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Final Project Report

GitHub: https://github.com/mollyscheitler/BAIS3250_Final_Project

Introduction

Topic

Economics is "a social science that focuses on the production, distribution, and consumption of goods and services" (Hayes, 2024). Unemployment rates, stock market indices, interest rates, and inflation rates are key factors that play crucial roles in economics worldwide. Economics connects to many other industries, including politics, government, law, and business, so understanding how the economy works and what factors affect it is incredibly significant (Hayes, 2024). Specifically, I want to explore how the major stock market indices, interest rates, and inflation rates affect the unemployment rates in the United States.

Motivation

The unemployment rates, stock market indices, interest rates, and inflation rates provide valuable insights about the economy. At the same time, all these factors affect one another, which affects the economy. Specifically, I want to dive into the effects these factors have on the unemployment rate in the United States. At the same time, I would like to explore the correlations between all the different components. I chose this topic because I find the economy very interesting, especially the unemployment rate. I am interested in finding hidden connections between different parts of the economy and predicting future trends. The unemployment rate is a significant indicator of economic stability, so I believe focusing on this factor is perfect for the data I have gathered.

Data

I focused on unemployment rates, stock market indices, interest rates, and inflation rates. An explanation of each dataset is below.

Unemployment Rate

When looking for data regarding the unemployment rate, I obtained a .csv file from the Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis, Unemployment Rate, 2025). This website provided a graph and a file regarding the unemployment rates from the U.S. Bureau of Labor Statistics. I downloaded the .csv file attached to the website. The file contained the monthly unemployment rates from January 1948 to February 2025; there is an “observation_date” column and an “UNRATE” column. I renamed the columns to “Date” and “Unemployment_Rate.” I shifted all the dates from the first to the last day of the month and converted them to a datetime data type to match all my other data and properly integrate it. The “Unemployment_Rate” column was already a float data type.

Stock Market Indices

As for the stock index data, I utilized the Yahoo Finance API to find the closing prices of the S&P 500 (^GSPC), Nasdaq Composite (^IXIC), and Dow Jones (^DJI) indices in the years available for each stock. The dates presented for the ^GSPC stock data were from January 1929 to March 2025. The ^IXIC stock contained dates from February 1971 to December 2023. Finally, the dates presented for the ^DJI stock were from January 1992 to December 2023. I found the opening, closing, high, and low prices of each stock I chose. After obtaining this information, I narrowed the data to the closing price at the end of the month, and I rounded it to two decimal places. I shifted all the monthly data from the first to the last of the month and converted the column to a datetime data type. After this step, the columns present for each stock were “Date” and “Ticker,” with the ticker being the symbol for each stock. The “Ticker” column was already a float data type.

Interest Rate

When searching for the interest rate data, I used a .csv file from the Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis, Federal Funds Effective Rate, 2025). This website provided a graph and a file regarding the interest rates from the Board of Governors of the Federal Reserve. I gathered this data by downloading the .csv file attached to the website. The file contained the monthly interest rate from July 1954 to February 2025; there was an “observation_date” column and a “FEDFUNDS” column. I renamed the columns to “Date” and “Interest_Rate.” I shifted all the dates from the first to the last day of the month and converted them to a datetime data type to integrate later. The “Interest_Rate” column was already a float data type.

Inflation Rate

Finally, when searching for the inflation rates, I scraped the U.S. Inflation Calculator website (Coinnews Media Group LLC, 2025). There is a table with years to the left and months and averages as the columns; the data includes monthly inflation rates. The table contained data from

January 1914 to February 2025. When writing the code, I found the table on the website using XPATH and then narrowed my search by looking for table rows using TAG_NAME. The year and month data were table headers, so I had to utilize the search for table headers using XPATH. The actual data, inflation rates per month, was table data, so I utilized XPATH to find this table data. I also initialized lists for each column, which were months and averages, to capture the scraped data. Following the initial data scraping, I created a pandas DataFrame to visualize all the data in the lists. After properly scraping all the data, I had to convert it from a wide format to a long format to match the layout of my other datasets. I removed the average column to include the accurate monthly data. I also removed a few rows at the end of the DataFrame because no dates were present. To obtain the proper dates, I mapped out month names to numbers, applied the mapping to the months, extracted the "Month" and "Year" columns, converted these columns to one column called "Date," converted this "Date" column to a datetime datatype, and found the last day of each month to integrate all data later. In the end, the columns present were "Date" and "Inflation_Rate" because I renamed them. The "Inflation_Rate" column was already a float data type.

Integration of Data

Finally, I horizontally integrated all my datasets (Unemployment_Rate, ^GSPC, ^IXIC, ^DJI, Interest_Rate, and Inflation_Rate) with the "Date" column and an outer join to include all data from each dataset. In my final analysis, I removed NaN values and used data from January 1992 to February 2025 because all columns (Date, Unemployment_Rate, ^GSPC, ^IXIC, ^DJI, Interest_Rate, and Inflation_Rate) have data present. At this step, I have 398 rows of data in my final_dataset pandas DataFrame. I then removed outliers (IQR *2.0) and am left with 344 rows of data in my final_dataset2 pandas DataFrame. In this final_dataset2 pandas DataFrame, the dates range from 1992 to 2023. I used the copy of my dataset with outliers (final_dataset) for machine learning and time series analysis questions. I used the dataset without outliers (final_dataset2) for all univariate and bivariate descriptive statistics.

Molly Scheitler

Data Dictionary

Field	Type	Description
Date	Datetime	Date (year, month, day)
Unemployment_Rate	Float	Rate of Unemployment (percentage of people without jobs that could have jobs)
^GSPC	Float	S&P 500 Stock Closing Price
^IXIC	Float	Nasdaq Composite Stock Closing Price
^DJI	Float	Dow Jones Stock Closing Price
Interest_Rate	Float	Interest Rate (percentage of a loan that is charged as interest to borrower)
Inflation_Rate	Float	Inflation Rate (percent change in the price of a basket of goods/services over a period of time)

Analysis

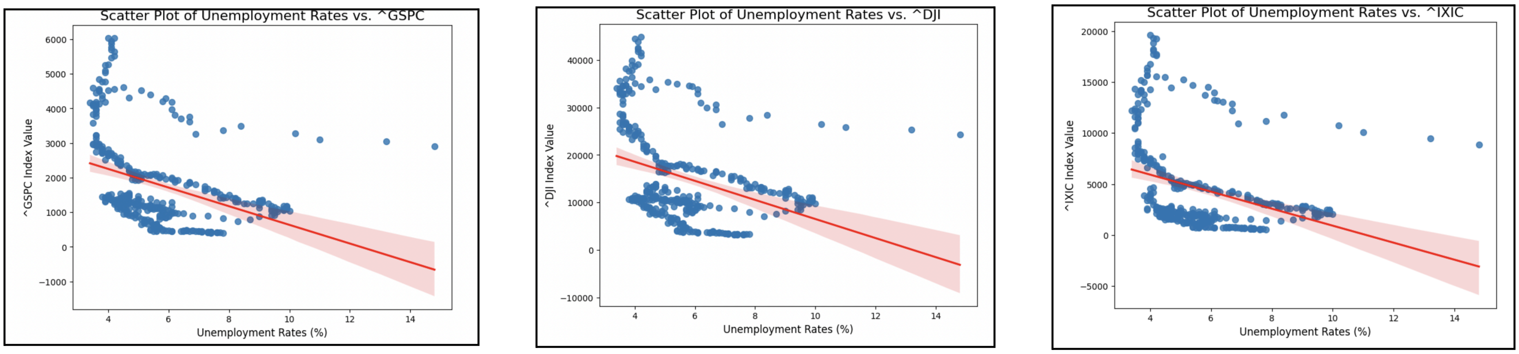
Stock Market Index Values versus Unemployment Rates

I hypothesized that all stock indices would negatively correlate with unemployment because there is less consumer consumption with an increased unemployment rate. I also thought the ^DJI stock index would be the most sensitive to the unemployment rate because it is made of industrial companies, which are directly linked with economic health.

Correlation Analysis

To begin my analysis, I examined the correlation between the three major stock market indices (^GSPC, ^IXIC, and ^DJI) and the unemployment rate. I used the Pearson Correlation Coefficient to measure the strength and direction of the linear relationships. The results were as follows: for ^GSPC and unemployment, the coefficient is -0.3523; for ^IXIC, the coefficient is -0.3033, and for ^DJI, the coefficient is -0.3134. The p-values for all three correlations were 0.0000, indicating that all relationships are statistically significant. Among the three, ^GSPC showed the strongest correlation with unemployment. These negative correlations align with my initial hypothesis: as unemployment rises, economic conditions typically worsen, negatively impacting stock market performance. The stronger correlation for ^GSPC may be because of its broad market exposure. To visually support these findings, I included scatter plots with regression lines for each index plotted against the unemployment rate (Figure A).

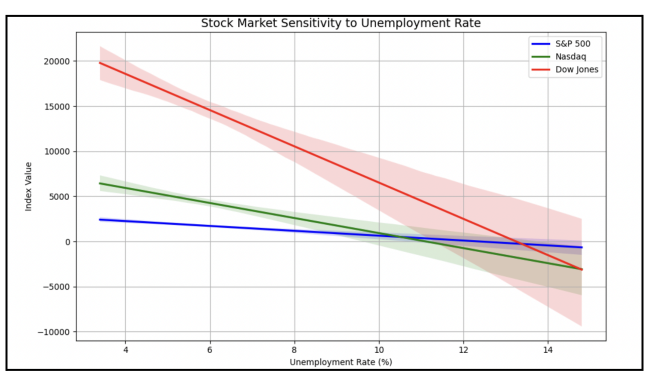
Figure A: Scatter Plots with Regression Lines (Unemployment versus All Stocks)



Sensitivity analysis

Additionally, I wanted to determine which stock index is most sensitive to changes in unemployment rates. To explore this, I created a combined regression line plot displaying all the regression lines from the previous scatter plots in a single graph (Figure B). Visually, ^DJI appeared to be the most sensitive to unemployment changes; its regression line is the steepest of the three. To support this observation, I calculated the slopes and R^2 values for each regression line. The slope of ^GSPC is -269.64 with an R^2 value of 0.141; the slope of ^IXIC is -834.02 with an R^2 value of 0.112; and the slope of ^DJI is -2009.59 with an R^2 value of 0.130. These results confirm that ^DJI is the most sensitive to unemployment rate changes due to its steepest negative slope. However, while all relationships are statistically significant, the relatively low R^2 values indicate that unemployment explains only a small portion of the variation in stock index values, suggesting that other economic factors also influence market performance.

Figure B: Plot with all the Stocks' Regression Lines

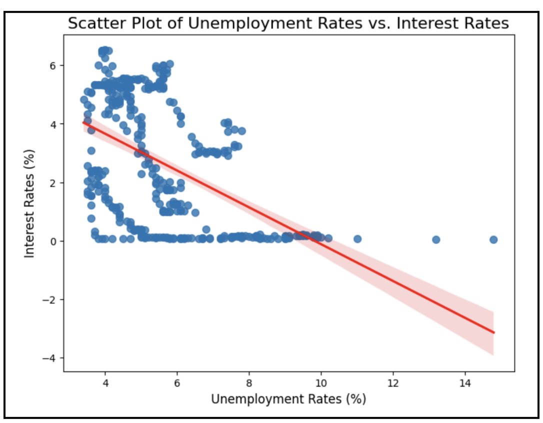


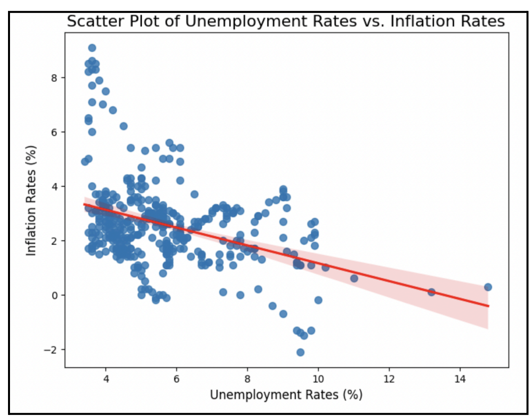
Interest and Inflation Rates versus Unemployment Rates

One of my research questions was to determine the strength of the relationships between interest rates, inflation rates, and unemployment rates. I hypothesized that both interest and inflation would negatively correlate with unemployment, with interest having a stronger relationship. To test this, I utilized the Pearson Correlation Coefficient. The correlation between interest and unemployment is -0.5303, indicating a moderate negative linear relationship. The correlation between inflation and unemployment is -0.1996, suggesting a weak negative relationship. Both relationships were statistically significant, with p-values of 0.0000 (interest) and 0.0002 (inflation), which are below the 0.05 significance threshold. This means the observed correlations are unlikely to have occurred by chance.

These results support my hypothesis that interest rates are more closely tied to unemployment than inflation. While both show negative relationships with unemployment, interest rates demonstrate a clear pattern. The inflation against unemployment correlation is statistically significant but weak and less meaningful. This suggests that unemployment has a stronger effect on interest rates than it does on inflation. To visualize these relationships, I included scatter plots with regression lines for both interest and inflation against unemployment (Figure C).

Figure C: Scatter Plots with Regression Lines (Unemployment versus Interest and Inflation)





Stock Market Index Values and Inflation Rates versus Interest Rates

Another research question I explored was how interest rates correlate with the major stock market indices (^GSPC, ^IXIC, and ^DJI) and inflation rates. I hypothesized that all three stock indices would have a negative correlation with interest rates and that inflation would have a positive correlation. Using the Pearson Correlation Coefficient, I found that ^GSPC has a correlation of -0.3956 with interest rates, ^IXIC has -0.3360, and ^DJI has the strongest negative correlation at -0.4163. All three relationships have p-values of 0.0000, indicating strong statistical significance. This supports the hypothesis that higher interest rates tend to negatively impact stock performance, particularly for ^DJI, which appears to be the most sensitive to changes in interest rates.

On the other hand, the correlation between inflation and interest rates is 0.4683, indicating a moderate positive linear relationship, which is also statistically significant (p-value = 0.0000). This aligns with the understanding that banks often raise interest rates to balance rising inflation. I visualized these relationships using scatter plots with regression lines: each stock index versus interest rate (Figure D), and the inflation versus interest rate plot (Figure E).

Figure D: Scatter Plots with Regression Lines (Interest versus All Stocks)

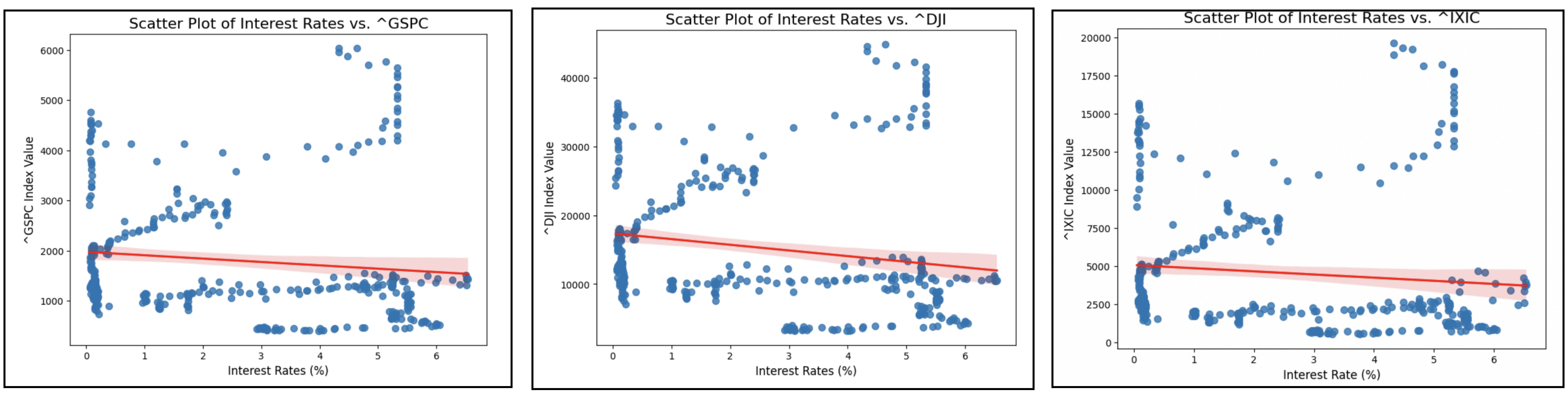
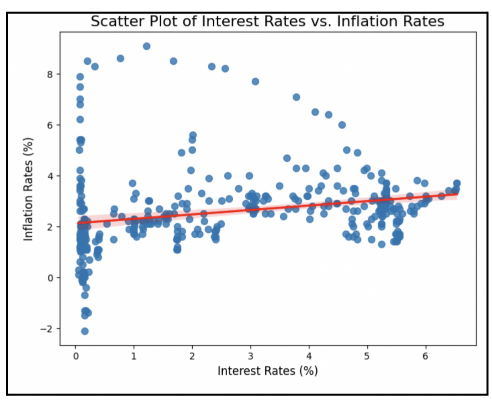


Figure E: Scatter Plot with a Regression Line (Interest versus Inflation)

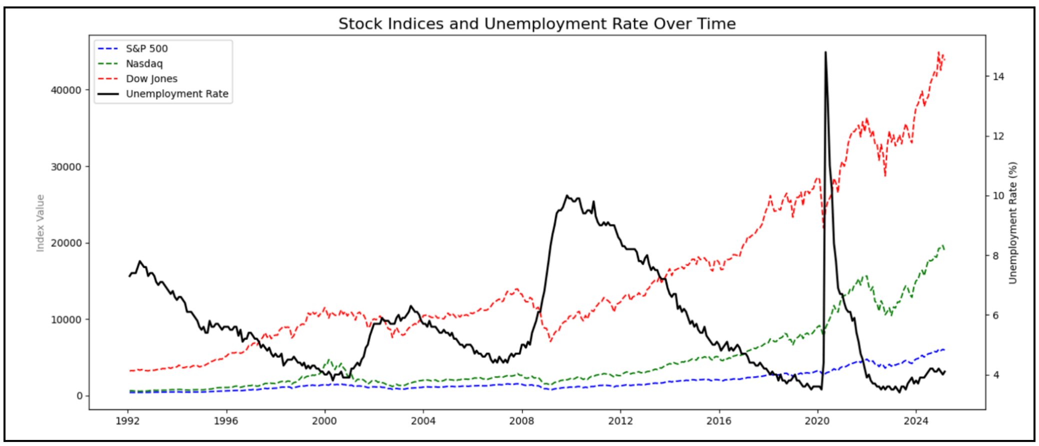


Stock Market Price Behavior versus Increase in Unemployment Rates

To investigate whether stock market declines occur before or after increases in unemployment rates, I conducted a lagged correlation analysis. My initial hypothesis was that stock market indices would decline before a rise in unemployment because of the expectations of worsening economic conditions. The lagged Pearson correlation coefficients supported this idea: ^GSPC has a lagged correlation of -0.3666, ^IXIC has -0.3244, and ^DJI has -0.3521. These results suggest that stock prices tend to decrease before rising unemployment, with ^GSPC and ^DJI showing moderately strong negative correlations and ^IXIC showing a slightly weaker relationship.

This pattern is consistent with the broader economic understanding that financial markets often respond ahead of actual economic indicators like unemployment, which tends to be a lagging indicator. To visualize these trends, I created a dual-axis time series plot showing all three stock indices alongside unemployment rates over time (Figure F). The visualization highlights how dips in stock index values often lead to peaks in unemployment, reinforcing the idea that markets anticipate economic downturns.

Figure F: Dual-Axis Time Series Plot (All Stocks versus Unemployment)



Rising Inflation and Unemployment Rates versus Stock Market Health

I wanted to explore which factor, inflation or unemployment, has a greater impact on the stock market indices I analyzed (^GSPC, ^IXIC, and ^DJI). My initial hypothesis was that unemployment would have a stronger negative effect on stock performance than inflation, which might show a weaker or mixed relationship.

To test this, I calculated the Pearson Correlation Coefficient for each index against both inflation and unemployment rates. The ^GSPC index has a correlation of 0.31 with inflation and -0.38 with unemployment. ^IXIC has a correlation of 0.32 with inflation and -0.34 with unemployment. ^DJI has a correlation of 0.29 with inflation and -0.36 with unemployment. While each index shows a weak positive correlation with inflation, they all show a moderate negative correlation with unemployment. The p-values for all relationships are 0.0000, indicating strong statistical significance.

These findings support the hypothesis that unemployment has a more substantial impact on stock prices than inflation. This aligns with economic expectations because high unemployment equals weaker consumer demand and economic activity. Inflation, on the other hand, may have both positive and negative effects depending on the broader economic context.

To visualize these patterns, I created scatter plots with regression lines for each index against both inflation and unemployment (Figure G). I also developed a correlation heat map to provide a quick reference of all relationships (Figure H) and a pairwise scatter matrix to explore interactions across all variables in the dataset (Figure I).

<u>Figure G: Scatter Plots with Regression Lines (All Stocks versus Unemployment and Inflation)</u>

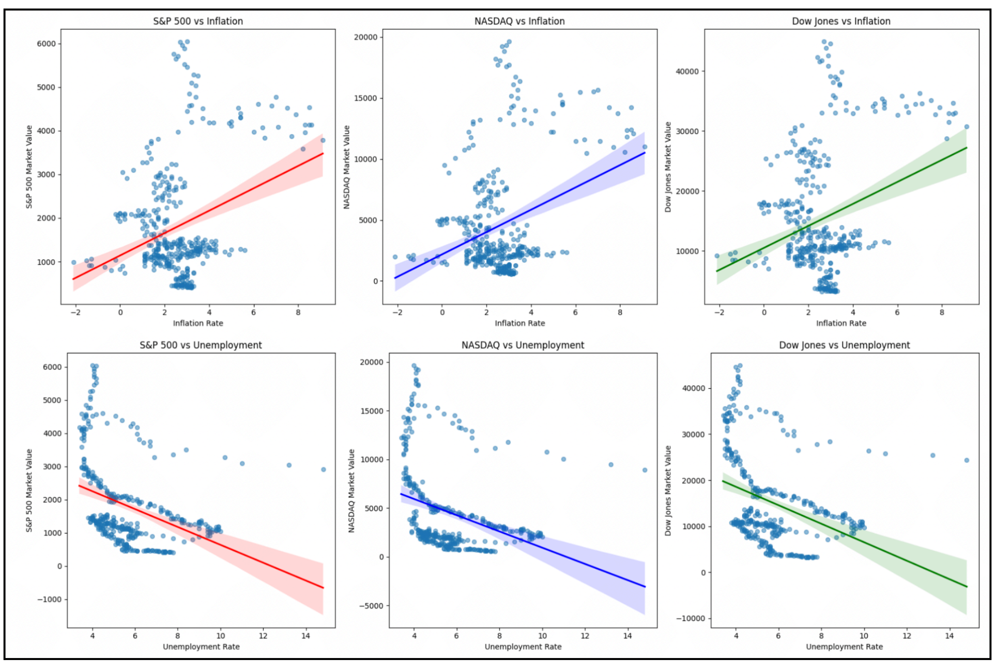


Figure H: Correlation Heat Map (Stocks, Inflation, Unemployment)

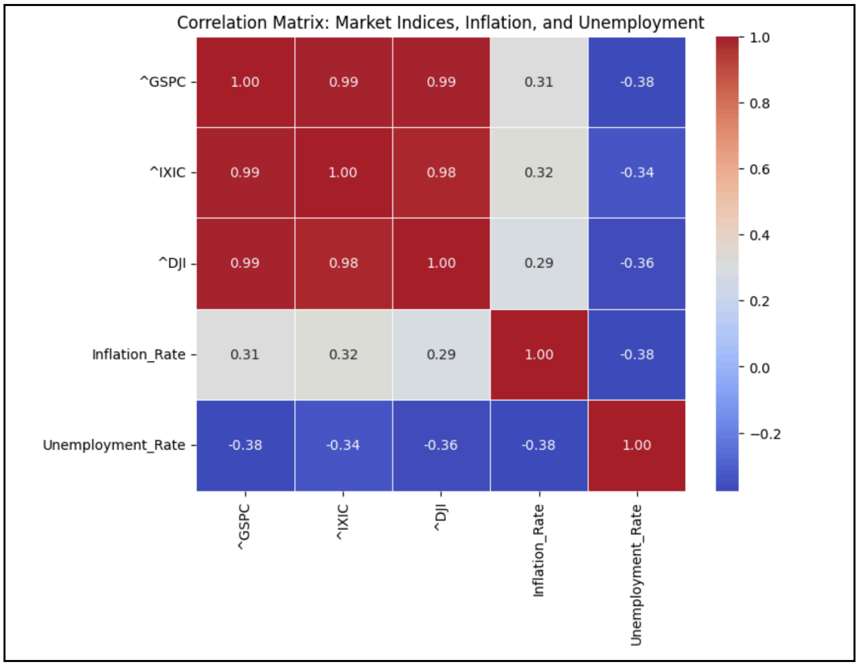
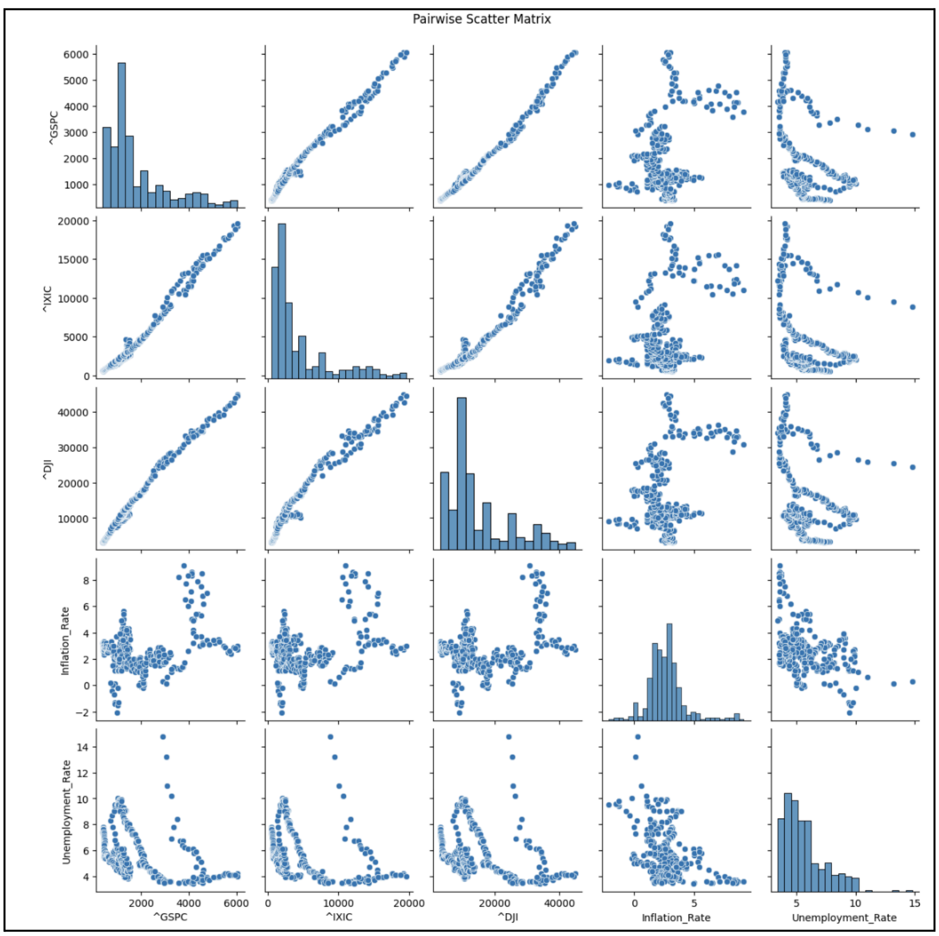


Figure I: Pairwise Scatter Matrix (Stocks, Inflation, Unemployment)



Molly Scheitler

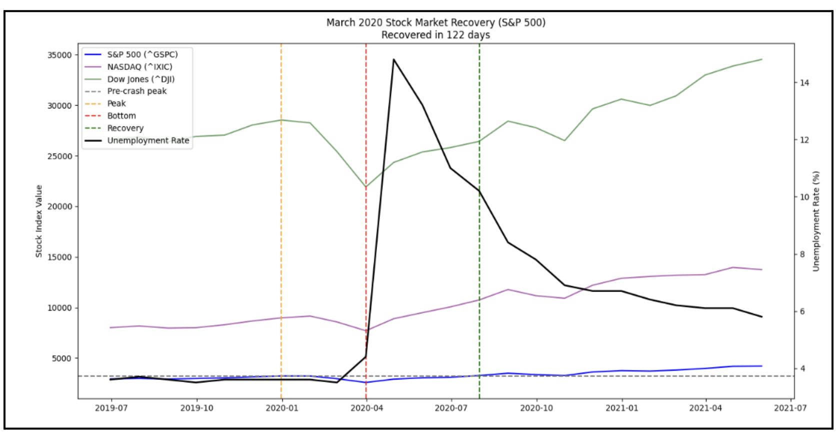
Stock Market Recovery versus Major Spike in Unemployment Rates

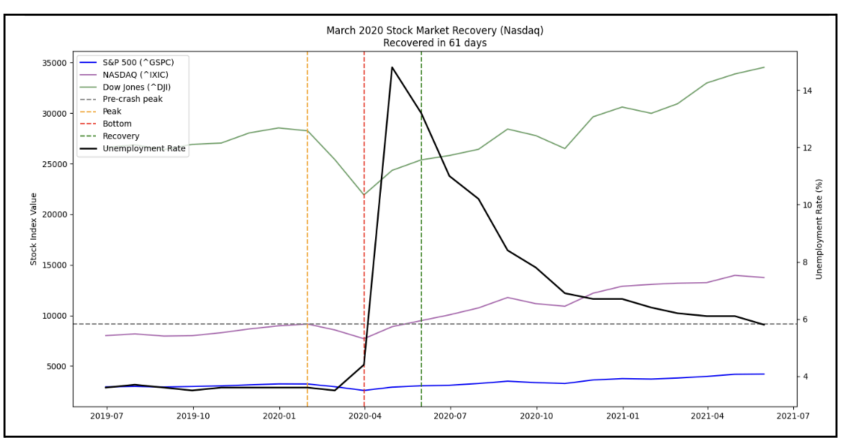
I investigated whether the stock indices (^GSPC, ^IXIC, and ^DJI) recovered similarly following a spike in unemployment, focusing on the COVID-19 pandemic period from 2019 to 2021. For each index, I identified the pre-crash peak value, the peak unemployment date, the post-crash low, and the date of full recovery. The results showed varying recovery times: ^GSPC recovered in 122 days, ^IXIC in 61 days, and ^DJI took the longest at 244 days.

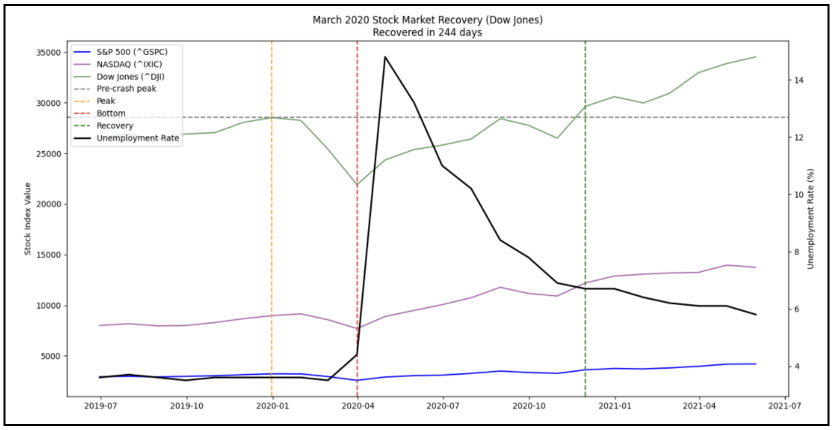
These findings suggest that ^IXIC was the most resilient during this period, likely due to increased reliance on technology during the pandemic. In contrast, ^DJI was slower to recover, possibly because it includes industries like energy and manufacturing, which were more heavily impacted. ^GSPC, being a broad-market index, includes a diverse range of industries, and some recover quickly while others lag.

To visualize these recovery timelines, I created a dual-axis time series line chart for each index, illustrating the period of decline and rebound related to the unemployment spike (Figure J). Understanding these recovery patterns provides insight into how different sectors respond to economic shocks.

Figure J: Dual-Axis Time Series Line Chart







Hypothesis Tests - Comparing Average Unemployment Across Decades

To examine how unemployment rates have changed over time, I grouped all dates in my final dataset into decades and compared average unemployment across them. Comparing the 1990s to the 2000s, there is no statistically significant difference in average unemployment; the P-value is 0.55125, so I failed to reject the null hypothesis (Figure K). However, when comparing the 2000s to the 2010s, the difference is statistically significant, with a P-value of 0.003489, indicating a meaningful shift in unemployment levels during that period. These findings suggest that while unemployment remained relatively stable between the 1990s and 2000s, economic changes in the 2010s likely influenced a shift in market conditions.

Figure K: Comparing Unemployment Across Decades

Comparing Unemployment Rates From the 1990s to the 2000s

```python
# Convert to datetime format
final_dataset['Date'] = pd.to_datetime(final_dataset['Date'])

# Create a new column for decade
final_dataset['Decade'] = (final_dataset['Date'].dt.year // 10) * 10

# Filter for two decades (1990s and 2000s)
unemployment_1990s = final_dataset[final_dataset['Decade'] == 1990]['Unemployment_Rate']
unemployment_2000s = final_dataset[final_dataset['Decade'] == 2000]['Unemployment_Rate']

# Run a two-sample t-test
t_stat, p_value = ttest_ind(unemployment_1990s, unemployment_2000s, equal_var=False)

# Show results for t-statistic and p-value
print("T-Statistic:", t_stat)
print("P-value:", p_value)

# Interpret the results according to alpha
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: Average unemployment is significantly different between the 1990s and 2000s.")
else:
    print("Fail to reject the null hypothesis: No significant difference in average unemployment the 1990s and 2000s.")
```

```
T-Statistic: 0.5968223622548725
P-value: 0.5512589310147289
Fail to reject the null hypothesis: No significant difference in average unemployment the 1990s and 2000s.
```

Comparing Unemployment Rates From the 2000s to the 2010s

```python
# Create a new column for decade
final_dataset['Decade'] = (final_dataset['Date'].dt.year // 10) * 10

# Filter for two decades (2000s and 2010s)
unemployment_2000s = final_dataset[final_dataset['Decade'] == 2000]['Unemployment_Rate']
unemployment_2010s = final_dataset[final_dataset['Decade'] == 2010]['Unemployment_Rate']

# Run a two-sample t-test
t_stat, p_value = ttest_ind(unemployment_2000s, unemployment_2010s, equal_var=False)

# Show results for t-statistic and p-value
print("T-Statistic:", t_stat)
print("P-value:", p_value)

# Interpret the results according to alpha
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: Average unemployment is significantly different between the 2000s and 2010s.")
else:
    print("Fail to reject the null hypothesis: No significant difference in average unemployment the 2000s and 2010s.")
```

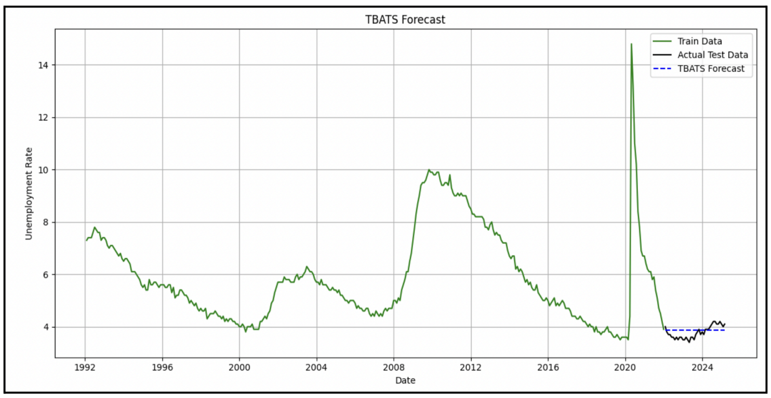
```
T-Statistic: -2.9539201415970164
P-value: 0.0034895472773083087
Reject the null hypothesis: Average unemployment is significantly different between the 2000s and 2010s.
```

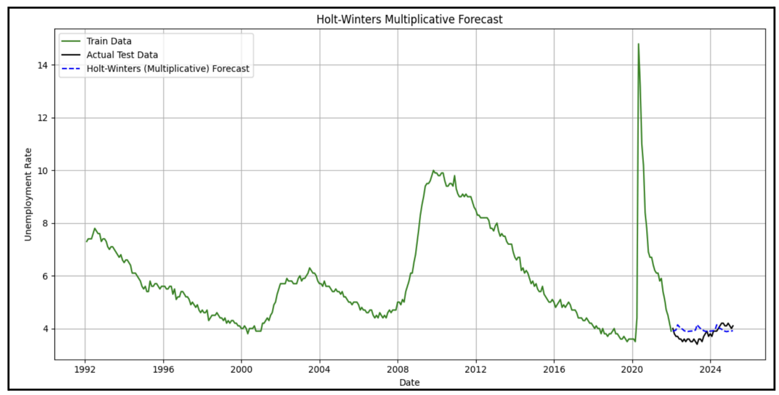
Time Series Analysis - Finding the Right Forecasting Method

To determine the most accurate forecasting method for my dataset, I split the data into training and testing sets to evaluate several techniques using Mean Absolute Error (MAE) as the performance metric. The methods tested included TBATS, Simple Exponential Smoothing (SES) with α=0.8 and α=0.2, SES with span=6 for both α values, Holt-Winters (multiplicative and additive), and Moving Average models with n=4 and n=6. Among these, TBATS produced the lowest MAE at 0.2239, indicating the best fit on the test data.

However, when visualizing the TBATS forecast, the predicted values formed a flat line with no apparent seasonality or trend, suggesting potential underfitting or overly smooth forecasts. For comparison, I also plotted the Holt-Winters Multiplicative method, which captured more variation in the test period (Figure L). This comparison highlights the trade-off between model accuracy and interpretability when forecasting time series data.

Figure L





<u>Machine Learning Techniques - Finding the Most Accurate Model or Classifier</u>

I performed a linear regression model using all continuous variables, which yielded an R^2 value of 0.6784, indicating that approximately 68% of the variance in the target variable is explained by the model. To explore classification approaches, I transformed the Unemployment_Rate column into a categorical variable with four bins: Very Low, Low, High, and Very High.

I then applied several classification models. The Decision Tree Classifier achieved the best performance, with an accuracy of 0.8875 and an F1 score of 0.8848. Next, the K-Nearest Neighbors (KNN) model has an accuracy of 0.8125 and an F1 score of 0.8153. The Logistic Regression model has an accuracy of 0.6375 and an F1 score of 0.6240, while the Support Vector Classifier (SVC) performed the weakest, with an accuracy of 0.5125 and an F1 score of 0.4614. The Decision Tree model performed the best. This model may capture nonlinear patterns that other models failed to detect (Figure M).

Figure M: Decision Tree Classifier Model (Accuracy and F1 Score)

Decision Tree Classifier Model

```
# Convert the Unemployment_Rate column to Unemployment_Group indicating the level of unemployment

final_dataset["Unemployment_Group"] = pd.qcut(final_dataset["Unemployment_Rate"], q=4, labels=["Very Low", "Low", "High", "Very High"])
```

```
# Find the target and predictor variables

X = final_dataset.drop(columns=["Unemployment_Rate", "Unemployment_Group", "Date", "Decade"])
y = final_dataset["Unemployment_Group"]
```

```
# Decision Tree Classifier Model

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Dec_tree = DecisionTreeClassifier(random_state=42)

# Fit the classifier to the training data
Dec_tree.fit(X_train, y_train)

# Get the predictions
y_pred = Dec_tree.predict(X_test)

# Print Accuracy Score
print(f'Decision Tree Accuracy: {Dec_tree.score(X_test,y_test)}')

# Print F1_score
print(f"Decision Tree F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
```

```
Decision Tree Accuracy: 0.8875
Decision Tree F1 Score: 0.8848
```

Conclusion

Analysis Questions

1) **How does the unemployment rate correlate with major stock market indices (S&P 500, Nasdaq Composite, and Dow Jones) over time? Which stock market index is most sensitive to changes in unemployment rates?**
    - The unemployment rate shows a negative correlation with all three major stock indices. Among them, the S&P 500 (^GSPC) stock has the highest overall correlation with unemployment, while the Dow Jones (^DJI) stock appears to be the most sensitive to changes in unemployment rates.
2) **How does the unemployment rate correlate with interest rates over time? How does the unemployment rate correlate with inflation rates over time?**
    - The unemployment rate has a moderately negative correlation with interest rates. In contrast, its relationship with inflation is weak or insignificant. Overall, unemployment correlates more strongly with interest rates than with inflation.
3) **How do interest rates correlate with stock indices and inflation rates?**
    - Interest rates exhibit a weak to moderate negative correlation with all three stock indices, with the Dow Jones (^DJI) stock showing the strongest inverse relationship. Additionally, interest rates have a weak positive correlation with inflation.

4) **Does the stock market decline before or after an increase in unemployment rates?**
    - When unemployment increases, stock index prices generally decline, but this reaction tends to occur with a delay. This lag may be influenced by other economic factors and market expectations.
5) **Does a rising inflation rate weaken the stock market more than an increasing unemployment rate?**
    - An increasing unemployment rate has a more substantial negative impact on the stock market than rising inflation. Stock indices show a moderate negative correlation with unemployment, but only a weak positive correlation with inflation.
6) **How long does it take for the stock market to recover after a major spike in unemployment?**
    - The S&P 500 (^GSPC) stock recovers in approximately 122 days, the Nasdaq Composite (^IXIC) stock in 61 days, and the Dow Jones (^DJI) stock in 244 days. Among these, the Dow Jones (^DJI) stock takes the longest to recover following a major unemployment spike.
7) **Is there a difference in average unemployment from decade to decade? 1990s-2000s? 2000s-2010s?**
    - There is little to no difference in average unemployment between the 1990s and the 2000s. However, a significant increase in average unemployment occurred from the 2000s to the 2010s.
8) **Which machine learning technique is the best fit for my data according to accuracy scores?**
    - Based on accuracy scores, the Decision Tree Classifier is the best-performing model for my data with an accuracy of 0.8875, the highest among all models evaluated.
9) **Which forecasting method is the best fit for my data in a time series analysis?**
    - While the TBATS model had the lowest Mean Absolute Error (MAE), the Holt-Winters Multiplicative method produced a more accurate overall forecast for my data.

Limitations

Some limitations are present with my data project. First, correlation does not equal causation. Even though there may be correlations between my variables, this does not indicate that one variable causes the other. For example, there is a negative correlation between interest and unemployment rates; this does not indicate that a rise in unemployment rates causes a decline in interest rates even though it is observed. External events can affect interest and unemployment rates, but these are not accounted for in my analysis, so we cannot indicate causation. Another limitation is the small number of economic variables I included in my analysis. There are other important factors, such as corporate earnings, geopolitical events, and monetary policy. These factors not included in my analysis may have major effects on the economy, but I did not include them. The third limitation has to do with my stock index prices because I utilized the closing price per month, eliminating its variability throughout the month. Showing the shift in stock prices may have brought additional insights into my analysis.

Suggestions

Future work on this project could include more macroeconomic or global variables in the analysis. For example, including GDP growth, consumer confidence, and government debt levels would provide for a deeper analysis of the economy. Someone could also analyze pre- and post-crisis periods. For example, someone could split the data by major economic events to see if relationships between variables have changed over time. In the future, it would be interesting for someone to create an interactive dashboard with insights into the economy's health.

References

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