Stein_QTS_Project

March 7, 2023

1 QTS Final Version

[ ]:
```
from matplotlib import pyplot as plt

import pandas as pd
import numpy as np
import functools
import statistics
import math
import os
from datetime import datetime, timedelta
import random
import scipy as sp
import warnings
import gzip
from collections import Counter
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
warnings.filterwarnings("ignore", category=UserWarning, module="pandas")
pd.options.mode.chained_assignment = None
import statsmodels
from statsmodels.regression.rolling import RollingOLS
import requests
import matplotlib as mpl
import statsmodels.formula.api as smf
import statsmodels.api as sm
import seaborn as sns
import scipy.stats as stats
plt.style.use('seaborn')
mpl.rcParams['font.family'] = 'serif'
```

2 Senate and House of Representatives Trading Data

[ ]:
```
data_senate = pd.read_csv('C:/Users/dcste/OneDrive/Economics_Research/
↪Economics_Research/trade_transactions.csv')
data_senate['disclosure_date'] = pd.to_datetime(data_senate['disclosure_date'])
```

```python
data_senate = data_senate.set_index(data_senate['disclosure_date'])
data_senate = data_senate.sort_index()
data_senate = data_senate.dropna(subset=['ticker'])
data_senate
```

[ ]:

```
                transaction_date disclosure_date   owner ticker  \
disclosure_date
2014-01-31             1/24/2014      2014-01-31  Spouse     GE
2014-01-31             1/24/2014      2014-01-31  Spouse    CRM
2014-01-31             1/24/2014      2014-01-31  Spouse     FB
2014-01-31             1/28/2014      2014-01-31  Spouse   EBAY
2014-01-31             1/29/2014      2014-01-31  Spouse      C
…                            …             …     …     …
2023-02-14              1/5/2023      2023-02-14   Joint      X
2023-02-14              1/5/2023      2023-02-14   Joint      X
2023-02-14              1/5/2023      2023-02-14   Joint      X
2023-02-14              1/5/2023      2023-02-14   Joint    CLF
2023-02-14             1/11/2023      2023-02-14   Joint    TXN

                                                 asset_description  \
disclosure_date
2014-01-31                             General Electric Company (NYSE)
2014-01-31                                  Salesforce.com, Inc (NYSE)
2014-01-31                                     Facebook, Inc. (NASDAQ)
2014-01-31                                          eBay Inc. (NASDAQ)
2014-01-31                                    Citigroup, Inc. (NYSE)
…                                                                 …
2023-02-14                   United States Steel Corporation Common Stock
2023-02-14                   United States Steel Corporation Common Stock
2023-02-14                   United States Steel Corporation Common Stock
2023-02-14               Cleveland-Cliffs Inc. Common Stock <div class=…
2023-02-14               Texas Instruments Incorporated - Common Stock …

                   asset_type             type              amount comment  \
disclosure_date
2014-01-31                NaN   Sale (Partial)    $1,001 - $15,000      --
2014-01-31                NaN         Purchase    $1,001 - $15,000      --
2014-01-31                NaN         Purchase    $1,001 - $15,000      --
2014-01-31                NaN   Sale (Partial)    $1,001 - $15,000      --
2014-01-31                NaN   Sale (Partial)    $1,001 - $15,000      --
…                         …              …                 …     …
2023-02-14              Stock   Sale (Partial)    $1,001 - $15,000      --
2023-02-14              Stock   Sale (Partial)   $15,001 - $50,000      --
2023-02-14              Stock   Sale (Partial)  $50,001 - $100,000      --
2023-02-14       Stock Option   Sale (Partial)   $15,001 - $50,000      --
2023-02-14       Stock Option   Sale (Partial)    $1,001 - $15,000      --
```

```
                            senator  \
disclosure_date
2014-01-31        Susan M. Collins
2014-01-31        Susan M. Collins
2014-01-31        Susan M. Collins
2014-01-31        Susan M. Collins
2014-01-31        Susan M. Collins
…                              …
2023-02-14        Tommy Tuberville
2023-02-14        Tommy Tuberville
2023-02-14        Tommy Tuberville
2023-02-14        Tommy Tuberville
2023-02-14        Tommy Tuberville

                                                        ptr_link  \
disclosure_date
2014-01-31        https://efdsearch.senate.gov/search/view/ptr/5…
2014-01-31        https://efdsearch.senate.gov/search/view/ptr/5…
2014-01-31        https://efdsearch.senate.gov/search/view/ptr/5…
2014-01-31        https://efdsearch.senate.gov/search/view/ptr/5…
2014-01-31        https://efdsearch.senate.gov/search/view/ptr/5…
…                                                             …
2023-02-14        https://efdsearch.senate.gov/search/view/ptr/9…
2023-02-14        https://efdsearch.senate.gov/search/view/ptr/9…
2023-02-14        https://efdsearch.senate.gov/search/view/ptr/9…
2023-02-14        https://efdsearch.senate.gov/search/view/ptr/9…
2023-02-14        https://efdsearch.senate.gov/search/view/ptr/9…

                      party state  \
disclosure_date
2014-01-31        Republican    ME
2014-01-31        Republican    ME
2014-01-31        Republican    ME
2014-01-31        Republican    ME
2014-01-31        Republican    ME
…                        …   …
2023-02-14        Republican    AL
2023-02-14        Republican    AL
2023-02-14        Republican    AL
2023-02-14        Republican    AL
2023-02-14        Republican    AL

                                                      industry  \
disclosure_date
2014-01-31                      Consumer Electronics/Appliances
2014-01-31                Computer Software: Prepackaged Software
2014-01-31        Computer Software: Programming, Data Processing
```

```
2014-01-31                                    Business Services
2014-01-31                                          Major Banks
…                                                       …
2023-02-14                                       Steel/Iron Ore
2023-02-14                                       Steel/Iron Ore
2023-02-14                                       Steel/Iron Ore
2023-02-14                                      Precious Metals
2023-02-14                                       Semiconductors

                           sector  Unnamed: 15  Unnamed: 16  Unnamed: 17  \
disclosure_date
2014-01-31                 Energy          NaN          NaN          NaN
2014-01-31             Technology          NaN          NaN          NaN
2014-01-31             Technology          NaN          NaN          NaN
2014-01-31          Miscellaneous          NaN          NaN          NaN
2014-01-31                Finance          NaN          NaN          NaN
…                             …          …          …          …
2023-02-14            Industrials          NaN          NaN          NaN
2023-02-14            Industrials          NaN          NaN          NaN
2023-02-14            Industrials          NaN          NaN          NaN
2023-02-14      Basic Industries          NaN          NaN          NaN
2023-02-14             Technology          NaN          NaN          NaN

                 Unnamed: 18  Unnamed: 19
disclosure_date
2014-01-31               NaN          NaN
2014-01-31               NaN          NaN
2014-01-31               NaN          NaN
2014-01-31               NaN          NaN
2014-01-31               NaN          NaN
…                      …          …
2023-02-14               NaN          NaN
2023-02-14               NaN          NaN
2023-02-14               NaN          NaN
2023-02-14               NaN          NaN
2023-02-14               NaN          NaN

[7463 rows x 20 columns]
```

[ ]:

```
data_house = pd.read_csv('C:/Users/dcste/OneDrive/Economics_Research/
↪Economics_Research/all_transactions_house (2).csv')
data_house['disclosure_date'] = pd.to_datetime(data_house['disclosure_date'])
data_house = data_house.set_index(data_house['disclosure_date'])
data_house = data_house.sort_index()
data_house = data_house.dropna(subset=['ticker'])
data_house = data_house[data_house['ticker'] != "--"]
```

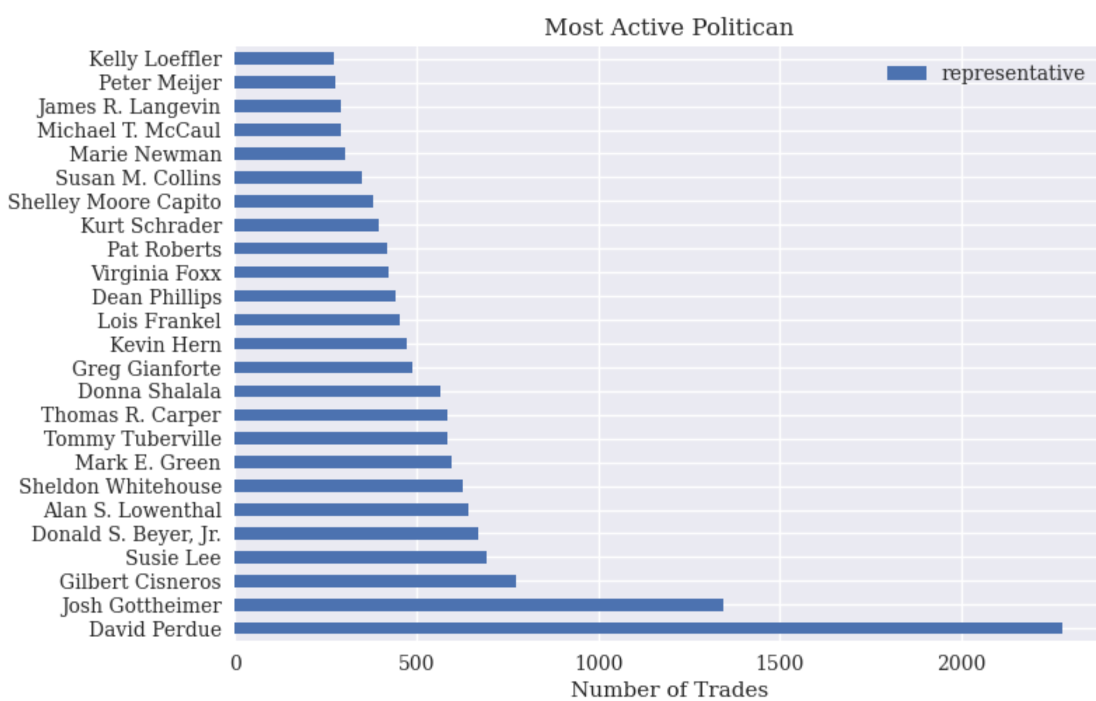
```
data_house = data_house[['disclosure_date', 'transaction_date', 'ticker',␣
↪'asset_description', 'type', 'amount', 'representative', 'party','state',␣
↪'industry' , 'sector' ]]
```

```
[ ]: data_senate = data_senate[['disclosure_date', 'transaction_date', 'ticker',␣
↪'asset_description', 'type', 'amount', 'senator', 'party','state',␣
↪'industry' , 'sector' ]]
data = pd.concat([data_house, data_senate]).sort_index()
data['representative'] = data['representative'].fillna(data['senator'])
del data['senator']
```

```
[ ]: prices = pd.read_csv('C:/Users/dcste/OneDrive/Economics_Research/
↪Economics_Research/project_price_df.csv')
most_frequent_tickers = pd.DataFrame(data['ticker'].value_counts()).iloc[:20,:]
most_frequent_sector = pd.DataFrame(data['sector'].value_counts())
most_frequent_politician = pd.DataFrame(data['representative'].value_counts()).
↪iloc[:25,:]
```

```
[ ]: most_frequent_politician.plot.barh(stacked = 'True',title = 'Most Active␣
↪Politican')
plt.xlabel('Number of Trades')
plt.legend()
```

```
[ ]: <matplotlib.legend.Legend at 0x1d6bbd9c100>
```



3 Importing Important Economic & Financial Variables

[ ]:
```
import quandl
import fredapi
apikey = 'J_fXGeVW_zC6RaDeJSQv'
quandl.ApiConfig.api_key = apikey
api_fred = 'caf2a437b55be8f56406870c1bed3521'
fred = fredapi.Fred(api_key= api_fred)
```

[ ]:
```
period_begin = '2004-01-01'
end_date = data.index[-1]
```

[ ]:
```
market = quandl.get_table('QUOTEMEDIA/PRICES', ticker = 'SPY',qopts =␣
  ↪{'columns' : ['adj_close','date']}, date = {'gte':period_begin,'lte':
  ↪end_date}).set_index('date').sort_index()
MARKET_RETURNS = market.resample('M').last().pct_change()
MARKET_RETURNS.columns = ['MKT_RETS']

interest_rates = quandl.get('YC/USA', start_date = period_begin,end_date =␣
  ↪end_date)[['1-Month','3-Month','10-Year']]*(1/100)
interest_rates['term_spread'] =␣
  ↪interest_rates['10-Year']-interest_rates['3-Month']
interest_rates = interest_rates.resample('M').last()
spy_earnings_yield = quandl.get('MULTPL/SP500_EARNINGS_YIELD_MONTH', start_date␣
  ↪= period_begin, end_date = end_date).rename(columns={'Value':'MKT_EPS'})
consumer_sentiment = quandl.get('UMICH/SOC1',start_date = period_begin,␣
  ↪end_date= end_date).rename(columns={'Value':'Industrial_Production'}).
  ↪pct_change().fillna(0)
```

[ ]:
```
oil  = quandl.get('OPEC/ORB', start_date = period_begin, end_date=end_date).
  ↪rename(columns={'Value':'OPEC_Crude_Price'})
oil = oil.resample('M').last()
oil_change = oil.pct_change()
inflation = quandl.get('RATEINF/CPI_USA', start_date = '2002-01-01', end_date =␣
  ↪end_date).rename(columns={'Value':'CPI'})
inflation_rets = inflation.pct_change()
inflation['inflation_shift'] = inflation.shift(12)
inflation['YoY_Change'] = (inflation['CPI']/inflation['inflation_shift'])-1
inflation.dropna(inplace=True)
```

[ ]:
```
# Downloading AAA and BAA corporate bond yield from FRED WEBSIDE
AAA = pd.DataFrame(fred.get_series('DAAA'), columns = ['AAA_Yield'])*(1/100)
BAA = pd.DataFrame(fred.get_series('DBAA'), columns=['BAA_Yield'])*(1/100)
corporate_bond_yields = BAA.join(AAA, how = 'inner')
corporate_bond_yields = corporate_bond_yields.fillna(corporate_bond_yields.
  ↪mean())
```

```
corporate_bond_yields['dsspread'] = corporate_bond_yields.BAA_Yield -␣
↪corporate_bond_yields.AAA_Yield
corporate_bonds = corporate_bond_yields.resample('M').last()
```

[ ]:
```
mprices = market.resample('M').last()
spy_mend_eps = spy_earnings_yield.resample('M').last()
spy_mend_eps = spy_mend_eps.rolling(12).sum()
EPRATIO = pd.DataFrame(np.log(spy_mend_eps).values - np.log(mprices).values,␣
↪columns=['EPRATIO'], index = mprices.index)
```

[ ]:
```
TB3_Rate_Lag1 = interest_rates[['3-Month']].shift(3)
TB3_Rate_Lag1.columns = ['Three_M_TBill_Lag3']
tsspread_lag1 = interest_rates[['term_spread']].shift(3)
tsspread_lag1.columns = ['term_spread_lag3']
dsspread_lag1 = corporate_bonds[['dsspread']].shift(6)
dsspread_lag1.columns = ['dsspread_lag6']
epratio_lag1 = EPRATIO.shift(1)
epratio_lag1.columns = ['epratio_lag1']
consumer_sentiment_lag1 = consumer_sentiment.shift(3)
oil_lag =  oil_change.shift(2)
oil_lag.columns = ['Oil_Rets_lag2']
oil_rets_sq = (oil_change.shift(2))**2
oil_rets_sq.columns =['Oil_Rets_Squared']
inflation_lag2 = inflation[['YoY_Change']].shift(2)
inflation_lag2.columns = ['Inflation_YOY_lag2']
inflation_yoy_sq = (inflation[['YoY_Change']].shift(2))**2
inflation_yoy_sq.columns = ['Inflation_YOY_Squared']

consumer_sentiment_lag1.columns = ['UMICH_Consumer_Sentiment_lag3']
```

3.1 Importing Tickers

[ ]:
```
trade_strat_tickers = ['SPY','SQQQ','TQQQ','TTT','UPRO','SDS']
trade_data = quandl.get_table('QUOTEMEDIA/PRICES', ticker =␣
↪trade_strat_tickers, qopts = {'columns':
↪['date','ticker','adj_close']},paginate = True, date = {'gte':
↪'2000-01-01','lte':'2023-03-01'}).set_index('date').sort_index()
trade_df_full = trade_data.pivot_table(columns='ticker',values = 'adj_close',␣
↪index = trade_data.index)
trade_df_cleaned = trade_data.pivot_table(columns='ticker',values =␣
↪'adj_close', index = trade_data.index).dropna()
trade_df_daily_rets = trade_df_cleaned.pct_change().dropna()
trade_df_monthly_rets = trade_df_cleaned.resample('M').last().pct_change().
↪dropna()
```

```
[ ]: # Getting Funding Rates for taking short positions
repo = (quandl.get('YC/USA1M', start_date = '2000-01-01', end_date =␣
 ↪'2023-03-01', returns = 'pandas')-1)*(1/100)
repo.columns = ['Funding_Rate']
```

```
[ ]: def filter_trade_type(trade_type:str):
    if trade_type == 'Purchase':
        trade_type = 'Buy'
    elif trade_type == 'purchase':
        trade_type = 'Buy'
    elif trade_type == 'sale':
        trade_type = 'Sell'
    elif trade_type == 'Sale (Partial)':
        trade_type = 'Sell'
    elif trade_type == 'sale_partial':
        trade_type = 'Sell'
    elif trade_type == 'Sale (Full)':
        trade_type = 'Sell'
    elif trade_type == 'sale_full':
        trade_type = 'Sell'
    return trade_type
```

```
[ ]: data_copy = data.copy()
```

```
[ ]: data_copy['type']  = data_copy['type'].apply(filter_trade_type)
data_copy = data_copy[(data_copy.type == "Buy")|(data_copy.type == "Sell")]
```

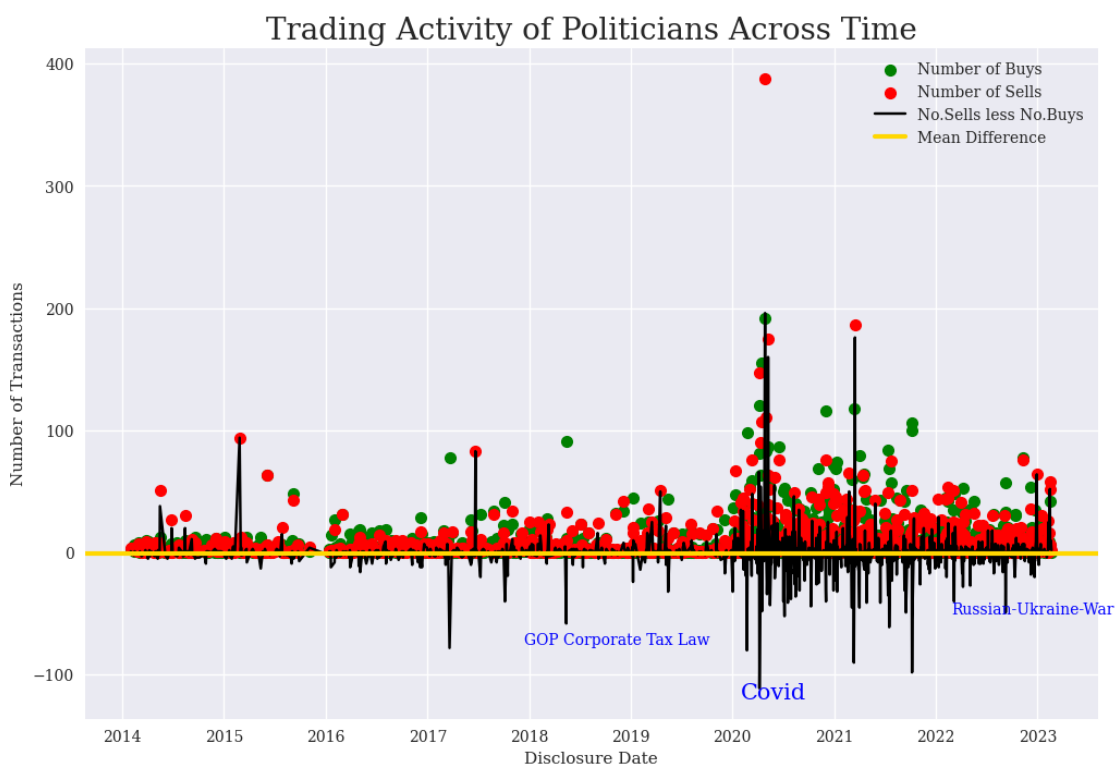
- Constructing PTI **Person-Based-Trading Index**

```
[ ]: PTI_df = data_copy[['transaction_date','ticker','type']]
p = data_copy[['ticker','type','representative']]
p['Date'] = p.index
trades_grouped = p.groupby([pd.
 ↪Grouper(key='Date'),'representative','ticker','type']).nunique().
 ↪reset_index()
trades_grouped = trades_grouped.pivot_table(index = 'Date',columns='type',␣
 ↪values='ticker',aggfunc='count').fillna(0)
```

```
[ ]: # Use Trades Grouped to Calculate Trading Index
trades_grouped['Difference'] = trades_grouped['Buy']-trades_grouped['Sell']
trades_grouped['No_Trades'] = trades_grouped['Buy'] + trades_grouped['Sell']
```

```
[ ]: buys_sells = PTI_df.pivot_table(index = PTI_df.index,␣
 ↪columns='type',values='ticker',aggfunc='count')
buys_sells = buys_sells.fillna(0)
buys_sells['Difference'] = buys_sells['Buy'] - buys_sells['Sell']
buys_sells['No_Trades'] = buys_sells['Buy'] + buys_sells['Sell']
```

```
[ ]: plt.figure(figsize=(12,8))
     plt.scatter(buys_sells.index,buys_sells.Buy, c = 'green', label = 'Number of␣
      ↪Buys', linewidth = 1)
     plt.scatter(buys_sells.index,buys_sells.Sell, c = 'red', label = 'Number of␣
      ↪Sells', linewidth = 1)
     plt.plot(buys_sells.Sell- buys_sells.Buy,c='black',label= 'No.Sells less No.
      ↪Buys')
     plt.axhline((buys_sells.Sell-buys_sells.Buy).mean(), label = 'Mean Difference',␣
      ↪linewidth = 3,color = 'gold')
     plt.text(pd.to_datetime('2020-01-30'), -120,'Covid', c ='blue', fontsize = 15)
     plt.text(pd.to_datetime('2022-02-24'),-50,'Russian-Ukraine-War', c = 'blue',␣
      ↪fontsize = 10)
     plt.text(pd.to_datetime('2017-12-15'),-75,'GOP Corporate Tax Law', c = 'blue',␣
      ↪fontsize = 10)
     plt.legend(loc =0)
     plt.xlabel('Disclosure Date')
     plt.ylabel('Number of Transactions')
     plt.title('Trading Activity of Politicians Across Time', fontsize = 20)
     plt.savefig('Trading_Activity.png')
```



- As you can see from the chart above there are spikes in the **Number of Buys** and **Number of Sells** on any given disclosure date. It begs the question of why? It is human nature that when it comes to money - generally speaking- we are always motiviated in our self interest. Yes, the **STOCK ACT** is *supposed* to prohibit members of Congress and employees of Congress from using priviate information derived from their official positions for their personal benefit. In the court of law, proving such insider trading is probably impossible and not a top priority for the Department of Justice. With that being said, I believe we can find a predictive signal from aggregate *buying* and *selling* activity of United States Politicians.

- Since politicians are privy to sensitive economic, geopolitical, and other important information before others know, we can get a better understanding of their psychological mindset. *Buying* and *Selling* relate to fear and greed. If politicians know senstive macroeconomic information, they will without a doubt react emotionally through buying and selling out of greed or fear.
- For example, even though many investors *knew* about Covid-19, **many investors did not know** just how bad it would affect the global economy. However, being that polticians are surrouded by top scientists and the most up-to-date information, they have a better perspective on the gravity of the situation. It would make sense they would trade on this knowledge by selling off assets and raising cash to protect their money.
- In the following week, month, or even quarter markets will begin to *price-in* this negative sentiment.

[ ]:
```
pti_index = trades_grouped.groupby(pd.Grouper(freq = '1m')).sum()
pti_index['PTI_Index'] = pti_index.Difference/pti_index['No_Trades']
pti_index = pti_index.replace(0,.0001)
# Calculating Z-score PTI_Index
pti_index['Z_PTI_Index'] = (pti_index['PTI_Index']-pti_index['PTI_Index'].
 ↪mean())/(pti_index['PTI_Index'].std())
```

[ ]:
```
pti_index.describe()
```

[ ]:
```
type          Buy        Sell  Difference    No_Trades   PTI_Index  \
count  110.000000  110.000000  110.000000   110.000000  108.000000
mean    77.400002   78.890911   -1.490904   156.290911    0.012422
std     96.077013  106.455257   36.027193   199.572217    0.252956
min      0.000100    0.000100 -162.000000     0.000100   -0.839286
25%     18.250000   16.000000  -10.000000    35.000000   -0.089661
50%     30.000000   32.000000    0.000100    66.000000    0.000100
75%    117.000000  123.000000   10.000000   243.250000    0.159278
max    626.000000  748.000000   89.000000  1374.000000    0.846154

type    Z_PTI_Index
count  1.080000e+02
mean  -2.261565e-17
std    1.000000e+00
min   -3.367020e+00
25%   -4.035606e-01
50%   -4.871139e-02
75%    5.805583e-01
max    3.295958e+00
```

[ ]:
```
PTI_lag1 = pti_index[['Z_PTI_Index']].shift(2)
PTI_lag1.columns = ['Z_PTI_Lag2']
#PTI_lag1['Z_PTI_Index_Shift_3'] = pti_index[['Z_PTI_Index']].shift(3)
#PTI_lag1.columns = ['Z_PTI_Lag2', 'Z_PTI_Lag3']

MARKET_lag1 = MARKET_RETURNS.shift(1)
MARKET_lag1.columns = ['MKT_Rets_Lag1']
MARKET_lag2 = MARKET_RETURNS.shift(2)
MARKET_lag2.columns = ['MKT_Rets_lag2']
MARKET_lag3 = MARKET_RETURNS.shift(3)
MARKET_lag3.columns = ['MKT_Rets_Lag3']
MARKET_lag4 = MARKET_RETURNS.shift(4)
MARKET_lag4.columns = ['MKT_Rets_lag4']
MARKET_lag6 = MARKET_RETURNS.shift(6)
MARKET_lag6.columns = ['MKT_Rets_Lag6']
MARKET_lag9 = MARKET_RETURNS.shift(9)
MARKET_lag9.columns = ['MKT_Rets_Lag9']
MARKET_lag12 = MARKET_RETURNS.shift(12)
MARKET_lag12.columns = ['MKT_Rets_Lag12']
MARKET_Lag24 = MARKET_RETURNS.shift(24)
MARKET_Lag24.columns = ['MKT_Rets_Lag24']
```

[ ]:
```
DATA_MATRIX = PTI_lag1
```

[ ]:
```
DATA_MATRIX = DATA_MATRIX.merge(MARKET_RETURNS,left_index=True,right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag1, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag2, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag3, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag4, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag6, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_lag12, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(MARKET_Lag24, left_index=True, right_index=True)
# Adding Macroeconomic and other Important Financial Variables

DATA_MATRIX = DATA_MATRIX.merge(TB3_Rate_Lag1, left_index=True,␣
 ↪right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(tsspread_lag1, left_index=True,␣
 ↪right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(dsspread_lag1, left_index=True,␣
 ↪right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(epratio_lag1, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(oil_lag, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(oil_rets_sq, left_index=True, right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(inflation_lag2, left_index=True,␣
 ↪right_index=True)
DATA_MATRIX = DATA_MATRIX.merge(inflation_yoy_sq, left_index=True,␣
 ↪right_index=True)
```

```
DATA_MATRIX = DATA_MATRIX.merge(consumer_sentiment_lag1, left_index=True,␣
 ↪right_index=True)
```

[ ]:
```
corr_mat = DATA_MATRIX.corr()
corr_mat = pd.DataFrame(corr_mat.unstack().sort_values(),␣
 ↪columns=['Correlation'])
corr_mat = corr_mat.loc[corr_mat.Correlation != 1]
```

[ ]:
```
corr_mat
```

[ ]:
```
                                             Correlation
Three_M_TBill_Lag3    term_spread_lag3         -0.697357
term_spread_lag3      Three_M_TBill_Lag3       -0.697357
Inflation_YOY_lag2    epratio_lag1             -0.688873
epratio_lag1          Inflation_YOY_lag2       -0.688873
                      Inflation_YOY_Squared    -0.617596
…                                                    …
MKT_Rets_lag2         Oil_Rets_lag2             0.390372
term_spread_lag3      epratio_lag1              0.449615
epratio_lag1          term_spread_lag3          0.449615
Inflation_YOY_lag2    Inflation_YOY_Squared     0.966515
Inflation_YOY_Squared Inflation_YOY_lag2        0.966515

[306 rows x 1 columns]
```

[ ]:
```
pti_index[['PTI_Index']].describe()
```

[ ]:
```
type     PTI_Index
count   108.000000
mean      0.012422
std       0.252956
min      -0.839286
25%      -0.089661
50%       0.000100
75%       0.159278
max       0.846154
```

[ ]:
```
pti_index[['No_Trades']].idxmax()
```

[ ]:
```
type
No_Trades   2020-04-30
dtype: datetime64[ns]
```

[ ]:
```
pti_index[['No_Trades']].idxmin()
```

[ ]:
```
type
No_Trades   2015-10-31
dtype: datetime64[ns]
```

```
[ ]: pti_index[['PTI_Index']].idxmin()
```

```
[ ]: type
     PTI_Index   2015-02-28
     dtype: datetime64[ns]
```

```
[ ]: pti_index[['PTI_Index']].idxmax()
```

```
[ ]: type
     PTI_Index   2015-08-31
     dtype: datetime64[ns]
```

- The average monthly change of aggregate buying and selling of politicians since 2014 is 1.242%. This means that on average, politicians were generally buying more *by 1.242%* than selling. The standard deviation of the index is 25.29%. Even though there was significant trading levels starting at the onset of the pandemic, the greatest percent changes in absolute values of the PTI Index happened at the beginning of 2015 and end of 2015. I believe the spike in selling in *early 2015* was closely related to the sharp rise of OIL Prices during early 2015.
- The sharp increase in the PTI index in the month of August 2015 could potentially be related to China's decision to weaken the Yuan in hopes of fostering further GDP growth and exportation of their cheap goods. Politicians may have reacted positively at this news.

```
[ ]: DATA_MATRIX.describe()
```

```
[ ]:        Z_PTI_Lag2    MKT_RETS  MKT_Rets_Lag1  MKT_Rets_lag2  MKT_Rets_Lag3  \
     count  105.000000  109.000000     109.000000     109.000000     109.000000
     mean     0.018455    0.009768       0.009429       0.010229       0.010144
     std      1.004145    0.044039       0.043767       0.043326       0.043245
     min     -3.367020   -0.124643      -0.124643      -0.124643      -0.124643
     25%     -0.387957   -0.013791      -0.013791      -0.013438      -0.013438
     50%     -0.011812    0.015119       0.015119       0.017012       0.017012
     75%      0.587050    0.036471       0.036198       0.036198       0.036198
     max      3.295958    0.126984       0.126984       0.126984       0.126984

            MKT_Rets_lag4  MKT_Rets_Lag6  MKT_Rets_Lag12  MKT_Rets_Lag24  \
     count     109.000000     109.000000      109.000000      109.000000
     mean        0.009689       0.011110        0.012938        0.012351
     std         0.042748       0.041667        0.038821        0.038110
     min        -0.124643      -0.124643       -0.124643       -0.124643
     25%        -0.013438      -0.010190       -0.002560       -0.002560
     50%         0.017012       0.017761        0.018079        0.017761
     75%         0.032416       0.036198        0.036198        0.032416
     max         0.126984       0.126984        0.126984        0.126984

            Three_M_TBill_Lag3  term_spread_lag3  dsspread_lag6  epratio_lag1  \
     count          109.000000        109.000000     109.000000    109.000000
     mean             0.008049          0.012953       0.009082     -1.583918
```

```
std               0.009516          0.008067       0.002341      0.468024
min               0.000000         -0.004900       0.005400     -2.545365
25%               0.000500          0.007500       0.007100     -1.876111
50%               0.002900          0.012800       0.008800     -1.563175
75%               0.015500          0.019300       0.010200     -1.223334
max               0.042200          0.029700       0.019000     -0.811184

       Oil_Rets_lag2  Oil_Rets_Squared  Inflation_YOY_lag2  \
count     109.000000        109.000000          109.000000
mean        0.006660          0.017244            0.025339
std         0.131753          0.047340            0.023325
min        -0.549512          0.000001           -0.001995
25%        -0.062847          0.000772            0.012371
50%         0.008126          0.004468            0.018115
75%         0.066841          0.014753            0.025000
max         0.607202          0.368695            0.090598

       Inflation_YOY_Squared  UMICH_Consumer_Sentiment_lag3
count           1.090000e+02                     109.000000
mean            1.181138e-03                      -0.001034
std             2.064326e-03                       0.051008
min             6.315069e-08                      -0.194164
25%             1.530348e-04                      -0.022335
50%             3.281405e-04                       0.002037
75%             6.250211e-04                       0.028807
max             8.207921e-03                       0.130097
```

	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
count	105	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109
mean	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-1.58392	[illegible]	[illegible]	[illegible]	[illegible]	-0.00103416
std	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
min	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	-0.0049	0.0054	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-0.194164
25%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.0005	0.0075	0.0071	[illegible]	-0.0628466	[illegible]	[illegible]	[illegible]	-0.022335
50%	-0.0118118	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.0128	0.0088	-1.56317	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
75%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.0193	0.0102	-1.22333	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
max	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.0297	0.019	-0.811184	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

3.2 Regression

- I will estimate this model:

$$
\begin{aligned}
\hat{r}_{spy,t} =& \beta_0 + \beta_1 \cdot Zpti_{t-2} + \beta_2 \cdot r_{spy,t-1} + \beta_3 \cdot r_{spy,t-2} \\
& + \beta_4 \cdot r_{spy,t-3} + \beta_5 \cdot r_{spy,t-4} + \beta_6 \cdot r_{TBILL,t-3} + \beta_7 \cdot TermSpread_{t-3} \\
& + \beta_8 \cdot DefaultSpread_{t-6} + \beta_9 \cdot EPRATIO_{t-1} + \beta_{10} \cdot r_{oil,t-2} \\
& + \beta_{11} \cdot r^2_{oil,t-2} + \beta_{12} \cdot Inflation_{yoy,t-2} + \beta_{13} \cdot Inflation^2_{yoy,t-2} + \varepsilon_t
\end{aligned}
$$

[ ]:
```
DATA_MATRIX.columns
```

[ ]:
```
Index(['Z_PTI_Lag2', 'MKT_RETS', 'MKT_Rets_Lag1', 'MKT_Rets_lag2',
       'MKT_Rets_Lag3', 'MKT_Rets_lag4', 'MKT_Rets_Lag6', 'MKT_Rets_Lag12',
       'MKT_Rets_Lag24', 'Three_M_TBill_Lag3', 'term_spread_lag3',
       'dsspread_lag6', 'epratio_lag1', 'Oil_Rets_lag2', 'Oil_Rets_Squared',
       'Inflation_YOY_lag2', 'Inflation_YOY_Squared',
       'UMICH_Consumer_Sentiment_lag3'],
      dtype='object')
```

[ ]:
```
multiple_ols = smf.ols(formula='MKT_RETS ~ Z_PTI_Lag2 + MKT_Rets_Lag1␣
 ↪+MKT_Rets_lag2 ++ MKT_Rets_Lag3+MKT_Rets_lag4+Three_M_TBill_Lag3 +\
   term_spread_lag3 + dsspread_lag6␣
 ↪+epratio_lag1+Oil_Rets_lag2+Oil_Rets_Squared+Inflation_YOY_lag2+Inflation_YOY_Squared+UMICH
 ↪data = DATA_MATRIX)
results = multiple_ols.fit(disp = 0)
```

[ ]:
```
results.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               MKT_RETS   R-squared:                       0.266
Model:                            OLS   Adj. R-squared:                  0.152
Method:                 Least Squares   F-statistic:                     2.330
Date:                Tue, 07 Mar 2023   Prob (F-statistic):            0.00862
Time:                        00:02:11   Log-Likelihood:                 194.70
No. Observations:                 105   AIC:                            -359.4
Df Residuals:                      90   BIC:                            -319.6
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
=================
                                    coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
-----------------
Intercept                         0.0823      0.059      1.394      0.167
-0.035       0.200
Z_PTI_Lag2                        0.0107      0.004      2.464      0.016
```

```
0.002        0.019
MKT_Rets_Lag1                    -0.3278      0.106     -3.099      0.003
-0.538       -0.118
MKT_Rets_lag2                    -0.2698      0.124     -2.174      0.032
-0.516       -0.023
MKT_Rets_Lag3                    -0.1569      0.117     -1.343      0.183
-0.389        0.075
MKT_Rets_lag4                    -0.1748      0.124     -1.412      0.161
-0.421        0.071
Three_M_TBill_Lag3               -1.2488      1.020     -1.224      0.224
-3.275        0.778
term_spread_lag3                 -2.2658      1.413     -1.603      0.112
-5.073        0.541
dsspread_lag6                    -2.1191      2.242     -0.945      0.347
-6.573        2.335
epratio_lag1                      0.0105      0.023      0.448      0.655
-0.036        0.057
Oil_Rets_lag2                     0.0512      0.038      1.364      0.176
-0.023        0.126
Oil_Rets_Squared                  0.1559      0.104      1.492      0.139
-0.052        0.363
Inflation_YOY_lag2                0.9976      1.049      0.951      0.344
-1.087        3.082
Inflation_YOY_Squared           -14.1639      9.933     -1.426      0.157
-33.898        5.570
UMICH_Consumer_Sentiment_lag3     0.2185      0.092      2.370      0.020
0.035        0.402
==============================================================================
Omnibus:                       33.862   Durbin-Watson:                   1.919
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               75.694
Skew:                          -1.231   Prob(JB):                     3.66e-17
Kurtosis:                       6.352   Cond. No.                     4.85e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.85e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[ ]:
```python
table = pd.DataFrame({'Beta_Coefficients': results.params,'SE':results.bse,'t_stat':results.tvalues,'pval':results.pvalues})
table = np.round(table, 5)
```

3.3 Model OLS Statisitics

	Beta_Coefficients	SE	t_stat	pval
Intercept	0.0823	0.05903	1.39422	0.16668
Z_PTI_Lag2	0.01075	0.00436	2.46382	0.01565
MKT_Rets_Lag1	-0.32779	0.10576	-3.09937	0.00259
MKT_Rets_lag2	-0.26984	0.1241	-2.17437	0.0323
MKT_Rets_Lag3	-0.15693	0.11687	-1.34279	0.18272
MKT_Rets_lag4	-0.17476	0.12374	-1.41229	0.16131
Three_M_TBill_Lag3	-1.2488	1.01994	-1.22438	0.22401
term_spread_lag3	-2.26582	1.41304	-1.6035	0.11233
dsspread_lag6	-2.11906	2.24185	-0.94523	0.34707
epratio_lag1	0.01047	0.02339	0.4477	0.65544
Oil_Rets_lag2	0.0512	0.03754	1.36384	0.17602
Oil_Rets_Squared	0.15586	0.10449	1.49167	0.13928
Inflation_YOY_lag2	0.99759	1.04922	0.95079	0.34426
Inflation_YOY_Squared	-14.1639	9.9331	-1.42593	0.15735
UMICH_Consumer_Sentiment_lag3	0.21848	0.09219	2.36977	0.01994

- The coefficient on **Z-PTI is very statistically significant.** .Thus,holding other factors fixed, a one-standard devation or roughly a 25% increase in the PTI index will *on average increase market returns by 100 basis points.*
- This partial effect is very large, however, one major problem I will have to address when I forcast future returns is that I will never know the **true distribution of the PTI Index**. This will force me to regress on the 2-month lagged PTI_index instead of the z-scored PTI_Index.

3.4 Eplanation of other Variables

- Above you can see that I controlled for the lagged market returns to try and control for serial correlation between ε_t and $\hat{r}_{spy,t}$.
- The *negative coefficients* on three month treasury bill rates, default spreads (defined as BAA yields less AAA yields) both make economic sense. If yields rise, **the present value of all future discounted cashflows declines.** This would cause returns to decline negatively, as investors would sell off equities and allocate more to fixed-income. Additionally, higher yields indicate **increased risk.** When risk aversion increases, it would economically make sense there would be a sell-off in assets.
- I wanted to square Oil returns and Inflation returns to uncover either increasing/decreasing marginal effects. It turns out that on average, 2-month lagged oil price percent changes have an increasing marginal effect. This was surprising to me, but the effect is *small.* The coefficient on inflation tells an interesting and economically logical story. While small year over year changes in inflation mean the market environment is *stable*, drastic increases in inflation actually will without a doubt hurt future one-month spy returns. In fact, the average partial effect of inflation can be characterized as $\frac{\partial r_{spy,t}}{\partial infl_{t-2}} = .99752 - 28.3278 \cdot r_{infl,t-2}$. This means if $r_{infl,t-2} > 3.5213\%$, then **expected future market returns will decline.**
- There is no meaningful interpretation from the intercept.

```
[ ]: smf.ols('MKT_RETS~MKT_Rets_Lag1', data =DATA_MATRIX ).fit(disp = 0).summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               MKT_RETS   R-squared:                       0.038
Model:                            OLS   Adj. R-squared:                  0.029
Method:                 Least Squares   F-statistic:                     4.185
Date:                Tue, 07 Mar 2023   Prob (F-statistic):             0.0432
Time:                        00:08:02   Log-Likelihood:                 188.30
No. Observations:                 109   AIC:                            -372.6
Df Residuals:                     107   BIC:                            -367.2
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
=
                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
Intercept        0.0116      0.004      2.729      0.007       0.003
0.020
MKT_Rets_Lag1   -0.1952      0.095     -2.046      0.043      -0.384
-0.006
==============================================================================
Omnibus:                       12.424   Durbin-Watson:                   2.043
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               13.373
Skew:                          -0.728   Prob(JB):                      0.00125
Kurtosis:                       3.908   Cond. No.                         23.0
==============================================================================

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

[ ]:
```
predictions = pd.DataFrame(results.fittedvalues,␣
 ↪columns=['Forecasted_Market_Return'])
observed_values  = DATA_MATRIX[['MKT_RETS']]
dependendent_variables = predictions.join(observed_values, how = 'inner')
errors = pd.DataFrame(results.resid,columns=['Residuals'])
```

[ ]:
```
dependendent_variables.corr()
```

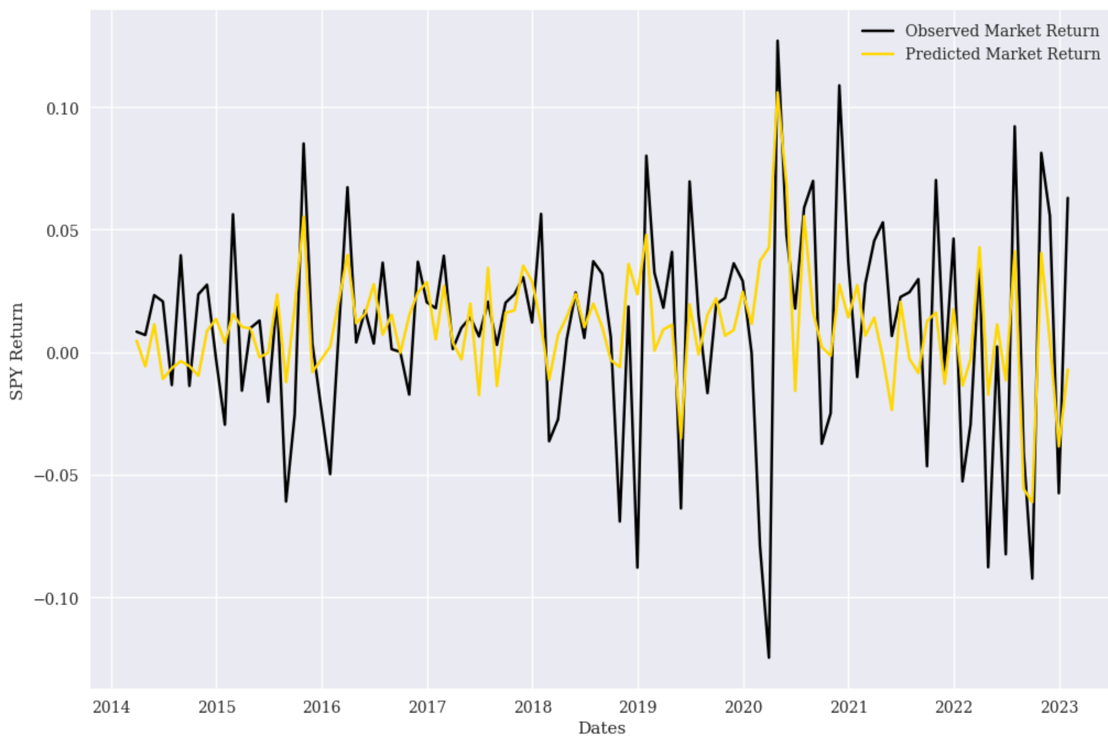
[ ]:

	Forecasted_Market_Return	MKT_RETS
Forecasted_Market_Return	1.000000	0.515763
MKT_RETS	0.515763	1.000000

[ ]:
```
txt = 'Correlation Coefficient Between Predicted returns and Observed Returns is equal to 51.57% on a monthly basis'
plt.figure(figsize=(12,8))

plt.plot(dependendent_variables.MKT_RETS, color = 'black',label = 'Observed Market Return')
plt.plot(dependendent_variables['Forecasted_Market_Return'], color = 'gold',label ='Predicted Market Return')
plt.figtext(x = .5,y = 0.01, s = txt, fontsize = '12', wrap = True, horizontalalignment = 'center')
plt.ylabel('SPY Return')
plt.xlabel('Dates')
plt.legend(loc = 0)
```

[ ]: <matplotlib.legend.Legend at 0x1d6c3425580>



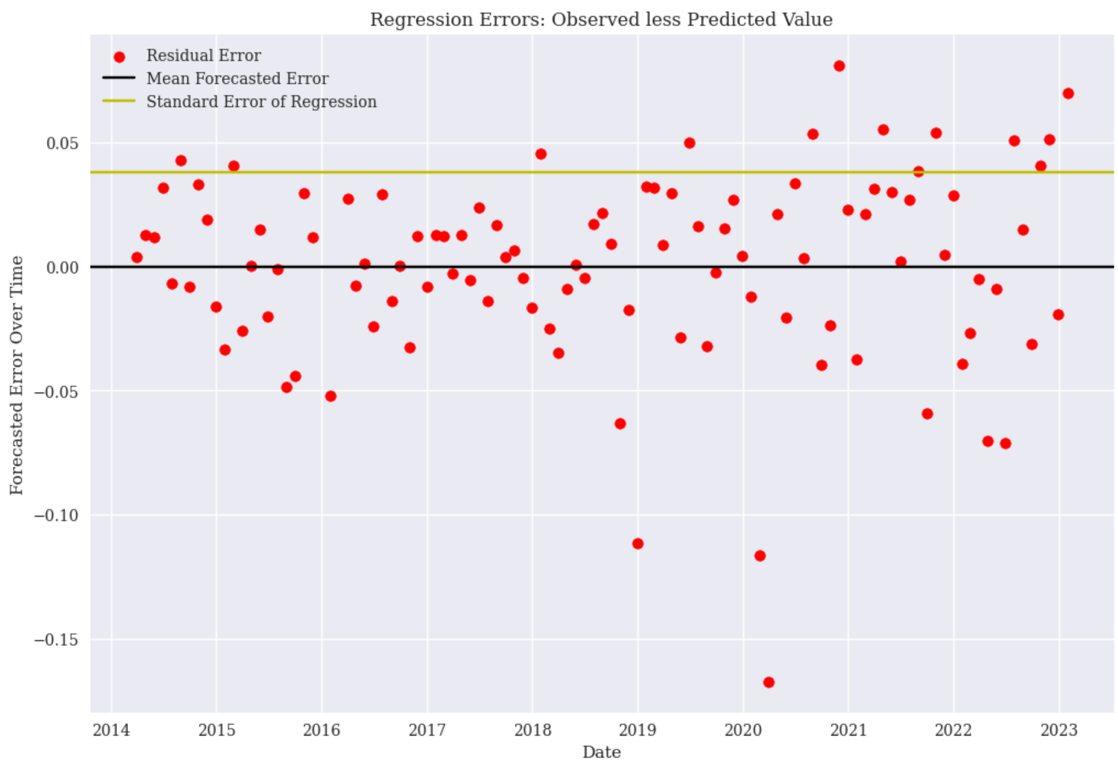
Correlation Coefficient Between Predicted returns and Observed Returns is equal to 51.57% on a monthly basis

[ ]:
```
plt.figure(figsize=(12,8))
plt.scatter(errors.index,errors, label = 'Residual Error', c = 'red')
plt.axhline(0,label = 'Mean Forecasted Error', c= 'black')
plt.axhline(errors.std().values, label = 'Standard Error of Regression', c = 'y')
plt.title('Regression Errors: Observed less Predicted Value')
```

```
plt.xlabel('Date')
plt.ylabel('Forecasted Error Over Time')

plt.legend(loc = 0)
```

[ ]: <matplotlib.legend.Legend at 0x1d6c6047dc0>



3.5 Test for Serial Correlation

```
[ ]: errors['Residual_Lag'] = errors.Residuals.shift(1)
```

```
[ ]: smf.ols(formula='Residuals~Residual_Lag',data = errors).fit(disp =0).summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              Residuals   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.009
Method:                 Least Squares   F-statistic:                   0.06080
Date:                Tue, 07 Mar 2023   Prob (F-statistic):              0.806
Time:                        02:45:37   Log-Likelihood:                 192.39
No. Observations:                 104   AIC:                            -380.8
```

```
Df Residuals:                     102   BIC:                            -375.5
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept   -1.868e-05      0.004     -0.005      0.996      -0.007       0.007
Residual_Lag     0.0248      0.101      0.247      0.806      -0.175       0.224
==============================================================================
Omnibus:                       31.151   Durbin-Watson:                   1.969
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               64.433
Skew:                          -1.172   Prob(JB):                     1.02e-14
Kurtosis:                       6.061   Cond. No.                         26.7
==============================================================================

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

4 Model 2 | Probit Regression Model

- Below is the probit regression model where I attempt to *predict* the one-month direction of spy returns. I define a *postive* market return as 1 and *negative* market return as 0.
- X are the same independend variables from the regression equation.
- \$P(r_{spy,t} = 1 X)= (x) = _{-∞}^{x} (v) , dv \$

```
[ ]: def _filter_mkt_rets(df:pd.DataFrame):
         if df >= 0:
             mkt_ret = 1
         else:
             mkt_ret = 0

         return mkt_ret
     direction_df = pd.DataFrame(MARKET_RETURNS.MKT_RETS.apply(_filter_mkt_rets)).
      ↪rename(columns={'MKT_RETS':'Direction'})
```

```
[ ]: probit_matrix = PTI_lag1
```

```
[ ]: probit_matrix = probit_matrix.merge(direction_df,left_index=True,␣
      ↪right_index=True)
     probit_matrix = probit_matrix.merge(MARKET_lag1, left_index=True,␣
      ↪right_index=True)
     probit_matrix = probit_matrix.merge(MARKET_lag2, left_index=True,␣
      ↪right_index=True)
```

```
probit_matrix = probit_matrix.merge(MARKET_lag3, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(MARKET_lag4, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(MARKET_lag6, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(MARKET_lag12, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(MARKET_Lag24, left_index=True,␣
↪right_index=True)
# Adding Macroeconomic and other Important Financial Variables

probit_matrix = probit_matrix.merge(TB3_Rate_Lag1, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(tsspread_lag1, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(dsspread_lag1, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(epratio_lag1, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(oil_lag, left_index=True, right_index=True)
probit_matrix = probit_matrix.merge(oil_rets_sq, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(inflation_lag2, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(inflation_yoy_sq, left_index=True,␣
↪right_index=True)
probit_matrix = probit_matrix.merge(consumer_sentiment_lag1, left_index=True,␣
↪right_index=True)
```

[ ]:
```
reg_probit = smf.probit(formula='Direction ~  Z_PTI_Lag2+MKT_Rets_Lag1␣
↪+MKT_Rets_lag2 ++ MKT_Rets_Lag3+MKT_Rets_lag4+Three_M_TBill_Lag3 +\
   term_spread_lag3 + dsspread_lag6␣
↪+epratio_lag1+Oil_Rets_lag2+Oil_Rets_Squared+Inflation_YOY_lag2+Inflation_YOY_Squared+UMICH
↪data = probit_matrix)
results_probit = reg_probit.fit(disp = 0)
```

[ ]:
```
results_probit.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                          Probit Regression Results
==============================================================================
Dep. Variable:              Direction   No. Observations:                  105
Model:                         Probit   Df Residuals:                       90
Method:                           MLE   Df Model:                           14
```

```
Date:                  Tue, 07 Mar 2023   Pseudo R-squ.:                  0.1392
Time:                          01:41:35   Log-Likelihood:                -54.841
converged:                         True   LL-Null:                       -63.711
Covariance Type:              nonrobust   LLR p-value:                    0.2188
================================================================================
=================
                                   coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
-----------------
Intercept                        1.4689      2.082      0.706      0.480
-2.611       5.549
Z_PTI_Lag2                       0.2504      0.163      1.538      0.124
-0.069       0.569
MKT_Rets_Lag1                   -7.5988      4.217     -1.802      0.072
-15.865       0.667
MKT_Rets_lag2                  -10.8535      4.953     -2.191      0.028
-20.561      -1.146
MKT_Rets_Lag3                   -8.0776      4.551     -1.775      0.076
-16.998       0.843
MKT_Rets_lag4                   -9.3771      4.488     -2.089      0.037
-18.174      -0.580
Three_M_TBill_Lag3             -17.0225     37.060     -0.459      0.646
-89.659      55.614
term_spread_lag3               -31.8742     50.761     -0.628      0.530
-131.363      67.615
dsspread_lag6                  -24.1884     80.512     -0.300      0.764
-181.989     133.612
epratio_lag1                     0.1721      0.798      0.216      0.829
-1.391       1.735
Oil_Rets_lag2                    1.8448      1.525      1.210      0.226
-1.144       4.834
Oil_Rets_Squared                 4.2957      6.819      0.630      0.529
-9.069      17.661
Inflation_YOY_lag2              54.9172     37.924      1.448      0.148
-19.413     129.248
Inflation_YOY_Squared         -792.9222    372.426     -2.129      0.033
-1522.864     -62.980
UMICH_Consumer_Sentiment_lag3    4.2928      3.277      1.310      0.190
-2.130      10.715
================================================================================
=================
"""
```

[ ]:

```python
coef_names = results_probit.model.exog_names
coef_names = np.delete(coef_names,0)
# Calculating Average Partial Effect
```

```
ape_probit = results_probit.get_margeff().margeff
table_probit = pd.DataFrame({'coef_names': coef_names, 'APE_Probit':ape_probit})
```

	coef_names	APE_Probit
0	Z_PTI_Lag2	0.0741154
1	MKT_Rets_Lag1	-2.24925
2	MKT_Rets_lag2	-3.21264
3	MKT_Rets_Lag3	-2.39097
4	MKT_Rets_lag4	-2.77562
5	Three_M_TBill_Lag3	-5.03869
6	term_spread_lag3	-9.43479
7	dsspread_lag6	-7.15978
8	epratio_lag1	0.050934
9	Oil_Rets_lag2	0.546073
10	Oil_Rets_Squared	1.27152
11	Inflation_YOY_lag2	16.2555
12	Inflation_YOY_Squared	-234.706
13	UMICH_Consumer_Sentiment_lag3	1.27066

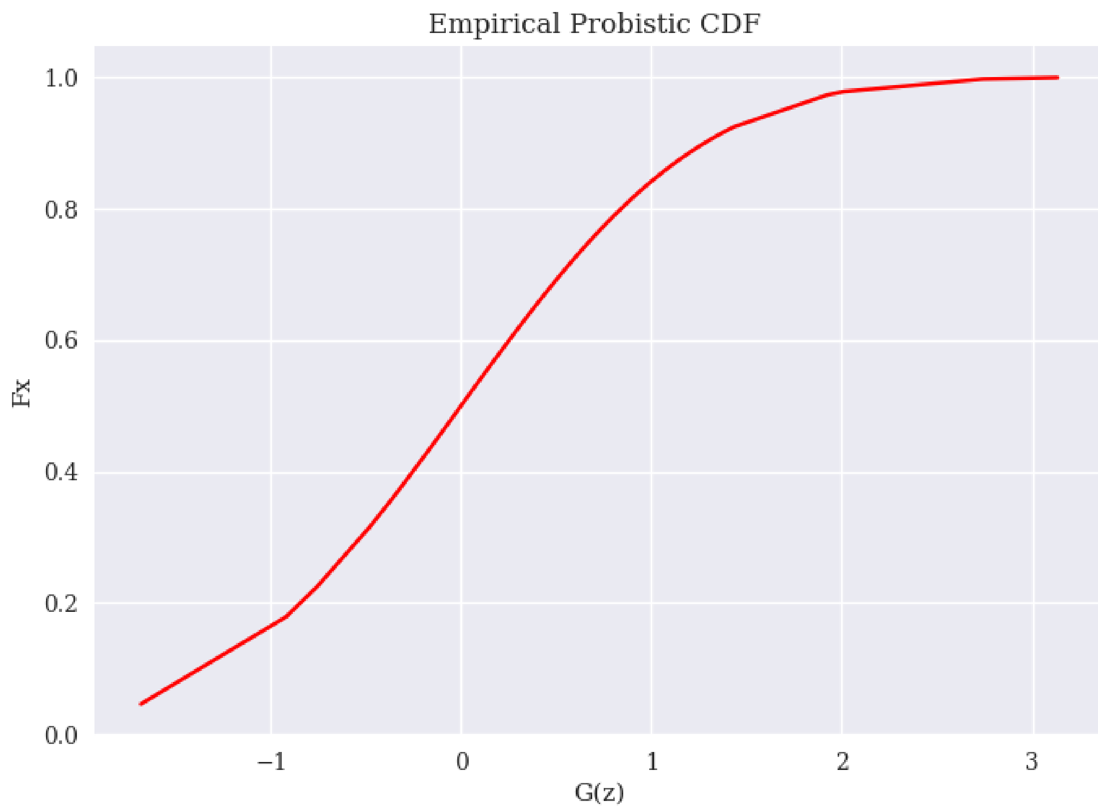
- The table above lists the average partial effects of the probit model. For the Z-scored PTI Index, the average partial effect of a one standard deviation increase in buying activity increases the probilility of a *positive* market return next month by $\phi(.074115 \cdot 1) - \phi(.074115 \cdot 0) = 2.95\%$
- This partial effect is not that large from a probabilistic standpoint. Considering the fact that approximately 68% of all observations lie within 1 standard deviation, it is **not likely the affect of the Z-scored PTI Index will affect my trading strategy returns.**
- Even a three standard deviation movement in Z_PTI only increases the probability of a positive return by 8.79%. Compared to other variables, the *average partial effect of Z_PTI is small.*

4.1 Full Probit Model Accuracy

[ ]:
```
xb_probit = results_probit.fittedvalues
factor_probit = stats.norm.cdf(xb_probit)
cdf_norm = results_probit.fittedvalues.sort_values()
```

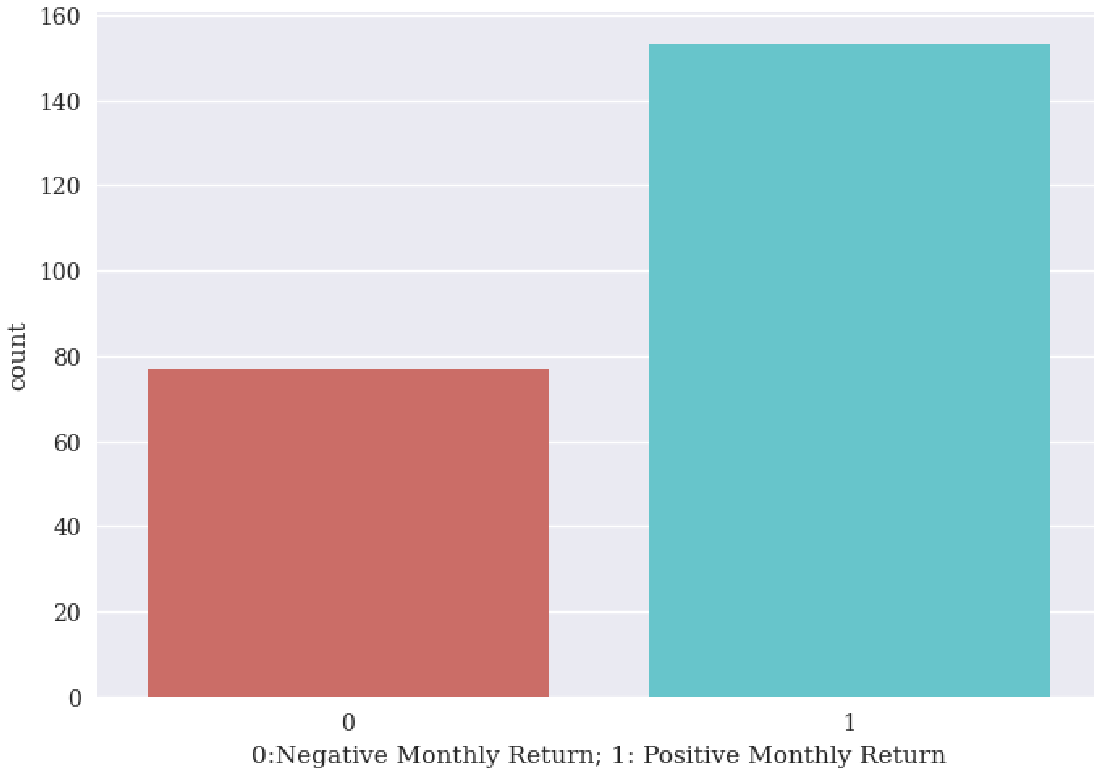
[ ]:
```
plt.plot(cdf_norm, stats.norm.cdf(cdf_norm), c = 'r')
plt.ylabel('Fx')
plt.xlabel('G(z)')
plt.title('Empirical Probistic CDF ')
```

[ ]:
```
Text(0.5, 1.0, 'Empirical Probistic CDF ')
```



[ ]:
```
sns.countplot(x = 'Direction', data = direction_df,palette='hls')
plt.xlabel('0:Negative Monthly Return; 1: Positive Monthly Return')
```

[ ]:
```
Text(0.5, 0, '0:Negative Monthly Return; 1: Positive Monthly Return')
```



[ ]:
```
print(f'The percent of positive monthly returns since March 2014 is {100*np.
↪round(len(direction_df.loc[direction_df.Direction == 1])/
↪len(direction_df),4)}%')
print(f'The percent of negative monthly returns since March 2014 is {100*np.
↪round(len(direction_df.loc[direction_df.Direction == 0])/
↪len(direction_df),4)}%')
```

```
The percent of positive monthly returns since March 2014 is 66.52%
The percent of negative monthly returns since March 2014 is 33.48%
```

[ ]:
```
xb_probit = pd.DataFrame(stats.norm.cdf(results_probit.fittedvalues), index =␣
↪results_probit.fittedvalues.index)
xb_probit = xb_probit.merge(direction_df, left_index=True, right_index=True)
xb_probit.columns = ['Predicted_Probability','Direction']
```

[ ]:
```
def probit_filter(df, threshold:float):
    if df > threshold:
        prob = 1
    else:
        prob = 0
    return prob
```

[ ]:
```python
xb_probit['Predicted_Direction']  =   xb_probit.Predicted_Probability.apply(probit_filter, threshold = .5)
```

[ ]:
```python
print(f'The full in sample accuracy is {100*np.round(len(xb_probit.loc[xb_probit.Direction == xb_probit.Predicted_Direction])/len(xb_probit),5)}%')
print(f'The full in sample error is {100*np.round(len(xb_probit.loc[xb_probit.Direction != xb_probit.Predicted_Direction])/len(xb_probit),5)}%')
```

```
The full in sample accuracy is 75.238%
The full in sample error is 24.762%
```

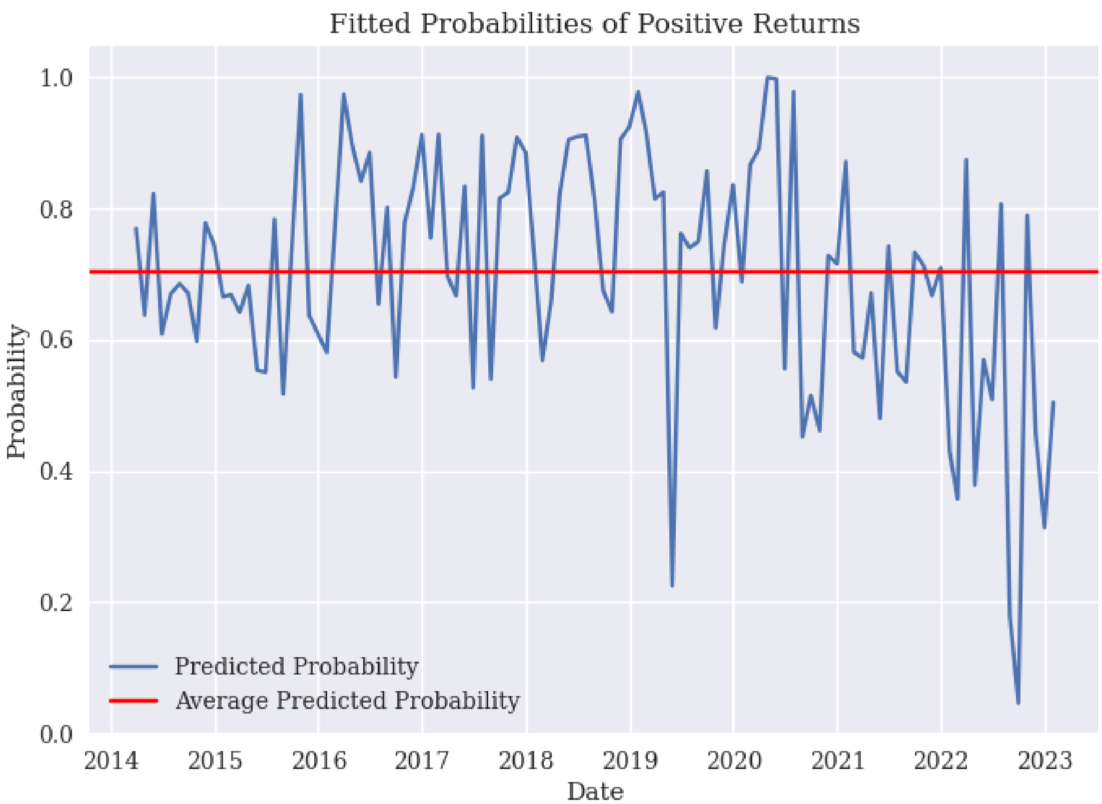
[ ]:
```python
print(f'The probability of predicting positive returns is {100*np.round(len(xb_probit.loc[(xb_probit.Direction == 1)&(xb_probit.Predicted_Direction == 1)])/len(xb_probit.loc[xb_probit.Direction ==1]),5)}%')
print(f'The probability of predicting negative returns is {100*np.round(len(xb_probit.loc[(xb_probit.Direction == 0)&(xb_probit.Predicted_Direction == 0)])/len(xb_probit.loc[xb_probit.Direction ==0]),5)}%')
```

```
The probability of predicting positive returns is 95.946%
The probability of predicting negative returns is 25.806%
```

- The probit regression's accuracy of predicting future positive returns is due to a combina

[ ]:
```python
plt.plot(figsize =(8,6))
plt.plot(xb_probit[['Predicted_Probability']], label = 'Predicted Probability')
plt.ylabel('Probability')
plt.title('Fitted Probabilities of Positive Returns')
plt.axhline(xb_probit.Predicted_Probability.mean(), c ='r', label = 'Average Predicted Probability')
plt.xlabel('Date')
plt.legend(loc = 0)
```

[ ]:
```
<matplotlib.legend.Legend at 0x1d6c32793d0>
```




```
[ ]: #
     xb_probit.loc[xb_probit.Direction == 1].mean()
```

```
[ ]: Predicted_Probability    0.750519
     Direction                1.000000
     Predicted_Direction      0.959459
     dtype: float64
```

```
[ ]: xb_probit[xb_probit.Direction == 0].mean()
```

```
[ ]: Predicted_Probability    0.588128
     Direction                0.000000
     Predicted_Direction      0.741935
     dtype: float64
```

- While my predicted probabilities from the probit model do correlate to observed market returns, there is still bias in my model. Particularly, the probit model generally always predicts positive market returns. This will definitely pose a challenge for when I run a rolling probit model. Just as in the full-regression model, I found evidence that the residuals always underestimate the observed return. I suspect this is the issue in the probit regression, and since 66% of all months generate positive returns, I am not surprised that full-probit regression does a poor job at predicting future market downturns.

- In order to correct for this, I will devise an an expanding regression model and an error correction model to correct for the biaseness in predicting *only the negative predicted directions*.