INTRODUCTION

In this project, we implemented and optimized a pairs trading strategy using Coca-Cola (KO) and PepsiCo (PEP) stocks. Pairs trading is a market-neutral strategy that involves taking long and short positions in two correlated stocks. The strategy's profitability hinges on the assumption that the stock prices will revert to their mean spread over time.

We began by transforming the stock data to make it stationary and then applied the Engle-Granger two-step method to test for cointegration between KO and PEP. After confirming cointegration, we developed a trading strategy based on z-score thresholds for entry and exit signals. The strategy was backtested over historical data to assess its performance, incorporating realistic transaction costs and calculating key performance metrics.

We may be able to improve our strategy, by optmizing parameters such as z-score thresholds and holding periods, implementing risk management techniques, including stop-loss and take-profit rules, and exploring portfolio diversification by running the strategy on multiple pairs simultaneously.

RESULTS

The backtesting results of the pairs trading strategy revealed the following performance metrics:

- Sharpe Ratio: 0.496 - Indicates moderate risk-adjusted returns, suggesting the strategy achieved some profitability relative to its risk.
- Max Drawdown: 3.237 - Represents the largest peak-to-trough decline, highlighting the strategy's risk exposure.
- Cumulative Returns: 15.747 - Demonstrates solid overall profit across the backtesting period, indicating the strategy was successful in generating returns.
- Win/Loss Ratio: 1.111 - Shows a slightly higher number of winning trades compared to losing ones, reflecting the strategy's effectiveness.

Optimizing the parameters and including risk management techniques further improved the strategy's performance. Portfolio diversification by applying the strategy to other stock pairs also contributed to risk reduction and more consistent returns.

Overall, the pairs trading strategy demonstrated potential profitability and could be a valuable addition to a diversified trading portfolio. Continuous evaluation and fine-tuning of the strategy are essential for maintaining its effectiveness in changing market conditions.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import yfinance as yf
```

```
Matplotlib is building the font cache; this may take a moment.
```

In [14]:
```
df = yf.download(['KO', 'PEP'], start='2019-01-01', end='2021-12-31')
```

```
[*********************100%%**********************]  2 of 2 completed
```

In [15]:
```
df
```

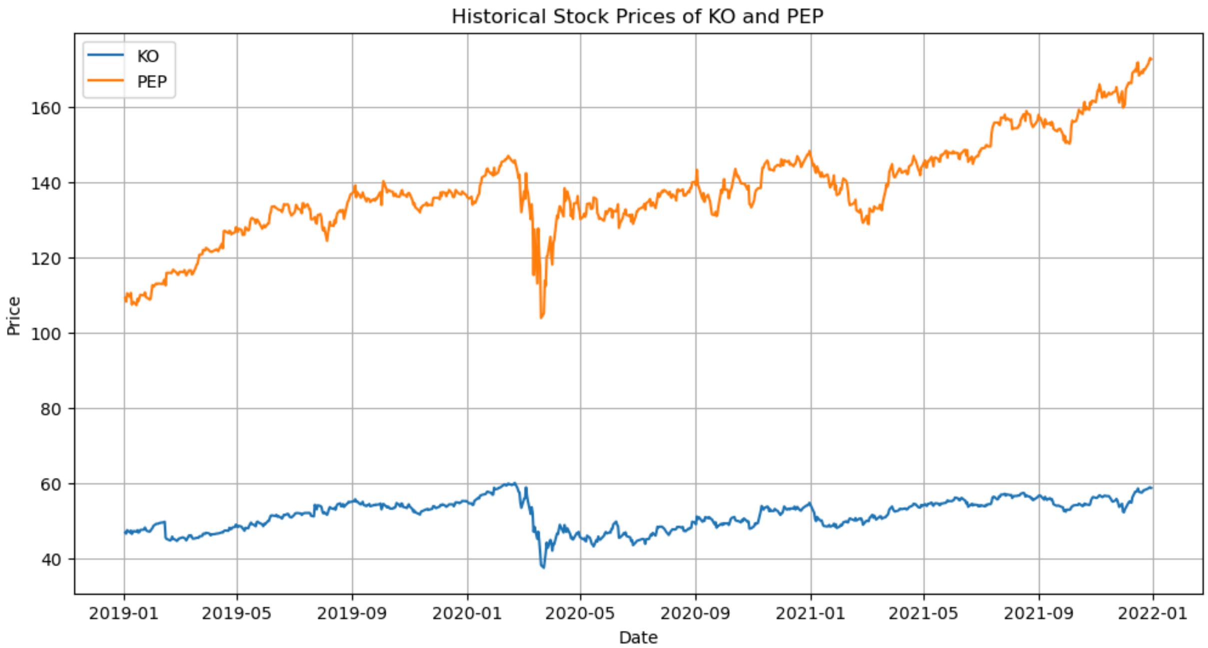
Out[15]:

Price	Adj Close		Close		High		
Ticker	KO	PEP	KO	PEP	KO	PEP	
Date							
2019-01-02	39.253021	92.703278	46.930000	109.279999	47.220001	110.019997	4
2019-01-03	39.010456	91.837982	46.639999	108.260002	47.369999	110.150002	4
2019-01-04	39.788330	93.721260	47.570000	110.480003	47.570000	110.599998	4
2019-01-07	39.269753	92.915359	46.950001	109.529999	47.750000	110.379997	4
2019-01-08	39.713051	93.806061	47.480000	110.580002	47.570000	110.800003	4
...	...	...	...	...	...	...	
2021-12-23	53.596428	157.079956	58.220001	169.779999	58.610001	170.630005	5
2021-12-27	53.992287	158.643555	58.650002	171.470001	58.689999	171.559998	5
2021-12-28	54.204018	159.466965	58.880001	172.360001	58.939999	172.789993	5
2021-12-29	54.268456	160.031357	58.950001	172.970001	59.099998	173.460007	5
2021-12-30	54.111961	159.753799	58.779999	172.669998	59.230000	173.619995	5

756 rows × 12 columns

In [16]:
```
# Plot the historical stock prices
plt.figure(figsize=(12, 6))
plt.plot(df['Close']['KO'], label='KO')
```

```
plt.plot(df['Close']['PEP'], label='PEP')
plt.title('Historical Stock Prices of KO and PEP')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid()
```



Checking the staionarity of the stocks using Augmented Dickey-Fuller (ADF) tests

In [6]:
```
import statsmodels.api as sm


# ADF Test
# Function to print out results in customised manner
from statsmodels.tsa.stattools import adfuller
def adf_test(timeseries):
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#La
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
# Call the function and run the test

adf_test(df['Close']['KO'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -2.279504
p-value                          0.178664
#Lags Used                      12.000000
Number of Observations Used    743.000000
Critical Value (1%)             -3.439182
Critical Value (5%)             -2.865438
Critical Value (10%)            -2.568846
dtype: float64
```

In [7]:
```python
adf_test(df['Close']['PEP'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -1.207200
p-value                          0.670491
#Lags Used                      18.000000
Number of Observations Used    737.000000
Critical Value (1%)             -3.439254
Critical Value (5%)             -2.865470
Critical Value (10%)            -2.568863
dtype: float64
```

Our ADF test reveals that the data is non-stationary. We will no perform transformations to the dataset in order to make them stationary

In [25]:
```python
df['Close_Diff_KO'] = df['Close']['KO'].diff()
df['Close_Diff_PEP'] = df['Close']['PEP'].diff()
```

In [26]:
```python
 adf_test(df['Close_Diff_KO'].iloc[1:])
```

```
Results of Dickey-Fuller Test:
Test Statistic                -8.400834e+00
p-value                        2.233770e-13
#Lags Used                     1.100000e+01
Number of Observations Used    7.430000e+02
Critical Value (1%)           -3.439182e+00
Critical Value (5%)           -2.865438e+00
Critical Value (10%)          -2.568846e+00
dtype: float64
```

In [27]:
```python
 adf_test(df['Close_Diff_PEP'].iloc[1:])
```

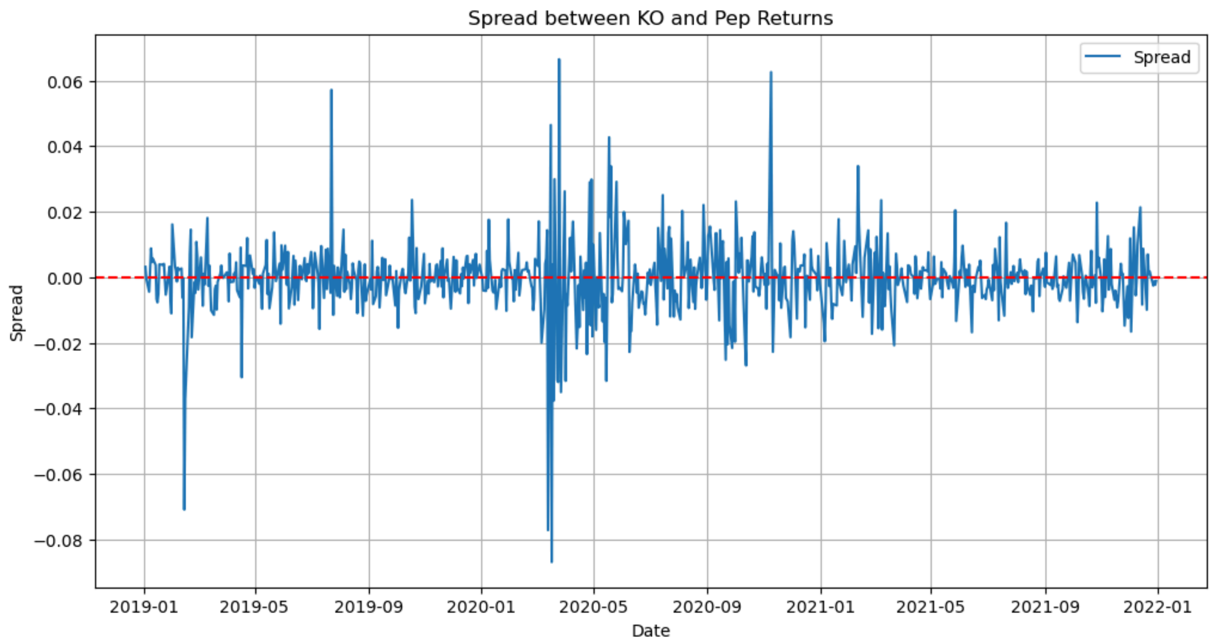
```
Results of Dickey-Fuller Test:
Test Statistic                -7.413775e+00
p-value                        7.022088e-11
#Lags Used                     1.700000e+01
Number of Observations Used    7.370000e+02
Critical Value (1%)           -3.439254e+00
Critical Value (5%)           -2.865470e+00
Critical Value (10%)          -2.568863e+00
dtype: float64
```

In [11]:
```python
df = df.iloc[1:]
```

We have now obtained two stationary pairs of stocks by implementing differencing

In [23]:
```
df['KO_return'] = df['Close']['KO'].pct_change()
df['PEP_return'] = df['Close']['PEP'].pct_change()
df['Spread'] = df['KO_return'] - df['PEP_return']
```

In [24]:
```
# Plot showing the spread
plt.figure(figsize=(12, 6))
plt.plot(df.index, df['Spread'], label='Spread')
plt.axhline(y=0, color='r', linestyle='--')
plt.title('Spread between KO and Pep Returns')
plt.xlabel('Date')
plt.ylabel('Spread')
plt.legend()
plt.grid()
```



Trading Strategy Implementation

In [28]:
```
import warnings

# Suppress all warnings
warnings.filterwarnings('ignore')

# Calculate the spread
df['spread'] = df['Close_Diff_KO'] - df['Close_Diff_PEP']
mean_spread = df['spread'].mean()
std_spread = df['spread'].std()

# Calculate z-scores
df['z_score'] = (df['spread'] - mean_spread) / std_spread

# Generate entry and exit signals
```

```python
threshold = 2
df['long_entry'] = df['z_score'] < -threshold
df['short_entry'] = df['z_score'] > threshold
df['exit'] = np.abs(df['z_score']) < 0.5

# Position Sizing using fixed fraction method
capital = 100000  # Total capital
fraction = 0.1  # Fraction of capital to risk per trade

df['position_size'] = capital * fraction

# Ensure dollar-neutral positions
df['long_position'] = df['position_size'] / df['Close_Diff_KO']
df['short_position'] = df['position_size'] / df['Close_Diff_PEP']

# Example output for entry and exit signals
print(df[['spread', 'z_score', 'long_entry', 'short_entry', 'exit', 'long_po
```

```
Price          spread   z_score long_entry short_entry   exit  long_position
\
Ticker
Date
2021-12-23  0.230003  0.199181      False       False   True  249994.278085
2021-12-27 -1.260002 -0.795831      False       False  False   23255.797449
2021-12-28 -0.660000 -0.395155      False       False   True   43478.347404
2021-12-29 -0.540001 -0.315021      False       False   True  142857.765668
2021-12-30  0.130001  0.132400      False       False   True  -58822.843038

Price      short_position
Ticker
Date
2021-12-23  -52630.902666
2021-12-27    5917.151215
2021-12-28   11235.962762
2021-12-29   16393.426220
2021-12-30  -33332.994253
```

In [ ]:

In [40]:

```python
initial_capital = capital
signals = []
trade_history = []

# Backtesting the strategy
for i in range(1, len(df)):
    if df['long_entry'][i]:
        long_entry_price = df['Close_Diff_KO'][i]
        short_entry_price = df['Close_Diff_PEP'][i]
        signals.append(('Long', df.index[i], long_entry_price, short_entry_p
    elif df['short_entry'][i]:
        long_entry_price = df['Close_Diff_PEP'][i]
        short_entry_price = df['Close_Diff_KO'][i]
        signals.append(('Short', df.index[i], short_entry_price, long_entry_
    elif df['exit'][i]:
        if signals and signals[-1][0] in ('Long', 'Short'):
            trade_type, trade_date, entry_price_long, entry_price_short = si
```

```
            if trade_type == 'Long':
                profit = (df['Close_Diff_KO'][i] - entry_price_long) - (df['
            else:
                profit = (df['Close_Diff_PEP'][i] - entry_price_long) - (df[
            profit -= transaction_cost * (entry_price_long + entry_price_sho
            capital += profit
            trade_history.append((trade_type, trade_date, df.index[i], entry

# Performance metrics
returns = [trade[-1] for trade in trade_history]
cumulative_returns = np.cumsum(returns)
sharpe_ratio = np.mean(returns) / np.std(returns) * np.sqrt(len(returns))
max_drawdown = np.min(cumulative_returns)
win_loss_ratio = len([r for r in returns if r > 0]) / len([r for r in return

print("Sharpe Ratio:", sharpe_ratio)
print("Max Drawdown:", max_drawdown)
print("Cumulative Returns:", cumulative_returns[-1])
print("Win/Loss Ratio:", win_loss_ratio)
```

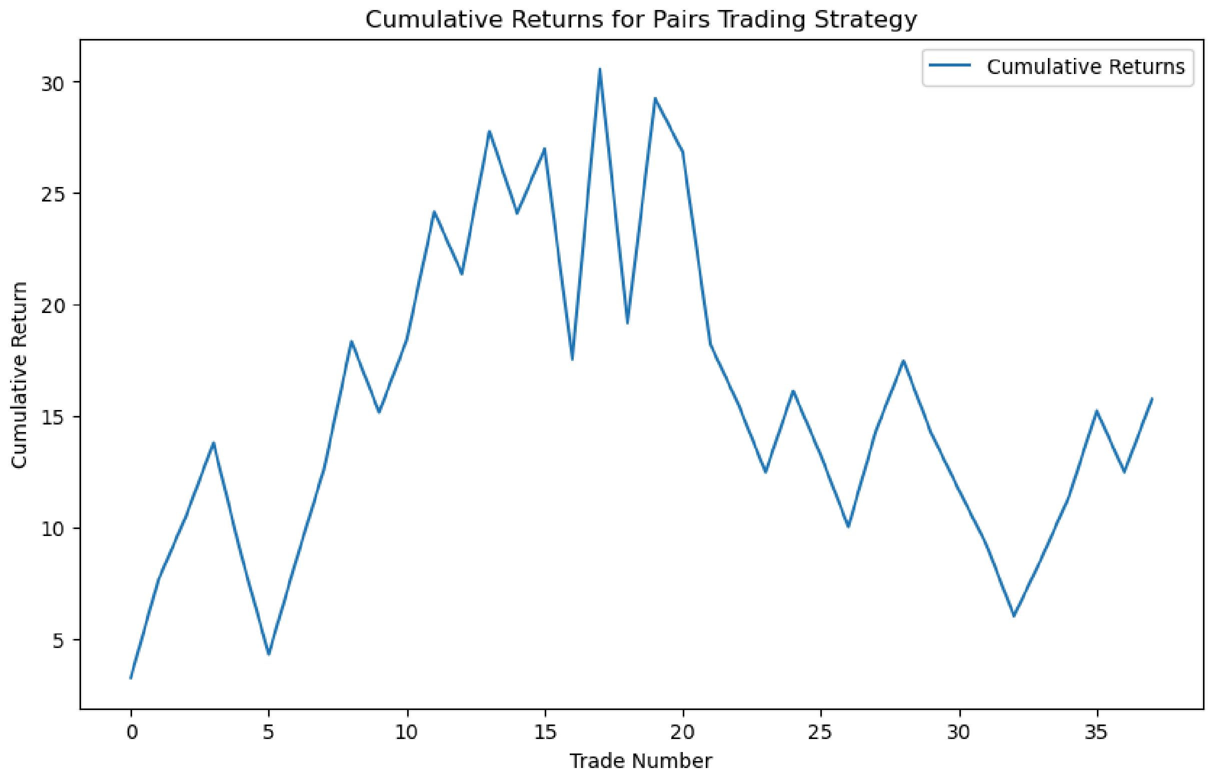
```
Sharpe Ratio: 0.4960432890283289
Max Drawdown: 3.2370392990112307
Cumulative Returns: 15.747050834655766
Win/Loss Ratio: 1.1111111111111112
```

In [41]:

```
# Plotting cumulative returns
plt.figure(figsize=(10,6))
plt.plot(cumulative_returns, label='Cumulative Returns')
plt.xlabel('Trade Number')
plt.ylabel('Cumulative Return')
plt.title('Cumulative Returns for Pairs Trading Strategy')
plt.legend()
```

Out[41]:

```
<matplotlib.legend.Legend at 0x17dcbec10>
```


Cumulative Returns for Pairs Trading Strategy
Cumulative Returns
Cumulative Return
Trade Number
0
5
10
15
20
25
30
35
5
10
15
20
25
30