How Do Daily Asset Prices React in the Days Leading Up To, During, and After Federal Reserve Meetings?

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Github link: https://github.com/LyWangPX/umich-milestone-project

Motivation

Understanding how financial markets react to Federal Reserve (Fed) meetings is important for investors, policymakers, and analysts. The Fed's decisions, especially changes in interest rates, affect prices of different assets like stocks, bonds, currencies, and commodities. Many studies have examined how markets react to these decisions, but there is still a need for a detailed, data-driven analysis that looks at price changes, volatility, and connections between different asset types over time.

This study focuses on three main questions:

1. How do different assets behave before Federal Reserve meetings?
2. What are the immediate and short-term changes in price, volatility, and trading activity after the Fed has a meeting?
3. Are there consistent patterns in how different assets react, and how do their relationships change during these events?

By analyzing 15 years of daily price data, this study aims to find trends that can help investors understand market behavior around Fed meetings. Most past research has focused on short-term reactions to a single asset. This study, however, looks at multiple asset types, including stock indices (S&P 500, Nasdaq, Dow Jones), bond yields (10-year Treasury), currency exchange rates (USD/EUR, USD/JPY) (later had to be excluded, however), and commodities (gold).

Additionally, this research does not just focus on price changes but also looks at trading volume and volatility, providing a more complete picture of how monetary policy affects markets. To do this, we use financial data from public sources and apply advanced analytical techniques, including data visualization and statistical modeling. The results will help investors and analysts make better decisions by improving their understanding of market reactions to Fed policies.

References

- Bernanke, B. S., & Kuttner, K. N. (2005). *What explains the stock market's reaction to Federal Reserve policy?* The Journal of Finance, 60(3), 1221-1257.
- Farka, M. (2009). *The effect of monetary policy shocks on stock prices: Evidence from the S&P 500.* Economic Inquiry, 47(4), 573-585.

Data Sources:

This project uses two main types of data: financial market data and Federal Reserve meeting information. These datasets help analyze how asset prices change before, during, and after Fed policy decisions.

The first dataset includes daily prices for major financial assets like stock indices, bond yields, exchange rates, and gold prices. It covers 15 years and about 120 Fed meetings, focusing on price changes 15 days before and after each meeting. We collect stock indices, gold prices, and bond yields using yfinance, and U.S. Treasury bond yield data from FRED. Forex data (USD/EUR, USD/JPY) was initially included using Alpha Vantage, but due to API limits, it was later removed. The data is stored in CSV format with columns for date, volume, open price, and close price.

The second dataset contains Federal Reserve meeting dates. Since no API or downloadable file includes all meeting dates, we manually gathered them from the Federal Reserve's official website, recording both start and end dates.

To process the data, we merged all datasets by date and standardized column names. We handled issues with Yahoo Finance's MultiIndex format and removed unnecessary columns like Close. Time delays were added in the script to avoid API rate limits. Finally, missing values were removed, and the cleaned data was saved as market_data_cleaned.csv, making it easier to analyze.

To provide a viable download method, we used yf.download API and the corresponding tickers are ["^GSPC", "^IXIC", "^DJI"] for stock indices and panda datareader to obtain bond data using pdr.get_data_fred("DGS10"). The usage of the API is straightforward and is open to all users without fee.

URLs:

https://ranaroussi.github.io/yfinance/index.html

https://pandas-datareader.readthedocs.io/en/latest/

Data Manipulation Methods:

Once the data had been cleaned and processed, the result was two csv files. The first had the asset data (market_data_cleaned.csv), and the second had the meeting data (meeting_dates.csv). The asset data had rows as dates, with the columns as the open, close, low, and high numbers for the stock indices and gold, as well as the value of 10 year treasury bond yields on that date. The meeting data had the rows as meetings, and the columns were the start date of the meeting and the end date. The csv files were first loaded into pandas DataFrames to begin.

First for manipulation, columns were created to represent the daily percentage change for (non treasury yield) asset prices. This was done by subtracting the close price columns from the open price columns and calculating percentage using pandas. Next, the focus was to categorize the dates in the asset price DataFrame as being in the pre-meeting, post-meeting, or during-meeting windows. The screenshot below gives some code to give some structure/clarity/further insight into the following explanation:

```
# Changing date columns in DataFrame to pandas datetime
market_data_df["Date"] = pd.to_datetime(market_data_df["Date"])
meetings_df["meeting_start"] = pd.to_datetime(meetings_df["meeting_start"])
meetings_df["meeting_end"] = pd.to_datetime(meetings_df["meeting_end"])

# Creating empty master lists of of pre, post, and during meeting window dates
pre_meeting_window_dates = []
meeting_dates = []
post_meeting_window_dates = []

# Going through the DataFrame of meetings
for meetings_df_index in range(len(meetings_df)):
    meeting = meetings_df.iloc[meetings_df_index]

    # Getting the date range of each window.
    pre_meeting_window = pd.date_range(start = meeting["meeting_start"] - pd.Timedelta("15 days"), end = meeting["meeting_st
    meeting_window = pd.date_range(start = meeting["meeting_start"], end = meeting["meeting_end"])
    post_meeting_window = pd.date_range(start = meeting["meeting_end"] + pd.Timedelta("1 days"), end = meeting["meeting_end"

    # Appending each date to the master list of pre, post, and during meeting window dates.
    for date in pre_meeting_window:
        pre_meeting_window_dates.append(date)
    for date in meeting_window:
        meeting_dates.append(date)
    for date in post_meeting_window:
        post_meeting_window_dates.append(date)

# Selecting new DataFrame for pre, post, and during meeting window dates.
# Note that.copy() is being used because of a warning that ocurred regarding chained indexing while trying to add a column
market_data_pre_meetings_df = market_data_df.copy()[market_data_df["Date"].isin(pre_meeting_window_dates)]
market_data_post_meetings_df = market_data_df.copy()[market_data_df["Date"].isin(post_meeting_window_dates)]
market_data_during_meetings_df = market_data_df.copy()[market_data_df["Date"].isin(meeting_dates)]
```

To accomplish this we first converted the columns with dates in the DataFrames to pandas datetime, then we went through each meeting in the meetings DataFrame (using iteration), and used TimeDeltas to calculate windows for each meeting (pre, post, and during meeting). Once each window had been collected, the dates within the window were collected into lists for pre, post, and during meeting window dates. Finally for each window three new DataFrame were created using boolean indexing on the original DataFrame of assets to see if a particular row had an applicable date

These new window DataFrames would then be used to create new DataFrames to show summary statistics for daily percentage changes for before, during and after meeting windows. Numpy was used on the columns of the window DataFrames to calculate the statistics (mean, median, range, standard deviation) and a new data frame for each statistic was created with the columns as the windows and the rows as the asset. A DataFrame was also calculated for comparing mean trading volumes, with the same windows in the columns and assets as the rows format. Then t-tests were used to examine the validity of relationships observed in these tables, using the data from these tables. Scipy was used to conduct the tests, and the p-values for the t tests were stored in DataFrames with the columns as the test performed and the rows as the asset. Finally, the correlations between each asset were examined using pandas .corr() on the original market data DataFrame to create a table with the correlations.

After these analyses were complete, it was time for the task of labeling how many days before or after a meeting each date was, so that analyses on the trends so many days before or after the meeting could be completed. To do this, we went through each meeting; for each meeting, the pre and most meeting windows were calculated using pd.TimeDeltas similar to previously. Then for each date in each window, entries were added to python dictionaries with the date as the key and the number of days before/after as the value. Negative days were used to represent days before and positive days after (with meeting days represented with zero in the final DataFrame). These dictionaries were then used to assign each date in the before/after/during DataFrames with the appropriate number of days. Finally, these DataFrames were concatenated (pd.concat) to create a large DataFrame with the number of days after a meeting each row was (negative values meaning days before). Here's a screenshot of code as a reference for some of this process:

```
1]: # We will create a column in the market data before/after DataFrames reflecting the number of days before/after each meeting the entries are.

    # Creating empty dictiomaries that will have dates and them number of days before and after a meeting each date in each window is
    days_before = {}
    days_after = {}

    # Going through the meeting dates again, we want to count how many days pre and post meeting each date is

    # Go through each meeting
    for i in range(len(meetings_df)):
        meeting = meetings_df.iloc[i]

        # Calulate days before and after meeting windows:
        pre_meeting_window = pd.date_range(start = meeting["meeting_start"] - pd.Timedelta("15 days"), end = meeting["meeting_start"] - pd.Timedelta("1 day")
        post_meeting_window = pd.date_range(start = meeting["meeting_end"] + pd.Timedelta("1 days"), end = meeting["meeting_end"] + pd.Timedelta("15 day"))

        # Fill the dictionaries with dates and days before/after a meeting
        for date in pre_meeting_window:

            # calculate the days before for each date in the range, and add to the days_before dictionary
            value_before = list(pre_meeting_window).index(date) - 15
            days_before[date] = value_before

        for date in post_meeting_window:

            # calculate the days after for each date in the range, and add to the days_before dictionary
            value_after = list(post_meeting_window).index(date) + 1
            days_after[date] = value_after

    # Now, we can add columns categorizing days before/after a meeting using our dictionaries
```

Analysis:

Here are the tables for the percentage changes summary statistics:

Means:

	Mean Before	Mean During	Mean After
10Y_Treasury_Yield	2.507262	2.496379	2.494611
SP500	0.015477	0.055214	0.014290
Nasdaq	-0.016611	0.054229	0.015231
DowJones	0.030060	0.044589	0.017218
Gold	-0.018045	0.021693	-0.038147

Medians:

	Median Before	Median During	Median After
10Y_Treasury_Yield	2.390000	2.335000	2.390000
SP500	0.046441	0.012019	0.045840
Nasdaq	0.070958	0.070569	0.094823
DowJones	0.060320	0.044182	0.059989
Gold	0.000000	0.000000	0.000000

Standard deviations:

	Std Before	Std During	Std After
10Y_Treasury_Yield	0.938890	0.940292	0.928656
SP500	0.912141	0.960833	0.946458
Nasdaq	0.992277	1.031093	1.018405
DowJones	0.880922	0.875158	0.935509
Gold	0.819150	0.706016	0.923378

Ranges:

	Range Before	Range During	Range After
10Y_Treasury_Yield	4.440000	4.340000	4.270000
SP500	12.080924	11.262042	11.741898
Nasdaq	10.903032	10.318753	11.341017
DowJones	10.972881	9.425054	10.506445
Gold	8.621547	9.086513	10.590750

Interestingly, it seemed that mean changes in asset prices sort of "spiked" during meetings, except treasury bond yields. Median price increases before, and after across all assets seemed to be higher than means (except gold and treasury bond yields), implying some rightward skew of daily price changes before and after meetings. Standard deviations also seemed to be higher after meetings vs. before, except treasury bond yields. Ranges did not seem to show exceptional trends except for gold ranges being higher after meetings vs. before.

We also used a table to look at mean trading volume:

	Mean Before	Mean During	Mean After
SP500	4.004404e+09	4.167314e+09	4.050805e+09
Nasdaq	2.983459e+09	3.118168e+09	3.095513e+09
DowJones	2.543337e+08	2.623236e+08	2.562970e+08
Gold	4.693318e+03	1.331755e+04	4.709494e+03

Notably, it looked as if asset volume might be peaking during meetings as well. This was very pronounced for Gold it seemed.

Next we conducted some t-tests to get some p-values to help confirm the statistical significance of some of our observations. We tested first whether some of those different asset prices spiked during meeting times, as we observed previously (percentage change spikes for S&P 500, Gold, Nasdaq, and Dow Jones):

	T-test for Before Meeting	T-test for After Meeting
SP500	0.281248	0.276991
Nasdaq	0.168611	0.299681
DowJones	0.408892	0.334146
Gold	0.223444	0.133403

```
ttest_for_before = stats.ttest_ind(market_data_pre_meetings_df[column],
                                   market_data_during_meetings_df[column],
                                   equal_var = False,
                                   alternative = "less")
ttest_for_after = stats.ttest_ind(market_data_post_meetings_df[column],
                                   market_data_during_meetings_df[column],
                                   equal_var = False,
                                   alternative = "less")
```

To the right of the above DataFrame is a code snippet showing the t-test used for each column, for reference. While these probabilities are kind of on the lower side, they were still far too high to achieve statistical significance at the 95% level and reject the null hypothesis that the means are the same. We then repeated the process from above, except this time checking our observations about volume:

	T-test for Before Meeting	T-test for After Meeting
SP500	0.007427	0.044425
Nasdaq	0.138924	0.428478
DowJones	0.214910	0.279479
Gold	0.003029	0.002809

Here, we have a lot more statistical significance. Gold before and after meeting and the S&P 500 before meeting and after meeting were statistically significant at the 95% level. This is very strong evidence that both the S&P 500 and Gold both trade at higher volume during meeting days. Nasdaq and DowJones though not statistically significant still have p-values that tend to be on the lower side.

We also looked at correlations between variables:

	SP500_Close	Nasdaq_Close	DowJones_Close	Gold_Close	10Y_Treasury_Yield
SP500_Close	1.000000	0.993518	0.992207	0.753691	0.301679
Nasdaq_Close	0.993518	1.000000	0.982320	0.773855	0.252721
DowJones_Close	0.992207	0.982320	1.000000	0.709920	0.273214
Gold_Close	0.753691	0.773855	0.709920	1.000000	0.259461
10Y_Treasury_Yield	0.301679	0.252721	0.273214	0.259461	1.000000

As we can see from the matrix above, the Dow, the Nasdaq, and the S&P 500 were all strongly related to each other. Gold was also related to these three less strongly. Finally, Treasury Bond Yields were weakly related to the other four assets.

Our study of market reactions to Federal Reserve meetings revealed a variety of significant results. We discovered that median asset price changes are generally greatest on meeting days, with the S&P 500, Nasdaq, and Gold having the greatest changes. We also discovered that median price changes were generally greater than median price changes, reflecting a rightward skew of daily price action, particularly during the pre- and post-meeting periods.

Volatility patterns also supported these findings, with higher standard deviations of meetings for the majority of all assets except for Treasury bond yields. Volume studies of trading likewise evidenced large elevations in level of activity within Fed meetings, the largest among them being for Gold and S&P 500.

Statistical tests proved that increases in volume were well established, but spikes in price changes had inconsistent results and deserve further scrutiny.

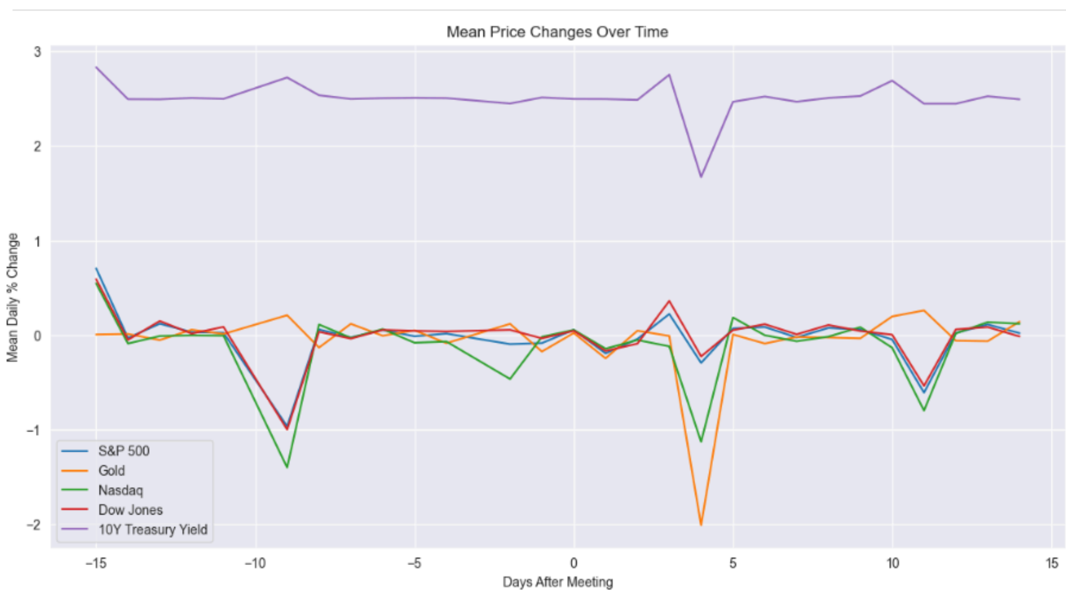
To further examine these results, we developed a series of visualizations to illustrate price trends, changes in volatility, volume of trading, and asset correlations leading up to, during, and following Fed meetings. We created key visualizations for the remainder of our analysis, these and their results are discussed in the next section.

Visualizations:

Visualizations are a central component of data analysis as they enable us to visualize trends, relationships, and outliers in the data that are difficult to identify in raw data. For this project, we employ various visualization techniques to analyze how Fed meetings affect leading financial markets. The selected visualizations are intended to inform some of the most important questions regarding asset price volatility, price direction, trading volume, and changes in correlation among different financial instruments around Fed meetings.

Mean Daily Percentage Change in Asset Prices Over Time

The first chart shows the mean daily percentage change of various financial assets such as S&P 500, Nasdaq, Dow Jones, Gold, and the 10-Year Treasury Yield. The line graph illustrates that there is tremendous volatility around the Fed meeting dates, and there is a significant drop seen a day or two before the meeting date. The 10-Year Treasury Yield is seen to have a comparatively smoother trend in comparison to the equities because of its diverse market dynamics.

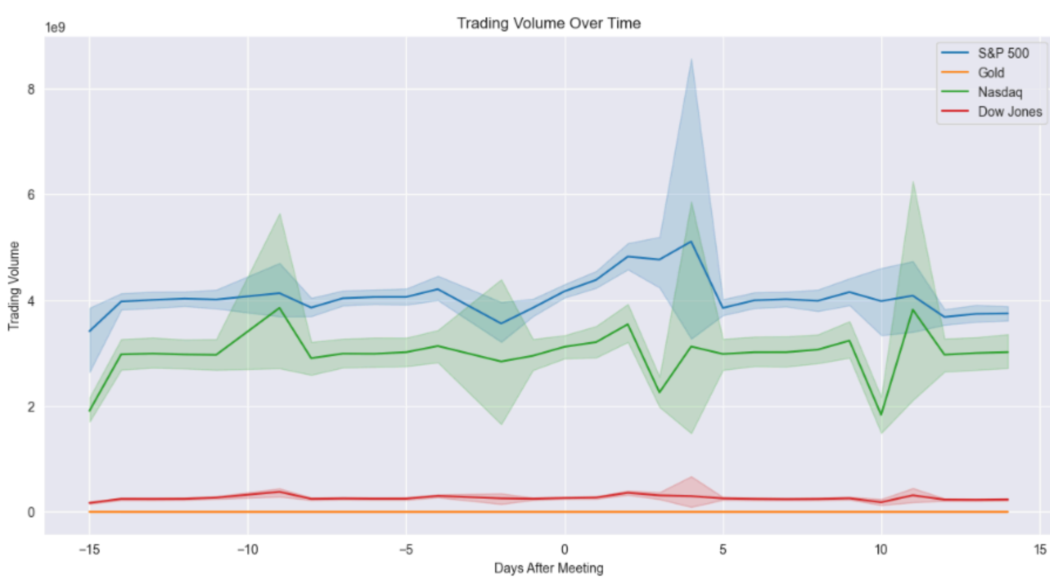


Standard Deviation of Prices Over Time

Another noteworthy visualization depicts price volatility before, at, and after Fed meetings. This visualization is employed to determine if the volatility of the markets is greater or lesser in the period around policy statements. The results show that stock market indices such as the Nasdaq and Dow Jones experience spikes in volatility, particularly immediately following the Fed meetings. Gold and the 10-Year Treasury Yield appear less nervous than equity indices, as would be expected from their traditional roles as relatively stable assets.

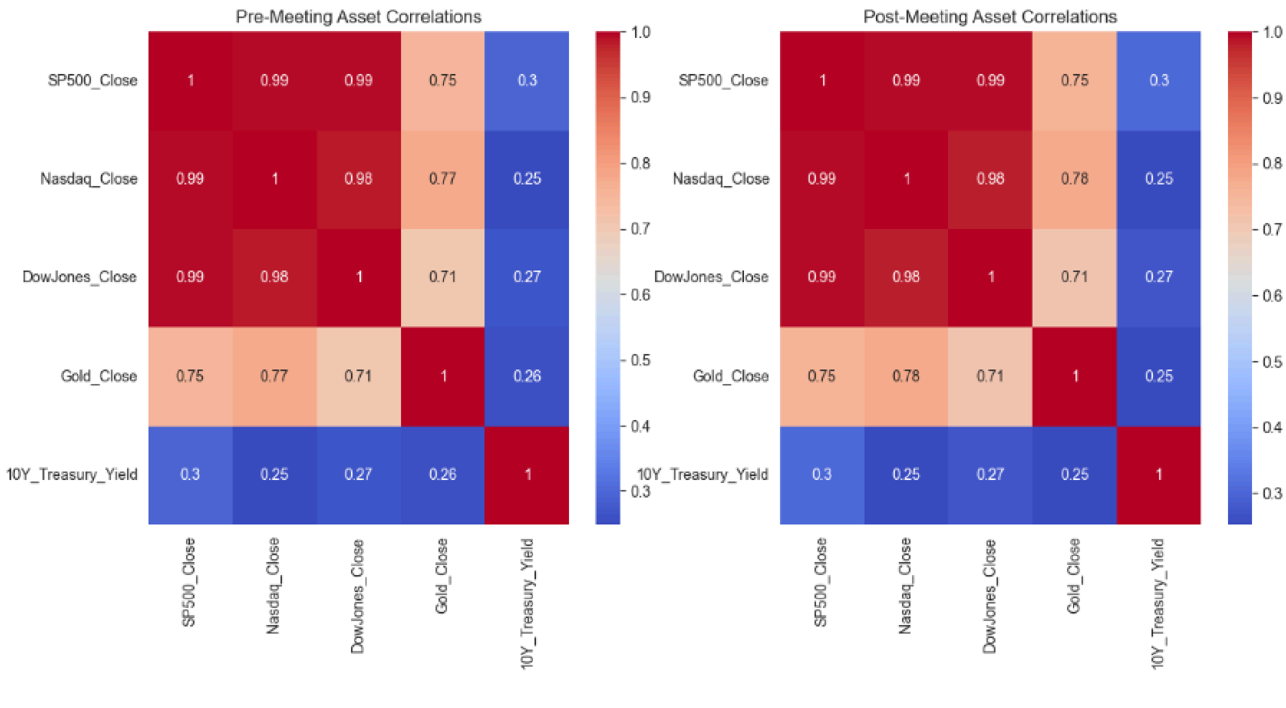
Trading Volume Trends

The above graph demonstrates volatility in trading activity over a period of time. The line graph shows volumes of trading in large stock indexes typically surge shortly before and shortly after Fed meetings, demonstrating that investors position aggressively ahead of monetary policy changes. The spikes in trading volume confirm that market players engage in excessive trading around meeting dates. Gold and Treasury securities show a less dramatic reaction than equities, affirming their lower short-term market event sensitivity.



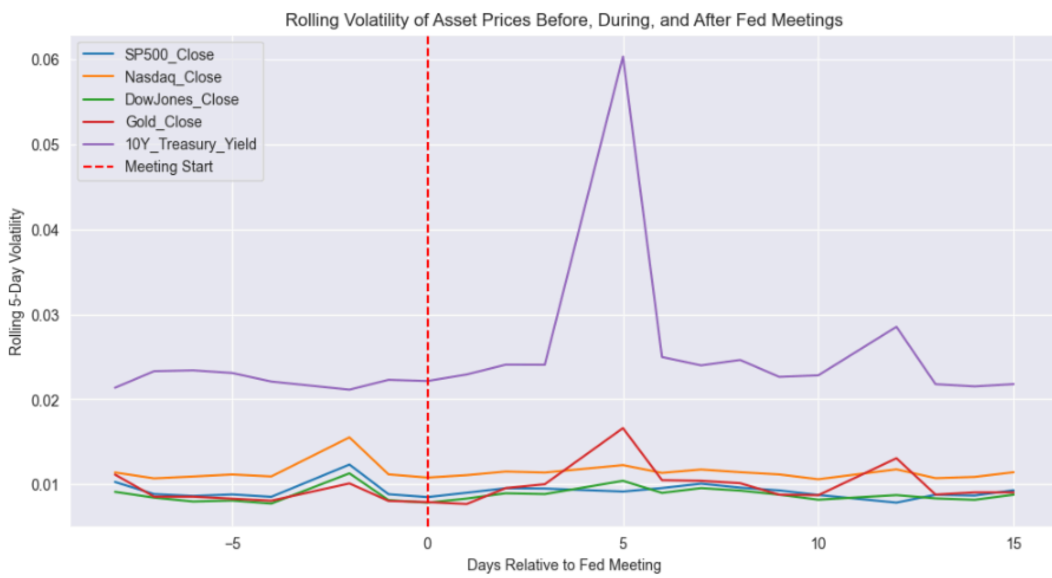
Correlation Heatmaps (Pre-Meeting vs. Post-Meeting)

This charting helps decide whether the correlation among assets changes after monetary policy actions. Comparison between before and after the meeting correlation indicates that the stock indexes remain well-correlated with themselves before and after Fed meetings. Minor shifts occur in gold vs. the 10-Year Treasury Yield correlation patterns, showing investors shift portfolios around as a reaction to monetary policy signals.



Rolling 5-Day Volatility

This visualization examines how short-term volatility plays out leading up to Fed meetings. The results indicate that volatility rises in the days leading up to a Fed meeting and surges shortly afterward. The volatility spike represents the market reacting to the just-released policies, followed by a gradual return to normality as investors process and adapt to the fresh information. This pattern is most evident in stock indices, while gold and bonds experience a less dramatic reaction.



Key Insights:

From these visualizations, we observe several notable patterns. The Mean Daily Percentage Change in Asset Prices Over Time suggests that the S&P 500, Gold, and Nasdaq experience noticeable fluctuations around Fed meetings, indicating their sensitivity to monetary policy. The Standard Deviation of Prices Over Time and the Rolling 5-Day Volatility show that volatility in the markets rises ahead of Fed meetings and stabilizes after that, implying investor uncertainty before policy announcements. The Trading Volume Trends visualization shows higher trading near meeting dates to ensure that market participants react favorably to policy decisions. Lastly, the Correlation Heatmaps show that correlations between asset classes shift after Fed meetings, suggesting that monetary policy influences how different markets interact.

Statement of Work:

We decided to divide up the large part of the actual coding and analysis work, into dataset and cleaning (Yifan), analysis (Eldon), and visualizations (Ye). We collaborated using Github to make sure that we could look over each other's work and provide input, as well as communicate with each other about how things were going and how to tackle challenges. We initially were planning on using Google Colab but eventually found this inefficient and switched to Github. We used slack for communication with each other to make things simpler, especially when dealing with large time zone differences. This allowed us to quickly and effectively collaborate. For the report we worked together on a shared Google Doc, everyone drafted up different sections and then we worked together to make edits and modifications, tie everything together and make sure things flowed smoothly and clearly. These strategies felt very effective for the task at hand. One area where perhaps we could have improved was by trying to have a more collaborative process than we did when doing the coding and analysis. This would have made a more efficient process with regards to making it easier for everyone to follow along and see how the project was developing and tackle challenges in a collaborative way. Overall, we were pleased with how collaboration went and how work was divided up, and the project proceeded very smoothly.