Exploring the Relationship Between the Economy and US Interest Rates

Background Information:
The US Congress enacted the Federal Reserve to be the central bank of the United States in 1913. With this act, the Federal Reserve had autonomy over controlling and achieving a dual mandate: maximizing employment and having approximately 3-4% yearly inflation.

However, the economy ebbs and flows, and the Federal Reserve needs to act in accordance with the economies behavior and use tools given to them to help achieve their dual mandate. In early 2020, we experienced a contraction in GDP and a dramatic drop in the employment rate to near Great Depression levels.

The Federal Reserve needed to remedy the situation. It decided to decrease interest rates to near 0. This effectively made the cost of borrowing US dollars nil and allowed for a rapid velocity of money throughout the economy when it needed it most.

However, due to over-saturation, supply shocks, and demand growth, we are currently experiencing the highest rate of inflation that we have seen in the United States for over two decades. As a result, the Federal Reserve needed to increase interest rates at an unprecedented rate in order to “cool down” the economy. In the Federal Reserve’s Federal Open Market Committee (FOMC) meetings and pressers, they repeatedly emphasize their dependence on (and keen observation of) important economic indicators to drive and guide their policy decisions. They state that their most looked-at indicators are: Core PCE (changes in prices of goods and services by consumers excluding food and energy), Consumer Price Index, and Unemployment.

Defining EFFR:
The Federal Reserve adjusts what is known as the Effective Federal Funds Rate (EFFR). This acts as a short-term guide of market expectations for US Interest Rates during the next two years. This is why the two-year US treasury note is highly correlated to EFFR.

The Effective Federal Funds Rate is the rate at which banks lend excess reserves to each other overnight. The Federal Reserve sets these rates by having a range for EFFR. For example, the current target rate is 375 - 400 bps (3.75% - 4%), and the Federal Reserve, through the Repo Market, will offer to borrow from banks at the upper range (4%) and lend to banks at 3.75%; this sets the range in stone and influences the EFFR.

Dataset Description:
The dataset used to perform the analysis contains economic data and Federal Reserve EFFR decisions from 1973 to present-day. Each row of the dataset represents a month-year combination (e.g., March 1981). The columns are the economic features and EFFR.

Research Questions:

The first question asks if predictions can be successfully made regarding whether or not the Federal Reserve will change interest rates (EFFR) from their current rate using four key economic indicators: Core PCE, CPI, Unemployment Rate, and Real GDP. From this, the analysis can investigate if the Federal Reserve is truly dependent on economic data (and to what degree).

The second question asks which of the four economic features are historically deemed most important by the Federal Reserve. Specifically, if certain economic indicators are more relevant in different time periods and Federal Reserve (or presidential) regimes for determining the EFFR.

Question 1 Methods:
For the first question, the target variable EFFR was transformed into categories of ranges using the data's five-number summary. Then a Decision Tree and a Neural Network were trained, each using the corresponding scikit-learn library and knowledge discovery of data (KDD) lab implementation. Results were compared to gauge prediction accuracy.

Figure 1 illustrates the code used to transform the EFFR into four categories. The resulting list of "groups" is then treated as the column of data containing the response variable's information. Note that "five_num_sum" is formatted as: [minimum, 1st quartile, median, 3rd quartile, maximum]. The final categories are: [minimum, 1st quartile), [1st quartile, median), …, [3rd quartile, maximum].

Figure 1:

```
# Creating new categories based on the five number summary
groups = []
for r in df["EffectiveFederalFundsRate"]:
  for i, mn in enumerate(five_num_sum):
    if mn == five_num_sum[-1]:
      break
    mx = five_num_sum[i+1]
    if mx == five_num_sum[-1]:
      if r >= mn and r <= mx:
        cur_group = '[' + str(mn) + ', ' + str(mx) + ']'
        groups.append(cur_group)
        break
    elif r >= mn and r < mx:
      cur_group = '[' + str(mn) + ', ' + str(mx) + ')'
      groups.append(cur_group)
      break
```

This yields the following frequencies in the dataset, displayed in Table 1.

Table 1:

Interest Rate Range (measured in %)	**Frequency in Dataset**

[0.05, 1.225)	150
[1.225, 4.99)	150
[4.99, 7.1125)	150
[7.1125, 19.1]	148

Following the response variable transformation, the data was split into 75% training data and 25% testing data. The pair of Decision Trees and pair Neural Networks were then trained on the training data and evaluated on the testing data. Due to scikit-learn's variety of model hyperparameters, the corresponding decision tree and neural network were tuned to approximate the ideal hyperparameter values that maximize testing accuracy.

Question 1 Results:
The results for all four models are summarized in Table 2.

Table 2:

KDD Method	**Testing Accuracy (measured in %)**
Decision Tree (Scikit-Learn)	84.56%
Decision Tree (Lab)	59.73%
Neural Network (Scikit-Learn)	85.91%
Neural Network (Lab)	24.44%

Overall, the models perform well at predicting interest rate decisions exclusively using economic and market data. The scikit-learn decision tree and scikit-learn neural network achieve roughly 85% testing accuracy when classifying month-year combinations as having interest rates (EFFR) within specific ranges of percentages.

While the corresponding lab-based decision tree performs worse than its scikit-learn counterpart, it still achieves almost 60% accuracy (being much better than a random guess, which would yield roughly 25% accuracy). Our lab-based neural network is slightly worse than a random guess, but this is understandable given its primitive nature (having only one neuron and one layer). At the very least, economic data seems to be heavily associated with Federal Reserve interest rate decisions.

To transition from Question 1 to Question 2, permutation test-based feature importance was computed for the scikit-learn decision tree. Feature importances were calculated using the KDD lab implementation and scikit-learn implementation of the technique. They were extremely similar.

Table 3 documents these feature importances (defined as the average of "original accuracy - permutation accuracy").

Table 3:

Feature	Feature Importance
Core PCE	45.10%
Inflation Rate (CPI)	30.07%
Unemployment Rate	29.13%
Real GDP	7.85%

In conclusion, the "answer" to question 1 seems to be that EFFR can be accurately predicted using economic data. Core PCE, Inflation Rate, Unemployment Rate, and Real GDP are all fairly important features, but the most important ones are consistent with what the Federal Reserve states.

Question 2 Methods:

To answer Question 2 (investigating differences in feature importance across different time periods), the dataset was split into segmented historical time periods, and five-number summary categories were calculated within each of these time periods. The time periods are as follows:

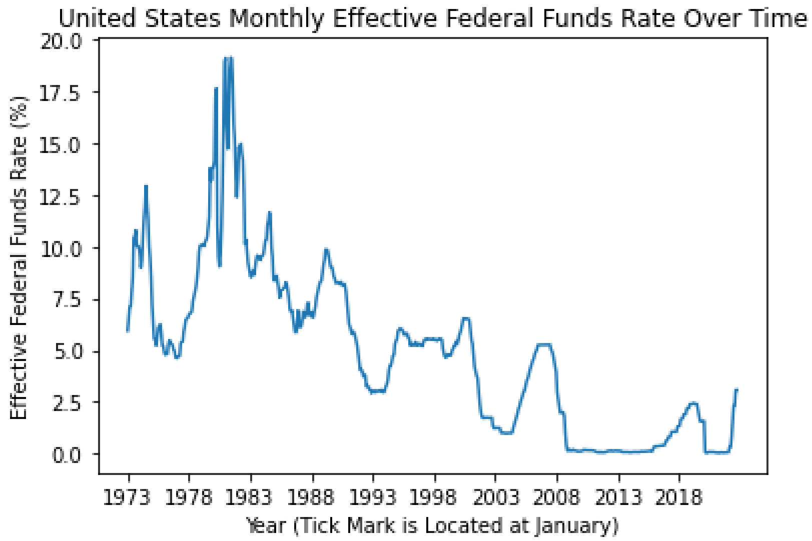
- The Stagflation Era (1973 - 1982)
- The Reagan/Bush Era (1983 - 1992)
- The Clinton Era (1993 - 2000)
- The War on Terror Era (2001 - 2007)
- Global Financial Crisis Era (2008 - 2015)
- Trump Era (2016 - 2019)
- Covid/Post-Covid Era (2020 - Present)

To reiterate, the EFFR values in each subset of data were used to define new categories for the target variable, much like in Question 1. However, these categories are defined on a per-subset basis, reflecting the five-number summary of the subset's time period.

The reason for not using Question 1's categorical ranges is that they were originally chosen to have equal representation in the full dataset. However, this is by no means true when the data is subset into different time periods. This means any model trained off of one of these subsets would suffer from class imbalance.

Figure 2 highlights this problem by illustrating how EFFR drastically changes overtime.

Figure 2:



For the purposes of model training and evaluation, each subset of data was split into 70% training data and 30% testing data. For each subset, a scikit-learn Decision Tree (using the tuned hyperparameters from Question 1) was trained on its training data and evaluated for accuracy on its testing data. From here, both scikit-learn feature importance and KDD lab permutation test-based feature importance were applied to each time period's decision tree. The results were then compared to answer Question 2.

Question 2 Results:

Table 4 through Table 10 illustrates the feature importances for each economic feature for each time period. A brief description follows each table.

Table 4:

Stagflation Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.0727	0.0729
Unemployment Rate	0.3368	0.3368
Inflation Rate (CPI)	0.2378	0.2380
Core PCE	-0.0102	-0.0093

The Stagflation era model places great importance on unemployment rate and inflation rate, but it places little to no importance on the other features. This is consistent with what we know about the era, where the odd interaction between inflation and unemployment was heavily scrutinized.

Table 5:

Reagan/Bush Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**

RealGDP	-0.0074	-0.0065
Unemployment Rate	0.1664	0.1723
Inflation Rate (CPI)	0.0584	0.0574
Core PCE	0.2509	0.2501

The Reagan era model places great importance on core PCE and unemployment rate, but it places little to no importance on the other features. This neither confirms nor contradicts our generally-understood ideas about the era.

Table 6:

Cinton Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.0147	0.0162
Unemployment Rate	0.3049	0.3017
Inflation Rate (CPI)	0.0274	0.0272
Core PCE	-0.0013	-0.0029

The Clinton era model places great importance on unemployment rate, but it places little to no importance on the other features. This is extremely fascinating, since it implies that the Clinton administration was almost exclusively focused on the USA's unemployment rate when setting their federal interest rates.

Table 7:

War-on-Terror Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.0243	0.2467
Unemployment Rate	0.4009	0.4002
Inflation Rate (CPI)	0.1606	0.1574
Core PCE	0.0329	0.0337

The War-on-Terror era model places immense importance on umemployment rate, moderate importance on inflation rate, and little importance on the other features. This suggests that the Bush Jr. administration was somewhat similar to the stagflation era in its focus when setting federal interest rates.

Table 8:

Recession Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.1340	0.1351

Unemployment Rate	0.0860	0.0886
Inflation Rate (CPI)	0.2950	0.2934
Core PCE	0.0677	0.0636

The Recession era model places great importance on inflation rate, moderate importance on real GDP, some importance on unemployment rate, and little importance on Core PCE. This, along with the relatively high standard deviations that these features have, suggests that the Obama administration may have taken a unique approach when setting their federal interest rates, relying on a mix of many economic features.

Table 9:

Trump Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.0009	0.0011
Unemployment Rate	0.4447	0.4468
Inflation Rate (CPI)	-0.0741	-0.0731
Core PCE	0.0643	0.0593

The Trump era model places immense importance on Unemployment Rate, little importance on CorePCE, and no importance on RealGDP and InflationRate. This suggests that the Trump administration mostly based its federal interest rate decisions on unemployment rate, being consistent with Mr. Trump's rhetoric about helping Americans obtain jobs.

Table 10:

Covid/Post-Covid Era	**Feature Importance (Lab)**	**Feature Importance (sklearn)**
RealGDP	0.0	0.0
Unemployment Rate	0.2659	0.2611
Inflation Rate (CPI)	0.1523	0.1549
Core PCE	0.1593	0.1635

The Covid/Post-Covid era model places great importance on Unemployment Rate, moderate importance on inflation rate and core PCE, and no importance on real GDP (being exactly 0). It should be noted that this era only has twelve months of data due to its recency, but predictions are relatively accurate (achieving 66% testing accuracy when random guessing would only achieve roughly 25% to 35%). The pandemic is known to have had a severe, negative impact on unemployment, so it is understandable why federal interest rate decisions might be heavily-influenced by it. Similarly, inflation rate and core PCE can be associated with quality of life, so it is reasonable why these are also important features. By contrast, real GDP has a less direct impact on people's lives than the other features, so it is understandable why the government might neglect it in favor of those other features.

Overall, we find that there is a stark contrast between the economic variables that are important in determining the Effective Federal Funds Rate across different Federal Reserve Chair (or presidential) regimes. Many of these findings are consistent with what one might expect (like the significance of unemployment and inflation during the Stagflation Era), but others are somewhat surprising (like the Clinton Era's Federal Reserve seeming to be almost exclusively focused on unemployment rate).

It should be noted that the testing accuracies of these time-period decision trees range from roughly 60% to 70%. This is likely due to the smaller sample sizes that resulted from subsetting the full dataset, as well as the fact that the decision tree hyperparameters were not re-tuned for each subset.

Summary and Next Steps:
The Federal Reserve has always stated that they are data-driven in their determination of interest rate hikes. We found this to be mostly true and their most looked-at economic indicator, Core PCE, matches the permutation test-based feature importance calculations on the full dataset.

However, in different Federal Reserve Chair (and presidential) regimes, there were notable differences in which economic feature was most important in determining EFFR. Furthermore, Core PCE was not the unanimously most important economic indicator across regimes.

Natural next steps include further investigating how KDD models can predict future *sizes and direction* of EFFR increases (i.e., evaluating regressors instead of classifiers). Due to the strong performance of the scikit-learn decision tree, the possibility of using bagging, boosting, or random forest to bolster performance should also be considered. Using these model predictions to, in turn, predict movements in Treasury, FX, and Equity markets could also prove fruitful.

Relevant Links

- **Link to Archived Code: https://github.com/jcurry777/CSC-466-Final-Project.git**
- Link to One Raw Data Source: https://www.newyorkfed.org/markets/reference-rates/effr
- Link to Helpful YouTube Tutorial: https://www.youtube.com/watch?v=Q9eDnBsAJ4w&t=600s