FIN3210 Week 4 Assignment Report

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Abstract

This report constructs two indexes for different purposes, and presents the indexes into several graphs and interpretations.

Data Preprocessing

The preprocessing procedures and some interpretations of the code are described in each code blocks in the appendix, please check.

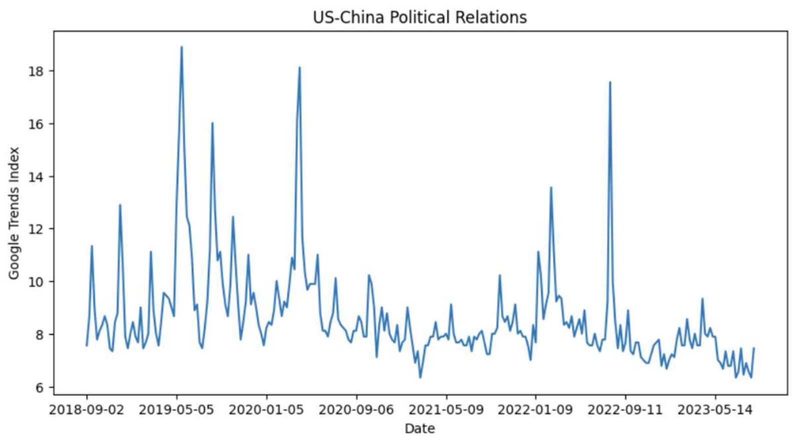
Questions

1) Using Google Trends (https://trends.google.com/trends/?geo=US), construct a weekly index to capture political relations between U.S. and China from the US perspective, draw the variable in a graph, and discuss its time-series variation.

For this question, I selected 10 distinct words to describe the relationship between U.S. and China from the US perspective, which are Tariffs, South China Sea, Huawei, Trade War, Made in China, Tibet, Hong Kong, Taiwan, U.S.-China, 5G. Most of which are relevant to name of "controvertible" area of China, and some of them are relevant to the new technology developed by China, which is somewhat more advanced than the same kind of techs in the US, and the rest are relevant to the trade between these two countries. It can be necessary to analyze the political relation using index relevant to these keywords. Below is a correlation map of these words, one thing to be mentioned is that the U.S-China keyword is dropped since there's not much information retracted by the Google Trend. By the correlation coefficient, we can see that these words are not so correlated, which means they can describe the relationship from quite different perspective.

	Tariffs	South China Sea	Huawei	Trade War	Made in China	Tibet	Hong Kong	Taiwan	5G
Tariffs	1.000000	0.064757	0.508916	0.887880	-0.133332	0.059853	0.293850	-0.151932	-0.372672
South China Sea	0.064757	1.000000	0.031378	0.046260	0.167426	0.068504	-0.009325	0.073614	-0.024228
Huawei	0.508916	0.031378	1.000000	0.528077	-0.212102	0.045272	0.220016	-0.214053	-0.350924
Trade War	0.887880	0.046260	0.528077	1.000000	-0.156281	0.088927	0.408141	-0.150847	-0.433250
Made in China	-0.133332	0.167426	-0.212102	-0.156281	1.000000	0.095936	-0.071522	0.113407	0.405090
Tibet	0.059853	0.068504	0.045272	0.088927	0.095936	1.000000	-0.080955	0.191257	-0.056895
Hong Kong	0.293850	-0.009325	0.220016	0.408141	-0.071522	-0.080955	1.000000	-0.097992	-0.289373
Taiwan	-0.151932	0.073614	-0.214053	-0.150847	0.113407	0.191257	-0.097992	1.000000	0.196832
5G	-0.372672	-0.024228	-0.350924	-0.433250	0.405090	-0.056895	-0.289373	0.196832	1.000000

The time series of the overall constructed index is shown below. We can see that the political relation between these two countries are at the pinnacle in 2019, 2020 and 2022. During 2019 and 2020, there were trade wars and the burst of the pandemic, which made the index relatively high. In the late 2022, the pinnacle happened because of the Taiwan issue.



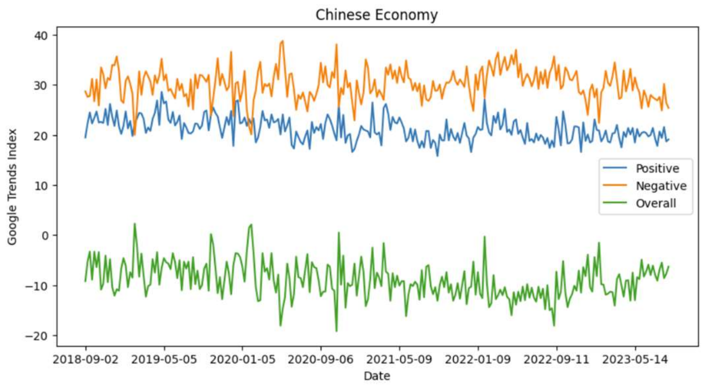
2) Using Baidu Index (http://index.baidu.com/) or Google Trends (https://trends.google.com/trends/?geo=US), construct an index to capture investor sentiment in the Chinese market, draw the variable in a graph, and discuss its time-series variation.

For this question, I provide 10 positive words and 10 negative words to describe the financial market sentiment in China. The positives are boom, buy, credit, gain, profit, reward, surge, rise, boost, win. The negatives are bankrupt, capital, decline, default, fall, inflation, liability, loss, recession, short. All of them have quite evident pos or neg sentiments. Then I use these words to aggregate a word-level search sentiment index. First, I perform an OLS to discover the linear relationship between the return and the sentiment index from last week. The result is shown below. Unfortunately, the p-values are so large that we are inconclusive about this relationship. This maybe can be interpreted as the sentiments are with some delay, since it is constructed based on weekly trends, and within the week, the sentiments have been already digested by the market, leading to no predictive power to the next week. Another possibility is that the words are not enough to cover the whole sentiment, which maybe improved by adding more words to construct the index.

Dep. Variable:	week_ret	**R-squared:**	0.002
Model:	OLS	**Adj. R-squared:**	-0.002
Method:	Least Squares	**F-statistic:**	0.5385
Date:	Sat, 14 Oct 2023	**Prob (F-statistic):**	0.464
Time:	18:18:13	**Log-Likelihood:**	601.44
No. Observations:	254	**AIC:**	-1199.
Df Residuals:	252	**BIC:**	-1192.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0035	0.004	0.862	0.389	-0.005	0.012
total_index	0.0003	0.000	0.734	0.464	-0.001	0.001

Omnibus:	4.268	**Durbin-Watson:**	2.123
Prob(Omnibus):	0.118	**Jarque-Bera (JB):**	4.990
Skew:	-0.118	**Prob(JB):**	0.0825
Kurtosis:	3.645	**Cond. No.**	28.0



The time series is also attached above. We can see that the Chinese Economy in the recent five years was quite fatigue. This was corroborated by the Shanghai main market index, which remains at 3000 points over the years. There're some of the points that the positive sentiment transcends the negative one. We can observe that during the whole year 2019, there was a quite bull trend in the A share market, so the positive market somewhat went beyond the negative one. Nevertheless, after the COVID-19 pandemic occurred, since the manufacturing process are retarded, the economy remained gloomy, which reflects the comparative numerical value of the positive sentiment and the negative sentiment of the market.

FIN3210 Week 4 Assignment

Ma Kexuan

October 14, 2023

[1]:
```
import pandas as pd
import numpy as np
from pytrends.request import TrendReq
import matplotlib.pyplot as plt
from matplotlib.pyplot import MultipleLocator
import time
import warnings
warnings.filterwarnings("ignore")
import statsmodels.api as sm
```

[2]:
```
def extract_trends(wordlist, location):
    """
    Extract the google trends data of the given word list
    :param wordlist: list of words
    :return: pandas dataframe
    """
    count = 0
    for i in range(0, len(wordlist), 5):
        pytrend = TrendReq()
        pytrend.build_payload(kw_list=wordlist[i:i+5], timeframe='2018-9-1␣
 ↪2023-8-31', geo = location)
        py_res = pytrend.interest_over_time().reset_index()
        if count == 0:
            py_res.drop(columns=['isPartial'], axis=1, inplace=True)
            res = py_res
        else:
            py_res.drop(columns=['isPartial', 'date'], axis=1, inplace=True)
            res = pd.concat([res, py_res], axis=1)
        count += 1
        time.sleep(120)
    return res
```

0.1 Q1. Using Google Trends (https://trends.google.com/trends/?geo=US), construct a weekly index to capture political relations between U.S. and China from the US perspective, draw the variable in a graph, and discuss its time-series variation

[3]:
```
us_china_keywords = [
    "Tariffs",
    "South China Sea",
    "Huawei",
    "Trade War",
    "Made in China",
    "Tibet",
    "Hong Kong",
    "Taiwan",
    "U.S.-China",
    "5G"
]
```

[4]:
```
# Use to extract data from Google Trend
# res = extract_trends(us_china_keywords, 'US')
# res
```

[5]:
```
origin_index = pd.read_csv('us_china.csv')
# Drop it since it contains no information according to the data
origin_index.drop(['U.S.-China'], axis=1, inplace=True)
index_list = origin_index.columns.tolist()[1:]
# Construct the index
origin_index['total_index'] = origin_index[index_list].mean(axis=1)
origin_index
```

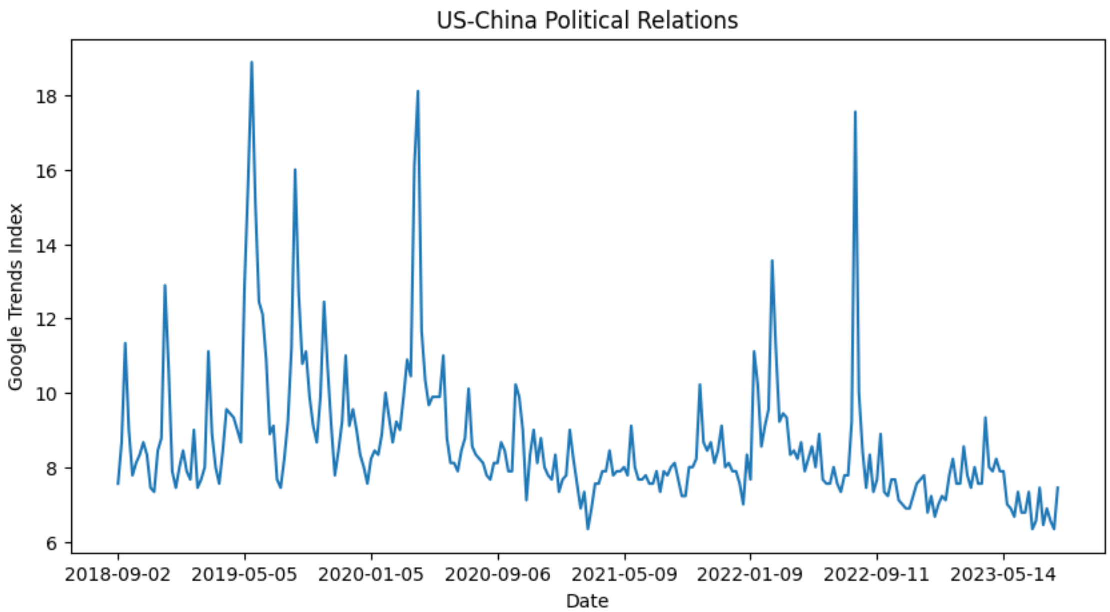
[5]:
```
           date  Tariffs  South China Sea  Huawei  Trade War  Made in China  \
0    2018-09-02       11                2      17          7              5
1    2018-09-09       11                2      19          8              5
2    2018-09-16       25                2      17         12              5
3    2018-09-23       15                2      19         10              5
4    2018-09-30       10                4      16          7              5
..          …        …              …       …         …            …
256  2023-07-30        1                1       6          1              5
257  2023-08-06        1                1       7          1              5
258  2023-08-13        2                1       6          2              5
259  2023-08-20        2                1       6          2              5
260  2023-08-27        3                2       9          3              6

     Tibet  Hong Kong  Taiwan  5G  total_index
0        1         16       6   3     7.555556
1        1         18       7   7     8.666667
2        1         24       9   7    11.333333
3        1         17       7   5     9.000000
```

```
4          1           15        6    6      7.777778
..       …          …        …    ..         …
256        1           14       10   19      6.444444
257        1           14       11   21      6.888889
258        1           13       10   19      6.555556
259        1           12       10   18      6.333333
260        1           14       10   19      7.444444

[261 rows x 11 columns]
```

[6]:
```python
corr_data = origin_index.drop(columns=['date','total_index'], axis=1)
corr_data.corr()
```

[6]:
```
                  Tariffs  South China Sea    Huawei  Trade War  \
Tariffs          1.000000         0.064757  0.508916   0.887880
South China Sea  0.064757         1.000000  0.031378   0.046260
Huawei           0.508916         0.031378  1.000000   0.528077
Trade War        0.887880         0.046260  0.528077   1.000000
Made in China   -0.133332         0.167426 -0.212102  -0.156281
Tibet            0.059853         0.068504  0.045272   0.088927
Hong Kong        0.293850        -0.009325  0.220016   0.408141
Taiwan          -0.151932         0.073614 -0.214053  -0.150847
5G              -0.372672        -0.024228 -0.350924  -0.433250

                 Made in China     Tibet  Hong Kong    Taiwan        5G
Tariffs              -0.133332  0.059853   0.293850 -0.151932 -0.372672
South China Sea       0.167426  0.068504  -0.009325  0.073614 -0.024228
Huawei               -0.212102  0.045272   0.220016 -0.214053 -0.350924
Trade War            -0.156281  0.088927   0.408141 -0.150847 -0.433250
Made in China         1.000000  0.095936  -0.071522  0.113407  0.405090
Tibet                 0.095936  1.000000  -0.080955  0.191257 -0.056895
Hong Kong            -0.071522 -0.080955   1.000000 -0.097992 -0.289373
Taiwan                0.113407  0.191257  -0.097992  1.000000  0.196832
5G                    0.405090 -0.056895  -0.289373  0.196832  1.000000
```

[7]:
```python
plt.figure(figsize=(10, 5))
plt.plot(origin_index['date'], origin_index['total_index'])
plt.title('US-China Political Relations')
plt.xlabel('Date')
plt.ylabel('Google Trends Index')
x_major_locator=MultipleLocator(35)
ax = plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.show()
```



0.2 Q2. Using Google Trends (https://trends.google.com/trends/?geo=US) or Baidu Index (http://index.baidu.com/), construct an index to capture investor sentiment in the Chinese market, draw the variable in a graph, and discuss its time-series variation.

[8]:
```
positive_words_list = ['boom', 'buy', 'credit', 'gain', 'profit',
                       'reward', 'surge', 'rise', 'boost', 'win']
negative_words_list = ['bankrupt', 'capital', 'decline', 'default', 'fall',
                       'inflation', 'liability', 'loss', 'recession', 'short']
```

[9]:
```
# Use to extract data from Google Trend
# pos_result = extract_trends(positive_words_list, 'CN')
# neg_result = extract_trends(negative_words_list, 'CN')
```

[10]:
```
pos_result = pd.read_csv('positive_words.csv')
neg_result = pd.read_csv('negative_words.csv')
```

[11]:
```
pos_result[positive_words_list].corr()
```

[11]:

	boom	buy	credit	gain	profit	reward	surge \
boom	1.000000	-0.229926	-0.112970	-0.003785	0.078841	0.060229	-0.248064
buy	-0.229926	1.000000	0.459562	-0.054518	-0.241693	-0.099755	0.111902
credit	-0.112970	0.459562	1.000000	-0.024404	-0.070394	-0.018074	0.114787
gain	-0.003785	-0.054518	-0.024404	1.000000	0.135644	-0.002035	-0.010019
profit	0.078841	-0.241693	-0.070394	0.135644	1.000000	0.137452	-0.014305
reward	0.060229	-0.099755	-0.018074	-0.002035	0.137452	1.000000	-0.011389
surge	-0.248064	0.111902	0.114787	-0.010019	-0.014305	-0.011389	1.000000

```
rise     0.002136 -0.042888 -0.079913  0.098343  0.126010  0.030958 -0.156459
boost   -0.093268  0.314673  0.274375 -0.112923 -0.117124 -0.088233 -0.053258
win      0.205413 -0.158791 -0.189805  0.053169  0.105871  0.077464 -0.073554

             rise     boost       win
boom     0.002136 -0.093268  0.205413
buy     -0.042888  0.314673 -0.158791
credit  -0.079913  0.274375 -0.189805
gain     0.098343 -0.112923  0.053169
profit   0.126010 -0.117124  0.105871
reward   0.030958 -0.088233  0.077464
surge   -0.156459 -0.053258 -0.073554
rise     1.000000 -0.158276 -0.006620
boost   -0.158276  1.000000 -0.078053
win     -0.006620 -0.078053  1.000000
```

[12]:
```python
neg_result[negative_words_list].corr()
```

[12]:
```
           bankrupt   capital   decline   default      fall  inflation  \
bankrupt   1.000000  0.172598 -0.074039  0.016845  0.036303  -0.000916
capital    0.172598  1.000000  0.024463 -0.042862  0.079861  -0.062564
decline   -0.074039  0.024463  1.000000  0.029648 -0.040891  -0.058599
default    0.016845 -0.042862  0.029648  1.000000 -0.004481   0.009918
fall       0.036303  0.079861 -0.040891 -0.004481  1.000000  -0.000501
inflation -0.000916 -0.062564 -0.058599  0.009918 -0.000501   1.000000
liability  0.087584  0.056222 -0.022007 -0.051609  0.015856  -0.057728
loss       0.076411  0.100815  0.011757  0.265133 -0.067665   0.003452
recession -0.116179 -0.093051  0.211840 -0.130195 -0.006859   0.169077
short      0.194869  0.146783 -0.029136  0.098861 -0.026079   0.192370

           liability      loss  recession     short
bankrupt    0.087584  0.076411  -0.116179  0.194869
capital     0.056222  0.100815  -0.093051  0.146783
decline    -0.022007  0.011757   0.211840 -0.029136
default    -0.051609  0.265133  -0.130195  0.098861
fall        0.015856 -0.067665  -0.006859 -0.026079
inflation  -0.057728  0.003452   0.169077  0.192370
liability   1.000000  0.004283   0.063456  0.048090
loss        0.004283  1.000000   0.006106  0.098029
recession   0.063456  0.006106   1.000000 -0.041244
short       0.048090  0.098029  -0.041244  1.000000
```

[13]:
```python
pos_result['pos_total_index'] = pos_result[positive_words_list].mean(axis=1)
neg_result['neg_total_index'] = neg_result[negative_words_list].mean(axis=1)
neg_result.drop(['date'], axis=1, inplace=True)
result = pd.concat([pos_result, neg_result], axis=1)
# Calculate the overall sentiment index based on pos&neg
```

```python
result['total_index'] = result['pos_total_index'] - result['neg_total_index']
result['y_w'] = pd.to_datetime(result['date']).dt.strftime('%Y-%U')
result
```

[13]:

```
           date  boom  buy  credit  gain  profit  reward  surge  rise  boost  \
0    2018-09-02     4   45      26     3       5       0      8    12     39
1    2018-09-09     4   55      32     5       9       3     11    11     42
2    2018-09-16     7   55      34     9      10       6      5    18     35
3    2018-09-23     3   58      31     9       5       4     16    22     30
4    2018-09-30     0   71      39     6       8       7     16     9     32
..          …     …    …       …     …       …       …      …     …      …
256  2023-07-30     4   48      31     7       6       8     16    16     21
257  2023-08-06     3   42      26     9       8       5     22    18     24
258  2023-08-13     0   43      36    11       9      11     15    12     27
259  2023-08-20     4   42      25     6       5       6     10    18     18
260  2023-08-27     4   51      20     6       4       7     16    13     21

     …  default  fall  inflation  liability  loss  recession  short  \
0    …       78    17          0          0    54          4     74
1    …       77    29         10          0    55          0     58
2    …       69    26         15         12    49          0     57
3    …       84    41          8          6    57          0     66
4    …       37    43         14          0    48          0     75
..   …        …     …          …          …     …          …      …
256  …       63    27         14          8    55          5     45
257  …       59    21          6          8    52          3     55
258  …       61    33         12          4    63          5     60
259  …       57    27          5          8    50          6     58
260  …       45    15          5          3    56          3     64

     neg_total_index  total_index      y_w
0               28.7         -9.2  2018-35
1               27.6         -5.3  2018-36
2               27.8         -3.3  2018-37
3               31.2         -8.9  2018-38
4               26.7         -3.3  2018-39
..               …            …        …
256             27.6         -6.9  2023-31
257             24.9         -5.5  2023-32
258             30.2         -8.6  2023-33
259             26.4         -7.7  2023-34
260             25.4         -6.3  2023-35

[261 rows x 25 columns]
```

[14]:

```python
ret_data = pd.read_csv('return.csv')
# Calculate the weekly return of Shanghai market index
```

```python
ret_data['Idxtrd08'] = ret_data['Idxtrd08']/100
ret_data['year_week'] = pd.to_datetime(ret_data['Idxtrd01']).dt.
    ↪strftime('%Y-%U')
ret_data['cum_ret'] = 1 + ret_data['Idxtrd08']
ret_idx = ret_data.groupby('year_week').agg({'cum_ret': np.prod}).reset_index()
ret_idx['week_ret'] = ret_idx['cum_ret'] - 1
ret_idx
```

[14]:

```
    year_week   cum_ret  week_ret
0     2018-35  0.991580 -0.008420
1     2018-36  0.992355 -0.007645
2     2018-37  1.043199  0.043199
3     2018-38  1.008531  0.008531
4     2018-40  0.923995 -0.076005
..        …         …         …
251   2023-31  1.003711  0.003711
252   2023-32  0.969941 -0.030059
253   2023-33  0.982035 -0.017965
254   2023-34  0.978328 -0.021672
255   2023-35  1.018212  0.018212

[256 rows x 3 columns]
```

[15]:

```python
reg_data = pd.merge(result, ret_idx, left_on='y_w', right_on='year_week',␣
    ↪how='left')
reg_data = reg_data[['year_week', 'total_index', 'week_ret']]
reg_data.dropna(inplace=True)
reg_data
```

[15]:

```
    year_week  total_index  week_ret
0     2018-35         -9.2 -0.008420
1     2018-36         -5.3 -0.007645
2     2018-37         -3.3  0.043199
3     2018-38         -8.9  0.008531
5     2018-40         -6.4 -0.076005
..        …           …         …
256   2023-31         -6.9  0.003711
257   2023-32         -5.5 -0.030059
258   2023-33         -8.6 -0.017965
259   2023-34         -7.7 -0.021672
260   2023-35         -6.3  0.018212

[254 rows x 3 columns]
```

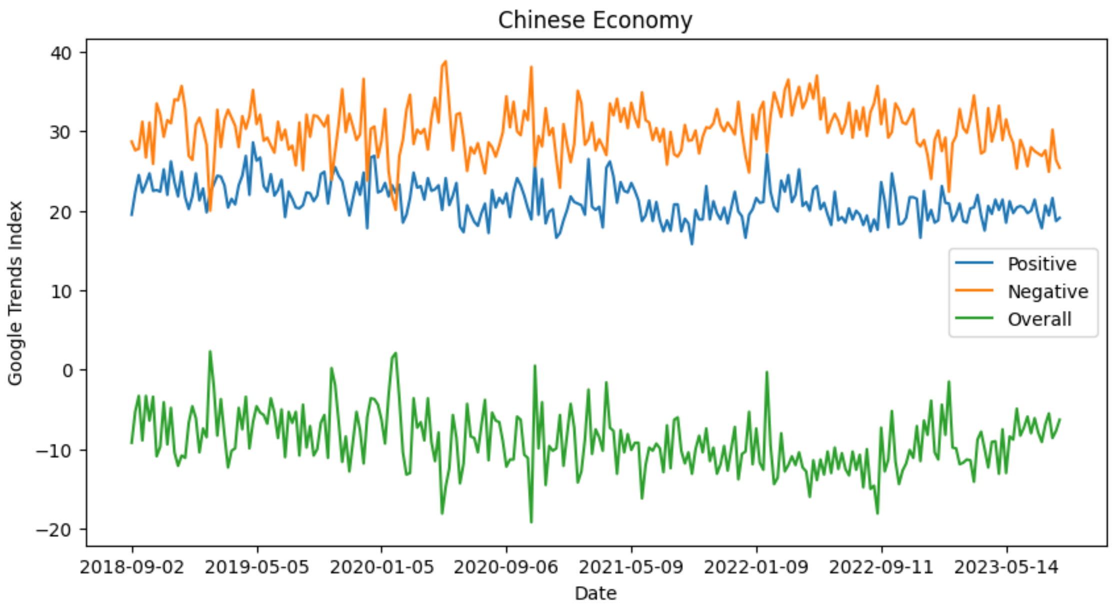
[16]:

```python
# Perform the OLS Regression
X = reg_data['total_index']
y = reg_data['week_ret']
```

```
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[16]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               week_ret   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.002
Method:                 Least Squares   F-statistic:                    0.5385
Date:                Sat, 14 Oct 2023   Prob (F-statistic):              0.464
Time:                        18:18:13   Log-Likelihood:                 601.44
No. Observations:                 254   AIC:                            -1199.
Df Residuals:                     252   BIC:                            -1192.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const           0.0035      0.004      0.862      0.389      -0.005       0.012
total_index     0.0003      0.000      0.734      0.464      -0.001       0.001
==============================================================================
Omnibus:                        4.268   Durbin-Watson:                   2.123
Prob(Omnibus):                  0.118   Jarque-Bera (JB):                4.990
Skew:                          -0.118   Prob(JB):                       0.0825
Kurtosis:                       3.645   Cond. No.                         28.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[17]:
```
plt.figure(figsize=(10, 5))
plt.plot(result['date'], result['pos_total_index'], label='Positive')
plt.plot(result['date'], result['neg_total_index'], label='Negative')
plt.plot(result['date'], result['total_index'], label='Overall')
plt.title('Chinese Economy')
plt.xlabel('Date')
plt.ylabel('Google Trends Index')
plt.legend()
x_major_locator=MultipleLocator(35)
ax = plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.show()
```


Chinese Economy
Google Trends Index
40
30
20
10
0
−10
−20
Positive
Negative
Overall
2018-09-02
2019-05-05
2020-01-05
2020-09-06
2021-05-09
2022-01-09
2022-09-11
2023-05-14
Date