In [ ]:

```
# packages

import pandas as pd
import numpy as np
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer
from nltk import tokenize
nltk.download('punkt')
nltk.download('vader_lexicon')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
```

Out[ ]:

```
True
```

In [ ]:

```
# mounting google drive

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Lexicon Data

We load the [lexicon data] used by the authors to supplant the VADER NLTK inbuilt lexicon for the purposes of our application

In [ ]:

```
# reading csv
LM_2011=pd.read_csv('/content/drive/MyDrive/Loughran-McDonald_MasterDictionary_1993-2021.
csv')
```

In [ ]:

```
# "Unwrapping" the sentiment columns into lists of words corresponding to "Uncertain", "C
onstraining", "Positive" and "Negative"
# why >0, and not ==1? because instead of dummies, the years of added words to the dictio
nary are used. conversely, !=0 could be used too
negative_words = LM_2011[LM_2011['Negative'] > 0]['Word'].tolist()
positive_words = LM_2011[LM_2011['Positive'] > 0]['Word'].tolist()
uncertainty_words = LM_2011[LM_2011['Uncertainty'] > 0]['Word'].tolist()
uncertainty_words=[word.lower() for word in uncertainty_words]

constraining_words = LM_2011[LM_2011['Constraining']> 0]['Word'].tolist()

print([len(negative_words),len(positive_words),len(uncertainty_words),len(constraining_wo
rds)])
```

```
[2345, 347, 297, 184]
```

In [ ]:

```
# Bodnaruk's(2015) list of constraining words with which NLTK sentence sentiments will be
reweighted
constraining_words=['abide', 'abiding', 'bound', 'bounded', 'commit', 'commitment', 'com
mitments', 'commits', 'committed', 'committing', 'compel', 'compelled', 'compelling', 'c
ompels', 'comply', 'compulsion', 'compulsory', 'confine', 'confined', 'confinement', 'co
nfines', 'confining', 'constrain', 'constrained', 'constraining', 'constrains', 'constra
int', 'constraints', 'covenant', 'covenanted', 'covenanting', 'covenants', 'depend', 'dép
```

```
endance', 'dependances', 'dependant', 'dependencies', 'dependent', 'depending', 'depends'
, 'dictate', 'dictated', 'dictates', 'dictating', 'directive', 'directives', 'earmark',
'earmarked', 'earmarking', 'earmarks', 'encumber', 'encumbered', 'encumbering', 'encumbe
rs', 'encumbrance', 'encumbrances', 'entail', 'entailed', 'entailing', 'entails', 'entren
ch', 'entrenched', 'escrow', 'escrowed', 'escrows', 'forbade', 'forbid', 'forbidden', 'fo
rbidding', 'forbids', 'impair', 'impaired', 'impairing', 'impairment', 'impairments', 'im
pairs', 'impose', 'imposed', 'imposes', 'imposing', 'imposition', 'impositions', 'indebte
d', 'inhibit', 'inhibited', 'inhibiting', 'inhibits', 'insist', 'insisted', 'insistence'
, 'insisting', 'insists', 'irrevocable', 'irrevocably', 'limit', 'limiting', 'limits', '
mandate', 'mandated', 'mandates', 'mandating', 'mandatory', 'manditorily', 'necessitate',
'necessitated', 'necessitates', 'necessitating', 'noncancelable', 'noncancellable', 'obli
gate', 'obligated', 'obligates', 'obligating', 'obligation', 'obligations', 'obligatory'
, 'oblige', 'obliged', 'obliges', 'permissible', 'permission', 'permissions', 'permitted'
, 'permitting', 'pledge', 'pledged', 'pledges', 'pledging', 'preclude', 'precluded', 'pr
ecludes', 'precluding', 'precondition', 'preconditions', 'preset', 'prevent', 'prevented'
, 'preventing', 'prevents', 'prohibit', 'prohibited', 'prohibiting', 'prohibition', 'pro
hibitions', 'prohibitive', 'prohibitively', 'prohibitory', 'prohibits', 'refrain', 'refra
ining', 'refrains', 'require', 'required', 'requirement', 'requirements', 'requires', 're
quiring', 'restrain', 'restrained', 'restraining', 'restrains', 'restraint', 'restraints
', 'restrict', 'restricted', 'restricting', 'restriction', 'restrictions', 'restrictive',
'restrictively', 'restrictiveness', 'restricts', 'stipulate', 'stipulated', 'stipulates'
, 'stipulating', 'stipulation', 'stipulations', 'strict', 'stricter', 'strictest', 'stric
tly', 'unavailability', 'unavailable']
```

In [ ]:

```
# Loading the statement data

fomc = pd.read_excel('/content/drive/MyDrive/FOMC_STATEMENTS.xlsx')
fomc=fomc[['Date','Statement']]

fomc
```

Out[ ]:

	Date	Statement
0	13.12.2023	Recent indicators suggest that growth of econo...
1	01.11.2023	Recent indicators suggest that economic activi...
2	20.09.2023	Recent indicators suggest that economic activi...
3	26.07.2023	Recent indicators suggest that economic activi...
4	14.06.2023	Recent indicators suggest that economic activi...
...	...	...
73	2013-07-31 00:00:00	Information received since the Federal Open Ma...
74	2013-06-19 00:00:00	Information received since the Federal Open Ma...
75	2013-05-01 00:00:00	Information received since the Federal Open Ma...
76	2013-03-20 00:00:00	Information received since the Federal Open Ma...
77	2013-01-30 00:00:00	Information received since the Federal Open Ma...

78 rows × 2 columns

Vader NLTK

As in Möller and Reichmann (2021), we make use of the Vader package and import the LM (2011) word list to somewhat approximate the sentiment-capturing approach of the authors, to be used in our event study.

The first task, as was the case in the Author's case, is to add additional words from the LM(2011) dictionary into the inbuilt Vader dictionary, i.e. "positive" and "negative" words.

[The Vader Documentation](#) states that Vader is "sensitive to both polarity and intensity" meaning that the strength of sentiment can be specified too, by 4 stages (i.e. for "negative" from -1 to -4), which is why we decided to go with the level 2, given that "Horrible" is associated with 2.5 already.

In [ ]:

```python
# for initializing VADER / usage:
sia = SentimentIntensityAnalyzer()

# Concatenating our words' sentiments
# to the Vader lexicon - now its a
# 'financeVader' of sorts

new_words = {word: 2.0 for
             word in
             positive_words}
new_words.update({word: -2.0
                  for word in
                  negative_words})
sia.lexicon.update(new_words)
```

Getting the *Tone* right

In [ ]:

```python
# sample of how this works

[sia.polarity_scores('You a pain in the ass, respectfully'), sia.polarity_scores('You a p
ain in the ass')]
```

Out[ ]:

```
[{'neg': 0.544, 'neu': 0.24, 'pos': 0.216, 'compound': -0.6249},
 {'neg': 0.694, 'neu': 0.306, 'pos': 0.0, 'compound': -0.7783}]
```

In [ ]:

```python
# Function to calculate weighted sentiment for a statement
def weighted_sentiment(statement):
    # Tokenize into sentences
    sentences = tokenize.sent_tokenize(statement)
    # Get the total word count for the statement
    total_words = len(tokenize.word_tokenize(statement))

    # Calculate sentiment for each sentence and weight it
    weighted_scores = 0
    for sentence in sentences:
        # Get the sentiment score for the sentence
        sentiment_score = sia.polarity_scores(sentence)['compound']
        # weighting
        sentence_weight = len(tokenize.word_tokenize(sentence)) / total_words
        # Add the weighted score to total, and the += is used as an adding operator in fo
r loops
        weighted_scores += sentiment_score * sentence_weight

    return weighted_scores

# Apply the weighted sentiment function to each row in the 'Statement' column
fomc['Tone'] = fomc['Statement'].apply(weighted_sentiment)
```

In [ ]:

```python
fomc.tail()
```

Out[ ]:

	Date	Statement	Tone
73	2013-07-31 00:00:00	Information received since the Federal Open Ma...	0.214167
74	2013-06-19 00:00:00	Information received since the Federal Open Ma...	0.219595
75	2013-05-01 00:00:00	Information received since the Federal Open Ma...	0.226860
76	2013-03-20 00:00:00	Information received since the Federal Open Ma...	0.218299

	Date	Statement	Tone
77	2013-01-30 00:00:00	Information received since the Federal Open Ma...	0.158982

Getting the *Uncertainty* right

We're remodelling the Vader lexicon. All the inbuilt words' sentiment scores will be reduced to 20% of their score, whereby our uncertainty word list will enter the lexicon with the values of -2. This way, we allow for words to interact but clearly aim towards singling out sentiments that emphasize uncertainty

In [ ]:

```
# resetting NLTK lexicon
sia = SentimentIntensityAnalyzer()
```

In [ ]:

```
# Modify the existing VADER lexicon to reduce the impact of its words
new_words = {word: 2.0*0.2 for word in positive_words}
new_words.update({word: -2.0*0.2 for word in negative_words})

modified_lexicon = {word: score * 0.2 for word, score in sia.lexicon.items()}
modified_lexicon.update(new_words)
sia.lexicon = modified_lexicon # Replace the entire lexicon

# Define your list of uncertainty words with a higher impact score
uncertainty_words_scores = {word: 2.0 for word in uncertainty_words}

# Update the lexicon with your uncertainty words scores
sia.lexicon.update(uncertainty_words_scores)
```

In [ ]:

```
# Function to calculate weighted sentiment for a statement
def weighted_sentiment(statement):
    # Tokenize into sentences
    sentences = tokenize.sent_tokenize(statement)
    # Get the total word count for the statement
    total_words = len(tokenize.word_tokenize(statement))

    # Calculate sentiment for each sentence and weight it
    weighted_scores = 0
    for sentence in sentences:
        # Get the sentiment score for the sentence
        sentiment_score = sia.polarity_scores(sentence)['compound']
        # weighting
        sentence_weight = len(tokenize.word_tokenize(sentence)) / total_words
        # Add the weighted score to total, and the += is used as an adding operator in for loops
        weighted_scores += sentiment_score * sentence_weight

    return weighted_scores

# Apply the weighted sentiment function to each row in the 'Statement' column
fomc['Unc'] = fomc['Statement'].apply(weighted_sentiment)
```

In [ ]:

```
fomc.head(10)
```

Out[ ]:

	Date	Statement	Tone	Unc
0	13.12.2023	Recent indicators suggest that growth of econo...	0.042163	0.195259
1	01.11.2023	Recent indicators suggest that economic activi...	0.023460	0.191942
2	20.09.2023	Recent indicators suggest that economic activi...	0.003494	0.189370
3	26.07.2023	Recent indicators suggest that economic activi...	-0.000555	0.190140

	Date	Statement	Tone	Unc
4	14.06.2023	Recent indicators suggest that economic activi...	[illegible]	[illegible]
5	03.05.2023	Economic activity expanded at a modest pace in...	-0.000558	0.171256
6	22.03.2023	Recent indicators point to modest growth in sp...	0.026065	0.156699
7	01.02.2023	Recent indicators point to modest growth in sp...	-0.041707	0.152102
8	14.12.2022	Recent indicators point to modest growth in sp...	-0.060071	0.148150
9	02.11.2022	Recent indicators point to modest growth in sp...	-0.053065	0.151392

Getting the *Constraints* right

In [ ]:

```
sia = SentimentIntensityAnalyzer()
```

In [ ]:

```
# Modify the existing VADER lexicon to reduce the impact of its words
new_words = {word: 2.0*0.2 for word in positive_words}
new_words.update({word: -2.0*0.2 for word in negative_words})

modified_lexicon = {word: score * 0.2 for word, score in sia.lexicon.items()}
modified_lexicon.update(new_words)
sia.lexicon = modified_lexicon # Replace the entire lexicon

# Define your list of uncertainty words with a higher impact score
constraining_words_scores = {word: 3.0 for word in constraining_words}

# Update the lexicon with your uncertainty words scores
sia.lexicon.update(constraining_words_scores)
```

In [ ]:

```
# Function to calculate weighted sentiment for a statement
def weighted_sentiment(statement):
    # Tokenize into sentences
    sentences = tokenize.sent_tokenize(statement)
    # Get the total word count for the statement
    total_words = len(tokenize.word_tokenize(statement))

    # Calculate sentiment for each sentence and weight it
    weighted_scores = 0
    for sentence in sentences:
        # Get the sentiment score for the sentence
        sentiment_score = sia.polarity_scores(sentence)['compound']
        # weighting
        sentence_weight = len(tokenize.word_tokenize(sentence)) / total_words
        # Add the weighted score to total, and the += is used as an adding operator in fo
r loops
        weighted_scores += sentiment_score * sentence_weight

    return weighted_scores

# Apply the weighted sentiment function to each row in the 'Statement' column
fomc['Con'] = fomc['Statement'].apply(weighted_sentiment)
```

In [ ]:

```
fomc.head(5)
```

Out[ ]:

	Date	Statement	Tone	Unc	Con
0	13.12.2023	Recent indicators suggest that growth of econo...	0.042163	0.195259	0.034022
1	01.11.2023	Recent indicators suggest that economic activi...	0.023460	0.191942	0.028708

	Date	Statement	Tone	Unc	Con
2	20.09.2023	Recent indicators suggest that economic activi...	0.003404	0.189370	0.024360
3	26.07.2023	Recent indicators suggest that economic activi...	-0.000555	0.190140	0.023688
4	14.06.2023	Recent indicators suggest that economic activi...	0.013922	0.188975	0.026159

Visualizing our sentiment components

In [ ]:

```
import matplotlib.pyplot as plt
from statsmodels.nonparametric.smoothers_lowess import lowess
from matplotlib.dates import DateFormatter
import seaborn as sns
```

In [ ]:

```
fomc['Date'] = pd.to_datetime(fomc['Date']).dt.strftime('%Y-%m-%d')
fomc['Date'] = pd.to_datetime(fomc['Date'], format='%Y-%m-%d')
fomc = fomc.sort_values('Date')
```

```
<ipython-input-22-20c26e985d41>:1: UserWarning: Parsing dates in DD/MM/YYYY format when d
ayfirst=False (the default) was specified. This may lead to inconsistently parsed dates!
Specify a format to ensure consistent parsing.
  fomc['Date'] = pd.to_datetime(fomc['Date']).dt.strftime('%Y-%m-%d')
```

In [ ]:

```
fomc.Con==fomc.Unc
```

Out[ ]:

```
77    False
76    False
75    False
74    False
73    False
      ...
6     False
4     False
3     False
2     False
0     False
Length: 78, dtype: bool
```

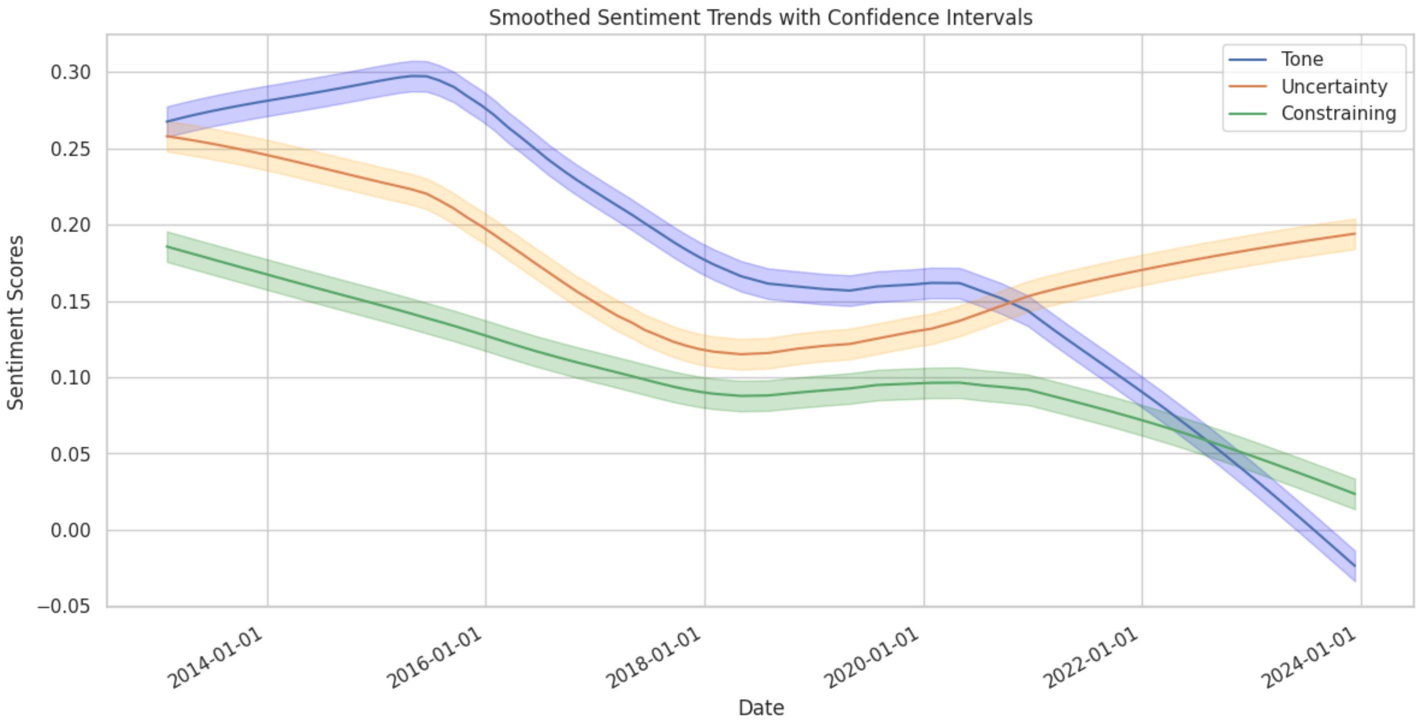
In [ ]:

```
import matplotlib.dates as mdates
from statsmodels.nonparametric.smoothers_lowess import lowess  # Importing lowess
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.dates as mdates

# Sample DataFrame 'fomc' with columns 'Date', 'Tone', 'Unc', 'Con'
# Assuming 'fomc' has already been created with the 'Date' column converted to datetime o
bjects

# Calculate the lowess smoothed trend line for each sentiment
frac = 0.5  # Fraction of data used when estimating each y-value
smoothed_tone = lowess(fomc['Tone'], mdates.date2num(fomc['Date']), frac=frac)
smoothed_unc = lowess(fomc['Unc'], mdates.date2num(fomc['Date']), frac=frac)
smoothed_con = lowess(fomc['Con'], mdates.date2num(fomc['Date']), frac=frac)
```

In [ ]:

```
# Set the figure size and style
plt.figure(figsize=(14, 7))
sns.set(style="whitegrid")

# Plot the smoothed trend lines
```

```
plt.plot(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1], label='Tone')
plt.plot(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1], label='Uncertainty')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1], label='Constraining')

# Assuming a fixed CI just to demonstrate the plotting (replace with actual CI calculatio
ns)
ci = 0.01  # Example confidence interval value
plt.fill_between(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1] - ci, smoothed
_tone[:, 1] + ci, color='blue', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1] - ci, smoothed_
unc[:, 1] + ci, color='orange', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1] - ci, smoothed_
con[:, 1] + ci, color='green', alpha=0.2)

# Improve formatting
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))  # Format the dates
on the x-axis
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())  # Set locator

# Rotate date labels for better readability
plt.gcf().autofmt_xdate()

# Adding legend, title, and labels
plt.legend()
plt.title('Smoothed Sentiment Trends with Confidence Intervals')
plt.xlabel('Date')
plt.ylabel('Sentiment Scores')

# Show the plot
plt.show()
```



In [ ]:

```
fomc
```

Out[ ]:

	Date	Statement	Tone	Unc	Con
77	2013-01-30	Information received since the Federal Open Ma...	0.158982	0.218965	0.145807
76	2013-03-20	Information received since the Federal Open Ma...	0.218299	0.222498	0.196278
75	2013-05-01	Information received since the Federal Open Ma...	0.226860	0.217891	0.188608
74	2013-06-19	Information received since the Federal Open Ma...	0.219595	0.208304	0.186254
73	2013-07-31	Information received since the Federal Open Ma...	0.214167	0.223509	0.186759

...	Date	Statement	Tone	Unc	Con
6	2023-03-22	Recent indicators point to modest growth in sp...	0.026065	0.156699	0.084138
4	2023-06-14	Recent indicators suggest that economic activi...	0.013922	0.188975	0.026159
3	2023-07-26	Recent indicators suggest that economic activi...	-0.000555	0.190140	0.023688
2	2023-09-20	Recent indicators suggest that economic activi...	0.003494	0.189370	0.024360
0	2023-12-13	Recent indicators suggest that growth of econo...	0.042163	0.195259	0.034022

78 rows × 5 columns

In [ ]:

```
fomc.to_excel('/content/drive/MyDrive/SENTIMENTS_FOMC_FINAL.xlsx', index=False)
```

FinBERT FOMC Sentiment Approach

In [ ]:

```
from transformers import BertTokenizer, BertForSequenceClassification, pipeline
```

In [ ]:

```
finbert = BertForSequenceClassification.from_pretrained('ZiweiChen/FinBERT-FOMC',num_labe
ls=3)
tokenizer = BertTokenizer.from_pretrained('ZiweiChen/FinBERT-FOMC')
finbert_fomc = pipeline("text-classification", model=finbert, tokenizer=tokenizer)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:88: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://h
uggingface.co/settings/tokens), set it as secret in your Google Colab and restart your se
ssion.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models
or datasets.
  warnings.warn(
```

In [ ]:

```
def bert_sentiment(statement):
    # Tokenize into sentences
    sentences = tokenize.sent_tokenize(statement)
    # Get the total word count for the statement
    total_words = len(tokenize.word_tokenize(statement))

    # Calculate sentiment for each sentence and weight it
    weighted_scores = 0
    for sentence in sentences:
        # Get the sentiment score for the sentence
        sentiment_score = finbert_fomc(sentence)[0]['score']
        # weighting
        sentence_weight = len(tokenize.word_tokenize(sentence)) / total_words
        # Add the weighted score to total, and the += is used as an adding operator in fo
r loops
        weighted_scores += sentiment_score * sentence_weight

    return weighted_scores
```

In [ ]:

```
fomc['Bert'] = fomc['Statement'].apply(bert_sentiment)
```

In [ ]:

```
fomc.var()
```

```
<ipython-input-39-9ae428623dfc>:1: FutureWarning: The default value of numeric_only in DataFrame.var is deprecated. In a future version, it will default to False. In addition, specifying 'numeric_only=None' is deprecated. Select only valid columns or specify the value of numeric_only to silence this warning.
  fomc.var()
```

Out[ ]:

```
Tone    0.016221
Unc     0.003795
Con     0.002620
Bert    0.000750
dtype: float64
```

In [ ]:

```
fomc.head(50)
```

Out[ ]:

	Date	Statement	Tone	Unc	Con	Bert
77	2013-01-30	Information received since the Federal Open Ma...	0.158982	0.218965	0.145807	0.899695
76	2013-03-20	Information received since the Federal Open Ma...	0.218299	0.222498	0.196278	0.871355
75	2013-05-01	Information received since the Federal Open Ma...	0.226860	0.217891	0.188608	0.868783
74	2013-06-19	Information received since the Federal Open Ma...	0.219595	0.208304	0.186254	0.887783
73	2013-07-31	Information received since the Federal Open Ma...	0.214167	0.223509	0.186759	0.904340
72	2013-09-18	Information received since the Federal Open Ma...	0.328732	0.292917	0.175251	0.943618
71	2013-10-30	Information received since the Federal Open Ma...	0.287443	0.276222	0.148949	0.944651
70	2013-12-18	Information received since the Federal Open Ma...	0.297705	0.230987	0.155775	0.938980
69	2014-01-29	Information received since the Federal Open Ma...	0.312795	0.225664	0.157624	0.934972
68	2014-03-19	Information received since the Federal Open Ma...	0.397755	0.274117	0.174250	0.932421
67	2014-04-30	Information received since the Federal Open Ma...	0.420296	0.318309	0.182280	0.928179
66	2014-06-18	Information received since the Federal Open Ma...	0.431110	0.305250	0.185978	0.925792
65	2014-07-30	Information received since the Federal Open Ma...	0.426888	0.298945	0.186330	0.915120
64	2014-09-17	Information received since the Federal Open Ma...	0.415347	0.320909	0.183066	0.911983
63	2014-10-29	Information received since the Federal Open Ma...	0.267901	0.282041	0.116005	0.906475
62	2014-12-17	Information received since the Federal Open Ma...	0.238267	0.206016	0.105923	0.905794
61	2015-01-28	Information received since the Federal Open Ma...	0.239300	0.236658	0.111297	0.926314
60	2015-03-18	Information received since the Federal Open Ma...	0.289587	0.228532	0.128008	0.930929
59	2015-04-29	Information received since the Federal Open Ma...	0.305666	0.247295	0.147038	0.915375
58	2015-06-17	Information received since the Federal Open Ma...	0.281098	0.275962	0.132879	0.913076
57	2015-07-29	Information received since the Federal Open Ma...	0.284989	0.234676	0.134192	0.927022
56	2015-09-17	Information received since the Federal Open Ma...	0.249940	0.231966	0.152900	0.926858
55	2015-10-28	Information received since the Federal Open Ma...	0.263202	0.221877	0.128227	0.923407
54	2015-12-16	Information received since the Federal Open Ma...	0.277086	0.168770	0.114807	0.956182
53	2016-01-27	Information received since the Federal Open Ma...	0.318235	0.189233	0.128902	0.976214
52	2016-03-16	Information received since the Federal Open Ma...	0.285279	0.174151	0.123018	0.953124
51	2016-04-27	Information received since the Federal Open Ma...	0.323156	0.166754	0.132942	0.977089
50	2016-06-15	Information received since the Federal Open Ma...	0.304258	0.178981	0.126528	0.976978
49	2016-07-27	Information received since the Federal Open Ma...	0.285939	0.151392	0.120916	0.973555
48	2016-09-21	Information received since the Federal Open Ma...	0.310877	0.154283	0.126506	0.976622
47	2016-11-02	Information received since the Federal Open Ma...	0.287064	0.146005	0.117795	0.976644

	Date	Statement	Tone	Unc	Con	Bert
46	2016-12-14	Information received since the Federal Open Ma...	0.229452	0.134894	0.104695	0.974993
45	2017-02-01	Information received since the Federal Open Ma...	0.222506	0.139109	0.106749	0.970942
44	2017-03-15	Information received since the Federal Open Ma...	0.230393	0.155876	0.108200	0.951608
43	2017-05-03	Information received since the Federal Open Ma...	0.253298	0.146965	0.116195	0.973521
42	2017-06-14	Information received since the Federal Open Ma...	0.157817	0.127618	0.083836	0.979787
41	2017-07-27	Information received since the Federal Open Ma...	0.128477	0.113198	0.078917	0.978656
40	2017-09-20	Information received since the Federal Open Ma...	0.070633	0.101666	0.061149	0.975691
39	2017-11-01	Information received since the Federal Open Ma...	0.096149	0.122464	0.072602	0.979270
38	2017-12-13	Information received since the Federal Open Ma...	0.101184	0.092710	0.078576	0.963797
37	2018-01-31	Information received since the Federal Open Ma...	0.078184	0.076394	0.080257	0.975867
36	2018-05-02	Information received since the Federal Open Ma...	0.151616	0.104586	0.099651	0.978179
35	2018-08-01	Information received since the Federal Open Ma...	0.204563	0.079921	0.087691	0.981696
34	2018-11-08	Information received since the Federal Open Ma...	0.208650	0.079314	0.087323	0.981503
33	2019-01-30	Information received since the Federal Open Ma...	0.161040	0.095721	0.069887	0.983603
32	2019-05-01	Information received since the Federal Open Ma...	0.119141	0.088889	0.062382	0.915947
31	2019-07-31	Information received since the Federal Open Ma...	0.095584	0.103300	0.052299	0.977986
30	2019-11-29	Information received since the Federal Open Ma...	-0.041689	0.084917	0.025067	0.981188
29	2020-01-29	Information received since the Federal Open Ma...	0.020689	0.011589	0.046176	0.977730
28	2020-04-29	The Federal Reserve is committed to using its ...	0.203118	0.124485	0.153529	0.930123

In [ ]:

```
fomc['Bert_normed']= fomc['Bert']*(fomc['Tone'][77]/fomc['Bert'][77])
```

In [ ]:

```
fomc.to_excel('/content/drive/MyDrive/SENTIMENTS_FOMC_FINAL_with_BERT.xlsx', index=False)
```

UP TO HERE CODE SHOULD BE PROPER - after this point experiments/graveyard

In [ ]:

```
Core=pd.read_excel('/content/drive/MyDrive/Core.xlsx')
```

In [ ]:

```
ir_data=Core[['Date','IR']]
```

In [ ]:

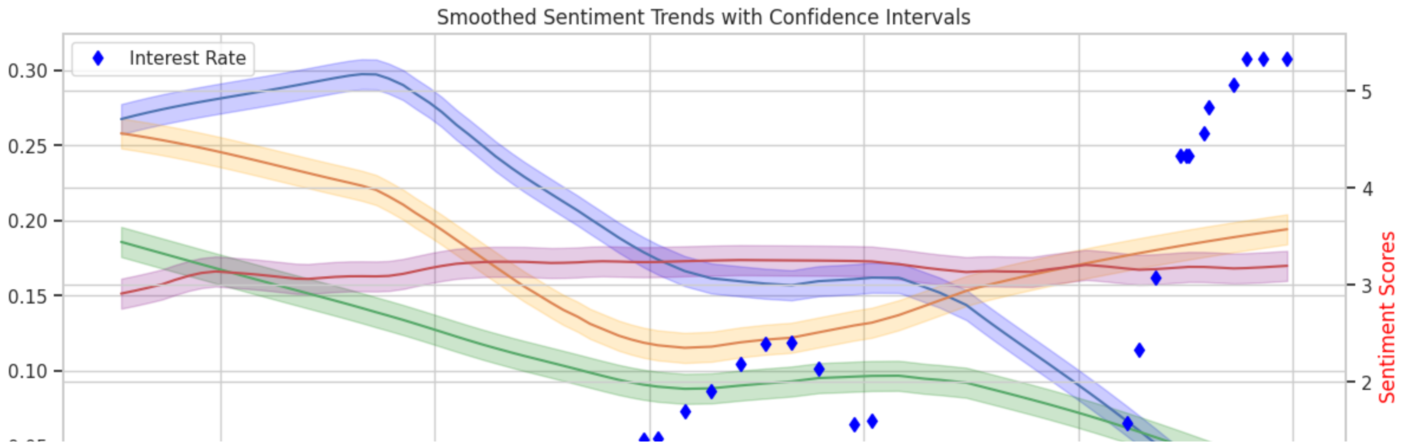
```
# Calculate the lowess smoothed trend line for each sentiment
frac = .1 # Fraction of data used when estimating each y-value
smoothed_bert = lowess(fomc['Bert_normed'], mdates.date2num(fomc['Date']), frac=frac)
```

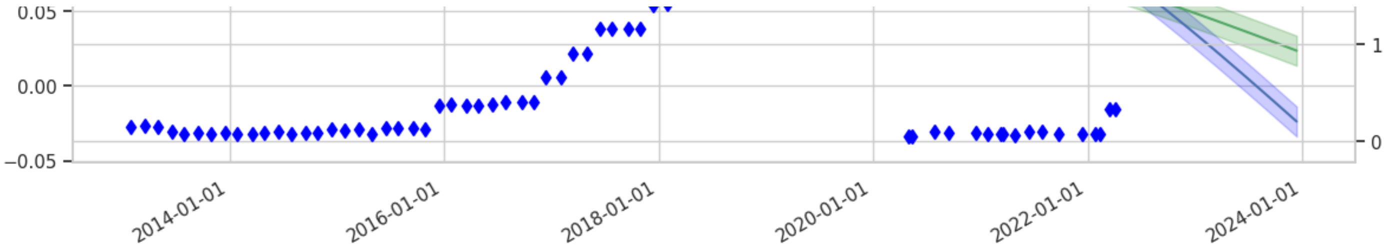
In [ ]:

```
ir_data['Date'] = pd.to_datetime(ir_data['Date'])
ir_data.sort_values('Date', inplace=True)

# Create the plot for sentiment scores as you've done before
plt.figure(figsize=(14, 7))
sns.set(style="whitegrid")
# Plot the smoothed trend lines
plt.plot(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1], label='Tone')
plt.plot(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1], label='Uncertainty')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1], label='Constraining')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1], label='BerTone')
```

```python
# Assuming a fixed CI just to demonstrate the plotting (replace with actual CI calculations)
ci = 0.01  # Example confidence interval value
plt.fill_between(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1] - ci, smoothed_tone[:, 1] + ci, color='blue', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1] - ci, smoothed_unc[:, 1] + ci, color='orange', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1] - ci, smoothed_con[:, 1] + ci, color='green', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1] - ci, smoothed_bert[:, 1] + ci, color='purple', alpha=0.2)

ax2 = plt.gca().twinx()

# Plot the IR data
ax2.plot(ir_data['Date'], ir_data['IR'], 'd', color='Blue', label='Interest Rate')  # 'd' for diamond marker

# Set the y-axis label for the IR data
ax2.set_ylabel('Interest Rate', color='red')

# Rotate date labels for better readability
plt.gcf().autofmt_xdate()

# Adding legend to the right axis
ax2.legend(loc='upper left')

# Improve formatting
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))  # Format the dates on the x-axis
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())  # Set locator

# Rotate date labels for better readability
plt.gcf().autofmt_xdate()

# Adding legend, title, and labels
plt.legend()
plt.title('Smoothed Sentiment Trends with Confidence Intervals')
plt.xlabel('Date')
plt.ylabel('Sentiment Scores')

# Show the plot
plt.show()
```

```
<ipython-input-47-30d20d9dbcbf>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ir_data['Date'] = pd.to_datetime(ir_data['Date'])
<ipython-input-47-30d20d9dbcbf>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ir_data.sort_values('Date', inplace=True)
```

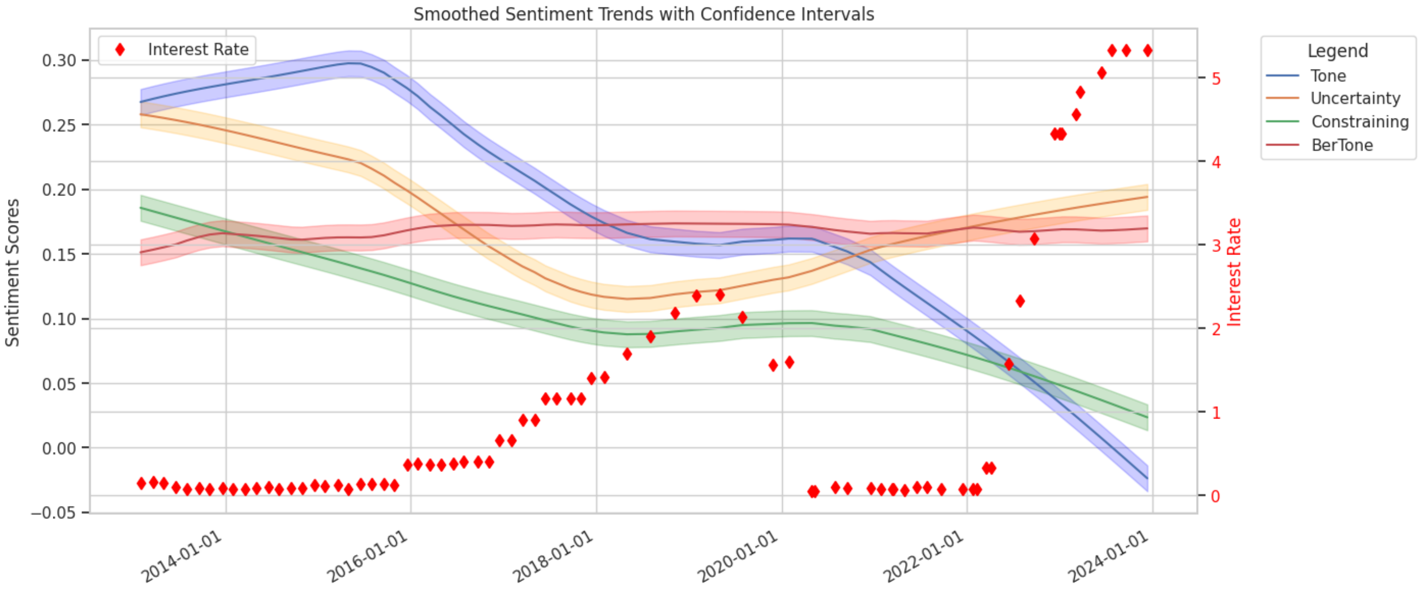




In [ ]:

```
import matplotlib.dates as mdates
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# ... your data loading and processing ...

# Create the plot for sentiment scores
plt.figure(figsize=(14, 7))
sns.set(style="whitegrid")

# Plot the smoothed trend lines for sentiment
plt.plot(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1], label='Tone')
plt.plot(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1], label='Uncertainty')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1], label='Constraining')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1], label='BerTone')

# Fill between for confidence intervals
ci = 0.01  # Example confidence interval value
plt.fill_between(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1] - ci, smoothed_tone[:, 1] + ci, color='blue', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1] - ci, smoothed_unc[:, 1] + ci, color='orange', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1] - ci, smoothed_con[:, 1] + ci, color='green', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1] - ci, smoothed_bert[:, 1] + ci, color='red', alpha=0.2)

# Set primary y-axis label
plt.ylabel('Sentiment Scores')

# Add legend for sentiment trends
plt.legend(title="Legend", bbox_to_anchor=(1.05, 1), loc='upper left')

# Format x-axis dates
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())

# Rotate date labels for better readability
plt.gcf().autofmt_xdate()

# Create a second y-axis for the IR data
ax2 = plt.gca().twinx()

# Plot the IR data as diamonds
ax2.plot(ir_data['Date'], ir_data['IR'], 'd', color='red', label='Interest Rate')  # 'd' for diamond marker

# Set the secondary y-axis label and change its color to match the plot
ax2.set_ylabel('Interest Rate', color='red')
ax2.tick_params(axis='y', labelcolor='red')

# Add legend for IR data on the second y-axis
ax2.legend(loc='upper left')

# Title and x-axis label
plt.title('Smoothed Sentiment Trends with Confidence Intervals')
plt.xlabel('Date')

# Show the plot
```

```
plt.show()
```

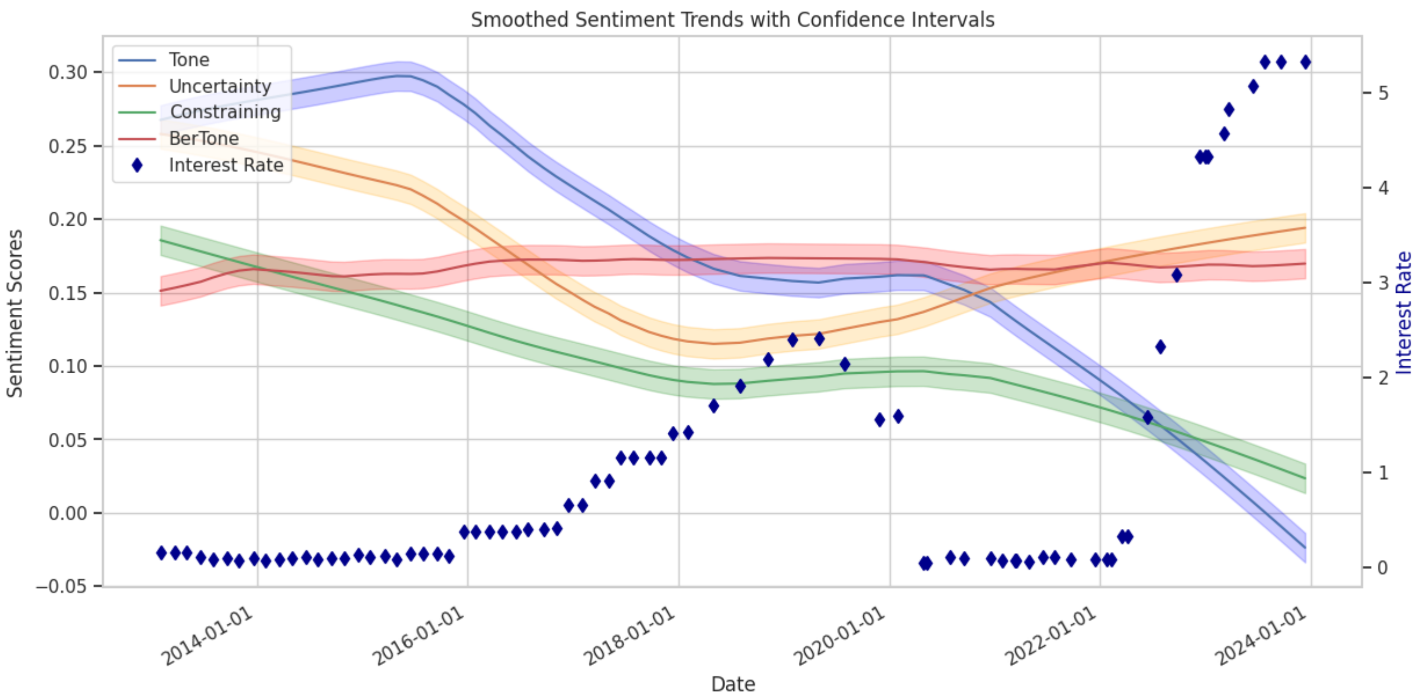


In [ ]:

```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
import pandas as pd
import numpy as np

# Assume ir_data, smoothed_tone, smoothed_unc, smoothed_con, smoothed_bert are defined
# For example, let's say ir_data is a DataFrame with 'Date' and 'IR' columns

# Convert 'Date' to datetime and sort the DataFrame
ir_data['Date'] = pd.to_datetime(ir_data['Date'])
ir_data.sort_values('Date', inplace=True)

# Create the plot for sentiment scores as you've done before
plt.figure(figsize=(14, 7))
sns.set(style="whitegrid")

# Plot the smoothed trend lines for sentiment scores
plt.plot(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1], label='Tone')
plt.plot(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1], label='Uncertainty')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1], label='Constraining')
plt.plot(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1], label='BerTone')

# Assuming a fixed CI just to demonstrate the plotting (replace with actual CI calculatio
ns)
ci = 0.01  # Example confidence interval value
plt.fill_between(mdates.num2date(smoothed_tone[:, 0]), smoothed_tone[:, 1] - ci, smoothed
_tone[:, 1] + ci, color='blue', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_unc[:, 0]), smoothed_unc[:, 1] - ci, smoothed_
unc[:, 1] + ci, color='orange', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_con[:, 1] - ci, smoothed_
con[:, 1] + ci, color='green', alpha=0.2)
plt.fill_between(mdates.num2date(smoothed_con[:, 0]), smoothed_bert[:, 1] - ci, smoothed_
bert[:, 1] + ci, color='red', alpha=0.2)

# Create a secondary y-axis for the IR data
ax1 = plt.gca()
ax2 = ax1.twinx()

# Plot the IR data
ax2.plot(ir_data['Date'], ir_data['IR'], 'd', color='darkblue', label='Interest Rate')
# 'd' for diamond marker

# Set the y-axis label for the IR data
ax2.set_ylabel('Interest Rate', color='darkblue')

# Remove gridlines from the interest rate axis
```

```
ax2.grid(False)

# Create a legend for all items
handles1, labels1 = ax1.get_legend_handles_labels()
handles2, labels2 = ax2.get_legend_handles_labels()
ax2.legend(handles1 + handles2, labels1 + labels2, loc='upper left')

# Formatting dates on the x-axis
ax1.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
ax1.xaxis.set_major_locator(mdates.AutoDateLocator())

# Rotate date labels for better readability
plt.gcf().autofmt_xdate()

# Adding title and axis labels
plt.title('Smoothed Sentiment Trends with Confidence Intervals')
ax1.set_xlabel('Date')
ax1.set_ylabel('Sentiment Scores')

# Show the plot
plt.show()
```

```
<ipython-input-51-8199892ce295>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  ir_data['Date'] = pd.to_datetime(ir_data['Date'])
<ipython-input-51-8199892ce295>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  ir_data.sort_values('Date', inplace=True)
```



In [ ]:

```
# Define your specialized word lists
uncertainty_words = set([...])  # Load your actual words here
constraining_words = set([...])  # Load your actual words here

# Function to calculate sentiment for a whole statement
def statement_sentiment(statement, uncertainty_words, constraining_words):
    sentences = nltk.sent_tokenize(statement)
    tone_scores = [reweight_vader_score(sentence, uncertainty_words | constraining_words
) for sentence in sentences]
    unc_scores = [reweight_vader_score(sentence, uncertainty_words) for sentence in sent
```

```
ences]
    con_scores = [reweight_vader_score(sentence, constraining_words) for sentence in sent
ences]

    # Calculate aggregate score; you can choose average, sum, or any other method
    tone = sum(tone_scores) / len(sentences) if sentences else 0
    unc = sum(unc_scores) / len(sentences) if sentences else 0
    con = sum(con_scores) / len(sentences) if sentences else 0

    return tone, unc, con

# Apply sentiment analysis to each statement
results = df['Statement_Column_Name'].apply(lambda x: statement_sentiment(x, uncertainty
_words, constraining_words))

# The results are tuples, so separate them into different columns
df['Tone'] = results.apply(lambda x: x[0])
df['Uncertainty'] = results.apply(lambda x: x[1])
df['Constraining'] = results.apply(lambda x: x[2])

# Save the results back to a new Excel file
df.to_excel('path_to_your_output_excel_file.xlsx', index=False)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-127-b45be613e08e> in <cell line: 20>()
     18
     19 # Apply sentiment analysis to each statement
---> 20 results = df['Statement_Column_Name'].apply(lambda x: statement_sentiment(x, unce
rtainty_words, constraining_words))
     21
     22 # The results are tuples, so separate them into different columns

NameError: name 'df' is not defined
```

In [ ]:

```

```