Deciphering Federal Reserve Communication via Text Analysis of Alternative FOMC Statements

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Section 1

Introduction

Motivation: December 2010 FOMC

Component	Alternative A	Alternative D
Inflation Development	Longer-term inflation expectations have remained stable, but measures of underlying inflation have continued to trend downward.	Although measures of underlying inflation have trended lower in recent quarters, longer-term inflation expectations have remained stable.

Source: Federal Reserve Board.

Contribution

- Provide a framework to quantify the monetary policy stance based on texts.
- Identify tones in different texts based on the similarity of a given text with benchmark texts intended to signal alternative monetary policy stances (alternative FOMC statements).
- Quantify contexts in texts using a novel natural language processing algorithm (Universal Sentence Encoding).
- **Existing Approach**: Back out unexpected information in the statement from the response of interest rates. (bond market response $\rightarrow$ text shock)
- Evaluate asset market responses under **alternative** statements with **market expectation** of the statement fixed.

Main Findings

- Monetary policy surprises identified by text analysis of alternative FOMC statements are highly correlated with forward guidance shocks in the literature.
- Unexpected tightening reduces stock market return on average (consistent with the absence of information channel during the post-2004 period).
- Changes in the description of economic factors regarding outlook matters can be even more powerful than the size of the rate cut.
- Providing context behind the outlook and the risk assessment can make forward guidance more effective.

Section 2

Text Analysis Methodology Review

Natural Language Processing Tools

- Two Groups of Natural language processing (NLP) tools
  1. Word count based methods: TF-IDF, LSA (word similarity evaluated by co-frequency of words).
  2. Prediction based methods: CBOW, Skip-gram, USE, BERT etc. (find out word embeddings by maximizing the prediction of neighboring words in the document).
- Count based methods are easy to implement but cannot capture complex dependencies among words (e.g., context).
- Prediction based methods are more computationally challenging to train but can capture context better.
- "You shall know a word by the company it keeps "(J. R. Firth 1957).

Universal Sentence Encoding (USE)

- Given a text $D_i = (w_{i,1}, \cdots, w_{i,n_i})$ for $i = 1, \cdots, D$, generate an embedding vector U_i for D_i.

$$U_i = (U_{i,1}, \cdots, U_{i,512}),$$
$$Sim(Text_1, Text_2) = \frac{U_1' U_2}{\|U_1\| \times \|U_2\|} \tag{1}$$

- Multiple hidden layers with self attention channels: context-aware word representation (e.g., word order).
- Pre-trained with a large number of texts in STS benchmarks.
- Available through **Google Tensorflow Hub**.
- Sentiment analysis: to mimic human understanding of text.

Text Similarity Calculation: Example

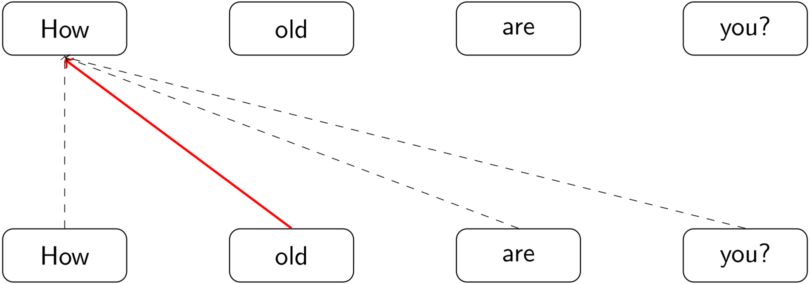
- Consider the following three sentences.
  - **S1** : How old are you?
  - **S2** : What is your age?
  - **S3** : How are you?
- **S1** and **S2** ask the same question but based on word counting **S1** is more similar to **S3** than **S2**.

Table: Sentence similarity

	TF-IDF	USE
$\text{Sim}(S_1, S_2)$	0	0.91
$\text{Sim}(S_1, S_3)$	0.78	0.28

- For TF-IDF, frequency vectors instead of embedding vectors are used.

Context-aware Word Representation through Attention: Example



Notes: The red arrow highlights the contextual link between “How” and “old”.

FOMC Statement Example : October 2013

FOMC STATEMENT—OCTOBER 2013 ALTERNATIVE A

1. **The effects of the temporary shutdown of the federal government [, including delays in releases of some key data,] have made the evolution of economic conditions during the intermeeting period somewhat more difficult to assess. However,** information received since the Federal Open Market Committee met in ~~July~~ **September generally** suggests that economic activity has been expanding at a ~~moderate~~ **modest** pace. ~~Some~~ Indicators of labor market conditions have shown **some** further improvement ~~in recent months~~, but the unemployment rate remains elevated. **Available data suggest that** household spending and business fixed investment advanced, ~~and~~ **but that the recovery in** the housing sector ~~has been strengthening, but mortgage rates have risen further~~ **has slowed in response to higher mortgage rates.** ~~and~~ Fiscal policy is restraining economic growth. Apart from fluctuations due to changes in energy prices, inflation has been running below the Committee's longer-run objective, ~~but~~ **even though** longer-term inflation expectations have remained stable.

Similarity Score for Oct. 2013 FOMC Statements

	TF-IDF	USE
Sim($FOMC_{A,t}$, $FOMC_t$)	0.975	0.895
Sim($FOMC_{C,t}$, $FOMC_t$)	0.972	0.990

- Alt A mentions challenges in interpreting improvements in incoming data due to government shutdown while Alt C and the released statement do not.
- The phrase provides information on the FOMC's interpretation of the recent data.

Section 3

Identifying Monetary Policy Stance with Text Analysis

Assumptions

1. Alternative FOMC statements prepared by the Board staff roughly capture tail parts of market expectations of monetary policy stance tilt (hawkish or dovish).
2. Dissimilarity between the previous FOMC statement and the current FOMC statement captures the magnitude of monetary policy tilt.
3. The sign of change is identified by using alternative FOMC statements, side-stepping the costly training process for the tone identification.
4. High-frequency financial market data responds to **surprises** in monetary policy stance tilt.

Text-based Identification of Monetary Policy Stance Tilt (mp_t)

- Text-based shock: novelty × tone (KKX 2019).
- Novelty: 1-similarity between statements released after two consecutive meetings.
- Tone: sign of $|mp_t - mp_{t-1}|$

$$Sign(|mp_{A,t} - mp_{t-1}|) = -1,$$
$$Sign(|mp_{C,t} - mp_{t-1}|) = 1,$$

$$mp_t = \underbrace{(1 - \text{Sim}(FOMC_t, FOMC_{t-1}))}_{\text{Novelty}} \underbrace{\left(\frac{\text{Sim}(FOMC_t, FOMC_{C,t}) - \text{Sim}(FOMC_t, FOMC_{A,t})}{1 - \text{Sim}(FOMC_{A,t}, FOMC_{C,t})} \right)}_{\text{Tone}} \quad (2)$$

- Tone always belongs to the interval $[-1, 1]$.
- Monotonicity: $Sign(|mp_{A,t} - mp_{t-1}|) \geqslant Sign(|mp_t - mp_{t-1}|) \geqslant Sign(|mp_{C,t} - mp_{t-1}|)$.

Surprises in Monetary Policy Stance Tilt

- $E_{t-\delta}(mp_t - mp_{t-1})$: Market expectations of the change in the intended policy stance (mp_t) prior to the meeting.

$$E_{t-\delta}(mp_t - mp_{t-1}) = -p_t|mp_t - mp_{t-1}| + (1 - p_t)|mp_t - mp_{t-1}|. \quad (3)$$

- Financial market (i-th asset) response to surprises in the announced policy stance.

$$\ln\left(\frac{P_{i,t+\Delta_h}}{P_{i,t-\Delta_l}}\right) = \alpha_i + \beta_i(mp_t - mp_{t-1} - E_{t-\delta}(mp_t - mp_{t-1})) + \epsilon_{i,t}. \quad (4)$$

- Δ_h and Δ_l capture the event window for high-frequency variations in financial market variables.

Calibration p_t

- Monetary policy surprise:
  $MPS(p_t; t-\Delta) = mp_t - mp_{t-1} - E_{t-\Delta}(mp_t - mp_{t-1})$.
- Maximize the negative rank correlation between $MPS(p_t; t-\Delta)$ and high-frequency bond returns.

$$(p_{\tau_i})_{i=1}^{T} = \text{argmax} \sum_{t \neq t'} 1(r^b_{\tau_t - \Delta_l, \tau_t - \Delta_h} > r^b_{\tau_{t'} - \Delta_l, \tau_{t'} - \Delta_h}) 1(MPS(p_{\tau_t}) < MPS(p_{\tau_{t'}})). \quad (5)$$

- Grid search w.r.t. p_{τ_t} to achieve the largest negative correlation.

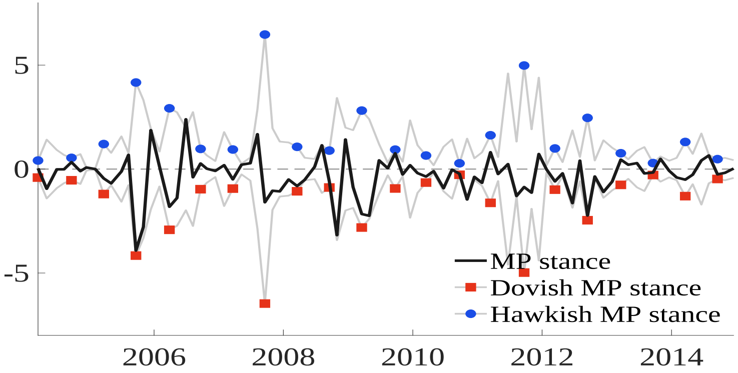
Section 4

Empirical Analysis

Data

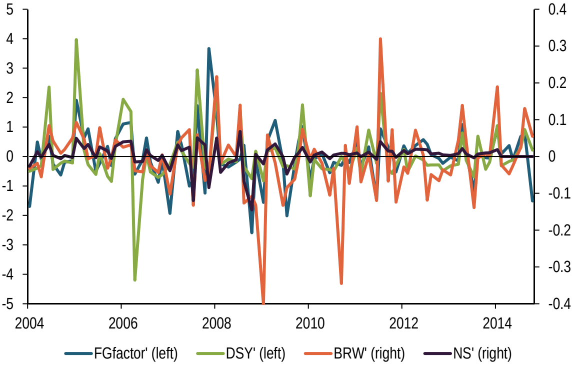
- 87 Statements (March 2004 to December 2014) excluding two intermeeting announcements (Aug 2007, Jan 2008).
- Normalize MP level to make the sample standard deviation equal to one.
- Alternative statements help us to identify changes in the tone by construction.

Estimates of MP



- Estimates also robust to different event window intervals/bond maturity.

Estimates of Monetary Policy Surprise



Stock Market Response to MPS

$[\Delta_l$	$\Delta_h]$	α	β	t-stat (α)	t-stat (β)	R^2
[—10	10]	0.05	-0.23	1.08	-4.75	0.19
[—20	20]	0.04	-0.20	0.75	-4.78	0.12
[—30	30]	0.10	-0.18	1.49	-4.45	0.08
[—40	40]	0.16	-0.19	2.25	-3.33	0.07
[—50	50]	0.16	-0.18	2.21	-3.20	0.07
[—60	60]	0.20	-0.22	2.56	-3.35	0.08
[—90	90]	0.19	-0.21	2.25	-2.43	0.06
[—120	120]	0.17	-0.21	1.72	-1.85	0.05

Interpretation

- No evidence for “Information Channel ”in Nakamura and Steinsson (2018).
- Consistent with Bauer and Swanson (2020).
- Also consistent with Lunsford (2020) who show the absence of “Information Channel ”since August 2003.
- But unlike Bu et al. (2020), the maturity of the target bond return doesn't matter.

Comparison with Existing MPS Estimates

	MPS
Bu et al. (2020)	0.50
NS (2018)	0.50
Swanson (2017) (FFR+FG+LSAP)	0.50
FFR	0.20
FG	0.52
LSAP	-0.12

Section 5

Conclusion

Summary

- Analysis of FOMC public communications using a novel natural language processing tool.
- Alternative policy statements provide a way to identify the tone in statements naturally.
- Our text-based monetary policy surprises are highly correlated with forward guidance shock estimates in literature.
- Context matter: changing wording in the risk assessment and/or providing a color to the interpretation of incoming data.