

# Does FED Communication cause immediate and abnormal returns stock market?

A sentiment analysis on the S&P 500 Stock Market Index

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## Abstract

## 1. Literature Review

The following research project is mostly based on the work done by Möller and Reichmann (2021) in the field of sentiment analysis. In their paper “ECB Language and Stock Returns - A Textual analysis of ECB Press Conferences” they explore the impact of the language used by the ECB in their regular press conferences on stock returns in the Euro Area.

They achieve this by mining the statements and ranking the sentiments of each statement based on general tone, uncertainty and constraint. Once this is classified, the researchers then cross-check the high frequency intraday data for Euro Area stock returns on each statement day, by employing the technique of an event study. This allows them to see how stock returns reacted to statements by the ECB at whatever point they wanted to examine them.

As mentioned, the researchers focused on tone, uncertainty and constraining language for the sentiment analysis. Tone captures the overall language - or the overarching narrative - of a statement, uncertainty measures how ambiguous a statement may be and constraining language quantifies how constraining the ECB communicates to be in the future. Of course the researchers did not read through every single statement by the ECB, instead, they employed a dictionary-based sentiment mining approach that considered grammatical and syntactical cues to analyze the sentiment expressed in ECB press conferences. Afterwards they scored each statement with regards to each category by employing heuristic-adjusted sentiment scores based on word lists used in previous studies. Möller and Reichmann (2021a) The Authors had used a plethora of controls in their regression analyses, an approach that we were more reluctant to follow due to our slightly smaller sample size. The main reason behind that is that our sample could hardly accommodate the sheer number of variables used in the initial analysis. Below, we delve into the subset of data used, and into our methodology for modelling Möller and Reichmann’s (2021) sentiment methodology. In addition, we explore whether transformer-based approaches that are bespoke to Federal Reserve Statements can outperform heuristics-adjusted sentiment approaches using dictionaries, i.e. our proprietary approach. We do so by investigating the explanatory power of regressions using each sentiment approach.

## 2. Data

The data used for this project consists of the following:

- Federal Reserve (FED) Meetings: The U.S. American FED holds regular meetings multiple times per year where they talk about the current economic situation and what the plan is going forwards. This leaves us with 74 statements over 10 years from January 30th 2013 until July 26th 2023.
- Standard & Poor’s 500 stock market index pricing: We cross-check the statements and their nature with the price of the S&P 500 stock market index on each day of a statement. This index is of particular interest since it incorporates 500 U.S. american companies representing a large part of the whole market itself. This means that we can use the S&P 500 as a proxy for how the market behaves at a given day. Alongside that we obtained weighted debt to equity ratios of the index to see if higher leverage leads to stronger reactions to sentiment. A third and final element of S&P 500 data was lagged returns that were used in some of our analysis
- Federal Funds Futures data: the rate or price equivalent of the interest rate that the market prices in for the next 30 days was obtained as well, as a proxy for market expectations on interest rates.

All of our data, save for the FOMC meeting minutes were obtained via the Bloomberg Terminal data services, whereas the FOMC minutes were manually extracted.

## 3. Methodology

Our analysis of equity returns following FOMC sentiment levels can be partitioned in two. The first part is sentiment extraction, with our approach closely following that of Möller and Reichmann (2021), as well as an implementation of Google’s FinBERT NLP transformer for an alternative gauge of the tone of FOMC minutes. The second part focuses on the construction of the variables needed in our regression, both core

variables as are equity returns and sentiment, as well as various controls inspired by the paper from Möller and Reichmann.

### 3.1 Sentiment Extraction - VADER Method

Our first approach to modelling the sentiment of FOMC minutes closely resembles that of Möller and Reichmann (2021), who use the NLTK VADER package in Python to extract sentiment. The VADER package is special insofar as it adjusts sentiment for heuristics, which gives it an advantage over conventional dictionary-based NLP methods (Hutto, 2014) Hutto and Gilbert (2014). Furthermore, sentiment can be modeled for intensity as well, with Sentiment  $S \in [-4, 4]$ . Möller and Reichmann (2021) expand the inbuilt dictionary of words and corresponding stand-alone sentiment scores by financial terms that correspond to mere Tone, Uncertainty, as well as Constraining language, so as to be able to capture different dimensions of speech.

Our approach to this was to update the lexicon in VADER as well, whereby our extraction of Tone merely necessitated the updating of the pre-existing lexicon. For Unc and Con, however, we used the libraries by Bodnaruk (2015) Bodnaruk, Loughran, and McDonald (2015) for constraining language and Loughran and McDonald (2011) Loughran and McDonald (2011) to construct scores for uncertain language and for extending the VADER dictionary by financial terms. To extract the nuances of uncertain and constraining language, the sentiment scores of all tokens not included in the respective external libraries received reduced sentiment scores, to 20% of their initial sentiment score. Meanwhile, the tokens from the libraries were weighted regularly, i.e. with sentiment scores  $S \in \{2, -2\}$ , as 2 is equivalent to moderate intensity in the VADER package. Adjusting every word's sentiment score manually for its intensity was not deemed feasible for the scope of a project.

Once these transformations took place, the FOMC data was tokenized into sentences, which were then tokenized for each constituent word. The sentiment score for every sentence is weighted by the word count in each sentence relative to the total word count in the statement.

Finally, we constructed the three sentiment elements and saw their trajectory move as follows:

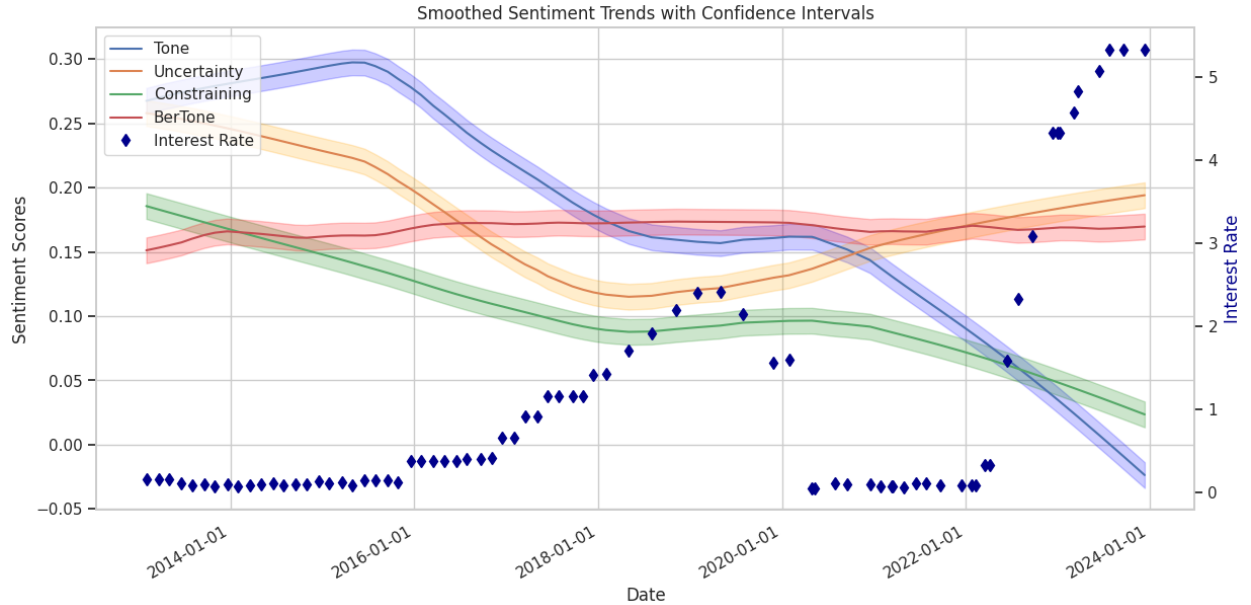


Figure 1: Sentiment Trajectory

In the plot above, we can see the trajectory of each sentiment element of FOMC minutes over time, along with the Fed's interest rate, offering some interesting insights into the interplay between monetary policy, forward

guidance and sentiment. Notably, as sentiment in FOMC minutes deteriorated in the periods of 2020, mostly attributable to the adverse impacts of COVID as well as in the period of 2021 to 2023, mostly attributable to the flare-ups of armed conflict around the world, a rise in interest rates would follow a drop in sentiment. This is a very interesting development, as historically a deterioration in economic outlook, i.e. during the time of the great financial crisis, lead to a decrease in interest rates. However, one must discriminate between sentiment deterioration lead by financial instability shocks which necessitate an injection of liquidity into capital markets, and the contemporary drivers of sentiment deterioration, which are geopolitical woes and inflationary pressures resulting from them. Whether it be Russian aggression or Houthi attacks on global commerce, these factors incessantly are inflationary phenomena from a monetary perspective. When looking at the graph, the amount of uncertainty around monetary policy seems to rise more poignantly as well, whereby the Fed seems to have turned to a less binding language, in line with that of the ECB, that points to more data-driven decision making and allows for more flexibility, so as to not cause volatility due to policy deviations and surprises, an occurrence forward guidance was meant to alleviate in the first place.

Constraining language, interestingly, does seem to exhibit some form of relationship with tone, which could indicate that as economic conditions deteriorate, the Federal Reserve’s decision set is considerably reduced.

### 3.2 Sentiment Extraction - FinBERT Method

Another route we took to sentiment construction was that of FinBERT. FinBERT is a transformer-based natural language processing model that can analyze phrases contextually by looking at both preceding and succeeding words, i.e. it is bidirectional, which our VADER approach is not. FinBERT is an adaptation of BERT which was a generalized sentiment analysis tool developed by Google, whereby Araci (2019) Araci (2019) trained it on an extensive corpus of financial data. Luckily for us, Chen et al. (2023) Chen et al. (2023) took it one step further and trained BERT on FOMC statement sentiment, which seemed like an ideal approach to pit our tone construction against in our analysis. Similarly to the approach with VADER, we constructed sentiments by BERT on a sentence by sentence basis and weighted every sentence by its relative word count.

As a next step, we had to transform and prepare all of our financial data for analysis, which we delve into below.

### 3.3 Financial Data Processing

For every data point of our financial data, the last available datapoint was carried forward to the day of the FOMC minute issue, whereby returns were constructed via log-returns, in order to facilitate the computation of average returns in order to calculate abnormal returns. The abnormal returns, our independent variable of interest, was constructed using the model of MacKinlay (1997) MacKinlay (1997), who computed abnormal returns as the of cumulative returns after an event over average returns over a period, in our case 3 years.

Furthermore, we constructed a variable which captures the surprise effect of interest rate changes, in line with Möller and Reichmann’s (2021) method in order to truly isolate the effect of sentiment from the mechanical effect of interest rate levels. This variable was constructed via the difference of implied interest rate expectations from federal funds rate futures one day before the announcement and the actual interest rate that was announced.

The point where we depart from the methodology of Möller and Reichmann (2021) is the fact that we also investigate the effects on returns for heterogeneity based on general debt levels of companies, essentially posing the question if returns react to negative sentiment more in times of high indebtedness.

### 3.4 Regression Sepcifications

```
simple_tone <- lm(abnormal_return ~ Tone, data = Core)
simple_unc <- lm(abnormal_return ~ Unc, data = Core)
simple_con <- lm(abnormal_return ~ Con, data = Core)
simple_bert <- lm(abnormal_return ~ Bert, data = Core)
```

```
stargazer(simple_tone, simple_con, simple_unc, simple_bert, column.labels = c("Tone", "Unc", "Con", "Be
```

Table 1:

	<i>Dependent variable:</i>			
	Tone	abnormal_return Unc	Con	Bert
	(1)	(2)	(3)	(4)
Tone	0.013 (0.010)			
Con		0.009 (0.024)		
Unc			0.018 (0.019)	
Bert				0.001 (0.043)
Constant	-0.002 (0.002)	-0.001 (0.003)	-0.003 (0.004)	-0.00003 (0.041)
Observations	76	76	76	76
R <sup>2</sup>	0.023	0.002	0.011	0.00000
Adjusted R <sup>2</sup>	0.010	-0.011	-0.002	-0.014
Residual Std. Error (df = 74)	0.010	0.010	0.010	0.010
F Statistic (df = 1; 74)	1.774	0.156	0.859	0.0002

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Looking at Table 1, the intuition seems to be correct. We can see neither of those sentiment variables are significant in our baseline regression. Model fit also seems to be an issue as the R<sup>2</sup> and adjusted R<sup>2</sup> are no way near 1. Therefore, we can shortly conclude, that only (for example) constraining messages or uncertainty messages from the FED will not impact abnormal returns by themselves. Regressing all sentiment variables in one model also does not seem to be the correct approach, as those sentiment variables might be correlated due to their nature. Also, the authors of the original paper stayed away from such an approach. Furthermore, the potential for confounding factors that cloud the effect that sentiment could have on returns is not taken into account here, which, given the diverse nature of the information set that capital markets absorb concurrently, does seem relevant.

Because the sentiments alone do not seem to have the a significant standalone impact on abnormal returns, we start looking at different economic circumstances which could extract the partial impact of sentiments on abnormal returns. By adding a different variables one step at a time, we can fully grasp what impacts abnormal returns on “FED announcement days” and prevent overfitting, which could be an issue when looking at the fully specified model immediately. Firstly, a good variable to start off with is interest rates. Interest rates will paint the picture of monetary conditions in the economy at the moment. We therefore include IR into our models.

```

simple_tone_IR <- lm(abnormal_return~Tone + IR, data = Core)
simple_unc_IR <- lm(abnormal_return~Unc + IR, data = Core)
simple_con_IR <- lm(abnormal_return~Con + IR, data = Core)
simple_bert_IR <- lm(abnormal_return~Bert + IR, data = Core)

stargazer(simple_bert_IR, simple_bert_IR, simple_bert_IR, simple_bert_IR,
          column.labels = c("Tone", "Unc", "Con", "Bert"), header = F)

```

Table 2:

	<i>Dependent variable:</i>			
		abnormal_return		
	Tone	Unc	Con	Bert
	(1)	(2)	(3)	(4)
Bert	0.009 (0.045)	0.009 (0.045)	0.009 (0.045)	0.009 (0.045)
IR	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Constant	-0.007 (0.043)	-0.007 (0.043)	-0.007 (0.043)	-0.007 (0.043)
Observations	76	76	76	76
R <sup>2</sup>	0.006	0.006	0.006	0.006
Adjusted R <sup>2</sup>	-0.021	-0.021	-0.021	-0.021
Residual Std. Error (df = 73)	0.010	0.010	0.010	0.010
F Statistic (df = 2; 73)	0.211	0.211	0.211	0.211

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Looking at Table 2, we unfortunately can see that there is still no significant impact on abnormal returns, when regressing the sentiments alongside interest rates. This would generally make sense as the prevailing interest rate is known to the market. It also can be argued that those sentiment scores and interest rates could possibly correlated a bit. High constraining language, by theory, could easily go hand in hand with higher interest rates, and so on. Model fit, i.e. R<sup>2</sup> and adjusted R<sup>2</sup> seemed to have also deteriorated by adding interest rates. The latter part is to be expected, as adjusted R<sup>2</sup> takes adding variables into account via a penalty term. However, we still stick by our step-wise addition of variables in order to in the end arrive at a feasible model, where interest rates will likely not be included. We therefore built upon this model and added the lagged returns on in our model to account for any autoregressive impact of past returns on abnormal returns. We now regress abnormal returns on Tone, Con, Unc, as well as on IR and lagged\_return.

```

simple_tone_LR <- lm(abnormal_return ~ Tone + IR + lagged_return, data = Core)
simple_unc_LR <- lm(abnormal_return ~ Unc + IR + lagged_return, data = Core)
simple_con_LR <- lm(abnormal_return ~ Con + IR + lagged_return, data = Core)
simple_bert_LR <- lm(abnormal_return ~ Bert + IR + lagged_return, data = Core)

stargazer(simple_tone_LR, simple_con_LR, simple_unc_LR, simple_bert_LR, column.labels = c("Tone", "Unc"

```

Table 3:

	<i>Dependent variable:</i>			
		abnormal_return		
	Tone	Unc	Con	Bert
	(1)	(2)	(3)	(4)
Tone	0.018 (0.014)			
Con		−0.001 (0.034)		
Unc			0.016 (0.020)	
Bert				0.010 (0.046)
IR	0.001 (0.001)	−0.001 (0.001)	−0.0003 (0.001)	−0.001 (0.001)
lagged_return	−0.090 (0.162)	−0.060 (0.163)	−0.067 (0.162)	−0.062 (0.162)
Constant	−0.003 (0.004)	0.001 (0.005)	−0.002 (0.004)	−0.008 (0.043)
Observations	76	76	76	76
R <sup>2</sup>	0.030	0.007	0.016	0.008
Adjusted R <sup>2</sup>	−0.011	−0.034	−0.025	−0.034
Residual Std. Error (df = 72)	0.010	0.011	0.010	0.011
F Statistic (df = 3; 72)	0.736	0.172	0.382	0.188

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Unfortunately, looking at the results from table 3, there are still no significant impacts on abnormal returns, which is a bit disheartening. However, model fit seems to have improved a bit. We still have a lot more variables which could help our ordeal though. We now add a special variable which could be a key contributor in the process. The other variables are self-explanatory (for the most part) – but how was the Surprise variable constructed? It is, as mentioned above, the difference between the Federal Funds rate on announcement day and Fed Funds Futures as a gauge for market expectations, i.e. the surprise effect of the interest rate change on the market. This means that, this variable will account for unexpected announcement results from the fed and discounts it.



```

simple_tone_SUR <- lm(abnormal_return ~ Tone + IR + lagged_return + Surprise, data = Core)
simple_unc_SUR <- lm(abnormal_return ~ Unc + IR + lagged_return + Surprise, data = Core)
simple_con_SUR <- lm(abnormal_return ~ Con + IR + lagged_return + Surprise, data = Core)
simple_bert_SUR <- lm(abnormal_return ~ Bert + IR + lagged_return + Surprise, data = Core)

stargazer(simple_tone_SUR, simple_unc_SUR, simple_con_SUR, simple_bert_SUR, column.labels = c("Tone", "Unc", "Con", "Bert"))

```

Table 4:

	<i>Dependent variable:</i>			
	Tone	Unc	Con	Bert
	(1)	(2)	(3)	(4)
Tone	0.024* (0.014)			
Unc		0.012 (0.020)		
Con			0.013 (0.034)	
Bert				0.015 (0.045)
IR	0.0004 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)
lagged_return	−0.047 (0.160)	−0.023 (0.162)	−0.018 (0.162)	−0.019 (0.162)
Surprise	0.022** (0.011)	0.017 (0.011)	0.019* (0.011)	0.018* (0.011)
Constant	−0.005 (0.004)	−0.001 (0.004)	−0.001 (0.005)	−0.013 (0.043)
Observations	76	76	76	76
R <sup>2</sup>	0.084	0.049	0.046	0.046
Adjusted R <sup>2</sup>	0.033	−0.004	−0.007	−0.008
Residual Std. Error (df = 71)	0.010	0.010	0.010	0.010
F Statistic (df = 4; 71)	1.635	0.919	0.862	0.855

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Analysing table 4, one can now start to understand why we think highly of the surprise variable. By adding surprise, we can now start to see how abnormal returns react to FED Statements. In our model now, Tone is significant. According to the authors, this indicates that a more positive (negative) language of the FED is associated with higher (lower) intraday abnormal returns. This is in line with the findings of Schmeling and Wagner (2019), who found that negative changes in the fraction of negative words within an introductory statement of an ECB press conferences have a positive influence on stock prices and a negative influence on volatility risk premia and credit spreads. We also find that, Surprise is significant in every model other than

Unc. This can be explained, intuitively, as any information not included in the market price is bound to move it once it becomes available to its participants, which in the case of interest rates is on the day of the announcement.

Last but not least, we include the debt to equity ratio of the index into our model. This variable tells us the rate of debt those firms have in relation to their equity. The higher this ratio is the higher the leverage of its firm, the more it might react to interest rates changes. This will now complete our intended model. However, before we delve into that analysis, we must ensure the soundness of our model. Up to this point, the model was constructed following Möller and Reichmann (2021). Including a variable for indebtedness would hence depart from their analysis and open an additional avenue of investigation, on top of the one we opened by investigating whether a “plug and play” NLP program such as BERT would clearly outperform a more bespoke approach, as conducted by Möller and Reichmann (2021).

Therefore, we now ensure the soundness of our models and the inclusion of our variables, especially of the interest rate variable which prompted a negative R2, via a bayesian model averaging algorithm. By cycling over all potential combinations of models, we want to ascertain the relative importance of each variable. The bayesian model averaging algorithm does so by determining the post-inclusion probability for each of our variables. We see that....

```
simple_tone_DE <- lm(abnormal_return ~ Tone + IR + lagged_return + Surprise + debt_equity, data = Core)
simple_unc_DE <- lm(abnormal_return ~ Con + IR + lagged_return + Surprise + debt_equity, data = Core)
simple_con_DE <- lm(abnormal_return ~ Con + IR + lagged_return + Surprise + debt_equity, data = Core)
simple_bert_DE <- lm(abnormal_return ~ Bert + IR + lagged_return + Surprise + debt_equity, data = Core)

stargazer(simple_tone_DE, simple_unc_DE, simple_con_DE, simple_bert_DE, column.labels = c("Tone", "Unc"
```

As seen in Table 5, we still have a significant value of tone, but the significance of surprise has changed in some variables. Instead of our FinBERT sentiment being significant, uncertainty has now become significant. Generally an overall underperformance of the BERT approach seems to become evident, something that we will delve into later. A model which could become interesting is our model with interaction terms. The idea is that by adding interaction the effect of “Tone”, “Unc”, “Con”, “Bert” or “Surprise” on abnormal returns is moderated by the company’s leverage. In other words, the impact of these sentiment on returns may vary depending on the leverage ratio. This is intuitive as a company with higher leverage will be much more sensitive to changes in its cost of capital, and hence, sensitive to indications that such a cost of capital change could come. Such an indication is the sentiment of FOMC statements.

```
interactions_tone <- lm(abnormal_return ~ Tone * debt_equity + IR + lagged_return + Surprise * debt_equity + debt_ratio)
interactions_unc<-lm(abnormal_return~Unc*debt_equity + IR + lagged_return + Surprise*debt_equity + debt_ratio)
interactions_con<-lm(abnormal_return~Con*debt_equity + IR + lagged_return + Surprise*debt_equity + debt_ratio)
interactions_bert <- lm(abnormal_return~Bert*debt_equity + IR + lagged_return + Surprise*debt_equity + debt_ratio)

stargazer(interactions_tone, interactions_unc, interactions_con, interactions_bert, column.labels = c("Tone", "Unc", "Con", "Bert"), header = F)

trial_tone<-lm(abnormal_return~Tone + IR + lagged_return + Surprise + debt_equity, data=Core)
trial_unc<-lm(abnormal_return~Unc + IR + lagged_return + Surprise + debt_equity, data=Core)
trial_con<-lm(abnormal_return~Con + IR + lagged_return + Surprise + debt_equity, data=Core)
trial_bert<-lm(abnormal_return~Bert + IR + lagged_return + Surprise + debt_equity, data=Core)

stargazer(trial_tone, trial_unc, trial_con, trial_bert,
          column.labels = c("Tone", "Unc", "Con", "Bert"), header = F)
```

Table 5:

	<i>Dependent variable:</i>			
	Tone	abnormal_return Unc	Con	Bert
	(1)	(2)	(3)	(4)
Tone	0.032** (0.015)			
Con		0.025 (0.037)	0.025 (0.037)	
Bert				0.003 (0.050)
IR	-0.0003 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
lagged_return	-0.057 (0.159)	-0.019 (0.162)	-0.019 (0.162)	-0.016 (0.163)
Surprise	0.022** (0.011)	0.019* (0.011)	0.019* (0.011)	0.017 (0.011)
debt_equity	0.00003 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)	0.00001 (0.00002)
Constant	-0.016** (0.008)	-0.008 (0.009)	-0.008 (0.009)	-0.005 (0.045)
Observations	76	76	76	76
R <sup>2</sup>	0.113	0.057	0.057	0.051
Adjusted R <sup>2</sup>	0.050	-0.010	-0.010	-0.017
Residual Std. Error (df = 70)	0.010	0.010	0.010	0.010
F Statistic (df = 5; 70)	1.792	0.853	0.853	0.756

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 6:

	<i>Dependent variable:</i>			
	Tone	abnormal_return		Bert
		Unc	Con	
	(1)	(2)	(3)	(4)
Tone	0.082 (0.053)			
Unc		0.143 (0.094)		
Con			0.147 (0.126)	
Bert				-0.095 (0.207)
debt_equity	0.0001 (0.00004)	0.0001 (0.0001)	0.0001 (0.0001)	-0.0002 (0.001)
IR	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.001)
lagged_return	-0.154 (0.158)	-0.166 (0.163)	-0.116 (0.161)	-0.086 (0.165)
Surprise	0.305*** (0.102)	0.356*** (0.107)	0.310*** (0.103)	0.279*** (0.103)
Tone:debt_equity	-0.0001 (0.0002)			
Unc:debt_equity		-0.0003 (0.0003)		
Con:debt_equity			-0.0003 (0.0004)	
Bert:debt_equity				0.0002 (0.001)
debt_equity:Surprise	-0.001*** (0.0002)	-0.001*** (0.0002)	-0.001*** (0.0002)	-0.001** (0.0002)
Constant	-0.032** (0.015)	-0.041* (0.022)	-0.029 (0.019)	0.082 (0.193)
Observations	76	76	76	76
R <sup>2</sup>	0.205	0.190	0.158	0.135
Adjusted R <sup>2</sup>	0.123	0.106	0.071	0.046
Residual Std. Error (df = 68)	0.010	0.010	0.010	0.010
F Statistic (df = 7; 68)	2.500**	2.272**	1.819*	1.514

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 7:

	<i>Dependent variable:</i>			
	Tone	abnormal_return		Bert
		Unc	Con	
	(1)	(2)	(3)	(4)
Tone	0.032** (0.015)			
Unc		0.024 (0.023)		
Con			0.025 (0.037)	
Bert				0.003 (0.050)
IR	−0.0003 (0.001)	−0.002 (0.001)	−0.001 (0.001)	−0.001 (0.001)
lagged_return	−0.057 (0.159)	−0.029 (0.162)	−0.019 (0.162)	−0.016 (0.163)
Surprise	0.022** (0.011)	0.015 (0.011)	0.019* (0.011)	0.017 (0.011)
debt_equity	0.00003 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)	0.00001 (0.00002)
Constant	−0.016** (0.008)	−0.011 (0.009)	−0.008 (0.009)	−0.005 (0.045)
Observations	76	76	76	76
R <sup>2</sup>	0.113	0.066	0.057	0.051
Adjusted R <sup>2</sup>	0.050	−0.001	−0.010	−0.017
Residual Std. Error (df = 70)	0.010	0.010	0.010	0.010
F Statistic (df = 5; 70)	1.792	0.990	0.853	0.756

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

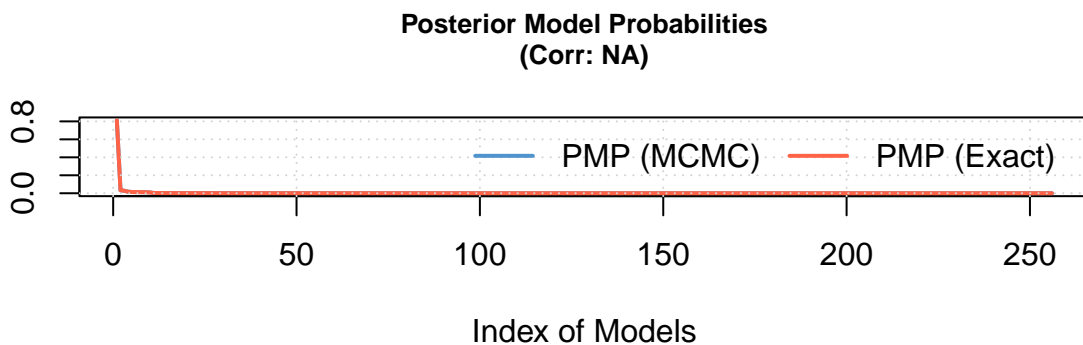
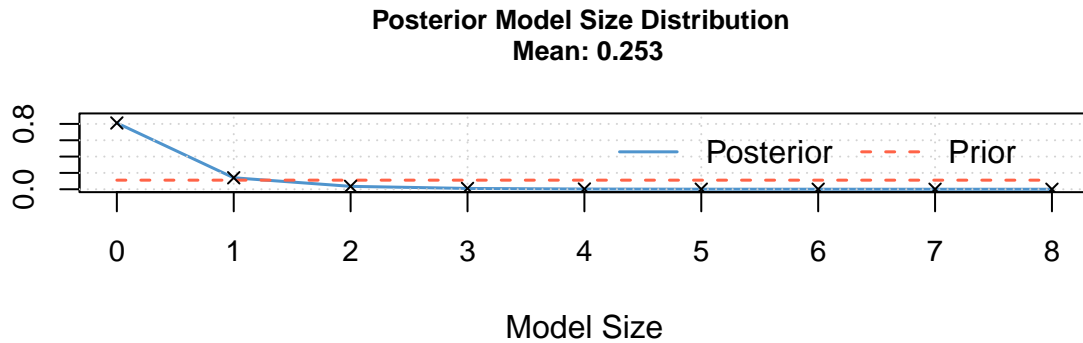
## 4. Bayesian Model Averaging

After regressing everything and getting the results we do a final check via Bayesian Model Averaging (BMA), where we can see which of the Variables from our Core data set truly are important to abnormal returns. This methodology is to check which variables have variable importance in a regression.

```
# Defining the Model
abnormal_return_model <- Core$abnormal_return ~ Core$Tone + Core$Unc + Core$Con + Core$Bert + Core$IR +

# Doing the BMA itself
bms_results <- bms(abnormal_return_model)

##
##          PIP      Post Mean      Post SD Cond.Pos.Sign Idx
## Core$Surprise 0.05896313 9.967645e-04 4.782526e-03 1.00000000 7
## Core$Tone      0.05623271 1.074809e-03 5.605947e-03 1.00000000 1
## Core$Unc       0.02703853 4.553171e-04 4.441457e-03 0.96803485 2
## Core$debt_equity 0.02421109 2.725401e-07 3.423660e-06 0.95062231 8
## Core$Con       0.02401279 -1.773257e-04 7.184673e-03 0.69543177 3
## Core$IR        0.02300608 -1.155113e-05 1.646098e-04 0.08399735 5
## Core$lagged_return 0.02023056 -1.327445e-03 2.449888e-02 0.00000000 6
## Core$Bert      0.01926924 1.154585e-04 6.683659e-03 0.88214338 4
##
## Mean no. regressors      Draws      Burnins      Time
##      "0.2530"      "256"      "0"      "0.06169891 secs"
## No. models visited      Modelspace 2^K      % visited      % Topmodels
##      "256"      "256"      "100"      "100"
##      Corr PMP      No. Obs.      Model Prior      g-Prior
##      "NA"      "76"      "random / 4"      "UIP"
##      Shrinkage-Stats
##      "Av=0.987"
##
## Time difference of 0.06169891 secs
```



## 5. Potential for Future Research

Considering the fact that FED statements have been forced to consider significant humanitarian crises such as the outbreak of the COVID-19 pandemic (First Lockdown in the U.S. began on March 12th, 2020), the invasion of Russia into Ukraine (February 24th, 2022 - immediately after economical from COVID began the lessen) and the Hamas terrorist attack on Israel and the war following after (since October 7th, 2023), there exists an avenue for future research.

While the U.S. interest rate policy must inevitably take into account global geopolitical events, it can only incorporate them to a limited extent. This means that a discrepancy between the U.S.-focused and more “fact-based” interest rate and the more “human” statements will likely occur, as shown in the graph in Chapter 3.3. Future research could seek to find a way to quantify the difference between economically relevant word-combinations by refining linguistic analysis methods, adjusting dictionaries, and filtering out word combinations that may focus on factors irrelevant to immediate, upcoming policy, thereby emphasizing a more financially centered context.

This research potential especially becomes apparent when observing the disparity between the overall trend the SPX shows since the “COVID-Crash” in March 2020 - particularly the clear positive trend since the beginning of 2023 - and the language employed by the FED in its statements since the beginning of the recorded statements in the data used. As mentioned, future research may seek to refine the dictionaries used and isolate sentences or word-combinations related to unforeseen geopolitical events, that cannot be ignored in a statement by a governing body.

```
window<- 50

RegressionDates<- FilterDates>window:length(FilterDates)]
Tone_SE<- c()
```

```

Tone<- c()

for (i in RegressionDates){
  # this part is tricky - how to filter the right window of data??
  index_end <- which(FilterDates==i)

  index_start <- index_end - window

  data<- Core[index_start:index_end,]
  reg <- summary(lm(abnormal_return ~ Tone + IR + lagged_return + Surprise + debt_equity, data = data))
  Tone<- c(Tone,reg$coefficients[2])
  Tone_SE<- c(Tone_SE,reg$coefficients[8])
}

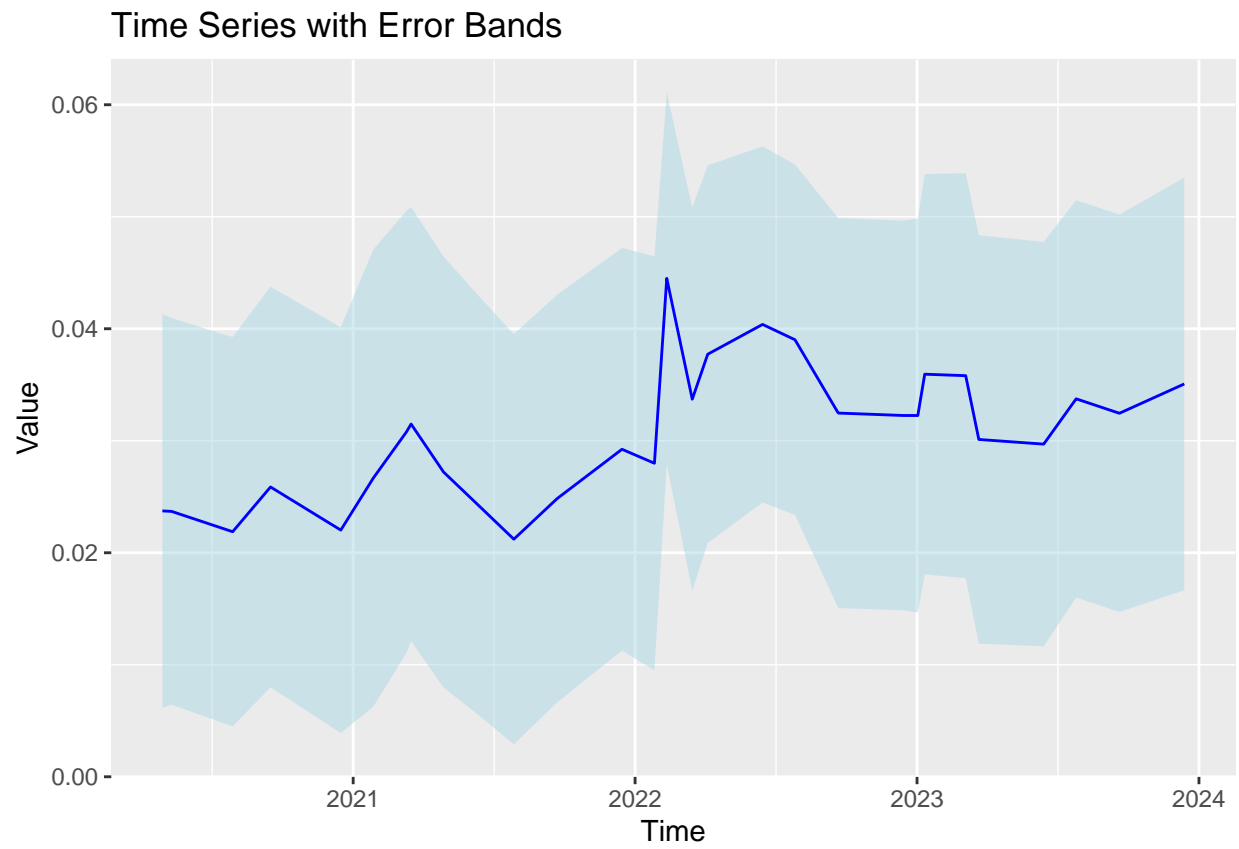
# add 0-line to get significance right at 10%

upper_Tone<- Tone+Tone_SE
lower_Tone<- Tone-Tone_SE
plotbands<-data.frame(cbind(Tone, lower_Tone,upper_Tone))
plotbands$date<-as.POSIXct(RegressionDates)

ggplot(plotbands, aes(x = RegressionDates, y = Tone)) +
  geom_ribbon(aes(ymin = lower_Tone, ymax = upper_Tone),
             fill = "lightblue", alpha = 0.5) +
  geom_line(color = "blue") +
  labs(title = "Time Series with Error Bands",
       x = "Time", y = "Value")

```





## 6. Conclusion

## 7. Bibliography

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