EPPS 6354 Database Final Report

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1 Database Topic: US-China Trade Database

2 Database Introduction

The database aims to serve people interested in US-China trade war and its effect on US-China trade volumes, and the impact on US multinational corporations (MNCs) which depend on global value chains (GVC) heavily.

The database provides mainly two types of data. The first type is the macroscopic data. Specifically, this database provides US-China monthly trade data by commodity, the volume and percentage of products under tariff data between US and China. It also contains the data about US annual trade with all countries and the basic development indicator information of these countries, including GDP, population, tariff rate in general, and tariff rate for manufactured products. The second type of data is the microcosmic data about MNCs, including S&P 500 company list with detailed information, such as stock symbol, location, sector, industry, etc., S&P 500 company stock price time-series data, fortune 500 company list and their annual revenues data, fortune 500 company stock price time-series data, top 20 companies list based on their level of sale in China, and top 20 companies list based on their share of sale in China.

People could utilize this dataset to explore how U.S.-China trade relations change in the 21st century, the connection between U.S.-China trade and their tariff change, the differences in the tendencies of US trade with different companies, how U.S.-China trade relations affect U.S. multinational corporations (MNCs).

3 Background Introduction

The trade between the U.S. and China started since 1971 when the U.S. officially ended its trade embargo on China. In 1979, when the two sides officially re-established diplomatic relations and signed a bilateral trade agreement, the U.S.-China trade volume began to grow. In 2001, China's entry into the World Trade Organization (WTO) changed China's economy to an export-driven pattern, contributing to China's rapid development of its economy and international trade (Wang 2013). The U.S. has become the largest destination for China's exports since 2000 (Shen et al. 2020). During the first decade of the twenty-first century, both U.S. and China attach great importance to their economic cooperation, and their trade relations have expanded rapidly. From China's side, bilateral trade with the U.S. and foreign investment from the U.S. side is crucial for China's continuous development and modernization. From the perspective of the U.S., China's rapid development speed brings enormous potential market and economic activity while the government begins to raise a concern about its national security (Wang 2013).

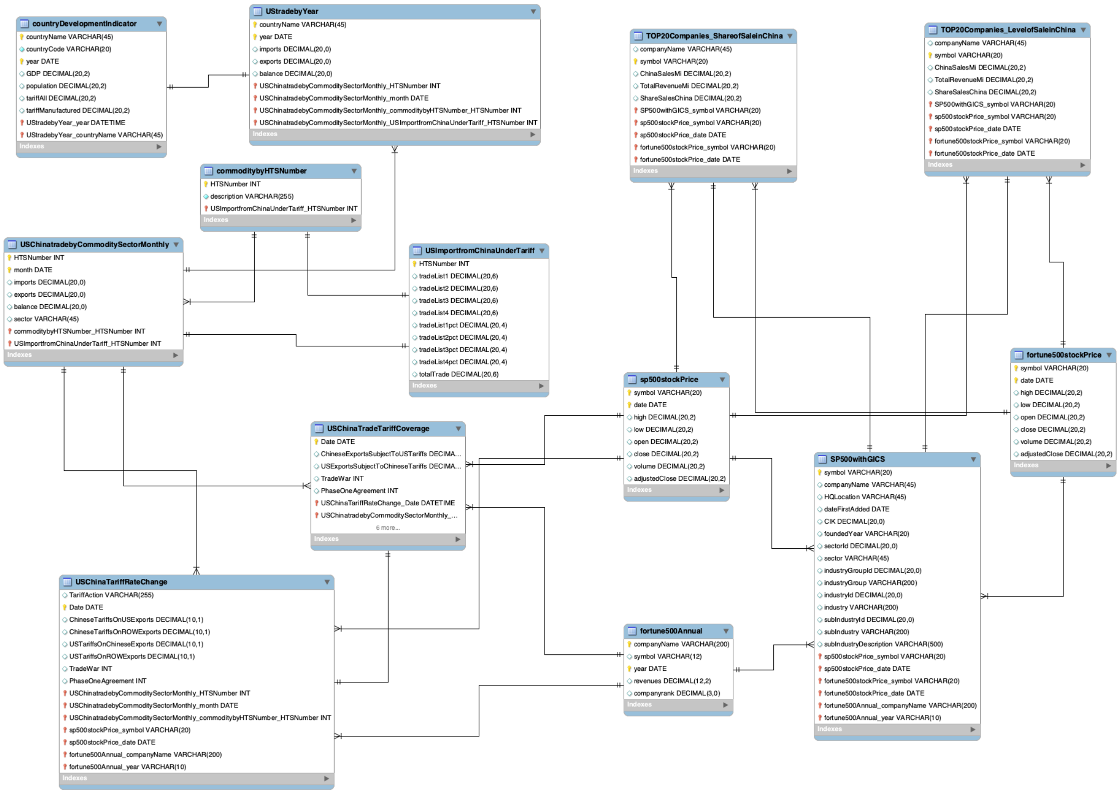
In 2010, China became the second-largest economy after the U.S. in terms of GDP. Since the Obama administration, the U.S. has treated China as the biggest challenger and a strategic competitor. After Donald Trump took office in 2017, the U.S. government focused on the trade unbalance between the U.S. and China. In January 2018, U.S. President Donald Trump began imposing tariffs and other trade barriers on China to force it to change what the U.S. calls "unfair trade practices" and theft of intellectual property (Wikipedia Foundation, 2021), which is a signal for the following outbreak of the U.S.-China trade war.

U.S. and China relations have worsened in the past few years, starting from the U.S.-China trade war. The imposed tariffs from both sides impede the normal GVC circulation, increase the manufacturing cost, and further reduce the profits margins of U.S. MNCs. Moreover, worsened U.S.-China relations bring growing anti-U.S. sentiment in China and raises the risk of nationalistic reactions and boycotts, which affect the sales of U.S. MNC productions in China, which holds the world's largest markets for retail, chemicals, chips, and other industries (Kapadia, 2021).

Thus, utilizing macroscopic and microcosmic data to explore the U.S.-China trade status and the revenues of MNCs overtime is necessary to evaluate the effect of the U.S.-China trade war on the economy.

4 US-China Trade Database Schema

This database includes thirteen tables and the relations among these tables are shown in the ER diagram below.

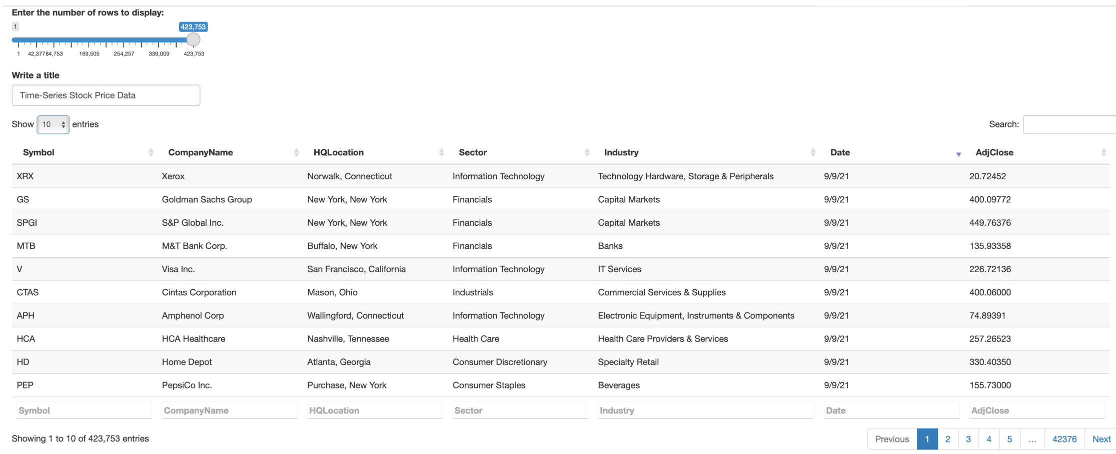


5 Database Implementation

The database implementation is mainly through the R Shiny app & python.

As for the Shiny app, I inner join the fortune500stockPrice Table and SP500withGICS Table on the Symbol column and generate a combined table about the daily time-series stock data of the public companies within the Fortune 500 list between 2017-01-01 and 2021-09-09 with 423,753 rows and seven columns, including symbol, company name, headquarter location, sector, industry, Date, AdjClose.

The results could be accessed through the shiny app link and the screenshot below shows what the Shiny App looks like.



Enter the number of rows to display:

1 423,753

1 42,37784,753 169,505 254,257 339,009 423,753

Write a title

Time-Series Stock Price Data

Show 10 entries

Search:

Symbol	CompanyName	HQLocation	Sector	Industry	Date	AdjClose
XRX	Xerox	Norwalk, Connecticut	Information Technology	Technology Hardware, Storage & Peripherals	9/9/21	20.72452
GS	Goldman Sachs Group	New York, New York	Financials	Capital Markets	9/9/21	400.09772
SPGI	S&P Global Inc.	New York, New York	Financials	Capital Markets	9/9/21	449.76376
MTB	M&T Bank Corp.	Buffalo, New York	Financials	Banks	9/9/21	135.93358
V	Visa Inc.	San Francisco, California	Information Technology	IT Services	9/9/21	226.72136
CTAS	Cintas Corporation	Mason, Ohio	Industrials	Commercial Services & Supplies	9/9/21	400.06000
APH	Amphenol Corp	Wallingford, Connecticut	Information Technology	Electronic Equipment, Instruments & Components	9/9/21	74.89391
HCA	HCA Healthcare	Nashville, Tennessee	Health Care	Health Care Providers & Services	9/9/21	257.26523
HD	Home Depot	Atlanta, Georgia	Consumer Discretionary	Specialty Retail	9/9/21	330.40350
PEP	PepsiCo Inc.	Purchase, New York	Consumer Staples	Beverages	9/9/21	155.73000
Symbol	CompanyName	HQLocation	Sector	Industry	Date	AdjClose

Showing 1 to 10 of 423,753 entries

Previous 1 2 3 4 5 … 42376 Next

As for python implementation, I connect to postgresql database through two steps. Firstly, I install ipython-sql package, and this package introduces a %sql (or %%sql) magic to your notebook, allowing you to connect to a database. Secondly, I install psycopg2 package, the most popular PostgreSQL database adapter for the Python programming language.

After connecting to PostgreSQL, I could extract data from the database using SQL command. Next, I use pandas and NumPy packages to deal with the data extracted. Besides, I use matplotlib and seaborn packages to do statistical visualization. Finally, the statsmodels package is utilized to do time-series analysis.

5.1 Using sql "magic" to connect to Postgresql

[1]:
```
#!pip install ipython-sql
```

[2]:
```
#!pip install psycopg2
```

[3]:
```
#!pip install nbconvert
```

[4]:
```
#!brew install pandoc
```

[5]:
```
%load_ext sql
```

[6]:
```
%sql postgresql://postgres:940915@127.0.0.1:5433/6354Database
```

[7]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import re
```

5.2 Exploring Annual Country GDP and Tariffs and US Trade with China Compared to Other Countries

[8]:
```
%%sql result_set1_1 <<
select * from countryDevelopmentIndicator cdi
where cdi.year >= '2014-01-01'
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
1519 rows affected.
Returning data to local variable result_set1_1
```

[9]:
```
df1_1 = result_set1_1.DataFrame()
df1_1['year'] = df1_1['year'].astype('datetime64')
df1_1.head()
```

[9]:

	countryname	countrycode	year	gdp	population	tariffall	\
0	Barbados	BRB	2017-01-01	4978000000.00	286229.00	None	
1	Aruba	ABW	2015-01-01	2962905028.00	104339.00	10.02	
2	Afghanistan	AFG	2015-01-01	19134211764.00	34413603.00	None	
3	Albania	ALB	2015-01-01	11386850130.00	2880703.00	3.58	
4	Algeria	DZA	2015-01-01	165979279263.00	39728020.00	12.02	

	tariffmanufactured
0	None
1	11.09
2	None
3	0.66
4	7.66

[10]:
```
%%sql result_set1_2 <<
select * from UStradebyCountryYear ust
where ust.year >= '2014-01-01'
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
1627 rows affected.
Returning data to local variable result_set1_2
```

[11]:
```
df1_2 = result_set1_2.DataFrame()
df1_2['year'] = df1_2['year'].astype('datetime64')
df1_2.head()
```

[11]:

	countryname	year	imports	exports	balance
0	Afghanistan	2015-01-01	23601251	478711524	455110273
1	Afghanistan	2016-01-01	33715926	913874351	880158425
2	Afghanistan	2017-01-01	14423622	942232031	927808409
3	Afghanistan	2018-01-01	29408728	1227404432	1197995704
4	Afghanistan	2019-01-01	38744074	757769159	719025085

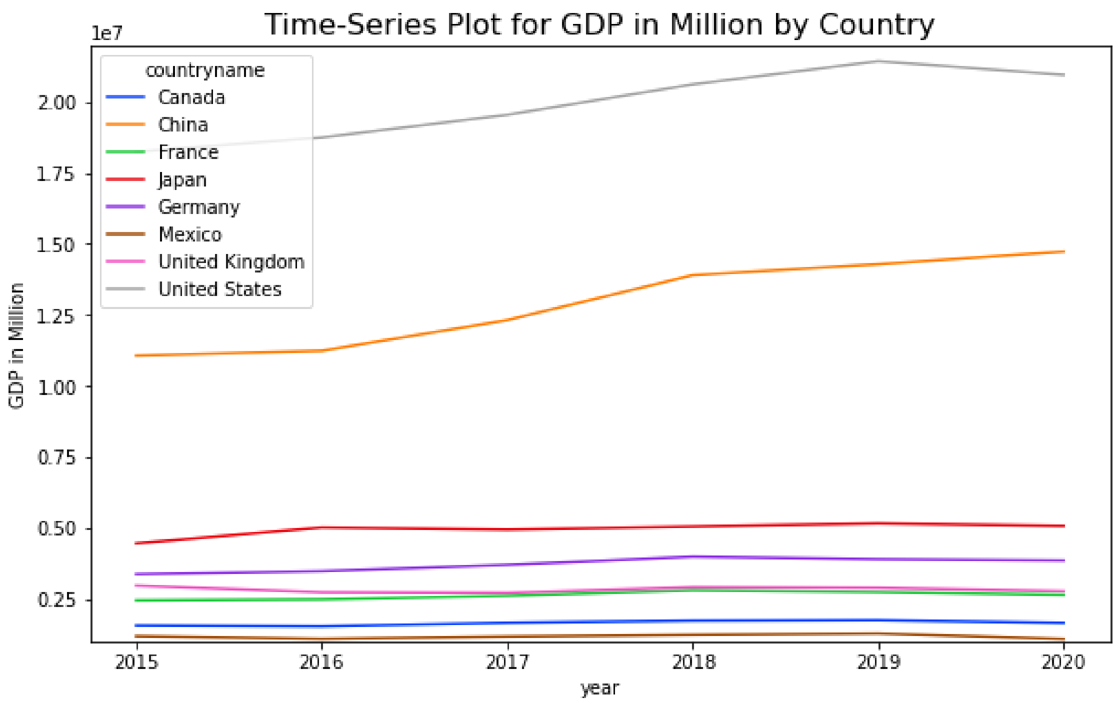
```
[12]: df1 = pd.merge(df1_1, df1_2, left_on = ['countryname', 'year'], right_on =␣
      ↪['countryname', 'year'], how = 'left')
      df1['gdp'] = df1['gdp']/1000000
      df1['population'] = df1['population']/1000000
      df1['imports'] = df1['imports']/1000000
      df1['exports'] = df1['exports']/1000000
      df1['balance'] = df1['balance']/1000000
```

```
[13]: ilocList = []
      for i in range(len(df1['countryname'])):
          if df1.iloc[i]['countryname'] in ['China', 'United States', 'Japan',␣
      ↪'United Kingdom', 'France', 'Germany', 'Canada','Mexico']:
              ilocList.append(i)
```

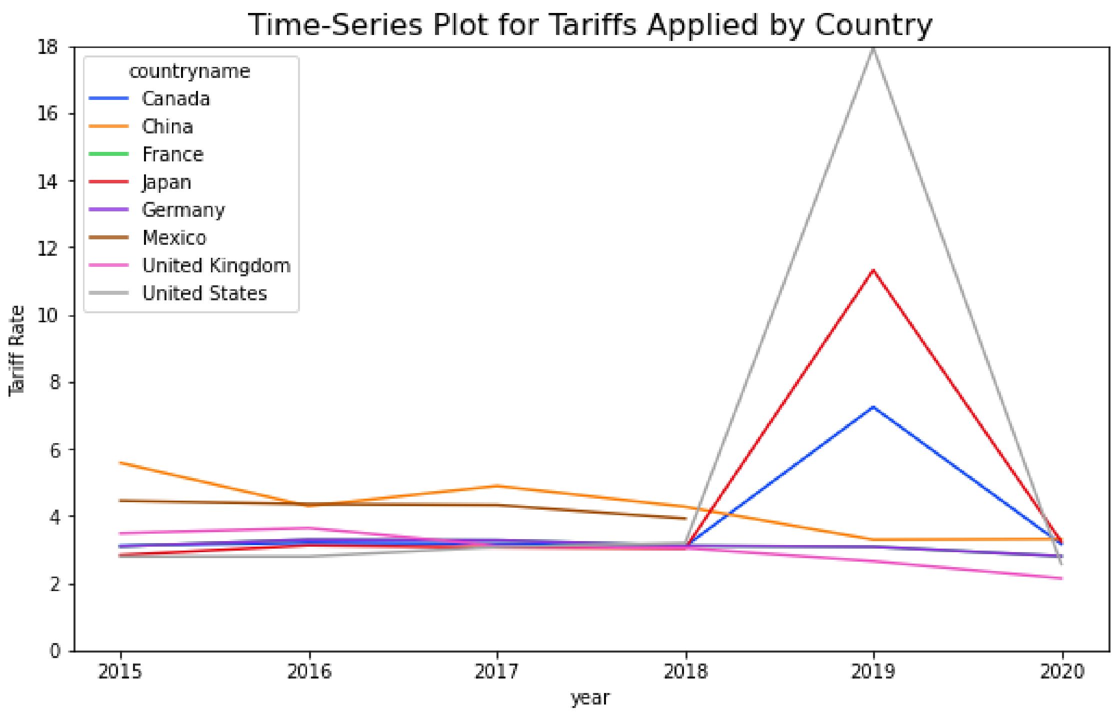
```
[14]: df1_3 = df1.iloc[ilocList]
      df1_3.sort_values(by = 'countryname')
      df1_3.head()
```

```
[14]:     countryname countrycode       year              gdp population tariffall  \
      35       Canada         CAN 2015-01-01   1556508.816217  35.702908      3.11
      41        China         CHN 2015-01-01  11061553.079872    1379.86      5.58
      67       France         FRA 2015-01-01   2439188.643163  66.548272      3.09
      99        Japan         JPN 2015-01-01   4444930.651964    127.141      2.83
      108     Germany         DEU 2015-01-01   3357585.719352  81.686611      3.09

          tariffmanufactured       imports       exports         balance
      35                1.12        296000        280855          -15145
      41                5.70        483000        115873         -367127
      67                2.26  47808.780079  30026.310133   -17782.469946
      99                1.47        131000  62387.809646   -68612.190354
      108               2.26        125000  49978.833642   -75021.166358
```

```
[15]: plt.figure(figsize = (10, 6))
      sns.lineplot(x="year", y = 'gdp', hue="countryname", palette = 'bright', data =␣
      ↪df1_3)
      plt.ylim(1000000, 22000000)
      plt.xlabel('year')
      plt.ylabel('GDP in Million')
      plt.title('Time-Series Plot for GDP in Million by Country', fontsize = 16)
      plt.show()
      # plt.savefig('Figure1.png')
```



[16]:
```
plt.figure(figsize = (10, 6))
sns.lineplot(x="year", y = 'tariffall', hue="countryname", palette = 'bright',␣
    ↪data = df1_3)
plt.ylim(0, 18)
plt.xlabel('year')
plt.ylabel('Tariff Rate')
plt.title('Time-Series Plot for Tariffs Applied by Country', fontsize = 16)
plt.show()
# plt.savefig('Figure2.png')
```



I select a sample of big countries and plot their annual GDP and tariff rates from 2015 to 2020. From the annual GDP tendency plot, we could find that China's GDP growth rate decreased starting in 2018. As for the U.S., its GDP growth rate decreased beginning in 2019, and the total GDP in 2020 was even lower than its GDP in 2019. Although the other countries' GDP growth rate also suffers a little bit, the U.S. and China are the two countries that suffer the most. As for the average tariff rates of these big countries, the tariff rate of the U.S. was lowest in 2015-2016 and maintained very low before 2018, but increased sharply and became the highest tariff rate during 2018 - 2020 among these countries. China's average tariff on imported products decreased during the U.S.-China trade war compared to the average tariff increase.

[17]:
```
ilocList2 = []
for i in range(len(df1['countryname'])):
    if df1.iloc[i]['countryname'] in ['China', 'Japan', 'United Kingdom',␣
 ↪'France', 'Germany', 'Canada', 'Mexico']:
        ilocList2.append(i)
```

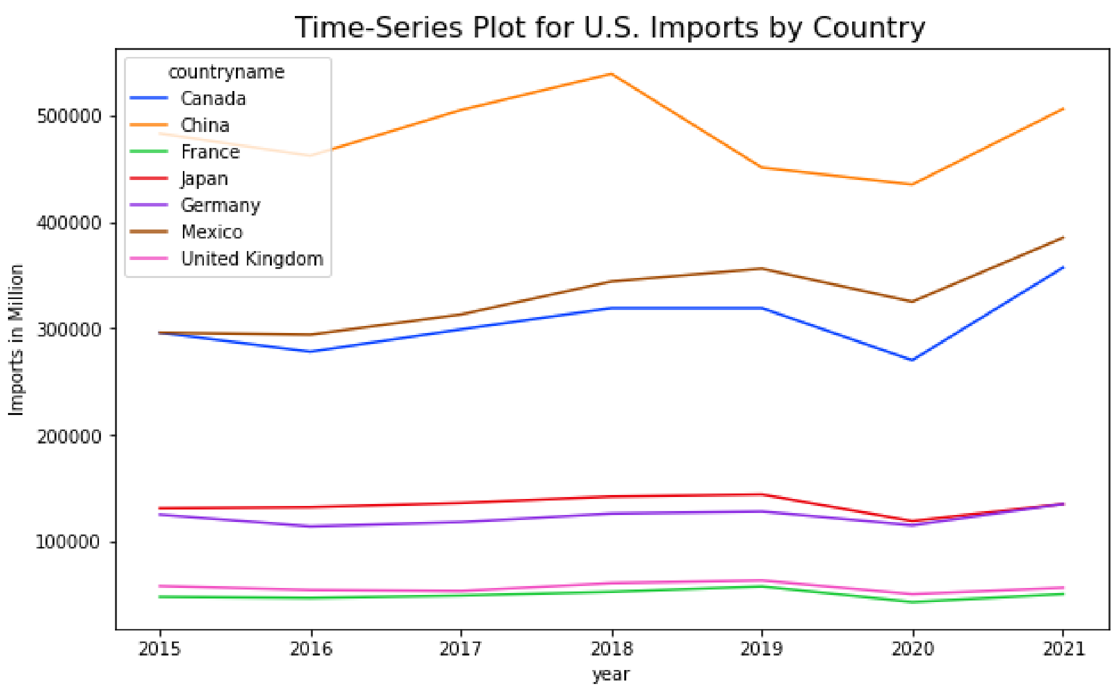
[18]:
```
df1_4 = df1.iloc[ilocList2]
df1_4.sort_values(by = 'countryname')
df1_4.head()
```

[18]:
```
    countryname countrycode       year               gdp population tariffall  \
35       Canada         CAN 2015-01-01    1556508.816217  35.702908      3.11
41        China         CHN 2015-01-01   11061553.079872    1379.86      5.58
```

```
67        France          FRA 2015-01-01   2439188.643163  66.548272       3.09
99         Japan          JPN 2015-01-01   4444930.651964    127.141       2.83
108      Germany          DEU 2015-01-01   3357585.719352  81.686611       3.09

    tariffmanufactured        imports        exports        balance
35                1.12         296000         280855         -15145
41                5.70         483000         115873        -367127
67                2.26   47808.780079   30026.310133  -17782.469946
99                1.47         131000   62387.809646  -68612.190354
108               2.26         125000   49978.833642  -75021.166358
```

[19]:

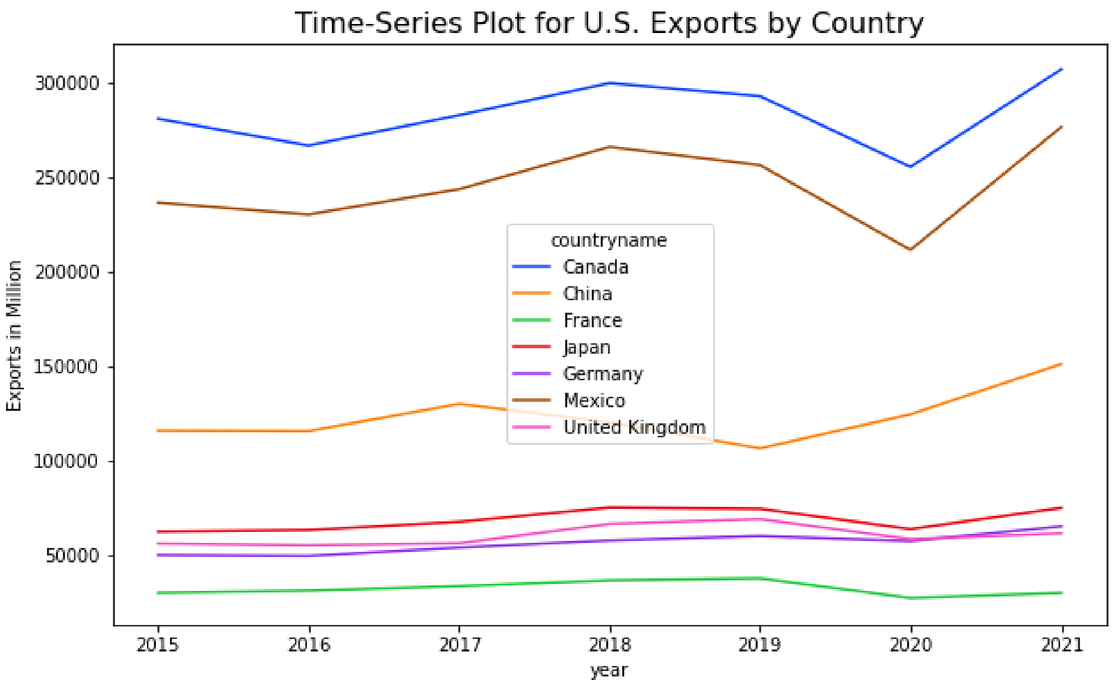
```
plt.figure(figsize = (10, 6))
sns.lineplot(x="year", y = 'imports', hue="countryname", palette = 'bright',␣
 ↪data = df1_4)
plt.xlabel('year')
plt.ylabel('Imports in Million')
plt.title('Time-Series Plot for U.S. Imports by Country', fontsize = 16)
plt.show()
# plt.savefig('Figure3.png')
```



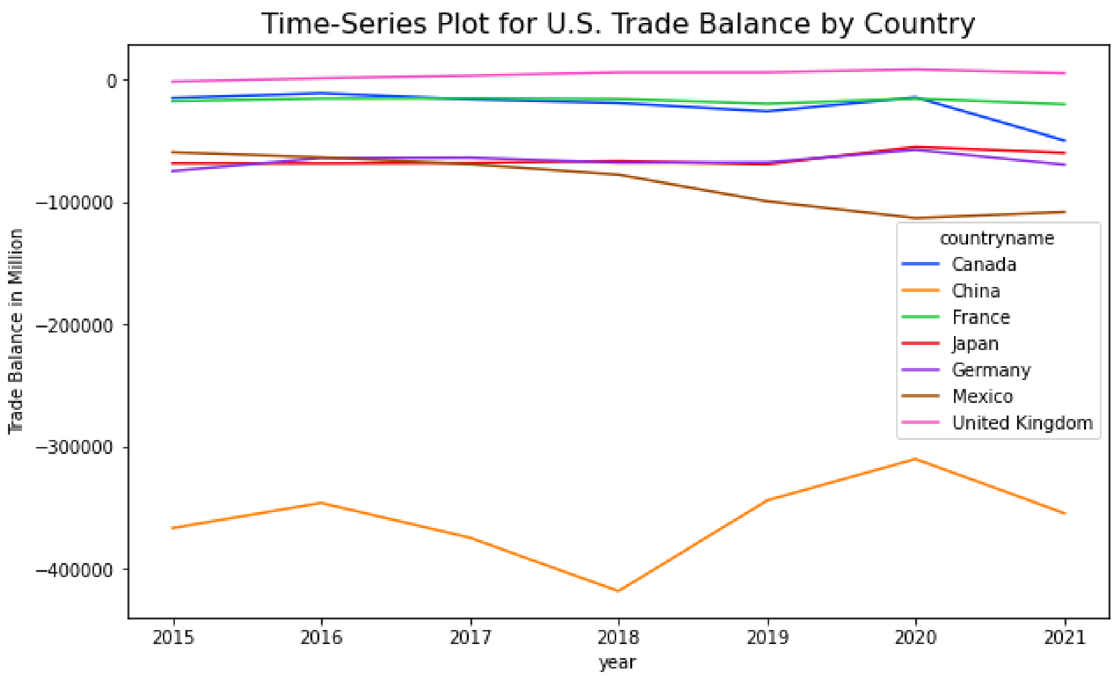
[20]:

```
plt.figure(figsize = (10, 6))
sns.lineplot(x="year", y = 'exports', hue="countryname", palette = 'bright',␣
 ↪data = df1_4)
plt.xlabel('year')
plt.ylabel('Exports in Million')
```

```
plt.title('Time-Series Plot for U.S. Exports by Country', fontsize = 16)
plt.show()
# plt.savefig('Figure4.png')
```



[21]:
```
plt.figure(figsize = (10, 6))
sns.lineplot(x="year", y = 'balance', hue="countryname", palette = 'bright',
 data = df1_4)
plt.xlabel('year')
plt.ylabel('Trade Balance in Million')
plt.title('Time-Series Plot for U.S. Trade Balance by Country', fontsize = 16)
plt.show()
# plt.savefig('Figure5.png')
```



The time-series plot for U.S. imports by countries above shows that U.S. imports from China decreased a lot from 2018 to 2019 compared to its imports from the other countries, but the volume started to increase after the signature of the Phase One Agreement Deal at the beginning of 2020. As for U.S. exports, its exports to China decreased in the first year of the trade war and began increasing in 2019. Besides, its trade balance plot shows that U.S. trade deficit with China has grown to the highest at the end of 2018, but it decreased during 2018 and 2010, the first two years of the U.S.-China trade war. Overall, the trade war helps U.S. reduce the trade deficit with China, but hurts China's exports to the U.S. and its economy heavily.

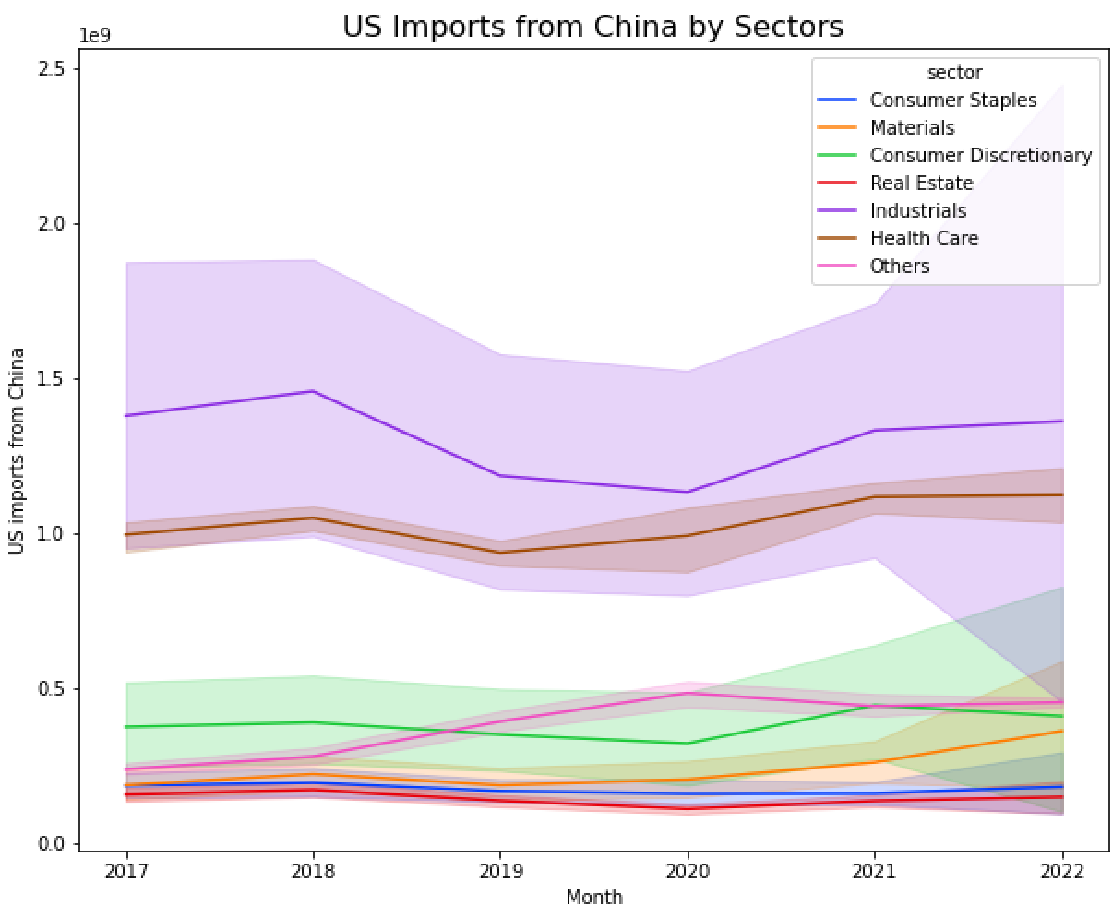
5.3 Exploring US-China Trade by Commodity and Sectors

[22]:
```
%%sql result_set2 <<
select tc.htsnumber, tc.month, tc.imports, tc.exports, tc.balance, tc. sector,
 ↪cn.description
from USChinatradebyCommoditySectorMonthly tc
inner join commoditybyhtsnumber cn
on tc.htsnumber = cn.htsnumber
where tc.month >= '2017-01-01';
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
6014 rows affected.
Returning data to local variable result_set2
```

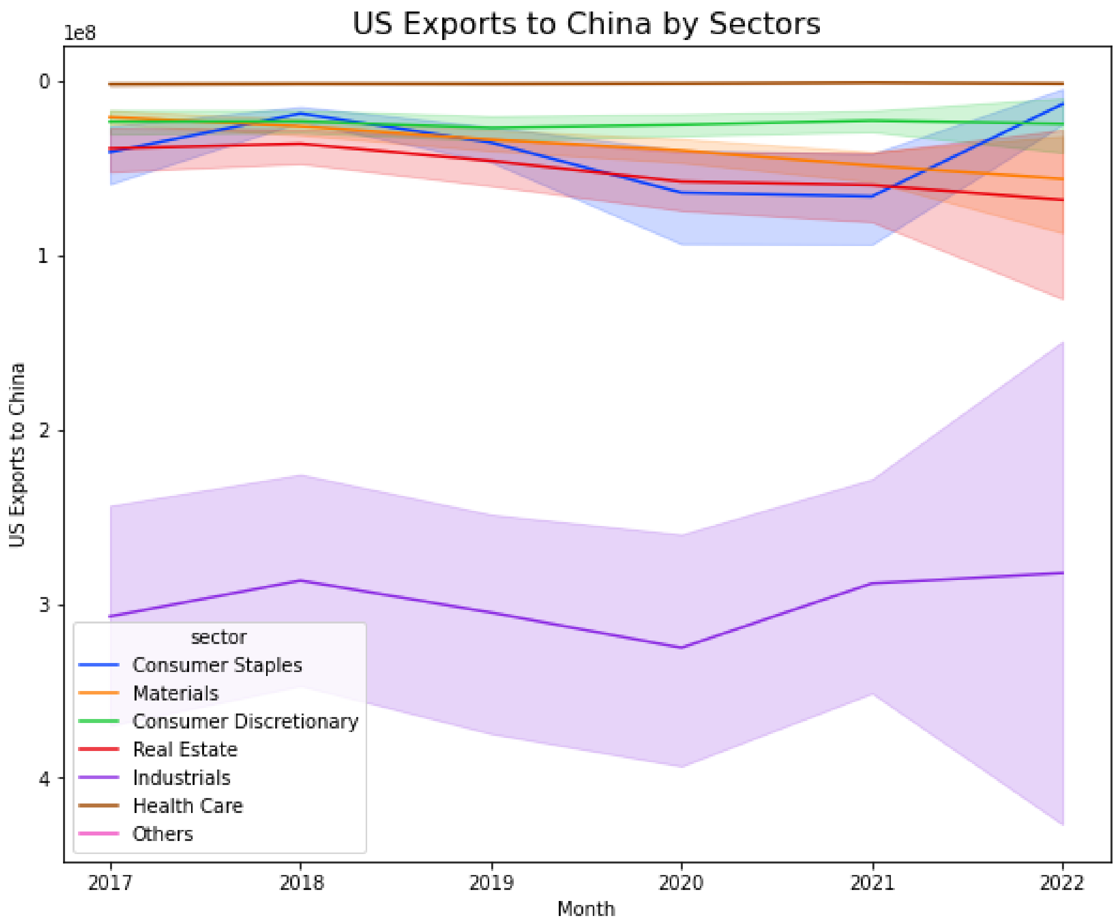
[23]:
```
df2 = result_set2.DataFrame()
df2['month'] = df2['month'].astype('datetime64').dt.year
```

[24]:
```
plt.figure(figsize = (10, 8))
sns.lineplot(x="month", y = 'imports', hue="sector", palette = 'bright', data =␣
↪df2)
plt.xlabel('Month')
plt.ylabel('US imports from China')
plt.title('US Imports from China by Sectors', fontsize = 16)
plt.show()
# plt.savefig('Figure6.png')
```

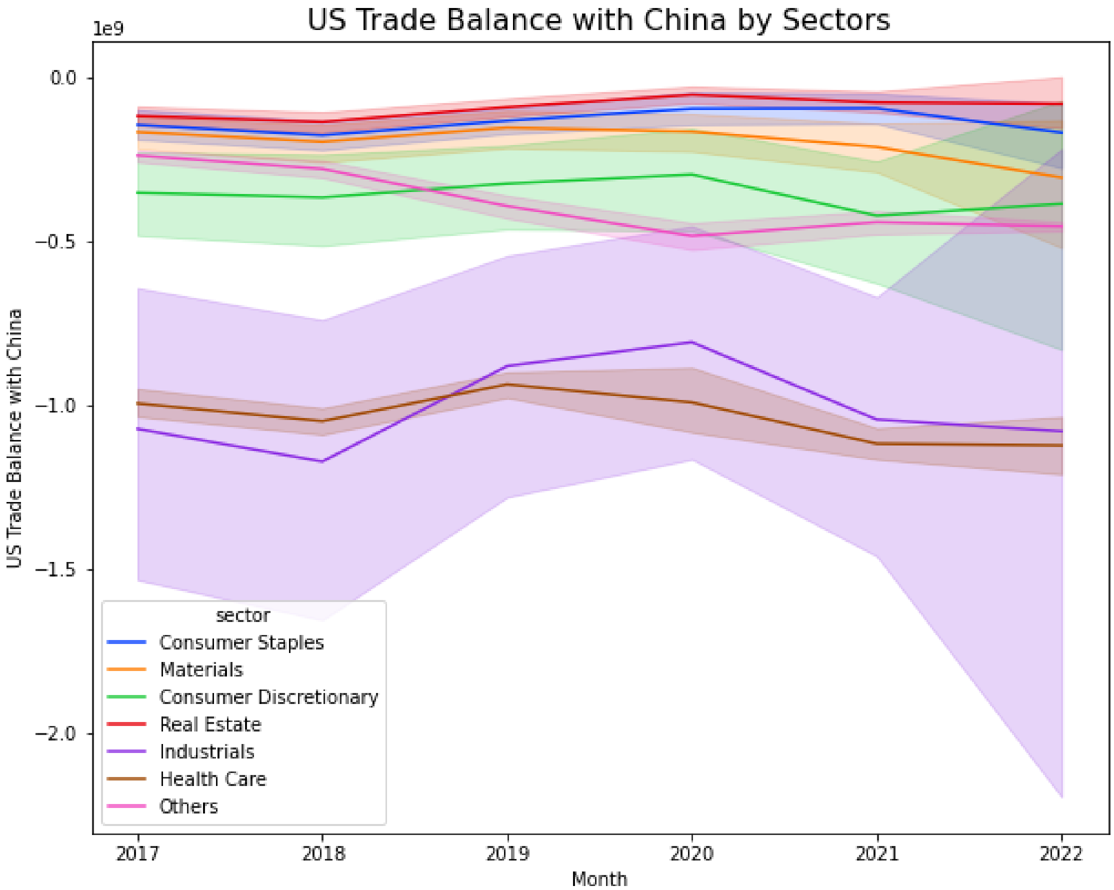


[25]:
```
plt.figure(figsize = (10, 8))
sns.lineplot(x="month", y = 'exports', hue="sector", palette = 'bright', data =␣
↪df2)
plt.xlabel('Month')
plt.ylabel('US Exports to China')
plt.title('US Exports to China by Sectors', fontsize = 16)
```

```
plt.show()
# plt.savefig('Figure7.png')
```



[26]:
```
plt.figure(figsize = (10,8))
sns.lineplot(x="month", y = 'balance', hue="sector", palette = 'bright', data =␣
  ↪df2)
plt.xlabel('Month')
plt.ylabel('US Trade Balance with China')
plt.title('US Trade Balance with China by Sectors', fontsize = 16)
plt.show()
# plt.savefig('Figure8.png')
```



From US trade with China by sectors plots, industrial imports from China decreased on a large scale, and consumer discretionary imports from China also decreased to some degree compared to other sectors during the trade war. Besides, the industrial products and consumer staples exported to China decreased on a large scale since China has imposed tariffs mainly on U.S. industrial and agricultural products.

As for the trade balance, U.S. trade with China in each sector experiences a trade deficit; industrial and health care sectors have the highest trade deficits. During the trade war, the trade deficit in the industrial sector decreased a little bit from 2018 to 2020 but rebounded back after 2020. And the trade deficit in the health care area decreases to a large degree but reincreases after 2020.

5.4 Exploring US-China Trade Tariff Data during Trade War Period

[27]:
```
%%sql result_set3 <<
select trc.TariffAction, trc.Date, trc.ChineseTariffsOnUSExports, trc.
  ↪ChineseTariffsOnROWExports, trc.USTariffsOnChineseExports,
trc.USTariffsOnROWExports, tc.ChineseExportsSubjectToUSTariffs, tc.
  ↪USExportsSubjectToChineseTariffs,
```

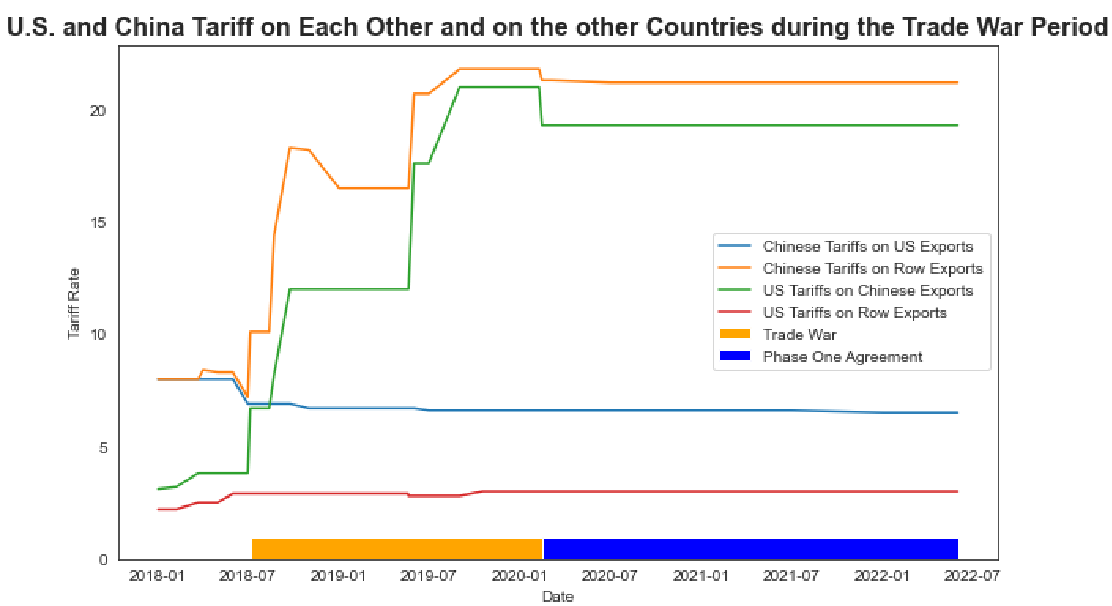
```
trc.TradeWar, trc.PhaseOneAgreement
from USChinaTariffRateChange trc
inner join USChinaTradeTariffCoverage tc
on trc.date = tc.date;
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
38 rows affected.
Returning data to local variable result_set3
```

[28]:
```
df3 = result_set3.DataFrame()
df3.head()
```

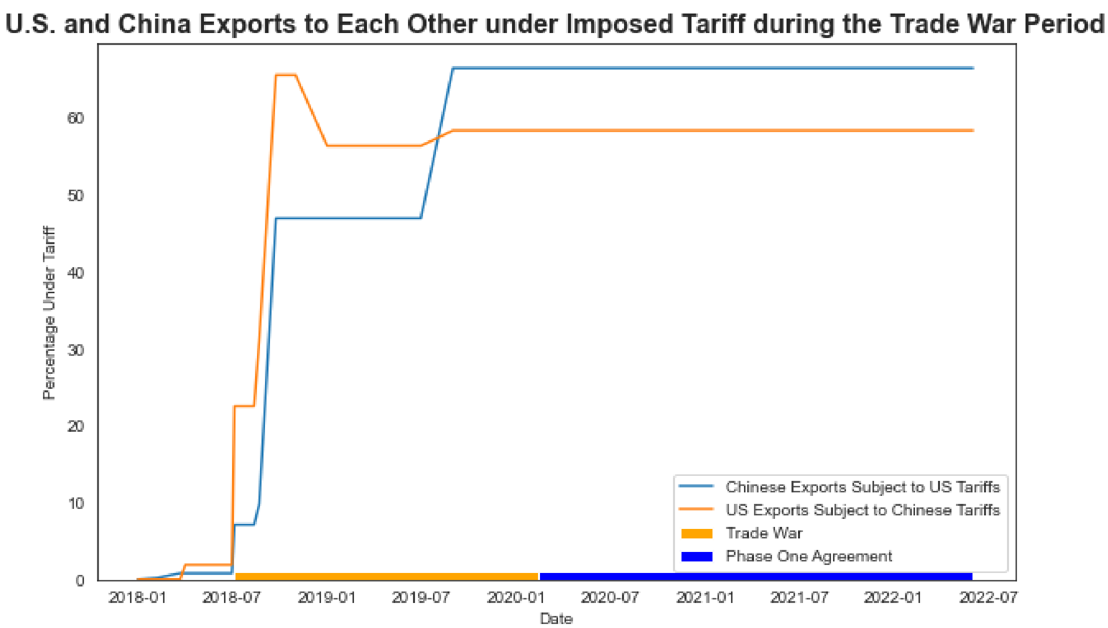
[28]:
```
                                        tariffaction        date  \
0                                          1-Jan-18  2018-01-01
1  US Section 201 tariffs on solar panels and was…  2018-02-07
2  US Section 232 tariffs on steel and aluminum, …  2018-03-23
3      China's retaliation to US Section 232 tariffs  2018-04-02
4          China's MFN tariff cut on pharmaceuticals  2018-05-01

  chinesetariffsonusexports chinesetariffsonrowexports  \
0                      8.0                        8.0
1                      8.0                        8.0
2                      8.0                        8.0
3                      8.0                        8.4
4                      8.0                        8.3

  ustariffsonchineseexports ustariffsonrowexports  \
0                      3.1                   2.2
1                      3.2                   2.2
2                      3.8                   2.5
3                      3.8                   2.5
4                      3.8                   2.5

  chineseexportssubjecttoustariffs usexportssubjecttochinesetariffs  tradewar  \
0                             0.0                              0.0       NaN
1                             0.2                              0.0       NaN
2                             0.8                              0.0       NaN
3                             0.8                              1.9       NaN
4                             0.8                              1.9       NaN

   phaseoneagreement
0                NaN
1                NaN
2                NaN
3                NaN
4                NaN
```

[29]:
```
plt.figure(figsize = (10, 6))
sns.set_style("white")
sns.lineplot(data=df3, x="date", y="chinesetariffsonusexports")
sns.lineplot(data=df3, x="date", y="chinesetariffsonrowexports")
sns.lineplot(data=df3, x="date", y="ustariffsonchineseexports")
sns.lineplot(data=df3, x="date", y="ustariffsonrowexports")

color_map = ['orange']
plt.stackplot(df3.date, df3.tradewar,colors=color_map)
color_map = ['blue']
plt.stackplot(df3.date, df3.phaseoneagreement,colors=color_map)
plt.legend(labels=["Chinese Tariffs on US Exports", "Chinese Tariffs on Row␣
↪Exports",
                   "US Tariffs on Chinese Exports", "US Tariffs on Row Exports",
                   'Trade War', 'Phase One Agreement'])
plt.xlabel('Date')
plt.ylabel('Tariff Rate')
plt.title('U.S. and China Tariff on Each Other and on the other Countries␣
↪during the Trade War Period',  weight = 'bold', fontsize = 16)
# plt.savefig('Figure.png')
plt.show()
# plt.savefig('Figure9.png')
```



[30]:
```
plt.figure(figsize = (10, 6))
sns.set_style("white")
sns.lineplot(data=df3, x="date", y="chineseexportssubjecttoustariffs")
sns.lineplot(data=df3, x="date", y="usexportssubjecttochinesetariffs")
```

```python
color_map = ['orange']
plt.stackplot(df3.date, df3.tradewar,colors=color_map)
color_map = ['blue']
plt.stackplot(df3.date, df3.phaseoneagreement,colors=color_map)
plt.legend(labels=["Chinese Exports Subject to US Tariffs", "US Exports Subject␣
↪to Chinese Tariffs",
                   'Trade War', 'Phase One Agreement'])
plt.xlabel('Date')
plt.ylabel('Percentage Under Tariff')
plt.title('U.S. and China Exports to Each Other under Imposed Tariff during the␣
↪Trade War Period',  weight = 'bold', fontsize = 16)
# plt.savefig('Figure.png')
plt.show()
# plt.savefig('Figure10.png')
```



From the above plots, we can see the tariff rates of the U.S. and China on each other before the trade war was relatively low, specifically 3% tariff rate from the U.S. side and an 8% tariff rate from China's side. During the tariff trade period (orange), the tariff rates have been increased through several phases. I mainly divide the whole period into four phases, and the following paragraphs introduce the four phases in detail.

In the first stage, the U.S. announced a preliminary tariff list for the imports from China on April 3, 2018, worth U.S. \$ 50 billion (list 1 & list 2); China also announced a list of the same amount on the second day. The final lists were decided in June and implemented in July (list 1) and August (list 2), 2018 (Wong & Koty, 2020).

In the second stage, the U.S. side announced the tariff plan on another list of Chinese goods (List 3) which are worth US\$ 200 billion on September 17, 2018; China announced the tariff on US$ 60 billion worth of U.S. goods on the next day. The tariffs on both sides came into effect on September 24, 2018. Later, in June 2019, the tariff rates from both sides increased to 25% (Mullen, 2021).

In the third stage of the trade war, the U.S. has announced tariffs on an additional US\$ 300 billion worth of Chinese exports to the U.S. on August 13, 2019, and China used retaliatory measures, and announced tariffs on US\$ 75 billion worth of American goods on August 23, 2019 (Liang & Ding 2020: 41-44). And the U.S. started implementing tariffs on more than US\$ 125 billion worth of Chinese products (list 4A) on September 1, 2019. China also imposed retaliated tariffs on a subset of the scheduled list.

The signature of the Phase One Deal marked the U.S.-China trade war marching into the next stage. Under the agreement, China agrees to purchase an additional \$ 200 billion worth of U.S. products. Besides, the U.S. and China reduce some tariffs on some exports from the other side. But the U.S.-China Phase One Deal plan does not go smoothly. Due to the pandemic, China only finished 59% of its 2020 purchasing U.S. products goal. As the Biden administration started, several trade talks were held, but there was still no bright signal of lifting all imposed tariffs. Until the end of 2021, China bought only 57% of the U.S. exports it had committed to purchase under the Phase One Deal. In February 2022, the U.S. House of Representatives passed America Competes Act, aiming to strengthen the U.S. competitive edge over China. Besides, U.S. Trade Representative (USTR) puts more effort into competing with China in an annual report (China Briefing Team, 2022).

5.5 Exploring the S&P 500 Companies with GICS classification

The Global Industry Classification Standard (GICS) is a four-tiered, hierarchical industry classification system developed in 1999 by MSCI and Standard & Poor's (S&P) Dow Jones Indices for use by the global financial community. The GICS structure consists of - 11 sectors - 24 industry groups, - 69 industries - 158 sub-industries.

And S&P has categorized all major public companies. GICS is used as a basis for S&P and MSCI financial market indexes in which each company is assigned to a sub-industry, and to an industry, industry group, and sector, by its principal business activity.

"GICS" is a registered trademark of McGraw Hill Financial and MSCI Inc.

[31]:
```
%%sql result_set4 <<
select * from sp500withgics;
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
505 rows affected.
Returning data to local variable result_set4
```

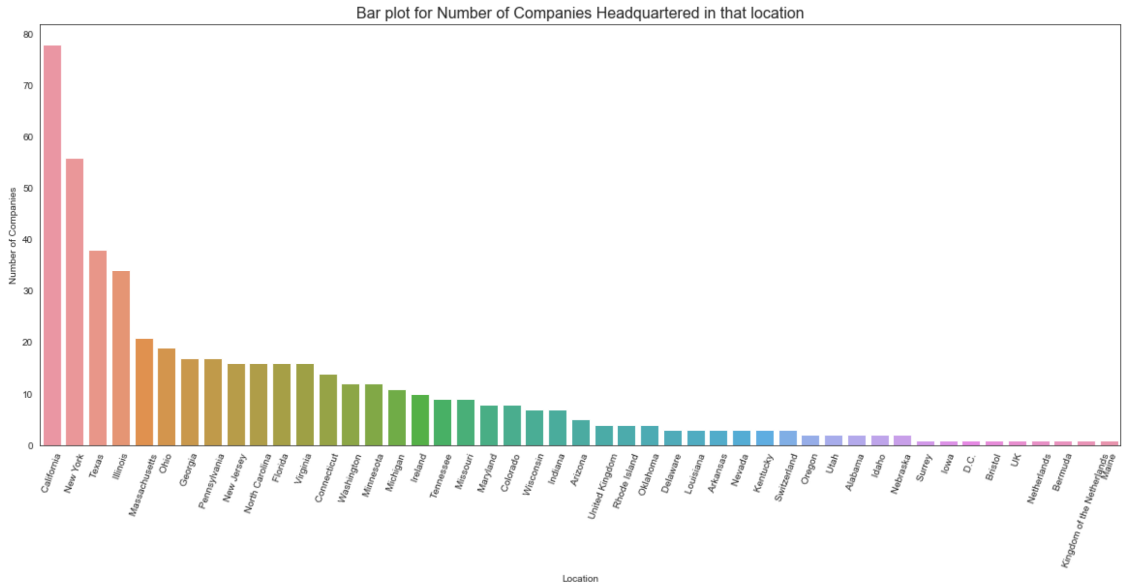
[32]:
```
df4 = result_set4.DataFrame()
df4['datefirstadded'] = df4['datefirstadded'].astype('datetime64')
df4['datefirstadded'] = pd.to_datetime(df4['datefirstadded'])
df4['yearfirstadded'] = df4['datefirstadded'].dt.year
```

[33]:
```
df4['hqlocation'] = df4['hqlocation'].apply(lambda x: re.split(r',', x)[1])
df4['hqlocation'] = df4['hqlocation'].apply(lambda x: re.split(r'\;|\[', x)[0])
```

[34]:
```
df4_1 = df4.groupby(['hqlocation']).count()
df4_1['Number of Companies in that location'] = df4_1['symbol']
df4_1 = df4_1[['Number of Companies in that location']].sort_values(by =␣
↪'Number of Companies in that location', ascending = False)
df4_1.head(10)
```

[34]:
```
                 Number of Companies in that location
hqlocation
 California                                        78
 New York                                          56
 Texas                                             38
 Illinois                                          34
 Massachusetts                                     21
 Ohio                                              19
 Georgia                                           17
 Pennsylvania                                      17
 New Jersey                                        16
 North Carolina                                    16
```

[35]:
```
plt.figure(figsize = (20, 8))
sns.barplot(x = df4_1.index, y = 'Number of Companies in that location', data =␣
↪df4_1)
plt.xticks(rotation=70)
plt.xlabel('Location')
plt.ylabel('Number of Companies')
plt.title('Bar plot for Number of Companies Headquartered in that location',␣
↪fontsize = 16)
plt.show()
# plt.savefig('Figure11.png')
```



[36]:
```
df4_2 = df4.groupby(['sector']).count()
```

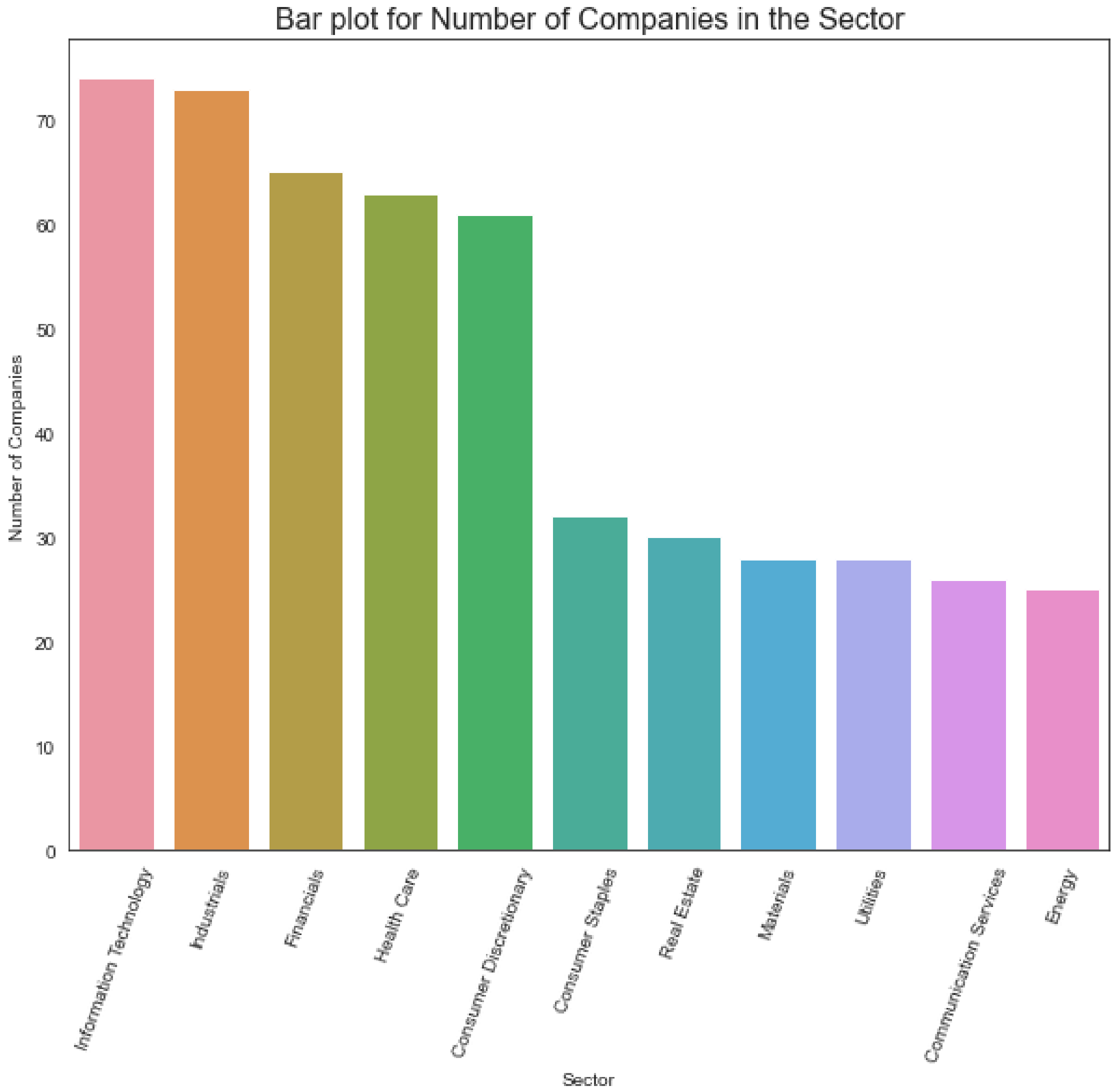
[37]:
```
df4_2['Number of Companies in the sector'] = df4_2['symbol']
df4_2 = df4_2[['Number of Companies in the sector']].sort_values(by = 'Number␣
↪of Companies in the sector', ascending = False)
df4_2.head(11)
```

[37]:

sector	Number of Companies in the sector
Information Technology	74
Industrials	73
Financials	65
Health Care	63
Consumer Discretionary	61
Consumer Staples	32
Real Estate	30
Materials	28
Utilities	28
Communication Services	26
Energy	25

[38]:
```
plt.figure(figsize = (10, 8))
sns.barplot(x = df4_2.index, y = 'Number of Companies in the sector', data =␣
↪df4_2)
plt.xticks(rotation=70)
plt.xlabel('Sector')
plt.ylabel('Number of Companies')
```

```python
plt.title('Bar plot for Number of Companies in the Sector', fontsize = 16)
plt.show()
# plt.savefig('Figure12.png')
```



From the line plot for the number of companies headquartered in the state or country, we could see California is the headquarter location for nearly 80 of the S&P 500 companies, followed by New York, Texas, and Illinois.

As for the number of companies by eleven sectors, information technology and industrial have more than 70 S&P 500 companies, followed by financial, health care, and consumer discretionary, including approximately 60 S&p 500 companies. The other six sectors contain approximately 30 S&P 500 companies.

Combing the result from the analysis of U.S.-China trade by sectors, I suppose that the tendencies of changes in companies' annual revenues and stock prices tend to be

similar within one sector but are more likely to be different among sectors. Next, I will firstly combine fortune 500 annual revenue data with the S&P 500 company list with GISC information to analyze the time series revenue changes by sector. Secondly, I will combine stock data with the S&P 500 company list with GISC information to analyze the time series stock data by sector.

5.6 Exploring Company Revenue Data by Sectors

[39]:
```
%%sql result_set5 <<
select sp.symbol, sp.companyName, sp.sector, forta.year, forta.revenues
from sp500withgics sp
inner join fortune500Annual forta
on sp.symbol = forta.symbol
where forta.year >= '2017';
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
1433 rows affected.
Returning data to local variable result_set5
```

[40]:
```
df5 = result_set5.DataFrame()
df5['year'] = df5['year'].astype('datetime64')
df5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1433 entries, 0 to 1432
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   symbol       1433 non-null   object
 1   companyname  1433 non-null   object
 2   sector       1433 non-null   object
 3   year         1433 non-null   datetime64[ns]
 4   revenues     1433 non-null   object
dtypes: datetime64[ns](1), object(4)
memory usage: 56.1+ KB
```

[41]:
```
df5['sector'].unique()
```

[41]:
```
array(['Consumer Staples', 'Financials', 'Information Technology',
       'Energy', 'Health Care', 'Consumer Discretionary',
       'Communication Services', 'Industrials', 'Utilities', 'Materials',
       'Real Estate'], dtype=object)
```

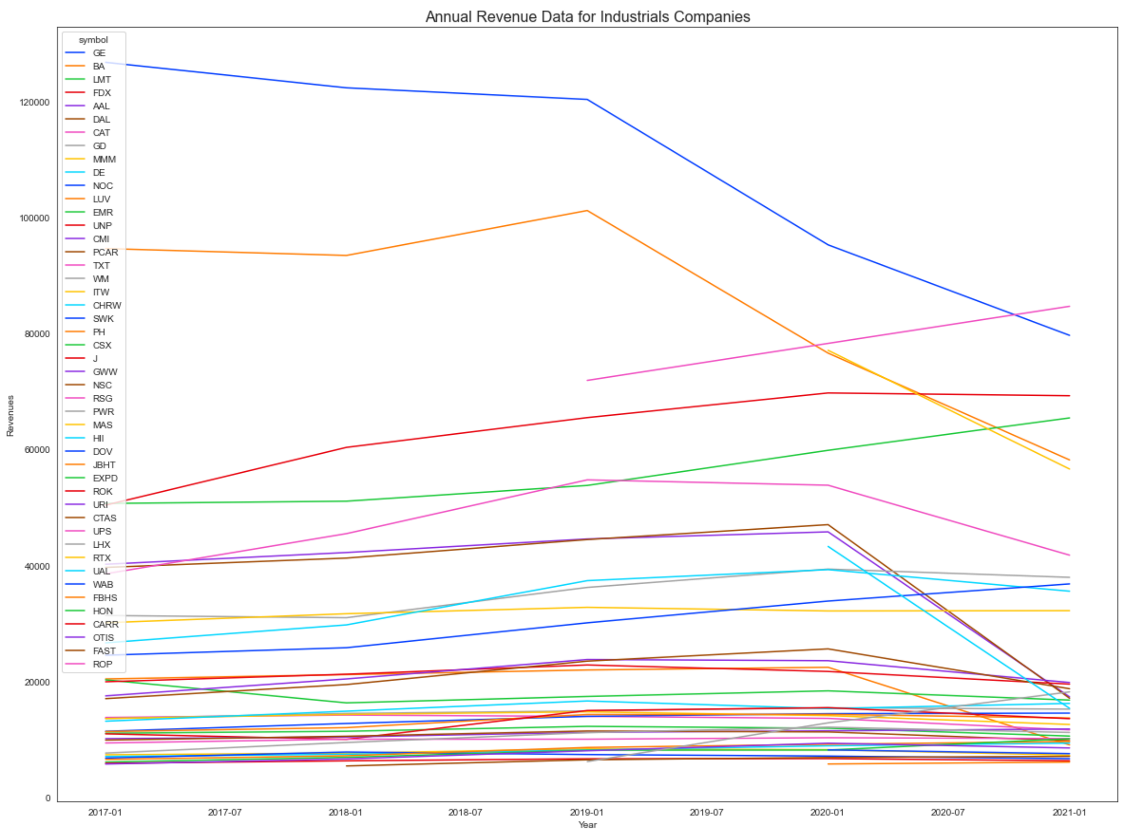
[42]:
```
df5_1 = df5[df5['sector'] == 'Information Technology']
```

[43]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 15))
```

```
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_1)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Information Technology Companies',␣
↪fontsize = 16)
# plt.show()
```

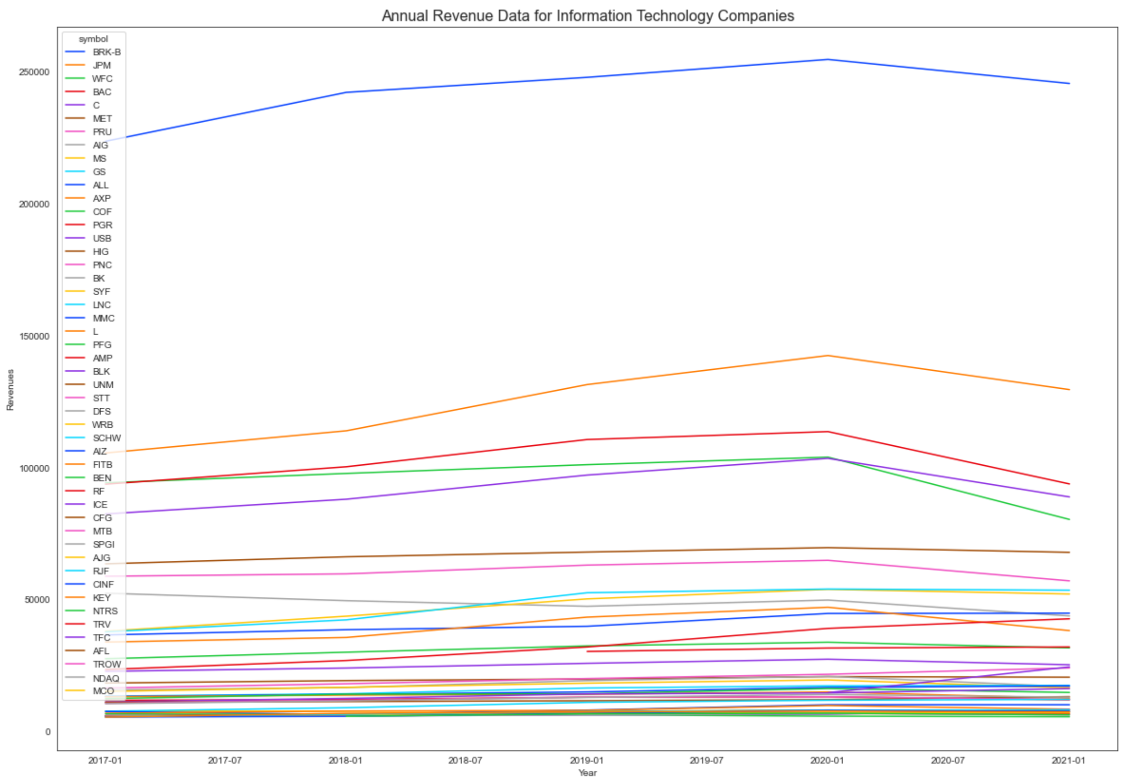
[44]:
```
df5_2 = df5[df5['sector'] == 'Industrials']
```

[45]:
```
plt.figure(figsize = (20, 15))
sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data =␣
↪df5_2)
plt.xlabel('Year')
plt.ylabel('Revenues')
plt.title('Annual Revenue Data for Industrials Companies', fontsize = 16)
plt.show()
# plt.savefig('Figure13.png')
```



[46]:
```
df5_3 = df5[df5['sector'] == 'Financials']
```

[47]:
```
plt.figure(figsize = (20, 14))
sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data = df5_3)
plt.xlabel('Year')
plt.ylabel('Revenues')
plt.title('Annual Revenue Data for Information Technology Companies', fontsize = 16)
plt.show()
# plt.savefig('Figure14.png')
```



[48]:
```
df5_4 = df5[df5['sector'] == 'Health Care']
```

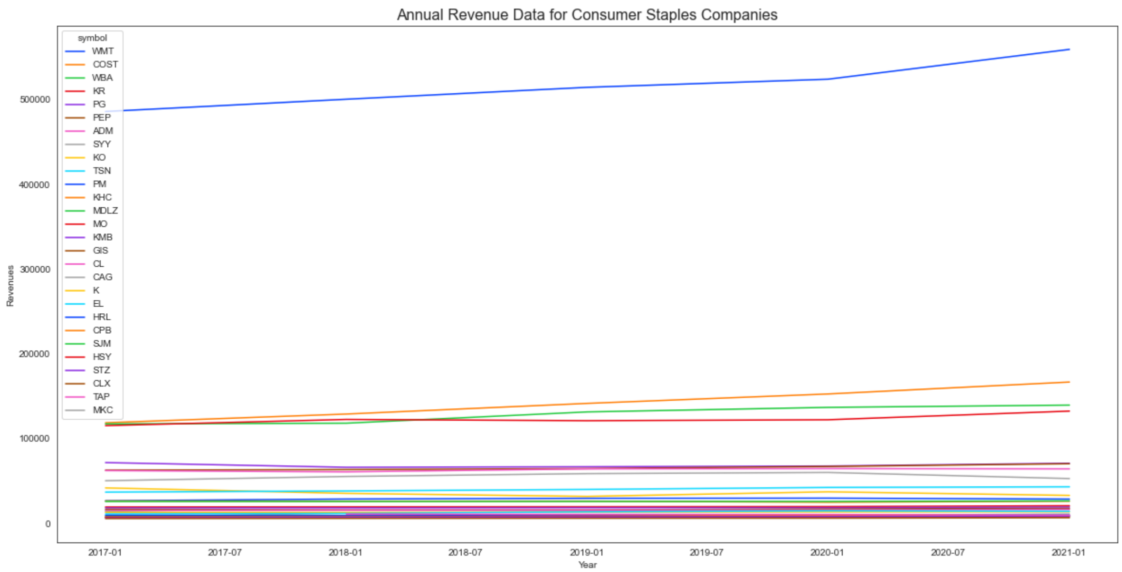
[49]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 12))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data = df5_4)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Health Care Companies', fontsize = 16)
# plt.show()
```

[50]:
```
df5_5 = df5[df5['sector'] == 'Consumer Discretionary']
```

[51]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 12))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_5)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Consumer Discretionary Companies',␣
↪fontsize = 16)
# plt.show()
```

[52]:
```
df5_6 = df5[df5['sector'] == 'Consumer Staples']
```

[53]:
```
plt.figure(figsize = (20, 10))
sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data =␣
↪df5_6)
plt.xlabel('Year')
plt.ylabel('Revenues')
plt.title('Annual Revenue Data for Consumer Staples Companies', fontsize = 16)
plt.show()
# plt.savefig('Figure15.png')
```



[54]:
```
df5_7 = df5[df5['sector'] == 'Real Estate']
```

[55]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_7)
# plt.xlabel('Year')
```

```
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Real Estate Companies', fontsize = 16)
# plt.show()
```

[56]:
```
df5_8 = df5[df5['sector'] == 'Materials']
```

[57]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_8)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Materials Companies', fontsize = 16)
# plt.show()
```

[58]:
```
df5_9 = df5[df5['sector'] == 'Utilities']
```

[59]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_9)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Utilities Companies', fontsize = 16)
# plt.show()
```

[60]:
```
df5_10 = df5[df5['sector'] == 'Communication Services']
```

[61]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_10)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Communication Services Companies',␣
↪fontsize = 16)
# plt.show()
```

[62]:
```
df5_11 = df5[df5['sector'] == 'Energy']
```

[63]:
```
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="year", y = 'revenues', hue="symbol", palette = 'bright', data␣
↪= df5_11)
# plt.xlabel('Year')
# plt.ylabel('Revenues')
# plt.title('Annual Revenue Data for Energy Companies', fontsize = 16)
```

```python
# plt.show()
```

From the annual revenue plots by sectors above, we could detect that companies' annual revenues from the same sector tend to have similar change tendencies. Among the sectors, the annual revenues of consumer staples companies have the most stable revenue change tendencies and are nearly not affected by the trade war. Industrial and energy companies suffer a lot during the trade war. Besides, the companies belonging to the other sectors maintain slightly increasing tendencies on average.

5.7 Exploring the Stock Price of S&P Companies by Sectors

[64]:
```python
%%sql result_set6 <<
select sp.symbol, sp.sector, sp.sectorid, s.date, s.adjustedclose
from sp500withgics sp
join sp500stockprice s
on sp.symbol = s.symbol;
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
661196 rows affected.
Returning data to local variable result_set6
```

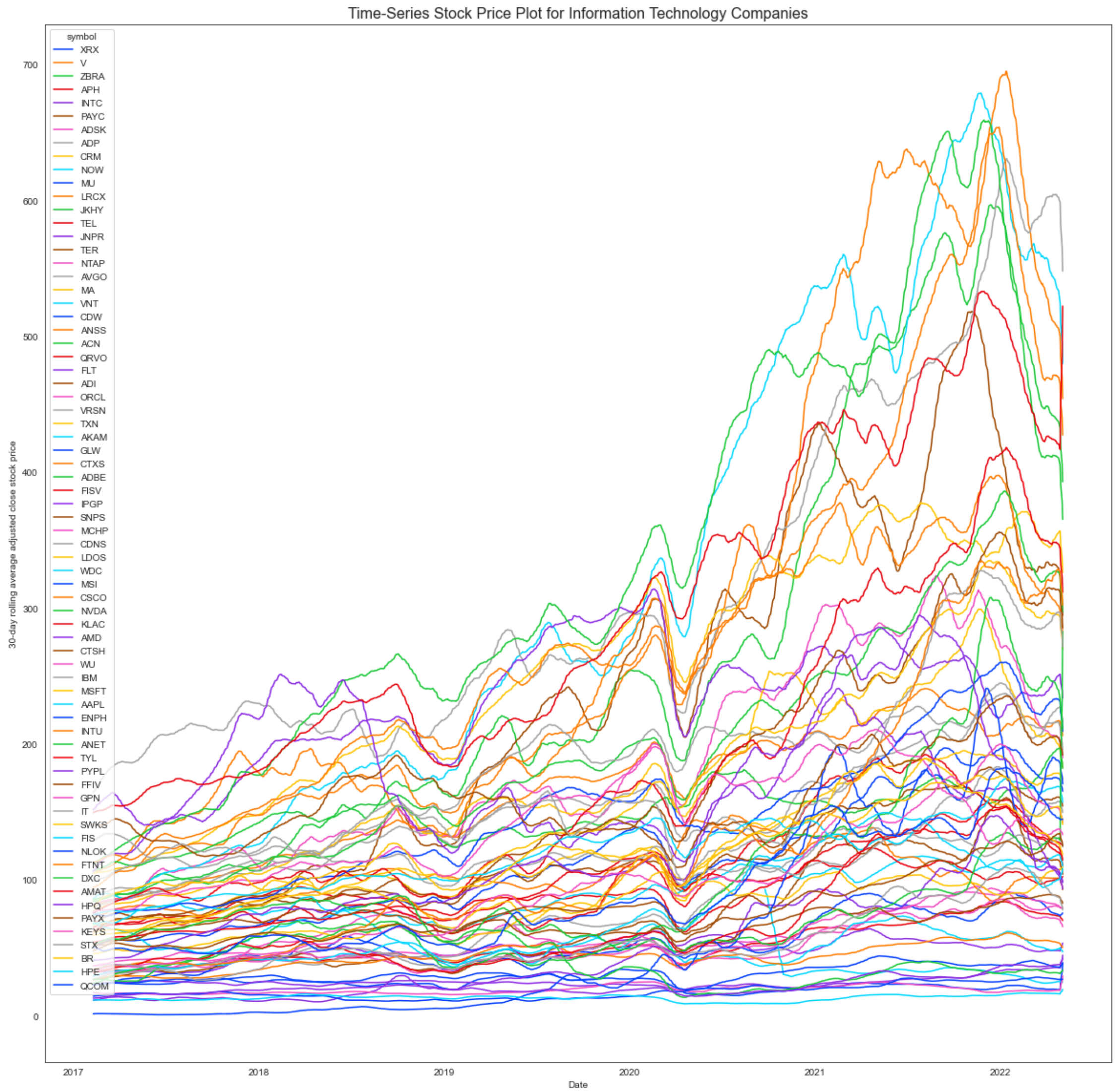
[65]:
```python
df6 = result_set6.DataFrame()
df6['30day_ave_close'] = df6.adjustedclose.rolling(30).mean().shift(-3)
df6['date'] = df6['date'].astype('datetime64')
df6.head(31)
df6 = df6[df6['date'] >= '2017-02-09']
```

[66]:
```python
df6['sector'].unique()
```

[66]:
```
array(['Information Technology', 'Financials', 'Industrials',
       'Health Care', 'Consumer Discretionary', 'Consumer Staples',
       'Materials', 'Communication Services', 'Utilities', 'Energy',
       'Real Estate'], dtype=object)
```

[67]:
```python
df6_1 = df6[df6['sector'] == 'Information Technology']
```

[68]:
```python
plt.figure(figsize = (20, 20))
sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette = 'bright',␣
 ↪data = df6_1)
plt.xlabel('Date')
plt.ylabel('30-day rolling average adjusted close stock price')
plt.title('Time-Series Stock Price Plot for Information Technology Companies',␣
 ↪fontsize = 16)
plt.show()
plt.savefig('Figure16.png')
```




```
<Figure size 432x288 with 0 Axes>
```

[69]:

```
df6_2 = df6[df6['sector'] == 'Industrials']
```

[70]:

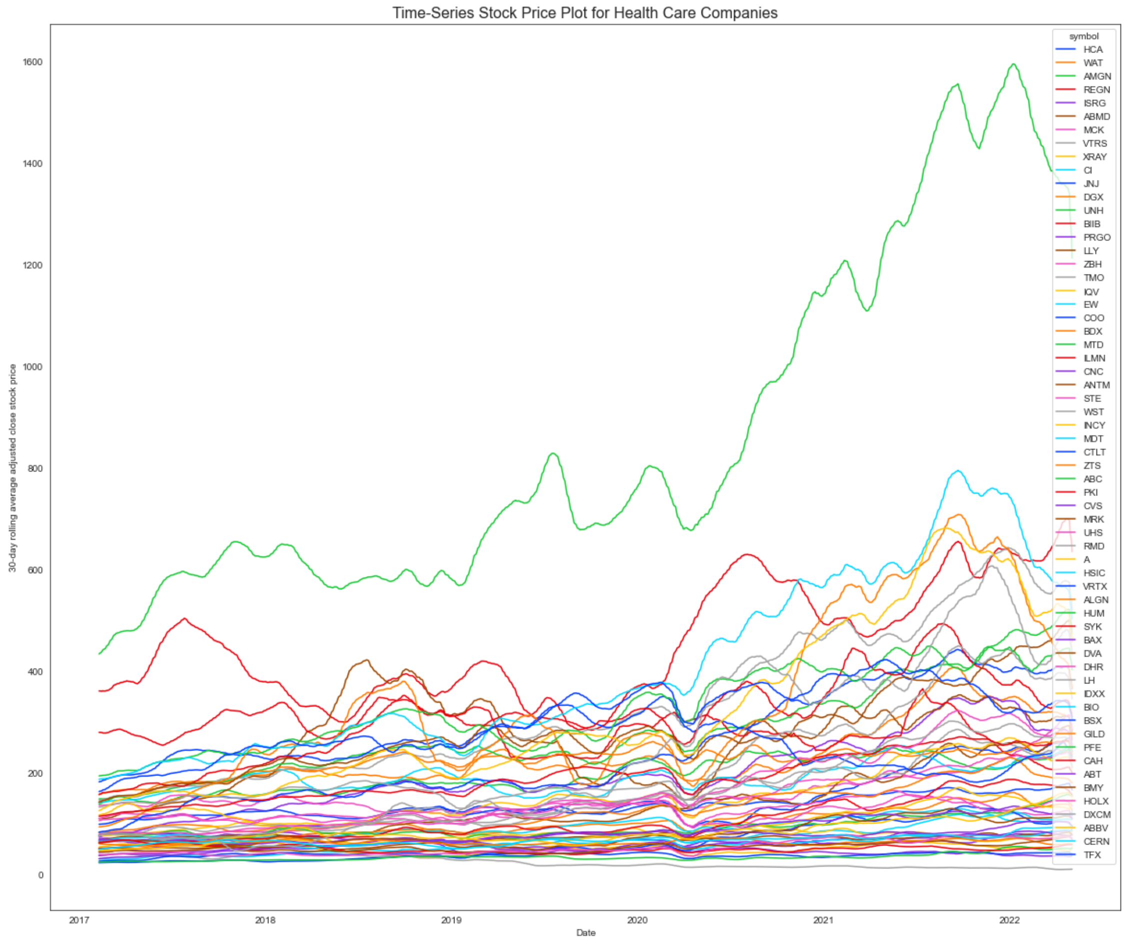
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 20))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette = 'bright', data = df6_2)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Industrials Companies', fontsize = 16)
# plt.show()
```

[71]:
```
df6_3 = df6[df6['sector'] == 'Financials']
```

[72]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 18))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =␣
↪'bright', data = df6_3)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Financials Companies', fontsize =␣
↪16)
# plt.show()
```

[73]:
```
df6_4 = df6[df6['sector'] == 'Health Care']
```

[74]:
```
plt.figure(figsize = (20, 17))
sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette = 'bright',␣
↪data = df6_4)
plt.xlabel('Date')
plt.ylabel('30-day rolling average adjusted close stock price')
plt.title('Time-Series Stock Price Plot for Health Care Companies', fontsize =␣
↪16)
plt.show()
plt.savefig('Figure17.png')
```



<Figure size 432x288 with 0 Axes>

[75]:
```python
df6_5 = df6[df6['sector'] == 'Consumer Discretionary']
```

[76]:
```python
## Commented to save space in the final report
# plt.figure(figsize = (20, 17))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette = 'bright', data = df6_5)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Consumer Discretionary Companies', fontsize = 16)
# plt.show()
```

[77]:
```python
df6_6 = df6[df6['sector'] == 'Consumer Staples']
```

[78]:
```python
## Commented to save space in the final report
# plt.figure(figsize = (20, 12))
```

```
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =␣
↪'bright', data = df6_6)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Consumer Staples Companies',␣
↪fontsize = 16)
# plt.show()
```

[79]:
```
df6_7 = df6[df6['sector'] == 'Real Estate']
```

[80]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 12))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =␣
↪'bright', data = df6_7)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Real Estate Companies', fontsize␣
↪= 16)
# plt.show()
```

[81]:
```
df6_8 = df6[df6['sector'] == 'Materials']
```

[82]:
```
# plt.figure(figsize = (20, 12))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =␣
↪'bright', data = df6_8)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Materials Companies', fontsize =␣
↪16)
# plt.show()
```

[83]:
```
df6_9 = df6[df6['sector'] == 'Utilities']
```

[84]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 12))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =␣
↪'bright', data = df6_9)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Utilities Companies', fontsize =␣
↪16)
# plt.show()
```

[85]:
```
df6_10 = df6[df6['sector'] == 'Communication Services']
```

[86]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =
 ↪'bright', data = df6_10)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Communication Services
 ↪Companies', fontsize = 16)
# plt.show()
```

[87]:
```
df6_11 = df6[df6['sector'] == 'Energy']
```

[88]:
```
## Commented to save space in the final report
# plt.figure(figsize = (20, 10))
# sns.lineplot(x="date", y = '30day_ave_close', hue="symbol", palette =
 ↪'bright', data = df6_11)
# plt.xlabel('Date')
# plt.ylabel('30-day rolling average adjusted close stock price')
# plt.title('Time-Series Stock Price Plot for Energy Companies', fontsize = 16)
# plt.show()
```

From time-series plots of companies' stock prices by sector, we could detect that the stock price change tendencies among the same sector are very similar. Also, companies' stock price change tendencies among different sectors tend to be different.

5.8 Exploring the Stock Price for 15 Companies with Highest Level of Sale in China

5.8.1 Data Extraction

[89]:
```
%%sql result_set7 <<
select fort.symbol, t20level.companyname, fort.date, fort.adjustedclose, spg.
 ↪sector, spg.industry
from fortune500stockprice fort
inner join TOP20Companies_LevelofSaleinChina t20level
on fort.symbol = t20level.symbol
inner join sp500withGICS spg
on t20level.symbol = spg.symbol
where date >= '2017-01-01';
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
20145 rows affected.
Returning data to local variable result_set7
```

[90]:
```
df7 = result_set7.DataFrame()
```

[91]:
```
df7['date'] = df7['date'].astype('datetime64')
df7['adjustedclose'] = df7['adjustedclose'].astype('float')
df7.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20145 entries, 0 to 20144
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   symbol         20145 non-null  object
 1   companyname    20145 non-null  object
 2   date           20145 non-null  datetime64[ns]
 3   adjustedclose  20145 non-null  float64
 4   sector         20145 non-null  object
 5   industry       20145 non-null  object
dtypes: datetime64[ns](1), float64(1), object(4)
memory usage: 944.4+ KB
```

[92]:
```
df7['symbol'].unique()
```

[92]:
```
array(['APH', 'INTC', 'MU', 'AVGO', 'TXN', 'GLW', 'WDC', 'AAPL', 'MMM',
       'BA', 'PG', 'AMAT', 'ABT', 'NKE', 'QCOM'], dtype=object)
```

[93]:
```
df7.companyname.unique()
```

[93]:
```
array(['Amphenol Corp. Class A', 'Intel Corp.', 'Micron Technology Inc.',
       'Broadcom Ltd.', 'Texas Instruments Inc.', 'Corning Inc',
       'Western Digital Corp.', 'Apple Inc.', '3M co.', 'Boeing Co.',
       'Procter & Gamble co.', 'Applied Materials Inc.',
       'Abbott Laboratories', 'Nike Inc. Class B', 'Qualcomm Inc.'],
      dtype=object)
```

[94]:
```
s1 = pd.Series(df7['symbol'].unique())
s2 = pd.Series(df7.companyname.unique())
company_list = zip(s1, s2)
list(company_list)
```

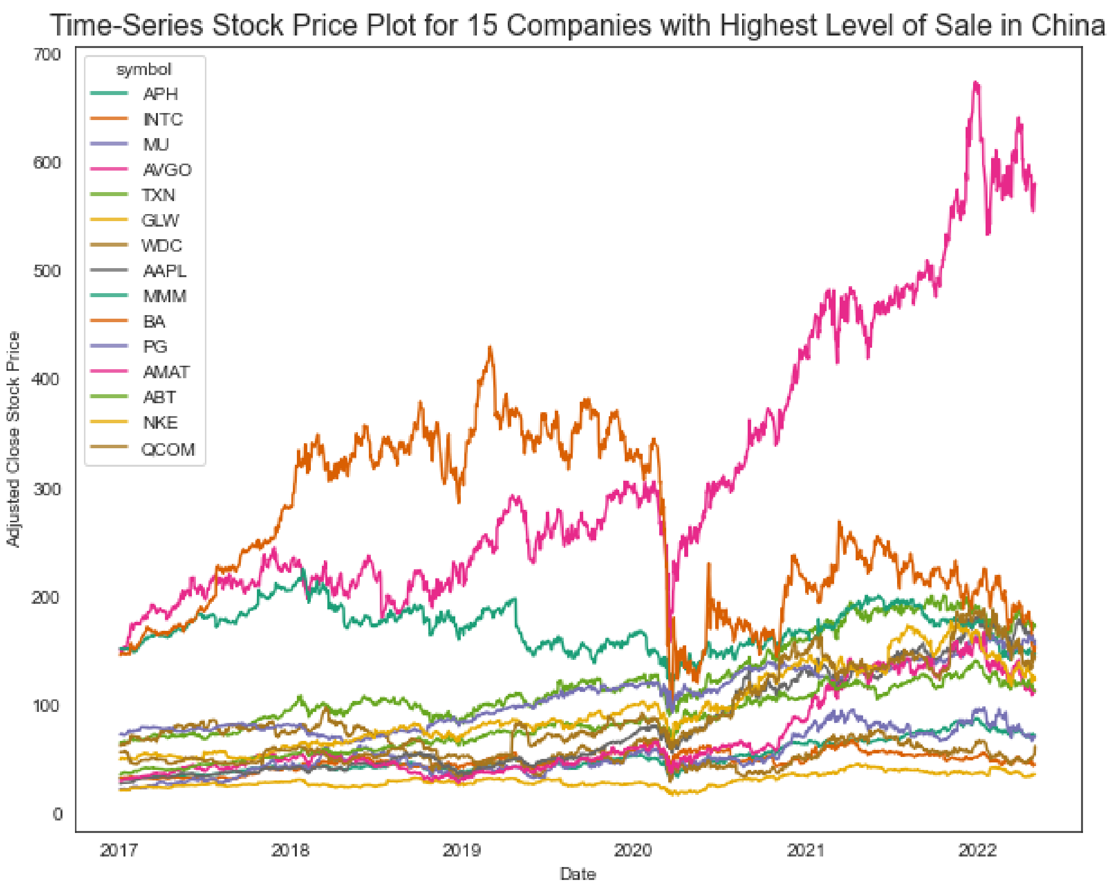
[94]:
```
[('APH', 'Amphenol Corp. Class A'),
 ('INTC', 'Intel Corp.'),
 ('MU', 'Micron Technology Inc.'),
 ('AVGO', 'Broadcom Ltd.'),
 ('TXN', 'Texas Instruments Inc.'),
 ('GLW', 'Corning Inc'),
 ('WDC', 'Western Digital Corp.'),
 ('AAPL', 'Apple Inc.'),
 ('MMM', '3M co.'),
 ('BA', 'Boeing Co.'),
```

```
('PG', 'Procter & Gamble co.'),
('AMAT', 'Applied Materials Inc.'),
('ABT', 'Abbott Laboratories'),
('NKE', 'Nike Inc. Class B'),
('QCOM', 'Qualcomm Inc.')]
```

5.8.2 Data Visualization

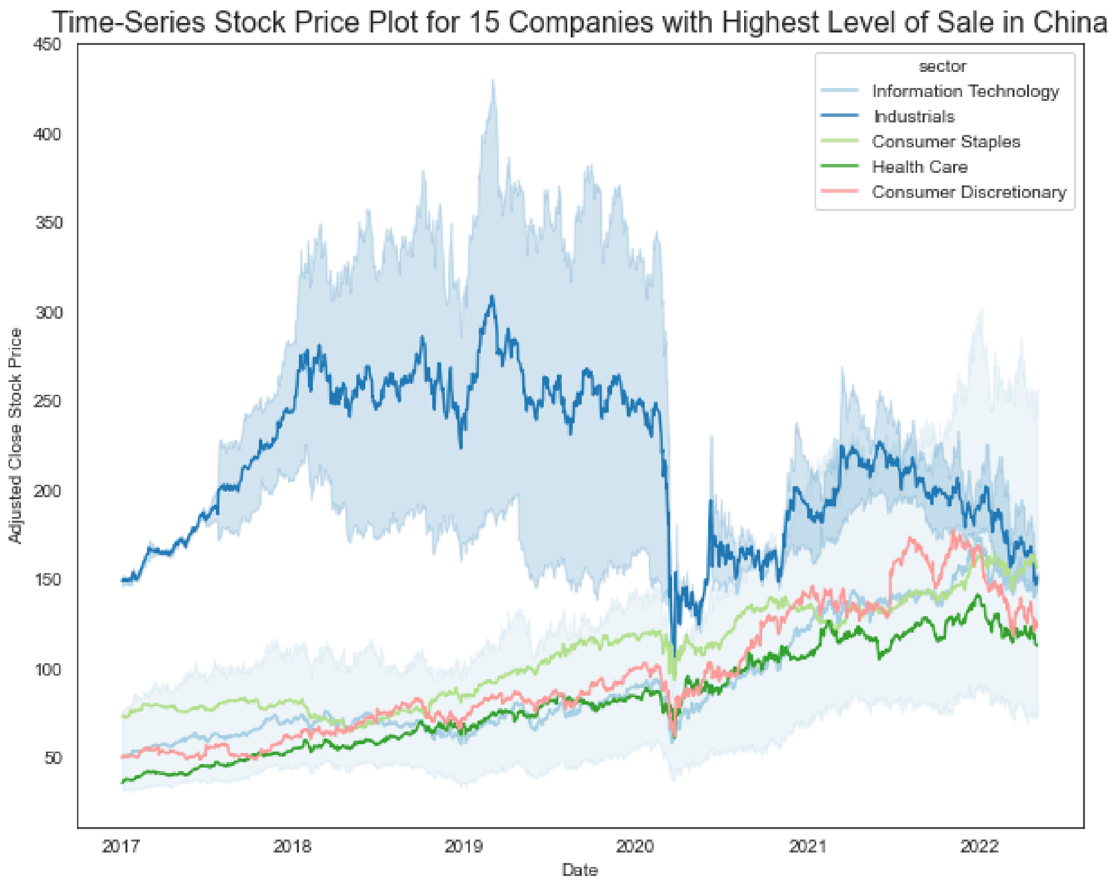
Plot for Stock Price of 15 Companies with Highest Level of Sale in China by Company

[95]:
```python
plt.figure(figsize = (10, 8))
sns.lineplot(x="date", y = 'adjustedclose', hue="symbol", palette = 'Dark2',␣
↪data = df7)
plt.xlabel('Date')
plt.ylabel('Adjusted Close Stock Price')
plt.title('Time-Series Stock Price Plot for 15 Companies with Highest Level of␣
↪Sale in China', fontsize = 16)
plt.show()
# plt.savefig('Figure18.png')
```



Plot for Stock Price of 15 Companies with Highest Level of Sale in China by Sector

[96]:
```
plt.figure(figsize = (10, 8))
sns.lineplot(x="date", y = 'adjustedclose', hue="sector", palette = 'Paired',␣
 ↪data = df7)
plt.xlabel('Date')
plt.ylabel('Adjusted Close Stock Price')
plt.title('Time-Series Stock Price Plot for 15 Companies with Highest Level of␣
 ↪Sale in China', fontsize = 16)
plt.show()
# plt.savefig('Figure19.png')
```



The 15 companies with the highest level of sales in China are mainly information technology companies, but a few companies from the other sectors, the stock price fluctuation tendency among different companies are quite different. After averaging the company stock price by sectors, we could detect that industrial companies' stock prices fluctuate most hugely and have a decreasing tendency during the trade war period, while the other companies' stock prices have an increasing tendency in general.

5.8.3 Data Analysis

[97]:
```
# Amphenol Corp. Class A
APH = df7[df7.symbol == 'APH'].set_index(['date'])
# Intel Corp.
INTC = df7[df7.symbol == 'INTC'].set_index(['date'])
# Micron Technology Inc.
MU = df7[df7.symbol == 'MU'].set_index(['date'])
# Broadcom Ltd.
AVGO = df7[df7.symbol == 'AVGO'].set_index(['date'])
# Texas Instruments Inc.
TXN = df7[df7.symbol == 'TXN'].set_index(['date'])
# Corning Inc
GLW = df7[df7.symbol == 'GLW'].set_index(['date'])
# Western Digital Corp.
WDC = df7[df7.symbol == 'WDC'].set_index(['date'])
# Apple Inc.
AAPL = df7[df7.symbol == 'AAPL'].set_index(['date'])
# 3M co.
MMM = df7[df7.symbol == 'MMM'].set_index(['date'])
# Boeing Co.
BA = df7[df7.symbol == 'BA'].set_index(['date'])
# Procter & Gamble co.
PG = df7[df7.symbol == 'PG'].set_index(['date'])
# Applied Materials Inc.
AMAT = df7[df7.symbol == 'AMAT'].set_index(['date'])
# Abbott Laboratories
ABT = df7[df7.symbol == 'ABT'].set_index(['date'])
# Nike Inc. Class B
NKE = df7[df7.symbol == 'NKE'].set_index(['date'])
# Qualcomm Inc.
QCOM = df7[df7.symbol == 'QCOM'].set_index(['date'])
```

Time Series Plot for Stock Price and Daily Changes of Stock Price

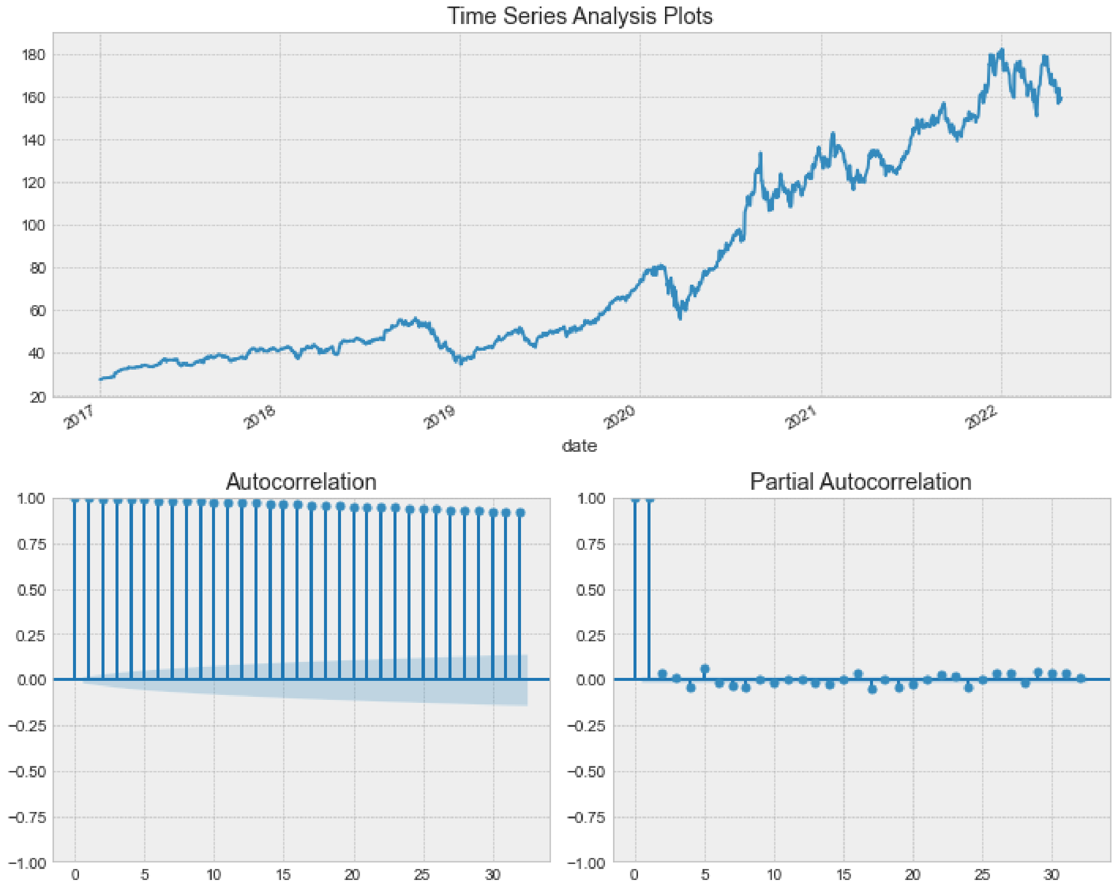
[98]:
```
import os
import sys

import pandas_datareader.data as web

import statsmodels.formula.api as smf
import statsmodels.tsa.api as smt
import statsmodels.api as sm
import scipy.stats as scs
import statsmodels.tsa as smta
from arch import arch_model

import matplotlib as mpl
```

```
%matplotlib inline
p = print
```

[99]:
```
def tsplot(y, lags=None, figsize=(10, 8), style='bmh'):
    if not isinstance(y, pd.Series):
        y = pd.Series(y)
    with plt.style.context(style):
        fig = plt.figure(figsize=figsize)
        #mpl.rcParams['font.family'] = 'Ubuntu Mono'
        layout = (2, 2)
        ts_ax = plt.subplot2grid(layout, (0, 0), colspan=2)
        acf_ax = plt.subplot2grid(layout, (1, 0))
        pacf_ax = plt.subplot2grid(layout, (1, 1))
        #qq_ax = plt.subplot2grid(layout, (2, 0))
        #pp_ax = plt.subplot2grid(layout, (2, 1))

        y.plot(ax=ts_ax)
        ts_ax.set_title('Time Series Analysis Plots')
        smt.graphics.plot_acf(y, lags=lags, ax=acf_ax, alpha=0.5)
        smt.graphics.plot_pacf(y, lags=lags, ax=pacf_ax, alpha=0.5)
        #sm.qqplot(y, line='s', ax=qq_ax)
        #qq_ax.set_title('QQ Plot')
        #scs.probplot(y, sparams=(y.mean(), y.std()), plot=pp_ax)

        plt.tight_layout()
    return
```

[100]:
```
tsplot(AAPL.adjustedclose)
# plt.savefig('Figure20.png')
```

```
/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-
packages/statsmodels/graphics/tsaplots.py:348: FutureWarning: The default method
'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```



In reality, time-series stock data is always non-stationary; for example, the plot for Apple stock data above is non-stationary. And the autocorrelation (ACF) and partial autocorrelation (PACF) plots testify to the autocorrelation.

Next, I will do AD Fuller tests for each stock series to detect the stationarity.

[101]:
```
# Compute the ADF for the companies' stock data to detect stationarity
# The null hypothesis for each test is that the stock data is non-stationarity
from statsmodels.tsa.stattools import adfuller
adf_APH = adfuller(APH.adjustedclose)
print('The p-value for the ADF test on APH is ', adf_APH[1])
adf_INTC = adfuller(INTC.adjustedclose)
print('The p-value for the ADF test on INTC is ', adf_INTC[1])
adf_MU = adfuller(MU.adjustedclose)
print('The p-value for the ADF test on MU is ', adf_MU[1])
adf_AVGO = adfuller(AVGO.adjustedclose)
print('The p-value for the ADF test on AVGO is ', adf_AVGO[1])
adf_TXN = adfuller(TXN.adjustedclose)
print('The p-value for the ADF test on TXN is ', adf_TXN[1])
adf_GLW = adfuller(GLW.adjustedclose)
```

```python
print('The p-value for the ADF test on GLW is ', adf_GLW[1])
adf_WDC = adfuller(WDC.adjustedclose)
print('The p-value for the ADF test on WDC is ', adf_WDC[1])
adf_AAPL = adfuller(AAPL.adjustedclose)
print('The p-value for the ADF test on AAPL is ', adf_AAPL[1])
adf_MMM = adfuller(MMM.adjustedclose)
print('The p-value for the ADF test on MMM is ', adf_MMM[1])
adf_BA = adfuller(BA.adjustedclose)
print('The p-value for the ADF test on BA is ', adf_BA[1])
adf_PG = adfuller(PG.adjustedclose)
print('The p-value for the ADF test on PG is ', adf_PG[1])
adf_AMAT = adfuller(AMAT.adjustedclose)
print('The p-value for the ADF test on AMAT is ', adf_AMAT[1])
adf_ABT = adfuller(ABT.adjustedclose)
print('The p-value for the ADF test on ABT is ', adf_ABT[1])
adf_NKE = adfuller(NKE.adjustedclose)
print('The p-value for the ADF test on NKE is ', adf_NKE[1])
adf_QCOM = adfuller(QCOM.adjustedclose)
print('The p-value for the ADF test on QCOM is ', adf_QCOM[1])
```

```
The p-value for the ADF test on APH is  0.7806927548320779
The p-value for the ADF test on INTC is  0.11617598297062354
The p-value for the ADF test on MU is  0.4547967670790441
The p-value for the ADF test on AVGO is  0.9594796854371349
The p-value for the ADF test on TXN is  0.8104674553114753
The p-value for the ADF test on GLW is  0.31689572938294996
The p-value for the ADF test on WDC is  0.2567812379035717
The p-value for the ADF test on AAPL is  0.9679901691668595
The p-value for the ADF test on MMM is  0.17393968117077635
The p-value for the ADF test on BA is  0.4124168407482042
The p-value for the ADF test on PG is  0.9440275764100345
The p-value for the ADF test on AMAT is  0.8344203686797362
The p-value for the ADF test on ABT is  0.6978377846716866
The p-value for the ADF test on NKE is  0.6579612426694753
The p-value for the ADF test on QCOM is  0.7662105013199096
```

From the results of ADF test, we could see all p-values are larger than 0.05, so we could not reject the null hypotheses, which leads to the conclusion that the stock data is non-stationary.

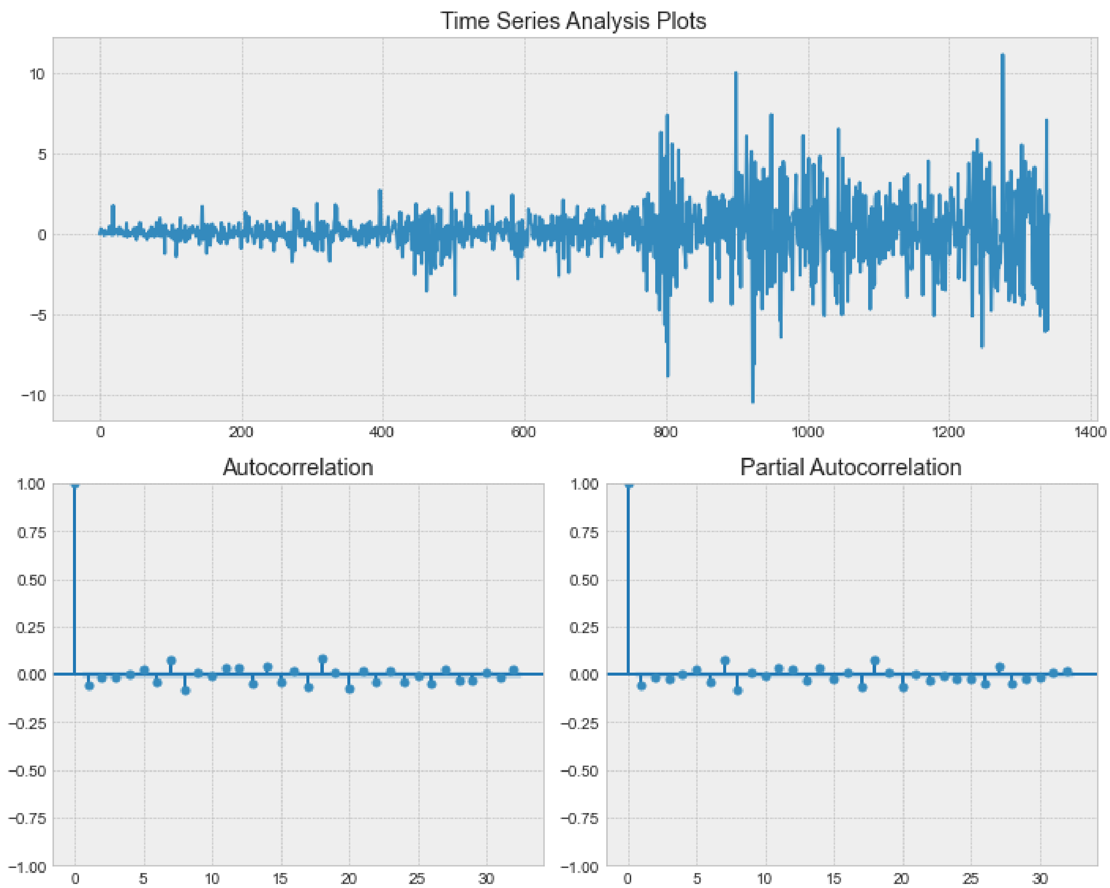
Working with non-stationary data is difficult. To model, we need to convert a non-stationary process to stationary.

First-difference is often used to convert a non-stationary process to stationary. And according to Dickey-Fuller Test, the first difference gives us stationary white noise w(t).

[102]:
```python
# Amphenol Corp. Class A
APH1d = np.diff(APH.adjustedclose)
# Intel Corp.
INTC1d = np.diff(INTC.adjustedclose)
# Micron Technology Inc.
MU1d = np.diff(MU.adjustedclose)
# Broadcom Ltd.
AVGO1d = np.diff(AVGO.adjustedclose)
# Texas Instruments Inc.
TXN1d = np.diff(TXN.adjustedclose)
# Corning Inc
GLW1d = np.diff(GLW.adjustedclose)
# Western Digital Corp.
WDC1d = np.diff(WDC.adjustedclose)
# Apple Inc.
AAPL1d = np.diff(AAPL.adjustedclose)
# 3M co.
MMM1d = np.diff(MMM.adjustedclose)
# Boeing Co.
BA1d = np.diff(BA.adjustedclose)
# Procter & Gamble co.
PG1d = np.diff(PG.adjustedclose)
# Applied Materials Inc.
AMAT1d = np.diff(AMAT.adjustedclose)
# Abbott Laboratories
ABT1d = np.diff(ABT.adjustedclose)
# Nike Inc. Class B
NKE1d = np.diff(NKE.adjustedclose)
# Qualcomm Inc.
QCOM1d = np.diff(QCOM.adjustedclose)
```

[103]:
```python
tsplot(AAPL1d)
# plt.savefig('Figure21.png')
```

```
/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-
packages/statsmodels/graphics/tsaplots.py:348: FutureWarning: The default method
'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```



Taking Apple's first-difference stock data as an example, through the ACF and PACF plots above, we could detect that the non-stationary data has been processed into difference-stationary data, and the autocorrelation is constant over time. Also, the first-difference stock data shows how the daily changes of one company's stock price change along the timeline, which would be useful for us to explore the cointegration between different companies' operating status by their first-difference stock price.

Next, I will convert the stock price data into first-difference stock data for all companies and detect the correlations among different first-difference stock data.

[104]:
```
dic = {'APH1d': APH1d,
       'INTC1d': INTC1d,
       'MU1d': MU1d,
       'AVGO1d': AVGO1d,
       'TXN1d': TXN1d,
       'GLW1d': GLW1d,
       'WDC1d': WDC1d,
       'AAPL1d': AAPL1d,
       'MMM1d': MMM1d,
       'BA1d': BA1d,
```

```
        'PG1d': PG1d,
        'AMAT1d': AMAT1d,
        'ABT1d': ABT1d,
        'NKE1d': NKE1d,
        'QCOM1d': QCOM1d}

diff_stock1 = pd.DataFrame(dic).set_index(APH.index[1:])
```

[105]:
```
diff_stock1.corr()
```

[105]:
```
           APH1d    INTC1d      MU1d    AVGO1d     TXN1d     GLW1d     WDC1d  \
APH1d   1.000000  0.554443  0.586354  0.682525  0.695802  0.687701  0.515437
INTC1d  0.554443  1.000000  0.568658  0.537787  0.635236  0.491718  0.477131
MU1d    0.586354  0.568658  1.000000  0.610272  0.663791  0.477479  0.675265
AVGO1d  0.682525  0.537787  0.610272  1.000000  0.732737  0.515984  0.454706
TXN1d   0.695802  0.635236  0.663791  0.732737  1.000000  0.595286  0.503309
GLW1d   0.687701  0.491718  0.477479  0.515984  0.595286  1.000000  0.453816
WDC1d   0.515437  0.477131  0.675265  0.454706  0.503309  0.453816  1.000000
AAPL1d  0.577050  0.462769  0.452169  0.626259  0.579147  0.421575  0.321376
MMM1d   0.529536  0.406278  0.328463  0.330900  0.405305  0.534043  0.371951
BA1d    0.506577  0.404452  0.385651  0.364109  0.385474  0.442728  0.394987
PG1d    0.403491  0.320036  0.215110  0.262114  0.340874  0.323734  0.209516
AMAT1d  0.635977  0.536106  0.707532  0.693326  0.723983  0.486482  0.498751
ABT1d   0.484340  0.426510  0.321977  0.419737  0.450565  0.408717  0.262745
NKE1d   0.547721  0.341716  0.407201  0.419180  0.447785  0.424017  0.347887
QCOM1d  0.593024  0.473530  0.557458  0.669334  0.641393  0.448999  0.371309

          AAPL1d     MMM1d      BA1d      PG1d    AMAT1d     ABT1d     NKE1d  \
APH1d   0.577050  0.529536  0.506577  0.403491  0.635977  0.484340  0.547721
INTC1d  0.462769  0.406278  0.404452  0.320036  0.536106  0.426510  0.341716
MU1d    0.452169  0.328463  0.385651  0.215110  0.707532  0.321977  0.407201
AVGO1d  0.626259  0.330900  0.364109  0.262114  0.693326  0.419737  0.419180
TXN1d   0.579147  0.405305  0.385474  0.340874  0.723983  0.450565  0.447785
GLW1d   0.421575  0.534043  0.442728  0.323734  0.486482  0.408717  0.424017
WDC1d   0.321376  0.371951  0.394987  0.209516  0.498751  0.262745  0.347887
AAPL1d  1.000000  0.290707  0.325890  0.339192  0.531770  0.430177  0.427189
MMM1d   0.290707  1.000000  0.420525  0.368972  0.263141  0.379677  0.359714
BA1d    0.325890  0.420525  1.000000  0.229176  0.343780  0.276824  0.369038
PG1d    0.339192  0.368972  0.229176  1.000000  0.214167  0.488965  0.324010
AMAT1d  0.531770  0.263141  0.343780  0.214167  1.000000  0.319375  0.379573
ABT1d   0.430177  0.379677  0.276824  0.488965  0.319375  1.000000  0.369688
NKE1d   0.427189  0.359714  0.369038  0.324010  0.379573  0.369688  1.000000
QCOM1d  0.579035  0.251334  0.298859  0.250163  0.660180  0.343556  0.405742

          QCOM1d
APH1d   0.593024
INTC1d  0.473530
```

```
MU1d     0.557458
AVGO1d   0.669334
TXN1d    0.641393
GLW1d    0.448999
WDC1d    0.371309
AAPL1d   0.579035
MMM1d    0.251334
BA1d     0.298859
PG1d     0.250163
AMAT1d   0.660180
ABT1d    0.343556
NKE1d    0.405742
QCOM1d   1.000000
```

[106]:
```
# Use AD Fuller test to detect cointegration among two sample first-difference␣
↪stock price
from statsmodels.tsa.stattools import adfuller
adf1 = adfuller(MU1d - PG1d)
print('The p-value for the ADF test on the spread between MU and PG␣
↪first-difference stock data is ', adf1[1])
```

```
The p-value for the ADF test on the spread between MU and PG first-difference
stock data is  0.0
```

Since p-value = 0 for the ADF test, we could reject the null hypothesis and conclude that the first-difference stock data of MU and PG are cointegrated with more than 99% certainty.

Besides, since the correlation coefficient between MU and PG is the smallest, and they are still cointegrated, we could conclude that the first-difference stock prices of all 15 companies with the highest level of sales in China are cointegrated.

The same situation happens in the stock price of 12 Companies with the Highest Share of Sales in China, as shown in the appendix. For all its imperfections, the stock market is one of the best indicators of corporate health. Different companies might have many specific issues impacting their stock market; however, there might be some common factors when multiple companies are highly cointegrated. Thus, I suppose that the U.S.-China trade war is a common factor.

To explore whether the U.S.-China affects only the companies exposed to China or all types of MNCs, I extract the stock price of another list of 12 companies randomly selected from the S&P 500 company list. The 12 companies cover multiple sectors.

[107]:
```
all_stock = result_set6.DataFrame()
#all_stock['30day_ave_close'] = all_stock.adjustedclose.rolling(30).mean().
↪shift(-3)
#all_stock = all_stock[all_stock['date'] >= '2017-02-09']
all_stock['date'] = all_stock['date'].astype('datetime64')
all_stock['adjustedclose'] = all_stock['adjustedclose'].astype('float')
```

[108]:
```python
## Extract stock price time-series data for each company in the sample
# Google
GOOG = all_stock[all_stock.symbol == 'GOOG'].set_index(['date'])
# Facebook (Meta)
FB = all_stock[all_stock.symbol == 'FB'].set_index(['date'])
# JPMorgan Chase & Co
JPM = all_stock[all_stock.symbol == 'JPM'].set_index(['date'])
# Bank of America Corp
BAC = all_stock[all_stock.symbol == 'BAC'].set_index(['date'])
# Cincinnati Financial -- Financials company
CINF = all_stock[all_stock.symbol == 'CINF'].set_index(['date'])
# Discover Financial Services -- Financials company
DFS = all_stock[all_stock.symbol == 'DFS'].set_index(['date'])
# Duke Realty Corp -- Real Estate
DRE = all_stock[all_stock.symbol == 'DRE'].set_index(['date'])
# Healthpeak Properties -- Real Estate
PEAK = all_stock[all_stock.symbol == 'PEAK'].set_index(['date'])
# Hormel Foods Corp. -- Consumer Staples
HRL = all_stock[all_stock.symbol == 'HRL'].set_index(['date'])
# Lamb Weston Holdings Inc -- Consumer Staples
LW = all_stock[all_stock.symbol == 'LW'].set_index(['date'])
# Las Vegas Sands -- Consumer Discretionary
LVS = all_stock[all_stock.symbol == 'LVS'].set_index(['date'])
# Marriott Int'l. -- Consumer Discretionary
MAR = all_stock[all_stock.symbol == 'MAR'].set_index(['date'])
```

[109]:
```python
adf_APH = adfuller(GOOG.adjustedclose)
print('The p-value for the ADF test on GOOG is ', adf_APH[1])
adf_INTC = adfuller(FB.adjustedclose)
print('The p-value for the ADF test on FB is ', adf_INTC[1])
adf_MU = adfuller(JPM.adjustedclose)
print('The p-value for the ADF test on JPM is ', adf_MU[1])
adf_AVGO = adfuller(BAC.adjustedclose)
print('The p-value for the ADF test on BAC is ', adf_AVGO[1])
adf_TXN = adfuller(CINF.adjustedclose)
print('The p-value for the ADF test on CINF is ', adf_TXN[1])
adf_GLW = adfuller(DFS.adjustedclose)
print('The p-value for the ADF test on DFS is ', adf_GLW[1])
adf_WDC = adfuller(DRE.adjustedclose)
print('The p-value for the ADF test on DRE is ', adf_WDC[1])
adf_AAPL = adfuller(PEAK.adjustedclose)
print('The p-value for the ADF test on PEAK is ', adf_AAPL[1])
adf_MMM = adfuller(HRL.adjustedclose)
print('The p-value for the ADF test on HRL is ', adf_MMM[1])
adf_BA = adfuller(LW.adjustedclose)
print('The p-value for the ADF test on LW is ', adf_BA[1])
adf_PG = adfuller(LVS.adjustedclose)
```

```
print('The p-value for the ADF test on LVS is ', adf_PG[1])
adf_AMAT = adfuller(MAR.adjustedclose)
print('The p-value for the ADF test on MAR is ', adf_AMAT[1])
```

```
The p-value for the ADF test on GOOG is  0.9206452216305152
The p-value for the ADF test on FB is  0.4408830489570079
The p-value for the ADF test on JPM is  0.5164123596562111
The p-value for the ADF test on BAC is  0.527076862960515
The p-value for the ADF test on CINF is  0.6181210041301123
The p-value for the ADF test on DFS is  0.8236884846098547
The p-value for the ADF test on DRE is  0.9630232739124333
The p-value for the ADF test on PEAK is  0.7101643261104784
The p-value for the ADF test on HRL is  0.7724075446506207
The p-value for the ADF test on LW is  0.07904250900005483
The p-value for the ADF test on LVS is  0.17728913574082866
The p-value for the ADF test on MAR is  0.29830008378976064
```

From the results of ADF test above, we could see all p-values are larger than 0.05, so we could not reject the null hypotheses, which leads to the conclusion that the stock data for the above companies are also non-stationary.

Next, I will take the first-difference of each stock price data.

[110]:
```
# Amphenol Corp. Class A
GOOG1d = np.diff(GOOG.adjustedclose)
# Intel Corp.
FB1d = np.diff(FB.adjustedclose)
# Micron Technology Inc.
JPM1d = np.diff(JPM.adjustedclose)
# Broadcom Ltd.
BAC1d = np.diff(BAC.adjustedclose)
# Texas Instruments Inc.
CINF1d = np.diff(CINF.adjustedclose)
# Corning Inc
DFS1d = np.diff(DFS.adjustedclose)
# Western Digital Corp.
DRE1d = np.diff(DRE.adjustedclose)
# Apple Inc.
PEAK1d = np.diff(PEAK.adjustedclose)
# 3M co.
HRL1d = np.diff(HRL.adjustedclose)
# Boeing Co.
LW1d = np.diff(LW.adjustedclose)
# Procter & Gamble co.
LVS1d = np.diff(LVS.adjustedclose)
# Applied Materials Inc.
MAR1d = np.diff(MAR.adjustedclose)
```

[111]:
```
dic2 = {'GOOG1d': GOOG1d,
        'FB1d': FB1d,
        'JPM1d': JPM1d,
        'BAC1d': BAC1d,
        'CINF1d': CINF1d,
        'DFS1d': DFS1d,
        'DRE1d': DRE1d,
        'PEAK1d': PEAK1d,
        'HRL1d': HRL1d,
        'LW1d': LW1d,
        'LVS1d': LVS1d,
        'MAR1d': MAR1d}

diff_stock2 = pd.DataFrame(dic2).set_index(GOOG.index[1:])
```

[112]:
```
diff_stock2.corr()
```

[112]:
```
          GOOG1d      FB1d     JPM1d     BAC1d    CINF1d     DFS1d     DRE1d  \
GOOG1d  1.000000  0.622545  0.401207  0.407539  0.336213  0.409778  0.409614
FB1d    0.622545  1.000000  0.262858  0.268749  0.186599  0.294676  0.295006
JPM1d   0.401207  0.262858  1.000000  0.910234  0.633412  0.766945  0.392430
BAC1d   0.407539  0.268749  0.910234  1.000000  0.614743  0.762158  0.357351
CINF1d  0.336213  0.186599  0.633412  0.614743  1.000000  0.524034  0.513596
DFS1d   0.409778  0.294676  0.766945  0.762158  0.524034  1.000000  0.331441
DRE1d   0.409614  0.295006  0.392430  0.357351  0.513596  0.331441  1.000000
PEAK1d  0.314902  0.243506  0.427986  0.364705  0.469031  0.403606  0.692310
HRL1d   0.105119  0.075703  0.149557  0.142291  0.303622  0.074661  0.372041
LW1d    0.272933  0.191262  0.467209  0.446114  0.426689  0.476002  0.336983
LVS1d   0.410428  0.318553  0.530752  0.520625  0.328106  0.510200  0.259185
MAR1d   0.415559  0.270208  0.554273  0.550728  0.412689  0.590446  0.277077

          PEAK1d     HRL1d      LW1d     LVS1d     MAR1d
GOOG1d  0.314902  0.105119  0.272933  0.410428  0.415559
FB1d    0.243506  0.075703  0.191262  0.318553  0.270208
JPM1d   0.427986  0.149557  0.467209  0.530752  0.554273
BAC1d   0.364705  0.142291  0.446114  0.520625  0.550728
CINF1d  0.469031  0.303622  0.426689  0.328106  0.412689
DFS1d   0.403606  0.074661  0.476002  0.510200  0.590446
DRE1d   0.692310  0.372041  0.336983  0.259185  0.277077
PEAK1d  1.000000  0.244895  0.458210  0.329508  0.366395
HRL1d   0.244895  1.000000  0.166792  0.051794  0.029817
LW1d    0.458210  0.166792  1.000000  0.387316  0.430735
LVS1d   0.329508  0.051794  0.387316  1.000000  0.606739
MAR1d   0.366395  0.029817  0.430735  0.606739  1.000000
```

[113]:
```
# Use AD Fuller test to detect cointegration among two sample first-difference␣
↪stock price
```

```
from statsmodels.tsa.stattools import adfuller
adf1 = adfuller(GOOG1d - HRL1d)
print('The p-value for the ADF test on the spread between GOOG and HRL␣
 ↪first-difference stock data is ', adf1[1])
```

```
The p-value for the ADF test on the spread between GOOG and HRL first-difference
stock data is  7.498268890224783e-14
```

The correlation coefficient between GOOG1d and HRL1d is the lowest. However, the result of the ADF test still shows that they cointegrated since the p-value is less than 0.05, and we have more than 99% confidence in rejecting the null hypothesis.

Overall, through the stock price time series analysis, the first-difference stock price of most of the companies seems to be cointegrated. It shows they are all affected by the same factor. Combined with the stock price trend plots in the previous section, we could find evidence of the effect of U.S.-China trade war on most the companies in general.

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8 Appendix

8.1 Exploring the Stock Price for Top 12 Companies with Highest Share of Sale in China

8.1.1 Data Extraction

[114]:
```
%%sql result_set8 <<
select fort.symbol, t20share.companyname, fort.date, fort.adjustedclose, spg.
  ↪sector, spg.industry
from fortune500stockprice fort
inner join TOP20Companies_ShareofSaleinChina t20share
on fort.symbol = t20share.symbol
inner join SP500withGICS spg
on t20share.symbol = spg.symbol
where date >= '2017-01-01';
```

```
 * postgresql://postgres:***@127.0.0.1:5433/6354Database
16116 rows affected.
Returning data to local variable result_set8
```

[115]:
```
df8 = result_set8.DataFrame()
df8['date'] = df8['date'].astype('datetime64')
df8['adjustedclose'] = df8['adjustedclose'].astype('float')
df8.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16116 entries, 0 to 16115
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
```

```
---  ------        --------------  -----
 0   symbol        16116 non-null  object
 1   companyname   16116 non-null  object
 2   date          16116 non-null  datetime64[ns]
 3   adjustedclose 16116 non-null  float64
 4   sector        16116 non-null  object
 5   industry      16116 non-null  object
dtypes: datetime64[ns](1), float64(1), object(4)
memory usage: 755.6+ KB
```

[116]:
```
df8.symbol.unique()
```

[116]:
```
array(['APH', 'INTC', 'MU', 'AVGO', 'TXN', 'GLW', 'WDC', 'NVDA', 'AMD',
       'AAPL', 'AMAT', 'QCOM'], dtype=object)
```

[117]:
```
df8.companyname.unique()
```

[117]:
```
array(['Amphenol Corp. Class A', 'Intel Corp.', 'Micron Technology Inc.',
       'Broadcom Ltd.', 'Texas Instruments Inc.', 'Corning Inc',
       'Western Digital Corp.', 'Nvidia Corp.',
       'Advanced Micro Devices Inc.', 'Apple Inc.',
       'Applied Materials Inc.', 'Qualcomm Inc.'], dtype=object)
```

[118]:
```
s3 = pd.Series(df8['symbol'].unique())
s4 = pd.Series(df8.companyname.unique())
company_list2 = zip(s3, s4)
list(company_list2)
```

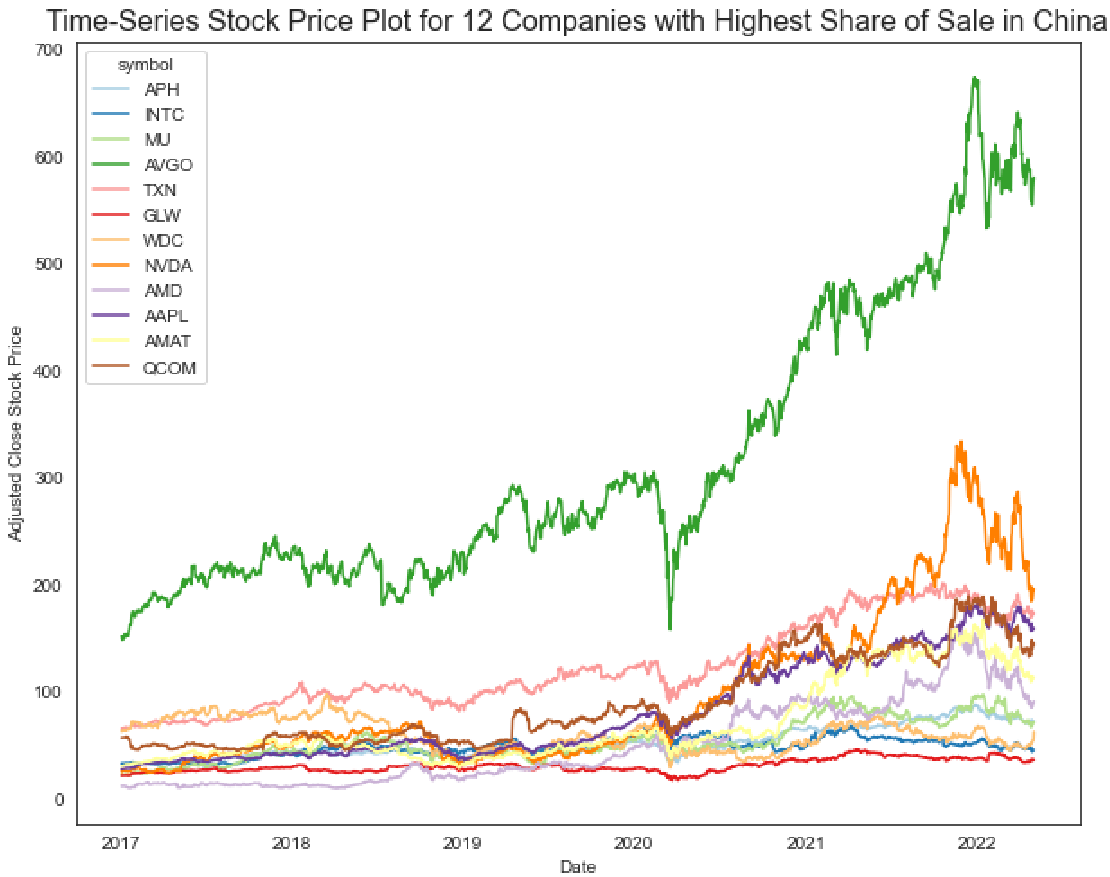
[118]:
```
[('APH', 'Amphenol Corp. Class A'),
 ('INTC', 'Intel Corp.'),
 ('MU', 'Micron Technology Inc.'),
 ('AVGO', 'Broadcom Ltd.'),
 ('TXN', 'Texas Instruments Inc.'),
 ('GLW', 'Corning Inc'),
 ('WDC', 'Western Digital Corp.'),
 ('NVDA', 'Nvidia Corp.'),
 ('AMD', 'Advanced Micro Devices Inc.'),
 ('AAPL', 'Apple Inc.'),
 ('AMAT', 'Applied Materials Inc.'),
 ('QCOM', 'Qualcomm Inc.')]
```

8.1.2 Data Visualization

Time-Series Stock Price Plot for 12 Companies with Highest Share of Sale in China

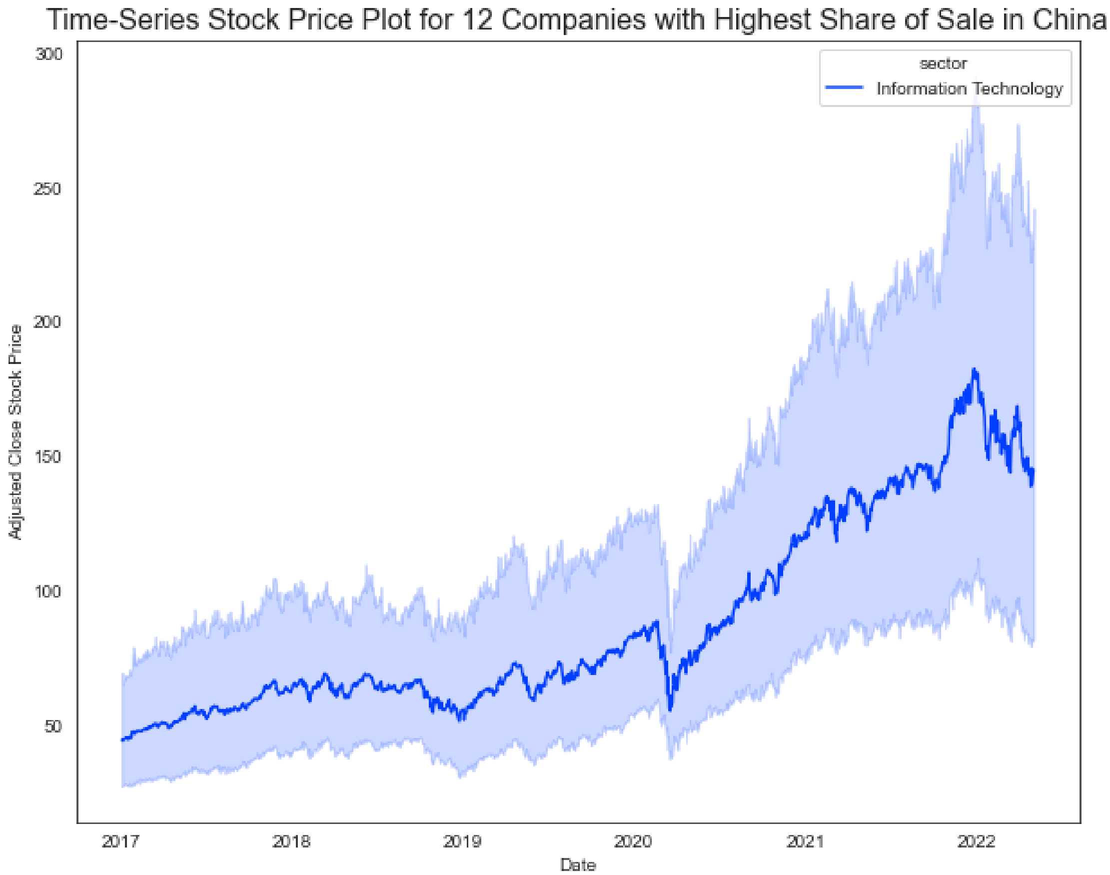
[119]:
```
plt.figure(figsize = (10, 8))
sns.lineplot(x="date", y = 'adjustedclose', hue="symbol", palette = 'Paired',␣
 ↪data = df8)
```

```
plt.xlabel('Date')
plt.ylabel('Adjusted Close Stock Price')
plt.title('Time-Series Stock Price Plot for 12 Companies with Highest Share of␣
  ↪Sale in China', fontsize = 16)
plt.show()
```



Time-Series Stock Price Plot for 12 Companies with Highest Share of Sale in China

[120]:
```
plt.figure(figsize = (10, 8))
sns.lineplot(x="date", y = 'adjustedclose', hue="sector", palette = 'bright',␣
  ↪data = df8)
plt.xlabel('Date')
plt.ylabel('Adjusted Close Stock Price')
plt.title('Time-Series Stock Price Plot for 12 Companies with Highest Share of␣
  ↪Sale in China', fontsize = 16)
plt.show()
```



The 12 companies with the highest share of sales in China are almost information technology companies. And the stock price change tendencies tend to be similar.

8.1.3 Data Analysis

[121]:
```
# Amphenol Corp. Class A
APH = df8[df8.symbol == 'APH'].set_index(['date'])
# Intel Corp.
INTC = df8[df8.symbol == 'INTC'].set_index(['date'])
# Micron Technology Inc.
MU = df8[df8.symbol == 'MU'].set_index(['date'])
# Broadcom Ltd.
AVGO = df8[df8.symbol == 'AVGO'].set_index(['date'])
# Texas Instruments Inc.
TXN = df8[df8.symbol == 'TXN'].set_index(['date'])
# Corning Inc
GLW = df8[df8.symbol == 'GLW'].set_index(['date'])
# Western Digital Corp.
WDC = df8[df8.symbol == 'WDC'].set_index(['date'])
```

```
# Nvidia Corp.
NVDA = df8[df8.symbol == 'NVDA'].set_index(['date'])
# Advanced Micro Devices Inc.
AMD = df8[df8.symbol == 'AMD'].set_index(['date'])
# Apple Inc.
AAPL = df8[df8.symbol == 'AAPL'].set_index(['date'])
# Applied Materials Inc.
AMAT = df8[df8.symbol == 'AMAT'].set_index(['date'])
# Qualcomm Inc.
QCOM = df8[df8.symbol == 'QCOM'].set_index(['date'])
```

[122]:
```
# Amphenol Corp. Class A
APH1d = np.diff(APH.adjustedclose)
# Intel Corp.
INTC1d = np.diff(INTC.adjustedclose)
# Micron Technology Inc.
MU1d = np.diff(MU.adjustedclose)
# Broadcom Ltd.
AVGO1d = np.diff(AVGO.adjustedclose)
# Texas Instruments Inc.
TXN1d = np.diff(TXN.adjustedclose)
# Corning Inc
GLW1d = np.diff(GLW.adjustedclose)
# Western Digital Corp.
WDC1d = np.diff(WDC.adjustedclose)
# Nvidia Corp.
NVDA1d = np.diff(NVDA.adjustedclose)
# Advanced Micro Devices Inc.
AMD1d = np.diff(AMD.adjustedclose)
# Apple Inc.
AAPL1d = np.diff(AAPL.adjustedclose)
# Applied Materials Inc.
AMAT1d = np.diff(AMAT.adjustedclose)
# Qualcomm Inc.
QCOM1d = np.diff(QCOM.adjustedclose)
```

[123]:
```
dic2 = {'APH1d': APH1d,
       'INTC1d': INTC1d,
       'MU1d': MU1d,
       'AVGO1d': AVGO1d,
       'TXN1d': TXN1d,
       'GLW1d': GLW1d,
       'WDC1d': WDC1d,
       'NVDA1d': NVDA1d,
       'AMD1d': AMD1d,
       'AAPL1d': AAPL1d,
       'AMAT1d': AMAT1d,
```

```
        'QCOM1d': QCOM1d}

diff_stock2 = pd.DataFrame(dic2).set_index(APH.index[1:])
```

[124]:
```
diff_stock2.corr()
```

[124]:

	APH1d	INTC1d	MU1d	AVGO1d	TXN1d	GLW1d	WDC1d \
APH1d	1.000000	0.554443	0.586354	0.682525	0.695802	0.687701	0.515437
INTC1d	0.554443	1.000000	0.568658	0.537787	0.635236	0.491718	0.477131
MU1d	0.586354	0.568658	1.000000	0.610272	0.663791	0.477479	0.675265
AVGO1d	0.682525	0.537787	0.610272	1.000000	0.732737	0.515984	0.454706
TXN1d	0.695802	0.635236	0.663791	0.732737	1.000000	0.595286	0.503309
GLW1d	0.687701	0.491718	0.477479	0.515984	0.595286	1.000000	0.453816
WDC1d	0.515437	0.477131	0.675265	0.454706	0.503309	0.453816	1.000000
NVDA1d	0.512636	0.385342	0.517104	0.624587	0.572283	0.328301	0.291919
AMD1d	0.476918	0.342456	0.487191	0.566220	0.537589	0.326096	0.276868
AAPL1d	0.577050	0.462769	0.452169	0.626259	0.579147	0.421575	0.321376
AMAT1d	0.635977	0.536106	0.707532	0.693326	0.723983	0.486482	0.498751
QCOM1d	0.593024	0.473530	0.557458	0.669334	0.641393	0.448999	0.371309

	NVDA1d	AMD1d	AAPL1d	AMAT1d	QCOM1d
APH1d	0.512636	0.476918	0.577050	0.635977	0.593024
INTC1d	0.385342	0.342456	0.462769	0.536106	0.473530
MU1d	0.517104	0.487191	0.452169	0.707532	0.557458
AVGO1d	0.624587	0.566220	0.626259	0.693326	0.669334
TXN1d	0.572283	0.537589	0.579147	0.723983	0.641393
GLW1d	0.328301	0.326096	0.421575	0.486482	0.448999
WDC1d	0.291919	0.276868	0.321376	0.498751	0.371309
NVDA1d	1.000000	0.750125	0.584230	0.641828	0.633838
AMD1d	0.750125	1.000000	0.544282	0.586245	0.605426
AAPL1d	0.584230	0.544282	1.000000	0.531770	0.579035
AMAT1d	0.641828	0.586245	0.531770	1.000000	0.660180
QCOM1d	0.633838	0.605426	0.579035	0.660180	1.000000