sta141b final

March 15, 2025

[68]:
```
import pandas as pd

stock_data_path = r"C:\Users\L0145\Downloads\stock_data.csv"
industry_data_path = r"C:\Users\L0145\Downloads\tickers_industry_data.csv"

stock_data = pd.read_csv(stock_data_path, header=[0, 1], index_col=0)
industry_data = pd.read_csv(industry_data_path)

print(stock_data.head())
print(industry_data.head())
```

```
Ticker           AMZN                                                PATH       \
Price            Open       High        Low      Close     Volume Open High
Date
2019-01-02  73.260002  77.667999  73.046501  76.956497  159662000  NaN  NaN
2019-01-03  76.000504  76.900002  74.855499  75.014000  139512000  NaN  NaN
2019-01-04  76.500000  79.699997  75.915497  78.769501  183652000  NaN  NaN
2019-01-07  80.115501  81.727997  79.459503  81.475502  159864000  NaN  NaN
2019-01-08  83.234497  83.830498  80.830498  82.829002  177628000  NaN  NaN

Ticker                        …       PARA                                \
Price      Low Close Volume   …       Open       High        Low      Close
Date                          …
2019-01-02 NaN   NaN    NaN   …  37.383789  39.209270  37.143820  39.132137
2019-01-03 NaN   NaN    NaN   …  38.849324  40.014887  38.677917  39.534950
2019-01-04 NaN   NaN    NaN   …  39.937761  40.580536  39.569236  40.426270
2019-01-07 NaN   NaN    NaN   …  40.391987  41.377573  40.169156  40.854782
2019-01-08 NaN   NaN    NaN   …  41.146176  41.711817  40.494832  41.454708

Ticker                    BCS
Price        Volume      Open      High       Low     Close   Volume
Date
2019-01-02  4704600  5.797587  5.969947  5.797587  5.954278  4504100
2019-01-03  5106600  5.962112  5.993450  5.891600  5.930773  2911500
2019-01-04  3917700  6.150141  6.197149  6.103134  6.173645  2985800
2019-01-07  3413800  6.181479  6.259825  6.150141  6.236321  3045500
2019-01-08  3219900  6.306834  6.322503  6.228488  6.275496  2109400
```

```
[5 rows x 1763 columns]
  Ticker            Industry
0   NVDA      Semiconductors
1      F  Auto Manufacturers
2   TSLA  Auto Manufacturers
3    NIO  Auto Manufacturers
4   LCID  Auto Manufacturers
```

[69]:
```
# Double check
print(stock_data_reset.columns)
print(stock_data_reset.head())
```

```
MultiIndex([('Date',       ''),
            ('AMZN',   'Open'),
            ('AMZN',   'High'),
            ('AMZN',    'Low'),
            ('AMZN',  'Close'),
            ('AMZN', 'Volume'),
            ('PATH',   'Open'),
            ('PATH',   'High'),
            ('PATH',    'Low'),
            ('PATH',  'Close'),
            …
            ('PARA',   'Open'),
            ('PARA',   'High'),
            ('PARA',    'Low'),
            ('PARA',  'Close'),
            ('PARA', 'Volume'),
            ( 'BCS',   'Open'),
            ( 'BCS',   'High'),
            ( 'BCS',    'Low'),
            ( 'BCS',  'Close'),
            ( 'BCS', 'Volume')],
           names=['Ticker', 'Price'], length=1764)
Ticker        Date       AMZN                                          \
Price                     Open       High        Low      Close     Volume
0       2019-01-02  73.260002  77.667999  73.046501  76.956497  159662000
1       2019-01-03  76.000504  76.900002  74.855499  75.014000  139512000
2       2019-01-04  76.500000  79.699997  75.915497  78.769501  183652000
3       2019-01-07  80.115501  81.727997  79.459503  81.475502  159864000
4       2019-01-08  83.234497  83.830498  80.830498  82.829002  177628000

Ticker PATH                 …       PARA                                \
Price  Open High Low Close  …       Open       High        Low      Close
0       NaN  NaN NaN   NaN  …  37.383789  39.209270  37.143820  39.132137
1       NaN  NaN NaN   NaN  …  38.849324  40.014887  38.677917  39.534950
2       NaN  NaN NaN   NaN  …  39.937761  40.580536  39.569236  40.426270
3       NaN  NaN NaN   NaN  …  40.391987  41.377573  40.169156  40.854782
```

```
4       NaN  NaN NaN   NaN  …  41.146176  41.711817  40.494832  41.454708

Ticker                BCS
Price    Volume      Open      High       Low     Close   Volume
0       4704600  5.797587  5.969947  5.797587  5.954278  4504100
1       5106600  5.962112  5.993450  5.891600  5.930773  2911500
2       3917700  6.150141  6.197149  6.103134  6.173645  2985800
3       3413800  6.181479  6.259825  6.150141  6.236321  3045500
4       3219900  6.306834  6.322503  6.228488  6.275496  2109400

[5 rows x 1764 columns]
```

[70]:
```
# Fix column names (flatten multi-index)
stock_data.columns = ['_'.join(col).strip() for col in stock_data.columns]
stock_data.reset_index(inplace=True)
stock_data.rename(columns={"Date_": "Date"}, inplace=True)

# Convert from wide to long format
stock_data_long = stock_data.melt(id_vars=["Date"], var_name="Ticker_Metric",␣
 ↪value_name="Value")

# Split 'Ticker_Metric' into separate 'Ticker' and 'Metric' columns
stock_data_long[["Ticker", "Metric"]] = stock_data_long["Ticker_Metric"].str.
 ↪rsplit("_", n=1, expand=True)

stock_data_long.drop(columns=["Ticker_Metric"], inplace=True)

# Pivot so that Open, High, Low, Close, and Volume are columns
stock_data_long = stock_data_long.pivot(index=["Date", "Ticker"],␣
 ↪columns="Metric", values="Value").reset_index()

# Merge with industry data
stock_data_merged = stock_data_long.merge(industry_data, on="Ticker",␣
 ↪how="left")

print(stock_data_merged.head())
```

```
         Date Ticker  Adj Close      Close       High        Low       Open  \
0  2019-01-02     AA        NaN  25.303432  25.888768  24.570558  25.028605
1  2019-01-02    AAL        NaN  31.963158  32.130454  30.555912  30.959388
2  2019-01-02   AAPL        NaN  37.667175  37.889001  36.787034  36.944458
3  2019-01-02   ABBV        NaN  67.518402  69.054458  66.905489  69.039321
4  2019-01-02   ABEV        NaN   3.439978   3.472740   3.251598   3.276170

        Volume                    Industry
0    3067000.0                    Aluminum
1    5229500.0                    Airlines
2  148158800.0          Consumer Electronics
```

```
3    6908400.0  Drug Manufacturers - General
4   20573600.0           Beverages - Brewers
```

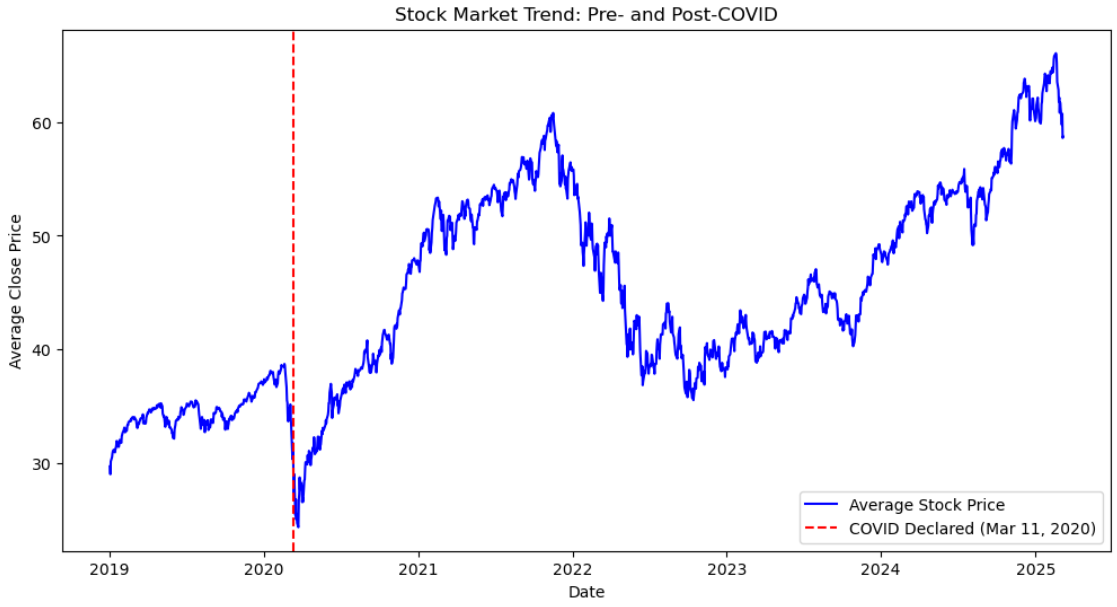
[71]:
```
import numpy as np

# Convert 'Date' column to datetime format
stock_data_merged["Date"] = pd.to_datetime(stock_data_merged["Date"])

stock_data_merged.sort_values(by=["Ticker", "Date"], inplace=True)
stock_data_merged["Return"] = stock_data_merged.groupby("Ticker")["Close"].
 ↪pct_change()

# Compute rolling 30-day volatility
stock_data_merged["Volatility"] = (
    stock_data_merged.groupby("Ticker")["Return"].rolling(window=30).std().
 ↪reset_index(level=0, drop=True)
)

covid_cutoff = pd.Timestamp("2020-03-11")
stock_data_merged["Period"] = np.where(stock_data_merged["Date"] <␣
 ↪covid_cutoff, "Pre-COVID", "Post-COVID")

# Aggregate sector-wise statistics
sector_analysis = stock_data_merged.groupby(["Industry", "Period"]).agg(
    Avg_Return=("Return", "mean"),
    Avg_Volatility=("Volatility", "mean")
).reset_index()

print(sector_analysis.head())
```

```
C:\Users\L0145\AppData\Local\Temp\ipykernel_2828\1755420765.py:7: FutureWarning:
The default fill_method='ffill' in SeriesGroupBy.pct_change is deprecated and
will be removed in a future version. Either fill in any non-leading NA values
prior to calling pct_change or specify 'fill_method=None' to not fill NA values.
  stock_data_merged["Return"] =
stock_data_merged.groupby("Ticker")["Close"].pct_change()
```

	Industry	Period	Avg_Return	Avg_Volatility
0	Advertising Agencies	Post-COVID	0.000648	0.019326
1	Advertising Agencies	Pre-COVID	-0.000054	0.012656
2	Aerospace & Defense	Post-COVID	0.001081	0.034008
3	Aerospace & Defense	Pre-COVID	0.000019	0.021397
4	Airlines	Post-COVID	0.000587	0.029239

[59]:
```
import matplotlib.pyplot as plt

# Compute average closing price across all stocks for each date
market_trend = stock_data_merged.groupby("Date")["Close"].mean()
```

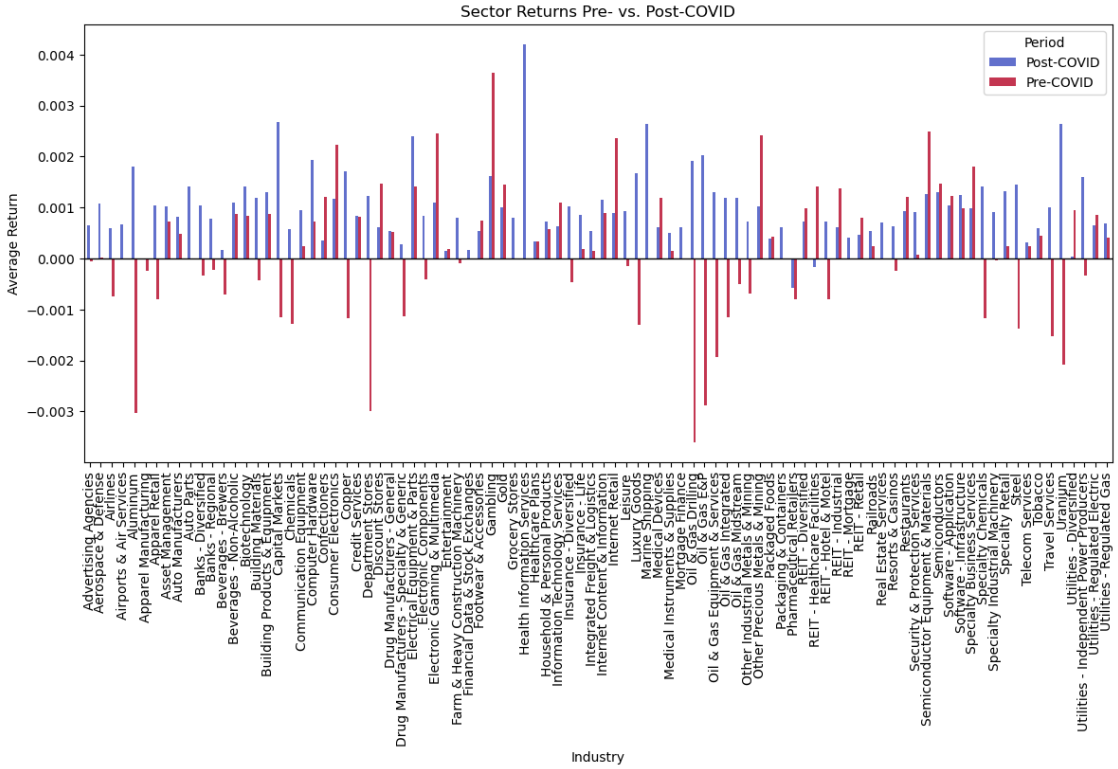
```
plt.figure(figsize=(12, 6))
plt.plot(market_trend.index, market_trend, label="Average Stock Price",␣
 ↪color="blue")
plt.axvline(pd.Timestamp("2020-03-11"), color="red", linestyle="--",␣
 ↪label="COVID Declared (Mar 11, 2020)")
plt.xlabel("Date")
plt.ylabel("Average Close Price")
plt.title("Stock Market Trend: Pre- and Post-COVID")
plt.legend()
plt.show()
```



[72]:
```
import seaborn as sns

# Pivot for easier plotting
sector_pivot = sector_analysis.pivot(index="Industry", columns="Period",␣
 ↪values="Avg_Return")

plt.figure(figsize=(14, 6))
sector_pivot.plot(kind="bar", figsize=(14, 6), colormap="coolwarm", alpha=0.8)
plt.axhline(0, color="black", linewidth=1)  # Add a reference line at y=0
plt.xlabel("Industry")
plt.ylabel("Average Return")
plt.title("Sector Returns Pre- vs. Post-COVID")
plt.legend(title="Period")
plt.xticks(rotation=90)
```

```
plt.show()
```

```
<Figure size 1400x600 with 0 Axes>
```



[61]:
```
# Check unique industries in data
print(stock_data_merged["Industry"].unique())

# Adjust selected sectors to match actual labels
selected_sectors = ["Software - Application", "Drug Manufacturers - General",␣
 ↪"Oil & Gas E&P"]
```

```
['Aluminum' 'Airlines' 'Consumer Electronics'
 'Drug Manufacturers - General' 'Beverages - Brewers' 'Travel Services'
 'Medical Devices' 'Aerospace & Defense' 'Grocery Stores'
 'Security & Protection Services' 'Insurance - Diversified'
 'Apparel Retail' 'Utilities - Diversified' 'Software - Infrastructure'
 'REIT - Mortgage' 'Semiconductors' 'Software - Application'
 'Specialty Chemicals' 'Semiconductor Equipment & Materials'
 'Packaging & Containers' 'Internet Retail' 'Computer Hardware'
 'Oil & Gas E&P' 'REIT - Hotel & Motel' 'Asset Management' 'Leisure'
 'Communication Equipment' 'Information Technology Services'
 'Medical Instruments & Supplies' 'Banks - Diversified' 'Banks - Regional'
 'Specialty Retail' 'Electrical Equipment & Parts' 'Real Estate Services'
```

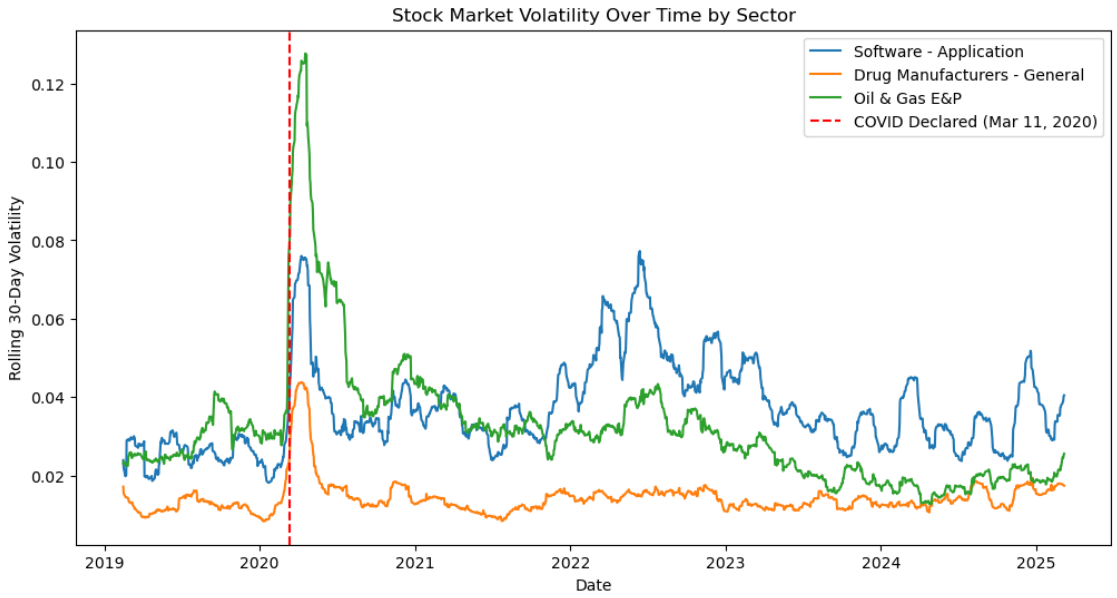
```
'Electronic Gaming & Multimedia' 'Oil & Gas Equipment & Services'
'Oil & Gas Integrated' 'Gold' 'Tobacco' 'Internet Content & Information'
'Packaged Foods' 'Building Products & Equipment'
'Beverages - Non-Alcoholic' 'Steel' 'Capital Markets' 'Telecom Services'
'Restaurants' 'Healthcare Plans' 'Farm & Heavy Construction Machinery'
'Utilities - Regulated Electric' 'Credit Services'
'Financial Data & Stock Exchanges' 'Household & Personal Products'
'Specialty Business Services' 'Building Materials' 'Railroads'
'Resorts & Casinos' 'Entertainment' 'Gambling' 'Chemicals'
'Drug Manufacturers - Specialty & Generic'
'Specialty Industrial Machinery' 'Oil & Gas Midstream'
'Auto Manufacturers' 'Copper' 'Electronic Components' 'Insurance - Life'
'Apparel Manufacturing' 'Other Precious Metals & Mining' 'Auto Parts'
'Advertising Agencies' 'Airports & Air Services' 'REIT - Retail'
'Department Stores' 'Confectioners' 'REIT - Healthcare Facilities'
'Biotechnology' 'Utilities - Regulated Gas' 'Footwear & Accessories'
'Utilities - Independent Power Producers' 'Uranium' nan
'REIT - Industrial' 'Oil & Gas Drilling' 'Mortgage Finance'
'Health Information Services' 'Discount Stores' 'Luxury Goods'
'Integrated Freight & Logistics' 'Other Industrial Metals & Mining'
'REIT - Diversified' 'Pharmaceutical Retailers' 'Marine Shipping']
```

[62]:
```
sector_volatility = stock_data_merged[stock_data_merged["Industry"].
 ↪isin(selected_sectors)]
print("Sectors in filtered data:", sector_volatility["Industry"].unique())
print("Number of rows:", len(sector_volatility))
```

```
Sectors in filtered data: ['Drug Manufacturers - General' 'Software -
Application' 'Oil & Gas E&P']
Number of rows: 59052
```

[63]:
```
plt.figure(figsize=(12, 6))
for sector in selected_sectors:
    # Filter data for the sector and drop NaN volatility values
    sector_data = sector_volatility[sector_volatility["Industry"] == sector].
 ↪dropna(subset=["Volatility"])
    if not sector_data.empty:
        # Calculate mean volatility by date
        avg_volatility = sector_data.groupby("Date")["Volatility"].mean()
        plt.plot(avg_volatility.index, avg_volatility, label=sector)
    else:
        print(f"No data for sector: {sector}")

plt.axvline(pd.Timestamp("2020-03-11"), color="red", linestyle="--",␣
 ↪label="COVID Declared (Mar 11, 2020)")
plt.xlabel("Date")
plt.ylabel("Rolling 30-Day Volatility")
plt.title("Stock Market Volatility Over Time by Sector")
```

```
plt.legend()
plt.show()
```



[64]:
```
# Convert Date to datetime
stock_data_merged["Date"] = pd.to_datetime(stock_data_merged["Date"])

# Calculate average closing price across all stocks for each date
market_trend = stock_data_merged.groupby("Date")["Close"].mean().reset_index()

# Find peak (pre-crash) and trough (crash bottom) dates
peak_date = market_trend[market_trend["Date"] < "2020-03-11"]["Close"].idxmax()
trough_date = market_trend["Close"].idxmin()

peak_price = market_trend.loc[peak_date, "Close"]
trough_price = market_trend.loc[trough_date, "Close"]

# Calculate percentage decline
percentage_decline = ((peak_price - trough_price) / peak_price) * 100
print(f"Market Decline: {percentage_decline:.2f}%")
```

```
Market Decline: 37.08%
```

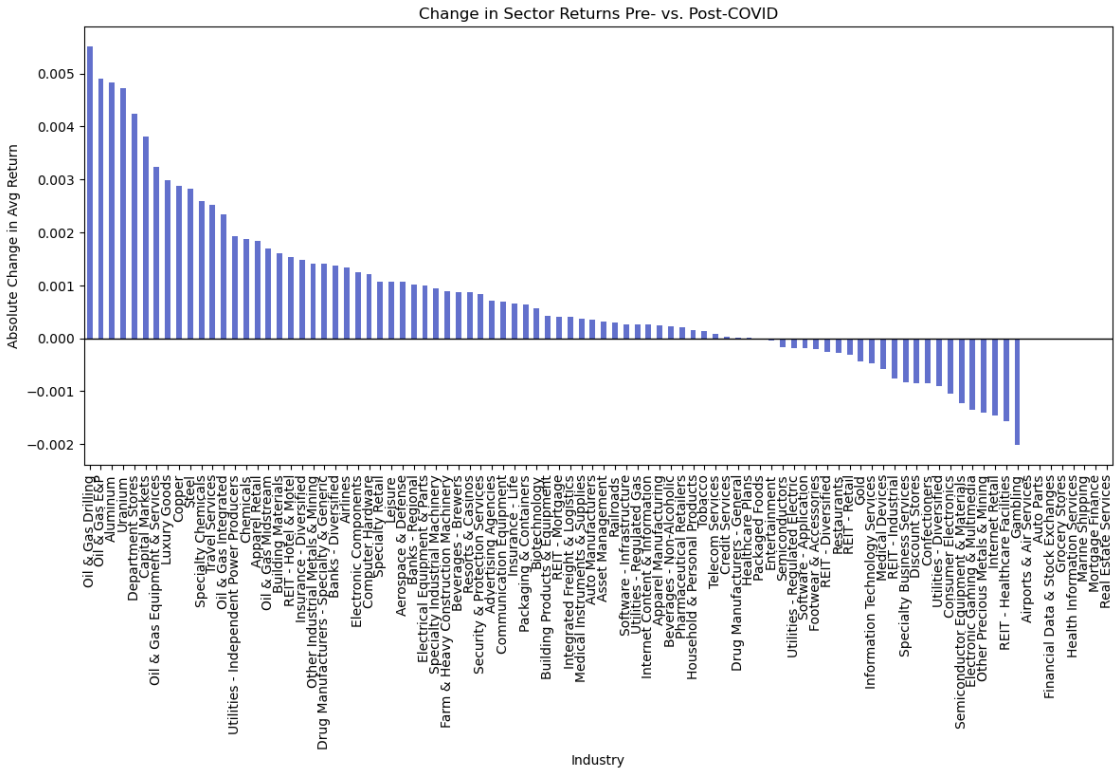
[73]:
```
# Calculate performance divergence
sector_pivot["Absolute_Change"] = sector_pivot["Post-COVID"] -␣
 ↪sector_pivot["Pre-COVID"]
sector_pivot["Relative_Change"] = (sector_pivot["Absolute_Change"] /␣
 ↪sector_pivot["Pre-COVID"].replace(0, np.nan)) * 100  # Avoid division by zero
```

```
# Display sorted results for better interpretation
sector_pivot_sorted = sector_pivot.sort_values(by="Absolute_Change",␣
 ↪ascending=False)

# Print top sectors with highest changes
print(sector_pivot_sorted.head(10))  # Top 10 positive changes
print(sector_pivot_sorted.tail(10))  # Top 10 negative changes

# Plot the change in returns
plt.figure(figsize=(14, 6))
sector_pivot_sorted["Absolute_Change"].plot(kind="bar", colormap="coolwarm",␣
 ↪alpha=0.8)
plt.axhline(0, color="black", linewidth=1)  # Reference line at y=0
plt.xlabel("Industry")
plt.ylabel("Absolute Change in Avg Return")
plt.title("Change in Sector Returns Pre- vs. Post-COVID")
plt.xticks(rotation=90)
plt.show()
```

```
Period                          Post-COVID  Pre-COVID  Absolute_Change  \
Industry
Oil & Gas Drilling                0.001909  -0.003605         0.005514
Oil & Gas E&P                     0.002025  -0.002872         0.004898
Aluminum                          0.001799  -0.003035         0.004833
Uranium                           0.002642  -0.002075         0.004716
Department Stores                 0.001231  -0.003001         0.004231
Capital Markets                   0.002673  -0.001144         0.003816
Oil & Gas Equipment & Services    0.001296  -0.001934         0.003229
Luxury Goods                      0.001681  -0.001299         0.002981
Copper                            0.001714  -0.001172         0.002885
Steel                             0.001445  -0.001371         0.002817

Period                          Relative_Change
Industry
Oil & Gas Drilling                 -152.940741
Oil & Gas E&P                      -170.512338
Aluminum                           -159.268487
Uranium                            -227.354854
Department Stores                  -141.009879
Capital Markets                    -333.743156
Oil & Gas Equipment & Services     -166.987767
Luxury Goods                       -229.414639
Copper                             -246.271492
Steel                              -205.392756
Period                            Post-COVID  Pre-COVID  Absolute_Change  \
Industry
```

REIT - Healthcare Facilities	-0.000159	0.001407	-0.001566
Gambling	0.001618	0.003634	-0.002016
Airports & Air Services	0.000673	NaN	NaN
Auto Parts	0.001410	NaN	NaN
Financial Data & Stock Exchanges	0.000166	NaN	NaN
Grocery Stores	0.000804	NaN	NaN
Health Information Services	0.004200	NaN	NaN
Marine Shipping	0.002645	NaN	NaN
Mortgage Finance	0.000615	NaN	NaN
Real Estate Services	0.000701	NaN	NaN

Period	Relative_Change
Industry	
REIT - Healthcare Facilities	-111.302811
Gambling	-55.486591
Airports & Air Services	NaN
Auto Parts	NaN
Financial Data & Stock Exchanges	NaN
Grocery Stores	NaN
Health Information Services	NaN
Marine Shipping	NaN
Mortgage Finance	NaN
Real Estate Services	NaN



[ ]: