Interest Rate Impact on Stock Prices

Impact of US Federal Interest Rate Policy on Forward-Looking Valuations of Large Businesses, 1954 - 2017

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GitHub repo: https://github.com/ryanmcr17/project1

Executive Summary

Project Description and Background

Analysis of US interest rate policy relative to large US company valuations. Interest rate policy is represented by effective federal funds rates, set by the Federal Open Market Committee (FOMC) within the Federal Reserve central bank of the US. Forward-looking valuations of large companies are represented by S&P 500 Price-to-Earnings (PE) Ratio data.

Anecdotally, and very generally, businesses typically see stronger revenue/earnings growth when interest rates are lower, at least when other economic conditions are equivalent (employment rates / labor market conditions and inflation rates especially). When the Fed/FOMC 'tightens' interest rate policy by raising their Fed Funds target rate range (i.e. 'raising interest rates') that often negatively impacts future business growth/profits and therefore current forward-looking valuations (in the form of stock prices). However, forward-looking valuations of large US businesses are dependent upon many factors beyond just interest rates, and many of those factors likely impact both valuations as well as federal interest rates themselves (confounding factors).

For this project I am analyzing the direct relationship between US Fed Funds effective rates and overall S&P 500 P/E ratios to see how strong it may be (while understanding that a much more thorough analysis would be necessary to truly understand the complex relationship between these two variables and that an especially strong negative correlation (r-value close to -1) is highly unlikely).

Key Questions Considered

- What do the distributions of values look like from each individual dataset?

- What values/periods from each dataset could be considered outliers?

- Is there a consistent (negative) correlation between Effective Fed Funds Rates and S&P 500 PE ratios/valuations?

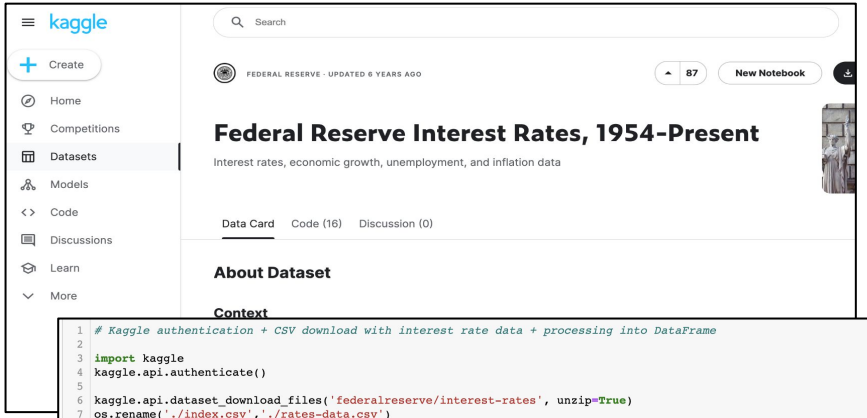
- Do potential outlier data points (whether included or removed) have a significant impact on the level of correlation between the two datasets?

Analysis

Data Collection, Exploration, and Cleanup

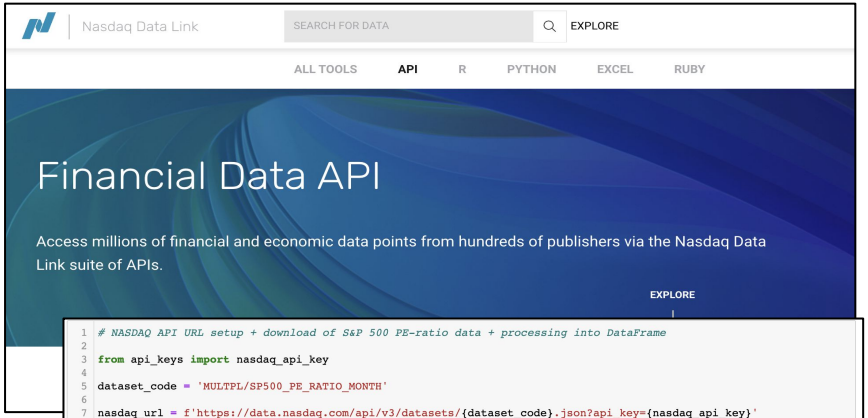
Data Sources

US federal interest rate data by month obtained from [Kaggle](), S&P 500 PE ratios by month obtained from [NASDAQ Data Link API]()




```
# Kaggle authentication + CSV download with interest rate data + processing into DataFrame

import kaggle
kaggle.api.authenticate()

kaggle.api.dataset_download_files('federalreserve/interest-rates', unzip=True)
os.rename('./index.csv','./rates-data.csv')
rates_df = pd.read_csv('./rates-data.csv')

rates_df.head(10)
```

	Year	Month	Day	Federal Funds Target Rate	Federal Funds Upper Target	Federal Funds Lower Target	Effective Federal Funds Rate	Real GDP (Percent Change)	Unemployment Rate	Inflation Rate
0	1954	7	1	NaN	NaN	NaN	0.80	4.6	5.8	NaN
1	1954	8	1	NaN	NaN	NaN	1.22	NaN	6.0	NaN
2	1954	9	1	NaN	NaN	NaN	1.06	NaN	6.1	NaN
3	1954	10	1	NaN	NaN	NaN	0.85	8.0	5.7	NaN
4	1954	11	1	NaN	NaN	NaN	0.83	NaN	5.3	NaN
5	1954	12	1	NaN	NaN	NaN	1.28	NaN	5.0	NaN
6	1955	1	1	NaN	NaN	NaN	1.39	11.9	4.9	NaN
7	1955	2	1	NaN	NaN	NaN	1.29	NaN	4.7	NaN
8	1955	3	1	NaN	NaN	NaN	1.35	NaN	4.6	NaN




```
# NASDAQ API URL setup + download of S&P 500 PE-ratio data + processing into DataFrame

from api_keys import nasdaq_api_key

dataset_code = 'MULTPL/SP500_PE_RATIO_MONTH'

nasdaq_url = f'https://data.nasdaq.com/api/v3/datasets/{dataset_code}.json?api_key={nasdaq_api_key}'

response = requests.get(nasdaq_url).json()


pe_df = pd.DataFrame(response['dataset']['data'])

pe_df.rename(columns={0:'Date',1:'S&P 500 PE Ratio'},inplace=True)

pe_df.head(10)

```

	Date	S&P 500 PE Ratio
0	2023-07-01	25.78
1	2023-06-30	25.76
2	2023-06-01	25.15
3	2023-05-31	24.20
4	2023-05-01	24.00
5	2023-04-01	23.86
6	2023-03-31	21.97

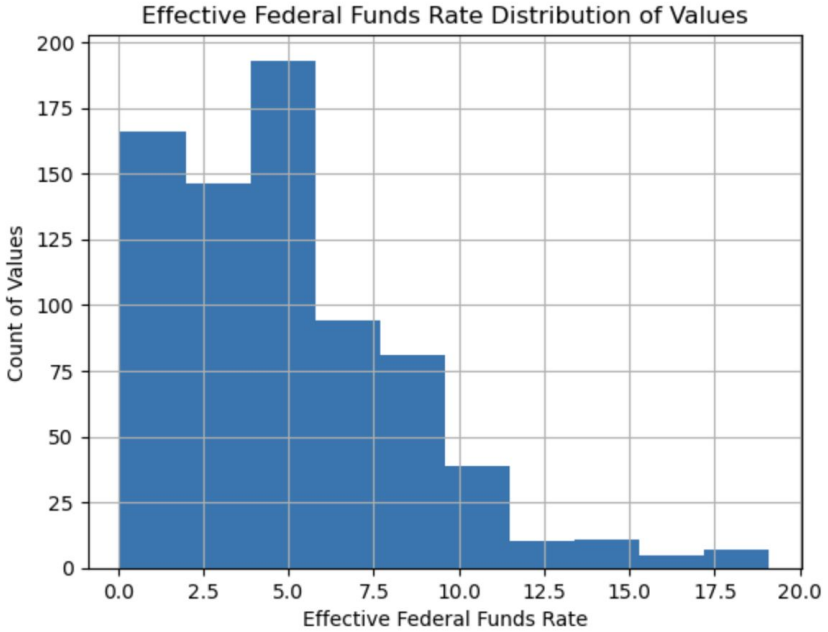
Interest Rate Data Exploration

Decided to use 'Effective' rates due to more consistent availability of data, equivalent to monthly availability of PE datapoints in other dataframe

Effective rate data is right-skewed with mean of ~4.9% and long-tail of rarely-occurring higher values

Year	904
Month	904
Day	904
Federal Funds Target Rate	462
Federal Funds Upper Target	103
Federal Funds Lower Target	103
Effective Federal Funds Rate	752
Real GDP (Percent Change)	250
Unemployment Rate	752
Inflation Rate	710
dtype: int64	

	Effective Federal Funds Rate
count	752.000000
mean	4.910997
std	3.611431
min	0.070000
25%	2.427500
50%	4.700000
75%	6.580000
max	19.100000

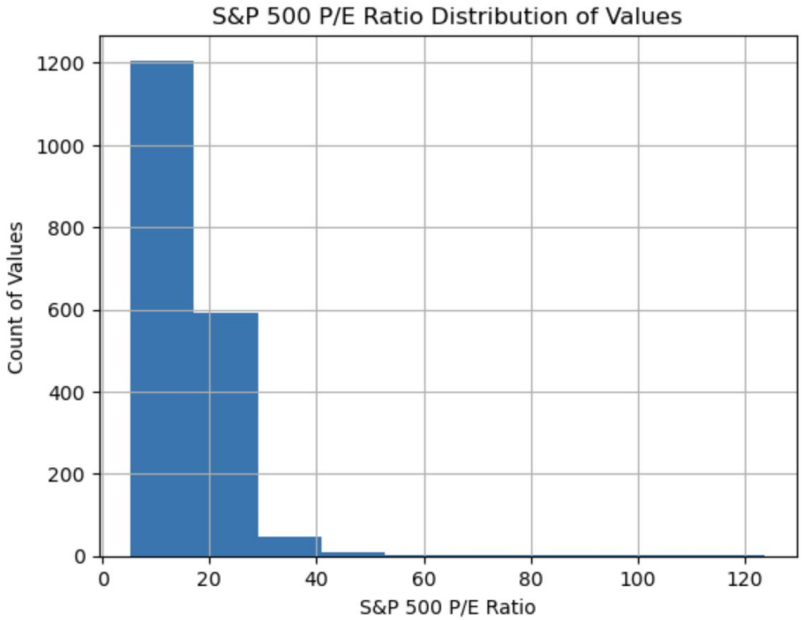


P/E Data Exploration

Many more values in PE dataframe than interest rate values in other dataframe, due to inclusion of both start-of-month and largely-duplicative end-of-month values for PE data as well as data from many more years being included in PE dataset vs rate dataset

PE data is also right-skewed, with mean of ~16 and a few especially high + very-rarely-occurring values (max value is >12 standard deviations from the mean value)

	S&P 500 PE Ratio
count	1864.000000
mean	16.209179
std	8.571940
min	5.310000
25%	11.595000
50%	15.070000
75%	18.552500
max	123.730000



Merged Data

Matched formatting of date data between dataframes, used inner merge to combine while dropping duplicative end-of-month datapoints, created new clean dataframe with only necessary columns/data

	Date	S&P 500 PE Ratio	Year	Month	Day	Federal Funds Target Rate	Federal Funds Upper Target	Federal Funds Lower Target	Effective Federal Funds Rate	Real GDP (Percent Change)	Unemployment Rate	Inflation Rate	Month2	Day2
0	2017-03-01	23.60	2017	3	1	NaN	0.75							
1	2017-02-01	23.68	2017	2	1	NaN	0.75							
2	2017-01-01	23.59	2017	1	1	NaN	0.75							
3	2016-12-01	23.76	2016	12	1	NaN	0.50							
4	2016-11-01	23.35	2016	11	1	NaN	0.50							

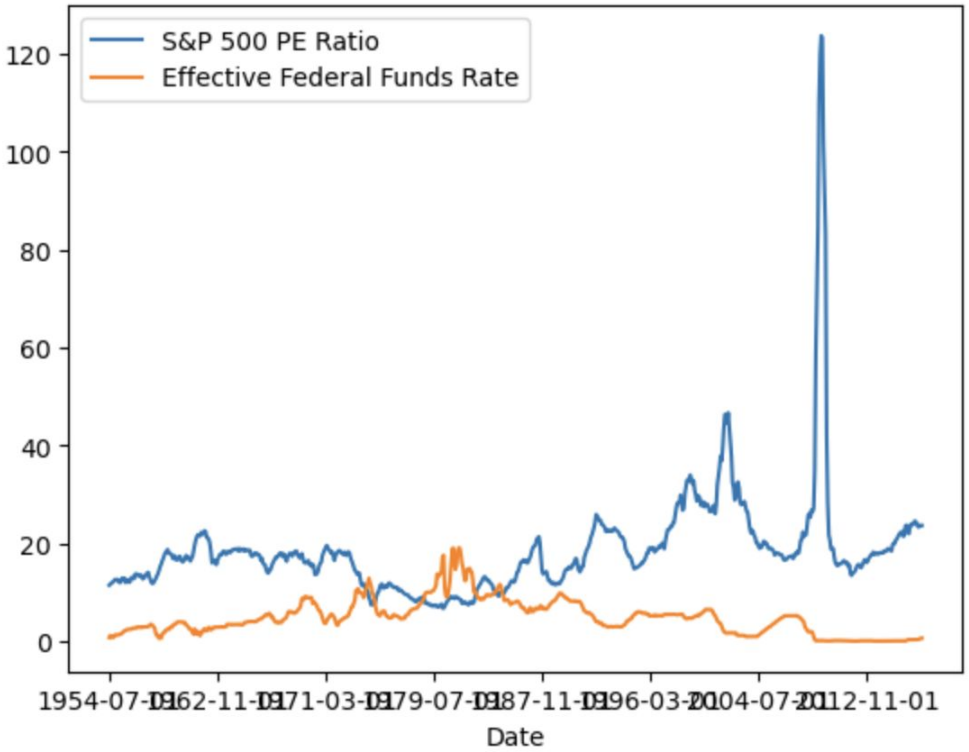
```
# Reduce to primary columns for analysis, using Effective Federal Funds Rate to represent rates

clean_df = combined_df[['Date','S&P 500 PE Ratio','Effective Federal Funds Rate']].dropna().sort_values('Date',ignc

print(clean_df.count())

clean_df.head(50)

```

```
Date                          752
S&P 500 PE Ratio              752
Effective Federal Funds Rate  752
dtype: int64
```

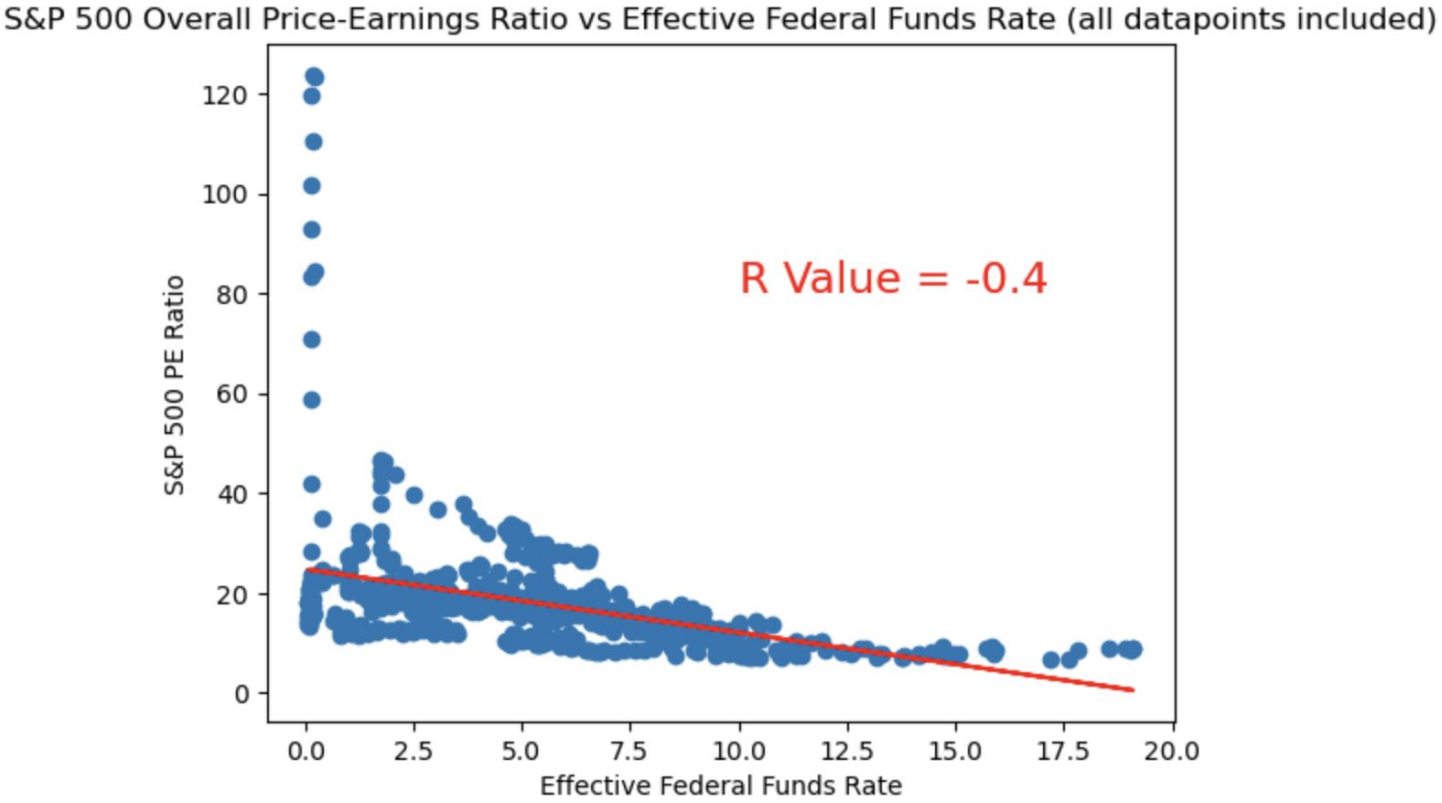
	Date	S&P 500 PE Ratio	Effective Federal Funds Rate
0	1954-07-01	11.49	0.80
1	1954-08-01	11.70	1.22
2	1954-09-01	11.96	1.06
3	1954-10-01	12.02	0.85
4	1954-11-01	12.28	0.83
5	1954-12-01	12.62	1.28
6	1955-01-01	12.56	1.39
7	1955-02-01	12.70	1.29
8	1955-03-01	12.33	1.35
9	1955-04-01	12.39	1.43

Correlation and Outlier Analysis

Initial Plot of Both Time Series (all datapoints included)

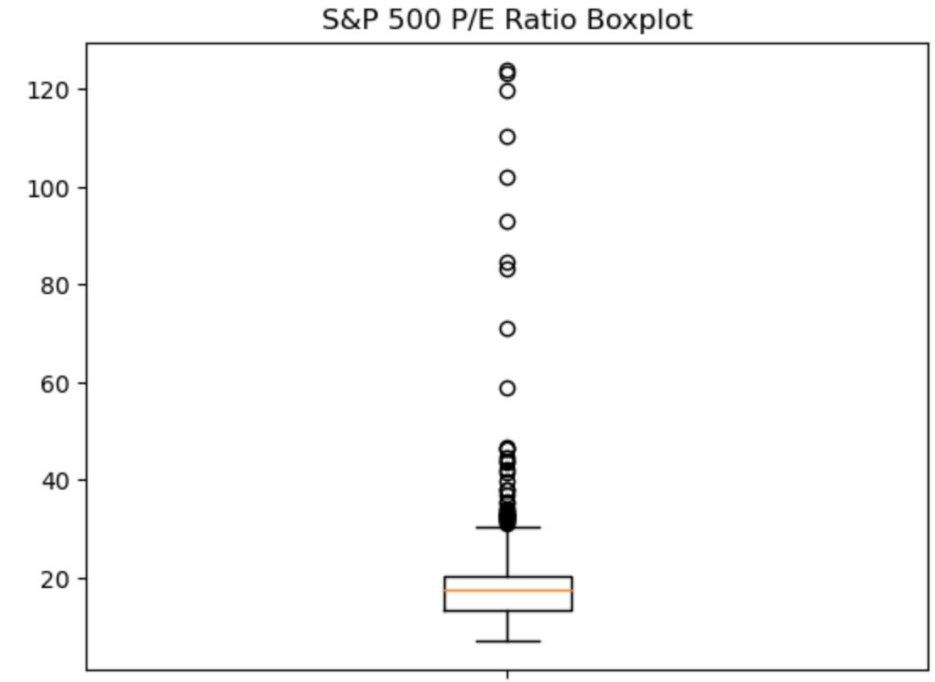


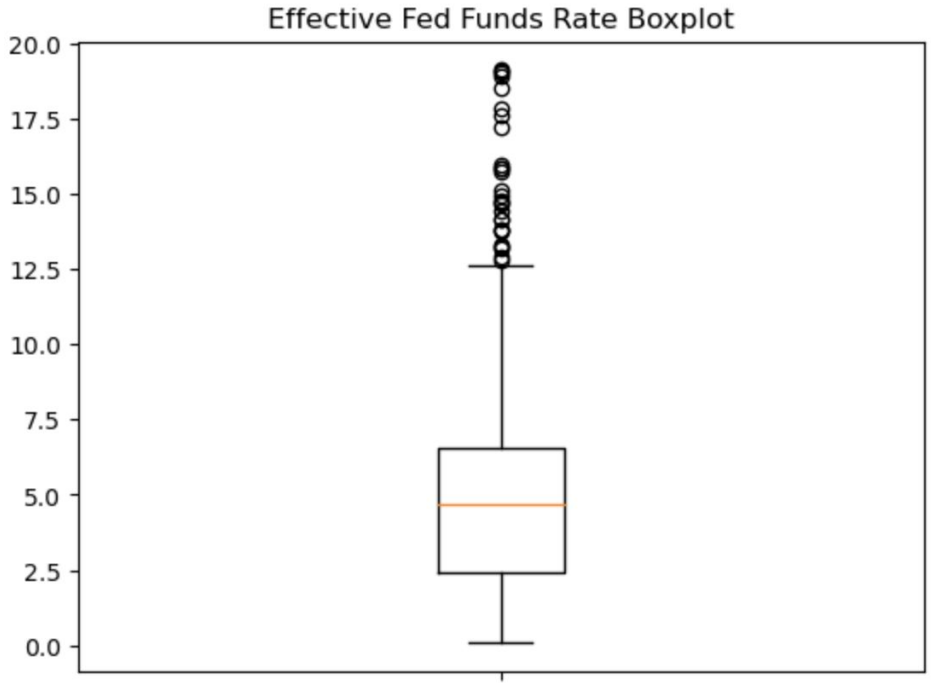
Initial Scatter Plot + Regression Line (all datapoints included)



Initial Boxplots of Each Dataset (all datapoints included)

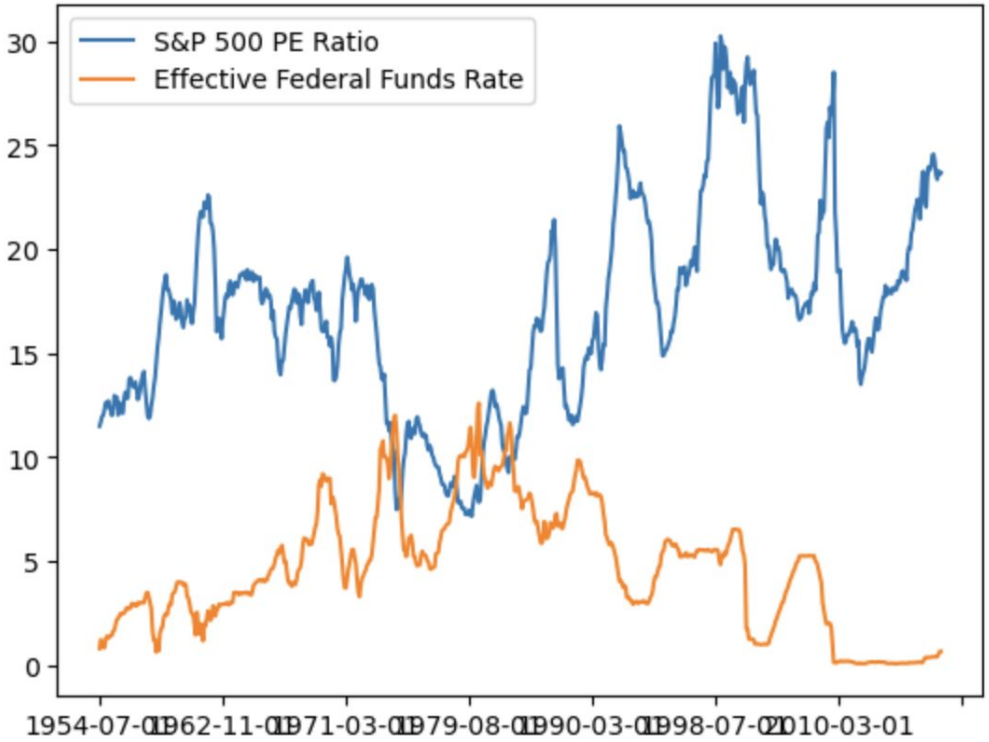
*Used standard (quartile +/- 1.5*IQR) calculation for estimating outliers*





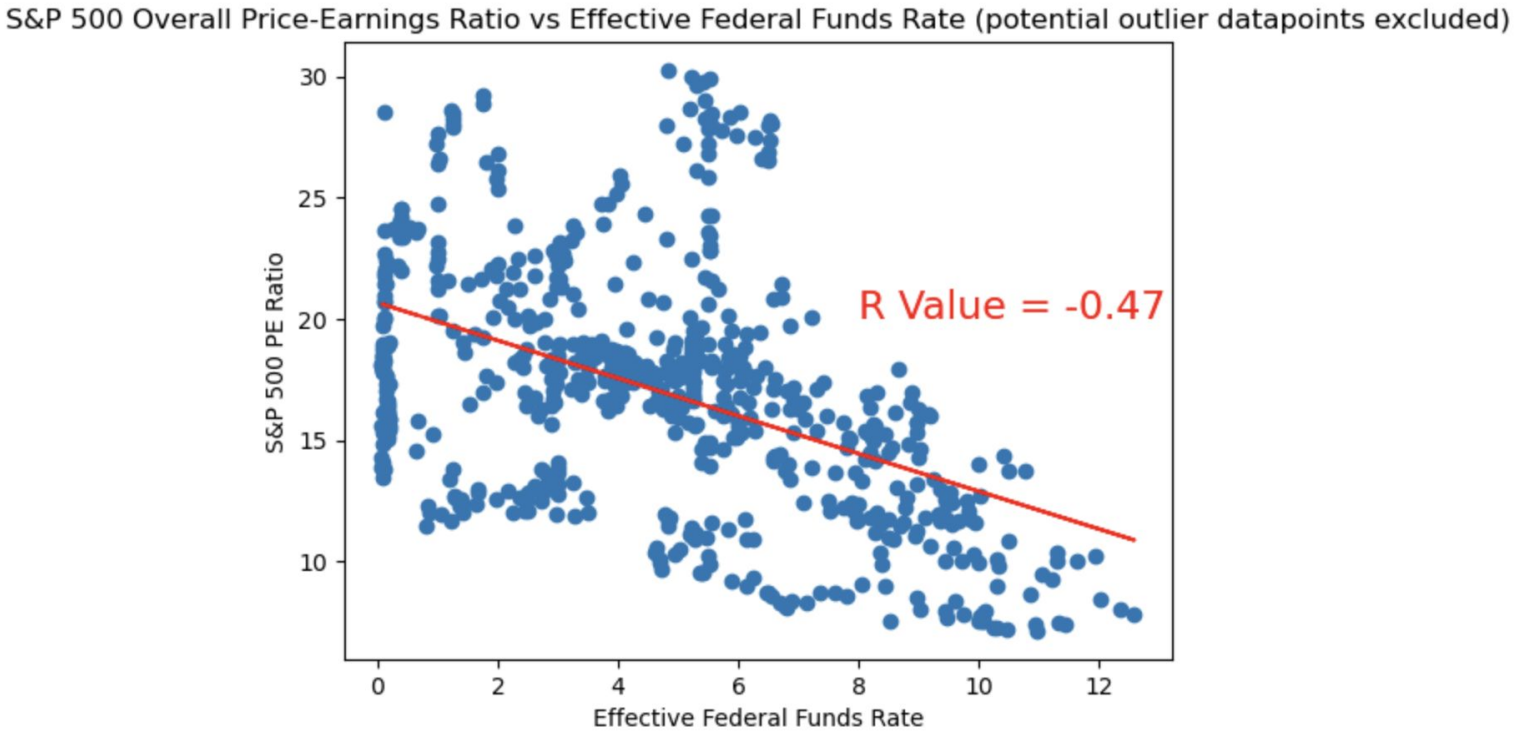
Removed Potential Outliers and Re-Plotted Both Variables

*Used standard (quartile +/- 1.5*IQR) calculation for estimating outliers*



Scatter + Regression Line with Potential Outliers Removed

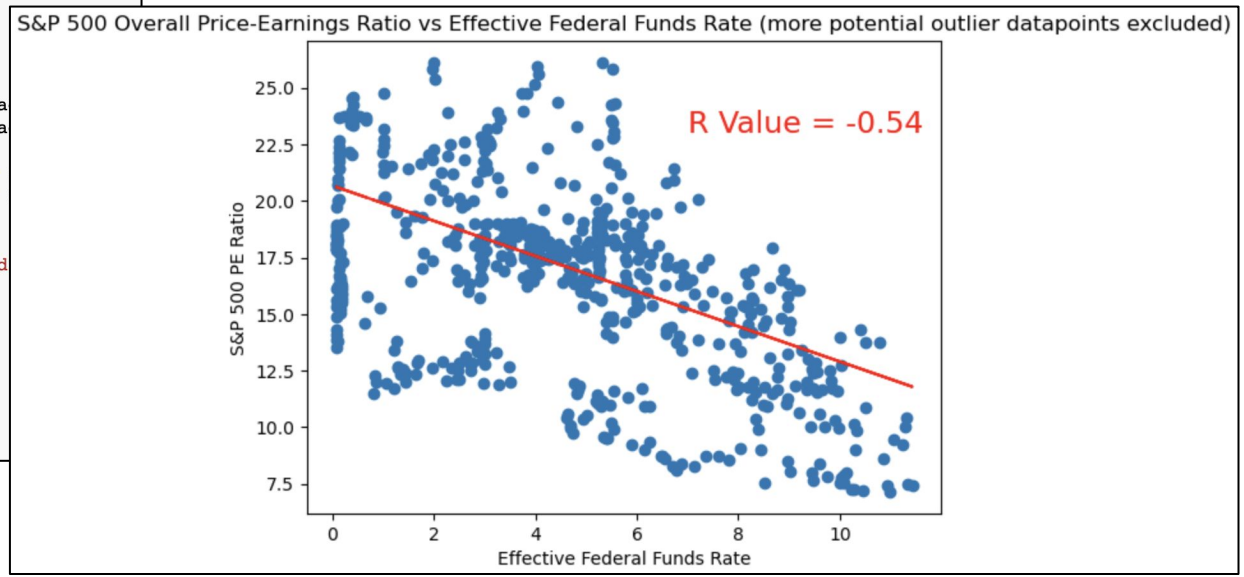
*Used standard (quartile +/- 1.5*IQR) calculation for estimating outliers*



Additional Potential Outliers Removed

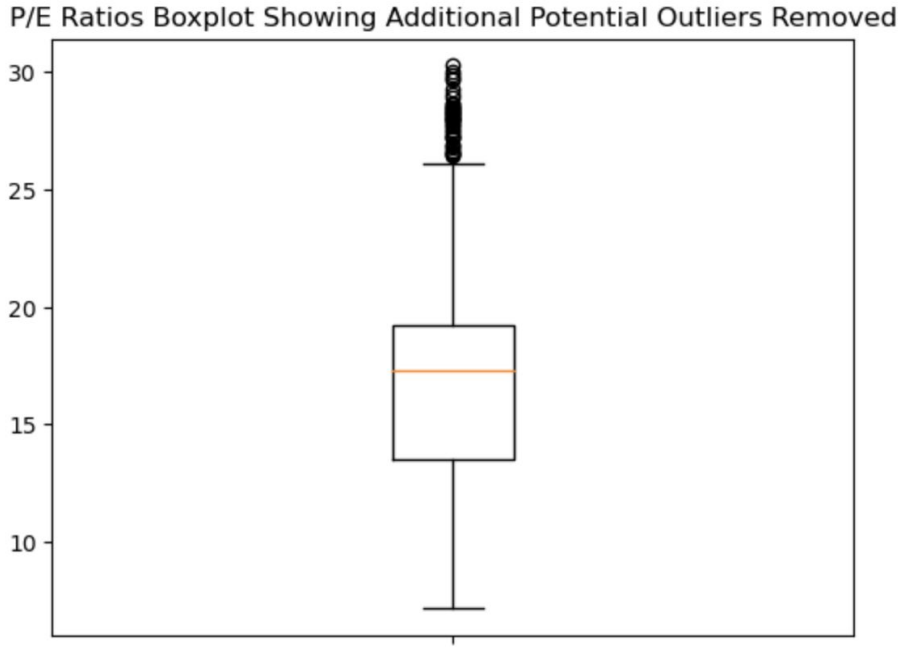
Tested multiple values for the 'IQR factor' used in estimating+removing additional outliers from each dataset
'IQR factor' of 1.25 so far produced the largest (in absolute terms) r-value of ~ -0.54

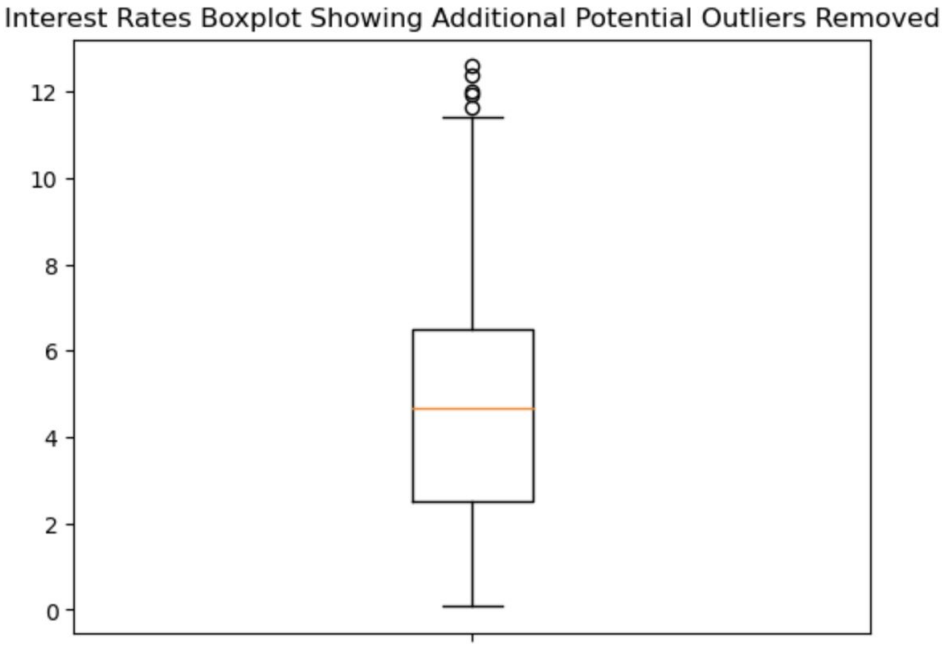
```
# Outlier removal (again)

outlier_free_df['pe_outliers2'] = ''
outlier_free_df['rate_outliers2'] = ''


pe_outliers2 = []
rate_outliers2 = []

iqr_factor = 1.25

pe_lb2 = pe_quartiles2[0.25] - (pe_iqr2 * iqr_fa
pe_ub2 = pe_quartiles2[0.75] + (pe_iqr2 * iqr_fa

rate_lb2 = rate_quartiles2[0.25] - (rate_iqr2 *
rate_ub2 = rate_quartiles2[0.75] + (rate_iqr2 *


for x in outlier_free_df['Effective Federal Fund

    if x < rate_lb2 or x > rate_ub2:

        rate_outliers2.append(True)

    else:

        rate_outliers2.append(False)
```



Boxplots Showing Additional Potential Outliers Removed

'IQR factor' of 1.25 used in 'whis=' argument to match these boxplots with outliers removed in second round





Conclusions and Next Steps

Conclusions

- S&P 500 P/E ratios and US Federal Funds effective rates do generally show a negative correlation
- Both datasets do contain very ‘extreme’ values which could be considered outliers, especially the P/E ratio data, and removing those potential outliers iteratively does lead progressively to r-values closer to -1 (higher R^2 values), at least to a point
- However, these 2 variables can only be considered ‘moderately correlated’, with the largest r-value I observed (in absolute terms) being -0.54
- There are many other variables which likely impact/influence average US company valuations, some of which may also influence US interest rate policy itself as well
    - In order to more thoroughly explain the relationship between these two variables, and ideally to attempt to predict company valuations based on expected changes in interest rates (as well as other factors), would require a much more complex analysis across more variables

Next Steps / Future Analysis

- Considering the potential time-lag in impact of interest rates on PE ratios, is there a stronger correlation between the two variables if accounting for that time-lag by shifting the x-axis for one of the variables relative to the other?

- What other factors/variables likely impact US company valuations / PE ratios that should be considered through additional analyses? Which of those may also have an impact on interest rate policy / future rates themselves?

- Are there specific sectors / business types that respond more directly/immediately to changes in federal interest rate policy?

- Is there a ‘better’ dependent variable for representing interest rate policy in the US, in terms of showing a closer real-time correlation with PE ratios and therefore higher potential for causality/predictability (i.e. producing an r-value closer to -1)?

Appendix

Additional Notes on Original Plan/Datasets

Originally considered looking at tech company valuations specifically, via NASDAQ index PE ratios and because interest rates anecdotally seem to have a greater impact on tech company valuations due to longer average time-to-value industry-wide. Went with broader S&P 500 index data because it's available across a much longer time period, and Fed interest rates move quite slowly over years and differently over decades.

Acknowledgements and Data Sources

- pulling code from week-06/module-06 'WeatherPy' challenge as starting point for data loading

- federal interest rate data by month obtained from Kaggle (https://www.kaggle.com/datasets/federalreserve/interest-rates)

- S&P 500 PE ratios by month obtained from NASDAQ Data Link API (https://docs.data.nasdaq.com/docs/python-time-series)