Presentation Overview

1. Summary of Objectives and Results
2. Review of Existing Research
3. Discussion of Project Pipeline
4. Method 1: Factor Similarity
5. Method 2: Word List
6. Method 3: FinBERT sentiment analysis
7. Conclusion

1. Summary of Objectives and Results

Objectives:

- Use Natural Language Processing to analyze structure of Federal Reserve documents
- Test explanatory power of processed documents on asset prices

Results:

- Robust automated project pipeline developed to process Fed documents and train NLP models
- Each of the methods employed (Factor Similarity, Word List, and finBERT Sentiment) had strengths and weaknesses
- All three methods showed promising explanatory power on asset prices

2. Review Of Existing Research

- **Loughran and McDonald (2011)**
    - Expand Word Classification in H4N to include negative financial word list (Fin-Neg)
    - Use proportion of negative words in 10-K filings to predict excess returns of stock
    - **Advantages**
        - Uses tf.idf methodology
        - Improves upon BERT for financial applications
    - **Disadvantages**
        - Does not incorporate context of words
        - Not specific to Federal Reserve

2. Review Of Existing Research (Cont.)

- **Doh, Song, Yang (2020)**
  - Use Universal Sentence Encoder (USE) to encode FOMC Statement document as a large-dimensional vector
  - Compare cosine distance to Alternate statements to determine Hawkish/Dovish-ness
  - Regress on stock market returns for different time windows
  - **Advantages**
    - Specific to Federal Reserve
    - Employs context through vector encoding
  - **Disadvantages**
    - Relies on delayed alternate statements
    - Requires calibrating market expectations

Project Pipeline Schematic

1. Collect and Store Data

- FOMC Statements
- Press Releases
- Minutes

2. Process Data

- Cleaning
- Parsing (Reg Ex)
- Tagging

3. Transform Data Using NLP

- I. Factor Similarity
- II. Word List
- III. FinBERT Sentiment

4. Test Market Impact

- 10Y-2Y Spread
- 1Y Treasury
- DXY (USD Index)
- Growth - Value Spread

Method 1: Factor Similarity

- FinBERT can represent a sentence as a vector
- We can quantify the similarity between two vectors using cosine similarity
- Idea: See how “similar” the statements are to some key sentences
- Key sentences: “Interest rates will rise” and “Inflation will rise”
- Linear regression on these Factor Similarity scores

I. Factor Similarity

1. Convert Document Sentences to Vectors Using finBERT

Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability.

v_1

$(0.04498, -0.05743, 0.00221, \ldots)$

Currently, the unemployment rate is elevated, and measures of underlying inflation are somewhat low, relative to levels that the Committee judges to be consistent, over the longer run, with its dual mandate.

v_2

$(0.03874, 0.07652, -0.00079, \ldots)$

$\vdots$

The Committee will maintain the target range for the federal funds rate at 0 to 1/4 percent and continues to anticipate that economic conditions, including low rates of resource utilization, subdued inflation trends, and stable inflation expectations, are likely to warrant exceptionally low levels for the federal funds rate for an extended period.

v_n

$(0.05568, -0.00960, 0.00624, \ldots)$

I. Factor Similarity

2. Convert Factor Sentences to Vectors Using finBERT

`Inflation will rise` $\longrightarrow$ θ_1 $(-0.07438, 0.00146, -0.03219, \ldots)$

`Interest rates will rise` $\longrightarrow$ θ_2 $(0.06611, 0.00114, -0.00099, \ldots)$

3. Take Average Cosine Distance Between Sentence and Factor Vectors

$$x_1 = \frac{1}{n} \sum_{i=1}^{n} CosSim\,(v_i\,,\ \theta_1)$$

$$x_2 = \frac{1}{n} \sum_{i=1}^{n} CosSim\,(v_i\,,\ \theta_2)$$

I. Factor Similarity

4. Compute Scores for each document

	x_1 inf score	x_2 int score
Dates		
2011-04-27	0.496361	0.500582
2011-06-22	0.503241	0.50943
2011-11-02	0.502128	0.508735
2012-01-25	0.487765	0.486021

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5. Regress Scores on Change in Asset Price

$$\Delta p_{10Y-2Y} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

$$\Delta p_{DXY} = \cdots$$

$$\Delta p_{G-V} = \cdots$$

Results: Factor Similarity explaining growth spread

	1-year Treasury Change	Treasury Yield Spread Change	USD Change	Growth Value Spread
const	-0.214	-0.013	-0.068	18.03
	(0.28)	(0.31)	(0.05)	(4.94)
rate score	1.56	0.215	0.34	$\boxed{-48.515}$
	(1.58)	(1.75)	(0.26)	(27.56)
inf score	-1.163	-0.187	-0.205	13.128
	(1.25)	(1.39)	(0.21)	(21.90)
R-squared	0.019	0	0.044	$\boxed{0.216}$

Method 2: Word List

- Handcrafted lexicon of phrases
  - Phrases taken from introductory remarks in the press transcript
  - Words in a phrase need not be consecutive
  - Topic and sentiment provided (manual labeling)

- Information retrieval and aggregation
  - Iterate through sentences
  - Assign each sentence a topic score by looking for phrases relevant to that topic

II. Word List/Phrase Lexicon

1. Collect and Label Significant Sentences

Topic	D/H	Text	keywords
Economy	D	Household spending and investment in equipment and software continue to expand, supporting the recovery, but nonresidential investment is still weak and the **housing sector** is **depressed**.	housing sector, depressed
Economy	H	On the inflation front, commodity prices have risen significantly recently, reflecting geopolitical developments and **robust global demand**, among other factors.	robust global demand
Job Market	D	As indicated in today's policy statement, the economic recovery appears to be proceeding at a moderate pace, though somewhat more slowly than the Committee had expected, and some recent **labor market** indicators have also been **weaker** than expected.	labor market, weaker
Interest Rate	H	Earlier **today**, the Federal Open Market Committee **decided** to **raise** the target range for the federal funds **rate** by ¼ percentage point, bringing it to ¼ to ½ percent.	today, decided, raise, rate

2. Assign Scores to Keywords and Classify by Topic

Score

Topic	Sentiment	Phrase	Subtopic
Sentiment	1	abrupt halt	Word/Phrase
Economy	-1	accomodative financial conditions	Economy
Sentiment	1	affected	Word/Phrase
Sentiment	1	bear the burden	Word/Phrase
Economy	-1	boosting the economy	Economy
Economy	-1	bounceback, spending	Spending
Economy	1	broad and forceful	Monetary/Fiscal Policy
Sentiment	1	burden	Word/Phrase
Interest Rate	0	committee, kept, rate	Interest Rate
Economy	0	complete its planned purchases	Monetary/Fiscal Policy
Economy	1	concerns, supply chains	Economy

II. Word List

3. Scan Documents. Calculate Weighted Average Sentiment By Topic

$$x_k(t) = \frac{1}{n_k} \sum_{i=1}^{n} \textbf{sign} \left(\sum_{p=1}^{m} L(p) S(p) \mathbf{1}_k(i) \right)$$

$S(x)$: **sentiment of phrase** x

$L(x)$: **length of phrase** x

$\mathbf{1}_x(y)$: **presence of topic** x **in sentence y**

$k \in \{eco, smt, job\}$

II. Word List

Data Structure:

Date	Interest Rate	Economy	Job Market	Sentiment
2011-04-27	$x_{int}(0)$	$x_{eco}(0)$	$x_{job}(0)$	$x_{smt}(0)$
2011-06-22	$x_{int}(1)$	$x_{eco}(1)$	$x_{job}(1)$	$x_{smt}(1)$
	⋮	⋮	⋮	⋮

Date	Interest	Econ	Job	Sentiment
2011-04-27	0	-0.011765	-0.047059	-0.070588
2011-06-22	0	-0.014706	0.000000	0.000000
2011-11-02	0	-0.013158	-0.039474	-0.078947
2012-01-25	0	-0.011364	0.000000	-0.011364
2012-04-25	0	-0.023810	-0.023810	0.047619

II. Word List

4. Regress Factor Scores on Change in Asset Prices

$$\Delta p_{10Y-2Y} = \alpha + (\beta_{eco} x_{eco} \mid \beta_{job} x_{job}) + \beta_{int} x_{int} + \beta_{smt} x_{smt} + \epsilon$$

$$\Delta p_{1Y} = \cdots$$

$$\Delta p_{DXY} = \cdots$$

$$\Delta p_{G-V} = \cdots$$

Method 2: Word List - Results

Market impact regressions of Fed Press Transcript category scores during 2011-2021.

	1-year Treasury Yield Change	Treasury Yield Spread Change	USD Change	Growth Value Spread
const	-0.0133 (0.008)	-0.0066 (0.010)	-0.2427* (0.133)	0.1011 (0.287)
Interest Rate	**-0.0504**** **(0.014)**	0.0217 (0.017)	-0.1406 (0.234)	0.3808 (0.277)
Economy	0.2829* (0.119)	-0.1941 (0.146)	-3.7960* (1.971)	
Job Market				-1.6813 (2.745)
Sentiment	-0.0616 (0.063)	0.0774 (0.077)	1.1095 (1.046)	**3.8796**** **(1.327)**
R-squared	24.9%	5.9%	8.6%	23.2%

Method 3: FinBERT Sentiment

- FinBERT model takes sentences and maps them to sentiment scores
- The possibility that a sentence is classified as positive in the FinBERT model is the sentiment score.

III. FinBERT Sentiment

Different approaches to assigning sentiment scores to documents…

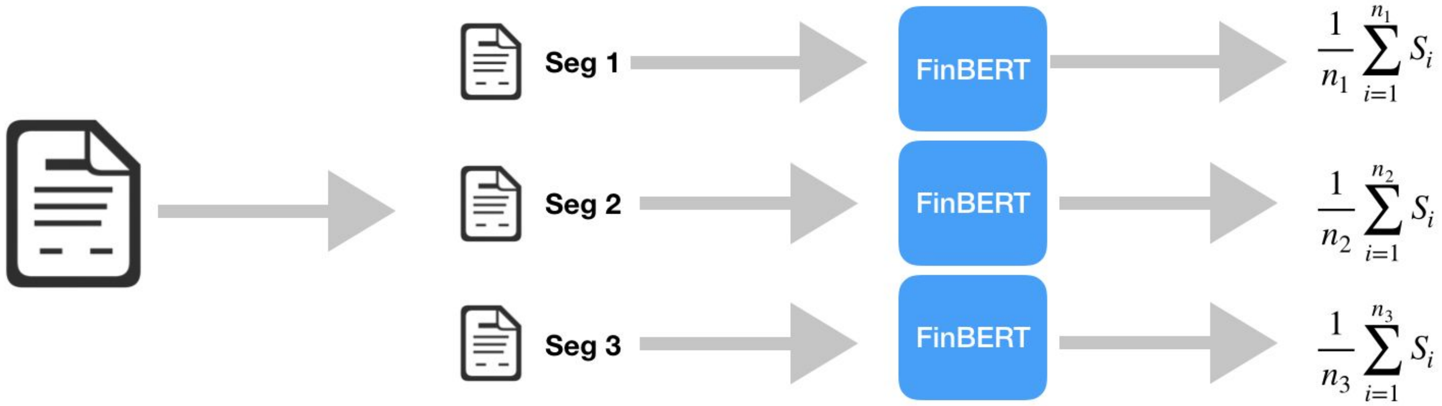
1. Average finBERT sentiment by sentence

$$\frac{1}{n}\sum_{i=1}^{n} S_i$$

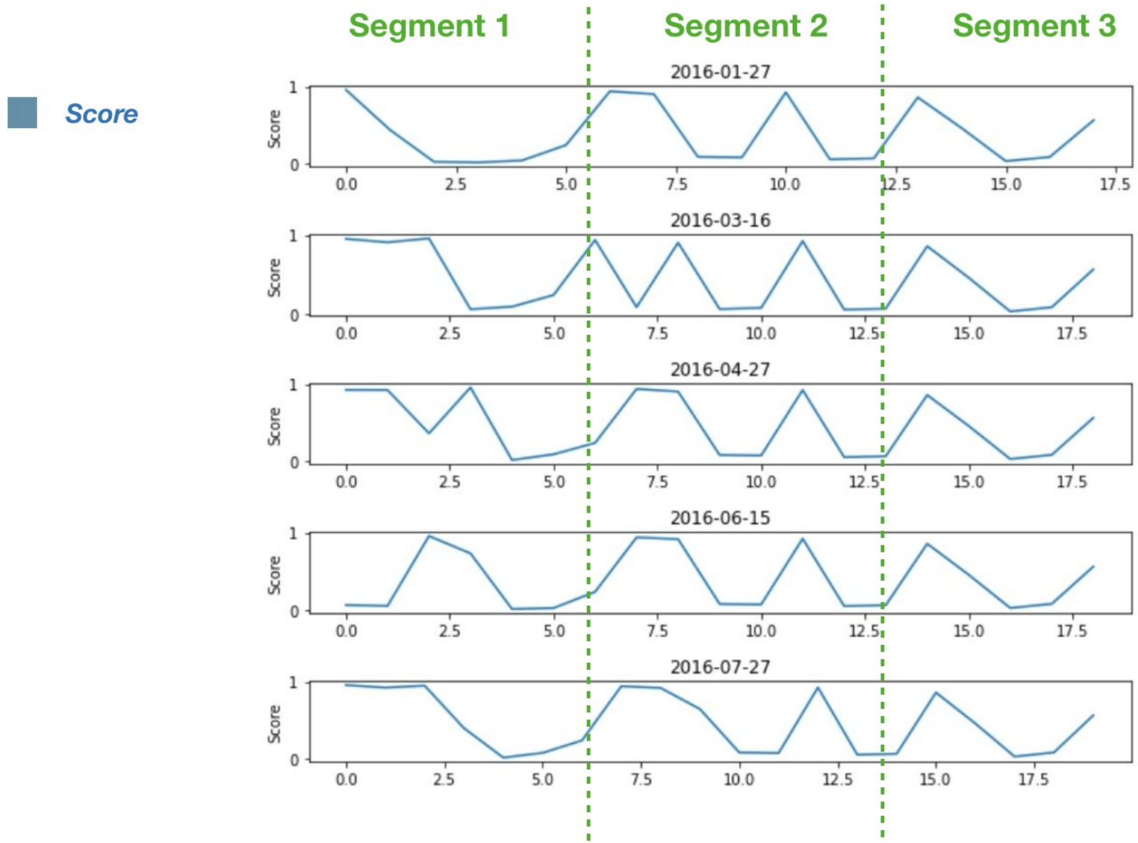
III. FinBERT Sentiment

Different approaches to assigning sentiment scores to documents…

2. Score By Segment



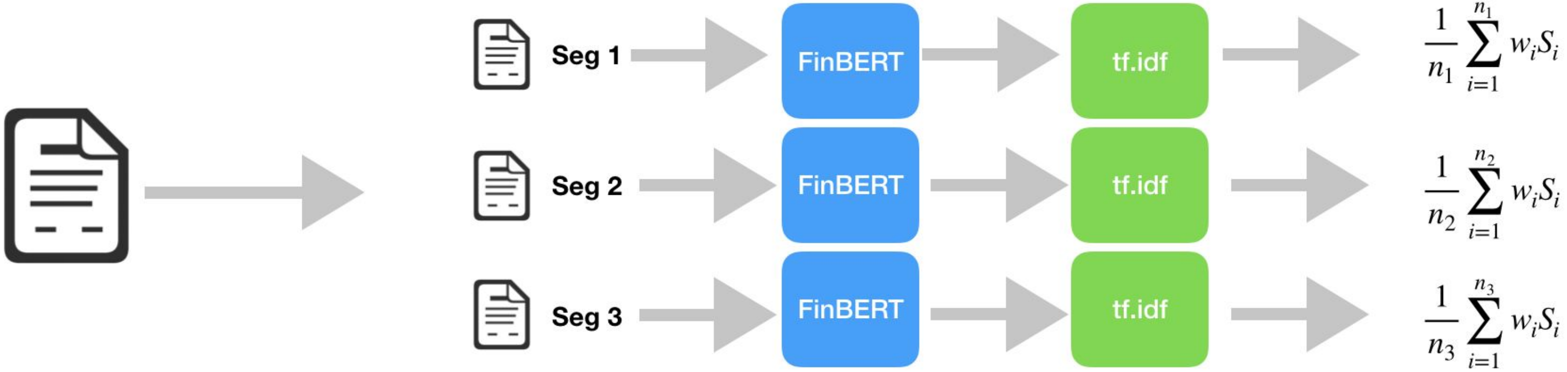
Segmentation Example:



III. FinBERT Sentiment

Different approaches to assigning sentiment scores to documents…

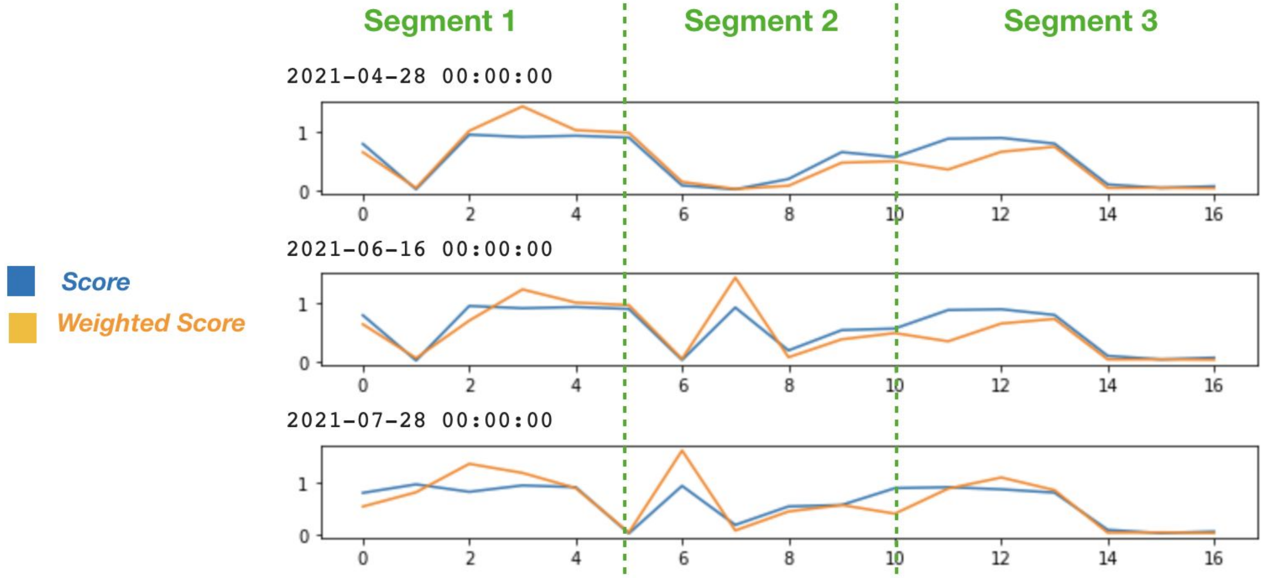
3. Weighted Score By Segment



III. FinBERT Sentiment

Different approaches to assigning sentiment scores to documents…

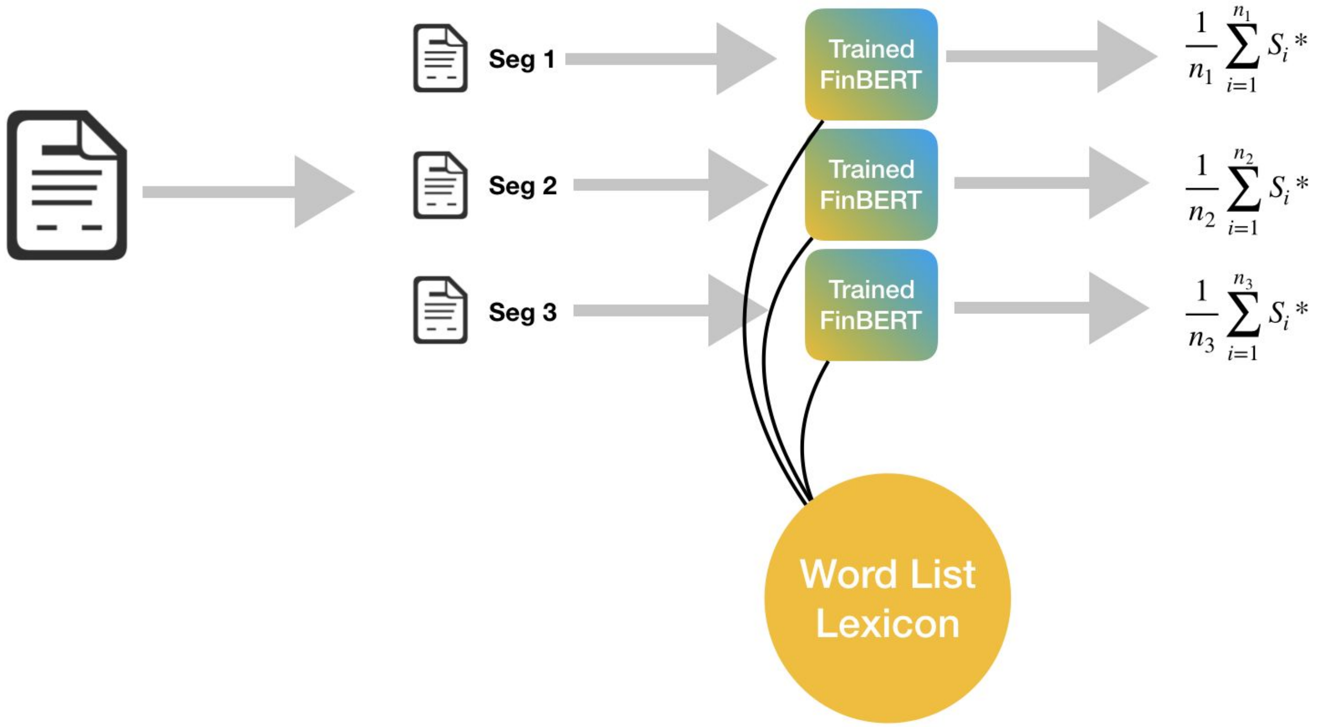
Example:



III. FinBERT Sentiment

Different approaches to assigning sentiment scores to documents…

4. Fine-Tuned FinBERT



III. FinBERT Sentiment

4. Regress Segment Scores on Change in Asset Prices

$$\Delta p_{10Y-2Y} = \alpha + \beta_{seg1} x_{seg1} + \beta_{seg2} x_{seg2} + \beta_{seg3} x_{seg3} + \epsilon$$

$$\Delta p_{1Y} = \cdots$$

$$\Delta p_{DXY} = \cdots$$

$$\Delta p_{G-V} = \cdots$$

Method 3: finBERT Sentiment - Original model

Market impact regressions of Fed Statements sentiment scores during 2016-2021.
The estimates use a sample of 47 Fed Statements over 2016 to 2021

	1-year Treasury Yield Change	Treasury Yield Spread Change	USD Change	Growth Value Spread
const	-0.0227	-0.0653**	-0.0039	0.7358
	(0.025)	(0.029)	(0.005)	(0.501)
Segment 1	-0.0166	0.0374	0.0029	-1.1291
	(0.036)	(0.043)	(0.008)	(0.653)
Segment 2	0.0369	-0.0145	0.0021	-0.0229
	(0.032)	(0.039)	(0.007)	(0.566)
Segment 3	0.0187	0.1439*	0.0008	0.0312
	(0.062)	(0.074)	(0.013)	(1.150)
R-squared	3.0%	11.2%	0.9%	3.7%

- Positive sentiment (as defined by FinBERT) is associated with increases in short term interest rate and stronger dollar

Method 3: finBERT Sentiment - Original model & weighting

Market impact regressions of Fed Statements sentiment scores during 2016-2021.
The estimates use a sample of 47 Fed Statements over 2016 to 2021.

	1-year Treasury Yield Change	Treasury Yield Spread Change	USD Change	Growth Value Spread
	Weighted	Weighted	Weighted	Weighted
const	0.0078 (0.021)	-0.0626** (0.025)	-0.0013 (0.004)	0.7091* (0.730)
Segment 1	-0.0086 (0.018)	0.0293 (0.022)	0.0020 (0.004)	-0.8358 (1.071)
Segment 2	0.0177 (0.026)	-0.0041 (0.031)	-0.0008 (0.006)	-0.6471 (0.960)
Segment 3	-0.0586 (0.039)	**0.1143**** (0.047)	-0.0031 (0.008)	0.8699 (1.846)
R-squared	7.1%	14.8%	1%	6.2%

- With the use of weighting, explanatory power of the model has enhanced

Method 3: finBERT Sentiment - Fine-tuned model

Market impact regressions of Fed Statements sentiment scores (from fine-tuned model) during 2011 - 2021

	1-year Treasury Yield Change	Treasury Yield Spread Change	USD Change	Growth Value Spread
const	0.0109 (0.011)	-0.0092 (0.023)	-0.5519 (0.246)	0.7298 (0.297)
Segment 1	-0.0342 (0.016)	0.0126 (0.033)	-0.0251 (0.353)	-0.8429 (0.425)
Segment 2	0.0161 (0.020)	-0.0083 (0.044)	**1.2563**** **(0.461)**	-1.0743* (0.555)
Segment 3	-0.0254 (0.034)	0.0137 (0.073)	1.2483 (0.768)	1.2614 (0.925)
R-squared	10.3%	0.3%	10.6%	9.8%

- The fine-tuned model overall does a better job of explaining variance in asset price changes and coefficient significance has improved in the USD case

Conclusion

Method	Top R^2 Results (2016-2021)	Advantages	Disadvantages
Factor Similarity	Growth-Val Spread: 23.7%	• Considers Context • Generalizes Well • Flexible	• Factor selection • "Black Box" vector encoding
Word List (Phrase Lexicon)	Δ1Y Yield Change: 33.8% Growth-Val Spread: 24.4%	• Transparent Results • Flexible Implementation	• Maintenance Costs • Difficult to Scale • Doesn't Generalize Well
FinBERT Sentiment	Δ10Y-2Y Spread: 11.2%	• Out-of-the box toolkit • Specific to finance	• Interpretability of sentiment
FinBERT Sentiment Trained	Δ1Y Yield Change: 14.8% Growth-Val Spread: 14.8%	• Fed-Specific • Should improve with more training data	• Interpretability of sentiment • Maintanence • Potential for overfit

Sources

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Tim Loughran and Bill McDonald. “When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks.” *THE JOURNAL OF FINANCE • VOL. LXVI, NO. 1* (February 2011)

Federal Reserve Act, US Federal Reserve https://www.federalreserve.gov/aboutthefed/fract.htm

Appendix

Weighting Formula

let N represent the total number of documents in the sample, dfi the number of documents containing at least one occurrence of the ith word, tfi,j the raw count of the ith word in the jth document, and aj the word count in the jth document. We then define the weight of the ith word in the jth document as:

$$w_{i,j} = \begin{cases} \dfrac{1 + log(tf_{i,j})}{1 + log(a_j)} log\left(\dfrac{N}{df_i}\right) & \textbf{if } tf_{ij} \geq 1 \\ 0 & \textbf{otherwise} \end{cases}$$

A1. R^2 Values by method and time period

2016-2021

Method	Asset 1 Year Tsy	10Y-2Y	USD	G-V
Factor Similarity	0.03	0.093	0.036	0.237
Word List	0.338	0.125	0.044	0.244
FinBERT Sentiment	0.03	0.112	0.009	0.037
FinBERT Sentiment Trained	0.148	0.078	0.064	0.148

2011-2021

Method	Asset 1 Year Tsy	10Y-2Y	USD	G-V
Factor Similarity	0.016	0.005	0.044	0.015
Word List	0.249	0.059	0.086	0.232
FinBERT Sentiment	0.021	0.089	0.006	0.036
FinBERT Sentiment Trained	0.103	0.003	0.106	0.098

For 2016-2021 several methods did quite well on G-V and to a lesser extent 10Y-2Y. World List seems to consistently outperform the other methods in 1Y Treasury and G-V. Trained FinBERT did roughly the same or better the FinBERT in 2016-2021, and outperformed it in all categories but 10Y-2Y in 2011-2021

A2. Calculation Methodology for Dependent Variables

Dependent Variables	Construction Methodology
1-year Treasury Yield Change	The change in the yield of the 1 year treasury from the end of the previous day to the end of the next day.
Treasury Yield Spread Change	The change in the 10 - 2 year treasury spread from the end of the previous day to the end of the next day.
USD Change	The % change in the US Dollar Index from the end of the previous day to the end of the next day.
Growth Value Spread	The 1-day % change in Growth index minus Value index portfolio.

A3. Results from Doh, Song, Yang (2020)

Figure 2: Monetary policy stance

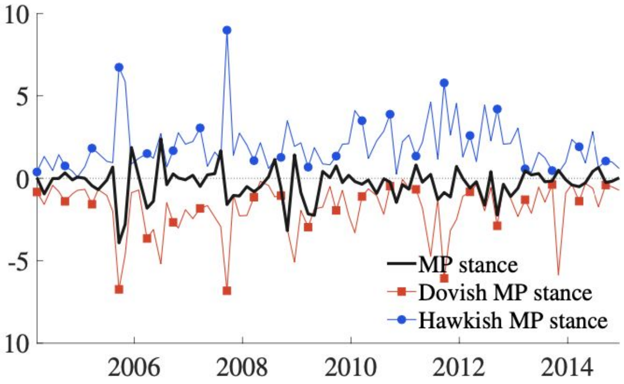

Table 3: Stock returns: Regression results

$[\Delta_l$	$\Delta_h]$	α	β	t-stat (α)	t-stat (β)	R^2
[−10	10]	0.05	-0.23	1.08 [1.07]	-4.75 [-4.43]	0.19 [0.19]
[−20	20]	0.04	-0.20	0.75 [0.74]	-4.78 [-4.24]	0.12 [0.12]
[−30	30]	0.10	-0.18	1.49 [1.48]	-4.45 [-3.81]	0.08 [0.08]
[−40	40]	0.16	-0.19	2.25 [2.24]	-3.33 [-2.92]	0.07 [0.07]
[−50	50]	0.16	-0.18	2.21 [2.13]	-3.20 [-2.77]	0.07 [0.07]
[−60	60]	0.20	-0.22	2.56 [2.59]	-3.35 [-2.96]	0.08 [0.08]
[−90	90]	0.19	-0.21	2.25 [2.21]	-2.43 [-2.18]	0.06 [0.06]
[−120	120]	0.17	-0.21	1.72 [1.69]	-1.85 [-1.64]	0.05 [0.05]

Doh, Sang, and Yang were able to construct Dovish and Hawkish stances by encoding alternate statements by the fed (Red and Blue lines in graph). They then compared to the actual Fed Statement for similarity (black line).

When regressing their results on equity returns they found strong explanatory power for shorter time frames than longer ones (as can be seen in the table)

Source: *Doh, Song, Yang (2020)*