FOMC SENTIMENT INDEX

Ada Kilic
CSCI 6917
Guided Research
August 8, 2023

Press Release

March 22, 2023

Federal Reserve issues FOMC statement

For release at 2:00 p.m. EDT

Share ➤

Recent indicators point to modest growth in spending and production. Job gains have picked up in recent months and are running at a robust pace; the unemployment rate has remained low. Inflation remains elevated.

The U.S. banking system is sound and resilient. Recent developments are likely to result in tighter credit conditions for households and businesses and to weigh on economic activity, hiring, and inflation. The extent of these effects is uncertain. The Committee remains highly attentive to inflation risks.

The Committee seeks to achieve maximum employment and inflation at the rate of 2 percent over the longer run. In support of these goals, the Committee decided to raise the target range for the federal funds rate to 4-3/4 to 5 percent. The Committee will closely monitor incoming information and assess the implications for monetary policy. The Committee anticipates that some additional policy firming may be appropriate in order to attain a stance of monetary policy that is sufficiently restrictive to return inflation to 2 percent over time. In determining the extent of future increases in the target range, the Committee will take into account the cumulative tightening of monetary policy, the lags with which monetary policy affects economic activity and inflation, and economic and financial developments. In addition, the Committee will continue reducing its holdings of Treasury securities and agency debt and agency mortgage-backed securities, as described in its previously announced plans. The Committee is strongly committed to returning inflation to its 2 percent objective.

Project Objective

This project aims first, to develop a sentiment index for the statements made by the chair of the Federal Reserve Board of Governors after the Federal Open Market Committee (FOMC) meetings; and second, to explore if such a sentiment index can be useful in predicting financial market conditions.

What are you going to do?

This research project builds an index that measures the overall sentiments in one of the most important US economic policy institutions, namely the FOMC meeting statements by implementing a state-of-the art Large Language Model (LLM), namely FinBERT. This index is named the FOMC Sentiment Index (FOMC-SI). FOMC-SI will be used to investigate if the overall sentiment in the FOMC meeting statements can predict economic or market conditions.

How is it done today? Current Limitations?

Currently, there are many studies that use sentiment analysis in various contexts. However, there is not any sentiment analysis designed on FOMC statements.

What is your idea to do something better?

This is the first sentiment index designed for the FOMC statements. Therefore, it will be the only index that can be used to assess the overall sentiment in these policy statements. Designing an FOMC sentiment index will allow users to (i) to assess the overall sentiment among the key monetary policy makers in the US over time; (ii) the index can be used to analyze link between the policy makers' sentiment and a number of economic and market variables via regressions.

Who will benefit from your work? Why?

Policy makers, central banks, market participants (investment companies, banks, hedge funds, etc.), and researchers in economics and finance...

What risks do you anticipate?

Although FinBERT is trained on a large textual data on economics and finance, the training data may not truly reflect/capture the textual data in FOMC policy statements as these policy statements generally contain specific jargons and hence, the context may not be clearly understood by the model.

Out of pocket costs? Complete within 11 weeks?

This project is feasible within the given time-frame. I decided to do sentiment analysis instead of topic modeling in order to finish within 11 weeks and also decided not to re-train the model.

Technical Approach: Key Steps

1 — DATA COLLECTION

For the FOMC-SI:
- The textual sample data for statements for this project covers all the available statements text made by the FOMC since 2000.

- The data collected has 202 statements corresponding to the period between January 2000 and June 2023.

2 — PREPROCESSING

- Cleaning and preprocessing text data is an important step before performing sentiment analysis.

- Splitting sentences for a given statement text.

- Tokenization: This process breaks the text into individual words or tokens.

3 — QUALITATIVE & QUANTITATIVE REVIEW

- Read papers that explains and discusses BERT and FinBERT and reviewed a subset of the statements for understanding the context.
- FinBERT is designed to conduct sentiment analysis of Financial text based on pre-trained language models. Results are a numerical score representing the sentiment conveyed in the text.

4 — SENTIMENT ANALYSIS & AVERAGING

- FinBERT produces five sentiment values. Three values represent the probabilities that the text is either positive, negative, or neutral.

- FinBERT also calculates a compound score as the positive probability minus the negative probability.

- FinBERT provides trinary sentiment prediction which is based on the highest of the three probabilities.

5 — FOMC INDEX CONSTRUCTION

- Use FinBERT's sentiment outcomes with their corresponding probabilities and construct a compound score to assign a numeric value of sentiment for each sentence in a FOMC statement.
- Assign 0 weight to "neutral" outcome, and -1 and 1 to negative and positive outcomes, respectively.
- FOMC-SI for a given meeting statement date is the negative of the sum of positive and negative probabilities divided by the number of sentences for a given statement date.
- FOMC-SI will be between -1 and +1

6 — ANALYSIS & INTERPRETATION OF RESULTS

- Results are discussed in future slides.

- The index is interpreted and linked to economic recessions and inflationary periods.

- The index is used to predict future market risk or fear in an application.

Technical Approach: Architecture

1) Function that Implements FinBERT

```python
# Function to perform sentiment analysis on text data
def predict_sentiment(text_data):
    # Tokenize the input text data
    tokens = tokenizer(text_data, padding=True, truncation=True, return_tensors='pt')

    # Pass the tokenized data through the finBERT model to get predicted sentiment scores
    with torch.no_grad():
        outputs = model(**tokens)
        logits = outputs.logits

    # Get predicted sentiment labels (positive, neutral, negative) from logits
    _, predicted_labels = torch.max(logits, dim=1)
    # Convert the logits to probabilities
    probs = torch.nn.functional.softmax(outputs.logits, dim=-1)
    # Convert probabilities tensor to numpy array
    probs_np = probs.detach().numpy()

    # Map numerical labels back to sentiment categories
    sentiment_mapping = {0: "negative", 1: "neutral", 2: "positive"}
    predicted_sentiments = [sentiment_mapping[label.item()] for label in predicted_labels]
    predicted_sentiments_pd=pd.DataFrame({"Text": text_data, "Predicted Sentiment": predicted_sentiments})
    # Create a new DataFrame with dates and probabilities
    df_probs = pd.DataFrame({
    'negative_prob': probs_np[:, 0],
    'neutral_prob': probs_np[:, 1],
    'positive_prob': probs_np[:, 2]
    })
    #print(probs_np)
    #print(df_results)
    predicted_sentiments_pr = pd.concat([predicted_sentiments_pd, df_probs], axis=1)

    # print(predicted_sentiments_pr)
    return predicted_sentiments_pr
```

2) Function that Calculates the Index

```python
if __name__ == "__main__":
    fomc_si = []
    for value in text_data:
        text_i = value
        #print(text_i)
        predicted_sentiments = predict_sentiment(text_i)
        predicted_sentiments['fomc_indx_num'] =
np.where(predicted_sentiments['Predicted Sentiment']== 'neutral', 0,
-1*predicted_sentiments['negative_prob'] +
1*predicted_sentiments['positive_prob'])
        fomc_si.append( -predicted_sentiments['fomc_indx_num'].mean())
```

3) FinBERT Outputs

	Text	Predicted Sentiment	negative_prob	neutral_prob	positive_prob	fomc_indx_num
0	Financial market conditions have deteriorated...	neutral	0.011720	0.965730	0.022550	0.000000
1	In these circumstances, although recent data s...	negative	0.898202	0.080262	0.021536	-0.876665
2	The Committee is monitoring the situation and ...	positive	0.208174	0.070815	0.721011	0.512837

4) FOMC Sentiment Index

	Date	Statement	Statement_sentence	FOMC Sentiment Index
0	2000-02-02	The Federal Open Market Committee voted today ...	[The Federal Open Market Committee voted today...	-0.070471
1	2000-03-21	The Federal Open Market Committee voted today ...	[The Federal Open Market Committee voted today...	-0.328228
2	2000-05-16	The Federal Open Market Committee voted today ...	[The Federal Open Market Committee voted today...	-0.189806
3	2000-06-28	The Federal Open Market Committee at its meeti...	[The Federal Open Market Committee at its meet...	0.261819
4	2000-08-22	The Federal Open Market Committee at its meeti...	[The Federal Open Market Committee at its meet...	0.157842
...	...	...	...	...
197	2023-02-01	Recent indicators point to modest growth in sp...	[Recent indicators point to modest growth in s...	-0.204597
198	2023-03-22	Recent indicators point to modest growth in sp...	[Recent indicators point to modest growth in s...	-0.215664
199	2023-05-03	Economic activity expanded at a modest pace in...	[Economic activity expanded at a modest pace i...	-0.331972
200	2023-06-14	Recent indicators suggest that economic activi...	[Recent indicators suggest that economic activ...	-0.338476
201	2023-07-26	Recent indicators suggest that economic activi...	[Recent indicators suggest that economic activ...	-0.303405

202 rows × 4 columns

5

Research & Innovation

This project is novel in a number of fronts:

- This is the first project that designs a sentiment index for one of the major policy statements in the US.
- It implements FinBERT that is based on BERT, a LLM on a textual data that is very specific in nature and drafted to reflect policy decisions and associated analysis of economic and financial conditions with specific jargons and language.
- It is a precursor to potentially a much larger project as it can lead to the development of Federal Reserve Board's and similar policy institutions development of their own LLMs.
- Provides an index that can be used as a tool for assessing the overall sentiment of FOMC members and provides a comprehensive view of sentiment trends over time. This can allow for potentially revealing patterns related to economic conditions and policy decisions.
- The Index can be used to build predictive models that can link it to economic and market conditions and variables.

Results: Description of FOMC Sentiment Index

```
count     202.000000
mean       -0.002321
std         0.195040
min        -0.521710
25%        -0.139679
50%        -0.020917
75%         0.116388
max         0.456938
Name: FOMC Sentiment Index, dtype: float64
```

FOMC-SI Summary Statistics:

- By construction, the index is between [-1, 1]
- A sentiment index of -1 means an extremely positive sentiment.
- A sentiment index close to +1 means a very negative sentiment.
- A sentiment index close to 0 means a neutral sentiment.
- The index range is between -0.52 and +0.46.
- Average for the entire history of statements is -0.002 which is close the a "neutral" sentiment!

Results: FOMC Sentiment Index Over Time
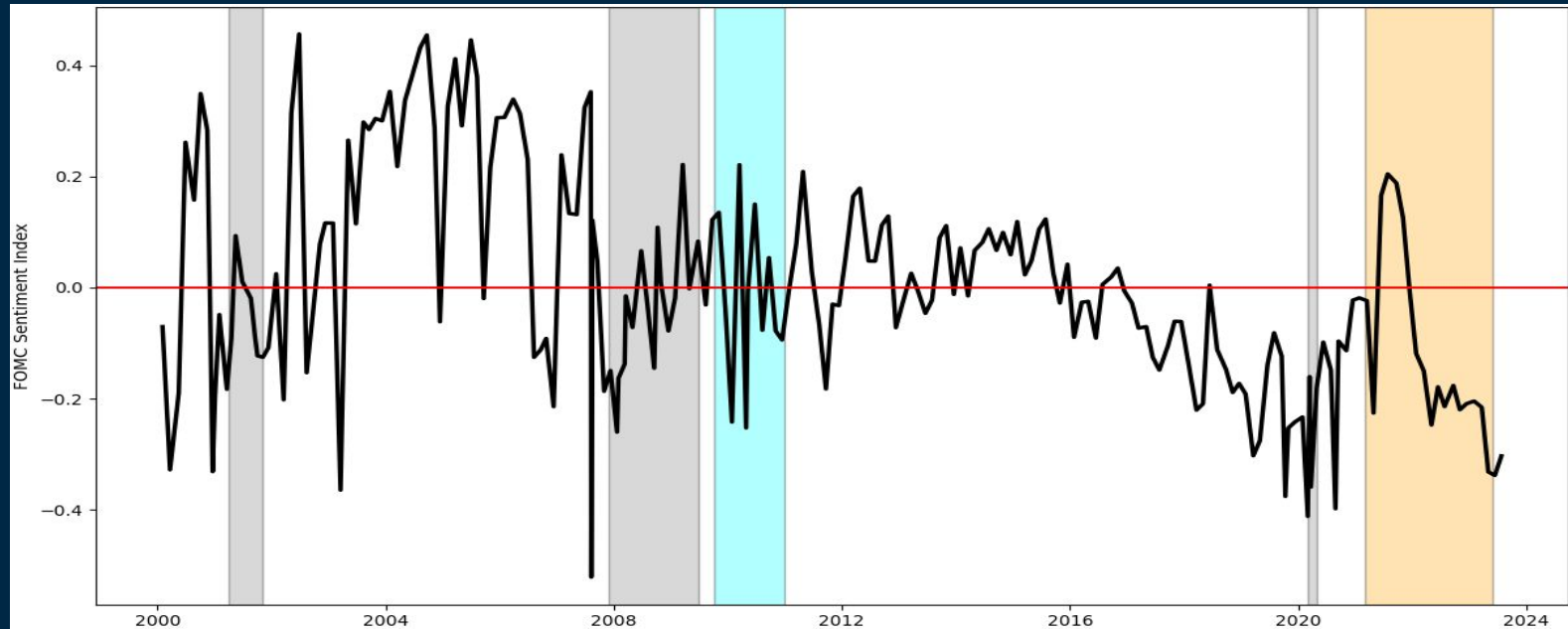
KEY:
FOMC Index: Positive -> Negative Sentiment;
   **Negative -> Positive Sentiment**
US Recessions
European Debt Crisis
Post Covid Inflationary Period

Application: Can FOMC-SI Predict VIX?

- This application explores if the FOMC-SI can be useful in predicting economic and financial conditions.
- To this end, the index is used to assess if it can predict future values of VIX.
- The VIX Index, often referred to as the "fear gauge," is a measure of expected price fluctuations in the S&P 500 Index options over the next 30 days.
- The Chicago Board Options Exchange (CBOE) introduced the VIX Index in 1993, and it has since become one of the most recognized measures of market volatility.
- The VIX also reflects how much risk is accumulated in the markets and used often by market participants and economic policy makers to get a sense of overall market sentiment and risk.
- The VIX index generally increases during recessions and bad economic periods as can be seen in the figure.
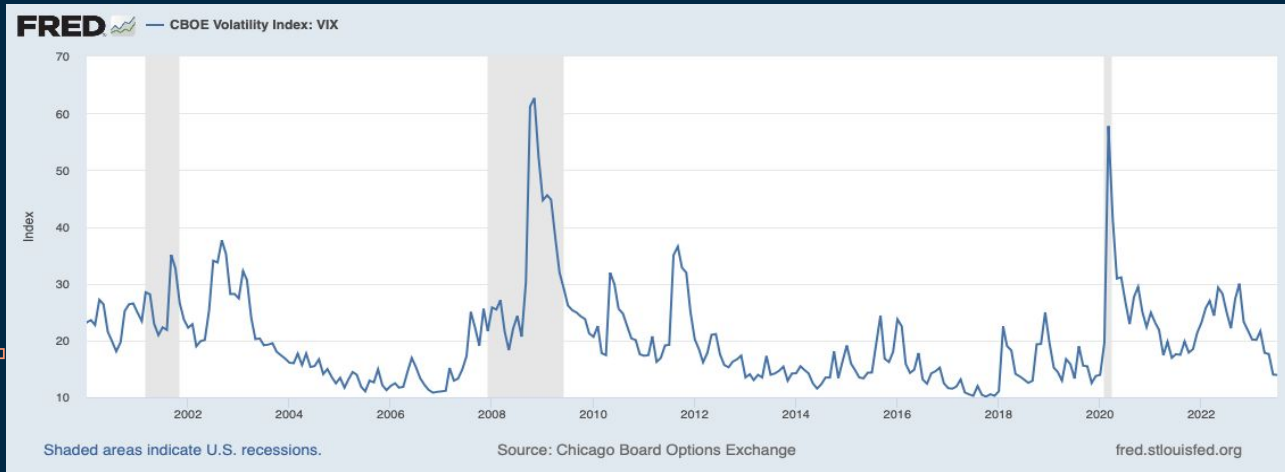
Application Results: FOMC Sentiment Index – VIX-Fear Index

- Collected daily VIX index from Bloomberg and calculated average VIX in between the FOMC statement dates for this analysis.
- The figure displays FOMC-SI together with the average VIX for the FOMC statement periods.
- Inspection of the plots reveals:
  - FOMC-SI generally high (sentiment in FOMC statements are more negative) during periods when VIX is low.
  - This seemingly counterintuitive observation in fact may not be that counterintuitive.
  - Because, during episodes of low VIX, the markets are calm and risks tend to accumulate gradually and hence, FOMC member having considerable information about the markets and economic conditions are more cautious and possibly has more negative sentiments reflected in the statements.
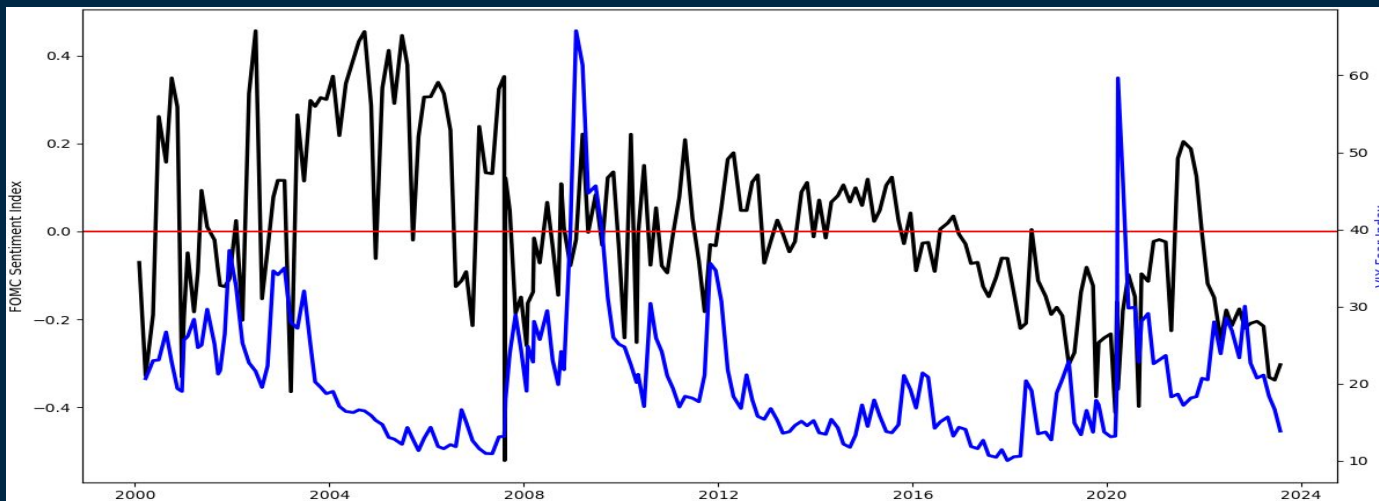
Results: Regression Analysis with FOMC-SI

$$VIX_t = \alpha + \beta\, FOMC - SI_{t-1} + error_t$$

```
                         OLS Regression Results
==============================================================================
Dep. Variable:              vix_mean   R-squared:                       0.036
Model:                           OLS   Adj. R-squared:                  0.031
Method:                Least Squares   F-statistic:                     5.401
Date:               Sat, 05 Aug 2023   Prob (F-statistic):             0.0211
Time:                       15:31:00   Log-Likelihood:                -717.20
No. Observations:                201   AIC:                             1438.
Df Residuals:                    199   BIC:                             1445.
Df Model:                          1
Covariance Type:                 HAC
==============================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept       20.7215      1.495     13.860      0.000      17.773      23.670
FOMC_SI.shift(1) -8.5314     3.671     -2.324      0.021     -15.770      -1.293
==============================================================================
Omnibus:                     107.125   Durbin-Watson:                   0.433
Prob(Omnibus):                 0.000   Jarque-Bera (JB):              528.598
Skew:                          2.094   Prob(JB):                     1.65e-115
Kurtosis:                      9.752   Cond. No.                         5.16
==============================================================================
```
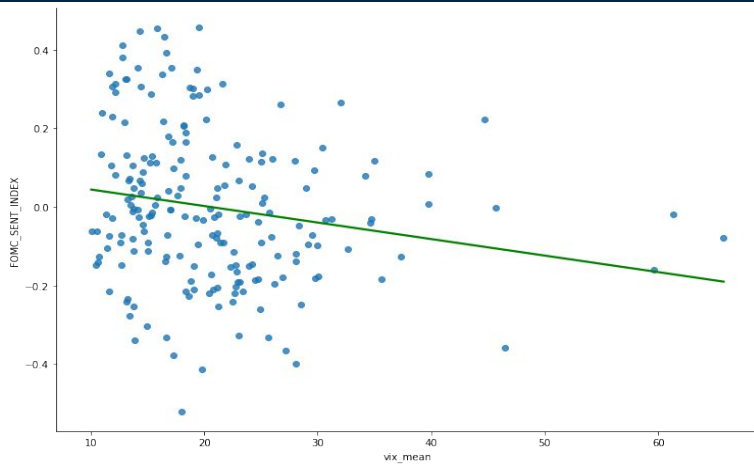

- Run two regressions.
- (1) First model regresses VIX on statement date t on a constant and FOMC-SI on the previous statement date (i.e., at date t-1).
- Results are reported in the Table.
- This models indicates a statistically significant coefficient for FOMC-SI (-8.531) with a p-value of 0.021 less than 0.05.
- This shows that the FOMC-SI is statistically significant and negative and hence, statistically predicts the future average value of VIX!
- As the displayed scatter plot with the fitted regression line show, higher average VIX tends to associate with lower FOMC-SI (i.e., positive sentiment in the statements).

Results: Regression Analysis with FOMC-SI

$$VIX_t = \alpha + \beta\,FOMC\text{-}SI_{t-1} + \delta VIX_{t-1} + error_t$$

```
                         OLS Regression Results
==============================================================================
Dep. Variable:              vix_mean   R-squared:                       0.650
Model:                           OLS   Adj. R-squared:                  0.646
Method:                Least Squares   F-statistic:                     105.6
Date:               Sat, 05 Aug 2023   Prob (F-statistic):           6.77e-32
Time:                       15:35:45   Log-Likelihood:                -612.91
No. Observations:                200   AIC:                             1232.
Df Residuals:                    197   BIC:                             1242.
Df Model:                          2
Covariance Type:                 HAC
==============================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept        4.2898      1.166      3.680      0.000       1.991       6.588
vix_mean.shift(1) 0.7917     0.057     13.984      0.000       0.680       0.903
FOMC_SI.shift(1) -3.7990     1.198     -3.172      0.002      -6.161      -1.437
==============================================================================
Omnibus:                     185.739   Durbin-Watson:                   1.778
Prob(Omnibus):                 0.000   Jarque-Bera (JB):             3958.497
Skew:                          3.508   Prob(JB):                         0.00
Kurtosis:                     23.635   Cond. No.                         117.
==============================================================================
```

- (2) The second model augments the first regression by also including the lagged VIX to control for the inertia high VIX periods usually followed by a period of high VIX or low VIX periods usually followed by a period of low VIX as can be observed from the figure on slide 11.
- Like the first model, this second model also indicates a statistically significant coefficient for FOMC-SI (-3.800) with a p-value of 0.002 and hence, the statistical significance of FOMC-SI in predicting the future average value of VIX!
- Results for this model suggests that even after controlling for the persistence in VIX, FOMC-SI is statistically significantly negative and predicts next statement period's average VIX.
- Results from both models are promising and shows that additional work with different economic and financial market variables such as unemployment rate, GDP growth, or inflation may be useful.

12

Conclusion

- Developed a sentiment index to gauge the overall sentiment in one of the major policy statements in the US.
- Developed a jupyter notebook that can be used to implement FinBERT in a given text data and implemented it to calculate FOMC-SI for each FOMC meeting date.
- FOMC-SI is calculated with all the publicly available FOMC statements and hence, historical evolution of the sentiment can be analyzed.
- Applied FOMC-SI to an important market fear gauge, namely VIX and showed that the FOMC-SI can predict future value of VIX!
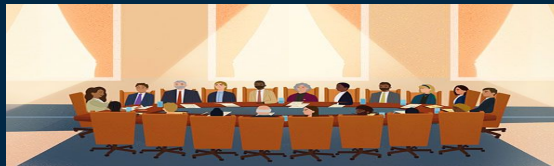
Future Work

- Create a sentiment analysis model trained on more relevant financial text.

- Training a domain-specific sentiment analysis model using financial data can potentially lead to more accurate and contextually relevant sentiment predictions for financial documents like FOMC speeches, economic reports, company earnings calls, news articles, and social media posts related to the financial market.

- This will allow for a more accurate and contextually meaningful sentiment analysis tool for financial applications.

- Suggest a project that develops Federal Reserve's own LLM training as the text data in policy institutions can be different from the text data BERT and FinBERT as well as other LLMs are trained on.

THANK YOU!