In [1]:
```
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 fixed rate for an unsecured purchase.

We use the German Credit Risk dataset from Kaggle (https://www.kaggle.com/datasets/uciml/german-credit). First, we need download and place the data in the working directory.

> Indented block

In [2]:
```
# Assuming the file is named 'german_credit_data.csv' and is located in the current directory
file_path = 'german_credit_data_target.csv'

# Load the dataset
credit_data = pd.read_csv(file_path)

# Drop the ID column
credit_data.drop(columns=['Unnamed: 0'], inplace=True)

# Display the first few rows of the dataset
print(credit_data.head())
```

```
   Age     Sex  Job Housing Saving accounts Checking account  Credit amount  \
0   67    male    2     own             NaN           little           1169
1   22  female    2     own          little         moderate           5951
2   49    male    1     own          little              NaN           2096
3   45    male    2    free          little           little           7882
4   53    male    2    free          little           little           4870

   Duration              Purpose  Risk
0         6             radio/TV  good
1        48             radio/TV   bad
2        12            education  good
3        42  furniture/equipment  good
4        24                  car   bad
```

In [3]:
```python
# Basic information about the dataset
print("Basic Information:")
print(credit_data.info())
```

```
Basic Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Age               1000 non-null   int64 
 1   Sex               1000 non-null   object
 2   Job               1000 non-null   int64 
 3   Housing           1000 non-null   object
 4   Saving accounts   817 non-null    object
 5   Checking account  606 non-null    object
 6   Credit amount     1000 non-null   int64 
 7   Duration          1000 non-null   int64 
 8   Purpose           1000 non-null   object
 9   Risk              1000 non-null   object
dtypes: int64(4), object(6)
memory usage: 78.2+ KB
None
```

In [4]:
```python
# Summary statistics for numerical columns
print("\nSummary Statistics for Numerical Columns:")
print(credit_data.describe())
```

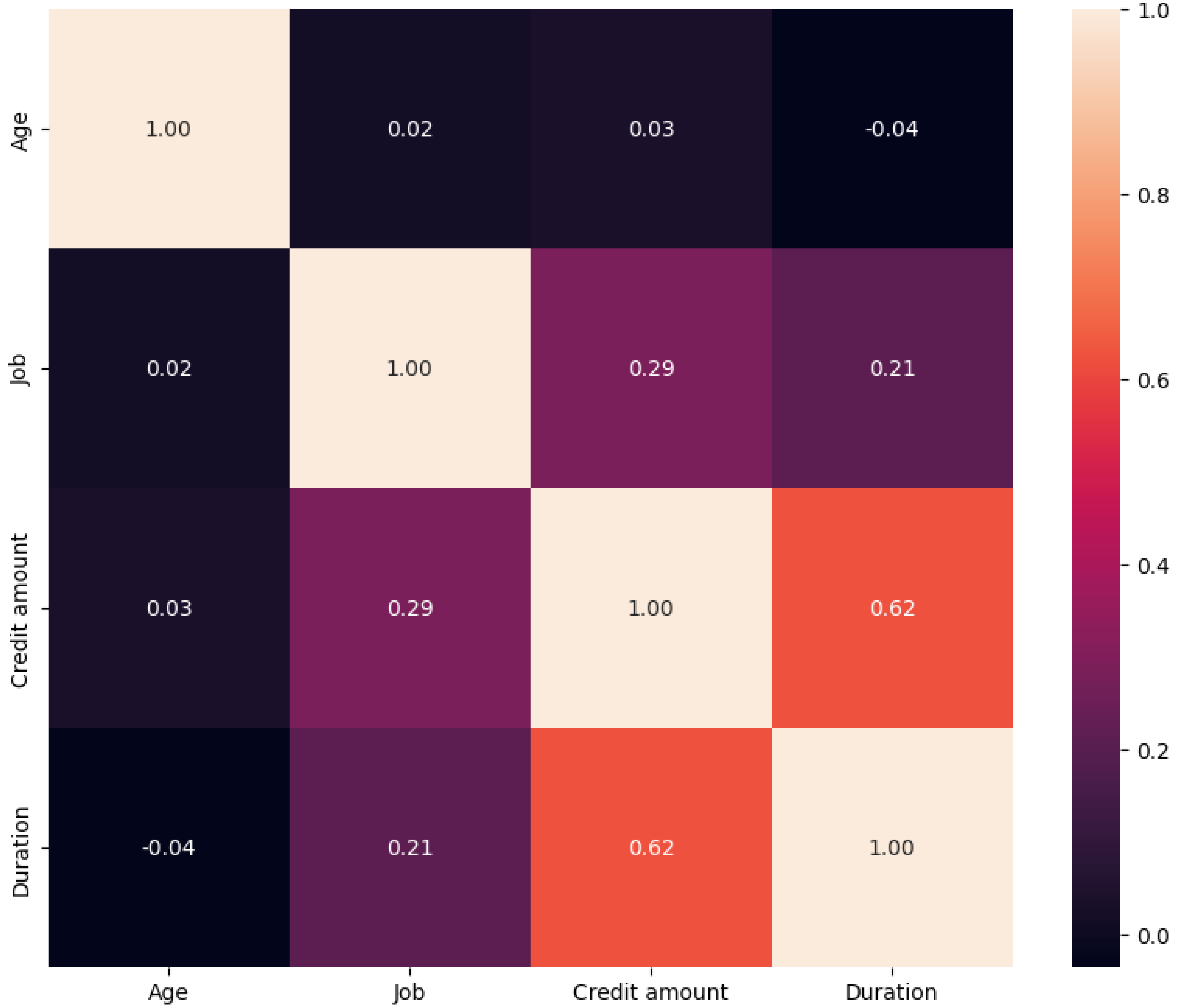
```
Summary Statistics for Numerical Columns:
               Age          Job  Credit amount     Duration
count  1000.000000  1000.000000    1000.000000  1000.000000
mean     35.546000     1.904000    3271.258000    20.903000
std      11.375469     0.653614    2822.736876    12.058814
min      19.000000     0.000000     250.000000     4.000000
25%      27.000000     2.000000    1365.500000    12.000000
50%      33.000000     2.000000    2319.500000    18.000000
75%      42.000000     2.000000    3972.250000    24.000000
max      75.000000     3.000000   18424.000000    72.000000
```

In [5]:
```
# Check for missing values
print(credit_data.isnull().sum())

# Handle missing values, for example, by filling them with a placeholder
# Here, filling missing values with 'unknown' for categorical columns
credit_data.fillna('unknown', inplace=True)
```

```
Age                   0
Sex                   0
Job                   0
Housing               0
Saving accounts     183
Checking account    394
Credit amount         0
Duration              0
Purpose               0
Risk                  0
dtype: int64
```

In [6]:
```
# Plotting a heatmap to visualize correlations
plt.figure(figsize=(10, 8))
sns.heatmap(credit_data.corr(), annot=True, fmt=".2f")
plt.show()
```

```
<ipython-input-6-cdf140947f29>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(credit_data.corr(), annot=True, fmt=".2f")
```

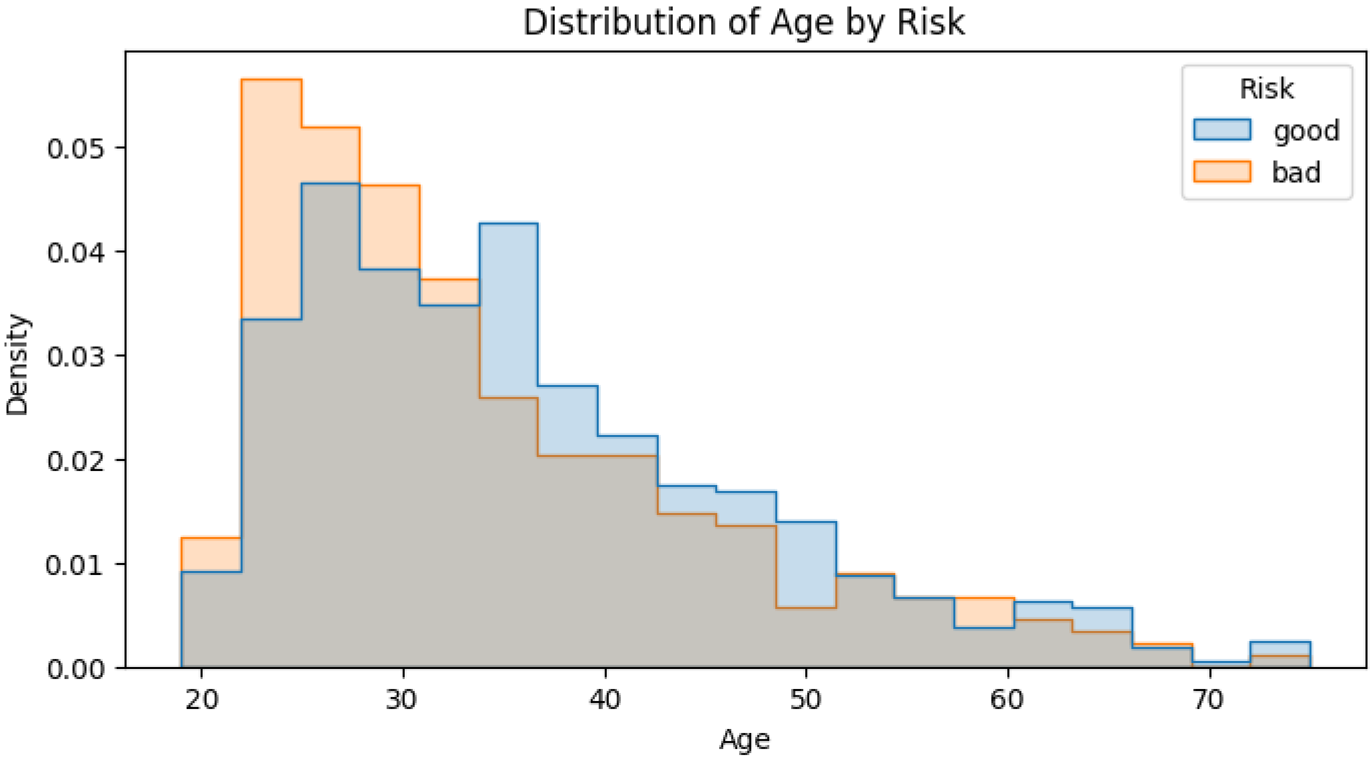

Age
Job
Credit amount
Duration
1.00
0.02
0.03
-0.04
0.02
1.00
0.29
0.21
0.03
0.29
1.00
0.62
-0.04
0.21
0.62
1.00
Age
Job
Credit amount
Duration
1.0
0.8
0.6
0.4
0.2
0.0

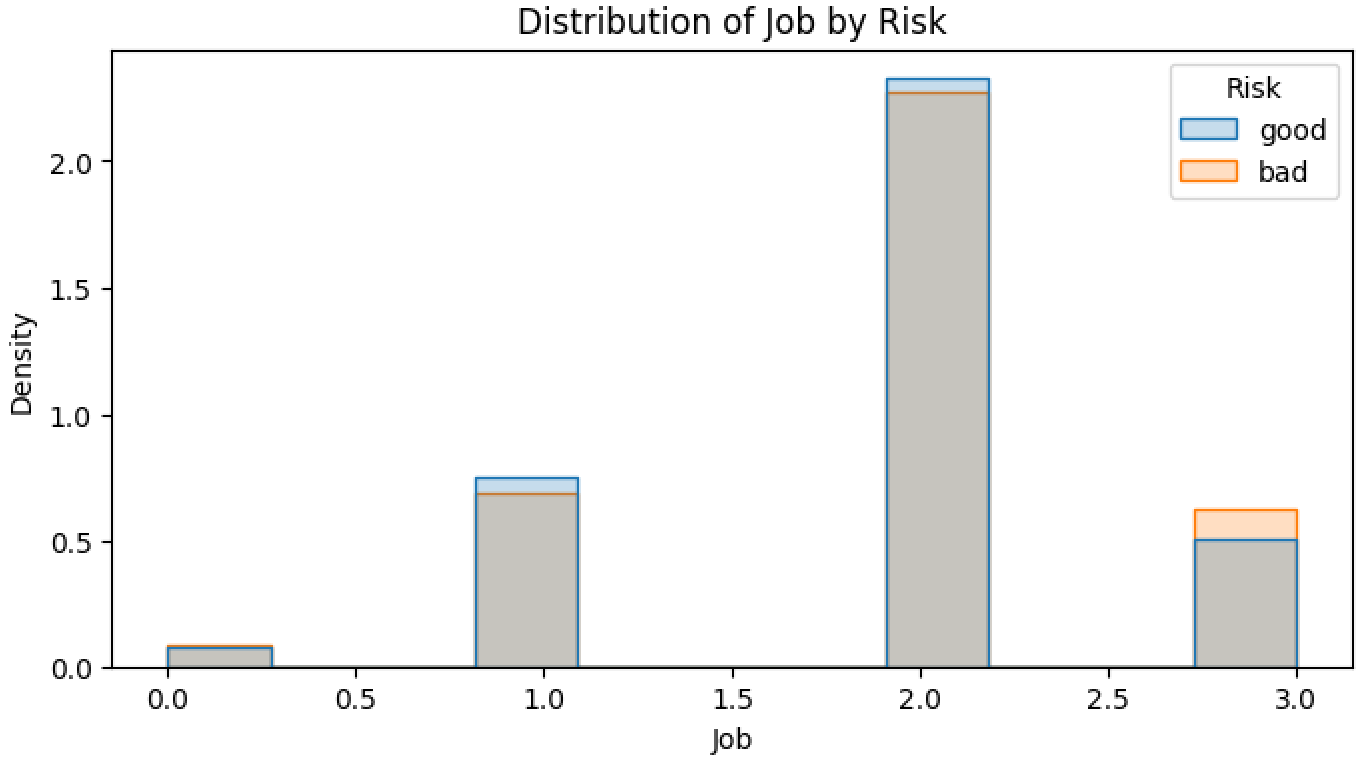
There is a moderately positive correlation (0.62) between the credit amount and the duration of the credit. This suggests that higher credit amounts are typically associated with longer repayment periods, which is intuitive as larger loans often require more time to repay.

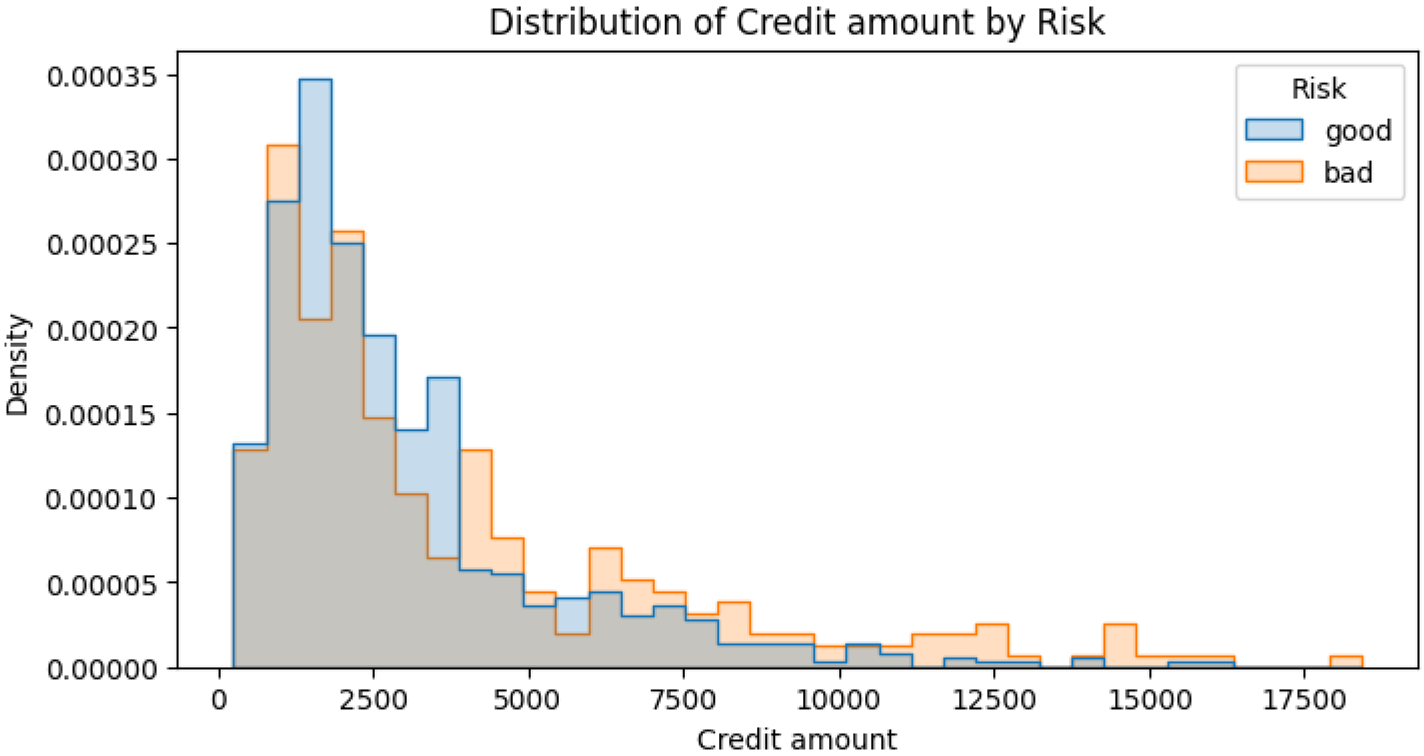
The correlation between job level and credit amount is very weak (0.29), suggesting that the job level of an individual has a minimal direct influence on the amount of credit granted. This may imply that other factors, such as credit history or income, play a more significant role in determining credit amounts.

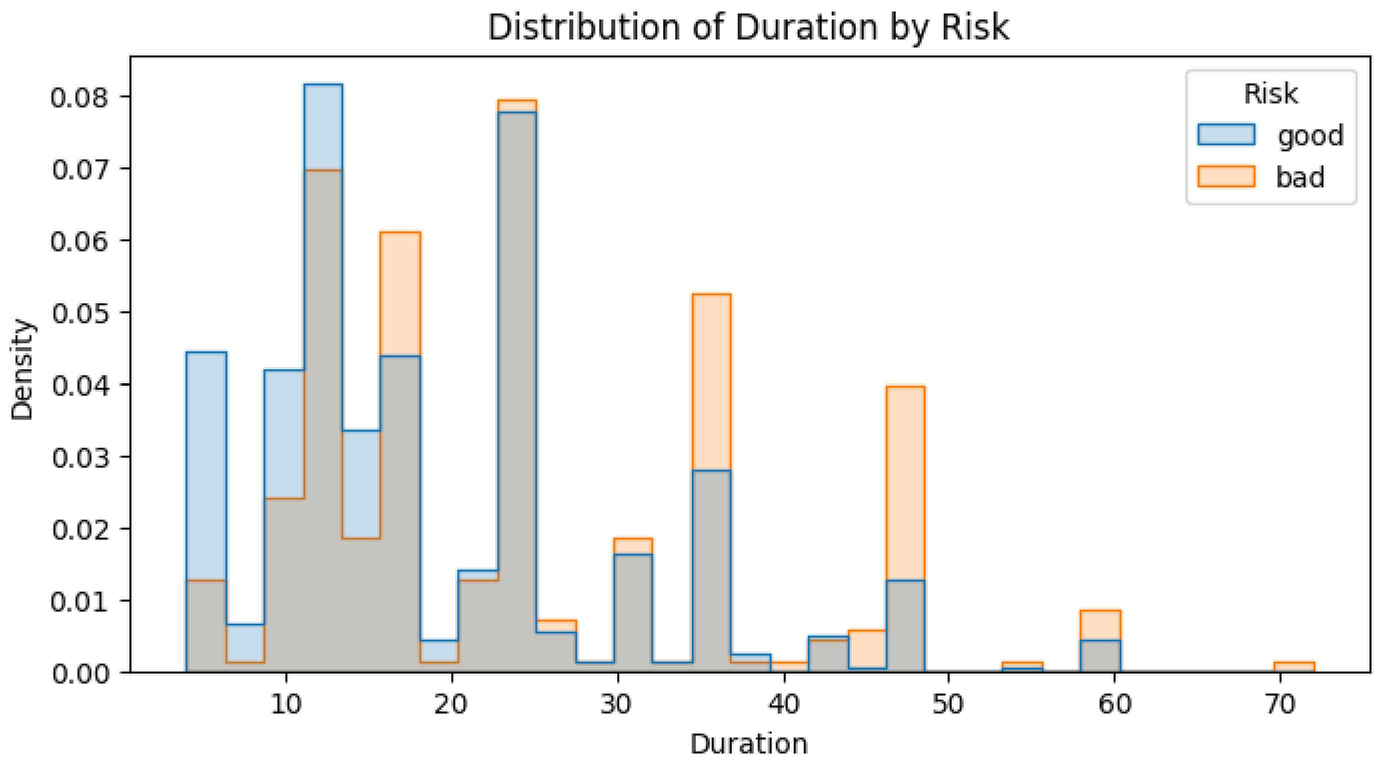
In [7]:

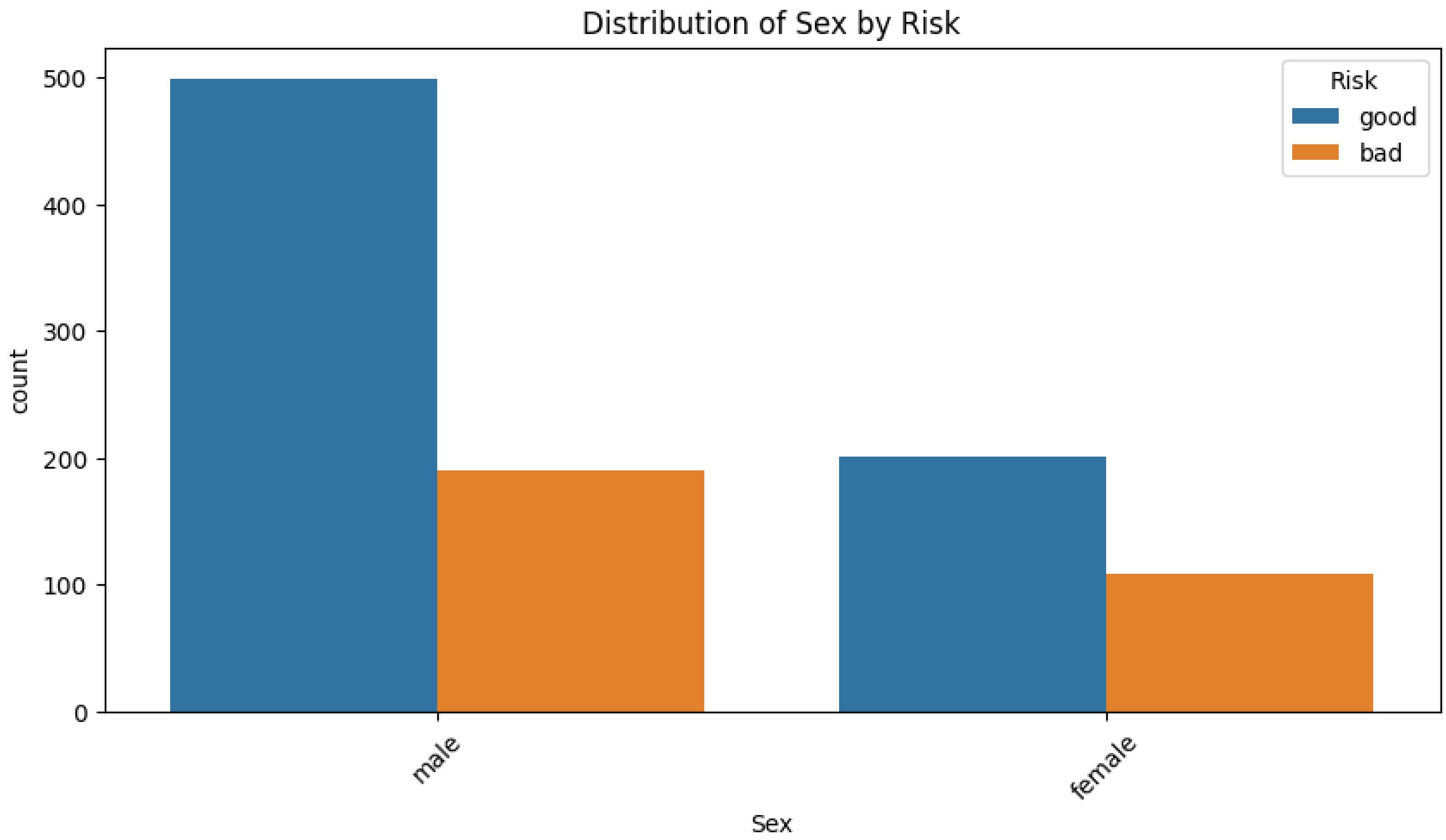
```
# Plotting histograms for numeric features with respect to Risk
numeric_features = ['Age', 'Job', 'Credit amount', 'Duration']
for feature in numeric_features:
    plt.figure(figsize=(8, 4))
    sns.histplot(credit_data, x=feature, hue='Risk', element='step', stat='density', common_norm=False)
    plt.title(f'Distribution of {feature} by Risk')
    plt.show()

# Analysis of categorical features with respect to Risk
categorical_features = ['Sex', 'Housing', 'Saving accounts', 'Checking account', 'Purpose']
for feature in categorical_features:
    plt.figure(figsize=(10, 5))
    sns.countplot(x=feature, hue='Risk', data=credit_data)
    plt.title(f'Distribution of {feature} by Risk')
    plt.xticks(rotation=45)
    plt.show()
```

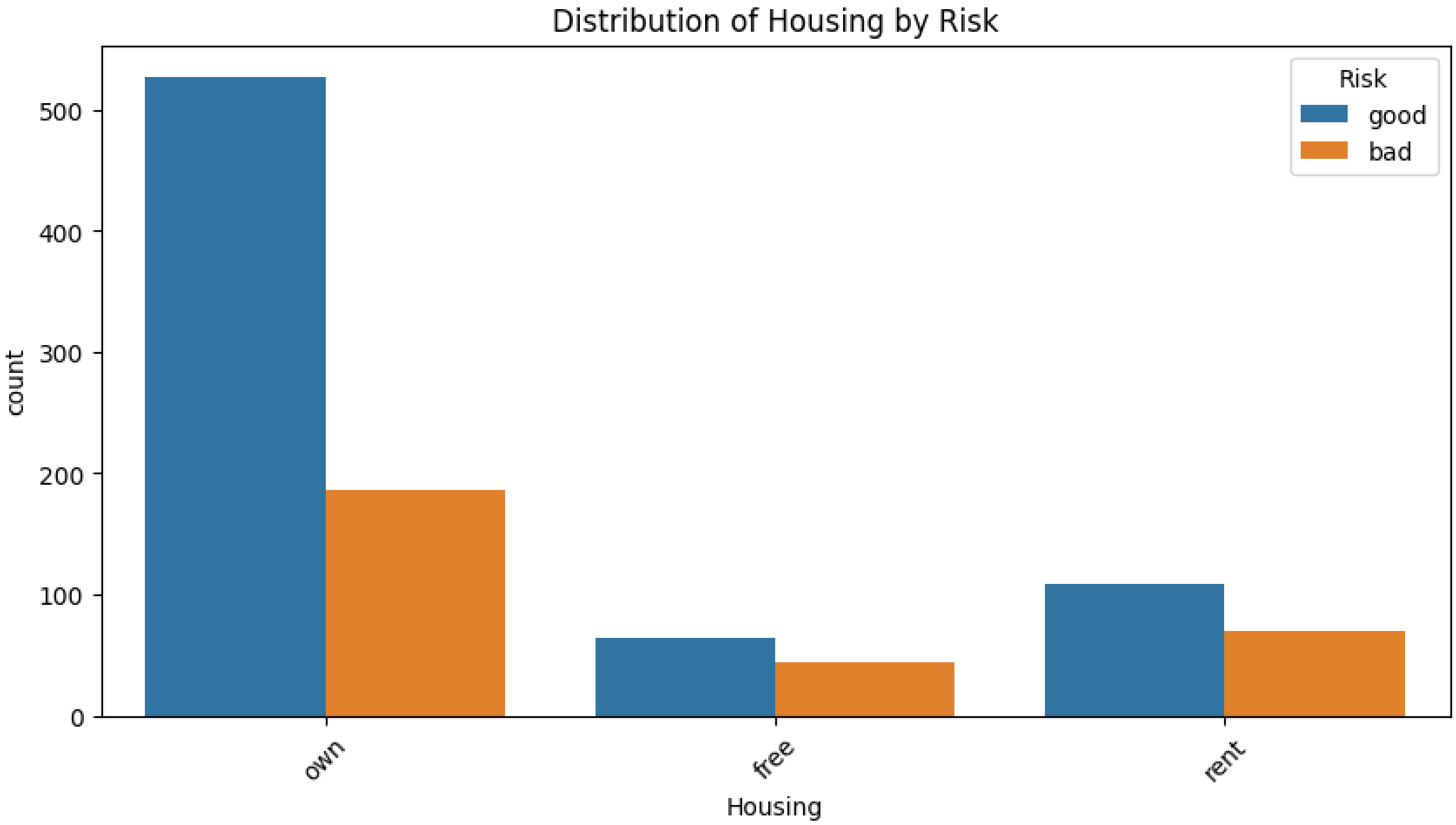

Distribution of Age by Risk
Risk
good
bad
Density
0.00
0.01
0.02
0.03
0.04
0.05
20
30
40
50
60
70
Age

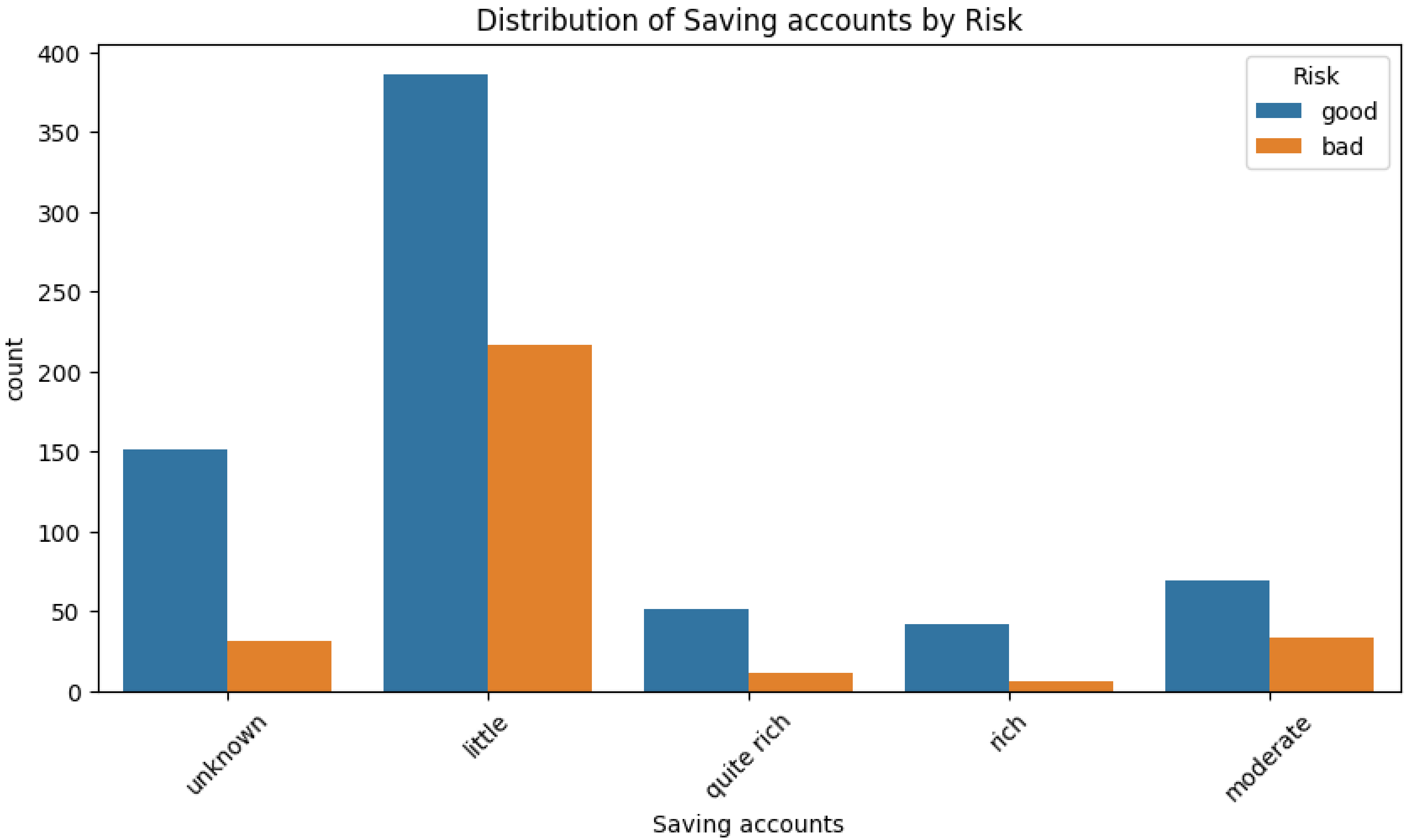

Distribution of Job by Risk
Risk
good
bad
Density
Job
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Distribution of Credit amount by Risk
Risk
good
bad
Density
0.00000
0.00005
0.00010
0.00015
0.00020
0.00025
0.00030
0.00035
0
2500
5000
7500
10000
12500
15000
17500
Credit amount

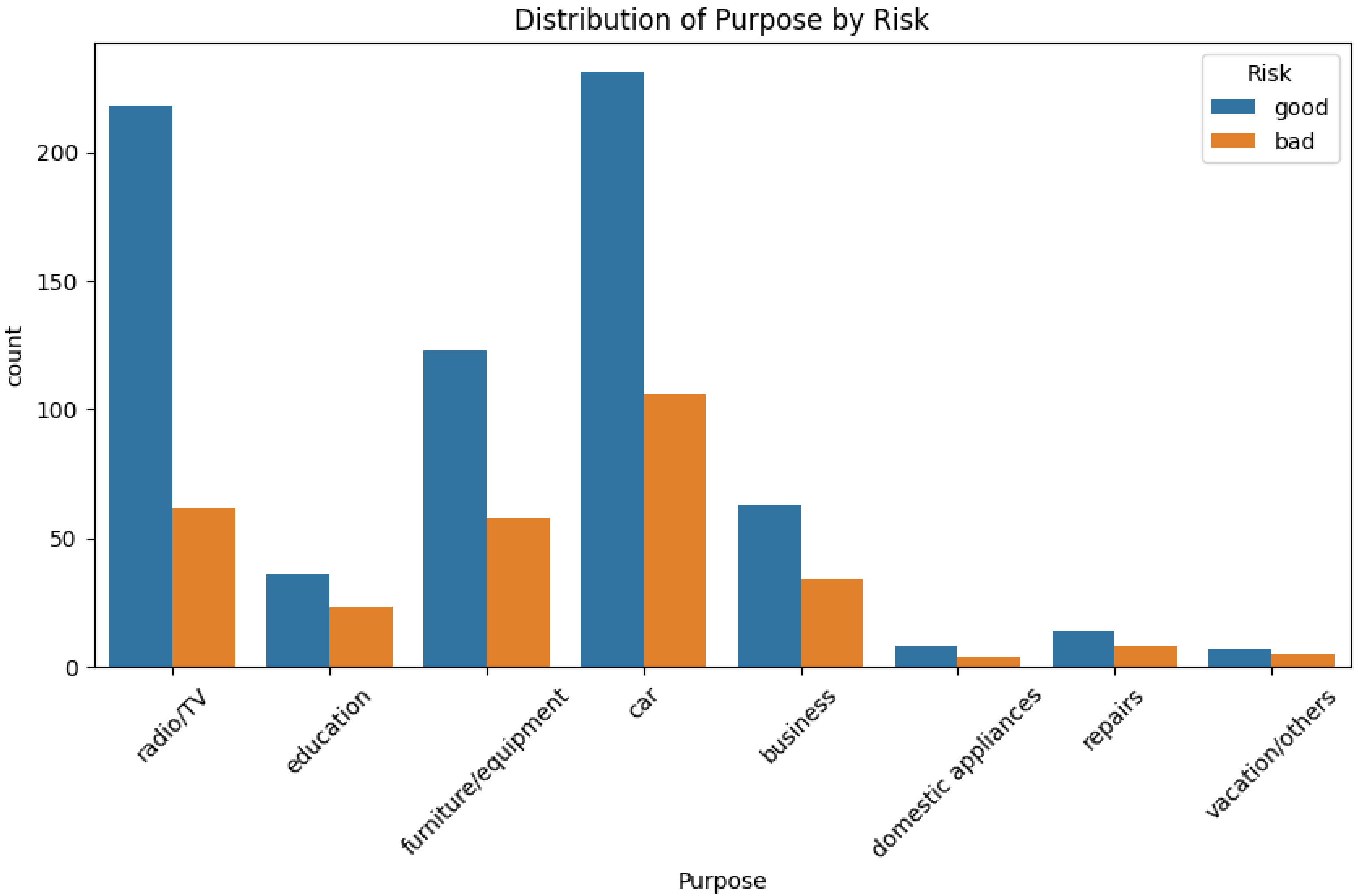

Distribution of Duration by Risk
Density
Duration
Risk
good
bad
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
10
20
30
40
50
60
70


Distribution of Sex by Risk
Risk
good
bad
count
500
400
300
200
100
0
male
female
Sex


Distribution of Housing by Risk
Risk
good
bad
count
500
400
300
200
100
0
own
free
rent
Housing


Distribution of Saving accounts by Risk
Risk
good
bad
count
400
350
300
250
200
150
100
50
0
unknown
little
quite rich
rich
moderate
Saving accounts


Distribution of Checking account by Risk
Risk
good
bad
count
0
50
100
150
200
250
300
350
little
moderate
unknown
rich
Checking account



Above figures allows to see which factors affects the outcome the most. Details will be discussed in the report.

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Encoding categorical variables
label_encoders = {}
```

```
for column in credit_data.select_dtypes(include=['object']).columns:
    label_encoders[column] = LabelEncoder()
    credit_data[column] = label_encoders[column].fit_transform(credit_data[column])

# Splitting the data into features and target
X = credit_data.drop('Risk', axis=1)
y = credit_data['Risk']

# Splitting the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [9]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

# Training the Random Forest Classifier
rf_classifier = RandomForestClassifier(random_state=42)
rf_classifier.fit(X_train, y_train)

# Predicting on test set
y_pred = rf_classifier.predict(X_test)

# Evaluating the model
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.60      0.40      0.48        91
           1       0.77      0.89      0.82       209

    accuracy                           0.74       300
   macro avg       0.69      0.64      0.65       300
weighted avg       0.72      0.74      0.72       300
```

In [10]:

```
import numpy as np

# Getting feature importances
importances = rf_classifier.feature_importances_
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")
for f in range(X_train.shape[1]):
    print(f"{f + 1}. feature {X_train.columns[indices[f]]} ({importances[indices[f]]})")
```

```
Feature ranking:
1. feature Credit amount (0.2429102833603888)
2. feature Age (0.18828154657398738)
3. feature Duration (0.1528232232069147)
4. feature Checking account (0.12797838806562198)
5. feature Purpose (0.08835438016216911)
6. feature Saving accounts (0.06685597568658981)
7. feature Job (0.05937968765275512)
8. feature Housing (0.043698702816807614)
9. feature Sex (0.02971781247476549)
```

Money at a floating rate for a secured purchase.

Beyond the personal credit data, the market data is also important when lending with collateral. In this part, we analyze the property market data. In this task, we assume we are a Singapore bank lending out for resale HDB flat purchase. We use data from the HDB Resale Price Index (which is normalized by location and etc.) to reflec percentage price change. See https://www.tech.gov.sg/products-and-services/data-gov-sg/

In [11]:
```
hdb_file = "HousingAndDevelopmentBoardResalePriceIndex1Q2009100Quarterly.csv"
hdb_data = pd.read_csv(hdb_file)
```

In [12]:
```
# Convert 'quarter' to datetime for better handling
def convert_quarter_to_date(quarter_str):
    year, quarter = quarter_str.split('-')
    month = {'Q1': '01', 'Q2': '04', 'Q3': '07', 'Q4': '10'}.get(quarter, '01')
    return f"{year}-{month}-01"

hdb_data['quarter'] = pd.to_datetime(hdb_data['quarter'].apply(convert_quarter_to_date))

# Replotting
plt.figure(figsize=(15, 6))
plt.plot(hdb_data['quarter'], hdb_data['index'], marker='o', linestyle='-', color='b')
plt.title('HDB Resale Price Index Over Time')
plt.xlabel('Year')
plt.ylabel('Index')
plt.grid(True)
plt.xticks(rotation=45)
```

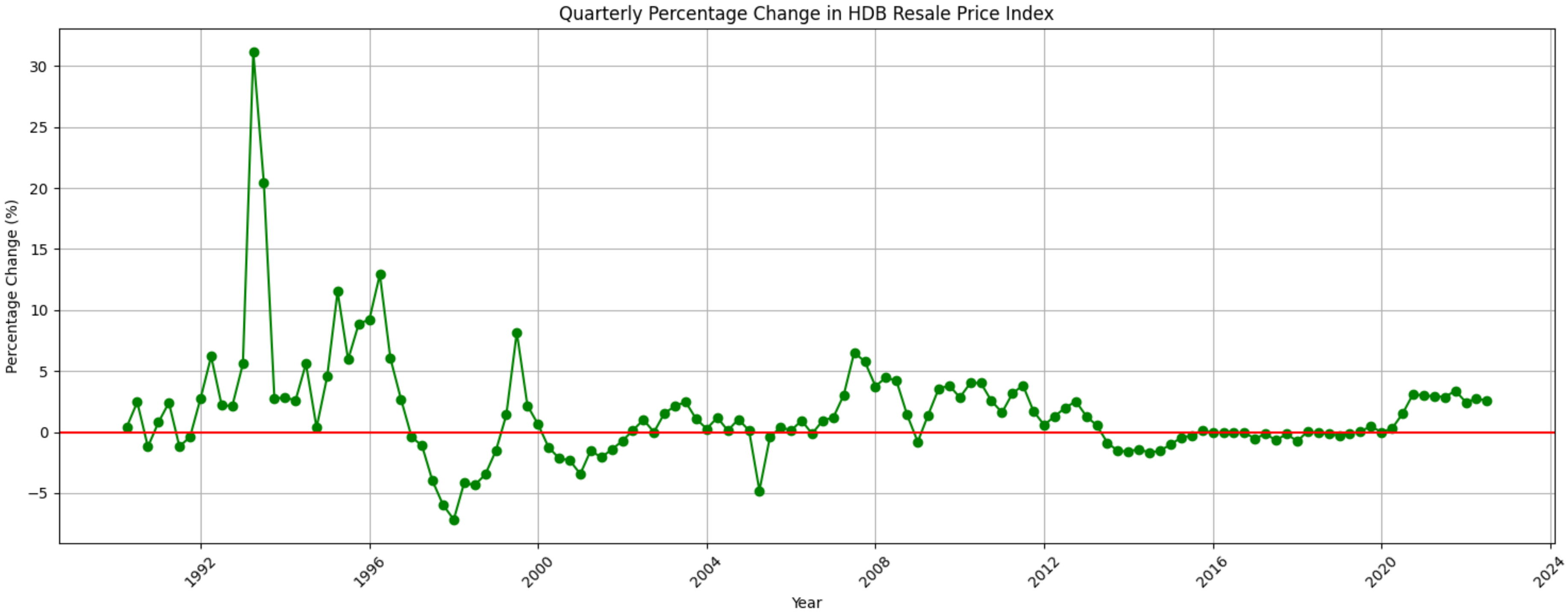
```
plt.tight_layout()

# Show the plot
plt.show()
```

We see a general upward trends with some downturns in the visualization above.

In [13]:
```
# Calculating the percentage change over quarters
hdb_data['percent_change'] = hdb_data['index'].pct_change() * 100

# Displaying the first few rows with percentage change
hdb_data.head()

# Calculating market volatility metrics
# Standard deviation of percentage change (a common measure of volatility)
mean_change = hdb_data['percent_change'].mean()
std_dev_change = hdb_data['percent_change'].std()

# Displaying the calculated metrics
mean_change, std_dev_change
```

Out[13]: (1.5839324830676489, 4.342077929643165)

In [14]:
```
# Plotting the percentage change (return) over time
plt.figure(figsize=(15, 6))
plt.plot(hdb_data['quarter'], hdb_data['percent_change'], marker='o', linestyle='-', color='g')
plt.title('Quarterly Percentage Change in HDB Resale Price Index')
plt.xlabel('Year')
plt.ylabel('Percentage Change (%)')
plt.grid(True)
plt.xticks(rotation=45)
plt.axhline(y=0, color='r', linestyle='-')  # Adding a line at 0% change for reference
plt.tight_layout()

# Show the plot
plt.show()
```



In [15]:
```
# For a 30-year period, which is 120 quarters, we need to adjust the standard deviation
# The standard deviation over multiple periods is the standard deviation of one period
# multiplied by the square root of the number of periods
```

```python
# Number of periods (quarters) in 30 years
num_periods = 120

# Adjusted standard deviation for 30 years
adjusted_std_dev = std_dev_change * (num_periods ** 0.5)

# Calculating the 95% confidence interval for 30 years
ci_lower_30_years = mean_change * num_periods - 1.96 * adjusted_std_dev
ci_upper_30_years = mean_change * num_periods + 1.96 * adjusted_std_dev

ci_lower_30_years, ci_upper_30_years
```

Out[15]:

```
(96.84434005049093, 283.2994558857448)
```

Money at a fixed rate for a business for a construction loan.

In [16]:

```python
#To analyze Money at a fixed rate for a business for a construction loan I have used 5 years of WellTower data using yahoo financ
```

In [17]:

```python
# Load the dataset
df_well = pd.read_csv("Scenerio_3.csv")

# Display the first few rows of the dataset
df_well.head()
```

Out[17]:

	Date	Total Construction Spending	All Employees	Average Hourly Earnings of All Employees	Producer Price Index by Construction Materials	Interest rate	Loans Secured by Real Estate	Stock price
0	1/1/2019	1296049	7424	30.32	238.5	2.40	353984.699	57.805672
1	2/1/2019	1312040	7396	30.42	238.1	2.40	NaN	63.552090
2	3/1/2019	1322532	7422	30.53	238.1	2.41	NaN	62.352749
3	4/1/2019	1353657	7459	30.64	237.2	2.42	357312.746	64.922333
4	5/1/2019	1364421	7486	30.70	237.3	2.39	NaN	63.077301

In [18]:

```python
df_well.describe()
```

Out[18]:

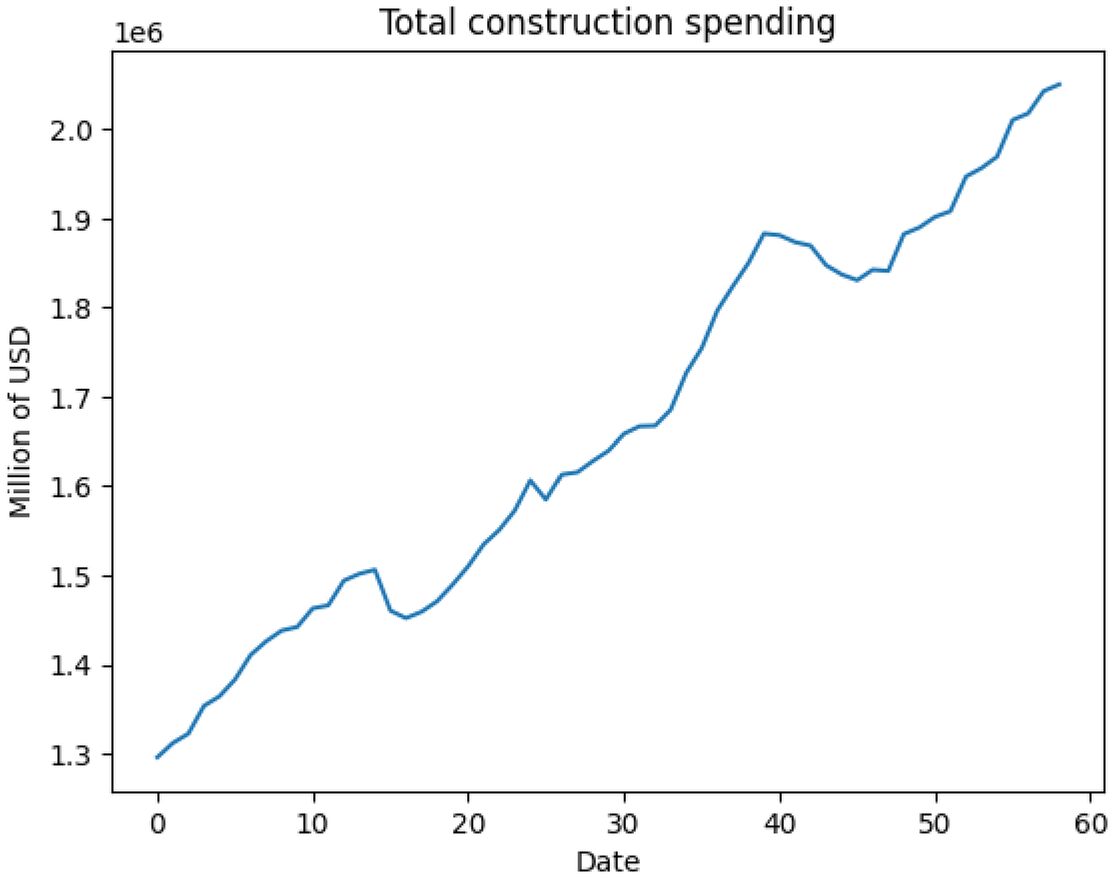
	Total Construction Spending	All Employees	Average Hourly Earnings of All Employees	Producer Price Index by Construction Materials	Interest rate	Loans Secured by Real Estate	Stock price
count	5.900000e+01	59.000000	59.000000	59.000000	59.000000	19.000000	59.000000
mean	1.665694e+06	7572.000000	33.230678	289.701203	1.805593	408681.082579	69.292731
std	2.169382e+05	281.865583	2.092600	47.033501	1.874228	46444.917103	12.221940
min	1.296049e+06	6527.000000	30.320000	232.200000	0.050000	353984.699000	35.661427
25%	1.468693e+06	7403.000000	31.400000	237.250000	0.090000	375461.859500	62.666167
50%	1.639779e+06	7545.000000	32.820000	313.083000	1.550000	393526.249000	71.316750
75%	1.859450e+06	7789.000000	34.980000	333.576000	2.490000	438319.020000	78.164929
max	2.050058e+06	8039.000000	37.200000	353.015000	5.330000	497084.978000	92.685661

In [19]:

```
#Charting economics and industry metrics
df_well["Total Construction Spending"].plot(title="Total construction spending", xlabel='Date', ylabel='Million of USD')
```

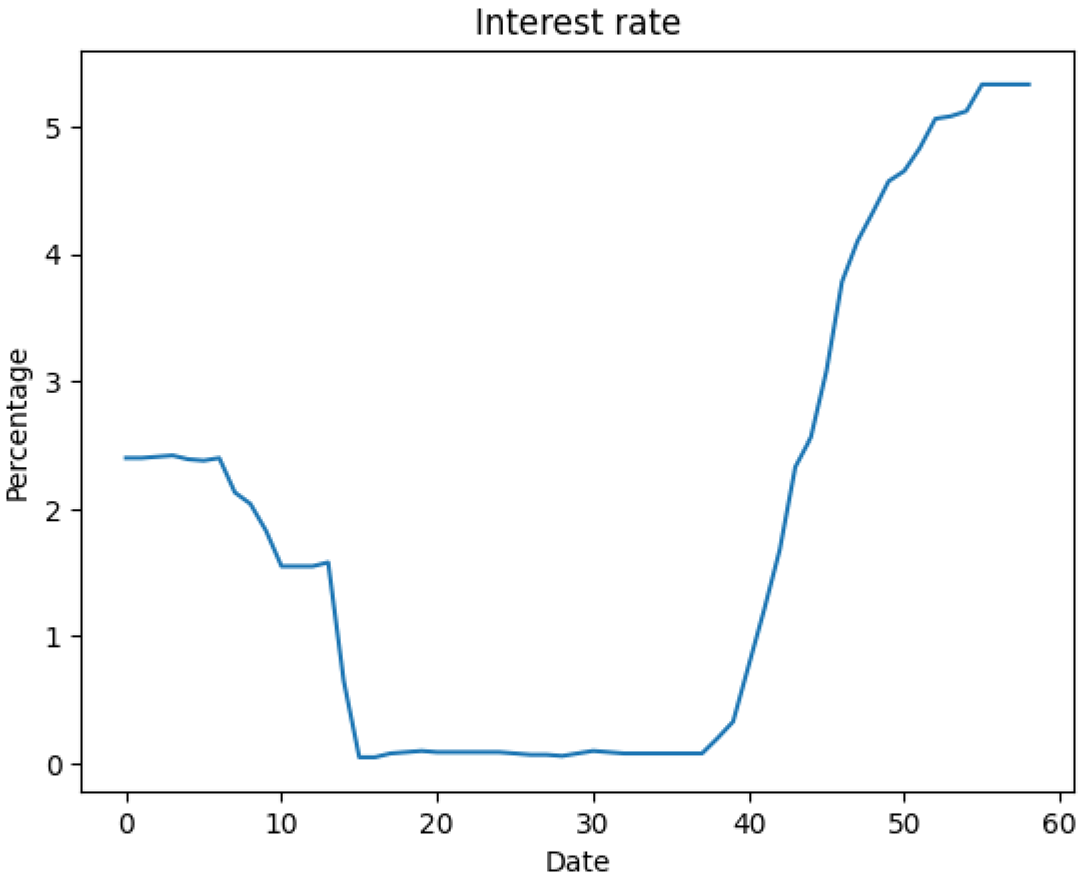
Out[19]:

```
<Axes: title={'center': 'Total construction spending'}, xlabel='Date', ylabel='Million of USD'>
```



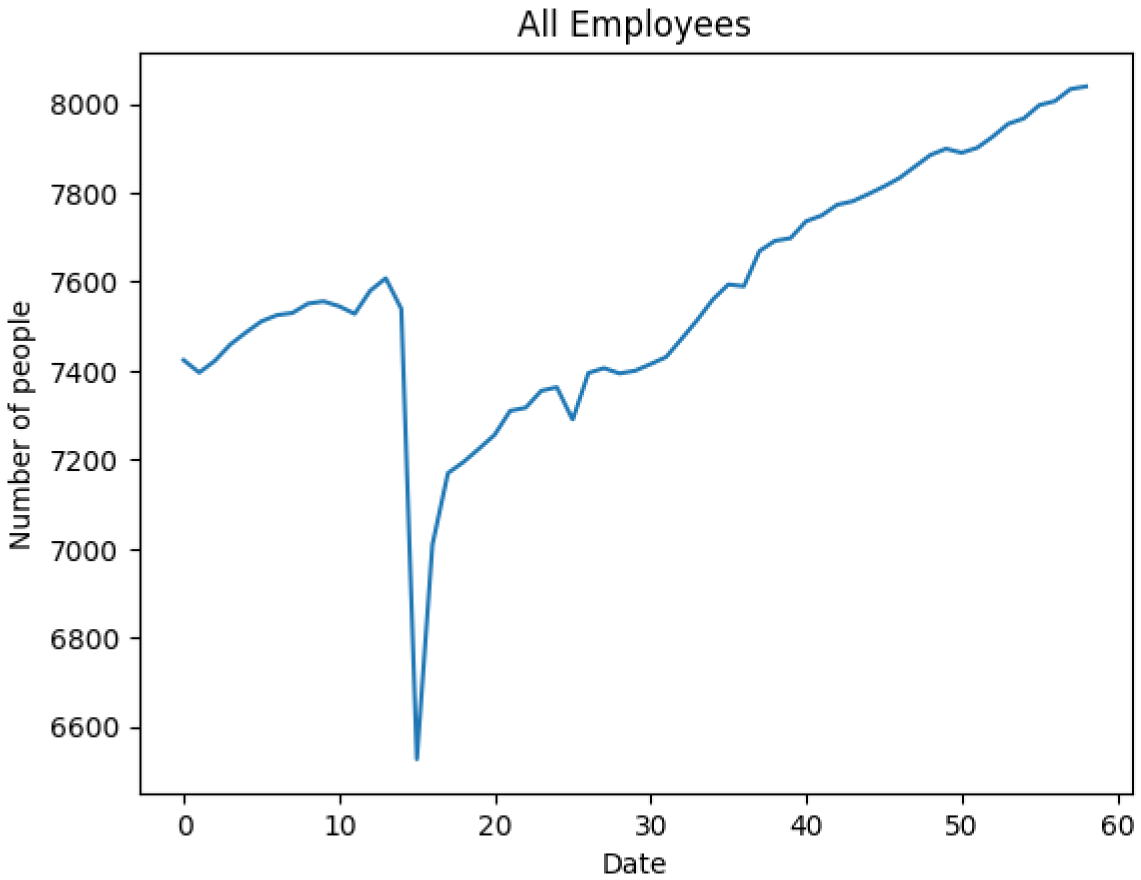
In [20]:
```
df_well["Interest rate"].plot(title="Interest rate", xlabel='Date', ylabel='Percentage')
```

Out[20]:
```
<Axes: title={'center': 'Interest rate'}, xlabel='Date', ylabel='Percentage'>
```



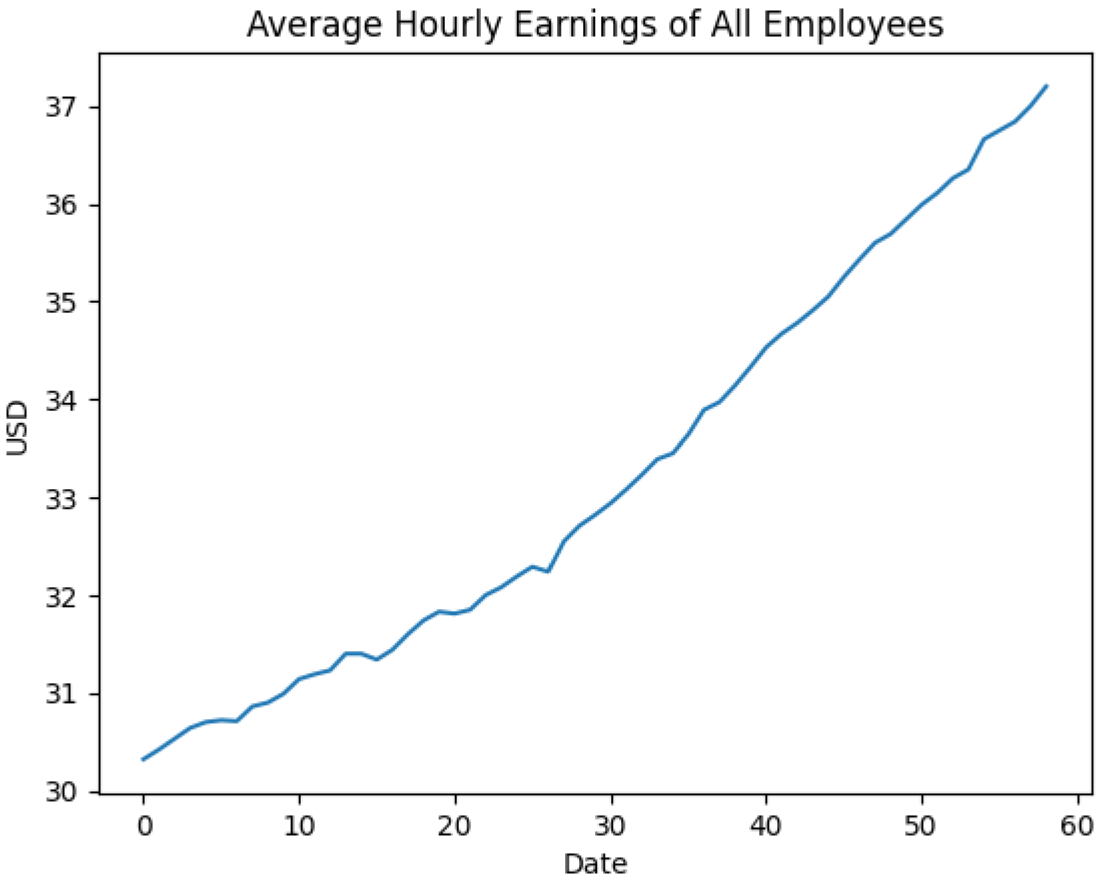
In [21]:
```
df_well["All Employees"].plot(title="All Employees", xlabel='Date', ylabel='Number of people')
```

Out[21]:
```
<Axes: title={'center': 'All Employees'}, xlabel='Date', ylabel='Number of people'>
```



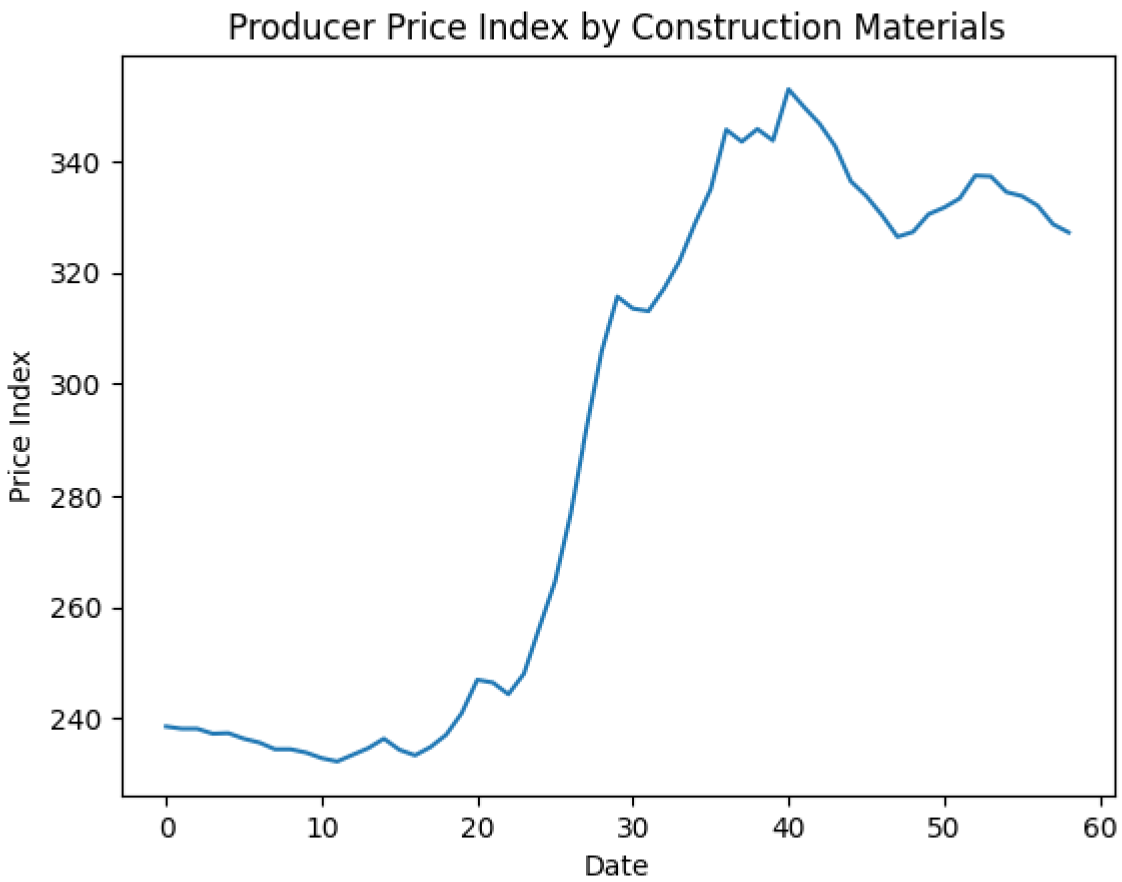
In [22]:
```
df_well["Average Hourly Earnings of All Employees"].plot(title="Average Hourly Earnings of All Employees", xlabel='Date', ylabel=
```

Out[22]:
```
<Axes: title={'center': 'Average Hourly Earnings of All Employees'}, xlabel='Date', ylabel='USD'>
```



In [23]:
```
df_well["Producer Price Index by Construction Materials"].plot(title="Producer Price Index by Construction Materials", xlabel='Da
```

Out[23]:
```
<Axes: title={'center': 'Producer Price Index by Construction Materials'}, xlabel='Date', ylabel='Price Index'>
```



In [24]:
```
df_well["Stock price "].plot(title="Stock price ", xlabel='Date', ylabel='USD')
```

Out[24]:
```
<Axes: title={'center': 'Stock price '}, xlabel='Date', ylabel='USD'>
```

In [25]:
```
# Create a new DataFrame with relevant columns for correlation analysis
correlation_df_well = df_well[['Total Construction Spending',   'All Employees',        'Average Hourly Earnings of All Employees
correlation_matrix = correlation_df_well.corr()
correlation_matrix
```

Out[25]:

	Total Construction Spending	All Employees	Average Hourly Earnings of All Employees	Producer Price Index by Construction Materials	Interest rate	Loans Secured by Real Estate	Stock price
Total Construction Spending	1.000000	0.764239	0.981062	0.915350	0.509093	0.934618	0.562920
All Employees	0.764239	1.000000	0.783897	0.681477	0.764367	0.654550	0.719459
Average Hourly Earnings of All Employees	0.981062	0.783897	1.000000	0.879501	0.627082	0.985315	0.489235
Producer Price Index by Construction Materials	0.915350	0.681477	0.879501	1.000000	0.323758	0.826115	0.628616
Interest rate	0.509093	0.764367	0.627082	0.323758	1.000000	0.599052	0.304177
Loans Secured by Real Estate	0.934618	0.654550	0.985315	0.826115	0.599052	1.000000	0.301036
Stock price	0.562920	0.719459	0.489235	0.628616	0.304177	0.301036	1.000000

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

NVIDIA Stock Analysis

In [26]:

```
#To analyze a publicly traded stock I have used 5 years of NVIDIA data using yahoo finance as my data source
```

In [27]:

```
#Downloading the data using yahoo Finance

start = datetime.date(2019, 1, 1)
end = datetime.date(2023, 12, 31)
df = web.DataReader(["NVDA"], start, end)
```

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

In [28]:

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

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

In [29]:
```
#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[29]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX index
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.000000
mean	177.352243	180.632174	173.983038	177.463569	177.238880	4.626251e+07	21.367917
std	124.757333	126.716487	122.525187	124.675773	124.722888	1.998936e+07	8.238798
min	32.660000	33.790001	31.922501	31.997499	31.748959	9.788400e+06	11.540000
25%	69.150000	70.550625	67.028126	68.320625	68.064875	3.246800e+07	15.960000
50%	145.784996	148.631248	142.300003	145.820000	145.548164	4.319750e+07	19.525001
75%	231.895000	236.667503	225.437496	230.927502	230.648746	5.645790e+07	24.799999
max	502.160004	505.480011	494.119995	504.089996	504.045685	2.511528e+08	82.690002

In [30]:
```
#Viewing the data
df.head()
```

Out[30]:

Date	Open	High	Low	Close	Adj Close_x	Volume	VIX index
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	31.748959	70555200	25.450001
2019-01-04	32.735001	34.432499	32.424999	34.047501	33.783039	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	34.685974	78601600	20.469999

In [31]:
```
#stats Summary of our data
df.describe()
```

Out[31]:

	Open	High	Low	Close	Adj Close_x	Volume	VIX index
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.000000
mean	177.352243	180.632174	173.983038	177.463569	177.238880	4.626251e+07	21.367917
std	124.757333	126.716487	122.525187	124.675773	124.722888	1.998936e+07	8.238798
min	32.660000	33.790001	31.922501	31.997499	31.748959	9.788400e+06	11.540000
25%	69.150000	70.550625	67.028126	68.320625	68.064875	3.246800e+07	15.960000
50%	145.784996	148.631248	142.300003	145.820000	145.548164	4.319750e+07	19.525001
75%	231.895000	236.667503	225.437496	230.927502	230.648746	5.645790e+07	24.799999
max	502.160004	505.480011	494.119995	504.089996	504.045685	2.511528e+08	82.690002

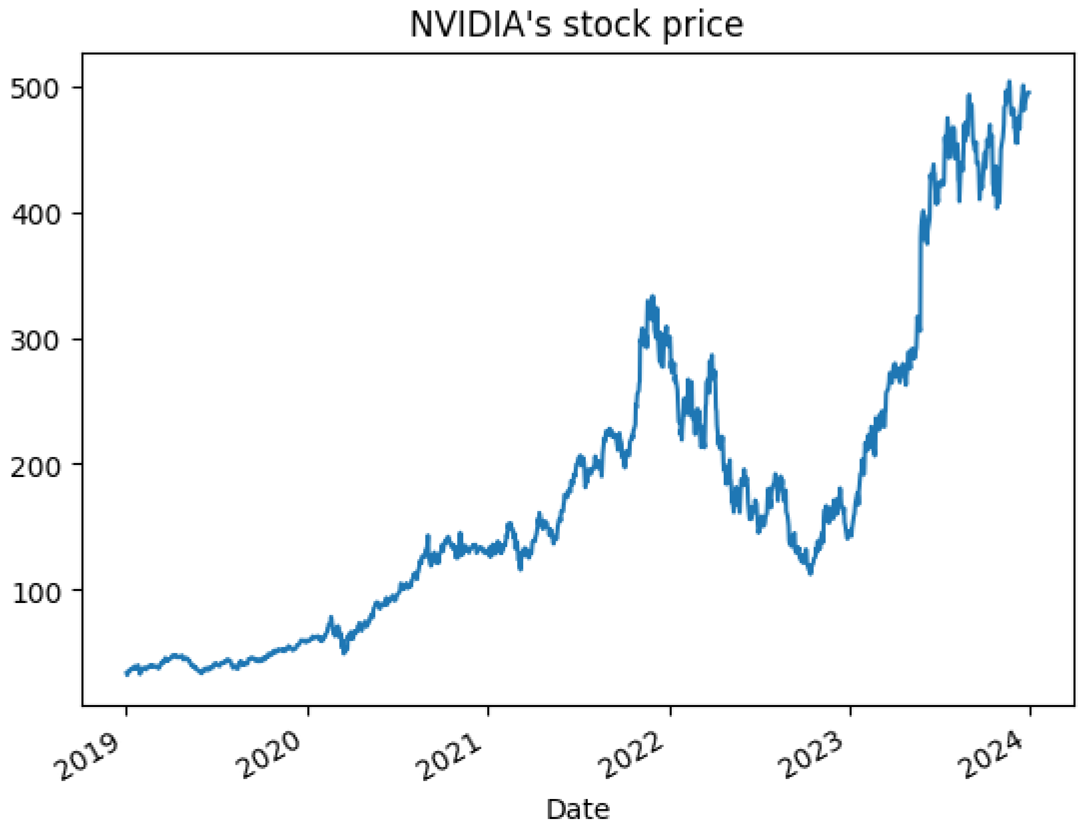
Time Series Analysis

In [32]:

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

Out[32]:

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



Time Series data from 2019-2023 of NVDIA stock

In [33]:
```
# Importing Plotply for Plotting
import plotly.graph_objects as go
from datetime import datetime
```

In [34]:
```
df.columns
```

Out[34]:
```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close_x', 'Volume', 'VIX index'], dtype='object')
```

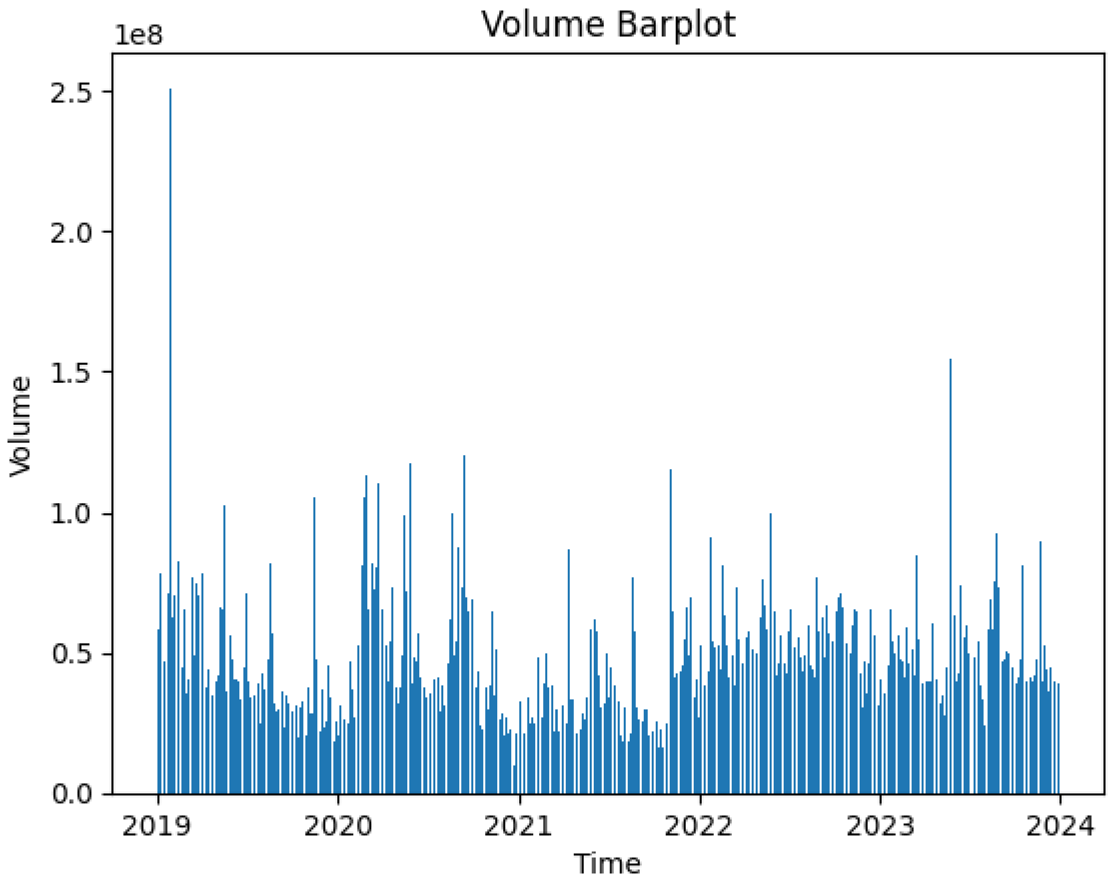
In [35]:
```
# Plotting stokck price data in candlestick pattern
fig = go.Figure(data=[go.Candlestick(x=df.index,
                open=df['Open'],
                high=df['High'],
                low=df['Low'],
```

```
                close=df['Close'])])

fig.show()
```

CandleStick Pattern oF NVDIA stock data

In [36]:
```
# Yearly volume Bar grph plot
plt.bar(df.index, df['Volume'], width=1.5)
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 [37]:
```
# Calculating Daily Returns
df['Daily_Return'] = df['Adj Close_x'].pct_change()
```

In [38]:
```
#Log returns
df['log_Return'] = np.log(df['Adj Close_x']) - np.log(df['Adj Close_x'].shift(1))
```

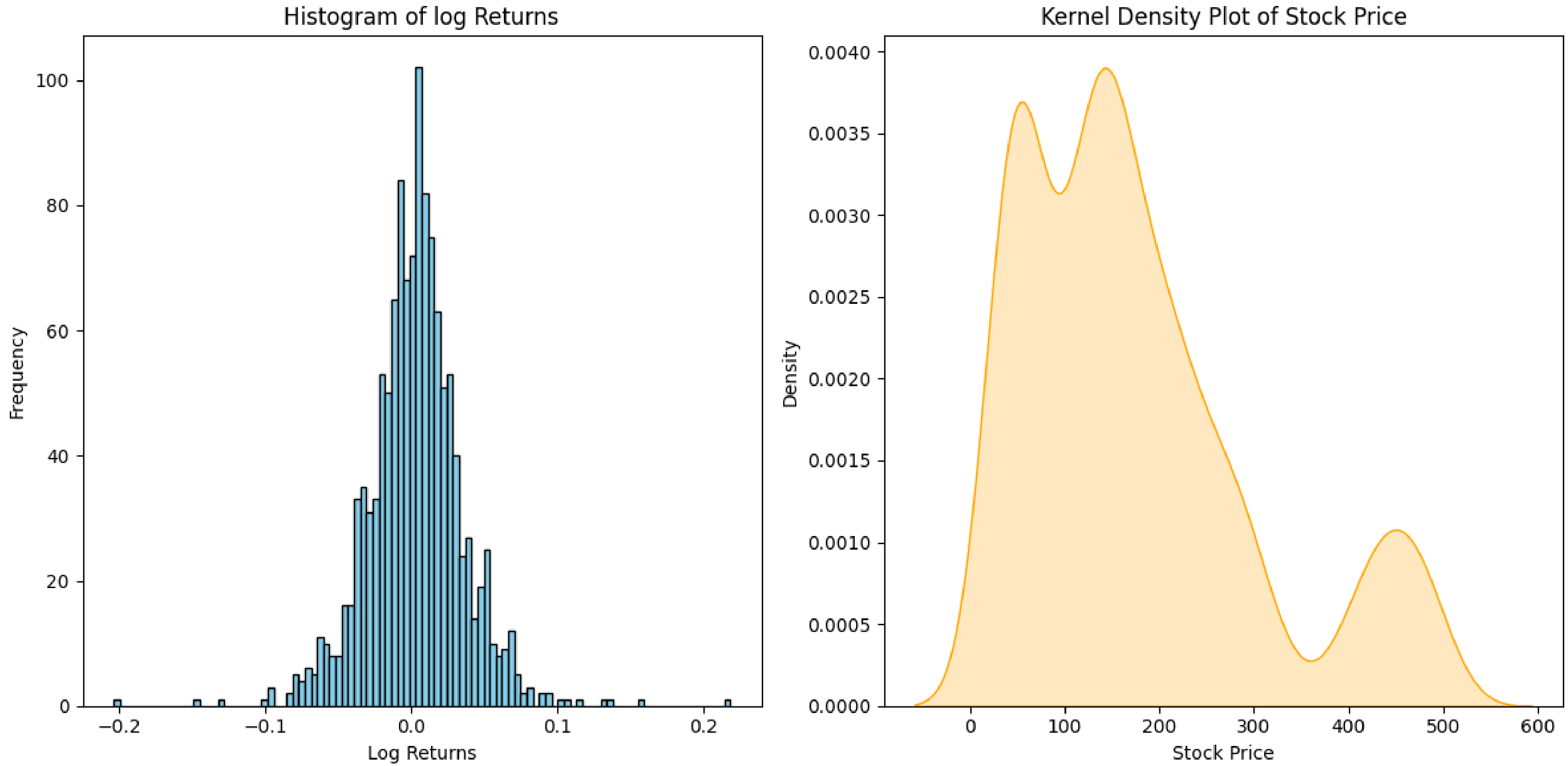
In [39]:
```
Max1 = df["log_Return"].max()
Min1 = df["log_Return"].min()
Max2 = (df["log_Return"].min() - df["log_Return"].mean()) / df["log_Return"].std()
Min2 = (df["log_Return"].max() - df["log_Return"].mean()) / df["log_Return"].std()
print("Over the last 5 years, NVDIA has had a maximum daily return of %.2f and a minimum daily return of %.2f If we use the formu
```

```
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 minimum and ma
ximum, respectively
```

In [40]:
```
df.log_Return
```

Out[40]:
```
Date
2019-01-02         NaN
2019-01-03   -0.062319
2019-01-04    0.062099
2019-01-07    0.051587
2019-01-08   -0.025210
                ...
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 [41]:
```
# 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 [42]:
```
df['Adj Close_x']
```

Out[42]:
```
Date
2019-01-02     33.790478
2019-01-03     31.748959
2019-01-04     33.783039
2019-01-07     35.571537
2019-01-08     34.685974
                 ...
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 [43]:
```
# 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[43]:
```
Date
2019-01-02         NaN
2019-01-03   -0.062319
2019-01-04    0.062099
2019-01-07    0.051587
2019-01-08   -0.025210
                ...
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 [44]:
```
df_stats.describe()
```

Out[44]:
```
count    1257.000000
mean        0.002136
std         0.032449
min        -0.203980
25%        -0.015275
50%         0.003049
75%         0.019616
max         0.218088
Name: Adj Close_x, dtype: float64
```

In [45]:
```
#Symmetric Test
(len(df[df_stats > df_stats.mean()])) / (len(df))
```

Out[45]:
```
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 [46]:
```
##Normality Test
stats.normaltest(np.array(df["log_Return"].dropna()))
```

Out[46]:
```
NormaltestResult(statistic=123.17419935507488, pvalue=1.7908633702215873e-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 [47]:
```
##Skewness and Kurtosis
stats.jarque_bera((np.array(df["log_Return"].dropna())))
```

Out[47]:
```
SignificanceResult(statistic=857.3010238309117, pvalue=6.909522097786102e-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 [48]:
```
df_stats.min()
```

Out[48]:
```
-0.20397950965585832
```

In [49]:
```
df_stats.max()
```

Out[49]:
```
0.2180878060373761
```

In [50]:
```
dfMax = df_stats.max()
dfMin = df_stats.min()
print(
    "Min return of sample data is %.4f and the maximum return of sample data is %.4f"
    % (dfMin, dfMax)
)
```

```
Min return of sample data is -0.2040 and the maximum return of sample data is 0.2181
```

In [51]:
```
(dfMin - df_stats.mean()) / df_stats.std()
```

Out[51]:
```
-6.3519622583565445
```

In [52]:
```
(dfMax - df_stats.mean()) / df_stats.std()
```

Out[52]:
```
6.655098677338764
```

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 [53]:
```
stats.norm.cdf(-6.35)
```

Out[53]:
```
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 [54]:
```
(3 * df_stats.std()) + df_stats.mean()
```

Out[54]:
```
0.09948317314105172
```

In [55]:
```
(-3 * df_stats.std()) + df_stats.mean()
```

Out[55]:
```
-0.09521137827830271
```

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 [56]:
```
df[(df['log_Return'] > 0.03699) | (df['log_Return'] < -0.0364)]['log_Return'].tail()
```

Out[56]:
```
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 [57]:
```
len(df[(df['log_Return'] > 0.03699) | (df['log_Return'] < -0.0364)])
```

Out[57]:
```
264
```

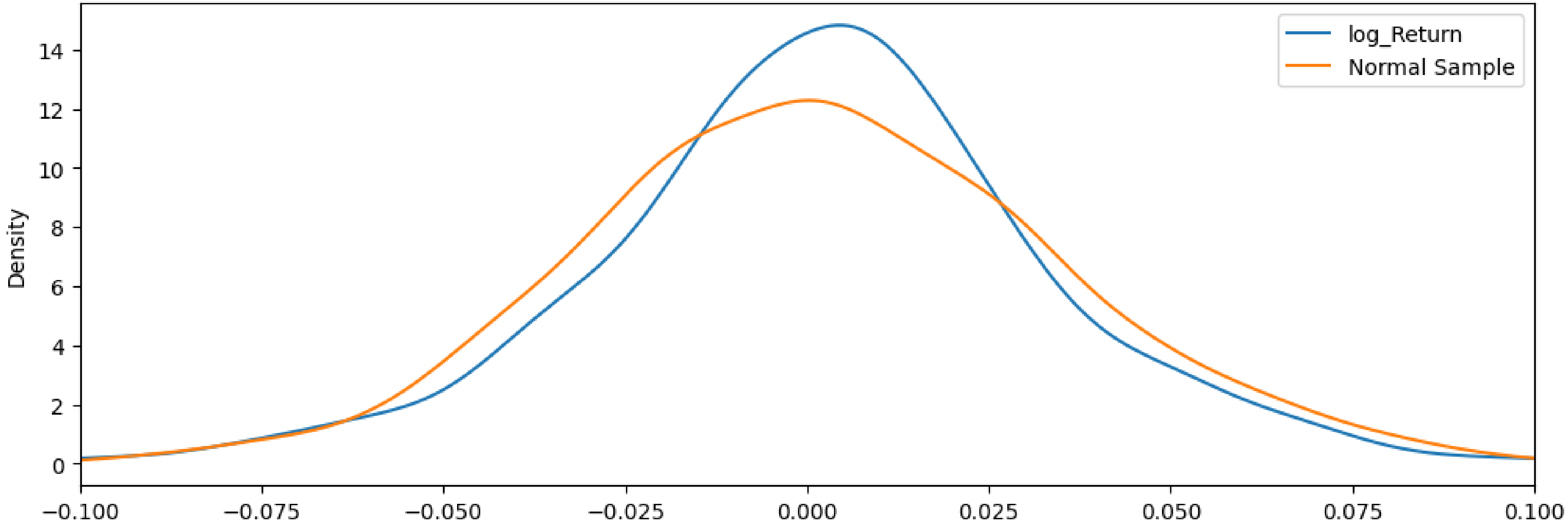
In [58]:
```
len(df[(df["log_Return"] > 0.05) | (df["log_Return"] < -0.05)])
```

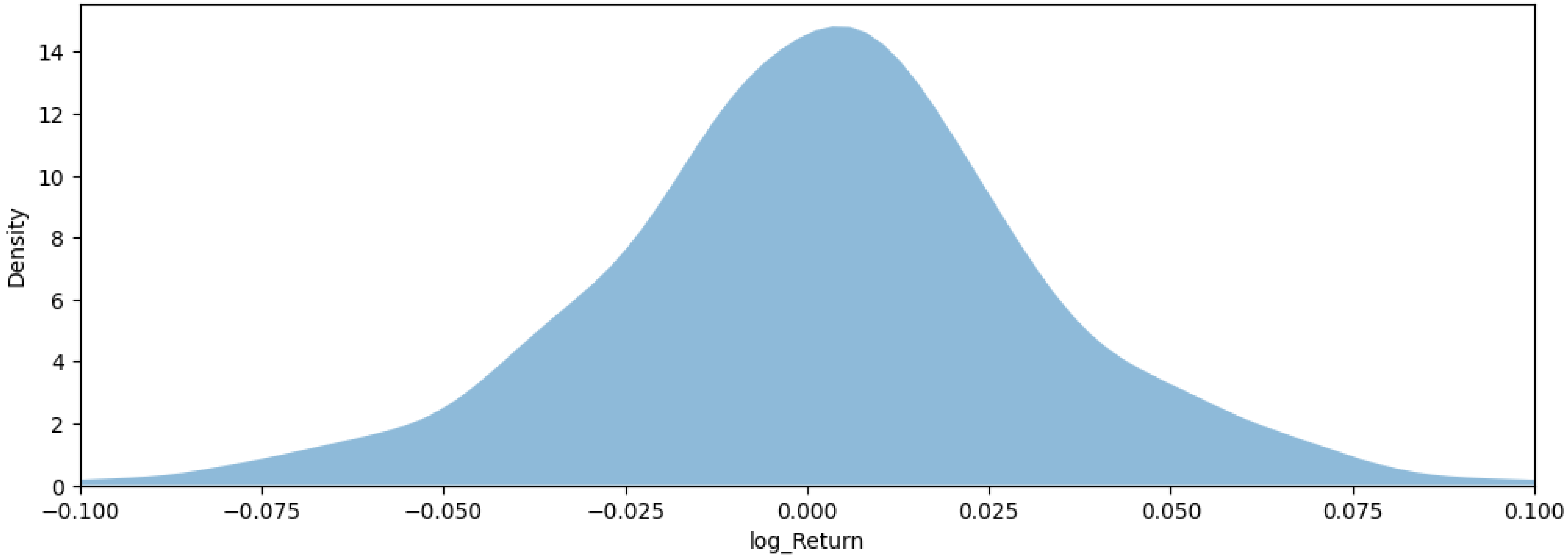
Out[58]:
```
139
```

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 [59]:
```
# 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"].std()
)

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

# Plotting the KDE plots
df[["log_Return", "Normal Sample"]].plot(kind="kde", xlim=(-0.1, 0.1), figsize=(12, 4))

#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, 0.1);
```





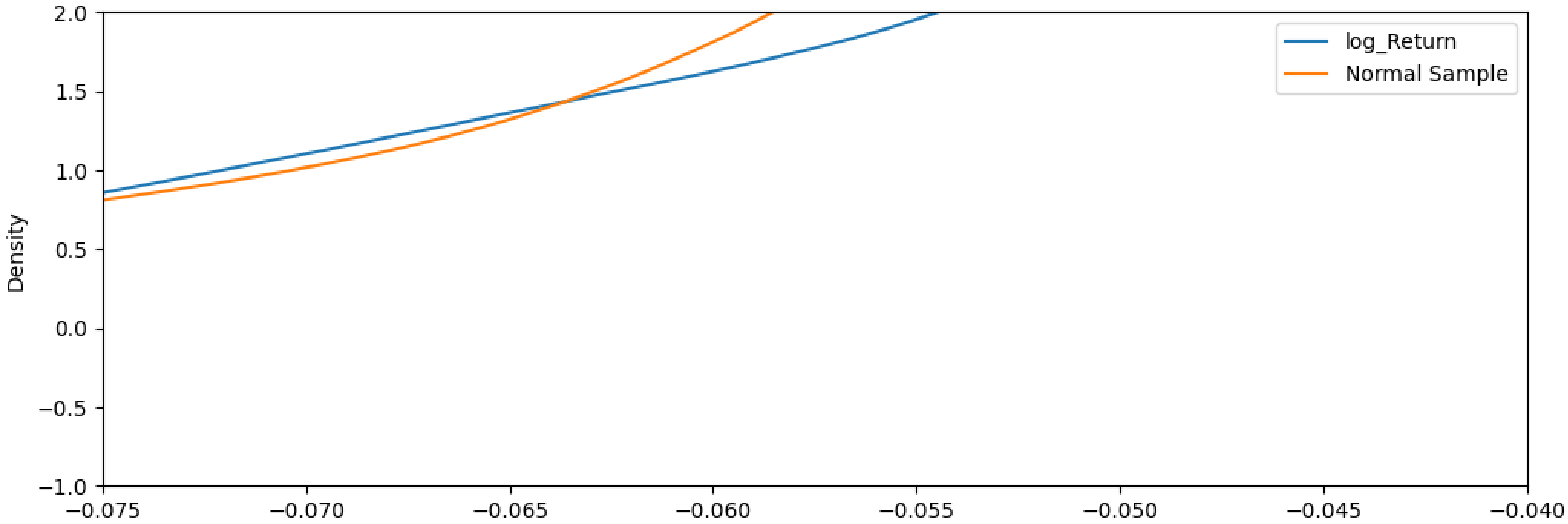
The NVDA returns seem a lot more leptokurtic. Indeed the excess kurtosis of NVDA is greater than 0:

In [60]:
```
df_stats.kurt()
```

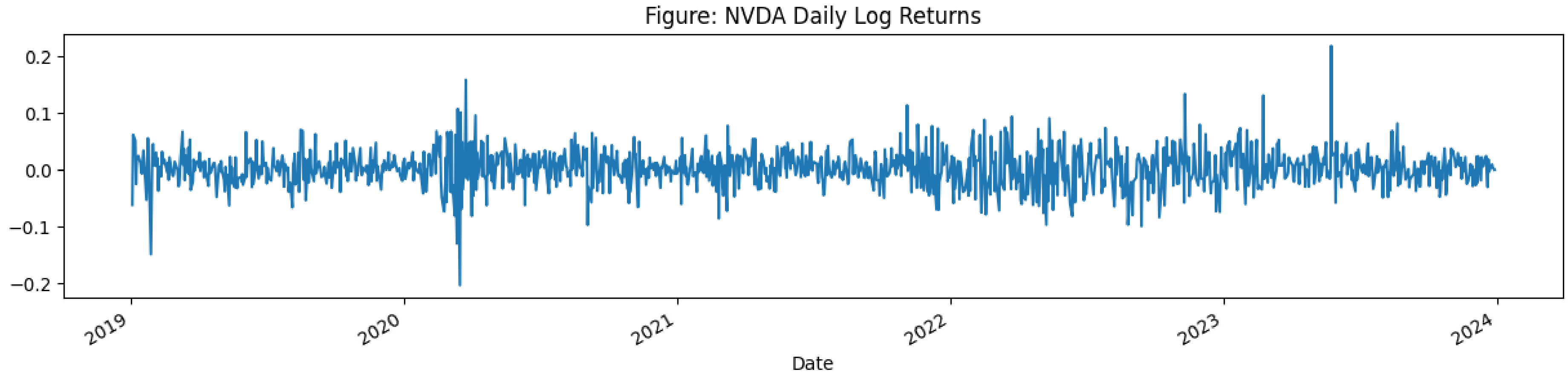
Out[60]:
```
4.06543272770758
```

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

In [61]:
```
# Observing the tails
df[["log_Return", "Normal Sample"]].plot(
    kind="kde", xlim=(-0.075, -0.04), ylim=(-1, 2), figsize=(12, 4)
);
```



In [62]:
```
ax1 = df_stats.plot(figsize=(15, 3), y="NVDA", title="Figure: NVDA Daily Log Returns")
```



Daily Log Return graph

In [63]:
```
nvda_std = df_stats.std()
nvda_mean = df_stats.mean()
```

In [64]:
```
# Sharpe Ratio
Sharpe_Ratio_NVDA = nvda_mean / nvda_std
Sharpe_Ratio_NVDA
```

Out[64]:
```
0.06582302634984279
```

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 [65]:
```
# Semi-Variance
nvda_semivariance = ((df[df_stats < nvda_mean]["log_Return"] - nvda_mean) ** 2).mean()
nvda_semivariance
```

Out[65]:
```
0.0010849324271162953
```

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

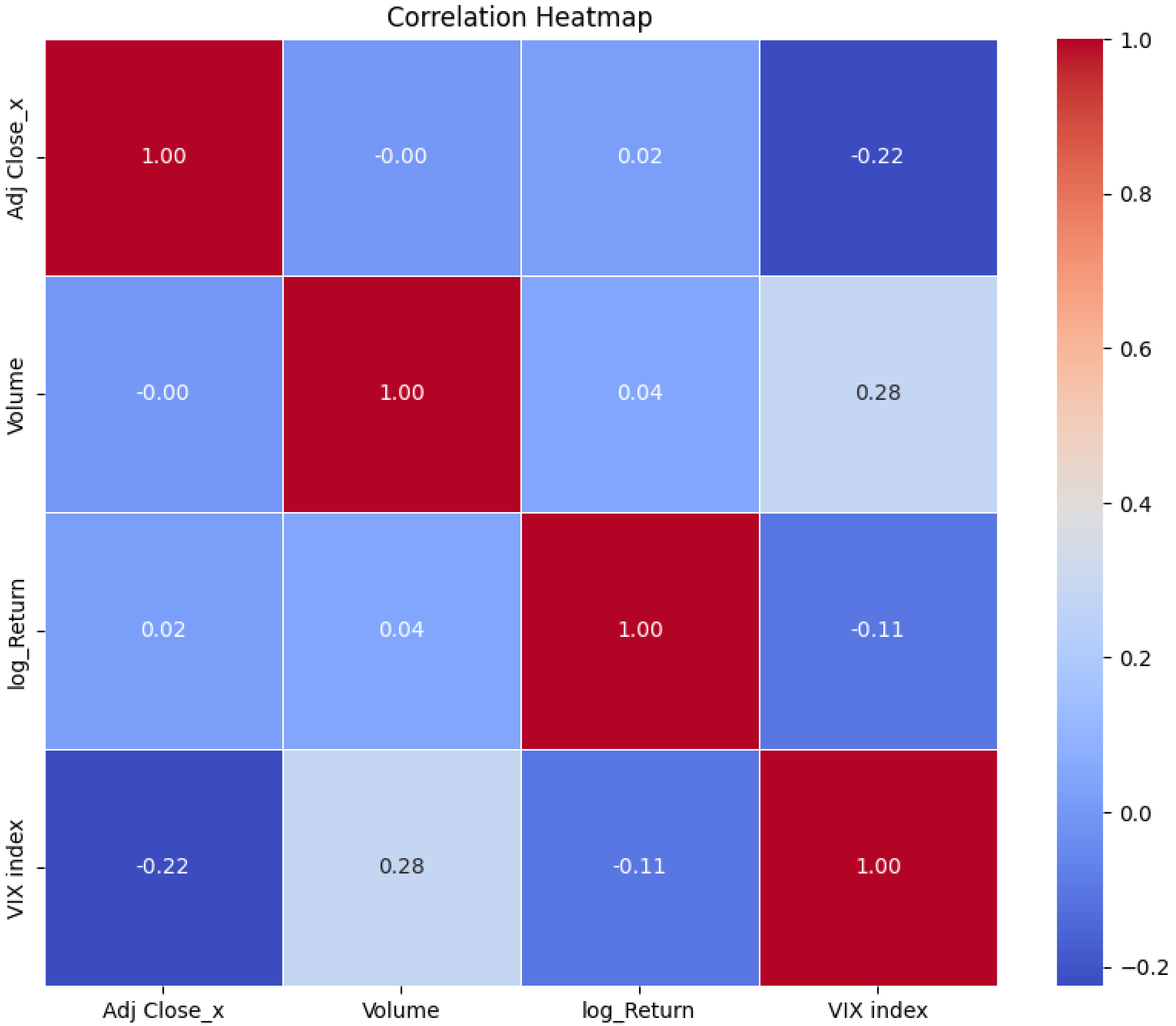
In [66]:
```
# Create a new DataFrame with relevant columns for correlation analysis
correlation_df = df[['Adj Close_x', 'Volume', 'log_Return', 'VIX index']]
```

In [67]:
```
# Calculate the correlation matrix
correlation_matrix = correlation_df.corr()
correlation_matrix
```

Out[67]:

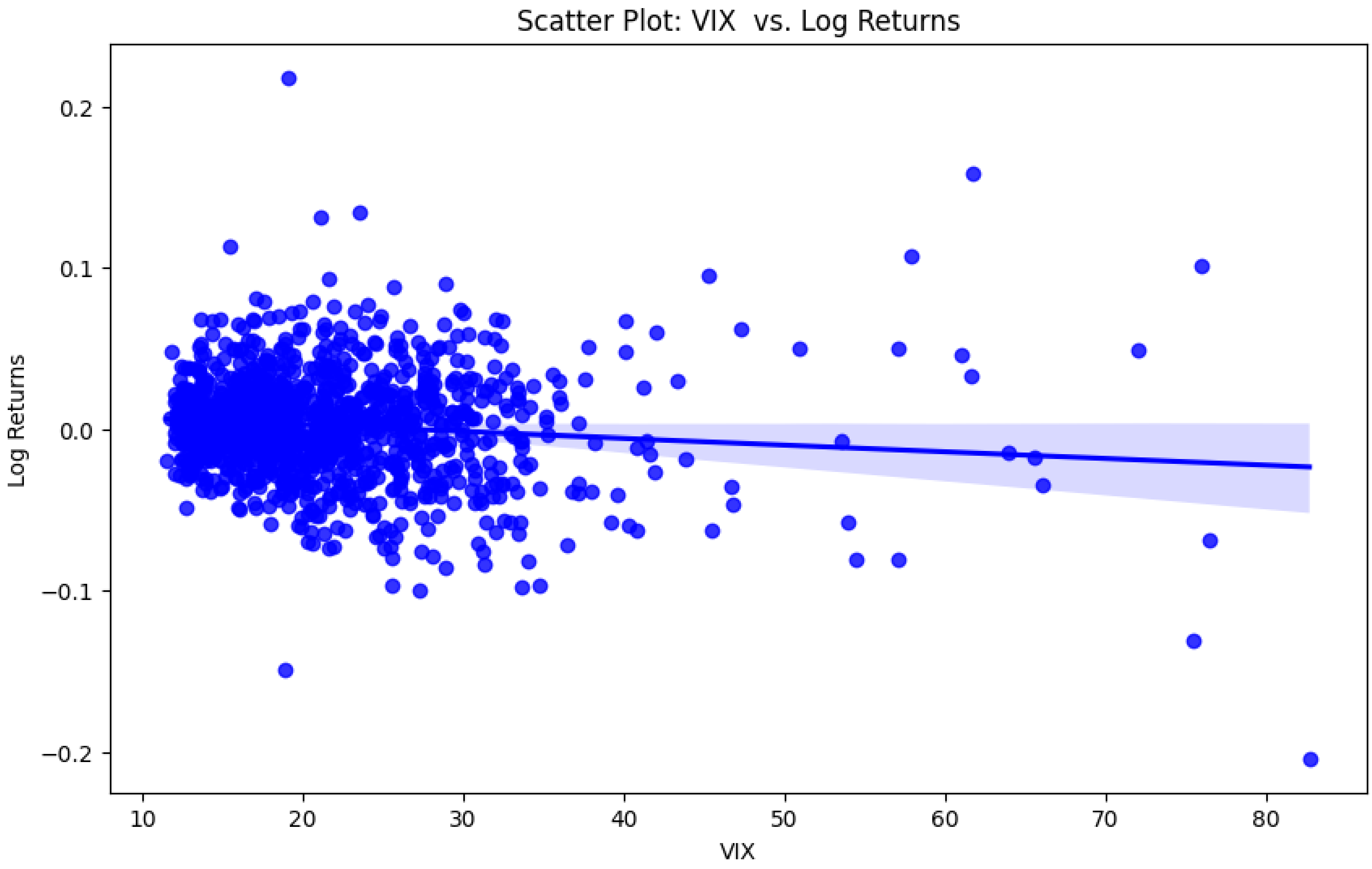
	Adj Close_x	Volume	log_Return	VIX index
Adj Close_x	1.000000	-0.000330	0.019155	-0.224991
Volume	-0.000330	1.000000	0.043212	0.283252
log_Return	0.019155	0.043212	1.000000	-0.105276
VIX index	-0.224991	0.283252	-0.105276	1.000000

In [68]:
```
# Plot Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



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

In [69]:
```
# 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 [70]:
```
# Volume data
nvda_volume = df['Volume']
nvda_bid_ask_spread = df['High'] - df['Low']
```

In [71]:
```
# 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()
```

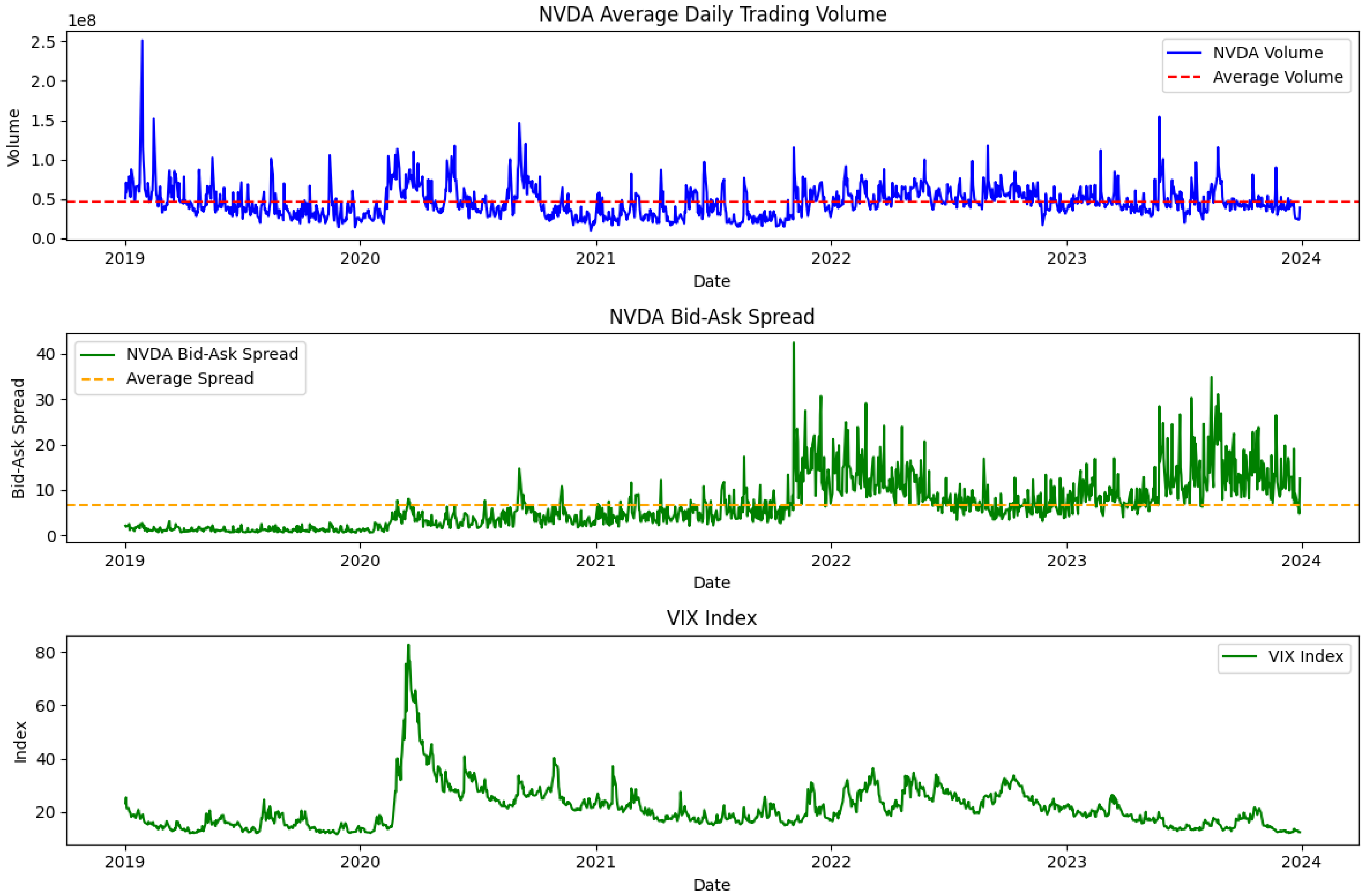
In [72]:
```
# Printing average daily volume and bid-ask spread
print(f"Average Daily Volume: {average_daily_volume:.2f}")
print(f"Average Bid-Ask Spread: {average_bid_ask_spread:.4f}")
```

```
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 [73]:
```
# 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 Volume')
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 Spread')
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)

Publicly traded bond (e.g. treasury bond, corporate bond) – that is, securities lending of a bond.

U.S. 30 Year Treasury Bond 5 years data

In [74]:
```
#Importing the data Locally
df_bond=pd.read_csv("/content/United States 30-Year Bond Yield Historical Data.csv")
df_bond['Date'] = pd.to_datetime(df_bond['Date'])
```

In [75]:
```
#Viewing the data
df_bond.head()
```

Out[75]:

	Date	Price	Open	High	Low	Change %
0	2023-12-29	4.019	3.994	4.048	3.985	0.58%
1	2023-12-28	3.996	3.957	4.002	3.943	1.27%
2	2023-12-27	3.946	4.048	4.052	3.940	-2.49%
3	2023-12-26	4.047	4.055	4.060	4.025	-0.23%
4	2023-12-25	4.056	4.056	4.056	4.056	0.06%

In [76]:
```
#stats Summary of our data
df_bond.describe()
```

Out[76]:

	Price	Open	High	Low
count	1299.000000	1299.000000	1299.000000	1299.000000
mean	2.683423	2.683516	2.724367	2.642987
std	0.963028	0.963733	0.967699	0.960457
min	1.031000	0.989000	1.088000	0.702000
25%	1.951000	1.947500	1.980000	1.915000
50%	2.362000	2.363000	2.395000	2.328000
75%	3.551500	3.557500	3.605500	3.499000
max	5.109000	5.122000	5.179000	5.046000

In [77]:

```
# Importing Intrest Rate data and Renaming Date columns and conveting it into Dataframe
df_fund=pd.read_csv("/content/RIFSPFFNB.csv")
df_fund['DATE'] = pd.to_datetime(df_fund['DATE'])
df_fund.rename(columns={'DATE': 'Date'}, inplace=True)
df_fund.head()
```

Out[77]:

	Date	RIFSPFFNB
0	2019-01-02	2.40
1	2019-01-03	2.40
2	2019-01-04	2.40
3	2019-01-07	2.40
4	2019-01-08	2.40

In [78]:

```
df_bond.head()
```

Out[78]:

	Date	Price	Open	High	Low	Change %
0	2023-12-29	4.019	3.994	4.048	3.985	0.58%
1	2023-12-28	3.996	3.957	4.002	3.943	1.27%
2	2023-12-27	3.946	4.048	4.052	3.940	-2.49%
3	2023-12-26	4.047	4.055	4.060	4.025	-0.23%
4	2023-12-25	4.056	4.056	4.056	4.056	0.06%

In [79]:
```
df_fund = df_fund[df_fund["RIFSPFFNB"] != "."]
```

In [80]:
```
df_fund['RIFSPFFNB'] = pd.to_numeric(df_fund['RIFSPFFNB'])
```

In [81]:
```
# Stats Summary of Fed rates data
df_fund.describe()
```

Out[81]:

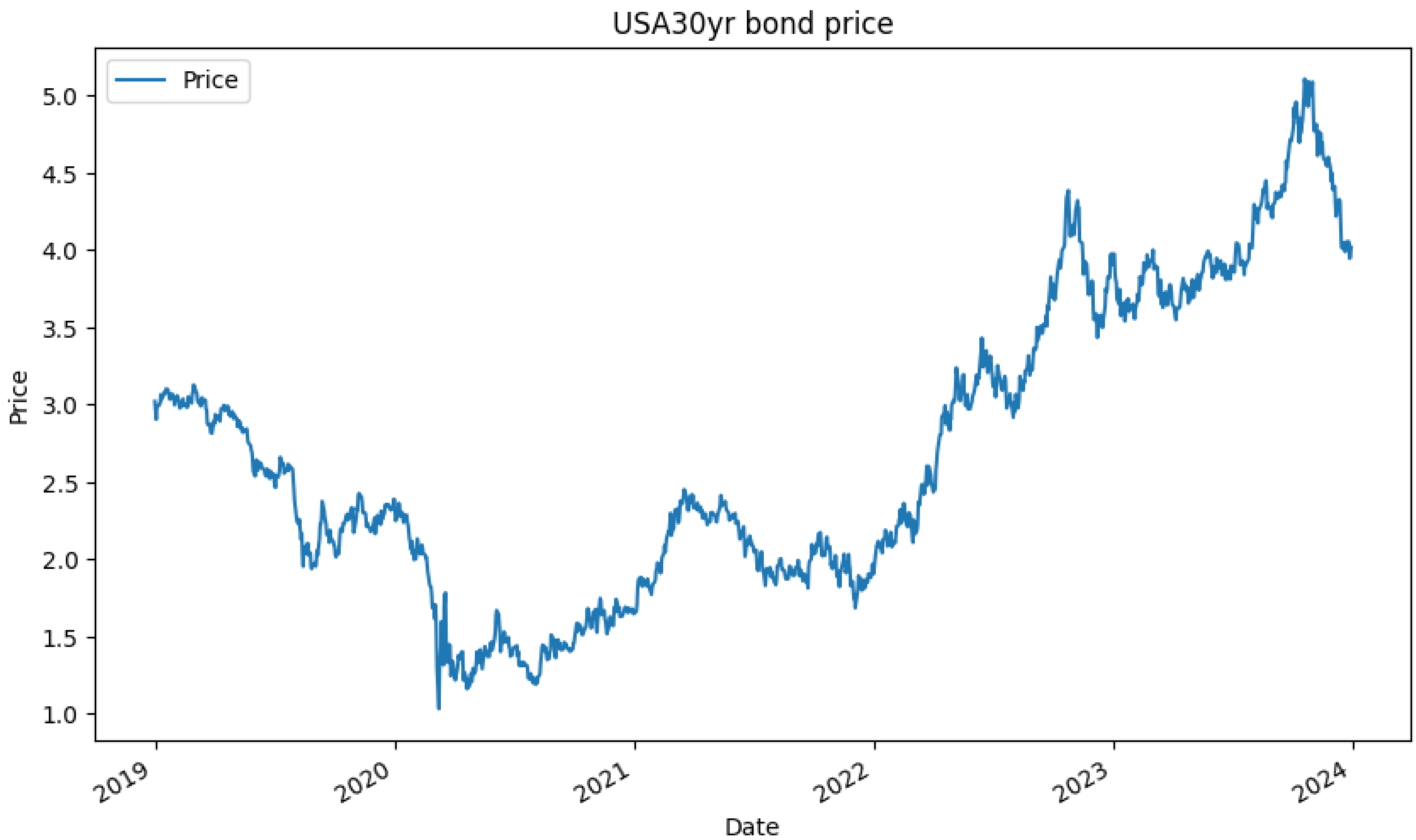
	RIFSPFFNB
count	1255.000000
mean	1.852382
std	1.899374
min	0.040000
25%	0.090000
50%	1.550000
75%	3.080000
max	5.330000

Time Series Analysis

In [82]:
```
df_bond.columns
```

Out[82]:
```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Change %'], dtype='object')
```

In [83]:
```
#Plotting the time series data
df_bond.plot(x='Date', y='Price', title="USA30yr bond price", xlabel='Date', ylabel='Price', figsize=(10, 6))
plt.show()
```



Time Series data from 2019-2023 of US 30 yr Govt Treasury Bond

In [84]:
```
df_fund.columns
```

Out[84]:
```
Index(['Date', 'RIFSPFFNB'], dtype='object')
```

In [85]:
```
df_fund.head()
```

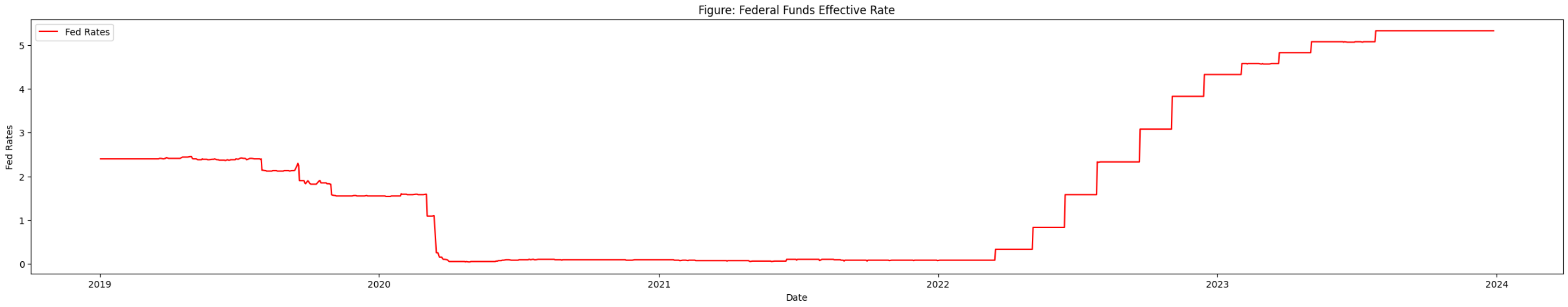
Out[85]:

	Date	RIFSPFFNB
0	2019-01-02	2.4
1	2019-01-03	2.4
2	2019-01-04	2.4
3	2019-01-07	2.4
4	2019-01-08	2.4

In [86]:
```
df_fund['Date']
```

Out[86]:
```
0       2019-01-02
1       2019-01-03
2       2019-01-04
3       2019-01-07
4       2019-01-08
           ...
1296    2023-12-21
1297    2023-12-22
1299    2023-12-26
1300    2023-12-27
1301    2023-12-28
Name: Date, Length: 1255, dtype: datetime64[ns]
```

In [87]:
```
# Plotting Fed Rate Data
fig, ax1 = plt.subplots(figsize=(30, 5))
ax1.plot(df_fund['Date'], df_fund['RIFSPFFNB'], label='Fed Rates', color='Red')
ax1.set_title("Figure: Federal Funds Effective Rate")
ax1.set_xlabel("Date")
ax1.set_ylabel("Fed Rates")
ax1.legend()

plt.show()
```



Federal effective rate from year 2019-2023

In [88]:
```
# Importing Plotply for Plotting
import plotly.graph_objects as go
from datetime import datetime
```

In [89]:
```
# Plotting Bond price data in candlestick pattern
fig = go.Figure(data=[go.Candlestick(x=df_bond['Date'],
                open=df_bond['Open'],
                high=df_bond['High'],
                low=df_bond['Low'],
                close=df_bond['Price'])])

fig.show()
```

Distribution analysis

In [90]:
```
#Log returns
df_bond['log_Return'] = np.log(df_bond['Price']) - np.log(df_bond['Price'].shift(1))
```

In [91]:
```
Max1 = df_bond["log_Return"].max()
Min1 = df_bond["log_Return"].min()
Max2 = (df_bond["log_Return"].min() - df_bond["log_Return"].mean()) / df_bond["log_Return"].std()
```

```
Min2 = (df_bond["log_Return"].max() - df_bond["log_Return"].mean()) / df_bond["log_Return"].std()
print("Over the last 5 years, USD30 Yr Bond has had a maximum daily return of %.2f and a minimum daily return of %.2f If we use t
```

```
Over the last 5 years, USD30 Yr Bond has had a maximum daily return of 0.23 and a minimum daily return of -0.26 If we use the fo
rmula to determine standard deviations from the mean, we get -9.63 and 8.51 standard deviations away from the mean for the minim
um and maximum, respectively
```

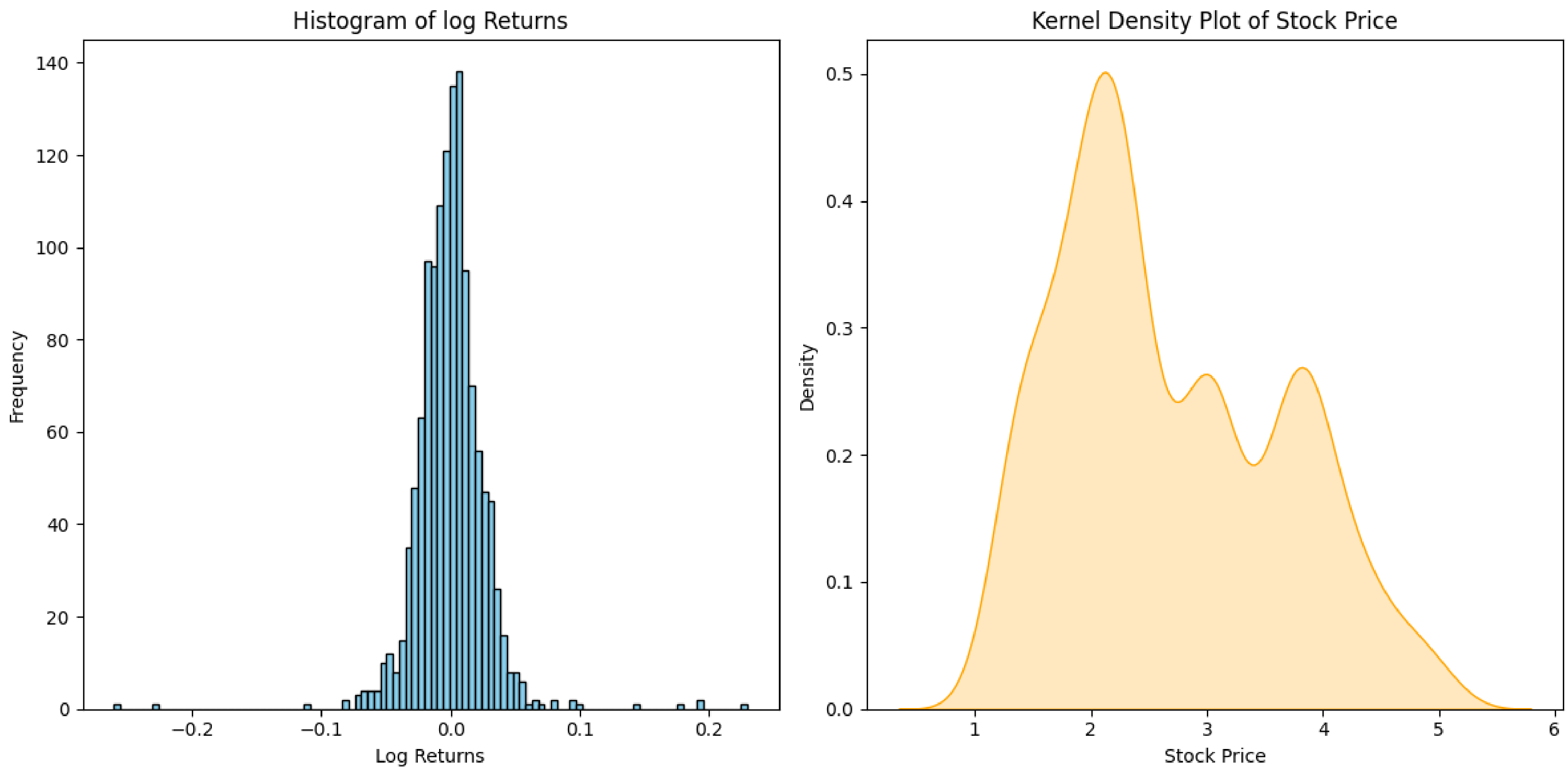
In [92]:
```
df_bond.columns
```

Out[92]:
```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Change %', 'log_Return'], dtype='object')
```

In [93]:
```
df_bond.log_Return
```

Out[93]:
```
0            NaN
1      -0.005739
2      -0.012591
3       0.025273
4       0.002221
          ...
1294   -0.003669
1295   -0.004017
1296   -0.026514
1297    0.020458
1298    0.019055
Name: log_Return, Length: 1299, dtype: float64
```

In [94]:
```
# Plot Histogram of Daily Returns
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.hist(df_bond['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_bond['Price'], 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 Bond price in a normal distribution, we will learn more about the distribution in further section. Also with that we have kernel density plot of Bond price where we can see the price is more dence between 1-3 price range.

Statstical analysis

In [95]:
```
df_bond["log_Return"].describe()
```

Out[95]:
```
count    1298.000000
mean       -0.000220
std         0.026997
min        -0.260315
25%        -0.014330
50%        -0.000391
75%         0.012262
max         0.229525
Name: log_Return, dtype: float64
```

In [96]:
```
#Symmetric Test
(len(df_bond[df_bond['log_Return'] > df_bond['log_Return'].mean()])) / (len(df_bond))
```

Out[96]:
```
0.49653579676674364
```

We're getting about 49.6% of data points being greater than the mean, which shows we have a slightly Positive 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 bond returns are symmetric or not, but it is still a reasonable assumption to make here.

In [97]:
```
##Normality Test
stats.normaltest(np.array(df_bond["log_Return"].dropna()))
```

Out[97]:
```
NormaltestResult(statistic=341.42931437914433, pvalue=7.237130477753114e-75)
```

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, 7.23e-75, is extremely small, which leads us to reject the null hypothesis that this data fits a normal distribution.

In [98]:
```
##Skewness and Kurtosis
stats.jarque_bera((np.array(df_bond["log_Return"].dropna())))
```

Out[98]:
```
SignificanceResult(statistic=21507.884059971573, pvalue=0.0)
```

The Jarque-Bera test was conducted on the log returns data. The test resulted in a statistic of 21507.884059971573 and an extremely low p-value of 0.0. 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 [99]:
```
df_bond_Max = df_bond['log_Return'].max()
df_bond_Min = df_bond['log_Return'].min()
print(
    "Min return of sample data is %.4f and the maximum return of sample data is %.4f"
    % (df_bond_Min, df_bond_Max)
)
```

```
Min return of sample data is -0.2603 and the maximum return of sample data is 0.2295
```

In [100…
```
(df_bond_Min - df_bond['log_Return'].mean()) / df_bond['log_Return'].std()
```

Out[100]:
```
-9.634345130739318
```

In [101…
```
(df_bond_Max - df_bond['log_Return'].mean()) / df_bond['log_Return'].std()
```

Out[101]:
```
8.51013899149708
```

Over the last 5 years, US 30 yr Bond has had a maximum daily return of 23% and a minimum daily return of -26.03%. If we use the formula to determine standard deviations from the mean, we get -9.63 and 8.51 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 [102…
```
stats.norm.cdf(-9.63)
```

Out[102]:
```
2.9864739444248O7e-22
```

This implies that the chance we could have a move as small as -26.03%, is 2.986473944424807e-22. 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 [103…
```
(3 * df_bond['log_Return'].std()) + df_bond['log_Return'].mean()
```

Out[103]:
```
0.08076965051448466
```

In [104…
```
(-3 * df_bond['log_Return'].std()) + df_bond['log_Return'].mean()
```

Out[104]:
```
-0.08120998377192733
```

The above two calculations would imply that 99.7% of all of our data points should be in between -0.0807 and 0.0812.

In [105…
```
df_bond[(df_bond['log_Return'] > 0.03699) | (df_bond['log_Return'] < -0.0364)]['log_Return'].tail()
```

Out[105]:
```
1132    0.037283
1137   -0.045030
1139    0.068366
1141    0.059740
1146    0.048285
Name: log_Return, dtype: float64
```

In [106…
```
len(df_bond[(df_bond['log_Return'] > 0.03699) | (df_bond['log_Return'] < -0.0364)])
```

Out[106]:
```
122
```

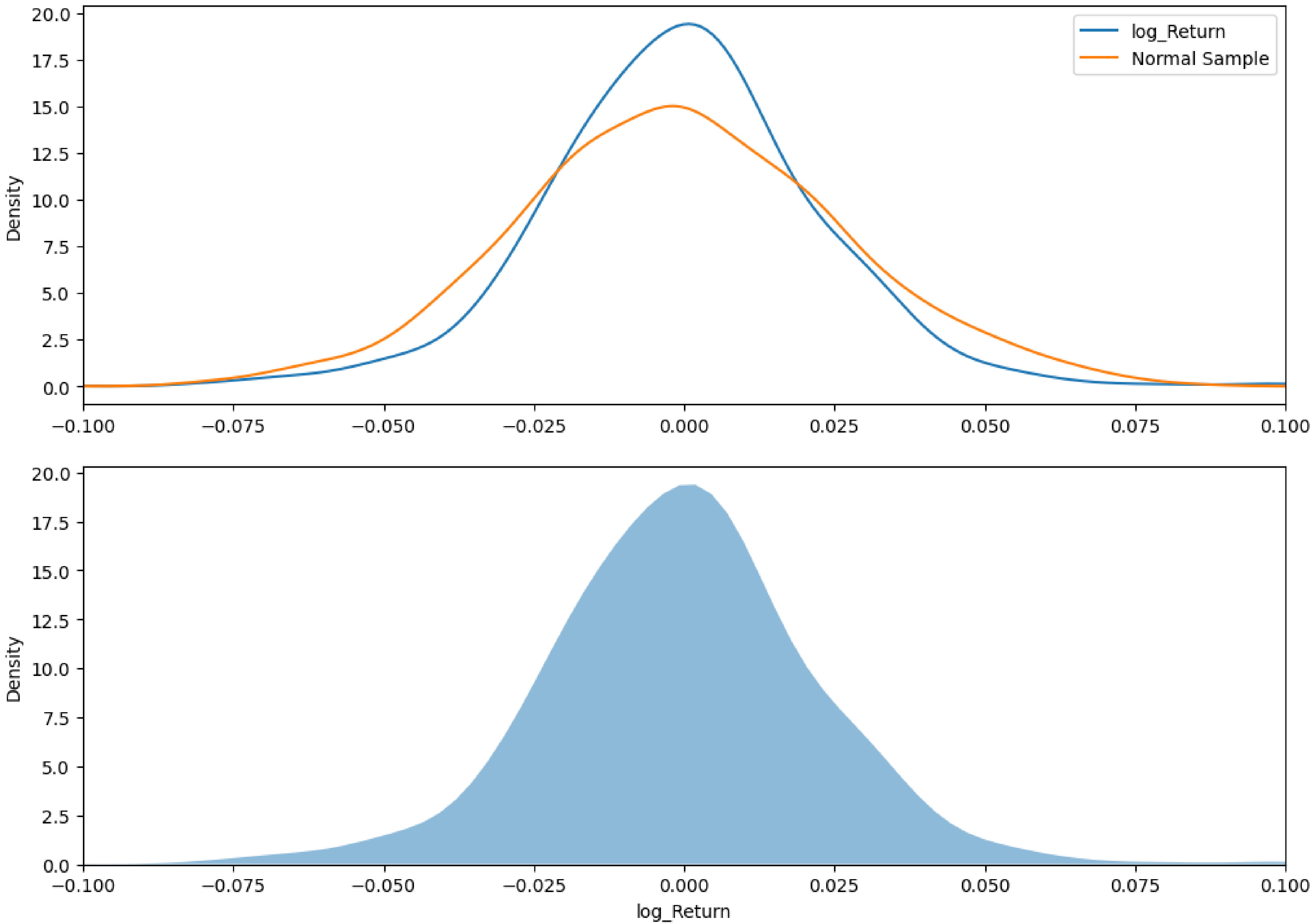
In [107…
```
len(df_bond[(df_bond["log_Return"] > 0.05) | (df_bond["log_Return"] < -0.05)])
```

Out[107]:
```
53
```

Not only do we get 122 values outside of our 3 standard deviation range, but we also get 53 values outside of +/- 5%, though you would almost never expect one of these events over 5 years, given a normal distribution.

In [108…
```
# Sampling from normal distribution
np.random.seed(222)
normal_dist = stats.norm.rvs(
    size=len(df_bond["log_Return"]), loc=df_bond["log_Return"].mean(), scale=df_bond["log_Return"].std()
)
```

In [109…
```
# Creating an additional column in df in order to use the KDE plot functionality of pandas
df_bond["Normal Sample"] = normal_dist

# Plotting the KDE plots
df_bond[["log_Return", "Normal Sample"]].plot(kind="kde", xlim=(-0.1, 0.1), figsize=(12, 4))

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



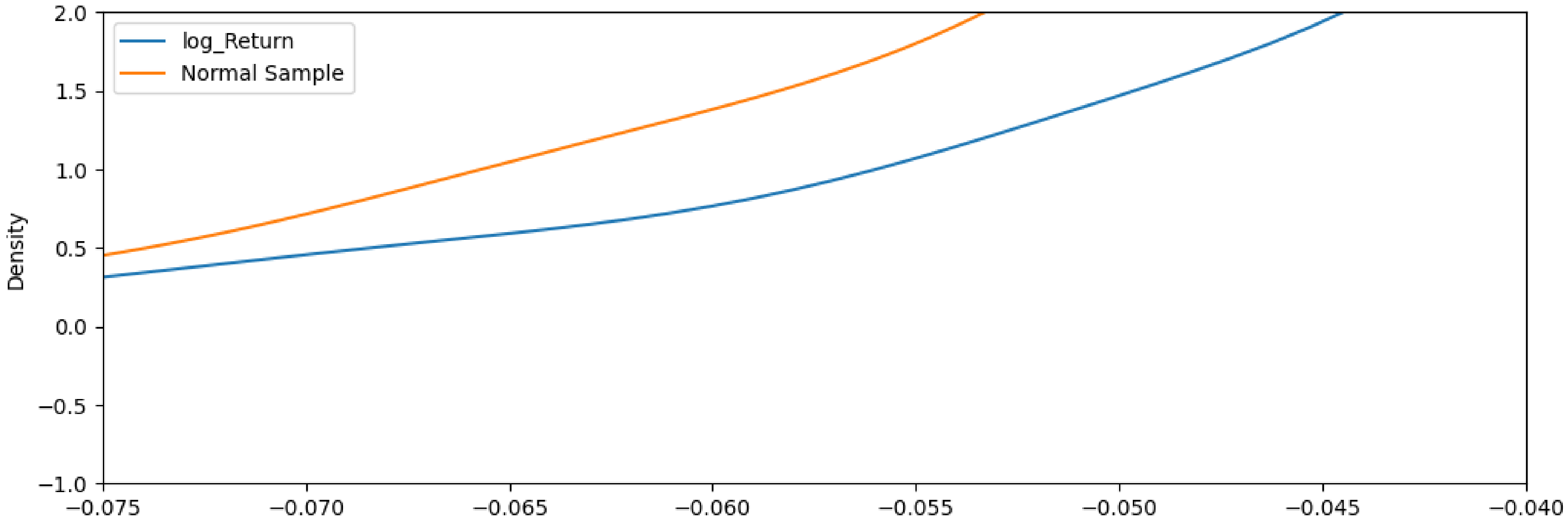
The Bond returns seem a lot more leptokurtic. Indeed the excess kurtosis of Bond is greater than 0:

In [110…
```
df_bond['log_Return'].kurt()
```

Out[110]:
```
20.019489802123687
```

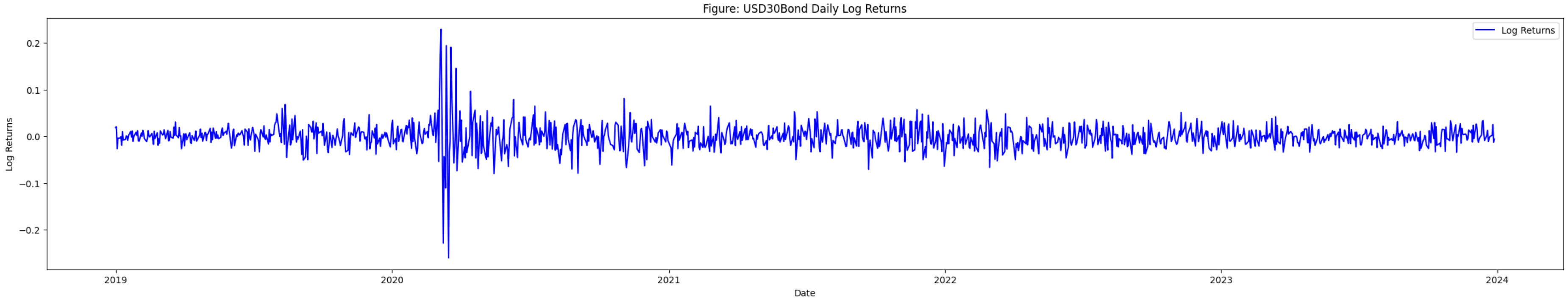
The tails of NDA are also fatter than those of a normal distribution:

In [111…
```
# Observing the tails
df_bond[["log_Return", "Normal Sample"]].plot(
    kind="kde", xlim=(-0.075, -0.04), ylim=(-1, 2), figsize=(12, 4)
);
```



In [112…
```
fig, ax1 = plt.subplots(figsize=(30, 5))
ax1.plot(df_bond['Date'], df_bond['log_Return'], label='Log Returns', color='blue')
ax1.set_title("Figure: USD30Bond Daily Log Returns")
ax1.set_xlabel("Date")
ax1.set_ylabel("Log Returns")
ax1.legend()
```

Out[112]:
```
<matplotlib.legend.Legend at 0x7b4b04ca8b80>
```



Daily Log Return graph

In [113...
```
usd30_std = df_bond['log_Return'].std()
usd30_mean = df_bond['log_Return'].mean()
```

In [114...
```
# Sharpe Ratio
Sharpe_Ratio_usd30 = usd30_mean / usd30_std
Sharpe_Ratio_usd30
```

Out[114]:
```
-0.008155344825585843
```

The calculated Sharpe Ratio for the Bond is approximately -0.0081. This ratio represents the risk-adjusted return, and in this case, a Sharpe Ratio of -0.0081 indicates the less return per unit of risk for the Bond investment.

In [115...
```
# Semi-Variance
usd30_semivariance = ((df_bond[df_bond['log_Return'] < usd30_mean]["log_Return"] - usd30_mean) ** 2).mean()
usd30_semivariance
```

Out[115]:
```
0.0006879129555858797
```

The calculated semi-variance for the NVDA log returns data is approximately 0.00687. 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.

Liquidity analysis

In [116…

```
# Calculating average daily trading volume and average bid-ask spread
usd30_bid_ask_spread = df_bond['High'] - df_bond['Low']
```

In [117…

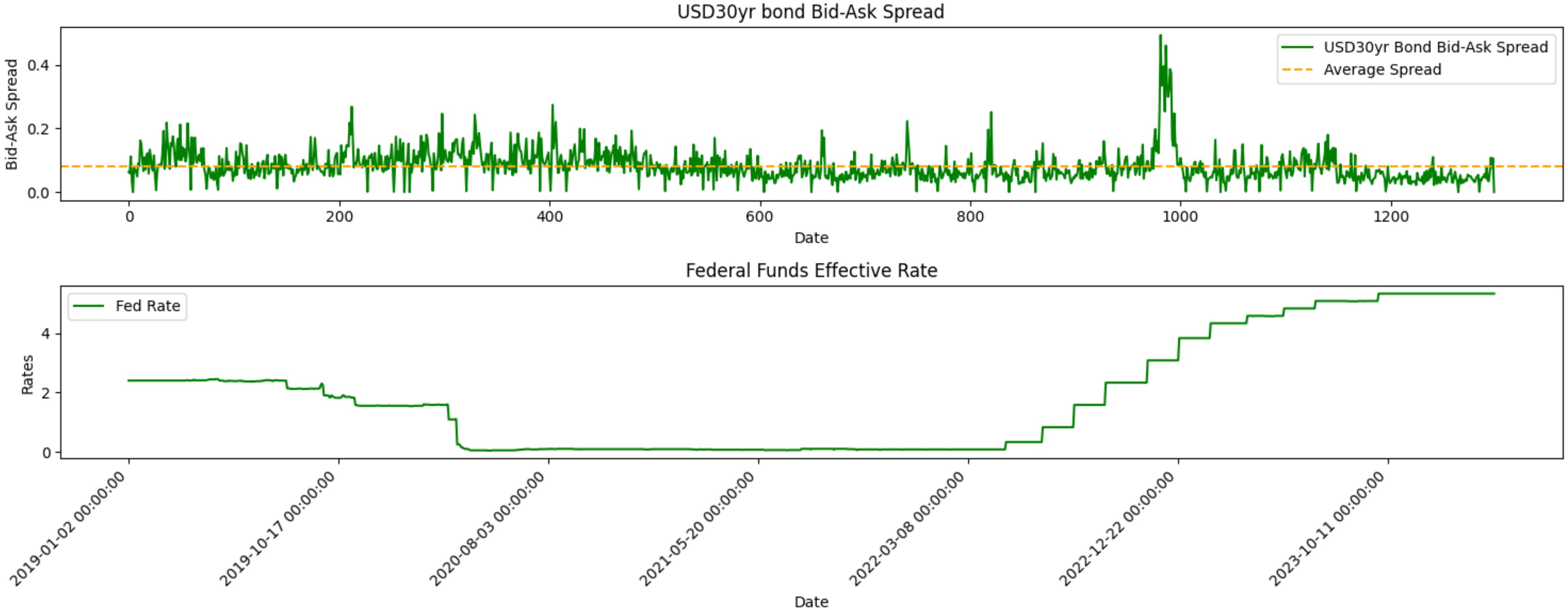
```
# Printing average daily volume and bid-ask spread
average_bid_ask_spread = usd30_bid_ask_spread.mean()
print(f"Average Bid-Ask Spread: {average_bid_ask_spread:.4f}")
```

```
Average Bid-Ask Spread: 0.0814
```

the average bid-ask spread of 0.0814 indicates a good level of liquidity.

In [118…

```
# Plotting average daily volume and bid-ask spread
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(15, 6))

# Plotting bid-ask spread
ax1.plot(usd30_bid_ask_spread, label="USD30yr Bond Bid-Ask Spread", color='green')
ax1.axhline(average_bid_ask_spread, color='orange', linestyle='--', label='Average Spread')
ax1.set_title("USD30yr bond Bid-Ask Spread")
ax1.set_xlabel("Date")
ax1.set_ylabel("Bid-Ask Spread")
ax1.legend()

date_range_ticks = range(0, len(df_bond), 200)
plt.xticks(date_range_ticks, df_bond["Date"].iloc[date_range_ticks], rotation=45, ha='right')


# Plotting FED Rates index
ax2.plot(df_fund["RIFSPFFNB"], label="Fed Rate", color='green')
ax2.set_title("Federal Funds Effective Rate")
ax2.set_xlabel("Date")
ax2.set_ylabel("Rates")
ax2.legend()

date_range_ticks = range(0, len(df_fund), 200)
plt.xticks(date_range_ticks, df_fund["Date"].iloc[date_range_ticks], rotation=45, ha='right')

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



This visualizations offer a comprehensive overview of Bond's trading dynamics, bid-ask spread variations, and the Fed Rates. (All the key Insights is Completely explained in Project Doc Step 6)

An illiquid security

MongoDB, Inc.

In [119…

```
#To analyze an illiquid security - small-cap stocks I have used 5 years of MongoDB data using yahoo finance as my data source
```

In [120…

```
import datetime
#Reading the data using yahoo Finance
start = datetime.date(2019, 1, 1)
end = datetime.date(2023, 12, 31)
df_mdb = web.DataReader(["MDB"],start,end)
df_VIX = web.DataReader(["^VIX"], start, end)["Adj Close"]
```

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

In [121…

```
#Describe data
df_mdb = df_mdb.merge(df_VIX, on="Date", how="outer")
df_mdb.rename(columns={'Adj Close_x': 'Price MDB', 'Adj Close_y': 'VIX index'}, inplace=True)
df_mdb = df_mdb.iloc[:, 0:7]
df_mdb.describe()
```

Out[121]:

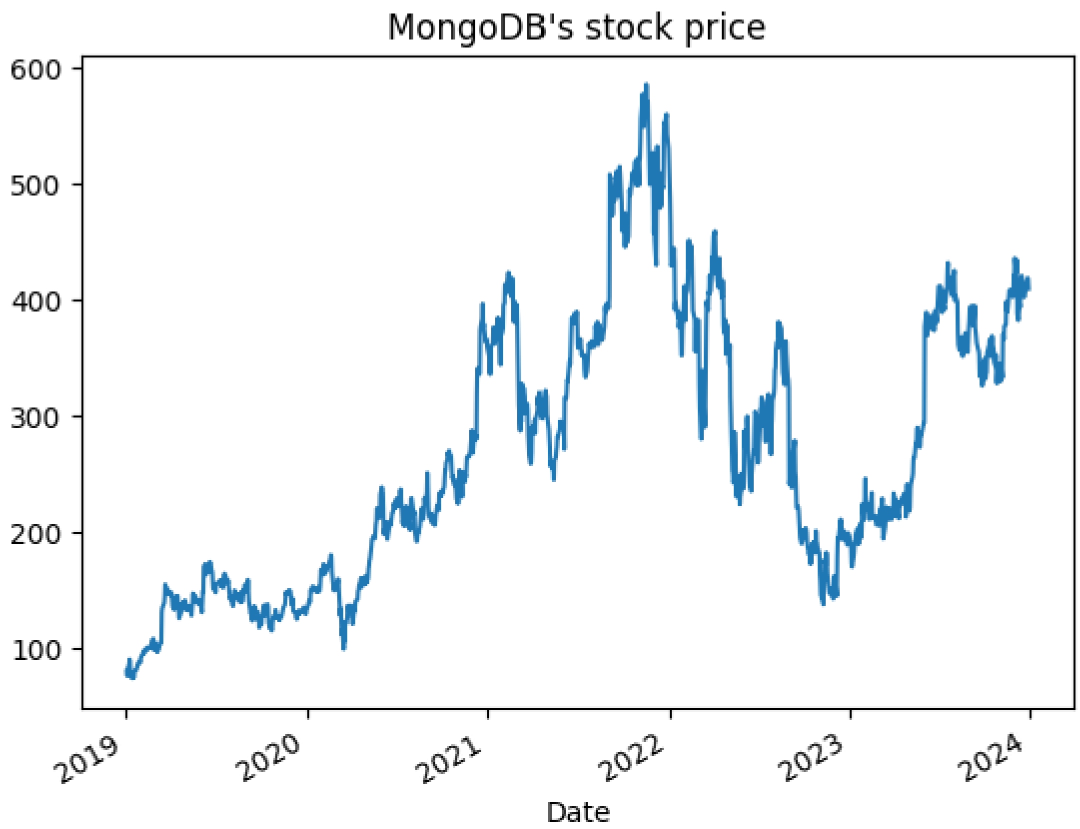
	Open	High	Low	Close	Price MDB	Volume	VIX index
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.000000
mean	268.310529	275.187817	261.609103	268.427977	268.427977	1.326268e+06	21.367917
std	117.055169	119.442969	114.500991	116.827281	116.827281	9.845323e+05	8.238798
min	72.720001	73.910004	70.660004	73.739998	73.739998	2.226000e+05	11.540000
25%	158.797497	162.972496	154.834000	159.895004	159.895004	7.586000e+05	15.960000
50%	243.904999	252.375000	236.779999	244.979996	244.979996	1.117750e+06	19.525001
75%	365.922493	374.664261	357.976250	365.437508	365.437508	1.576000e+06	24.799999
max	585.030029	590.000000	566.570007	585.030029	585.030029	1.254210e+07	82.690002

In [122…

```
#Charting price
df_mdb["Price MDB"].plot(title="MongoDB's stock price")
```

Out[122]:

```
<Axes: title={'center': "MongoDB's stock price"}, xlabel='Date'>
```

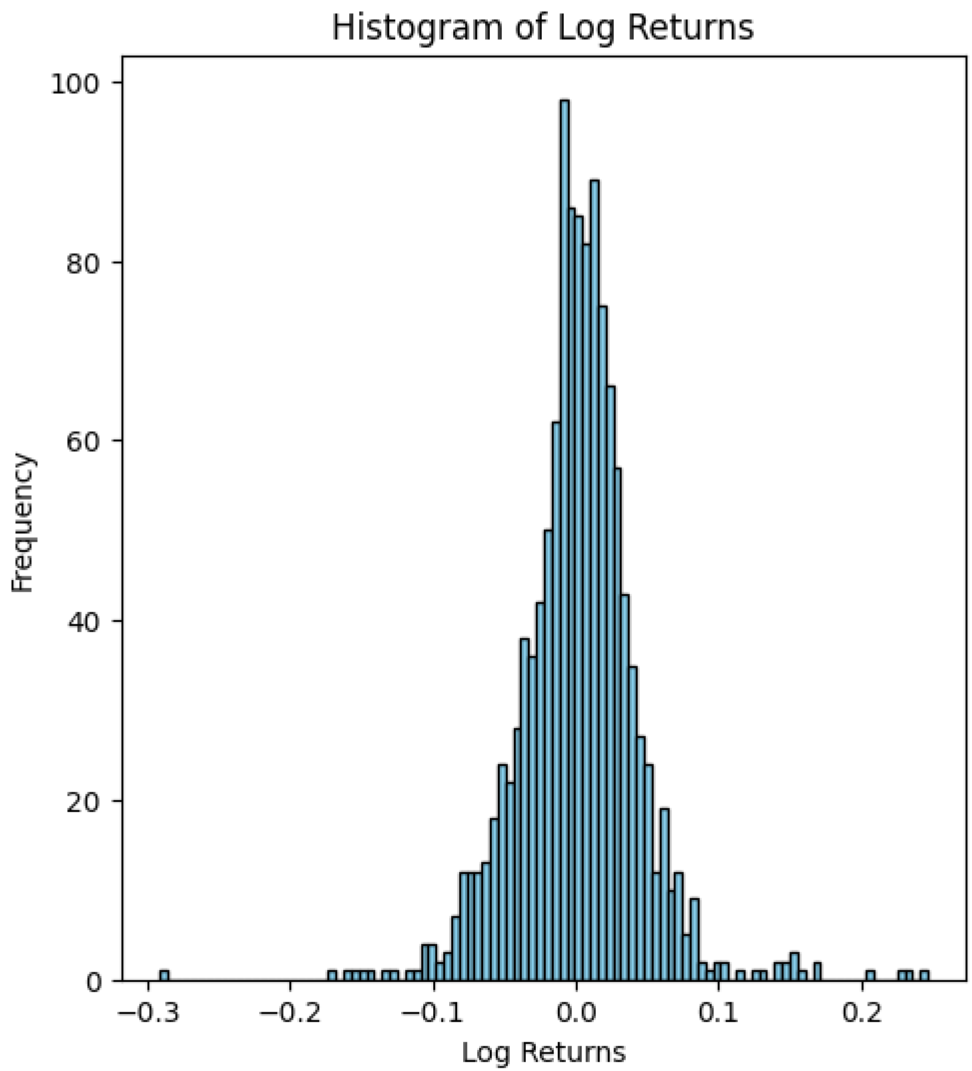


In [123…

```
#Caculate log return
df_mdb["Log_Return"] = np.log(df_mdb["Price MDB"])-np.log(df_mdb["Price MDB"].shift(1))
# Plot Histogram of Daily Returns
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.hist(df_mdb['Log_Return'], bins=100, color='skyblue', edgecolor='black')
plt.title('Histogram of Log Returns')
plt.xlabel('Log Returns')
plt.ylabel('Frequency')
```

Out[123]:

```
Text(0, 0.5, 'Frequency')
```



In [124…
```
#Describe Log-Return of MongoDB
df_mdb["Log_Return"].describe()
```

Out[124]:
```
count    1257.000000
mean        0.001298
std         0.042501
min        -0.291965
25%        -0.019930
50%         0.002146
75%         0.023005
max         0.246943
Name: Log_Return, dtype: float64
```

In [125…
```
#Distribution analysis
  ##Normality Test
stats.normaltest(np.array(df_mdb["Log_Return"].dropna()))
```

Out[125]:
```
NormaltestResult(statistic=165.89349381044588, pvalue=9.477319617865569e-37)
```

In [126…
```
##Skewness and Kurtosis
stats.jarque_bera((np.array(df_mdb["Log_Return"].dropna())))
```

Out[126]:
```
SignificanceResult(statistic=1593.955425492911, pvalue=0.0)
```

In [127…
```
Max1 = df_mdb["Log_Return"].max()
Min1 = df_mdb["Log_Return"].min()
Max2 = (df_mdb["Log_Return"].min() - df_mdb["Log_Return"].mean()) / df_mdb["Log_Return"].std()
Min2 = (df_mdb["Log_Return"].max() - df_mdb["Log_Return"].mean()) / df_mdb["Log_Return"].std()
print("Over the last 5 years, MongoDB has had a maximum daily return of %.2f and a minimum daily return of %.2f If we use the for
```

```
Over the last 5 years, MongoDB has had a maximum daily return of 0.25 and a minimum daily return of -0.29 If we use the formula
to determine standard deviations from the mean, we get -6.90 and 5.78 standard deviations away from the mean for the minimum and
maximum, respectively
```

In [128…
```
(3 * df_mdb["Log_Return"].std()) + df_mdb["Log_Return"].mean()
```

Out[128]:
```
0.12880271575567118
```

In [129…
```
(-3 * df_mdb["Log_Return"].std()) + df_mdb["Log_Return"].mean()
```

Out[129]:
```
-0.12620614144472872
```

In [130…
```
df_mdb[(df_mdb["Log_Return"] > 0.1288) | (df_mdb["Log_Return"] < -0.1262)].tail()
```

Out[130]:

Date	Open	High	Low	Close	Price MDB	Volume	VIX index	Log_Return
2022-06-02	262.000000	290.890015	249.080002	286.700012	286.700012	4986700	24.719999	0.170284
2022-09-01	266.940002	272.000000	238.470001	241.110001	241.110001	8212000	25.559999	-0.291965
2022-11-10	150.009995	165.509995	148.559998	161.000000	161.000000	3714300	23.530001	0.158872
2022-12-07	184.600006	186.750000	167.509995	178.300003	178.300003	12542100	22.680000	0.208874
2023-06-02	380.750000	397.980011	370.000000	376.299988	376.299988	9120700	14.600000	0.246943

In [131…

```
len(df_mdb[(df_mdb["Log_Return"] > 0.1288) | (df_mdb["Log_Return"] < -0.1262)])
```

Out[131]: 23

In [132…

```
#Correlation Log_Return and Volume
correlation_df = df_mdb[['Price MDB', 'Volume', 'Log_Return', 'VIX index']]
correlation_matrix = correlation_df.corr()
correlation_matrix
```

Out[132]:

	Price MDB	Volume	Log_Return	VIX index
Price MDB	1.000000	-0.144583	0.029989	-0.127921
Volume	-0.144583	1.000000	0.094532	0.018122
Log_Return	0.029989	0.094532	1.000000	-0.079290
VIX index	-0.127921	0.018122	-0.079290	1.000000

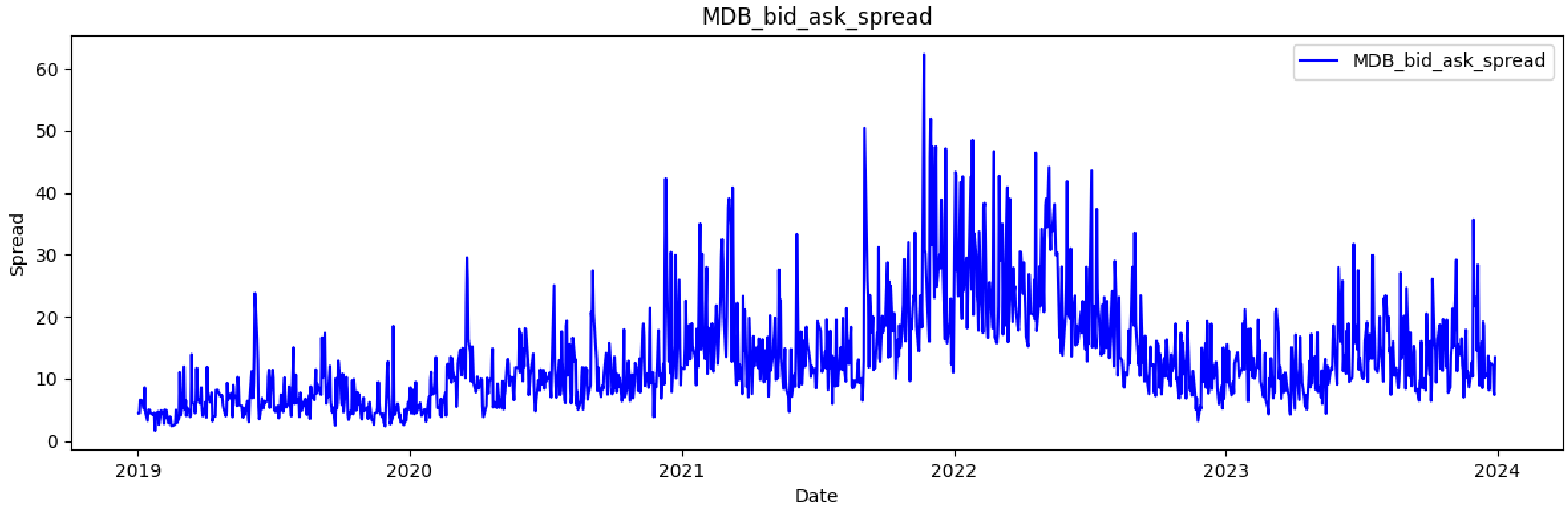
In [133…

```
MDB_bid_ask_spread = df_mdb['High'] - df_mdb['Low']
```

In [134…

```
# Plotting bid-ask spread and VIX index
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))

# Plotting bid-ask spred
ax1.plot(MDB_bid_ask_spread, label="MDB_bid_ask_spread", color='blue')
ax1.set_title("MDB_bid_ask_spread")
ax1.set_xlabel("Date")
```

```
ax1.set_ylabel("Spread")
ax1.legend()

# Plotting bid-ask spread
ax2.plot(df_mdb["VIX index"], label="VIX Index", color='green')
ax2.set_title("VIX Index")
ax2.set_xlabel("Date")
ax2.set_ylabel("Index")
ax2.legend()

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


MDB_bid_ask_spread
MDB_bid_ask_spread
Spread
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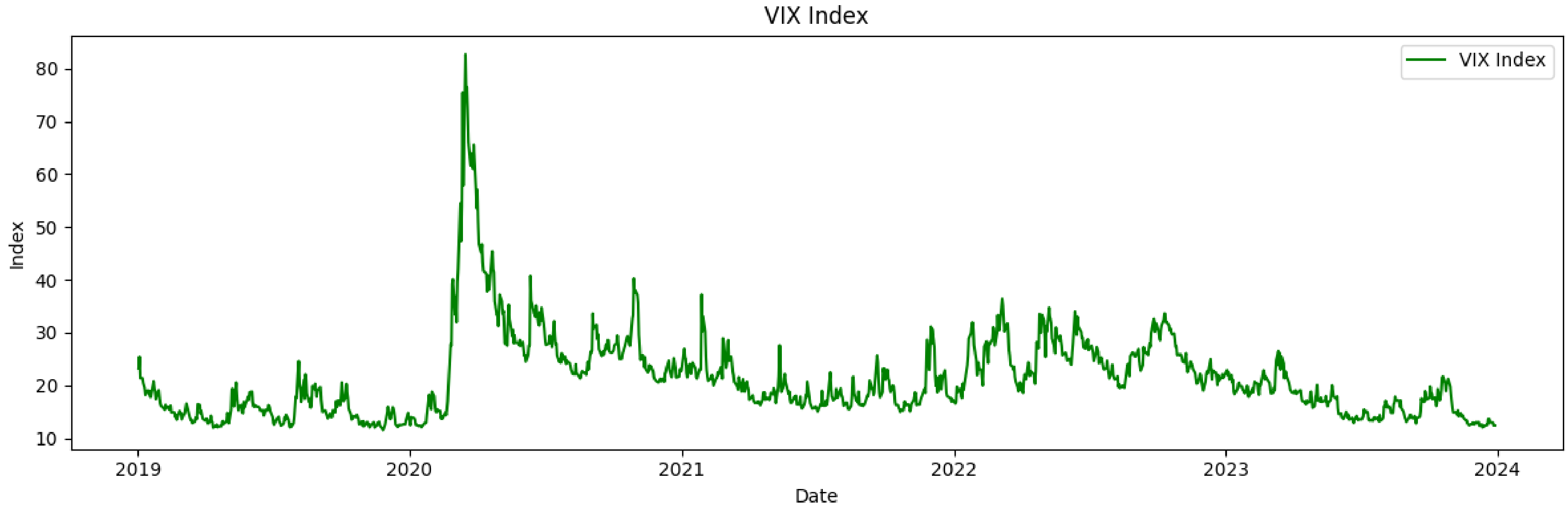
VIX Index
VIX Index
Index
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Date