Central Bank Communication on Social Media: What, To Whom, How?

Yuriy Gorodnichenko¹ Tho Pham² Oleksandr Talavera³

¹UC Berkeley and NBER

²University of York

³University of Birmingham

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Outline

- 1. Motivation
- 2. Research questions
- 3. Data

4. Text analysis

Topic modelling

Few-shot classification

5. Empirical analysis

6. Conclusions

Central bank communication: Communicating with the public



What central banks say can affect markets, the economy and people's lives. Central bank communication has become a tool of policy in recent years. The ECB needs to be understood by markets and experts, but also by the wider public so that people can have trust in the institution and its policies.

As a result of the strategy review, the Governing Council agreed to modernise its monetary policy communication, to reach out to wider audiences, and to make listening a regular feature of its communication.

The objectives of the Riksbank's communication are to:

- Make it possible for the Riksdag (the Swedish parliament), the general public and the media to understand, examine and evaluate the work of the Riksbank.
- Contribute to good knowledge and thereby to a high level of confidence in the Riksbank's activities, analysis and policy decisions.
- Give the employees relevant information so that they can carry out their work, feel involved and motivated and experience job satisfaction.

CHAIRMAN POWELL. Good afternoon. Thanks very much for being here. I know

that a number of you will want to talk about the details of our announcement today, and I am happy to do that in a few minutes. But because monetary policy affects everyone, I want to start with a plain-English summary of how the economy is doing, what my colleagues and I at the Federal Reserve are trying to do, and why. Clear and transparent communication is essential to the effectiveness of monetary policy, and serves a key role in the Bank's accountability to Canadians. That is why members of the Bank's Governing Council take part in regular communication activities, such as meetings, speeches, interviews and press conferences.

Engaging in two-way communication with the public, businesses, industry associations, academia, labour and other groups is invaluable to the formulation of monetary policy and to the Bank's accountability. Discussions with external groups help Governing Council members better understand prevailing dynamics in the economy and the financial system, as well as structural issues and economic research relevant to the work of the Bank. New communication channels:

Press release, press conferences

Large literature on the effectiveness of central bank communication via these channels

Social media: Twitter and Facebook

Empirical evidence is scant. The study closest to ours is Ehrmann and Wabitsch (JME 2022)

How information is perceived?

- Not all information is treated in the same way:
 - Individuals are more influenced by information that is easier to understand, e.g., supermarket prices (Cavallo et al., 2017)
 - FOMC inflation forecast \simeq FOMC statement > news article about FOMC meeting (Coibion et al., 2022)
 - In low inflation context, firms'/households' expectations do not respond much to monetary policy announcements (Cavallo et al., 2017; Coibion et al., 2020)
- Not all agents process information in the same way:
 - Large difference between firms'/households' vs. professional forecasters' inflation forecasts but the gap can be closed by intensive news coverage of inflation dynamics (Carroll, 2003; Dräger, 2015; Lamla and Maag, 2012)
 - Media is the main source of information for managers to form inflation expectations (Kumar et al., 2015)

Using a unique setup: Fed's communication on social media (public accounts, public information)

- Classify the Fed's communication based on topics
- Classify users who engaged with the Fed into different groups
- Examine reactions of heterogeneous groups of users to heterogeneous "information" provided by the Fed
- Extract inflation expectation signals from the tweets and examine the effects of the Fed communication on inflation expectations

- Twitter users do engage with the Fed, but the degree of engagement is limited
- Among all topics discussed by the Fed, Twitter users are most interested in central banking issues
- Among all groups of users, the media and economists are most active in engaging with the Fed
- More positive Fed tweets are correlated with higher inflation expectations expressed

- All historical (public) English tweets posted by the Twitter accounts of Federal Reserve System's Board of Governors and 12 regional Federal Reserve Banks
- 130,271 tweets (4.3% are retweets) covering the January 2012 December 2020 period
- The data contain: user statistics, tweet statistics, and tweet analytics (i.e., number of likes, retweets, and quotes)

	Mean	SD	Min	Median	Max	N
Replies	0.60	3.55	0.00	0.00	708.00	130,271
Retweets	3.65	8.55	0.00	2.00	689.00	130,271
Likes	3.31	11.41	0.00	1.00	1517.00	130,271
Quotes	0.37	3.06	0.00	0.00	355.00	130,271

Fed tweets over time



- All public English tweets mention the Fed's Twitter handles (e.g., @federalreserve) over the 2012-2020 period
- Excluding the self-mentioning tweets gives us a sample of 495,059 tweets
- Again, we can observe all public information related to the users, the tweets, and the tweet analytics

Number of Fed mentions



- Aims:
 - Topics of the text
 - Twitter user classification
- Challenges:
 - No prior about what central banks talk about on social media
 - No prior about the specific groups of users who interacted with central banks on social media

Keyword discovery approach



- Topics in central bank communications:
 - Pre-defined keywords (Cieslak and Vissing-Jorgensen, 2020) → limited (only keywords about the economy/financial market)
 - Apply LDA to FOMC statements (Hansen and McMahon, 2016) → LDA does not work well with short texts, issues with topics' interpretability
- Classify users based on the tweets' content: experts. vs non-experts (Ehrmann and Wabitsch, 2022)

Topic 2 end credit debt foreclosure borrowe bankruptcv

columnist author syndicate columnist conomist phd

assistant prof economics phd in C professor emeritus postdoc phd economics sociology professor department duke university ũ visiting professor ŏ distinguish professor assoc professor research associate SO S ٥) professor sociology associate director 0 adjunct professor

Topics



User classification



Share of unique users by user groups

We use TweetNLP (Camacho-Collados et al., 2022) to predict:

- Sentiment (negative, neutral, or positive) and its probability
- Irony (ironic or not) and its probability

Sentiment - Fed tweets



Sentiment - Fed mentions



- We are not able to measure inflation expectations per se (e.g., the 1-year ahead inflation rate is X%)
- But we could extract inflation expectation signals (e.g., inflation is expected to increase)
- Typical approach: Labeled data ⇒ Language model (e.g., GPT) ⇒ Classifier (e.g., neural net)

- Construct a small corpus of sentences referring to inflation expectations. Each sentence is assigned 1 of 3 labels: 0 (lower inflation), 1 (no change in inflation), and 2 (higher inflation)
- Contrastive learning:
 - · Generate sentence pairs from the small corpus
 - Using a SBERT (sentence BERT) transformer model to embed sentences and labels into a latent space
 - Fine-tuning the transformer model to minimize the distance between 2 sentences with the same label or maximize the distance between 2 sentences with different labels
- Train a classifier using embeddings from the fine-tuned transformer model
- Apply the classifier on the Fed mentions data

$$\begin{aligned} & \textit{Reaction}_{i,j,d}^{D} = \alpha + \beta_1 \textit{FOMC}_d^{\textit{Unchange}} + \beta_2 \textit{FOMC}_d^{\textit{Change}} + \beta_3 \textit{In}(\textit{EPU})_d + \textit{Fedtweet}_{i,j,d}\gamma + \epsilon_{i,j,d} \\ & (1) \\ & \textit{In}(\textit{Reaction}_{i,j,d}) = \alpha + \beta_1 \textit{FOMC}_d^{\textit{Unchange}} + \beta_2 \textit{FOMC}_d^{\textit{Change}} + \beta_3 \textit{In}(\textit{EPU})_d + \textit{Fedtweet}_{i,j,d}\gamma + \epsilon_{i,j,d} \\ & (2) \end{aligned}$$

- i, j, and d refer to tweet i posted by Fed account j on date d
- *Reaction^D* is a dummy indicating where tweet *i* received any likes, retweets, quotes, or replies; *In*(*Reaction*) is the natural log of the number of likes/retweets/quotes/replies
- *Fed tweet* is a vector of dummies indicating the post's characteristics (order of the post, topics mentioned, whether or not photos/videos/external links are included)

Extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Like		Retweet		Reply		Quote	
Unconditional prob.	0.69		0.77		0.27		0.16	
		(0.003)		(0.003)		(0.003)		(0.003)
In(EPU)		-0.001		0.005		-0.001		0.019***
		(0.003)		(0.003)		(0.003)		(0.003)
FOMC ^{Unchange}		-0.007		0.014		0.007		0.004
		(0.011)		(0.011)		(0.008)		(0.010)
FOMC ^{Change}		0.006		-0.020		-0.000		0.050**
		(0.017)		(0.020)		(0.021)		(0.021)
Growth	0.072***	0.073***	0.066***	0.065***	0.076***	0.077***	0.099***	0.098***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Unemployment	-0.002	-0.001	0.020***	0.022***	0.010*	0.010**	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Monetary	0.058***	0.060***	0.042***	0.044***	0.030***	0.031***	0.026***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	0.026***	0.026***	0.035***	0.037***	0.008*	0.009**	-0.002	-0.004
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Community	0.053***	0.051***	0.033***	0.032***	0.044***	0.042***	0.021**	0.013
	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
FinRisk	0.005	0.004	0.012**	0.008	-0.001	0.000	0.016***	0.015***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Fiscal	0.011	0.011	0.040***	0.039***	0.031***	0.028***	0.032***	0.031***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Sentiment	0.034***	0.035***	-0.042***	-0.044***	-0.022***	-0.021***	-0.031***	-0.029***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	130,254	130,271	130,254	130,271	130,254	130,271	130,254	130,271
R-squared	0.289	0.262	0.202	0.169	0.321	0.290	0.229	0.190

Intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	In(Likes)		In(Retweet	s)	In(Replies)	In(Quotes)	
Mean (raw number)	4.82		4.71		2.19		2.34	
In(EPU)		0.024***		0.021***		0.022***		0.024**
		(0.007)		(0.006)		(0.008)		(0.009)
FOMC ^{Unchange}		0.121***		0.145***		0.124***		0.281***
		(0.024)		(0.022)		(0.033)		(0.038)
FOMC ^{Change}		0.221***		0.348***		0.291***		0.461***
		(0.050)		(0.066)		(0.081)		(0.071)
Growth	0.310***	0.308***	0.415***	0.407***	0.094***	0.083***	0.275***	0.264***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.020)	(0.019)
Unemployment	-0.035***	-0.032***	0.044***	0.047***	-0.001	0.000	-0.019	-0.016
	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)	(0.018)	(0.017)
Monetary	0.106***	0.092***	0.200***	0.197***	0.086***	0.072***	0.041**	0.029
	(0.012)	(0.012)	(0.011)	(0.011)	(0.014)	(0.014)	(0.020)	(0.019)
Inflation	-0.029***	-0.032***	0.045***	0.047***	-0.001	-0.007	-0.040***	-0.046***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.015)	(0.015)
Community	0.124***	0.097***	0.020	0.007	0.037	0.008	0.073**	0.050*
	(0.023)	(0.024)	(0.022)	(0.022)	(0.028)	(0.027)	(0.031)	(0.029)
FinRisk	0.001	0.001	0.045***	0.046***	-0.017	-0.039***	0.002	-0.015
	(0.014)	(0.014)	(0.012)	(0.012)	(0.015)	(0.014)	(0.024)	(0.023)
Fiscal	0.035	0.028	0.053***	0.051***	-0.003	0.001	0.075**	0.069**
	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)	(0.033)	(0.031)
Sentiment	0.091***	0.098***	-0.108***	-0.109***	-0.024**	-0.015	-0.032**	-0.031**
	(0.009)	(0.010)	(0.008)	(0.008)	(0.010)	(0.010)	(0.014)	(0.014)
Observations	89,412	89,476	100,767	100,802	35,413	35,576	20,678	20,726
R-squared	0.384	0.350	0.370	0.335	0.400	0.324	0.230	0.166

$$Outcome_{d}^{Mentions} = \alpha + \beta_{1} FOMC_{d}^{Change} + \beta_{2} FOMC_{d}^{Unchange} + \beta_{3} In(EPU)_{d} + \gamma_{1} In(CentralBanking)_{d} + \gamma_{2} In(FedTweets)_{d}$$
(3)
+ $\gamma_{3} In(FedAccounts)_{d} + \gamma_{4} Sentiment_{d}^{Fedtweets} + \varepsilon_{d}$

- Number of Fed mentions, number of Fed mentions discussing central banking, sentiment, irony, HHI based on topics
- Number of unique users who mentioned the Fed, number of users by each user group, HHI based on users

Degree of engagement

	(1)	(2)	(3)	(4)	(5)
	In(Mentions)	Sentiment	Irony	In(Mentions ^{CentralBanking})	HHI ^{topics}
FOMC ^{Unchange}	0.695***	-0.018*	-0.009	1.183***	0.021***
	(0.056)	(0.010)	(0.015)	(0.074)	(0.004)
FOMC ^{Change}	1.385***	-0.052**	-0.062***	2.325***	0.107***
	(0.107)	(0.026)	(0.016)	(0.109)	(0.009)
ln(EPU)	0.038**	-0.011***	0.004	0.073***	-0.000
	(0.017)	(0.004)	(0.007)	(0.026)	(0.003)
In(CentralBanking)	0.005	-0.000	-0.000	0.152***	0.004***
	(0.021)	(0.005)	(0.008)	(0.030)	(0.002)
In(FedTweets)	0.515***	0.027**	-0.020	0.395***	-0.009***
	(0.042)	(0.011)	(0.015)	(0.057)	(0.003)
Sentiment ^{Fedtweets}	-0.123	0.123***	0.058*	-0.336***	0.004
	(0.085)	(0.024)	(0.035)	(0.125)	(0.008)
In(FedAccounts)	0.446***	0.012	0.019	0.393***	-0.006
	(0.044)	(0.011)	(0.017)	(0.062)	(0.004)
Observations	3,164	3,164	3,164	3,035	3,164
R-squared	0.713	0.178	0.132	0.566	0.125

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	In(Users)	In(Public)	In(Media)	In(Ecomomists)	In(Financial sector)	In(Managers)	HHI ^{Usergroups}
FOMC ^{Unchange}	0.661***	0.631***	1.160***	0.674***	0.353***	0.577***	-0.063***
	(0.053)	(0.057)	(0.070)	(0.093)	(0.092)	(0.095)	(0.011)
FOMC ^{Change}	1.329***	1.313***	2.007***	1.220***	0.993***	1.052***	-0.070***
	(0.103)	(0.108)	(0.097)	(0.120)	(0.208)	(0.204)	(0.015)
In(EPU)	0.047***	0.042**	0.090***	0.043	0.020	0.019	0.003
	(0.016)	(0.018)	(0.026)	(0.026)	(0.026)	(0.027)	(0.005)
In(Fed ^{CentralBanking})	-0.003	-0.002	0.033	0.005	-0.006	-0.061*	-0.004
	(0.019)	(0.022)	(0.031)	(0.033)	(0.029)	(0.033)	(0.005)
In(FedTweets)	0.464***	0.467***	0.708***	0.299***	0.175***	0.470***	-0.052***
	(0.038)	(0.044)	(0.063)	(0.062)	(0.054)	(0.066)	(0.010)
Sentiment ^{Fedtweets}	-0.111	-0.135	-0.324**	-0.097	-0.393***	-0.244	-0.004
	(0.079)	(0.089)	(0.135)	(0.136)	(0.136)	(0.153)	(0.025)
In(FedAccounts)	0.443***	0.446***	0.247***	0.117*	0.149**	-0.121*	-0.020*
	(0.040)	(0.046)	(0.067)	(0.065)	(0.064)	(0.071)	(0.012)
Observations	3,164	3,164	2,765	2,165	1,915	1,774	3,164
R-squared	0.735	0.669	0.501	0.329	0.300	0.176	0.181

Who engaged with the Fed about central banking issues?

	(1)	(2)	(3)	(4)	(5)
	In(Public)	In(Media)	In(Economists)	In(Financial sector)	In(Managers)
FOMC ^{Unchange}	1.061***	1.162***	0.420***	0.339***	0.197**
	(0.077)	(0.090)	(0.115)	(0.114)	(0.093)
FOMC ^{Change}	2.252***	2.421***	0.970***	0.964***	0.916***
	(0.112)	(0.103)	(0.166)	(0.217)	(0.156)
ln(EPU)	0.080***	0.077***	0.003	-0.009	0.011
	(0.028)	(0.030)	(0.029)	(0.031)	(0.034)
In(Fed ^{CentralBanking})	0.114***	0.135***	0.073*	0.056	0.004
	(0.030)	(0.035)	(0.038)	(0.034)	(0.038)
In(FedTweets)	0.310***	0.237***	-0.016	0.025	0.050
	(0.061)	(0.069)	(0.069)	(0.074)	(0.078)
Sentiment ^{Fedtweets}	-0.306**	-0.006	-0.154	0.085	0.001
	(0.128)	(0.158)	(0.148)	(0.186)	(0.176)
In(FedAccounts)	0.372***	0.102	0.200***	0.025	-0.014
	(0.067)	(0.074)	(0.071)	(0.079)	(0.092)
Observations	2,952	1,798	1,164	705	500
R-squared	0.498	0.307	0.202	0.199	0.220

What message was spread further?

	(1)	(2)	(3)	(4)	(5)
	In(Spread ^{Public})	In(Spread ^{Media})	In(Spread ^{Economists})	In(Spread ^{Financialsector})	In(Spread ^{Managers})
FOMC ^{Unchange}	0.847***	0.845***	0.795***	0.269	0.144
	(0.175)	(0.171)	(0.235)	(0.297)	(0.254)
FOMC ^{Change}	2.451***	2.508***	1.263***	1.028**	0.977***
	(0.233)	(0.298)	(0.440)	(0.486)	(0.340)
In(EPU)	0.008	0.120	0.064	-0.116	0.227
	(0.052)	(0.075)	(0.089)	(0.131)	(0.155)
In(Fed ^{CentralBanking})	0.039	0.160*	0.000	0.066	0.215
	(0.061)	(0.094)	(0.114)	(0.159)	(0.174)
In(FedTweets)	0.266**	-0.137	0.040	-0.017	-0.608
	(0.120)	(0.174)	(0.215)	(0.313)	(0.395)
Sentiment ^{Fedtweets}	-0.636**	-0.866**	0.078	0.921	-0.984
	(0.283)	(0.437)	(0.511)	(0.708)	(0.958)
In(FedAccounts)	0.240*	0.292	-0.153	-0.462	0.589
	(0.131)	(0.193)	(0.243)	(0.344)	(0.489)
Observations	2,208	1,468	840	389	319
R-squared	0.400	0.282	0.222	0.284	0.229

Fed tweets' sentiment and inflation expectations



- The Fed's attempt to communicate with the wider public is not "a road to nowhere", but...
- The degree of public outreach is limited
- Instead of trying to communicate with the general public, perhaps central bankers should take advantage of intermediated channels like media (Blinder et al., 2022)

User classification - Keywords 🔤

Academic	Economist	Journalist	News outlet	Firm director	Public with financial knowledge	Finance	
adjunct professor	economist	anchor	abacusnews	ceo	cfa	altcoin trader	
assistant prof	economista	correspondent	bbc	cfo	msc economics	asset management	
assistant professor		host podcast	bloomberg	chairman	msc finance	asset manager	
assoc professor		journalist	business insider	chairman boar	rd	bond trader	
associate professor		commentator	businessinsider	chief operate		commodity trader	
asst prof		podcast host	cbsnews	founder chairr	nan	community banker	
asst professor		radio host	channel	president ceo		currency trader	
distinguish fellow		reporter	cnbc			derivative trader	
distinguish professo	or	show host	cnn			economic analyst	
doctoral candidate		contributor	financial times			equity trader	
doctoral student		columnist	fox news			financial advisor	
economics phd			foxnews			financial analyst	
economist phd			ft			forex trader	
economista			media			fund manager	
economista profeso	r		news			fx trader	
environmental econ	nomist		newyork times			hedgefund manage	r
labor economist			nyt			intraday trader	
phd candidate			techcrunch			investment banker	
phd econ			the economist			management firm	
phd student			wall street journ	al		mortgage banker	
postdoc phd			wsj			option trader	
postdoctoral fellow						portfolio managem	ent
profesor universidad	b					portfolio manager	
profesor universitar	io					portfolio mgr	33 / 3

- Numerical representations of the texts
- Previously: rely on global document counts to generate vectors representing a word \rightarrow ignoring the semantic meaning
- Now:
 - Take into account the local context (Example)
 - Not only word embeddings but also sentence/paragraph embeddings
 - Texts with similar semantic meanings will be closer in the vector space
- We use Google's Universal Sentence Encoder model to convert each text (a Facebook post, a tweet, or a user's self-description) into a 512-dimensional vector

We use Uniform Manifold Approximation and Projection (UMAP) to lower the dimensionality of the text embeddings

- UMAP vs PCA: PCA is linear, natural language is not
- UMAP vs t-SNE (t-distributed Stochastic Neighbor Embedding): UMAP captures global structure better; t-SNE is mostly used for data visualization

Dimensionality reduction



We apply the Hierarchical *Density-Based* Spatial Clustering of Applications with *Noise* (HDBSCAN) algorithm on the reduced dimensionality embeddings to cluster tweets/users' description into groups. HDBSCAN vs K-means:

- HDBSCAN can work well for data where clusters have arbitrary shapes, different sizes, different densities
- HBDSCAN can deal with outliners
- K-means requires a pre-defined number of clusters, HDBSCAN does not

$$TFIDF = \frac{n_{t,d}}{\sum_{t'} n_{t',d}} \times \log(\frac{|D|}{|\{d \in D : t \in d\}|})$$
(4)

where $n_{t,d}$ is the freq. of word t in document d; $\sum_{t'} n_{t',d}$ is the total word freq. in the document; |D| is the number of documents in the data

$$TFIDF \times IDF_i = TFIDF \times \log(\frac{|K|}{|\{t \in K\}|})$$
(5)

where |K| is the number of clusters and $|\{t \in K\}|$ is the number of clusters that word t appears in