.23879
min	32.660000	33.790001	31.922501	31.997499	31.748953	9.788400e+06	11.54000
25%	69.150000	70.550625	67.028126	68.320625	68.064878	3.246800e+07	15.96000
50%	145.784996	148.631248	142.300003	145.820000	145.548157	4.319750e+07	19.52500
75%	231.895000	236.667503	225.437496	230.927502	230.648735	5.645790e+07	24.79999
max	502.160004	505.480011	494.119995	504.089996	504.045685	2.511528e+08	82.69000

In [6]:
```
#Viewing the data
df.head()
```

Out[6]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX index
Date							
2019-01-02	32.660000	34.619999	32.512501	34.055000	33.790478	50875200	23.219999
2019-01-03	33.447498	33.790001	31.922501	31.997499	31.748953	70555200	25.450001
2019-01-04	32.735001	34.432499	32.424999	34.047501	33.783035	58562000	21.379999
2019-01-07	34.625000	36.222500	34.107498	35.849998	35.571537	70916000	21.400000
2019-01-08	36.672501	36.695000	34.224998	34.957500	34.685959	78601600	20.469999

In [7]:
```
#stats Summary of our data
df.describe()
```

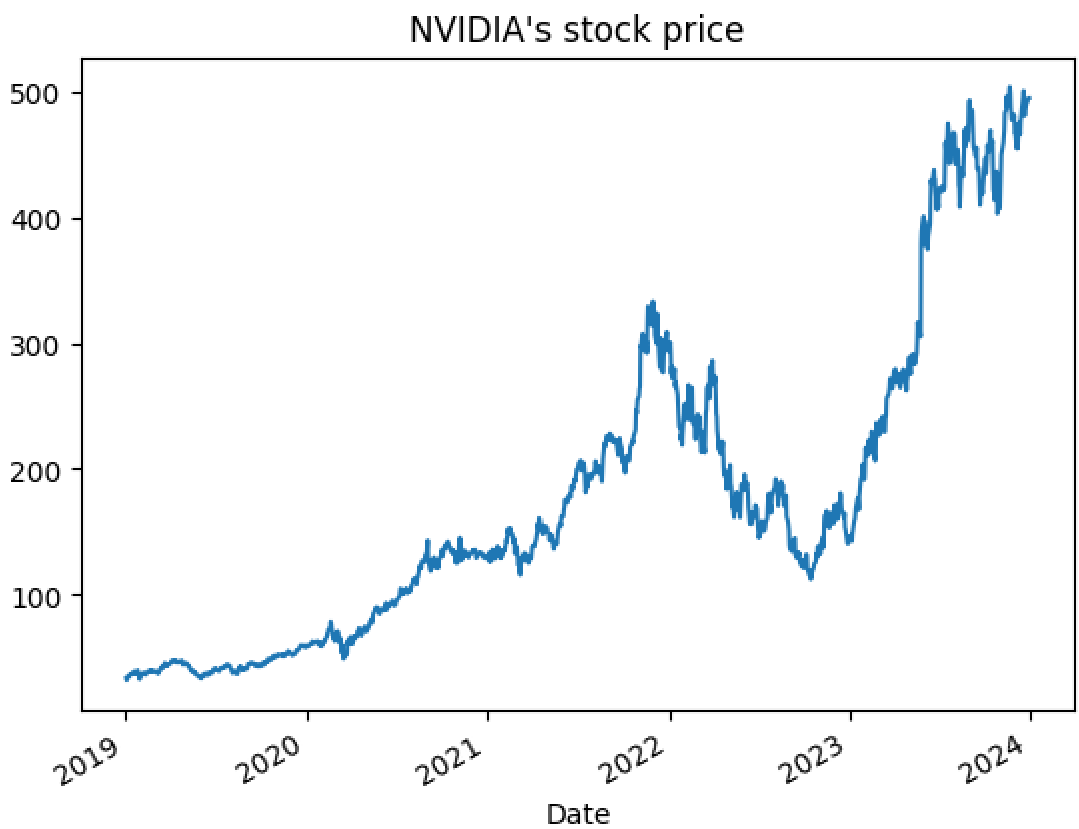
Out[7]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX inde
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.00000
mean	177.352243	180.632174	173.983038	177.463569	177.238880	4.626251e+07	21.36791
std	124.757333	126.716487	122.525187	124.675773	124.722888	1.998936e+07	8.23879
min	32.660000	33.790001	31.922501	31.997499	31.748953	9.788400e+06	11.54000
25%	69.150000	70.550625	67.028126	68.320625	68.064878	3.246800e+07	15.96000
50%	145.784996	148.631248	142.300003	145.820000	145.548157	4.319750e+07	19.52500
75%	231.895000	236.667503	225.437496	230.927502	230.648735	5.645790e+07	24.79999
max	502.160004	505.480011	494.119995	504.089996	504.045685	2.511528e+08	82.69000

Time Series Analysis

In [8]:
```
#Plotting the time series data
df['Adj Close_x'].plot(title="NVIDIA's stock price")
```

Out[8]:
```
<Axes: title={'center': "NVIDIA's stock price"}, xlabel='Date'>
```



Time Series data from 2019-2023 of NVDIA stock

In [9]:
```
# Importing Plotply for Plotting
import plotly.graph_objects as go
from datetime import datetime
```

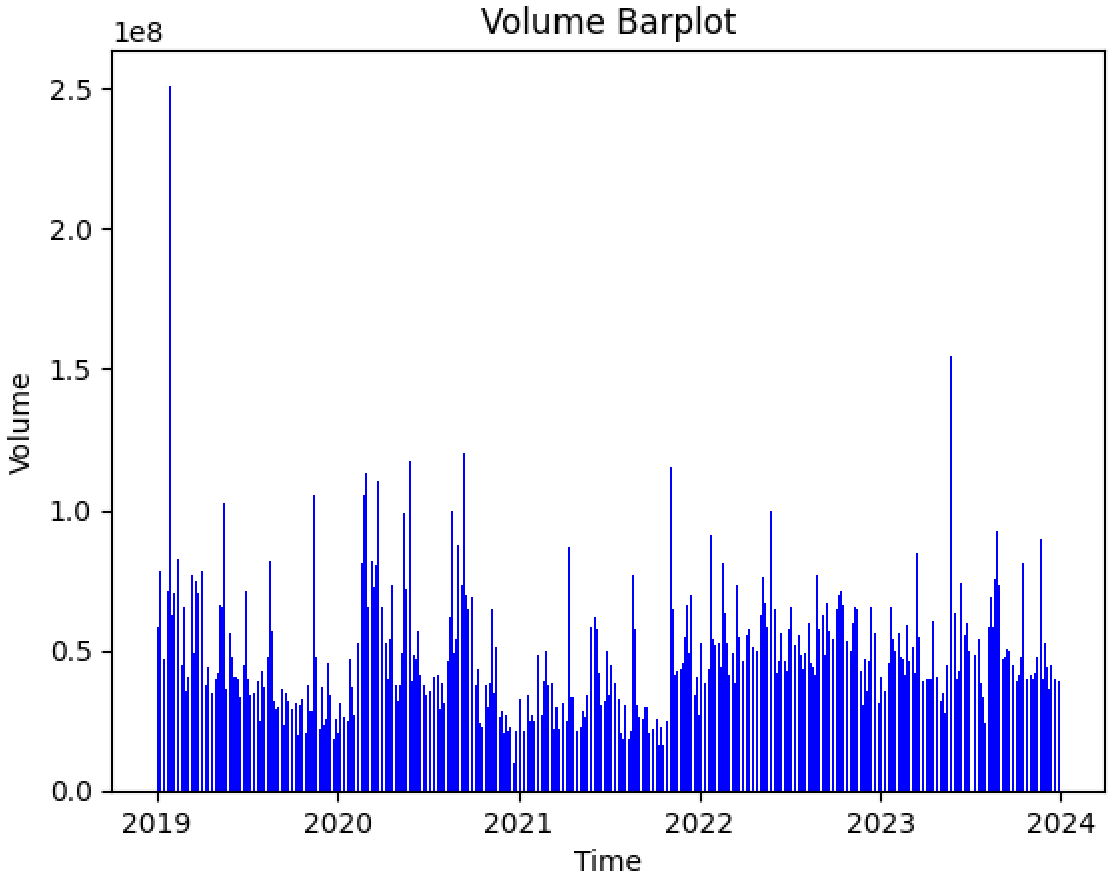
In [10]:
```
df.columns
```

Out[10]:
```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close_x', 'Volume', 'VIX index'], dtyp
e='object')
```

In [11]:
```
# Plotting stokck price data in candlestick pattern
fig = go.Figure(data=[go.Candlestick(x=df.index,
                open=df['Open'],
                high=df['High'],
                low=df['Low'],
                close=df['Close'])])

fig.show()
```

CandleStick Pattern oF NVDIA stock data

In [12]:
```
# Yearly volume Bar grph plot
plt.bar(df.index, df['Volume'], width=1.5, color='Blue')
plt.xlabel('Time')
plt.ylabel('Volume')
plt.title('Volume Barplot')
plt.show()
```



Here you can see Volume traded in NVDIA stock each year

Distribution Analysis

In [13]:
```
# Calculating Daily Returns
df['Daily_Return'] = df['Adj Close_x'].pct_change()
```

In [14]:
```
#Log returns
df['log_Return'] = np.log(df['Adj Close_x']) - np.log(df['Adj Close_x'].shift(1))
```

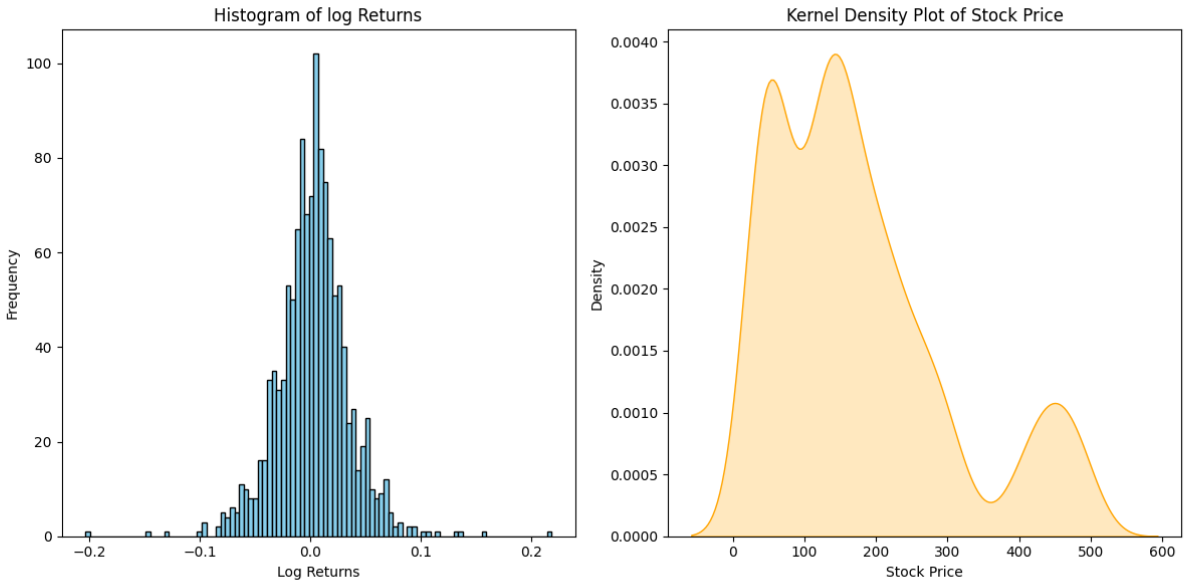
In [15]:
```
Max1 = df["log_Return"].max()
Min1 = df["log_Return"].min()
Max2 = (df["log_Return"].min() - df["log_Return"].mean()) / df["log_Return"].std()
Min2 = (df["log_Return"].max() - df["log_Return"].mean()) / df["log_Return"].std()
print("Over the last 5 years, NVDIA has had a maximum daily return of %.2f and a mi
```

```
Over the last 5 years, NVDIA has had a maximum daily return of 0.22 and a minimum
daily return of -0.20 If we use the formula to determine standard deviations from
the mean, we get -6.35 and 6.66 standard deviations away from the mean for the min
imum and maximum, respectively
```

In [16]:
```
df.log_Return
```

Out[16]:
```
Date
2019-01-02         NaN
2019-01-03   -0.062319
2019-01-04    0.062099
2019-01-07    0.051587
2019-01-08   -0.025211
                ...
2023-12-22   -0.003271
2023-12-26    0.009153
2023-12-27    0.002796
2023-12-28    0.002122
2023-12-29    0.000000
Name: log_Return, Length: 1258, dtype: float64
```

In [17]:
```
# Plot Histogram of Daily Returns
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.hist(df['log_Return'], bins=100, color='skyblue', edgecolor='black')
plt.title('Histogram of log Returns')
plt.xlabel('Log Returns')
plt.ylabel('Frequency')

# Plot Kernel Density Plot
plt.subplot(1, 2, 2)
sns.kdeplot(df['Adj Close_x'], fill=True, color='orange')
plt.title('Kernel Density Plot of Stock Price')
plt.xlabel('Stock Price')
plt.ylabel('Density')

plt.tight_layout()
plt.show()
```



Here we can see the log returns of NVDIA price in a normal distribution, we will learn more about the distribution in further section. Also with that we have kernel density plot of NVDIA price where we can see the price is more dence between 0-300 price range.

Statsical anlysis

In [18]:
```
df['Adj Close_x']
```

Out[18]:
```
Date
2019-01-02     33.790478
2019-01-03     31.748953
2019-01-04     33.783035
2019-01-07     35.571537
2019-01-08     34.685959
                 ...
2023-12-22    488.299988
2023-12-26    492.790009
2023-12-27    494.170013
2023-12-28    495.220001
2023-12-29    495.220001
Name: Adj Close_x, Length: 1258, dtype: float64
```

In [19]:
```
# Defining the log return into another data frame for ease of writing code.
df_stats = np.log(df['Adj Close_x']) - np.log(df['Adj Close_x'].shift(1))
df_stats
```

Out[19]:
```
Date
2019-01-02         NaN
2019-01-03   -0.062319
2019-01-04    0.062099
2019-01-07    0.051587
2019-01-08   -0.025211
                ...
2023-12-22   -0.003271
2023-12-26    0.009153
2023-12-27    0.002796
2023-12-28    0.002122
2023-12-29    0.000000
Name: Adj Close_x, Length: 1258, dtype: float64
```

In [20]:
```
df_stats.describe()
```

Out[20]:
```
count    1257.000000
mean        0.002136
std         0.032449
min        -0.203980
25%        -0.015274
50%         0.003049
75%         0.019616
max         0.218088
Name: Adj Close_x, dtype: float64
```

In [21]:
```
#Symmetric Test
(len(df[df_stats > df_stats.mean()])) / (len(df))
```

Out[21]:
```
0.5151033386327504
```

We're getting about 51.5% of data points being greater than the mean, which shows we have a slightly negative skew to this dataset. We can't rule out symmetric returns based on this since it is only a sample of data and is reasonably close to the 50% mark. This makes it hard to say for certain whether NVDA returns are symmetric or not, but it is still a reasonable assumption to make here.

In [22]:
```
##Normality Test
stats.normaltest(np.array(df["log_Return"].dropna()))
```

Out[22]:
```
NormaltestResult(statistic=123.1740576553762, pvalue=1.7909902571164515e-27)
```

We can use the `normaltest()` method here to determine if the sample data could fit a normal distribution. This method uses D'Agostino and Pearson's normality test, which combines skew and kurtosis to produce an omnibus test of normality.

The null hypothesis of this test is that the sample data fits a normal distribution. Let's assume we want to be 90% confident this data fits a normal distribution. We can compare this to the p-value to see if it's greater than 90%. In this case, the value, 1.79e-27, is extremely small, which leads us to reject the null hypothesis that this data fits a normal distribution.

In [23]:
```
##Skewness and Kurtosis
stats.jarque_bera((np.array(df["log_Return"].dropna())))
```

Out[23]:
```
SignificanceResult(statistic=857.2986407974145, pvalue=6.917759815805223e-187)
```

The Jarque-Bera test was conducted on the log returns data. The test resulted in a statistic of 857.2981128421397 and an extremely low p-value of 6.919586190747671e-187. This indicates strong evidence against the null hypothesis that the data follows a normal distribution. Therefore, the log returns data is found to be significantly non-normally distributed based on the results of the Jarque-Bera test.

In [24]:
```
df_stats.min()
```

Out[24]:
```
-0.2039795240391511
```

In [25]:
```
df_stats.max()
```

Out[25]:
```
0.2180878060373761
```

In [26]:
```
dfMax = df_stats.max()
dfMin = df_stats.min()
print(
    "Min return of sample data is %.4f and the maximum return of sample data is %.4
    % (dfMin, dfMax)
)
```

```
Min return of sample data is -0.2040 and the maximum return of sample data is 0.21
81
```

In [27]:
```
(dfMin - df_stats.mean()) / df_stats.std()
```

Out[27]:
```
-6.351962446744178
```

In [28]:
```
(dfMax - df_stats.mean()) / df_stats.std()
```

Out[28]:
```
6.655098410306035
```

Over the last 5 years, NVDA has had a maximum daily return of 20.40% and a minimum daily return of -21.80%. If we use the formula to determine standard deviations from the mean, we get -6.35 and 6.65 standard deviations away from the mean for the minimum and maximum, respectively. These standard deviations are humongous when compared to the normal distribution. We can see this analytically when we plug in the z score to the `norm.cdf()` method to determine the probability this value could be in a normal distribution:

In [29]:
```
stats.norm.cdf(-6.35)
```

Out[29]:
```
1.0765746385121636e-10
```

This implies that the chance we could have a move as small as -21.80%, is 1.0765746385121636e-10. This probability is so low that we would never expect an event like this to happen in our lifetime. We have multiple events like this, as illustrated by the minimum and maximum.

Going further with this idea, based on normal distribution z tables, we would expect 99.7% of our data points to be within +/- 3 standard deviations from the mean. Let's determine this for our sample data. First off, we need to find the cut-off values at +/- 3 standard deviations:

In [30]:
```
(3 * df_stats.std()) + df_stats.mean()
```

Out[30]:
```
0.0994831770470659
```

In [31]:
```
(-3 * df_stats.std()) + df_stats.mean()
```

Out[31]:
```
-0.09521138218431689
```

The above two calculations would imply that 99.7% of all of our data points should be in between -0.0952 and 0.0994.

In [32]:
```
df[(df['log_Return'] > 0.03699) | (df['log_Return'] < -0.0364)]['log_Return'].tail(
```

Out[32]:
```
Date
2023-10-17   -0.047925
2023-10-18   -0.040454
2023-10-23    0.037652
2023-10-25   -0.044107
2023-11-01    0.037186
Name: log_Return, dtype: float64
```

In [33]:
```
len(df[(df['log_Return'] > 0.03699) | (df['log_Return'] < -0.0364)])
```

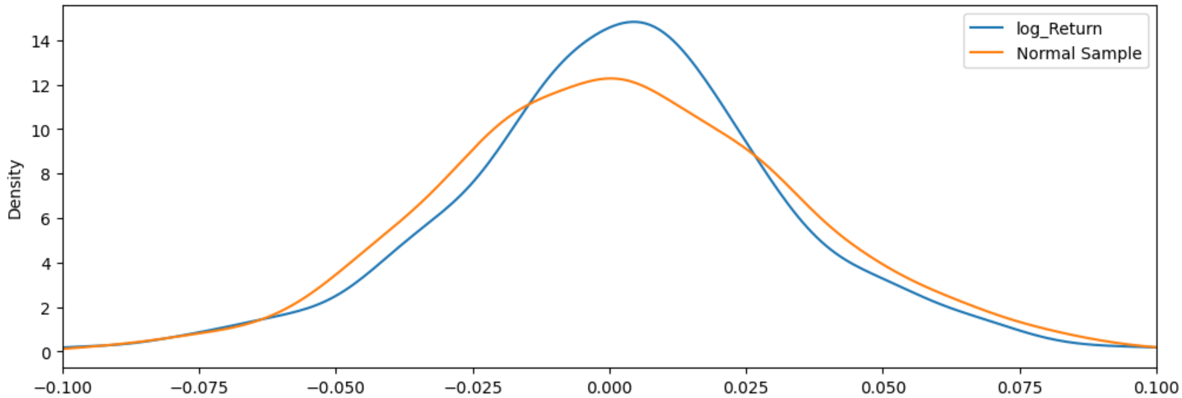
Out[33]:
```
264
```

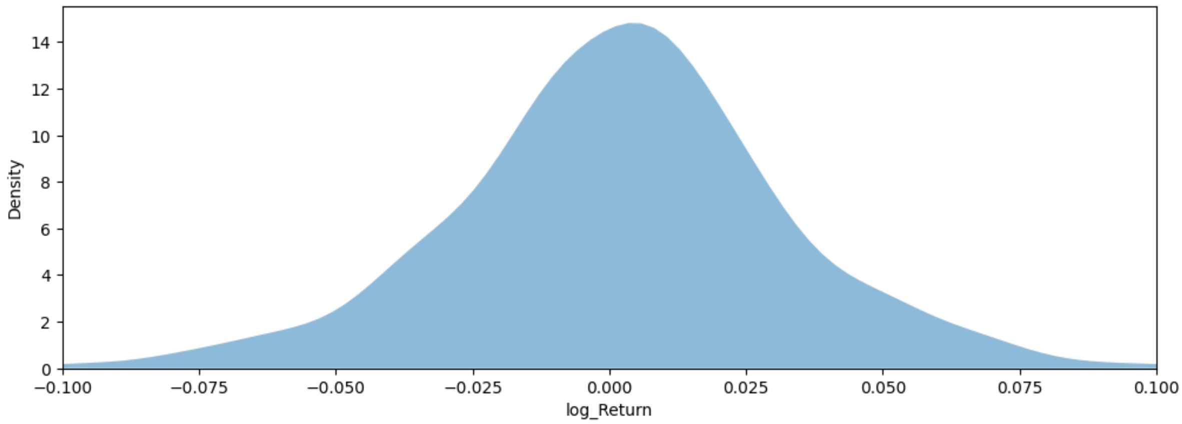
In [34]:
```
len(df[(df["log_Return"] > 0.05) | (df["log_Return"] < -0.05)])
```

Out[34]:
```
139
```

Not only do we get 264 values outside of our 3 standard deviation range, but we also get 139 values outside of +/- 5%, though you would almost never expect one of these events over 5 years, given a normal distribution.

In [35]:
```
# Sampling from normal distribution
np.random.seed(222)
normal_dist = stats.norm.rvs(
    size=len(df["log_Return"]), loc=df["log_Return"].mean(), scale=df["log_Return"]
)

# Creating an additional column in df in order to use the KDE plot functionality of
df["Normal Sample"] = normal_dist

# Plotting the KDE plots
df[["log_Return", "Normal Sample"]].plot(kind="kde", xlim=(-0.1, 0.1), figsize=(12,

#Using Seaborn to create KDE
plt.figure(figsize = (12,4))
kde = sns.kdeplot(df["log_Return"], fill=True, alpha=.5, linewidth=0).set_xlim(-0.1
```





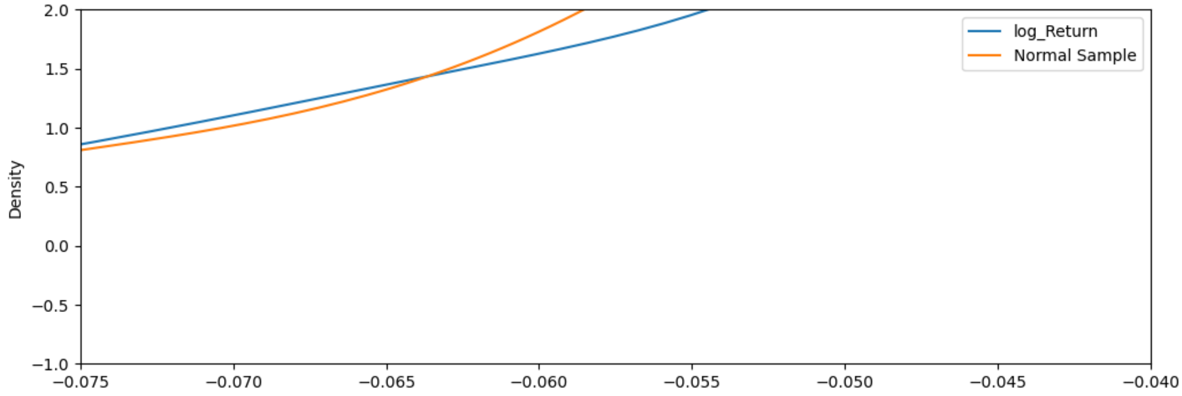
The NVDA returns seem a lot more leptokurtic. Indeed the excess kurtosis of NVDA is greater than 0:

In [36]:
```
df_stats.kurt()
```

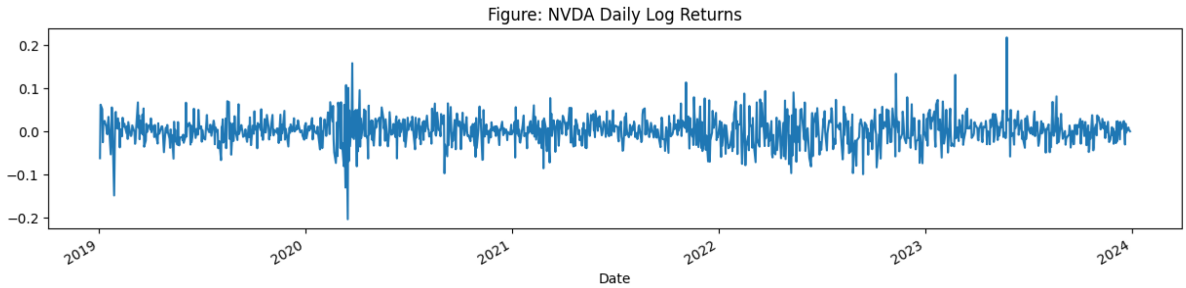
Out[36]:
```
4.065427073853175
```

The tails of NDA are also fatter than those of a normal distribution:

In [37]:
```
# Observing the tails
df[["log_Return", "Normal Sample"]].plot(
    kind="kde", xlim=(-0.075, -0.04), ylim=(-1, 2), figsize=(12, 4)
);
```



In [38]:
```
ax1 = df_stats.plot(figsize=(15, 3), y="NVDA", title="Figure: NVDA Daily Log Returr
```



Daily Log Return graph

In [39]:
```
nvda_std = df_stats.std()
nvda_mean = df_stats.mean()
```

In [40]:
```
# Sharpe Ratio
Sharpe_Ratio_NVDA = nvda_mean / nvda_std
Sharpe_Ratio_NVDA
```

Out[40]:
```
0.06582302370872457
```

The calculated Sharpe Ratio for the given data (NVDA) is approximately 0.0658. This ratio represents the risk-adjusted return, and in this case, a Sharpe Ratio of 0.0658 indicates the excess return per unit of risk for the NVDA investment.

In [41]:
```
# Semi-Variance
nvda_semivariance = ((df[df_stats < nvda_mean]["log_Return"] - nvda_mean) ** 2).mea
nvda_semivariance
```

Out[41]:
```
0.0010849324414159674
```

The calculated semi-variance for the NVDA log returns data is approximately 0.00108. This semi-variance is a measure of the average squared deviation of returns below the mean, providing insight into the downside risk associated with the NVDA investment.

Relationship Analysis

In [42]:
```
# Create a new DataFrame with relevant columns for correlation analysis
correlation_df = df[['Adj Close_x', 'Volume', 'log_Return', 'VIX index']]
```

In [43]:
```
# Calculate the correlation matrix
correlation_matrix = correlation_df.corr()
```

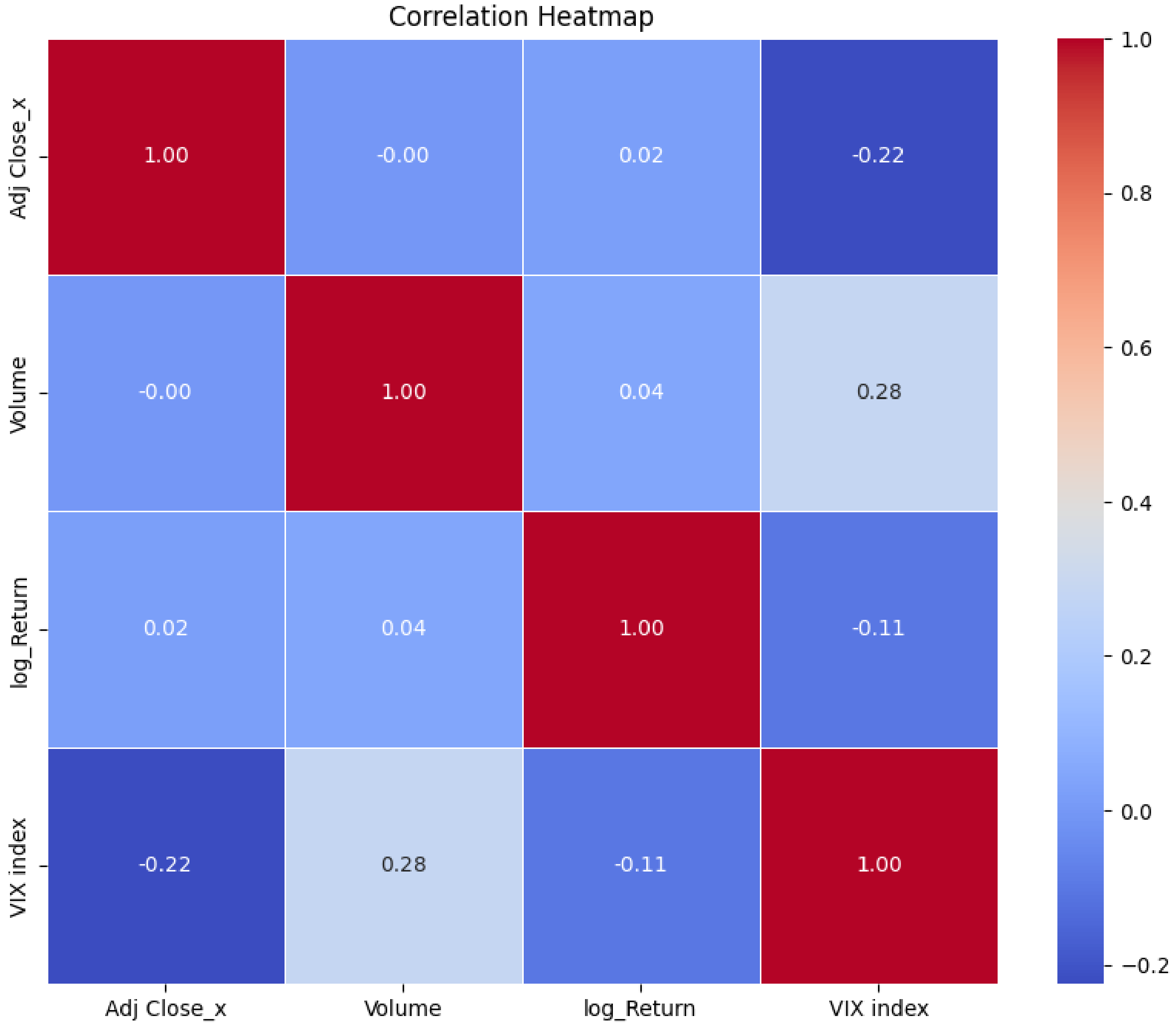
```
correlation_matrix
```

Out[43]:

	Adj Close_x	Volume	log_Return	VIX index
Adj Close_x	1.000000	-0.000330	0.019155	-0.224991
Volume	-0.000330	1.000000	0.043212	0.283252
log_Return	0.019155	0.043212	1.000000	-0.105276
VIX index	-0.224991	0.283252	-0.105276	1.000000

In [44]:

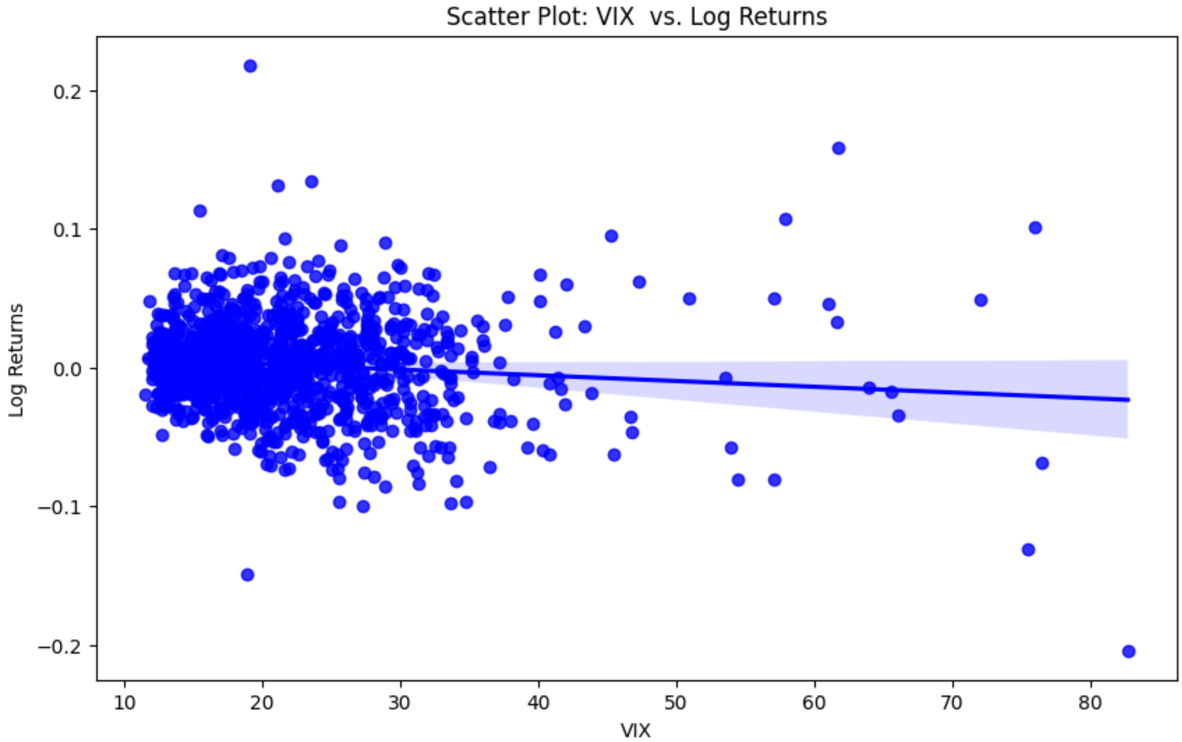
```
# Plot Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=
plt.title('Correlation Heatmap')
plt.show()
```



Correlation between columns Adj Close_x, Volume, VIX Index, Log Return

In [45]:

```
# Scatter Plot: Relationship between Trading Volume and Stock Returns
plt.figure(figsize=(10, 6))
sns.regplot(x='VIX index', y='log_Return', data=df, color='blue')
plt.title('Scatter Plot: VIX  vs. Log Returns')
plt.xlabel('VIX')
plt.ylabel('Log Returns')
plt.show()
```



In the above Correlation matrix Heatmap we have seen an negative realtionship between VIX return and Log retruns and we can confirm the same in the regplot below as we can the regression line slopping downwards and it concludes that volatitly in market has a slightly negative coorealtion with (NVDA) retruns.

Liquidity Analysis

In [46]:
```
# Volume data
nvda_volume = df['Volume']
nvda_bid_ask_spread = df['High'] - df['Low']
```

In [47]:
```
# Calculating average daily trading volume and average bid-ask spread
average_daily_volume = nvda_volume.mean()
average_bid_ask_spread = nvda_bid_ask_spread.mean()
```

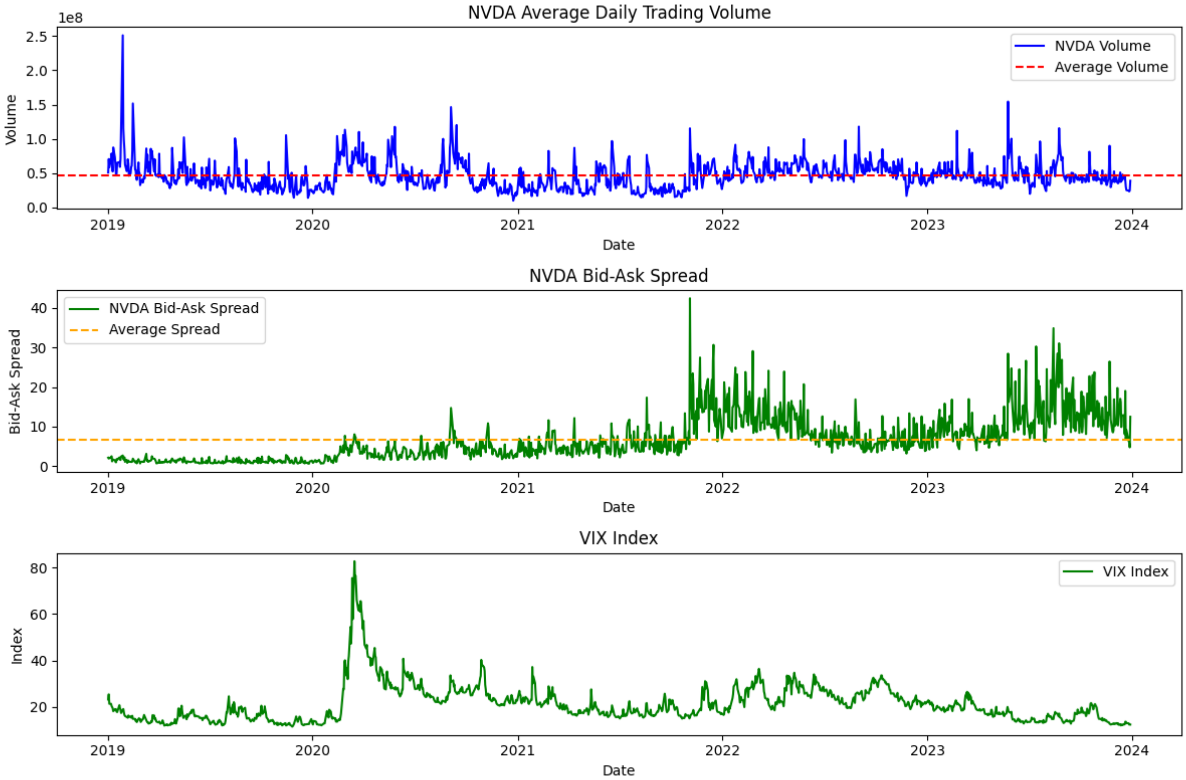
In [48]:
```
# Printing average daily volume and bid-ask spread
print(f"Average Daily Volume: {average_daily_volume:.2f}")
print(f"Average Bid-Ask Spread: {average_bid_ask_spread:.4f}")
```

```
Average Daily Volume: 46262513.43
Average Bid-Ask Spread: 6.6491
```

An average daily trading volume of 46,262,513.43 shares, suggesting a notable level of market activity. Additionally, the average bid-ask spread of 6.6491 indicates a moderate level of liquidity.

In [49]:
```
# Plotting average daily volume and bid-ask spread
fig, (ax1, ax2, ax3) = plt.subplots(3, 1, figsize=(12, 8))

# Plotting average daily volume
ax1.plot(nvda_volume, label="NVDA Volume", color='blue')
ax1.axhline(average_daily_volume, color='red', linestyle='--', label='Average Volum
ax1.set_title("NVDA Average Daily Trading Volume")
ax1.set_xlabel("Date")
ax1.set_ylabel("Volume")
```

```
ax1.legend()

# Plotting bid-ask spread
ax2.plot(nvda_bid_ask_spread, label="NVDA Bid-Ask Spread", color='green')
ax2.axhline(average_bid_ask_spread, color='orange', linestyle='--', label='Average
ax2.set_title("NVDA Bid-Ask Spread")
ax2.set_xlabel("Date")
ax2.set_ylabel("Bid-Ask Spread")
ax2.legend()

# Plotting VIX index
ax3.plot(df["VIX index"], label="VIX Index", color='green')
ax3.set_title("VIX Index")
ax3.set_xlabel("Date")
ax3.set_ylabel("Index")
ax3.legend()

plt.tight_layout()
plt.show()
```



This visualizations offer a comprehensive overview of NVDA's trading dynamics, bid-ask spread variations, and the broader market volatility captured by the VIX Index. (All the key Insights is Completely explained in Project Doc Step 6)

Volatility Analysis

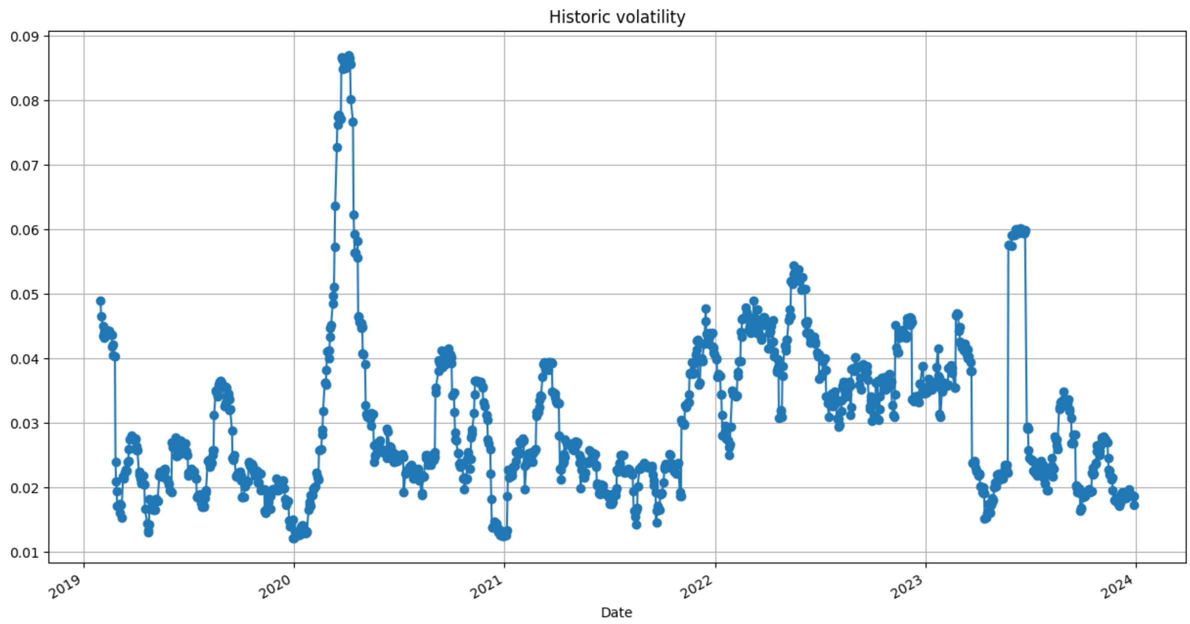
In [50]:
```
df.head()
```

Out[50]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX index	Daily_Return
Date								
2019-01-02	32.660000	34.619999	32.512501	34.055000	33.790478	50875200	23.219999	NaN
2019-01-03	33.447498	33.790001	31.922501	31.997499	31.748953	70555200	25.450001	-0.060417
2019-01-04	32.735001	34.432499	32.424999	34.047501	33.783035	58562000	21.379999	0.064068
2019-01-07	34.625000	36.222500	34.107498	35.849998	35.571537	70916000	21.400000	0.052941
2019-01-08	36.672501	36.695000	34.224998	34.957500	34.685959	78601600	20.469999	-0.024896

In [51]:

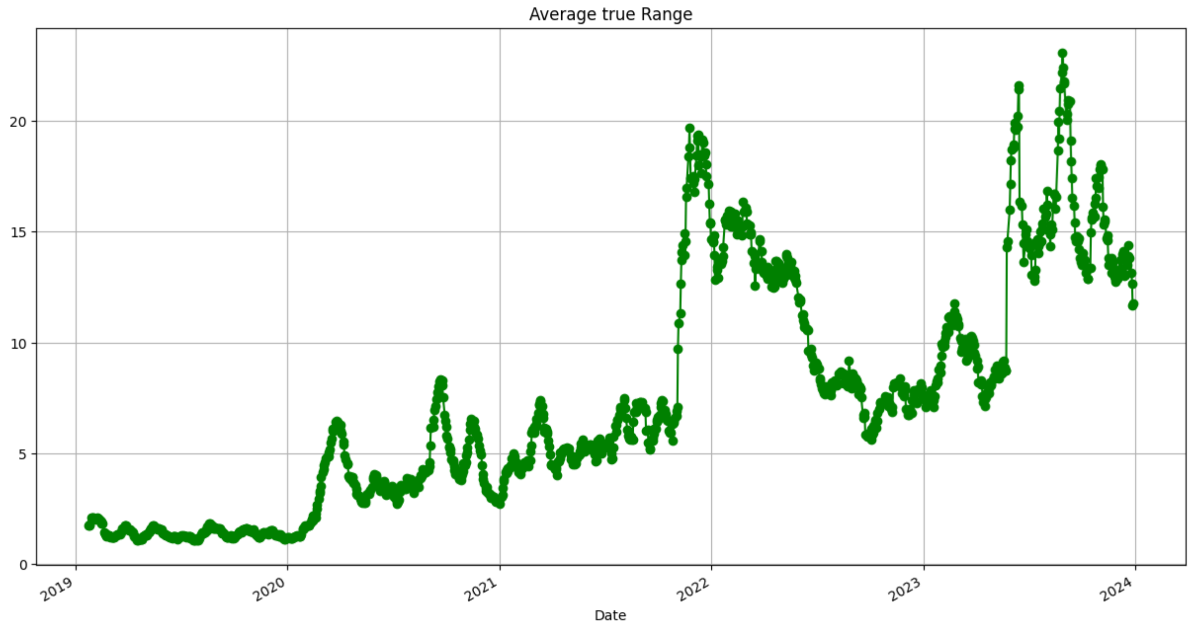
```
# Calculating historic volatility
df['Volatility'] = df['Close'].pct_change().rolling(window=20).std()
df['Volatility'].plot(title="Historic volatility", figsize=(15, 8), marker='o', lir
plt.grid(True)
```



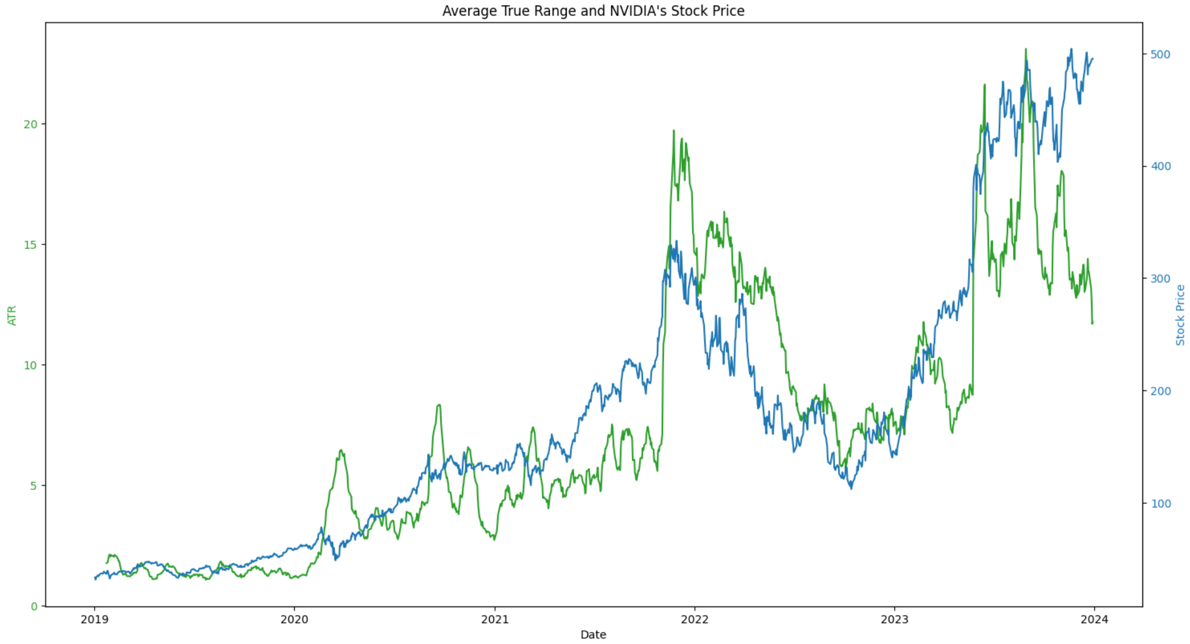
In [52]:

```
# ATR (Average true Range)

n = 15

# Calculate True Range (TR)
df['High-Low'] = df['High'] - df['Low']
df['High-PrevClose'] = abs(df['High'] - df['Close'].shift(1))
df['Low-PrevClose'] = abs(df['Low'] - df['Close'].shift(1))
df['TrueRange'] = df[['High-Low', 'High-PrevClose', 'Low-PrevClose']].max(axis=1)

# Calculate ATR
df['ATR'] = df['TrueRange'].rolling(window=n).mean()

# Drop intermediate columns
df.drop(['High-Low', 'High-PrevClose', 'Low-PrevClose', 'TrueRange'], axis=1, inpla
```

```
df['ATR'].plot(title="Average true Range", figsize=(15, 8), marker='o', linestyle='
plt.grid(True)
```



In [53]:
```
import matplotlib.pyplot as plt

# Assuming df DataFrame is already defined

n = 15

# Calculate True Range (TR)
df['High-Low'] = df['High'] - df['Low']
df['High-PrevClose'] = abs(df['High'] - df['Close'].shift(1))
df['Low-PrevClose'] = abs(df['Low'] - df['Close'].shift(1))
df['TrueRange'] = df[['High-Low', 'High-PrevClose', 'Low-PrevClose']].max(axis=1)

# Calculate ATR
df['ATR'] = df['TrueRange'].rolling(window=n).mean()

# Drop intermediate columns
df.drop(['High-Low', 'High-PrevClose', 'Low-PrevClose', 'TrueRange'], axis=1, inpla

# Create a figure and axis
fig, ax1 = plt.subplots(figsize=(15, 8))

# Plotting the ATR on the left y-axis
color = 'tab:green'
ax1.set_xlabel('Date')
ax1.set_ylabel('ATR', color=color)
ax1.plot(df.index, df['ATR'], label="ATR", color=color)
ax1.tick_params(axis='y', labelcolor=color)

# Create a twin Axes for the stock price on the right y-axis
ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('Stock Price', color=color)
ax2.plot(df.index, df['Adj Close_x'], label="Stock Price", color=color)
ax2.tick_params(axis='y', labelcolor=color)

# Display the plots
fig.tight_layout()
plt.title("Average True Range and NVIDIA's Stock Price")
plt.show()
```



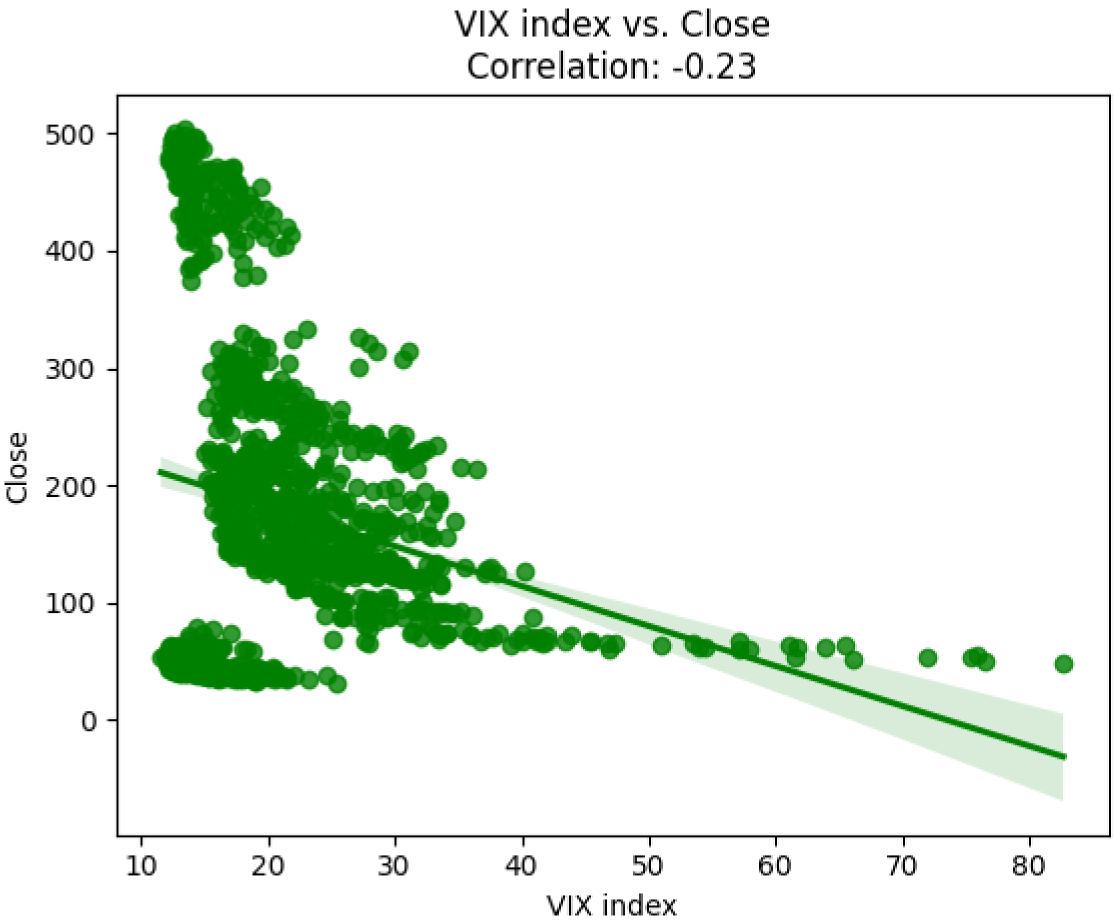
Average True Range (ATR) is a technical indicator designed to measure market volatility. It considers the trading range (high to low) for a financial instrument over a specified time period, accounting for gaps between consecutive days. Higher ATR values imply greater market volatility. Lower ATR values suggest a more stable market environment.

Leverage Analysis

In [54]:
```
# VIX relationship
correlation_vol = df['Close'].corr(df['VIX index'])
correlation_vol
```

Out[54]:
```
-0.22500708756046248
```

In [55]:
```
# Scatter plot
sns.regplot(x='VIX index', y='Close', data=df, color='green')
plt.title(f"VIX index vs. Close\nCorrelation: {correlation_vol:.2f}")
plt.xlabel("VIX index")
plt.ylabel("Close")
plt.show()
```

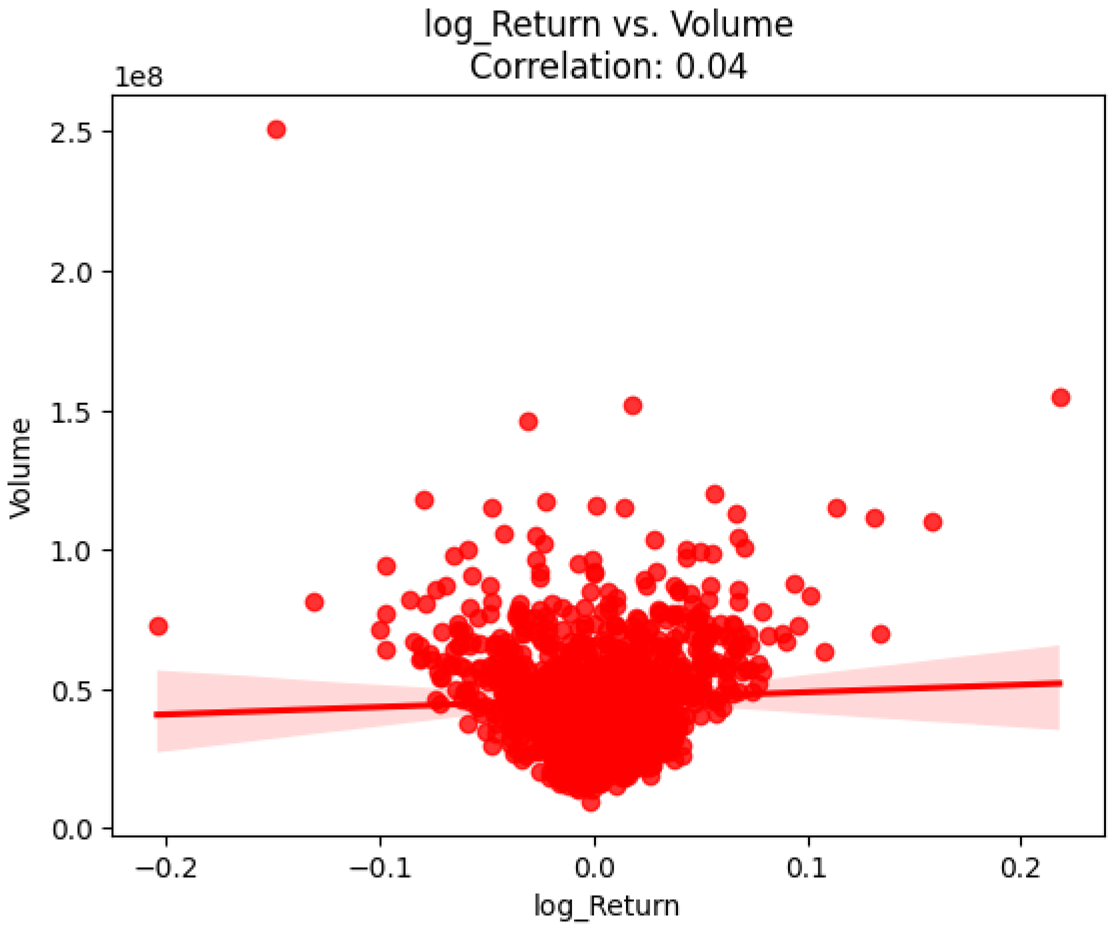


A correlation coefficient of -0.22500708756046248 indicates a negative correlation. The closer the value is to -1, the stronger the negative correlation. However, the value -0.225 suggests a relatively weak negative correlation.

In [56]:
```
# Calculate correlation between log returns and volume
correlation_leverage = df['log_Return'].corr(df['Volume'])
correlation_leverage
```

Out[56]: 0.04321217238759989

In [57]:
```
# Scatter plot
sns.regplot(x='log_Return', y='Volume', data=df, color='red')
plt.title(f"log_Return vs. Volume\nCorrelation: {correlation_leverage:.2f}")
plt.xlabel("log_Return")
plt.ylabel("Volume")
plt.show()
```

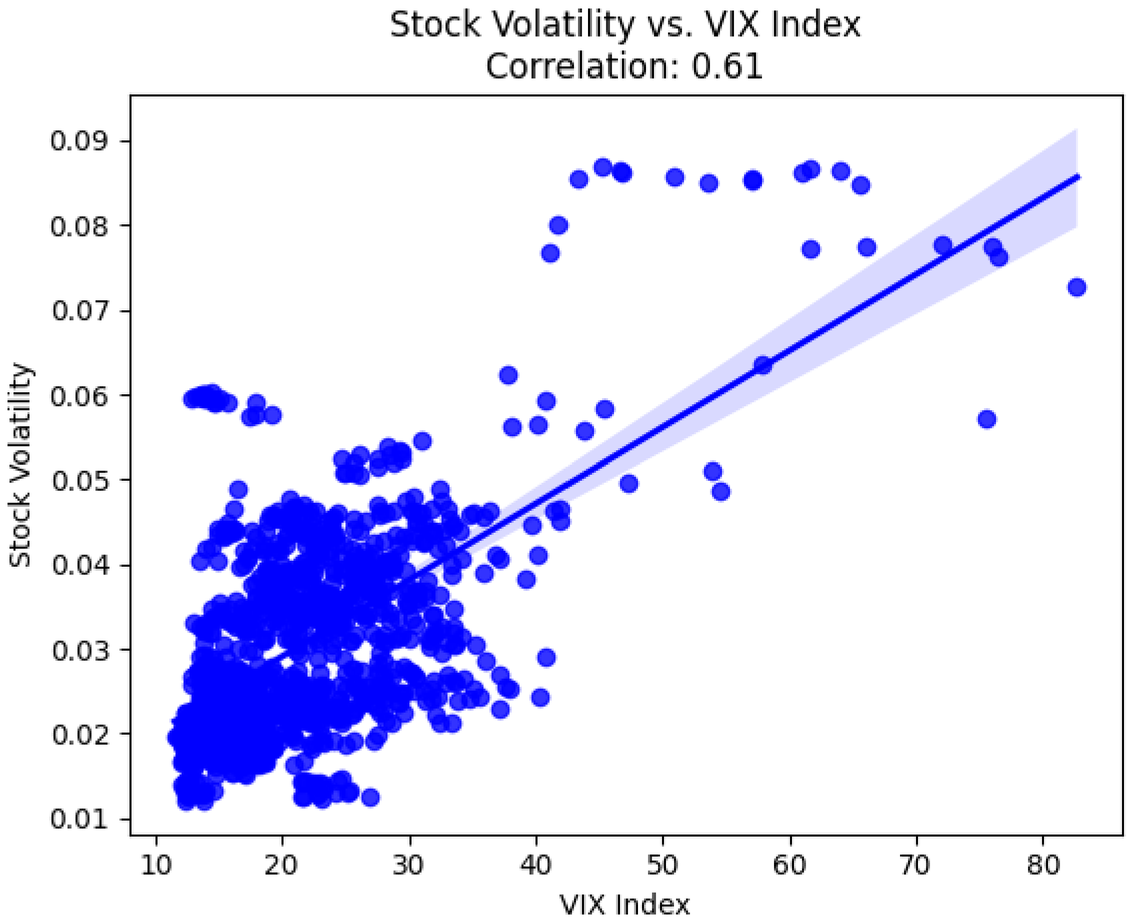


The leverage effect suggests that stocks tend to experience greater price movements when there is an increase in trading volumes. in our case the correlation between log_return and volume is positive i.e 0.043 which means the correlation is weak positive.

In [58]:
```
# Calculate correlation between log returns and volume
correlation_V = df['Volatility'].corr(df['VIX index'])
correlation_V
```

Out[58]: 0.6094960566496171

In [59]:
```
# Scatter plot
sns.regplot(x='VIX index', y='Volatility', data=df, color='blue')
plt.title(f"Stock Volatility vs. VIX Index\nCorrelation: {correlation_V:.2f}")
plt.xlabel("VIX Index")
plt.ylabel("Stock Volatility")
plt.show()
```

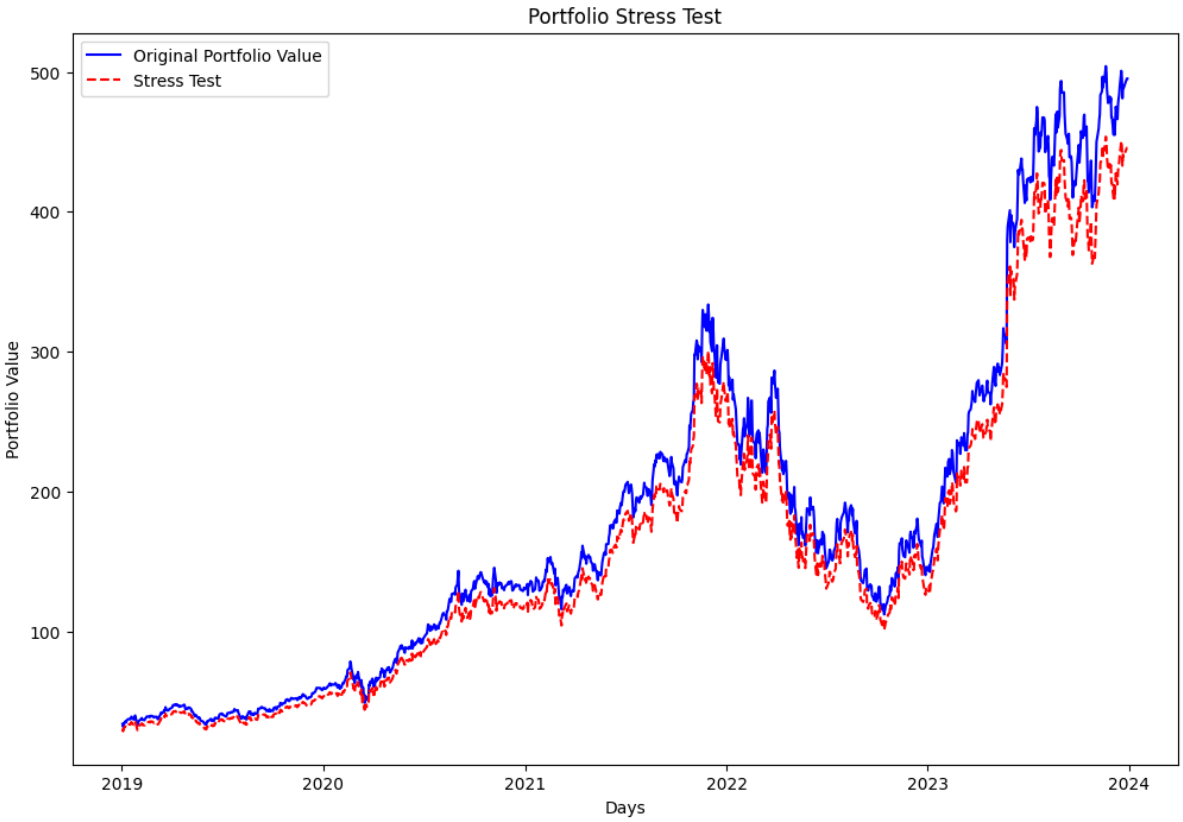


A correlation coefficient of 0.61 between stock volatility and the VIX (Volatility Index) signifies a moderately positive correlation. This positive correlation suggests that periods of higher stock market volatility are associated with higher values of the VIX. A positive correlation between stock volatility and the VIX is generally expected, as the VIX is designed to measure market volatility and is often referred to as the "fear index. A positive correlation could mean that monitoring the VIX can provide insights into potential changes in stock market volatility.

Stress test

In [60]:
```
# Assuming 'Close' is the closing price column
portfolio_data = df[['Close']].copy()

def stress_test(portfolio_data, stress_factor=0.1):
    # Apply stress factor to simulate extreme scenarios
    stressed_portfolio_values = portfolio_data['Close'] * (1 - stress_factor)

    return stressed_portfolio_values

def plot_stress_test_results(original_data, stressed_values):
    plt.figure(figsize=(12, 8))
    plt.plot(original_data['Close'], label='Original Portfolio Value', color='blue'
    plt.plot(stressed_values, label='Stress Test', color='red', linestyle='--')

    plt.title('Portfolio Stress Test')
    plt.xlabel('Days')
    plt.ylabel('Portfolio Value')
    plt.legend()
    plt.show()
```

```
stressed_values = stress_test(portfolio_data, stress_factor=0.1)

# Plot the results
plot_stress_test_results(portfolio_data, stressed_values)
```



In this simplified example, the stress_test_basic function applies a stress factor directly to the historical closing prices. The stressed_values represent the portfolio values under stress. The results are then plotted to compare the original portfolio values with the stressed scenario. hewre we are using 0.1 Stress factor which means we are checking how our portfolio will perform during extreme events of 10%. and we can see there is not very much difference in portfolio value and stress value.

Technical Analysis

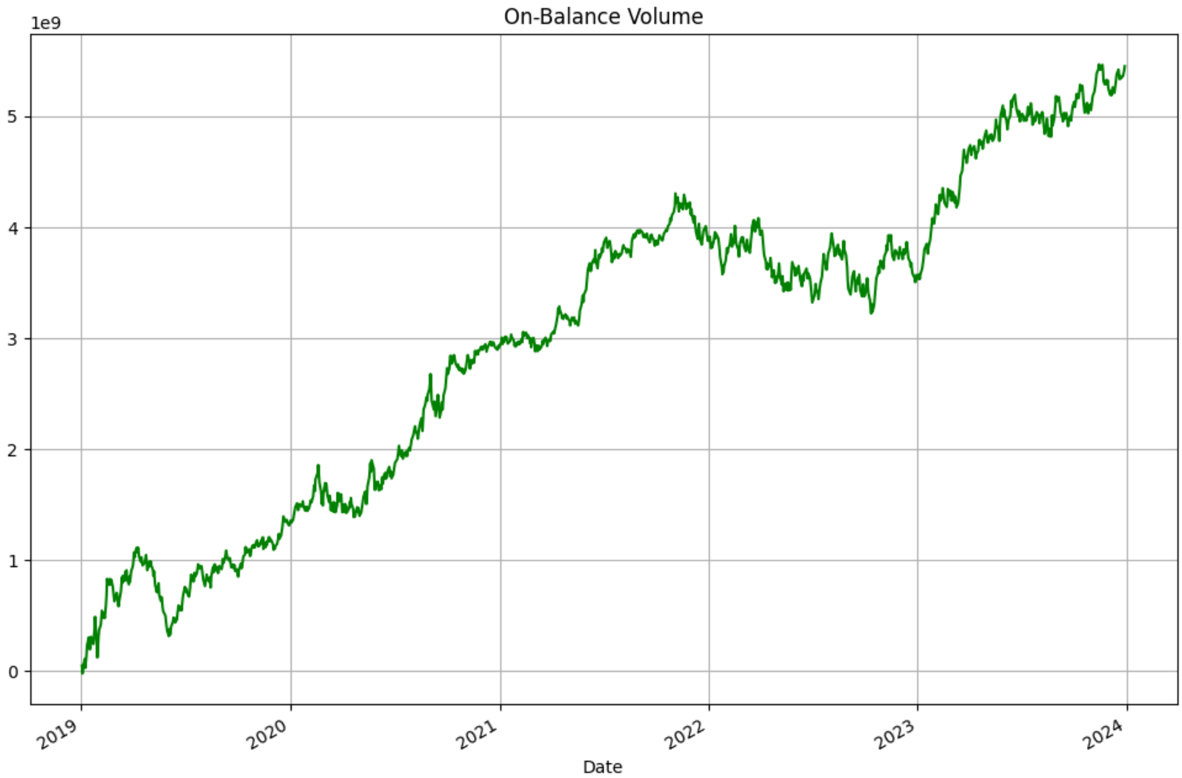
In [61]:
```
!pip install ta
```

```
Collecting ta
  Downloading ta-0.11.0.tar.gz (25 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (f
rom ta) (1.23.5)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(from ta) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.1
0/dist-packages (from pandas->ta) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-pack
ages (from pandas->ta) (2023.4)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages
(from python-dateutil>=2.8.1->pandas->ta) (1.16.0)
Building wheels for collected packages: ta
  Building wheel for ta (setup.py) ... done
  Created wheel for ta: filename=ta-0.11.0-py3-none-any.whl size=29413 sha256=29a9
25e971fb8975269dd208d536883ffb9a06c2e99152521aceea2d5d872b28
  Stored in directory: /root/.cache/pip/wheels/5f/67/4f/8a9f252836e053e532c6587a32
30bc72a4deb16b03a829610b
Successfully built ta
Installing collected packages: ta
Successfully installed ta-0.11.0
```

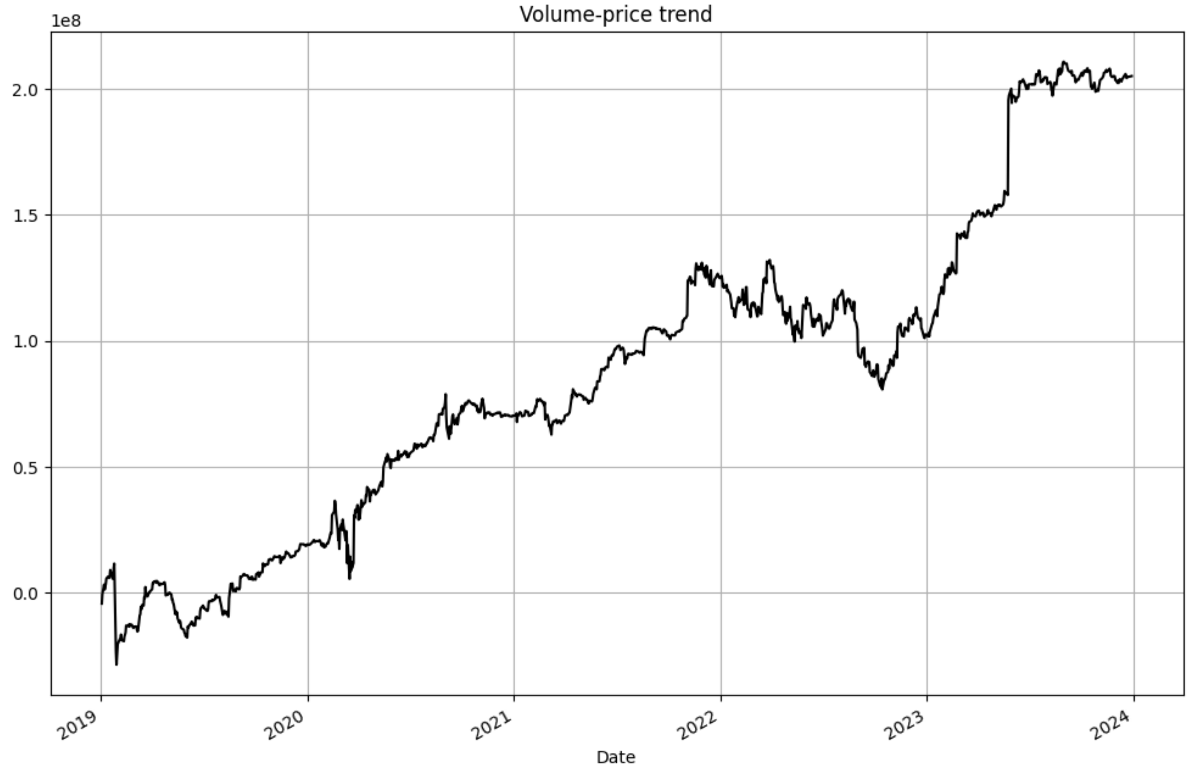
In [62]:
```python
from ta import add_all_ta_features
import ta
```

In [63]:
```python
df = ta.add_all_ta_features(df, "Open", "High", "Low", "Close", "Volume", fillna=Fa
```

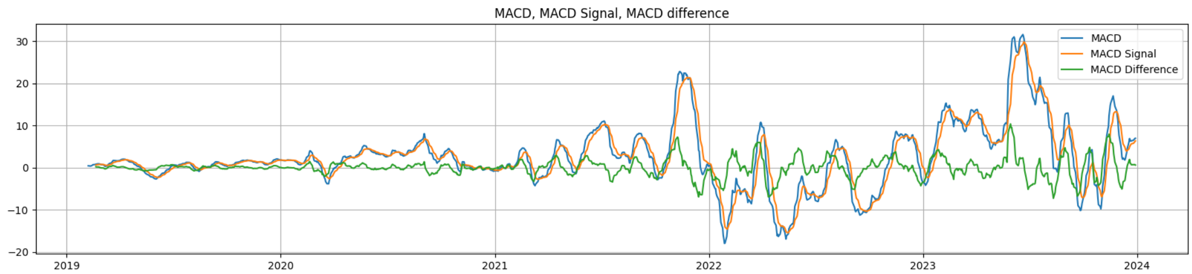
In [64]:
```python
# Volume: On-Balance Volume
df["volume_obv"].plot(title='On-Balance Volume', color='g', figsize=(12,8))
plt.grid(True)
```



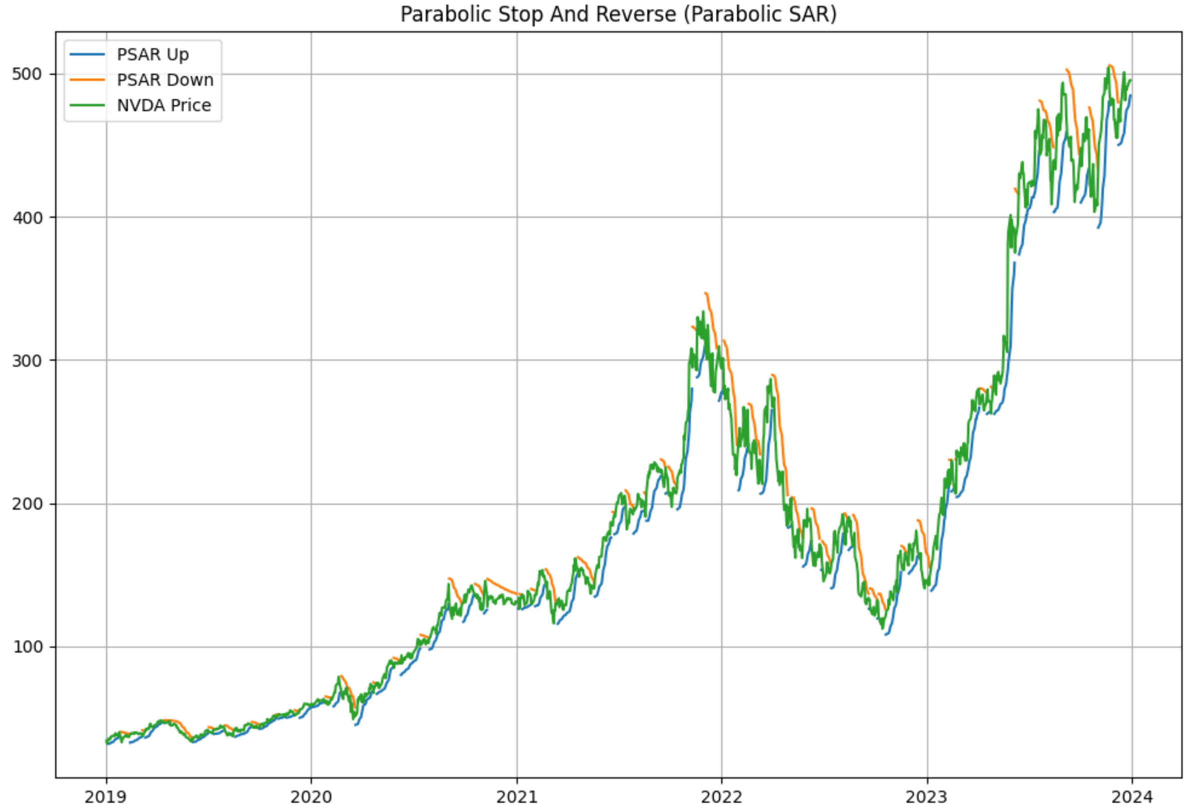
In [65]:
```python
# Volume: Volume Price Trend
df["volume_vpt"].plot(title='Volume-price trend', color='black', figsize=(12,8))
plt.grid(True)
```



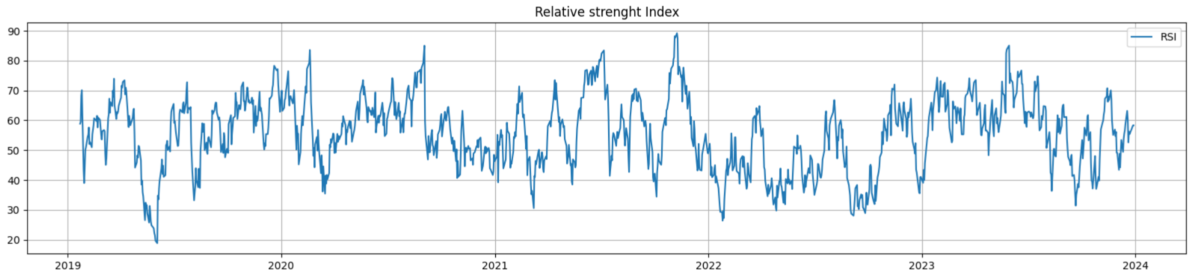
In [66]:
```
# Trend : MACD
fig, ax1 = plt.subplots(1, 1, figsize=(20, 4))
ax1.plot(df["trend_macd"], label='MACD')
ax1.plot(df["trend_macd_signal"], label='MACD Signal')
ax1.plot(df["trend_macd_diff"], label='MACD Difference')
#ax1.plot(df["Close"], label='NVDA Price')
plt.title('MACD, MACD Signal, MACD difference')
ax1.legend()
plt.grid(True)
plt.show()
```



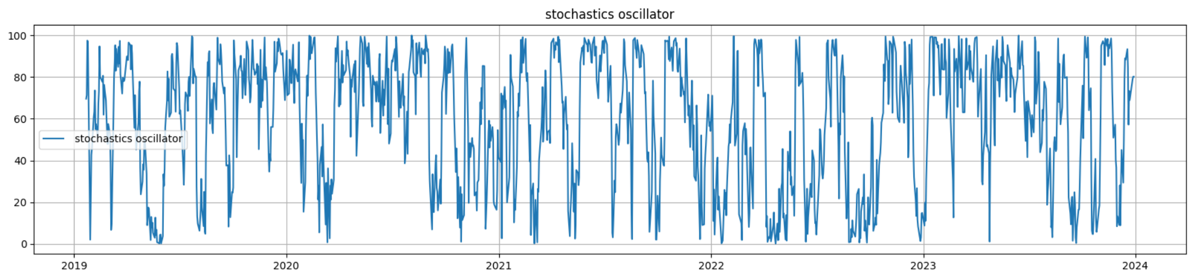
In [67]:
```
#Trend : Parabolic SAR
fig, ax2 = plt.subplots(1, 1, figsize=(12, 8))
ax2.plot(df["trend_psar_up"], label='PSAR Up')
ax2.plot(df["trend_psar_down"], label='PSAR Down')
ax2.plot(df["Close"], label='NVDA Price')
plt.title('Parabolic Stop And Reverse (Parabolic SAR)')
ax2.legend()
plt.grid(True)
plt.show()
```



In [68]:
```
# Momentum : Relative Strenght Index
fig, ax3 = plt.subplots(1, 1, figsize=(20, 4))
ax3.plot(df["momentum_rsi"], label='RSI')
#ax3.plot(df["Close"], label='NVDA Price')
plt.title('Relative strenght Index')
ax3.legend()
plt.grid(True)
plt.show()
```



In [69]:
```
# Momentum : stochastics oscillator
fig, ax4 = plt.subplots(1, 1, figsize=(20, 4))
ax4.plot(df["momentum_stoch"], label=' stochastics oscillator')
#ax4.plot(df["momentum_stoch_signal"], label=' stochastics oscillator Signal')
plt.title('stochastics oscillator')
ax4.legend()
plt.grid(True)
plt.show()
```



Fundamental Analysis

In [1]:
```
!pip install financetoolkit -U
```

```
Requirement already satisfied: financetoolkit in /usr/local/lib/python3.10/dist-pa
ckages (1.8.3)
Requirement already satisfied: pandas[computation,performance,plot]<3.0,>=2.2 in /
usr/local/lib/python3.10/dist-packages (from financetoolkit) (2.2.0)
Requirement already satisfied: requests<3.0,>=2.31 in /usr/local/lib/python3.10/di
st-packages (from financetoolkit) (2.31.0)
Requirement already satisfied: scikit-learn<2.0,>=1.3 in /usr/local/lib/python3.1
0/dist-packages (from financetoolkit) (1.4.0)
Requirement already satisfied: numpy<2,>=1.22.4 in /usr/local/lib/python3.10/dist-
packages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (1.
23.5)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.1
0/dist-packages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolk
it) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-pack
ages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (2023.
4)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-pa
ckages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (202
3.4)
Requirement already satisfied: matplotlib>=3.6.3 in /usr/local/lib/python3.10/dist
-packages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit)
(3.7.1)
Requirement already satisfied: scipy>=1.10.0 in /usr/local/lib/python3.10/dist-pac
kages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (1.11.
4)
Requirement already satisfied: xarray>=2022.12.0 in /usr/local/lib/python3.10/dist
-packages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (2
023.7.0)
Requirement already satisfied: bottleneck>=1.3.6 in /usr/local/lib/python3.10/dist
-packages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit)
(1.3.7)
Requirement already satisfied: numba>=0.56.4 in /usr/local/lib/python3.10/dist-pac
kages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (0.58.
1)
Requirement already satisfied: numexpr>=2.8.4 in /usr/local/lib/python3.10/dist-pa
ckages (from pandas[computation,performance,plot]<3.0,>=2.2->financetoolkit) (2.9.
0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.
10/dist-packages (from requests<3.0,>=2.31->financetoolkit) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-pack
ages (from requests<3.0,>=2.31->financetoolkit) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dis
t-packages (from requests<3.0,>=2.31->financetoolkit) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dis
t-packages (from requests<3.0,>=2.31->financetoolkit) (2023.11.17)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-pac
kages (from scikit-learn<2.0,>=1.3->financetoolkit) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/d
ist-packages (from scikit-learn<2.0,>=1.3->financetoolkit) (3.2.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-
packages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2->
financetoolkit) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-pack
ages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2->fina
ncetoolkit) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist
-packages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2-
>financetoolkit) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist
-packages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2-
>financetoolkit) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-p
ackages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2->f
```

```
inancetoolkit) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-pac
kages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2->fin
ancetoolkit) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-
packages (from matplotlib>=3.6.3->pandas[computation,performance,plot]<3.0,>=2.2->
financetoolkit) (3.1.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in /usr/local/lib/python
3.10/dist-packages (from numba>=0.56.4->pandas[computation,performance,plot]<3.0,>
=2.2->financetoolkit) (0.41.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages
(from python-dateutil>=2.8.2->pandas[computation,performance,plot]<3.0,>=2.2->fina
ncetoolkit) (1.16.0)
```

In [2]:

```
import pandas as pd

from financetoolkit import Toolkit

API_KEY = "aa4937f0afdc8136a24d30fd32fea303"
```

In [3]:

```
# Initialize the Toolkit with company tickers
companies = Toolkit(
    ["NVDA"], api_key=API_KEY, start_date="2019-01-02"
)
```

In [4]:

```
#getting company profile
companies.get_profile()
```

```
Obtaining company profiles: 100%|██████████| 1/1 [00:00<00:00,  9.59it/s]
```

Out[4]:

	NVDA
Symbol	NVDA
Price	693.32
Beta	1.6840000000000002
Average Volume	42346785
Market Capitalization	1712500400000
Last Dividend	0.16
Range	204.21-694.9699
Changes	31.72
Company Name	NVIDIA Corporation
Currency	USD
CIK	1045810
ISIN	US67066G1040
CUSIP	67066G104
Exchange	NASDAQ Global Select
Exchange Short Name	NASDAQ
Industry	Semiconductors
Website	https://www.nvidia.com
Description	NVIDIA Corporation provides graphics, and comp...
CEO	Mr. Jen-Hsun Huang
Sector	Technology
Country	US
Full Time Employees	26196
Phone	408 486 2000
Address	2788 San Tomas Expressway
City	Santa Clara
State	CA
ZIP Code	95051
DCF Difference	594.00444
DCF	95.10195535997276
IPO Date	1999-01-22

In [5]:

```
#Company Effective ratio
companies.ratios.get_effective_tax_rate()
```

```
Obtaining financial statements: 100%|██████████| 3/3 [00:01<00:00,  2.16it/s]
Obtaining historical data: 100%|██████████| 2/2 [00:00<00:00,  9.36it/s]
```

Out[5]:

date	2019	2020	2021	2022	2023
NVDA	-0.0629	0.0586	0.0175	0.019	-0.0447

In [6]:
```
#Overall Ratios
companies.ratios.collect_all_ratios()
```

Out[6]:

	2019	2020	2021	2022	2023
Days of Inventory Outstanding	NaN	112.3145	81.5277	85.6719	121.9599
Days of Sales Outstanding	NaN	51.5005	44.7193	48.0017	57.3535
Operating Cycle	NaN	163.815	126.2471	133.6736	179.3134
Days of Accounts Payable Outstanding	NaN	52.6831	54.875	57.6947	46.7481
Cash Conversion Cycle	NaN	111.1318	71.3721	75.979	132.5652
...	...	...	...	...	...
EV-to-EBIT	37.3561	103.7918	162.0998	37.3401	281.3375
EV-to-EBITDA	36.3271	92.1712	130.8249	33.4781	216.7099
EV-to-Operating-Cash-Flow	39.4619	65.8808	127.8812	41.7226	221.5888
Tangible Asset Value	8724000000.0	11586000000.0	12700000000.0	22263000000.0	17729000000.0
Net Current Asset Value	9228000000.0	11906000000.0	12130000000.0	24494000000.0	16510000000.0

67 rows × 5 columns

In [7]:
```
#profitability Ratio
companies.ratios.collect_profitability_ratios()
```

Out[7]:

date	2019	2020	2021	2022	2023
Gross Margin	0.6121	0.6199	0.6234	0.6493	0.5693
Operating Margin	0.3247	0.2607	0.2718	0.3731	0.1566
Net Profit Margin	0.3534	0.2561	0.2598	0.3623	0.1619
Interest Coverage Ratio	70.1034	65.4423	30.9293	48.0975	22.0153
Income Before Tax Profit Margin	0.3325	0.272	0.2644	0.3694	0.155
Effective Tax Rate	-0.0629	0.0586	0.0175	0.019	-0.0447
Return on Assets	NaN	0.1827	0.1879	0.2673	0.1023
Return on Equity	NaN	0.2595	0.2978	0.4483	0.1793
Return on Invested Capital	NaN	0.2443	0.2409	0.3233	0.1319
Return on Capital Employed	0.3305	0.1946	0.1847	0.2554	0.1283
Return on Tangible Assets	NaN	0.1406	0.1315	0.1814	0.0693
Income Quality Ratio	0.9039	1.7028	1.344	0.934	1.2914
Net Income per EBT	1.0629	0.9414	0.9825	0.981	1.0447
Free Cash Flow to Operating Cash Flow Ratio	0.8397	0.8973	0.8063	0.8928	0.6751
EBT to EBIT Ratio	0.9853	0.9828	0.9599	0.9768	0.941
EBIT to Revenue	0.3375	0.2768	0.2754	0.3781	0.1647

In [8]:

```
#efficiency Ratios
companies.ratios.collect_efficiency_ratios()
```

Out[8]:

date	2019	2020	2021	2022	2023
Days of Inventory Outstanding	NaN	112.3145	81.5277	85.6719	121.9599
Days of Sales Outstanding	NaN	51.5005	44.7193	48.0017	57.3535
Operating Cycle	NaN	163.815	126.2471	133.6736	179.3134
Days of Accounts Payable Outstanding	NaN	52.6831	54.875	57.6947	46.7481
Cash Conversion Cycle	NaN	111.1318	71.3721	75.979	132.5652
Cash Conversion Efficiency	0.3195	0.4361	0.3491	0.3384	0.2091
Receivables Turnover	NaN	0.1411	0.1225	0.1315	0.1571
Inventory Turnover Ratio	NaN	3.2498	4.477	4.2604	2.9928
Accounts Payable Turnover Ratio	NaN	6.9282	6.6515	6.3264	7.8078
SGA-to-Revenue Ratio	0.0846	0.1001	0.1163	0.0805	0.0905
Fixed Asset Turnover	NaN	3.4333	2.0384	1.916	1.612
Asset Turnover Ratio	NaN	0.7134	0.7233	0.7376	0.6319
Operating Ratio	0.6753	0.7393	0.7282	0.6269	0.7932

In [9]:

```
#Liquidty Ratio
companies.ratios.collect_liquidity_ratios()
```

Out[9]:

date	2019	2020	2021	2022	2023
Current Ratio	7.9436	7.6738	4.0904	6.6503	3.5156
Quick Ratio	6.6561	7.037	3.5643	5.9649	2.609
Cash Ratio	5.5847	6.1082	2.9455	4.8923	2.0259
Working Capital	9228000000.0	11906000000.0	12130000000.0	24494000000.0	16510000000.0
Operating Cash Flow Ratio	2.8164	2.6687	1.4833	2.101	0.8595
Operating Cash Flow to Sales Ratio	0.3195	0.4361	0.3491	0.3384	0.2091
Short Term Coverage Ratio	1.5044	2.4428	1.9064	1.6645	0.7239

In [10]:

```
#debt-to-Equity Ratio
companies.ratios.get_debt_to_equity_ratio()
```

Out[10]:

date	2019	2020	2021	2022	2023
NVDA	0.2128	0.2091	0.4497	0.4392	0.5364

Risk Modelling

In [48]:

```
#Dupont Anlysis
companies.models.get_dupont_analysis()
```

Out[48]:

date	2019	2020	2021	2022	2023
Net Profit Margin	0.3534	0.2561	0.2598	0.3623	0.1619
Asset Turnover	NaN	0.7134	0.7233	0.7376	0.6319
Equity Multiplier	NaN	1.4205	1.5846	1.6775	1.7525
Return on Equity	NaN	0.2595	0.2978	0.4483	0.1793

In [12]:

```
#WACC (Weighted Avg cost of Caital) Anlysis
companies.models.get_weighted_average_cost_of_capital(growth=True, lag=[1, 2, 3])
```

Out[12]:

		2019	2020	2021	2022	2023
Market Value Equity	**Lag 1**	NaN	1.198	1.2912	-0.4981	2.3526
	Lag 2	NaN	NaN	4.036	0.15	0.6828
	Lag 3	NaN	NaN	NaN	1.5277	2.8556
Market Value Debt	**Lag 1**	NaN	0.2837	1.9769	0.5384	0.0144
	Lag 2	NaN	NaN	2.8214	3.5795	0.5605
	Lag 3	NaN	NaN	NaN	4.8788	3.6454
Cost of Equity	**Lag 1**	NaN	-0.6391	1.2832	-1.7929	-2.0956
	Lag 2	NaN	NaN	-0.176	-2.8104	-0.1313
	Lag 3	NaN	NaN	NaN	-1.6534	0.9834
Cost of Debt	**Lag 1**	NaN	-0.3016	0.1886	-0.1663	0.0944
	Lag 2	NaN	NaN	-0.1698	-0.009	-0.0875
	Lag 3	NaN	NaN	NaN	-0.3079	0.0846
Corporate Tax Rate	**Lag 1**	NaN	-1.9316	-0.7019	0.0886	-3.3525
	Lag 2	NaN	NaN	-1.2777	-0.6755	-3.561
	Lag 3	NaN	NaN	NaN	-1.3023	-1.7634
Weighted Average Cost of Capital	**Lag 1**	NaN	-0.6371	1.2774	-1.7751	-2.1216
	Lag 2	NaN	NaN	-0.1735	-2.7653	-0.1306
	Lag 3	NaN	NaN	NaN	-1.6407	0.9799

In [49]:

```
# Altman-Z Score
companies.models.get_altman_z_score()
```

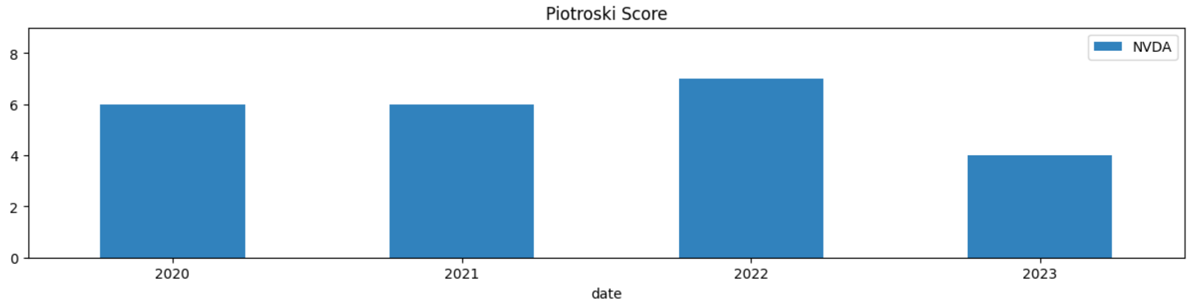
Out[49]:

		2019	2020	2021	2022	2023
NVDA	**Working Capital to Total Assets**	0.6943	0.6876	0.4213	0.5543	0.4009
	Retained Earnings to Total Assets	0.9453	0.8646	0.6567	0.3674	0.247
	EBIT to Total Assets	0.2975	0.1745	0.1595	0.2303	0.1079
	Market Value to Total Liabilities	37.0886	63.0019	62.0083	21.0704	65.0656
	Sales to Total Assets	0.8814	0.6306	0.5792	0.6091	0.655
	Altman Z-Score	26.2728	41.0433	39.7356	15.191	40.8772

In [50]:

```
#Piotroski score

companies.models.get_piotroski_score().loc[:, "Piotroski Score", :].T.plot.bar(
    figsize=(15, 3), rot=0, title="Piotroski Score", colormap="tab20c", ylim=(0, 9)
)
```

Out[50]: <Axes: title={'center': 'Piotroski Score'}, xlabel='date'>



In [14]:
```
#VaR: Value at Risk
companies.risk.get_value_at_risk()
```

Out[14]:

	NVDA	Benchmark
2018	-0.048	-0.0209
2019	-0.0355	-0.012
2020	-0.0561	-0.0314
2021	-0.0404	-0.0131
2022	-0.0656	-0.0262
2023	-0.0346	-0.0139
2024	-0.0188	-0.0078

In [15]:
```
# CVaR: Conditional Value at Risk
companies.risk.get_conditional_value_at_risk(period="yearly")
```

Out[15]:

	NVDA	Benchmark
2018	-0.0834	-0.0275
2019	-0.0548	-0.0196
2020	-0.0811	-0.0545
2021	-0.0541	-0.0183
2022	-0.0781	-0.0335
2023	-0.0438	-0.0157
2024	-0.0236	-0.0122

In [16]:
```
# Ulcer Index
companies.risk.get_ulcer_index(period="yearly", growth=True)
```

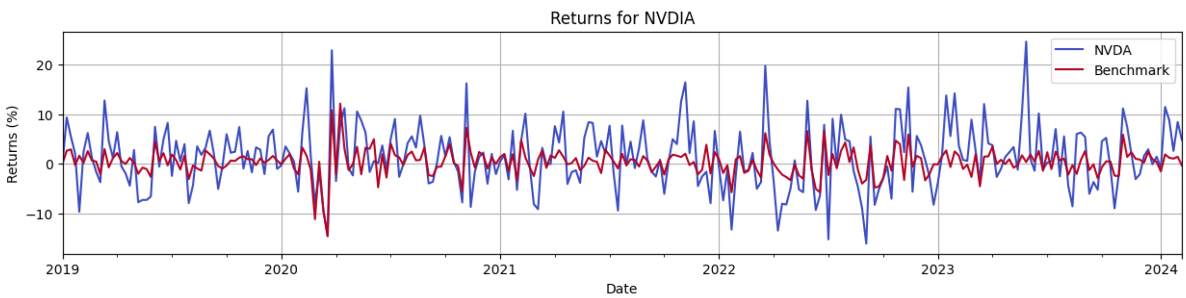
Out[16]:

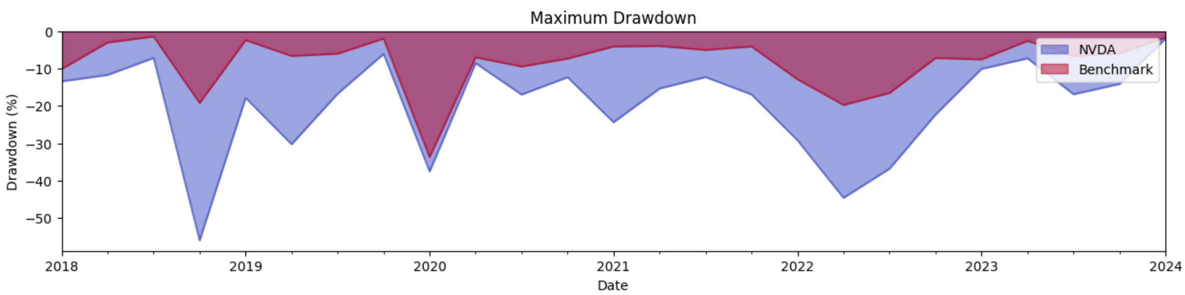
	NVDA	Benchmark
2018	NaN	NaN
2019	-0.3822	-0.557
2020	0.1962	2.7895
2021	-0.1982	-0.7731
2022	1.0884	2.6497
2023	-0.6044	-0.5857
2024	-0.8663	-0.7312

In [19]:

```
#Drawdown performance
(companies.get_historical_data(period="weekly")["Return"] * 100).plot(
    figsize=(15, 3),
    title="Returns for NVDIA",
    grid=True,
    xlabel="Date",
    ylabel="Returns (%)",
    colormap="coolwarm",
)

plt.legend(loc="upper right")

(companies.risk.get_maximum_drawdown(period="quarterly") * 100).plot.area(
    stacked=False,
    figsize=(15, 3),
    title="Maximum Drawdown",
    xlabel="Date",
    ylabel="Drawdown (%)",
    colormap="coolwarm",
)

plt.legend(loc="upper right")
```

Out[19]: <matplotlib.legend.Legend at 0x7c670dd6e470>





In [20]:

```
# NVDIA Beta
companies.performance.get_beta()
```

Out[20]:

Date	NVDA
2019	2.2687
2020	1.3649
2021	2.0148
2022	2.2014
2023	2.0227
2024	2.1026

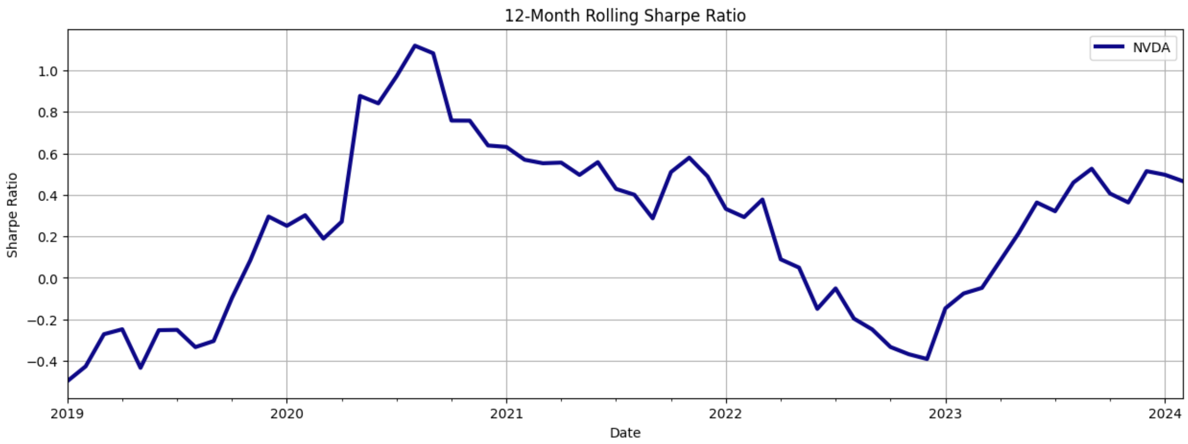
In [21]:
```
# CAPM : Capital asset pricing Model
companies.performance.get_capital_asset_pricing_model(period="yearly")
```

Out[21]:

Date	NVDA
2019	0.6839
2020	0.2468
2021	0.5635
2022	-0.4468
2023	0.4896
2024	0.0305

In [22]:
```
#12-Month Rolling Sharpe Ratio

companies.performance.get_sharpe_ratio(period="monthly", rolling=12).plot(
    figsize=(15, 5),
    title="12-Month Rolling Sharpe Ratio",
    grid=True,
    colormap="plasma",
    lw=3,
    linestyle="-",
    ylabel="Sharpe Ratio",
    xlabel="Date",
)
```

Out[22]:
```
<Axes: title={'center': '12-Month Rolling Sharpe Ratio'}, xlabel='Date', ylabel='Sharpe Ratio'>
```



In [23]:
```
fama_and_french = companies.performance.get_fama_and_french_model(
    period="yearly", method="simple"
)

# Show the Fama and French 5 Factor Model Results
fama_and_french
```

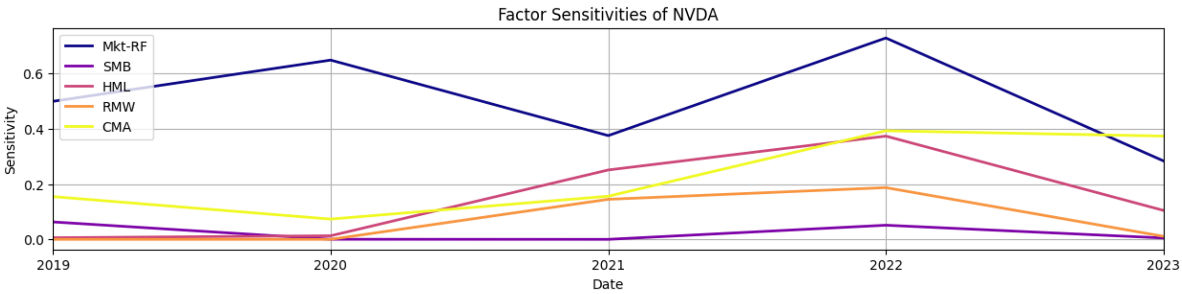
```
Calculating Individual Factor Exposures: 100%|██████████| 1/1 [00:15<00:00, 15.44
s/it]
```

Out[23]:

	Mkt-RF							SMB		
	Intercept	Slope	R Squared	P Value	Standard Error	Factor Value	Residuals	Intercept	Slope	R Squared
2019	0.2338	22.6596	0.4996	0.0	1.4344	0.28	-5.8092	0.0107	4.8636	0.063
2020	-0.0009	47.8862	0.6488	0.0	2.2239	0.39	-17.4518	0.0235	-0.4705	0.0003
2021	0.0181	19.1214	0.3755	0.0	1.5595	-0.31	7.1642	-0.0004	0.2062	0.0
2022	0.1776	34.0762	0.7288	0.0	1.3172	-0.22	6.8165	0.0218	3.2594	0.0512
2023	0.2841	14.8836	0.2839	0.0	1.5009	-0.43	8.5059	-0.0372	-1.6337	0.0049

5 rows × 35 columns

In [24]:
```
# R-Sqaquared over time
for ticker in companies._tickers:
    fama_and_french[ticker].xs("R Squared", level=1, axis=1).plot(
        figsize=(15, 3),
        title=f"Factor Sensitivities of {ticker}",
        grid=True,
        colormap="plasma",
        lw=2,
        linestyle="-",
        ylabel="Sensitivity",
        xlabel="Date",
    )
```



In [25]:
```
#Factor Asset Correlations
companies.performance.get_factor_asset_correlations(period="yearly")
```

```
Calculating Factor Asset Correlations: 100%|██████████| 1/1 [00:06<00:00,  6.35s/i
t]
```

Out[25]:

	NVDA				
	Mkt-RF	SMB	HML	RMW	CMA
2019	0.7068	0.2511	-0.0766	-0.0031	-0.3933
2020	0.8055	-0.016	-0.1137	0.0056	-0.2707
2021	0.6128	0.0067	-0.5011	-0.3806	-0.3951
2022	0.8537	0.2263	-0.6113	-0.4326	-0.6269
2023	0.5329	-0.0699	-0.3238	-0.1044	-0.6114

MacroEconomic Analysis

In [26]:
```
from financetoolkit import Economics
```

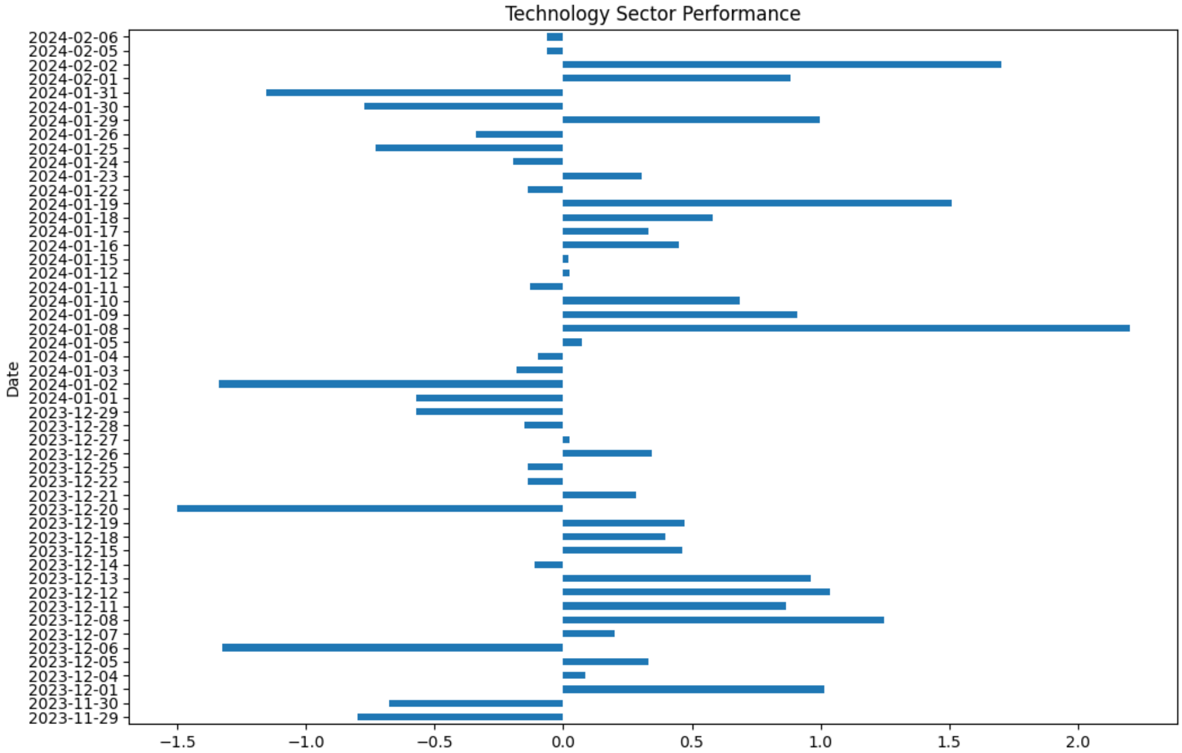
In [27]:
```
# United States GDP

economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

real_gdp = economics.get_gross_domestic_product(inflation_adjusted=True)

real_gdp.loc[:, ['United States']]
```

Out[27]:

	United States
2019	20136378.2764
2020	19690665.9565
2021	20832765.6564
2022	21235981.9981
2023	21737196.3148

In [45]:
```
# Sector performance

from financetoolkit import Discovery

discovery = Discovery(api_key=API_KEY)

sectors_performance = discovery.get_sectors_performance()

sectors_performance['Technology'].plot(kind='barh', title='Technology Sector Perfor
```

Out[45]:
```
<Axes: title={'center': 'Technology Sector Performance'}, ylabel='Date'>
```



In [29]:
```
# Business Confidence Index

economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

business_confidence_index = economics.get_business_confidence_index()

business_confidence_index.loc[:, ['United States']]
```

Out[29]:

	United States
2019-01	100.5237
2019-02	100.3598
2019-03	100.2286
2019-04	100.0084
2019-05	99.8061
2019-06	99.6238
2019-07	99.4055
2019-08	99.131
2019-09	98.9231
2019-10	98.8567
2019-11	98.8784
2019-12	98.9836
2020-01	99.1507
2020-02	99.0361
2020-03	98.6276
2020-04	98.1816
2020-05	98.4099
2020-06	99.2407
2020-07	99.9451
2020-08	100.4126
2020-09	100.7124
2020-10	100.9812
2020-11	101.1452
2020-12	101.3605
2021-01	101.5394
2021-02	101.7777
2021-03	101.9758
2021-04	101.934
2021-05	101.8517
2021-06	101.716
2021-07	101.5828
2021-08	101.536
2021-09	101.576
2021-10	101.5782
2021-11	101.4967
2021-12	101.2959

	United States
2022-01	101.1206
2022-02	101.0088
2022-03	100.8454
2022-04	100.6516
2022-05	100.4376
2022-06	100.1525
2022-07	99.9429
2022-08	99.7729
2022-09	99.5446
2022-10	99.3129
2022-11	99.092
2022-12	98.9105
2023-01	98.7656

In [30]:
```
#consumer confidence index

economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

consumer_confidence_index = economics.get_consumer_confidence_index()

consumer_confidence_index.loc[:, ['United States']]
```

Out[30]:

	United States
2019-01	101.0065
2019-02	101.0596
2019-03	101.2733
2019-04	101.4299
2019-05	101.5161
2019-06	101.4242
2019-07	101.1969
2019-08	100.9068
2019-09	100.9067
2019-10	101.1055
2019-11	101.3688
2019-12	101.592
2020-01	101.5904
2020-02	101.171
2020-03	100.1933
2020-04	99.1298
2020-05	98.6399
2020-06	98.5911
2020-07	98.6081
2020-08	98.8058
2020-09	99.1119
2020-10	99.2576
2020-11	99.2154
2020-12	99.2184
2021-01	99.2243
2021-02	99.3611
2021-03	99.7199
2021-04	99.9593
2021-05	99.9018
2021-06	99.6961
2021-07	99.2375
2021-08	98.6799
2021-09	98.3871
2021-10	98.2043
2021-11	98.0452
2021-12	97.9458

	United States
2022-01	97.7154
2022-02	97.4141
2022-03	97.1813
2022-04	97.0183
2022-05	96.6196
2022-06	96.2206
2022-07	96.1932
2022-08	96.4541
2022-09	96.6686
2022-10	96.781
2022-11	96.8468
2022-12	97.0624
2023-01	97.345

In [31]:

```
# CPI Data

economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

consumer_price_index = economics.get_consumer_price_index()

consumer_price_index.loc[:, ['United States']]
```

Out[31]:

	United States
2019	107.8646
2020	109.1952
2021	114.325
2022	123.4742

In [32]:

```
# PPI Data
economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

producer_price_index = economics.get_producer_price_index(period='yearly')

producer_price_index.loc[:, ['United States']]
```

Out[32]:

	United States
2019	106.0676
2020	103.8489
2021	116.5109
2022	134.4598

In [33]:

```
#Long term Interest rate
```

```
economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

long_term_interest_rate = economics.get_long_term_interest_rate(period='yearly')

long_term_interest_rate.loc[:, ['United States']]
```

Out[33]:

	United States
2019	0.0214
2020	0.0089
2021	0.0144
2022	0.0295

In [34]:

```
#Short term Interest rate

economics = Economics(start_date='2019-01-02', end_date='2023-01-01')

short_term_interest_rate = economics.get_short_term_interest_rate(period='yearly',

short_term_interest_rate.loc[:, ['United States']]
```

Out[34]:

	United States
2019	0.0221
2020	0.0062
2021	0.0011
2022	0.0223
2023	0.0518
2024	0.0501
2025	0.0419

In [47]:

```
# Federal Reserve Rates

economics = Economics(start_date='2019-01-02')

effr = economics.get_federal_reserve_rates()

effr.loc[:, ['Rate', '1st Percentile', '25th Percentile', '75th Percentile', '99th
```

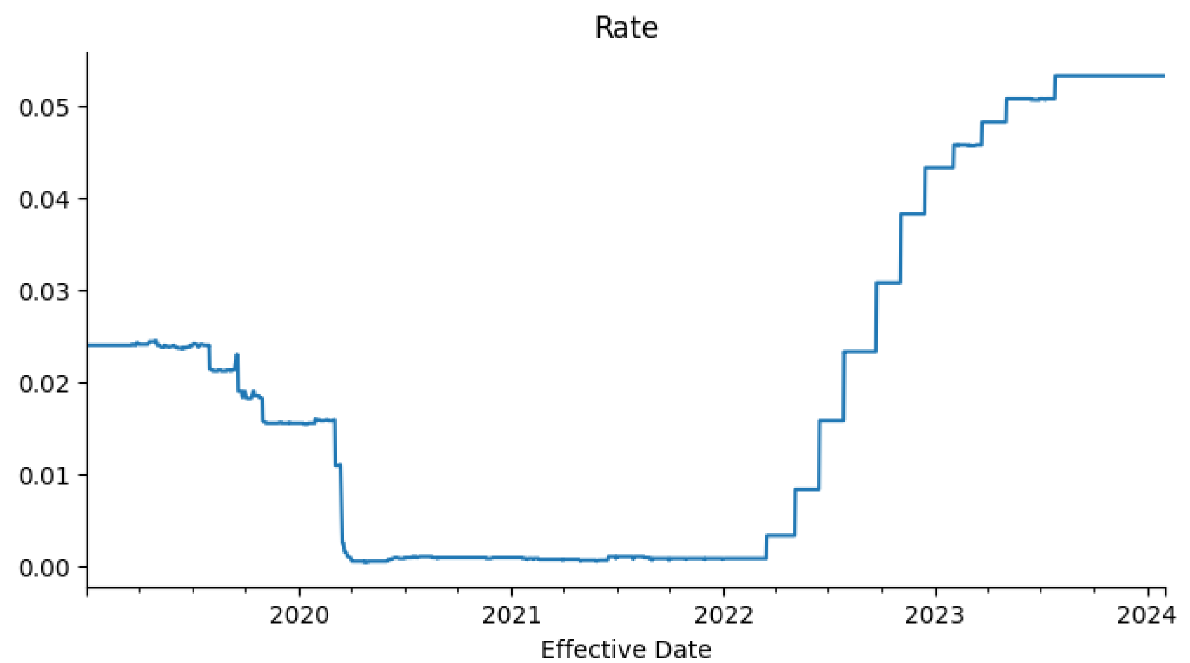
Out[47]:

Effective Date	Rate	1st Percentile	25th Percentile	75th Percentile	99th
2019-01-02	0.024	0.0236	0.024	0.0241	0.02600000000
2019-01-03	0.024	0.023399999999999997	0.024	0.0241	0.02600000000
2019-01-04	0.024	0.023700000000000002	0.024	0.0241	0.02600000000
2019-01-07	0.024	0.023399999999999997	0.024	0.0241	0.02600000000
2019-01-08	0.024	0.0235	0.024	0.0241	0.02600000000
...	...	...	...	...	
2024-01-29	0.0533	0.053099999999999994	0.053200000000000004	0.0533	
2024-01-30	0.0533	0.053099999999999994	0.053200000000000004	0.0533	
2024-01-31	0.0533	0.053	0.053200000000000004	0.053399999999999996	
2024-02-01	0.0533	0.053099999999999994	0.053200000000000004	0.053399999999999996	
2024-02-02	0.0533	0.053099999999999994	0.053200000000000004	0.0533	

1279 rows × 5 columns

In [46]:

```
from matplotlib import pyplot as plt
_df_8['Rate'].plot(kind='line', figsize=(8, 4), title='Rate')
plt.gca().spines[['top', 'right']].set_visible(False)
```



Ipynb to Html

In [ ]:
```
%%shell
jupyter nbconvert --to html /content/Group_4801_Group_Work_Project_2.ipynb
```

In [ ]: