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Central bank communication on social media: What, to whom, and how?*

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ABSTRACT

This study answers three questions about central bank communication on Twitter: : what was communicated, who were listeners, and how they reacted. Using various natural language processing techniques, we identify the main topics discussed by the Fed and major audiences. While the Fed tweets talking about central banking topics attract greater attention from Twitter users, only the extensive margin is economically meaningful. Among all groups of users, the media accounts and economists are most active in engaging with the Fed, especially when discussing central banking-related issues. We also show that information extracted from the tweets can provide a real-time, qualitative diagnostic for inflation expectations and some reaction of these Twitter-based inflation expectations to policy action and communication.

1. Introduction

Transparency is crucial for ensuring the effectiveness and credibility of monetary policy. Being transparent should help the public better understand the current state of the economy and adjust their economic decisions to the monetary policy accordingly. The higher degree of transparency should also help anchor the public's long-term expectations, which in turn could reduce economic volatility.[1] Recognizing its importance, central banks around the world have adopted various communication strategies to improve transparency and outreach to the general public. Among others, communication via social media has become a popular tool in many countries, such as the U.S. and the U.K. Yet, the understanding of how this communication tool is utilized and its effectiveness is still limited.

Against this backdrop, this study will provide a comprehensive analysis of the Federal Reserve System's (Fed) communication on Twitter, a popular social media platform. Specifically, we aim to provide answers to three questions: "What is communicated on Twitter?", "Who engages with the Fed on Twitter?", and "Is there any link between the Fed's communication on Twitter and individuals' inflation expectations?". To this end, we assemble large datasets of the Fed's communication and public engagement/

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[1] See https://tinyurl.com/ycww7na4 or https://tinyurl.com/y8bvl5a2, accessed on 22 May 2024.

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reactions on Twitter. The first set of data includes all historical tweets created by the official Twitter accounts of the Federal Reserve System's Board of Governors (Board) and 12 regional Federal Reserve Banks (Banks) since these accounts were created (the *Fed timeline* sample). The second dataset contains all public tweets that mention the Fed's Twitter accounts (the *Fed mentions* sample). In addition to the tweets' characteristics (e.g., tweet content, whether a post is a retweet), we also observe their "performance" or engagement metrics, such as the number of likes, retweets, replies, and quotes.

In the first part of the analysis, we develop a taxonomy construction framework that utilizes the recent advancements in natural language processing (NLP) to analyze the topics of tweets in our data. The main topics discussed in these tweets are related to the Fed's activities, macroeconomics, different sectors of the economy, and community (e.g., inequality, education). In other words, the Fed's communication on Twitter is quite broad and not limited to the central banking business. The empirical analysis at the Fed tweet level suggests that Twitter users are more likely to react to (i.e., like or share the content) and engage with (i.e., reply to or quote the content) the Fed tweets discussing the macroeconomics-related topics, especially the topics of inflation, economic conditions, and monetary policy. However, such reactions and engagement are only economically significant for the extensive margin, while the magnitude of the intensive margin is small. The results also show that Twitter users pay more attention to the Fed tweets during the Federal Open Market Committee (FOMC) meetings and during times of higher economic policy uncertainty.

Using the same keyword discovery approach, we categorize Twitter users who "engage" with the Fed (i.e., users who mention the Fed accounts in their tweets) into different groups: media, academics, financial sector, firm managers, and the general public. We then use this categorization to examine the extent to which each group of users engages with the Fed on Twitter. Consistent with the earlier studies (e.g., Ferrara and Angino, 2022), this investigation also shows a positive link between the degree of engagement and the Fed's tweeting activities. For example, on days when the Fed accounts tweet more, there are more Fed mentions. Similarly, when more Fed tweets talk about monetary economics, Twitter users are more likely to tag the Fed in their tweets discussing the same topics. Twitter accounts of media are most active in engaging with the Fed, especially in discussing economic issues. Such tweets are also more likely to be spread further to other users.

Finally, we examine whether the Fed's communication on Twitter has any influence on inflation expectations. While we are unable to quantify inflation expectations from the tweets (e.g., the expected inflation is X%), we employ a few-shot learning algorithm to infer the direction of inflation expectations (e.g., inflation is expected to be higher) for each Fed mention that talks about inflation. The results show that Twitter users tend to expect higher inflation in response to more (economic) positive Fed tweets. This positive and significant link between the Fed tweets' economic sentiment and inflation expectations is only observed during the zero-lower-bound periods.

Our paper builds on and contributes to the recent studies on the influence of monetary policy news on economic agents' expectations. Nakamura and Steinsson (2018) argue that economic agents update their beliefs about economic fundamentals, such as interest rates or output growth, in response to monetary policy surprises. However, the results of the change in inflation expectations are mixed. Binder (2017) finds that the anchoring of consumer inflation expectations increases following the Fed's inflation target announcement and the increase in the anchoring of informed consumers is larger than that of uninformed counterparts. While Lamla and Vinogradov (2019) observe little to no change in expectations and perceptions of inflation and interests around the FOMC announcements, Claus and Nguyen (2020) find that consumers update their expectations on economic activity in response to monetary policy shocks.

Moreover, the extent to which economic agents respond to monetary policy surprises varies across agents, sources of information, and the size of the shocks. For instance, households and firms are less likely to respond to policy change announcements, whereas the opposite is observed for professional forecasters and financial market participants (Coibion et al., 2020). Enders et al. (2019) observe that German firms tend to increase (decrease) their inflation expectation in response to the surprise increase (decrease) in the European Central Bank's target rate, but the response is weaker with larger surprises. Moreover, the FOMC statements and the simple inflation statistics have a similar impact on households' inflation forecasts, but the impact of media coverage of the FOMC decisions is smaller (Coibion et al., 2022). Our study expands this strand by examining the influence of the Fed's communication on social media on inflation expectations. We also make a methodological contribution in which state-of-the-art NPL tools are utilized to extract information expectation signals from social media posts. Although the inflation expectation indicator resulting from our approach is only directional, it could be a useful and timely source of inflation expectation data alternative to the survey-based and market-based inflation expectations.[2]

The second strand to which the study relates is the large literature on the effectiveness of central bank communication (see, e.g., Guthrie and Wright, 2000; Rosa, 2011; Lucca and Moench, 2015; Hansen and McMahon, 2016; Hansen et al., 2018; Cieslak et al., 2019; Cieslak and Schrimpf, 2019). In particular, our paper is closest to a small but increasing number of studies analyzing the use of social media as a central bank communication tool. Korhonen and Newby (2019) examine the Twitter activities of 40 central banks and financial supervisors in Europe and find a large variation across accounts. Moreover, European central banks and financial authorities are more likely to discuss financial stability while less likely to discuss monetary policy on Twitter. Masciandaro et al. (2020) compare tweets mentioning the European Central Bank, the Bank of England, and the Federal Reserve System with the respective central banks' press releases to create a measure of central bank surprise. Their examination suggests that the absolute change in the similarity between the tweets and the press releases is positively related to market volatility. In a recent study, Ehrmann and Wabitsch (2022) show that Twitter users are responsive to ECB communications, i.e., there is an increase in ECB-related tweets after ECB

[2] See Angelico et al. (2022) for a comprehensive comparison of Twitter-based inflation expectation measure with the market-based and survey-based measures.

communication events. Moreover, following certain events, the ECB-related tweets become less objective, and the tweets' sentiment becomes more homogenous.

The study closest to ours is Conti-Brown and Feinstein (2020), which examines the Fed's engagement on Twitter. We extend this work by not only looking at the Fed's tweeting activities (e.g., frequency of tweets, reactions to the Fed tweets) but also investigating the Fed tweets' features that help attract the public's attention. Moreover, we provide a more in-depth analysis of Twitter users' discussion of the Fed by examining (1) who these users are, (2) what they discuss, and (3) how they discuss the Fed. Additionally, we show evidence that the Fed tweets could be used to shape inflation expectations. More importantly, our paper makes a methodological contribution to the existing studies as we propose (1) a highly flexible taxonomy construction framework and (2) a few-shot learning classifier for inflation expectation classification, which can be applied in further research on central bank communication and (inflation) nowcasting.

The rest of this paper is organized as follows. The next section describes how data are collected and processed. A detailed discussion of our NPL frameworks is also provided in this section. Section 3 presents the empirical results of the reactions to the Fed communications on Twitter. In Section 4, we analyze the degree of public engagement with the Fed on Twitter as well as the heterogeneity of the engagement. Section 5 discusses the effects of the Fed tweets on Twitter users' inflation expectations. Section 6 concludes and discusses the implications.

2. Social media data

2.1. Samples for analysis

Fed timeline. We collect all historical (public) English tweets posted by the Twitter accounts of the Federal Reserve System's Board of Governors and 12 regional Federal Reserve Banks (as of 31 December 2020). Given that the first Fed account (New York Fed) was created in June 2008 and the latest Fed account (Kansas City Fed) was created in April 2011, we restrict our sample to the January 2012 – December 2020 period to have a more balanced coverage. This *Fed timeline* sample for analysis consists of 130,271 tweets, of which 4.3 % are retweets. The following information is observed: user statistics (e.g., user description), tweet statistics (e.g., tweet creation date and time, tweet content, types of tweet), and tweet analytics (e.g., number of likes, retweets, replies, and quotes).

As shown in Fig. 1, the total number of annual tweets created by all Fed accounts is quite stable during the sample period (10,000-15,000 tweets a year). The tweeting activity of each Fed account has also been stable over time, except for the Richmond Fed, which spiked in 2014-2015, and the New York Fed, which spiked in 2019.[3] Among all regional Feds, the St. Louis Fed's account is the most active in tweeting, with an average of about 4,000 tweets a year (about 30 % of all Fed tweets).

Tweets mentioning the Fed's Twitter accounts. All (public) English tweets that mention the Fed's Twitter handles (e.g., @federalreserve) over the 2012 – 2020 period are also collected. Since we are interested in examining the public engagement with the Fed on social media, we exclude the self-mentioning tweets, i.e., the tweets created by one of the Fed's Twitter accounts and mentioned itself or another Fed account. This *Fed mentions* sample contains (1) retweets (either retweeting a Fed tweet or retweeting a Fed-mentioned tweet), (2) quotes (either quoting a Fed tweet or quoting a Fed-mentioned tweet), (3) replies (either replying to a Fed tweet/thread or replying to another user's tweet/thread and tagging the Fed accounts), and (4) direct tagging (when a Twitter user tags the Fed accounts in their tweets). After removing duplicates, we obtain a sample of 488,393 tweets posted by 117,441 unique users. In this sample, 1.45 %, 44.08 %, and 4.96 % of tweets are retweets, replies, and quotes, respectively.

In Fig. 2, we plot the number of the Fed-mentioning tweets over time. The decline in the number of retweets suggests that Twitter users are less likely to merely disseminate the content of the Fed or Fed-related tweets over time. Instead, they tend to add their own comments (quotes), reply to the Fed tweets or Fed-related conversations (replies), or even attempt to initiate a conversation with the Fed accounts (tagging). Altogether, the total number of Fed mentions has increased since 2012 – this pattern is also documented in Conti-Brown and Feinstein (2020). However, the majority of such engagement is directed towards the Board of Governors account (@federalreserve), while engagement with other Fed accounts makes up only 32 % of the sample. A similar pattern is observed for the number of unique users (mentioners) who mentioned the Fed accounts in their posts (Fig. 3). Moreover, the statistics suggest that most mentioners only interacted with the Fed accounts once.

Despite the relatively large number of Fed tweets and Fed mentions, the tweets in both samples generally receive a very low level of attention and reactions (Table 1). That is, most tweets receive no interactions and conditional on being reacted to, they get only a few likes, retweets, replies, or quotes. Note that this low level of responses is not irregularity of our data as it is also shown by Conti-Brown and Feinstein (2020) when they look at the reactions to Fed tweets during the 2010-2019 period. Nevertheless, there are some "viral" tweets that received a reasonable number of likes, quotes, replies, and retweets.[4]

2.2. Text analysis

In this section, we will describe the natural language processing (NLP) processes used to analyze the content of social media posts.

[3] While we cannot find any particular events that could explain these spikes, exploring the tweets in detail suggests that the increases in the number of tweets posted by Fed Richmond in 2014-2015 could be partly explained by the tweets referring to the then-President Jeffrey Lacker (e.g., his public engagement).

[4] Examples of viral Fed tweets are shown in Appendix Table A1.

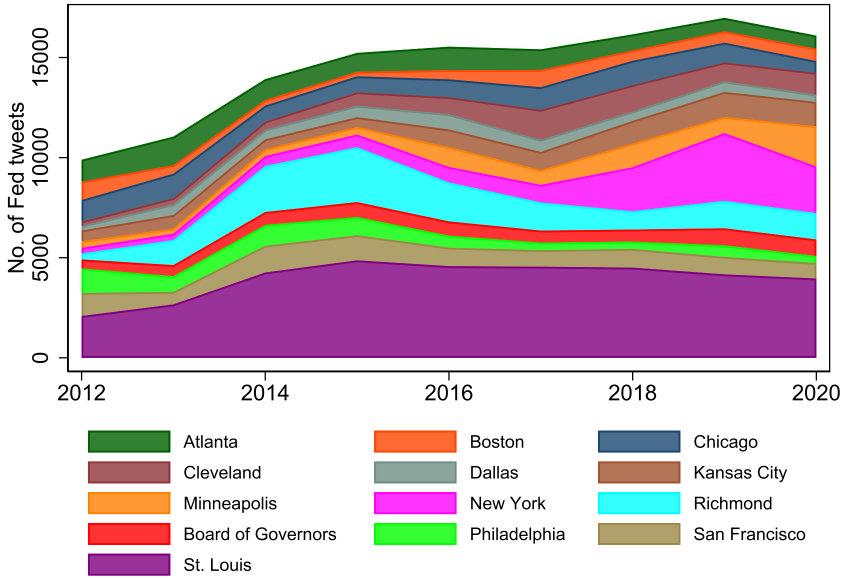


Fig. 1. Number of Fed tweets.
Notes: This figure shows the total number of English tweets posted by each Fed accounts during the 2012-2020 period.

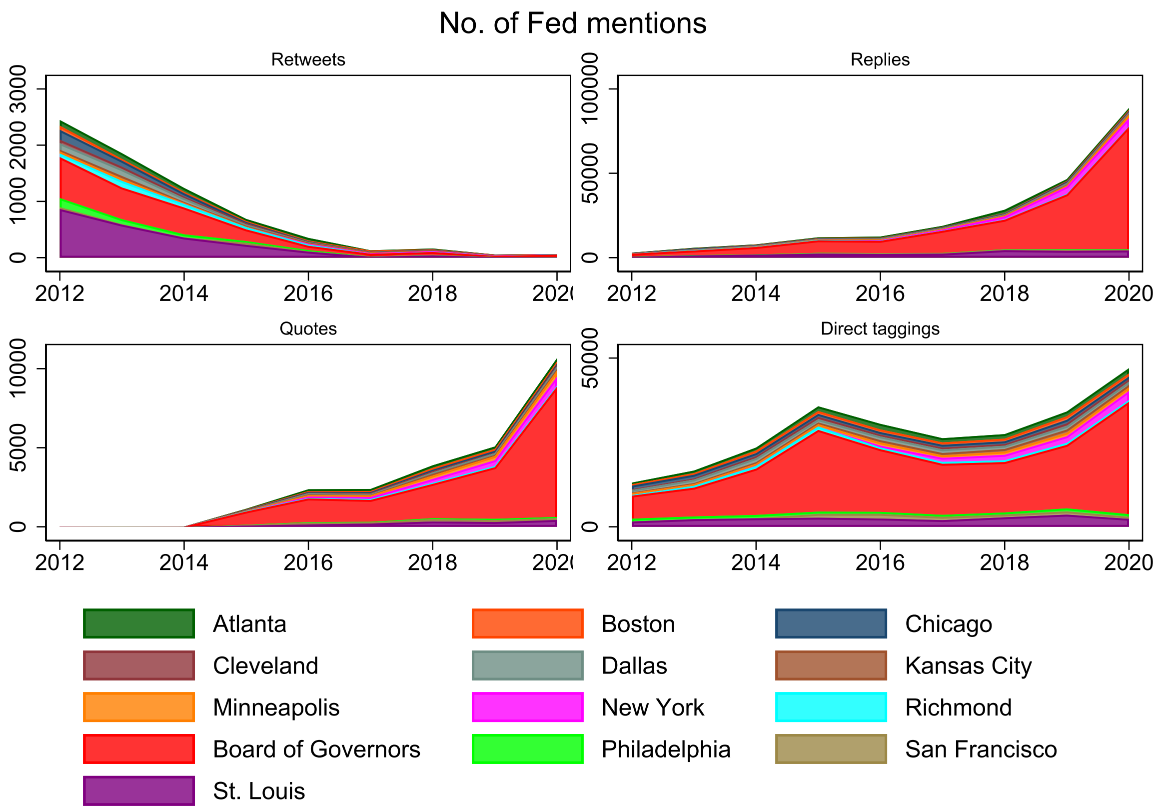


Fig. 2. Number of Fed mentions.
Notes: This figure shows the number of Fed mentions by four categories namely retweets, replies, quotes, and direct taggings over the 2012-2020 period.

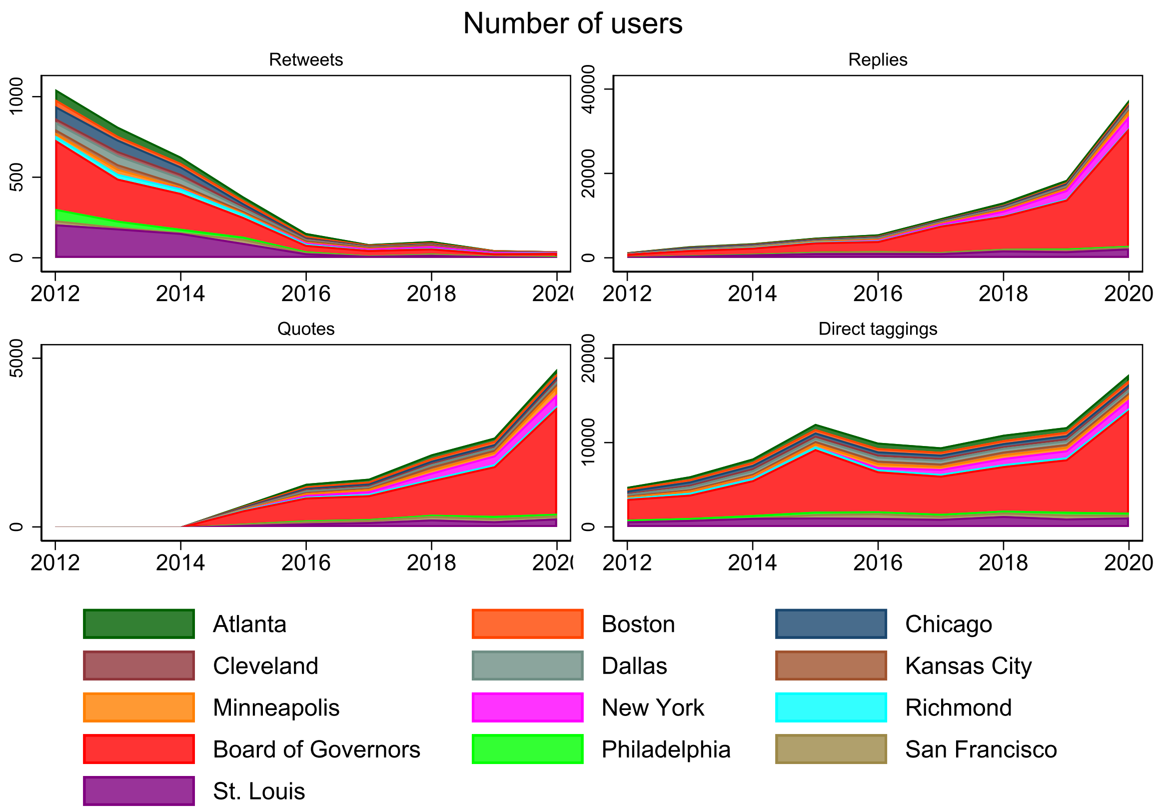


Fig. 3. Number of unique users who mentioned the Fed.
Notes: This figure shows the number of unique users who created Fed-mentioned retweets, replies, quotes, and direct taggings over the 2012-2020 period.

Table 1
Reaction statistics.

	Mean	SD	Min	P25	Median	P75	Max	N
Panel A. Fed timeline sample								
Reply count	0.60	3.55	0.00	0.00	0.00	1.00	708.00	130,271
Retweet count	3.65	8.55	0.00	1.00	2.00	4.00	689.00	130,271
Like count	3.31	11.41	0.00	0.00	1.00	4.00	1,517.00	130,271
Quote count	0.37	3.06	0.00	0.00	0.00	0.00	355.00	130,271
Panel B. Fed mentions sample								
Reply count	0.34	4.03	0.00	0.00	0.00	0.00	1,334.00	488,393
Retweet count	0.83	27.20	0.00	0.00	0.00	0.00	14,775.00	488,393
Like count	2.38	89.11	0.00	0.00	0.00	1.00	52,162.00	488,393
Quote count	0.09	3.99	0.00	0.00	0.00	0.00	2,037.00	488,393

Notes: This table shows the summary statistics for the number of likes, replies, quotes, and retweets of the tweets in the *Fed timeline* sample (Panel A) and the *Fed mentions* sample (Panel B).

Note that before analyzing the texts, we perform some cleaning steps to remove html links, numbers, tagging (e.g., @federalreserve), and hashtag symbols. We also lemmatize verbs before performing the NLP processes described in Section 2.2.2 below.

2.2.1. *Text sentiment*

Given that our data are domain-specific (tweets posted by or mentioned by the Fed), we will generate two measures of text sentiment. To measure general textual emotion, we use TweetNLP (Camacho-Collados et al., 2022), a Python library that provides NLP models for social media text classification. Particularly, the TweetNLP's Sentiment model is employed to classify each tweet in the *Fed* *timeline* and *Fed mentions* samples into negative, neutral, or positive emotions. The second sentiment measure is economic-specific, where positive sentiment would suggest an improvement in economic conditions while negative sentiment would indicate the opposite. This measure is generated by employing Sentiment-xDistil,[5] an open-source model trained to classify sentiment in the economic context.[6]

Using the predicted sentiment and probability, we calculate the monthly index for both general sentiment and economic sentiment by using the balance statistic weighted by probability: $\frac{\sum Probability^{Positive} - \sum Probability^{Negative}}{Number\ of\ tweets}$. As shown in Fig. 4, the Fed tweets are slightly positive, while the Fed mentions tend to be on the negative side, regardless of the sentiment measures. Moreover, we observe a sharp drop in the sentiment indices in early 2020, which coincides with the onset of the Covid-19 pandemic. A simple check for correlations between our measures of sentiment and different economic indicators, including the economic policy uncertainty (EPU) index (Baker et al., 2016) and the Weekly Economic Index (WEI), shows some interesting patterns. In particular, the Fed tweets' economic sentiment is negatively correlated with the EPU index (ρ=-0.48) but positively correlated with the WEI (ρ=0.46). Similar moderate correlations are also observed for the Fed mentions: the correlation coefficients with the EPU index and the WEI are −0.59 and 0.49, respectively. In other words, our sentiment measures track the policy uncertainty and the economic outlook reasonably well. Specifically, the tweets are likely to be positive during the period of low uncertainty or optimistic economic outlook.

Given that social media users often use sarcasm to express hidden information or (subtly) criticize others, we also use the irony detection model incorporated in TweetNLP to determine whether a tweet in the *Fed mentions* sample is ironic. As shown in Fig. 5, the irony index fluctuates over time. Yet, the average index over the sample period is 0.3, suggesting that Twitter users do use ironic language in their tweets directed at the Fed. Unlike the sentiment indices, the irony index is only weakly correlated with the EPU index (ρ=-0.31) and the WEI ($\rho = 0.17$).

2.2.2. *Taxonomy construction*

In addition to sentiment, it is also important to understand the text content (i.e., the "topics") as the public might react to central banks' communication differently depending on the topics. A standard and easy-to-apply approach is to generate a dictionary of potential topics and search for the relevant keywords. However, this would require prior knowledge about the topics and keywords, which is not possible for texts in contexts/domains that are not widely studied (such as this case). For example, in one of a few studies examining the Fed's activities on Twitter, Conti-Brown and Feinstein (2020) show five topics of the Fed tweets but do not specify how these topics were identified.[7] Alternatively, one could manually build a dictionary based on the term frequencies of unique words/-phrases in the data. However, this is not scalable for large datasets or diverse corpora. In terms of topic modeling using NLP techniques, existing literature has applied Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to classify topics of formal central bank communication such as FOMC statements (Hansen and McMahon, 2016; Hansen et al., 2018). Despite its popularity, LDA is known for its weaknesses related to the interpretation of topics. Moreover, a recent study by Zhang et al. (2022) shows that clustering with contextual embeddings could outperform LDA and neural topic modeling (i.e., topic modeling using neural networks) in producing more coherent and interpretable topics, especially for short texts. Given the unsupervised nature and the algorithms' underlying assumptions, this approach also has its cons related to the number of topics generated or generating topic representation.

In light of this consideration, we propose a weakly-supervised, scalable framework that incorporates both state-of-the-art NLP methods and experts' inputs to generate a dictionary of topics discussed in the Fed tweets. Essentially, our framework consists of 3 components: (1) unsupervised topic modeling, (2) fine-tuning hyperparameters, and (3) manual taxonomy construction. Each component is discussed below.

Component 1: Clustering with text embeddings for topic modeling.

Text embeddings. In the first step, we use different pre-trained language models to generate the text embeddings, which are the numerical representation of the semantic meaning of the words or sentences in a vector space. If the words/sentences have a similar meaning, they will have similar representations; hence, their respective embeddings will be closer in this vector space. The text embeddings can then be used in various text analysis tasks, including text classification, sentiment analysis, and topic modeling. After experimenting with various models, we choose Google's Universal Sentence Encoder (USE) model to generate the embeddings where each text is converted into a 512-dimensional vector.

Dimensionality reduction. In the second step, we use Uniform Manifold Approximation and Projection (UMAP), a non-linear dimension reduction technique, to lower the dimensionality of the text embeddings. This technique learns the topological structure (manifold structure) of the original data and tries to preserve this structure in lower dimensions.

Clustering. In the third step, we apply the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm proposed by Campello et al. (2013) on the reduced dimensionality embeddings to cluster the texts into groups based on their content. Unlike K-means clustering, HDBSCAN does not require a pre-defined number of clusters. Given that research on central bank communication on social media is still limited, we do not have any prior knowledge about the topics of such communication. Thus, using HDBSCAN would be more suitable for the task. Further, the HDBSCAN algorithm can deal with outliers better as it does not

[5] The model card can be found at Hugging Face's repository.

[6] Examples of sentiment classification outputs are reported in Appendix Table B1.

[7] Five topics include economic growth, bank regulation, interest rates, household finance & consumer protection, and housing & mortgage.

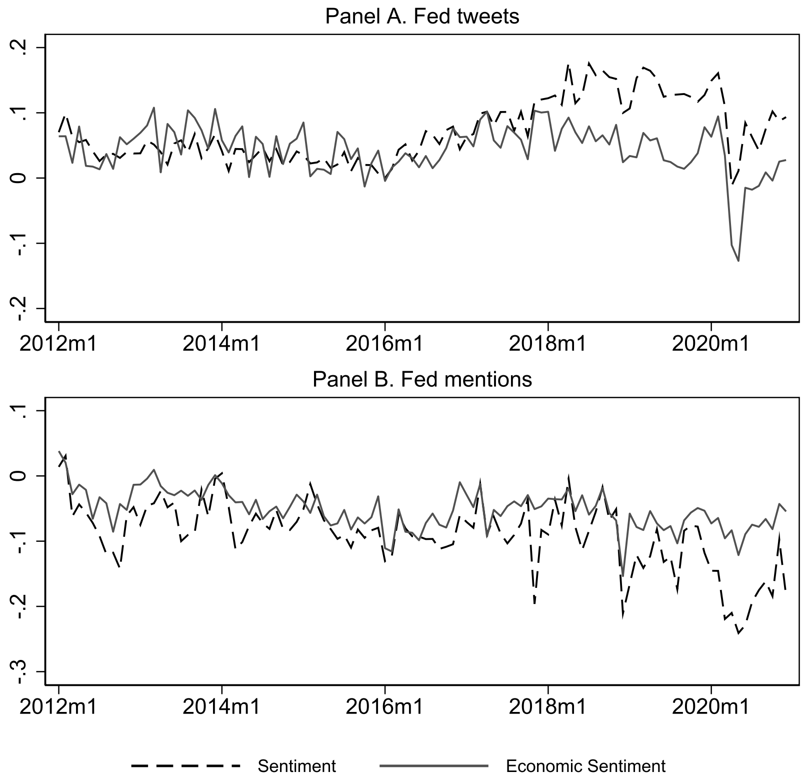


Fig. 4. Monthly sentiment index.
Notes: This figure shows the monthly (general) sentiment index (dashed line) and the monthly economic sentiment index (solid line) for the samples of *Fed tweets* (Panel A) and *Fed mentions* (Panel B).

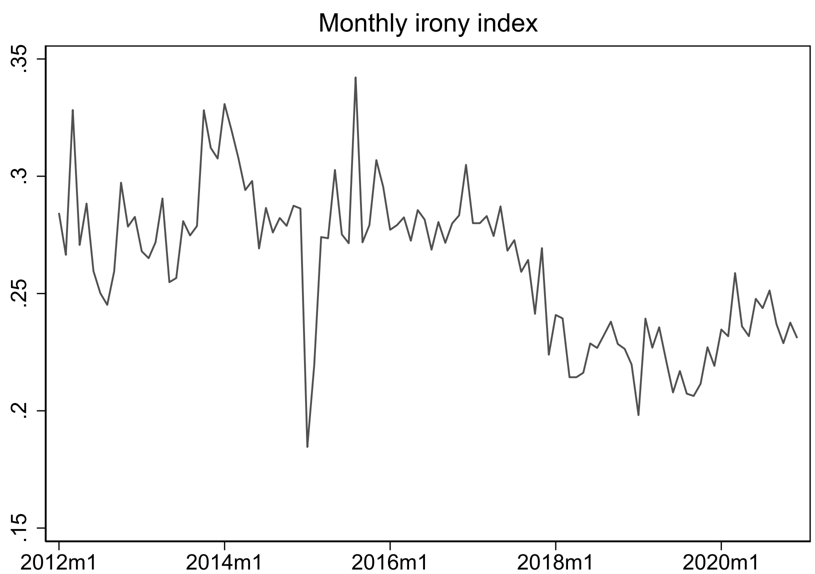


Fig. 5. Monthly irony index.
Notes: This figure shows the monthly irony index for the sample of *Fed mentions*.

“force” an observation to be in a cluster where it does not belong.

Generating keywords presenting topics. After clustering tweets into different clusters (topics), we follow the keyword selection method proposed by Zhang et al. (2022) that considers both locally important words/phrases and globally infrequent words/phrases.

Particularly, for each word, bigram, and 3-gram t in a document d, we calculate its Term Frequency-Inverse Document Frequency (TFIDF), which shows it importance across the entire corpus:

$$TFIDF_{t,d} = n_{t,d} \times \ln\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right)$$

where $n_{t,d}$ is the frequency of term t in document d, D is the number of documents in the entire corpus.

We then take the average of $TFIDF_{t,d}$ across documents in the same cluster k to get a term-cluster importance indicator $\overline{TFIDF_{t,k}}$. A higher value would indicate that the term is more important in representing that cluster. The final importance score is calculated as $\overline{TFIDF_{t,k}} \times \ln\left(\frac{|K|}{|k \in K : t \in k|}\right)$ where K is the total number of clusters. $\ln\left(\frac{|K|}{|k \in K : t \in k|}\right)$ is essentially a penalty: a term is penalized for being globally frequent.

Component 2: Hyperparameter finetuning.

Although the above steps have also been implemented in other topic modeling algorithms such as BERTopic, it is essential to note that the outcomes (e.g., the number of topics generated) depend on hyperparameters in Steps 2 and 3. While other algorithms allow for customizing such parameters, which values to choose, especially if the text data are new or in the lesser studied contexts/domains, remains a challenge. To overcome this problem, we incorporate all steps in a hyperparameter finetuning framework (Bayesian search) with maximizing topic diversity as the objective function. Our fine-tuned hyperparameters are as follows: neighboring points of 100, reduced dimensionality of 100 (step 2), and 150 as the minimum size of a cluster in HDBSCAN algorithm. To this end, our approach offers an advantage that can complement other well-known topic modeling algorithms such as BERTopic. For example, one could use our framework as an exploratory step to find the appropriate hyperparameters and then apply them in BERTopic. Moreover, our approach could be flexibly applied to suit various needs. For instance, one could change the objective function to find the hyperparameters that help improve topic coherence.

Component 3: Taxonomy construction

Our work with Components 2 and 3 returns 101 clusters (i.e., topics). As can be seen from the keywords representing the four most frequent topics (Appendix Fig. B1), the topics can be interpretable. For example, Topic 60 refers to the labor market, Topic 74 points to discussions about (financial) educational resources offered by the Fed, Topic 23 refers to the data/database released by the Fed, and Topic 88 represents careers at the Fed. Additionally, the unsupervised topic modeling results reveal not only the topics in content sense but also topics regarding the "types" of content (see Appendix Fig. B2). That is, in addition to "message" type (e.g., "We use treasury yields, inflation data, inflation swaps, and survey-based measures of inflation expectations to calculate the expected rate of inflation (CPI) over various time horizons. Our latest estimate of 10-year expected #inflation is 2.09 percent"), there are also "announcement" tweets talking about data releases, events, or research releases (e.g., "RT @federalreserve: interactive guide to our weekly #balancesheet report: #feddata").

Despite promising results, there are two issues requiring further attention. First, while the clusters are interpretable, they seem to be interrelated (i.e., many clusters point to the broader topics of macroeconomy, labor market, or banking sector). Second, HDBSCAN might over-classify data points as outliers (in our case, 57 % of observations are classified as noise; see Appendix Fig. B3). Several reasons could contribute to these issues. For example, the over-classification of noise is a known disadvantage of HDBSCAN. On the other hand, the data might contain texts that are too subtle to be clearly classified into one cluster. To deal with these drawbacks, we perform topic reduction to create a new, hierarchical taxonomy of topics discussed by the Fed on Twitter. We prefer manual topic reduction over automatic topic reduction as it gives us better control over outputs, especially in the case of domain-specific texts that might contain terminologies, jargon, or nuances requiring greater attention.

To this end, we manually reduce 101 topics obtained from the unsupervised topic modeling to 27 narrow topics related to the Fed's officials/business, the economy, macroeconomic policies, and the community.[8] These topics are then further grouped into broader topics when possible.[9] A tweet is classified as mentioning a topic if at least one keyword in that group appears in the text. As a result, only 32.5 % of the Fed tweets are classified as outliers, significantly lower than the proportion of outliers identified after unsupervised topic modeling. 45 % of the Fed tweets mention at least one of the topics, while almost 18 % mention at least two topics. As shown in the top left panel of Fig. 6 and Appendix Fig. A1, some topics that are consistently mentioned in the Fed tweets, unsurprisingly, are those talking about the Fed and their activities, the banking sector, and macroeconomics, especially monetary policy. Interestingly, our approach discovers not only the established topics but also the "emergent" ones, such as the topics of *Education* and *Pandemic*. The former topic that emerges over time reflects the Fed's effort in education outreach, while the latter only became prominent in 2020 and reflects the public health shock that started in early 2020. Moreover, there are heterogeneities in terms of prominent topics posted by different Fed accounts. For example, the Board of Governors account was more active in talking about the Fed's activities (e.g.,

[8] Doing so allows us to classify topics for 67 % of Fed tweets. Of which, almost 68 % of tweets are assigned to only 1 narrow topic while 26 % are assigned to 2 narrow topics.

[9] The detailed hierarchical taxonomy is reported in Appendix Table B2.

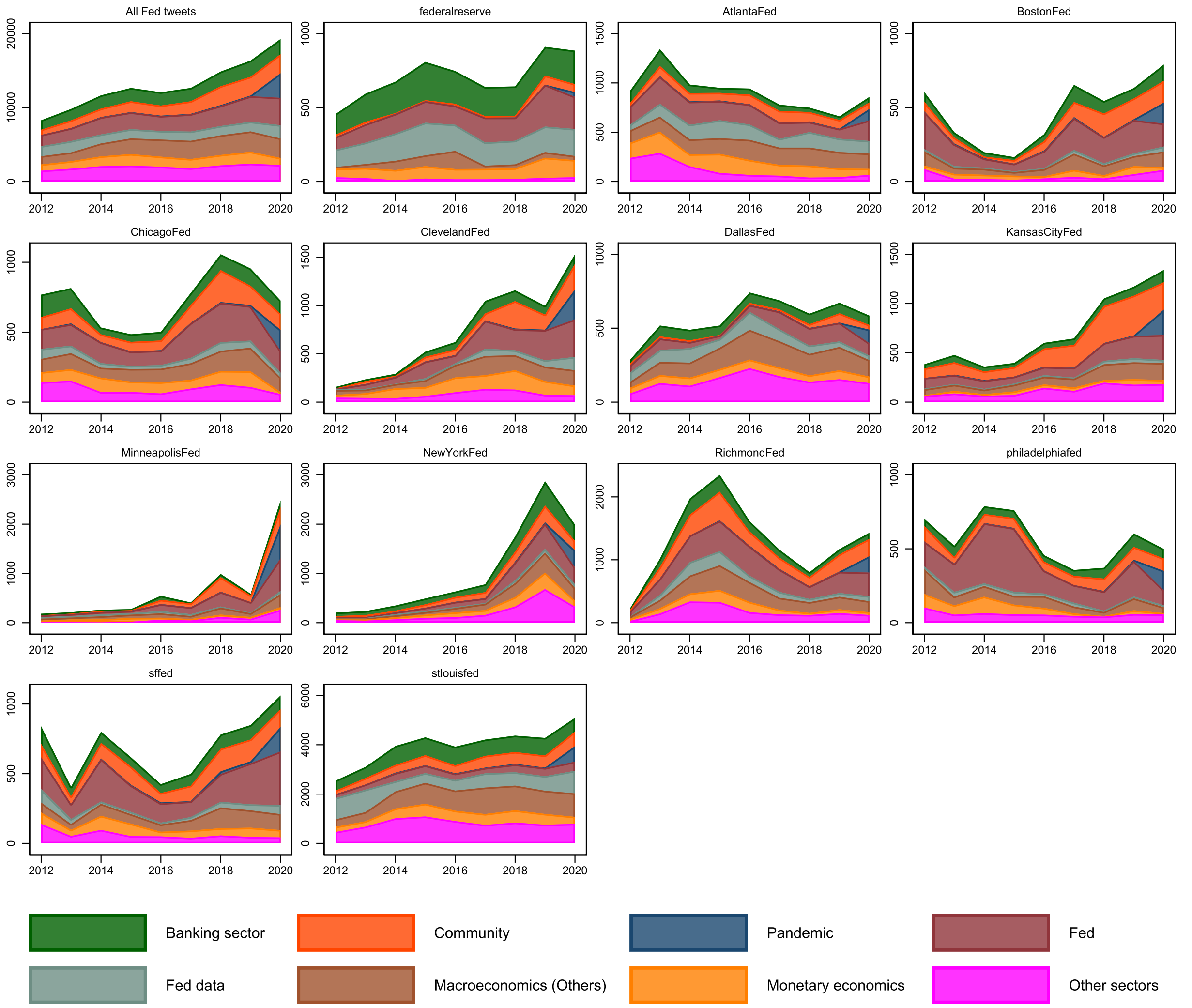


Fig. 6. Number of Fed tweets by broad topics and Fed accounts.
Notes: The top left panel represents the number of all Fed tweets by broad topics. Other panels show the number of Fed tweets by broad topics and Fed accounts. The tweet counts are not mutually exclusive across topics as one tweet can be counted multiple times if it belongs to multiple topics.

research, public engagement events), matters related to the banking sector, and Fed data. The Dallas Fed and St. Louis Fed often talked about macroeconomic matters (other than monetary economics) and other sectors of the economy (other than the banking sector). Among all topics, the Kansas City Fed was most active in taking about the free economic and personal finance resources offered to the public.

2.2.3. User classification

To understand whether using social media can facilitate central banks', and the Fed's in particular, objective to communicate with the public, it is important to identify groups of users who engage with the Fed on Twitter. Yet, this remains a challenge, likely due to a lack of data. Recently, Ehrmann and Wabitsch (2022) examine the tweets' content to differentiate experts in central banking and monetary policy from non-experts. Complementing this study, we apply the taxonomy construction framework described earlier on the texts of users' descriptions to generate a dictionary of five user groups (see Appendix Table B3).

Media is the group of users who are journalists, columnists, contributors, or media outlets' accounts. ***Economist*** group includes users who describe themselves as economists or academics/researchers who have economics majors. Non-economic-majored academics (***Academic***) are users who are academics (e.g., PhD students, research fellows, professors) but do not mention economics as their major.[10] ***Finance*** group includes traders, fund/asset managers, financial analysts, bankers, and other users who claim to have

[10] In other words, *Economist* and *Academic* groups are mutually exclusive.

financial knowledge (i.e., CFA qualifications or postgraduate degrees in economics or finance). ***Manager*** accounts are accounts of CEO, CFO, or chairman of a company. Using the verification status and username, we further identify two other groups: ***Central banks*** (official accounts of other central banks) and ***Other verified accounts*** (verified accounts that cannot be classified into other groups). All remaining accounts are considered the general public (***Public***).

It should be noted that a user can be classified into more than one group, but the number of multi-group users accounts for less than 0.5 % of all unique mentioners in the sample. Fig. 7 depicts the share of each group over time. The proportion of *Public* accounts is about 78 % in 2012 then increases to 87 % in 2020. Note that these statistics are likely to be the over-representation of the actual number of public accounts due to the fact that we have to rely on users' self-description for classification. Nevertheless, we obtain reasonable proportions of accounts in other groups. For example, the average share of *Media* and *Other verified accounts* is 5-6 %, of *Economist, Academic, Manager*, and *Finance* is 2 %.

3. Fed communication on Twitter: direct engagement

In this section, we will examine the degree of *direct public outreach* by empirically quantifying the public reactions to the social media posts sent from the Fed accounts. To do so, we first employ the following linear probability model to examine the extensive margin of the reactions:

$$Reaction^{D}_{i,j,d} = \alpha + \beta_1 FOMC^{Unchange}_{d} + \beta_2 FOMC^{Change}_{d} + \beta_3 ln\ (EPU)_d + Fed\ tweet_{i,j,d}\gamma + \varepsilon_{i,j,d} \tag{1}$$

where *i, j*, and *d* refer to post *i* created by the Fed account *j* on date *d. Reaction^D* ($Reaction \in \{Like, Retweet, Reply, Quote\}$) equals to 1 if the number of the respective reaction type is non-zero, and 0 otherwise. *FOMC^{Unchange}* equals to 1 for the FOMC days with no change in target rate and 0 otherwise. *FOMC^{Change}* equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty (EPU) index.

Fed tweet is a vector of Fed tweet-specific characteristics, including the text sentiment (both general sentiment and financial sentiment), topics, order of the post, and type of post. Specifically, *First-in-Day* equals 1 if tweet *i* is the first tweet posted by account *j* on date *d* and 0 otherwise. *Last-in-Day* equals 1 if tweet *i* is the last tweet posted on date d and 0 otherwise. *First-in-Thread* equals 1 if the tweet is the beginning of a thread, while *Last-in-Thread* equals 1 if the tweet is the last tweet in a thread. *Is-retweet* equals 1 if tweet *i* is a retweet and 0 otherwise. *Mention-Fed* equals 1 if other Fed accounts were mentioned/tagged and 0 otherwise. *External-media* equals 1 if tweet *i* contains photos, videos, or external URLs and 0 otherwise. *Sentiment* is the tweet's sentiment weighted by the probability, i.e., $Sentiment = Prediction \times Probability$ where *Prediction* equals to -1 for negative, 0 for neutral, and 1 for positive. By construction, all neutral tweets will have a sentiment score of 0 and a higher score means more positive.

In the baseline estimations, we include dummy variables representing 8 broad topics including *Banking sector, Other sectors, Community, Pandemic, Fed, Fed data, Monetary economics*, and *Macroeconomics (Others)*. To investigate the potential heterogeneity across narrow topics within the same broad ones, we then estimate specification (1) using a vector of 27 dummy variables representing 27 narrow topics. A set of fixed effects, including Fed account fixed effects, hour of day, day of week, day of month, month of year, and year fixed effects is also included. Standard errors are clustered by the date of posting.[11]

The results (Table 2) suggest that a tweet discussing macroeconomics, including both monetary economics and other macroeconomic-related matters, is more likely to be liked, retweeted, replied to, or quoted. This appears to be driven by social users' interests in the topics of *Economic conditions, Monetary policy*, and *Inflation* (Fig. 8): discussing one of these topics could increase the likelihood of reaction by 5-10 percentage points. Additionally, although tweets talking about the banking sector and other sectors of the economy generally receive fewer reactions, there are differences in reactions to narrow topics within these broad categories. For example, the probability of like (quote) is 2 (6) percentage points lower for *Banking regulations* but 10 (6) percentage points higher for *Fintech*. It should be noted that the point estimates are similar even when we remove the viral tweets from the estimation sample (see Appendix Table A2, Appendix Table A3, Appendix Fig. A2, and Appendix Fig. A3). While these changes might not be important for the probability of being liked or retweeted of which the unconditional probability is quite high (69–77 %), they are meaningful for the probability of receiving replies or being quoted where the unconditional probability is relatively low (16 % for quotes and 27 % for replies). Moreover, unlike likes or retweets, which are merely indicators of "attention" to the Fed tweets, replying and quoting indicate engaging in a conversation with the Fed accounts. Thus, strategic tweeting (e.g., discussing certain topics) could significantly improve public engagement, at least in terms of extensive margin.

Other characteristics of a tweet are also important determinants of attention/engagement. For instance, although more positive messages are more likely to be liked, they are less likely to be retweeted, quoted, or replied to. A similar pattern is found for tweets that are more positive in economic sense. These findings are consistent with the informational negativity bias, which suggests that people tend to be more attentive to negative information (Rozin and Royzman, 2001; Vaish et al., 2008; Soroka et al., 2019). We also observe that social media users react to (1) the original tweets, (2) the first tweet in a thread, (3) and the "coordinated" tweets (i.e., the tweets mention other Fed accounts) more often. Moreover, the possibility of engaging with the Fed tweets is higher when there is a change in the policy rate or when the economic policy uncertainty is high. In other words, the public turns to central bank communication on

[11] As robustness checks, we also estimate specification (1) using the alternative proxies for economic uncertainty such as VIX or controlling for date of posting fixed effect and obtain the consistent results. Similarly, our results are qualitatively similar if we include the Fed tweets over the 2008-2011 period or if we add in additional controls such as the length of Fed tweets. These results are available upon request.

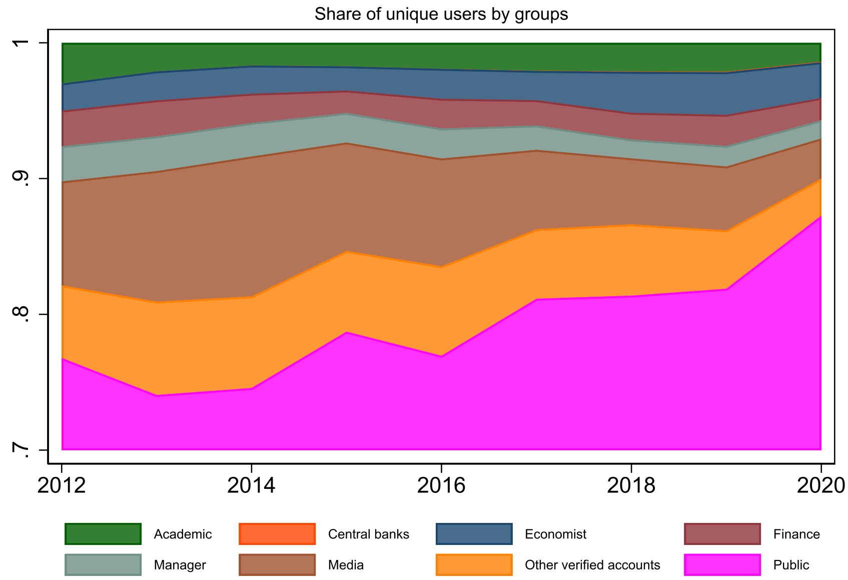


Fig. 7. Number of mentioners by groups.
Notes: This figure shows the share of the number of unique mentioners by user groups over the 2012-2020 period. 540 users, who are classified into more than one group, are excluded but including them would not materially change the shape of the figure.

social media to seek more information/clarification in times of uncertainty.

Next, to understand the intensive margin of attention to/engagement with the Fed's communication on Twitter, we replace the dependent variable in Eq. (1) with the natural log of the number of reactions. Consistent with the results for the extensive margin, the tweets talking about macroeconomic-related topics (Table 3), especially *Monetary policy* and *Economic conditions* (Fig. 9), receive more likes, retweets, replies, and quotes. Yet, unlike the economically significant impact of the Fed tweets' characteristics on the extensive margin (i.e., probability of paying attention to/engaging with the Fed accounts), the economic significance of the effects on intensive margin is marginal. This result agrees with the evidence in previous studies showing that the general public is generally inattentive to central bank communication (e.g., Blinder et al., 2024). In other words, while discussing certain topics can draw some attention/engagement from social media users, the degree of attention/engagement is still very limited.

4. Fed communication on Twitter: indirect engagement

One unique feature of central bank communication on social media is the 2-way "interactions". Not only central bankers can send a message to the public and receive direct reactions, as examined in Section 3, the public could also indirectly engage with the Fed by initiating tweets directed at the Fed. In this section, we will focus on understanding this type of indirect engagement by analyzing the extent to which Twitter users engage in Fed-tagging tweeting activities and whether there is any difference across groups of users. To do so, we restrict the *Fed mentions* sample to the tweets that were "initiated" by the users, i.e., those that were not retweets, replies, or quotes of a Fed tweet. The data are then aggregated at a daily frequency and merged with the daily tweeting activities of the Fed accounts.

In Table 4, we report the results for the first set of outcomes related to the Fed mentions' content. Specifically, we examine the link between daily tweeting activities of the Fed accounts and (1) the number of Fed mentions, (2) the sentiment of Fed mentions, and (3) the number of Fed mentions referring to the topics of *Monetary economics, Macroeconomics (Others), Banking sector*, and *Other sectors*, as well as (4) the diversity of topics. Consistent with the results in Section 3, we find that Twitter users are most active in engaging with the Fed on the FOMC meeting days, especially when there are policy changes. Relative to the non-FOMC meeting days, the number of Fed mentions is twice as high on the no-change policy days and three times higher on the policy-changed days. The effect is both statistically and economically significant, given that the geometric mean for Fed mentions on the non-FOMC meeting days is 143. Moreover, comparing the FOMC meeting effects across *Monetary economics, Macroeconomics (Others), Banking sector*, and *Other sectors* topics, the effect is largest for *Monetary economics* with an increase of 21 and 34 Monetary economics-related mentions on the no-change policy days and the policy-changed days, respectively. A similar pattern of public engagement with the Fed's Twitter accounts is also observed when the level of economic uncertainty is high, although the effect is smaller in magnitude: a 10 % increase in the EPU index is related to 0.3 % in the number of Fed mentions, and a 1 % increase in the number of Fed mentions discussing monetary economics topics.

Further, the Fed's tweeting activities have a positive spillover to the Fed-tagging activities of other users. For example, more positive Fed tweets are associated with more positive Fed mentions, regardless of sentiment measures. Similarly, when more Fed accounts tweet and/or generate more tweets, Twitter users also attempt to "talk to" the Fed more. Further, Fed-generated discussions

Table 2
Extensive margin (broad topics).

	Dependent variable:			
	Like^D (1)	*Retweet^D* (2)	*Reply^D* (3)	*Quote^D* (4)
FOMC^{Unchange}	−0.018*	0.007	−0.001	−0.002
	(0.011)	(0.011)	(0.008)	(0.010)
FOMC^{Change}	−0.005	−0.027	−0.009	0.042**
	(0.017)	(0.020)	(0.021)	(0.021)
Pandemic	0.015**	0.003	0.008	−0.039***
	(0.007)	(0.008)	(0.008)	(0.008)
Fed data	0.020***	0.010***	−0.016***	−0.008**
	(0.004)	(0.003)	(0.004)	(0.003)
Monetary economics	0.060***	0.055***	0.047***	0.029***
	(0.004)	(0.004)	(0.004)	(0.004)
Macroeconomics (Others)	0.016***	0.040***	0.013***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)
Other sectors	−0.016***	0.028***	−0.018***	−0.007**
	(0.004)	(0.003)	(0.003)	(0.003)
Banking sector	−0.009**	0.010***	−0.009***	−0.011***
	(0.004)	(0.003)	(0.003)	(0.003)
Community	0.031***	0.005	−0.002	−0.003
	(0.004)	(0.004)	(0.003)	(0.003)
Fed	−0.003	0.009***	−0.007***	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment	0.042***	−0.046***	−0.019***	−0.029***
	(0.004)	(0.004)	(0.004)	(0.003)
Economic sentiment	−0.017***	0.003	−0.005**	−0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Is-retweet	−0.134***	−0.231***	−0.040***	0.013***
	(0.008)	(0.009)	(0.005)	(0.004)
Mention-Fed	0.032***	0.023***	−0.006	0.024***
	(0.006)	(0.007)	(0.005)	(0.005)
External-media	0.062***	0.093***	−0.029***	0.018***
	(0.007)	(0.010)	(0.005)	(0.005)
First-in-day	0.027***	0.025***	0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Last-in-day	0.038***	0.029***	0.034***	−0.000
	(0.003)	(0.003)	(0.003)	(0.002)
First-in-Thread	0.102***	0.213***	0.024***	0.165***
	(0.008)	(0.009)	(0.007)	(0.008)
Last-in-Thread	−0.061***	−0.078***	−0.706***	−0.057***
	(0.007)	(0.008)	(0.007)	(0.008)
ln(EPU)	−0.002	0.004	−0.001	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)
Obs.	130,271	130,271	130,271	130,271
R-squared	0.263	0.169	0.290	0.188

Notes: This table shows the results for extensive margin. *Like^D*, *Retweet^D*, *Reply^D*, and *Quote^D* equal to 1 if the Fed retweet receives at least 1 like, retweet, reply, and quote, respectively and 0 otherwise. *FOMC^{Unchange}* equals to 1 for the FOMC days with no change in target rate and 0 otherwise. *FOMC^{Change}* equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *First-in-Day* equals to 1 if the tweet is the first tweet on a given day and 0 otherwise. *Last-in-Day* equals to 1 if the tweet the last tweet on a given day and 0 otherwise. *First-in-Thread* equals to 1 if the tweet is the beginning of a thread. *Last-inThread* equals to 1 if the tweet is the last tweet in a thread. *Is-retweet* equals to 1 if the tweet is a retweet and 0 otherwise. *Mention-Fed* equals to 1 if other Fed accounts were mentioned/tagged and 0 otherwise. *External-media* equals to 1 if the tweet contains photos, videos, or external URLs and 0 otherwise. *CentralBank* is a dummy variable which equals to 1 of the tweet mentions one of the following topics: *Pandemic, Fed data, Monetary economics, Macroeconomics (Others), Other sectors, Banking sector, Community,* and *Fed* equal to 1 if the tweet refers to the respective topic and 0 otherwise. *Sentiment* is the tweet's general sentiment weighted by the probability. *Economic sentiment* is the tweet's economic sentiment weighted by the probability. In all estimations, a constant as well as Fed account fixed effects, hour of day, day of week, day of month, month of year, and year fixed effects are included but not reported. The standard errors clustered by date of posting are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

related to monetary economics, other macroeconomic matters, the banking sector, and other sectors encourage Twitter users to discuss similar topics. However, the magnitude of these effects is small, with an elasticity of 0.12-0.27. The findings, coupled with the results in Section 3, suggest that more efforts are required if the Fed is to improve its public outreach via this channel.

Given that communicating with the general public is one of the main aims of the Fed's communication strategies, it is equally, if not more, important to understand what user groups engage with the Fed. Thus, in Table 5, we report the estimates for the impacts of Fed tweeting activities on different groups of users. In addition to confirming the previous results (e.g., Twitter users are most reactive to the Fed's discussions about monetary economics), we also find that the effects are strongest for *Media*, followed by *Economist* and

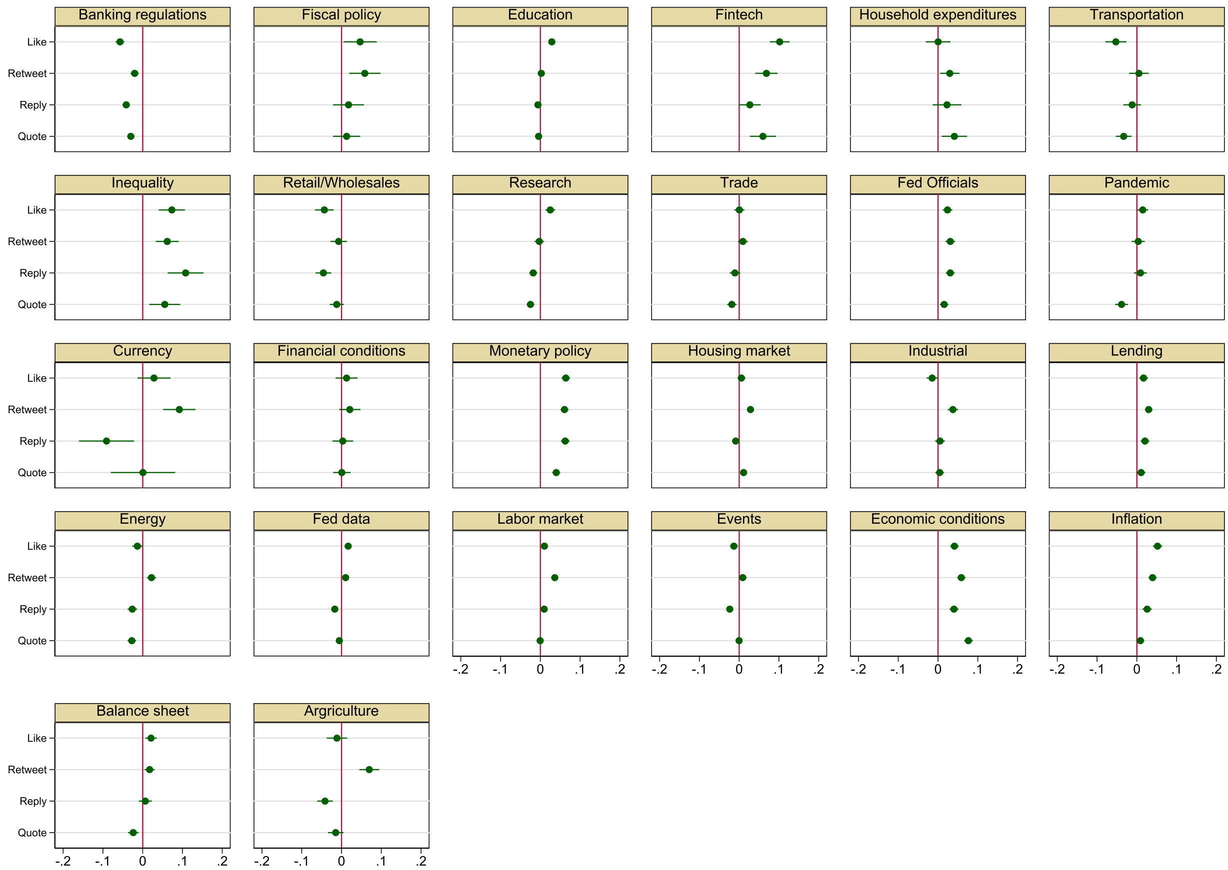


Fig. 8. Extensive margin (narrow topics).
Notes: This figure shows the estimates for 27 narrow topics in the extensive margin analysis of reactions to the Fed tweets.

Finance groups. In addition, these groups are also most active in engaging with the Fed to discuss economic-related issues (Table 6), and these tweets are more "viral" (Table 7). In other words, in response to the Fed's tweets about *monetary economics, media* accounts tend to post about the *economy and economic policies* more, and such posts are then *spread further* to other users (i.e., are shared and replied to more).[12]

These findings suggest an important implication for central bank communication. Specifically, instead of using social media to directly communicate with the general public, central bankers could use intermediaries such as media accounts to indirectly disseminate central bank messages to the general public. Doing so would help the general public, and especially households, acquire relevant information at a low cost (Blinder et al., 2024).

5. Fed communication on Twitter and inflation expectations

So far, we have documented the extent to which and how the messages created by the Fed on Twitter reach the public. However, further analysis is required to understand the economic impacts of the Fed's communication on Twitter. Among others, the effect on inflation expectations is one of the most important outcomes because inflation expectations could affect economic agents' investment and spending decisions. Ideally, one would like to conduct a randomized controlled trial (RCT) to examine whether and the extent to which economic agents update their inflation expectations in response to different Twitter-based Fed information treatments. Since we are unable to conduct such RCTs within the scope of this study, we need to generate a proxy of inflation expectations that can be linked to the Fed tweeting activities.

Recently, Angelico et al. (2022) show that Twitter data can be utilized for measuring real-time inflation expectations. Essentially, the idea of their method is similar to what we propose in Section 2.2.2., that is, employing the topic modeling techniques to filter noise and build a dictionary to be used for tweet classification (higher inflation vs. lower inflation). However, the data used by Angelico et al. (2022) have quite broad coverage (more than 1.5 million tweets) as they collected (Italian) tweets related to inflation, prices, and price dynamics. In contrast, our *Fed mentions* sample is restricted to only more than 480,000 tweets that mention the Fed accounts and even a

[12] By construction of our data, our results are likely to be under-estimated for media accounts.

Table 3
Intensive margin (broad topics).

	Dependent variable:			
	Like (1)	*Retweet* (2)	*Reply* (3)	*Quote* (4)
$FOMC^{Unchange}$	0.096***	0.117***	0.092***	0.249***
	(0.024)	(0.022)	(0.033)	(0.039)
$FOMC^{Change}$	0.188***	0.309***	0.249***	0.419***
	(0.049)	(0.064)	(0.078)	(0.071)
Pandemic	−0.122***	−0.027*	−0.174***	−0.088***
	(0.018)	(0.016)	(0.020)	(0.020)
Fed data	0.041***	−0.003	−0.054***	−0.093***
	(0.009)	(0.009)	(0.011)	(0.015)
Monetary economics	0.115***	0.191***	0.086***	0.116***
	(0.010)	(0.010)	(0.012)	(0.018)
Macroeconomics (Others)	0.052***	0.145***	0.002	0.096***
	(0.008)	(0.007)	(0.008)	(0.012)
Other sectors	−0.056***	0.064***	−0.057***	−0.049***
	(0.008)	(0.007)	(0.008)	(0.012)
Banking sector	−0.038***	0.023***	−0.031***	−0.021
	(0.008)	(0.008)	(0.009)	(0.013)
Community	0.033***	−0.019**	0.002	−0.020
	(0.009)	(0.008)	(0.009)	(0.012)
Fed	0.028***	−0.040***	0.000	−0.011
	(0.008)	(0.007)	(0.011)	(0.013)
Sentiment	0.110***	−0.102***	−0.029***	−0.030**
	(0.011)	(0.009)	(0.011)	(0.015)
Economic sentiment	-0.040***	−0.014***	0.004	−0.008
	(0.005)	(0.005)	(0.005)	(0.008)
Is-retweet	−0.065***	−0.275***	0.082***	−0.075**
	(0.016)	(0.015)	(0.018)	(0.035)
Mention-Fed	0.117***	0.037***	−0.060***	−0.054***
	(0.015)	(0.014)	(0.014)	(0.020)
External-media	0.142***	0.108***	−0.016	0.121***
	(0.019)	(0.016)	(0.012)	(0.024)
First-in-day	0.026***	0.046***	0.014	0.022
	(0.008)	(0.007)	(0.010)	(0.014)
Last-in-day	0.048***	0.063***	0.120***	0.038***
	(0.007)	(0.007)	(0.009)	(0.013)
First-in-Thread	0.589***	0.553***	0.245***	0.256***
	(0.019)	(0.021)	(0.014)	(0.028)
Last-in-Thread	−0.326***	−0.280***	−0.038***	−0.218***
	(0.018)	(0.018)	(0.014)	(0.028)
ln(EPU)	0.025***	0.020***	0.027***	0.027***
	(0.007)	(0.006)	(0.008)	(0.009)
Obs.	89,476	100,802	35,576	20,726
R-squared	0.348	0.331	0.328	0.164

Notes: This table shows the results for intensive margin. *Like, Retweet, Reply*, and *Quote* are the natural log of the number of likes, retweets, replies, and quotes received by a Fed tweet, respectively. $FOMC^{Unchange}$ equals to 1 for the FOMC days with no change in target rate and 0 otherwise. $FOMC^{Change}$ equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *First-in-Day* equals to 1 if the tweet is the first tweet on a given day and 0 otherwise. *Last-in-Day* equals to 1 if the tweet the last tweet on a given day and 0 otherwise. *First-in-Thread* equals to 1 if the tweet is the beginning of a thread. *Last-inThread* equals to 1 if the tweet is the last tweet in a thread. *Is-retweet* equals to 1 if the tweet is a retweet and 0 otherwise. *Mention-Fed* equals to 1 if other Fed accounts were mentioned/tagged and 0 otherwise. *External-media* equals to 1 if the tweet contains photos, videos, or external URLs and 0 otherwise. *CentralBank* is a dummy variable which equals to 1 of the tweet mentions one of the following topics: *Pandemic, Fed data, Monetary economics, Macroeconomics (Others), Other sectors, Banking sector, Community,* and *Fed* equal to 1 if the tweet refers to the respective topic and 0 otherwise. *Sentiment* is the tweet's general sentiment weighted by the probability. *Economic sentiment* is the tweet's economic sentiment weighted by the probability. In all estimations, a constant as well as Fed account fixed effects, hour of day, day of week, day of month, month of year, and year fixed effects are included but not reported. The standard errors clustered by date of posting are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

smaller subset is related to price or inflation. Consequently, the inflation expectation signal, if any, embedded in the Fed mentions could be too subtle to be captured by keywords. By implementing the approach discussed in Angelico et al. (2022), we can only generate very few keywords indicating the directions of inflation, making the empirical analysis of impacts on inflation expectations not feasible.

To address this challenge, we employ the few-shot learning (FSL) classification, which could be useful in extracting inflation

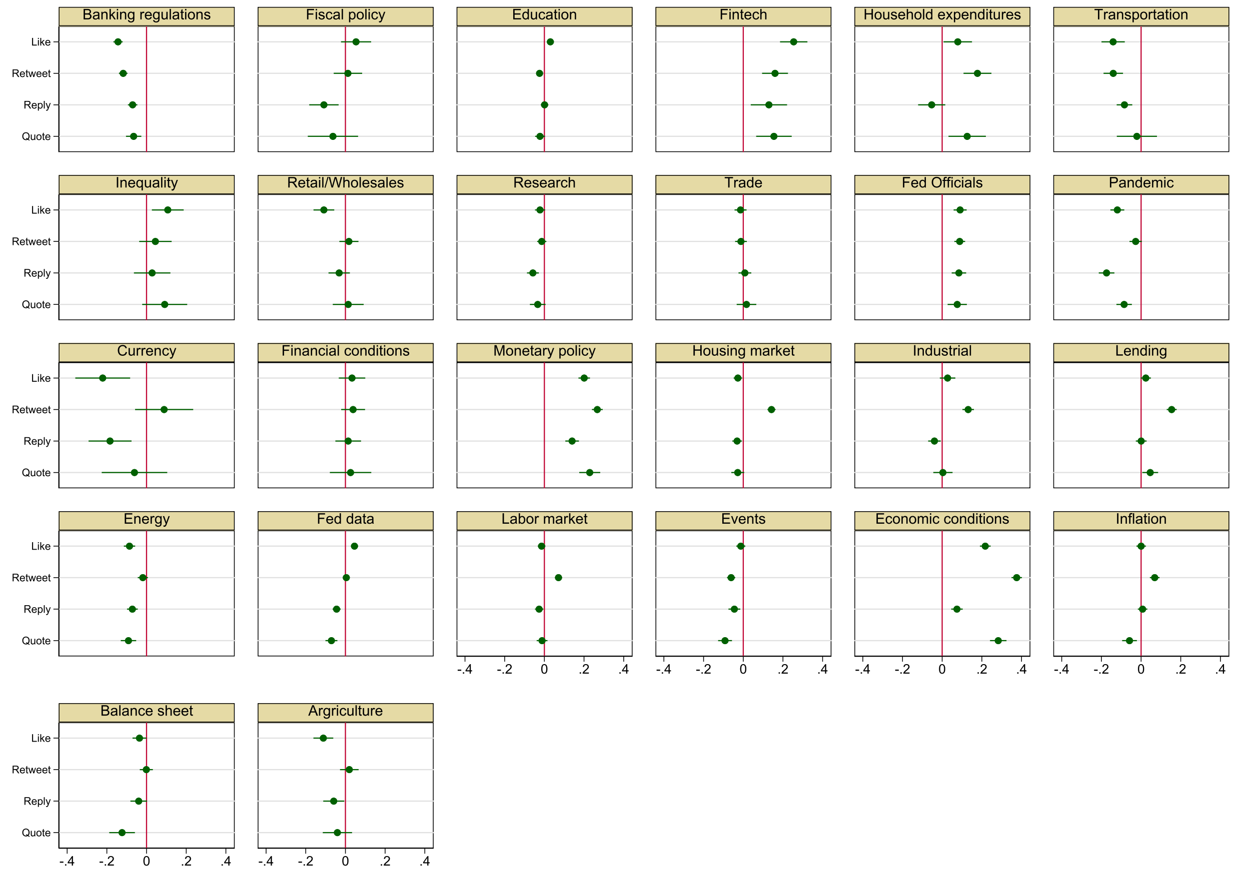


Fig. 9. Intensive margin (narrow topics).
Notes: This figure shows the estimates for 27 narrow topics in the intensive margin analysis of reactions to the Fed tweets.

expectation signals in the nuanced text (Prabhumoye et al., 2021).[13] Specifically, we employ the SetFit framework (Tunstall et al., 2022), which involved the following steps.

Step #1	A small corpus of 307 sentences/phrases referring to inflation expectations was constructed by using the post-2012 inflation-related Fed tweets as guidance. Three research assistants independently annotated each sentence as either 0 (lower inflation), 1 (no change in inflation), or 2 (higher inflation).
Step #2	Contrastive learning: • Generate sentence pairs by in-class and out-class selection from the small corpus (e.g., a sentence in label class 0 is paired with a sentence in label class 1 or a sentence in label class 2 is paired with another sentence in the same class) • 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 (i.e., the loss class is CosineSimilarityLoss)
Step #3	The classification head is trained on the embeddings from the fine-tuned transformer model.

We performed a hyperparameter search and found the following fine-tuned hyperparameters: learning rate of 1e-6, batch size of 32, maximum number of text pairs to be generated for contrastive learning, and number of epochs of 15. After training, we apply the trained classifier on a subset of *Fed mentions* that include “price” in the tweets. This subset contains 10,936 tweets posted by 4,951 unique users, of which about 5 % were classified as *Media*, 3.5 % were classified as *Economist*, and 2-2.6 % were classified as either *Finance, Manager*, or *Academic*.

To understand the performance of this approach in producing qualitative inflation expectation measures, for any given day d, we calculate the “balance” statistic to construct a monthly Twitter-based inflation expectation (IE) indicator as follows:

$$IE_t^{Twitter} = \frac{\sum Mentions^{Higher} - \sum Mentions^{Lower}}{All\ ''Price''\ mentions_t}$$

[13] See Appendix Table B4 for examples of inflation expectation classification outputs.

Table 4
Engagement with the Fed – By content.

	Dependent variable:								
	Mentions	*Sentiment*^{M}	*Economic sentiment*^{M}	*Irony*^{M}	*Monetary economics*^{M}	*Macroeconomics (Others)*^{M}	*Other sectors*^{M}	*Banking sector*^{M}	*HHI*^{Topics}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FOMC$^{\text{Unchange}}$	0.636***	−0.004	−0.003	0.022***	1.422***	0.717***	0.402***	0.315***	0.011***
	(0.051)	(0.008)	(0.007)	(0.006)	(0.084)	(0.077)	(0.075)	(0.080)	(0.003)
FOMC$^{\text{Change}}$	1.121***	−0.020	0.025	0.029***	1.795***	1.331***	1.038***	0.951***	0.013**
	(0.122)	(0.025)	(0.029)	(0.009)	(0.113)	(0.095)	(0.131)	(0.122)	(0.005)
ln(EPU)	0.032*	−0.006	0.002	−0.001	0.100***	0.068***	0.043	0.019	0.002**
	(0.019)	(0.004)	(0.003)	(0.002)	(0.028)	(0.023)	(0.027)	(0.026)	(0.001)
ln(Monetary economics)	0.030**	−0.004	−0.000	−0.002	0.270***	0.041**	−0.006	0.004	0.001
	(0.012)	(0.003)	(0.002)	(0.002)	(0.022)	(0.019)	(0.019)	(0.021)	(0.001)
ln(Macroeconomics (Others))	−0.014	0.002	0.003	0.002	−0.067**	0.221***	−0.019	−0.039	−0.003*
	(0.016)	(0.004)	(0.003)	(0.002)	(0.029)	(0.025)	(0.024)	(0.027)	(0.002)
ln(Other sectors)	−0.019	−0.005	−0.002	−0.002	0.015	−0.021	0.173***	−0.058**	0.000
	(0.015)	(0.003)	(0.003)	(0.002)	(0.028)	(0.024)	(0.025)	(0.025)	(0.001)
ln(Banking sector)	−0.014	0.004	0.003	−0.005**	−0.011	−0.010	0.001	0.124***	0.001
	(0.016)	(0.003)	(0.003)	(0.002)	(0.029)	(0.024)	(0.025)	(0.026)	(0.001)
Sentiment	−0.281*	0.179***	0.061***	−0.019	0.052	0.071	−0.244	−0.270	0.014*
	(0.145)	(0.030)	(0.023)	(0.018)	(0.228)	(0.203)	(0.213)	(0.212)	(0.007)
Economic sentiment	−0.164*	−0.036*	0.071***	0.006	−0.272*	−0.208	−0.251**	−0.122	0.004
	(0.091)	(0.019)	(0.015)	(0.013)	(0.155)	(0.129)	(0.125)	(0.147)	(0.006)
ln(Fed accounts)	0.350***	0.007	0.010	−0.003	0.238***	0.298***	0.347***	0.219***	−0.008***
	(0.045)	(0.009)	(0.008)	(0.006)	(0.073)	(0.071)	(0.062)	(0.067)	(0.003)
ln(Fed tweets)	0.556***	0.032***	0.004	0.020***	0.383***	0.405***	0.389***	0.512***	0.006
	(0.049)	(0.010)	(0.008)	(0.007)	(0.080)	(0.074)	(0.070)	(0.078)	(0.004)
Obs.	2,445	2,445	2,445	2,445	2,341	2,397	2,402	2,409	2,445
R-squared	0.749	0.235	0.138	0.235	0.536	0.622	0.580	0.626	0.084

Notes: This table reports the results for the indirect engagement with the Fed. *Mentions* is the natural log of all Fed mentions posted on a given day. *Sentiment*^{M} and *Economic sentiment*^{M} are the daily weighted general sentiment and economic sentiment of the Fed mentions. *Irony*^{M} is the daily weighted ironic score. The dependent variable in Columns (5)-(8) is the natural log of the number of Fed mentions referring to monetary economics, other macroeconomic topics, other sectors, and banking sector, respectively. *HHI*^{M} is the Herfindahl–Hirschman index of Fed mentions by topics. *FOMC*^{Unchange} equals to 1 for the FOMC days with no change in target rate and 0 otherwise. *FOMC*^{Change} equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *ln(Monetary economics)* is the natural log of Fed tweets discussing monetary economic-related topics. *ln(Macroeconomics (Others))* is the natural log of Fed tweets discussing other macroeonomic-related topics. *ln(Banking sector)* is the natural log of Fed tweets discussing banking sector topics. *ln(Other sectors)* is the natural log of Fed tweets discussing topics related to other sectors. *ln(Fed tweets)* is the natural log of all Fed tweets on a given day. *ln(Fed accounts)* is the natural log of the number of Fed accounts tweeting on a given day. *Sentiment* is the daily weighted general sentiment of the Fed tweets. *Economic sentiment* is the daily weighted economic sentiment of the Fed tweets. In all estimations, a constant term as well as day of month, month of year, and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

Table 5
Engagement with the Fed—By user groups.

	Dependent variable:							
	Mentioners (1)	*Followers^M* (2)	*Public* (3)	*Media* (4)	*Economist* (5)	*Finance* (6)	*Manager* (7)	*HHI^{Users}* (8)
FOMC^{Unchange}	0.638***	0.818***	0.590***	1.081***	0.748***	0.549***	0.682***	−0.053***
	(0.046)	(0.079)	(0.053)	(0.072)	(0.095)	(0.099)	(0.100)	(0.009)
FOMC^{Change}	1.153***	1.178***	1.060***	1.852***	1.105***	0.989***	1.255***	−0.069***
	(0.115)	(0.152)	(0.126)	(0.129)	(0.118)	(0.180)	(0.173)	(0.016)
ln(EPU)	0.038**	−0.019	0.035*	0.070**	0.036	0.028	0.050	0.004
	(0.017)	(0.033)	(0.020)	(0.027)	(0.030)	(0.031)	(0.033)	(0.004)
ln(Monetary economics)	0.020*	0.030	0.025*	0.087***	0.051**	0.045*	−0.022	−0.005
	(0.012)	(0.025)	(0.013)	(0.022)	(0.023)	(0.023)	(0.026)	(0.003)
ln(Macroeconomics (Others))	−0.007	−0.045	−0.016	−0.031	0.031	−0.053*	−0.046	−0.002
	(0.015)	(0.034)	(0.017)	(0.029)	(0.030)	(0.030)	(0.032)	(0.004)
ln(Other sectors)	−0.017	0.010	−0.014	−0.048*	−0.031	−0.042	−0.051	0.004
	(0.014)	(0.033)	(0.016)	(0.029)	(0.031)	(0.029)	(0.033)	(0.004)
ln(Banking sector)	−0.002	−0.031	−0.014	−0.021	−0.003	0.006	0.030	0.002
	(0.015)	(0.033)	(0.017)	(0.028)	(0.030)	(0.031)	(0.033)	(0.004)
Sentiment	−0.228*	−0.140	−0.303**	−0.276	0.010	−0.460*	−0.227	−0.032
	(0.138)	(0.268)	(0.152)	(0.250)	(0.259)	(0.277)	(0.294)	(0.032)
Economic sentiment	−0.155*	−0.117	−0.133	−0.387**	−0.275*	−0.161	−0.089	0.034
	(0.083)	(0.181)	(0.096)	(0.156)	(0.162)	(0.165)	(0.185)	(0.021)
ln(Fed accounts)	0.339***	0.315***	0.324***	0.409***	0.164**	0.087	−0.035	−0.039***
	(0.043)	(0.089)	(0.047)	(0.079)	(0.081)	(0.081)	(0.092)	(0.011)
ln(Fed tweets)	0.498***	0.131	0.516***	0.862***	0.450***	0.557***	0.549***	−0.047***
	(0.046)	(0.095)	(0.052)	(0.083)	(0.086)	(0.083)	(0.093)	(0.011)
Obs.	2,445	2,445	2,445	2,338	2,050	2,090	2,001	2,445
R-squared	0.766	0.119	0.734	0.512	0.515	0.404	0.227	0.302

Notes: This table reports the results for the indirect engagement with the Fed by user groups. *Mentioners* is the natural log of unique users who mention the Fed on a given day. *Followers^M* is the natural log of the average follower counts of the mentioners. *Public, Media, Economist, Finance*, and *Manager* is the natural log of unique users who mention the Fed and belong to the respective groups. *HHI^{Users}* is the Herfindahl–Hirschman index of Fed mentions by groups of users. *FOMC^{Unchange}* equals to 1 for the FOMC days with no change in target rate and 0 otherwise. *FOMC^{Change}* equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). ***ln(Monetary economics)*** is the natural log of Fed tweets discussing monetary economic-related topics. ***ln(Macroeconomics (Others))*** is the natural log of Fed tweets discussing other macroeonomic-related topics. ***ln(Banking sector)*** is the natural log of Fed tweets discussing banking sector topics. ***ln(Other sectors)*** is the natural log of Fed tweets discussing topics related to other sectors. ***ln(Fed tweets)*** is the natural log of all Fed tweets on a given day. ***ln(Fed accounts)*** is the natural log of the number of Fed accounts tweeting on a given day. ***Sentiment*** is the daily weighted general sentiment of the Fed tweets. ***Economic sentiment*** is the daily weighted economic sentiment of the Fed tweets. In all estimations, a constant term as well as day of month, month of year, and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

where $Mentions^{Higher}$ is the number of tweets having the predicted label of 2, $Mentions^{Lower}$ is the number of tweets with the predicted label of 0. The alternative measure is weighted by the predicted probability: $wIE_t^{Twitter} = \frac{\sum Probability^{Higher} - \sum Probability^{Lower}}{All\ \text{"Price"}\ mentions_t}$.

To gauge the correlation between our Twitter-based inflation expectations measure and the survey-based ones, we use data from the Michigan Survey of Consumers and the Federal Reserve Bank of New York's Survey of Consumer Expectations data to generate monthly survey-based indicators: the expected inflation rate ($Rate^{MICH}$ and $Rate^{NY}$), the balance statistics (IE^{MICH} and IE^{NY}), and the first difference of the balance statistics (ΔIE^{MICH} and ΔIE^{NY}). As shown in Column (1) of Table 8, the correlation coefficient between monthly *Twitter-based IE* and monthly IE^{MICH} is small (0.03) and the coefficient of the correlation with the monthly IE^{NY} is even negative (−0.03). The poor performance of our index could be due to the sampling issues as the Twitter-based measure is calculated using a few data points for some months. To partially address this problem, we restrict the sample further to include only the observations of which $IE^{Twitter}$ is calculated using more than the median number of tweets. The estimates yield somewhat higher correlations: 0.09 for IE^{MICH} and 0.12 for IE^{NY} (Column 2). The *Twitter-based IE* measure seems to be more correlated with *changes* in inflation expectations: the correlations are 0.19 for ΔIE^{MICH} and 0.27 for ΔIE^{NY}. Our measure is also correlated with the survey-based expected inflation rates (Rows 1 and 4) and the actual month-on-month inflation rate (Row 7). Particularly, the correlation coefficients with $Rate^{MICH}$ and $Rate^{NY}$ are ≈0.2-0.3, while the correlation coefficients with the month-on-month inflation are ≈0.4-0.5.[14] These findings suggest that our inflation expectations measure could be a mixture of expectations and perceptions. That is, our measure could indicate either (1) Twitter users' expected price changes in the future (given the correlations with the survey-based inflation expectations) or (2) Twitter users' perceived inflations in the past/present (given the correlations with the actual inflation rates).

While our Twitter-based inflation expectations measures are not representative and by no means the most accurate indicator of inflation expectations, our Twitter-based measures and the corresponding approach could open new venues for future research. For

[14] Similar patterns are observed when we use the weighted Twitter-based measure.

Table 6
Engagement with the Fed on economic-related topics—By user groups.

	Dependent variable:				
	Public (1)	Media (2)	Economist (3)	Finance (4)	Manager (5)
$FOMC^{Unchange}$	0.751***	1.107***	0.713***	0.405***	0.357***
	(0.062)	(0.075)	(0.092)	(0.093)	(0.103)
$FOMC^{Change}$	1.221***	1.709***	1.047***	0.629***	0.902***
	(0.092)	(0.106)	(0.138)	(0.225)	(0.162)
ln(EPU)	0.058***	0.066**	−0.001	0.040	0.016
	(0.021)	(0.029)	(0.031)	(0.032)	(0.032)
ln(Monetary economics)	0.054***	0.101***	0.010	0.073***	0.013
	(0.016)	(0.024)	(0.025)	(0.025)	(0.027)
ln(Macroeconomics (Others))	0.020	−0.020	0.026	−0.008	−0.020
	(0.020)	(0.031)	(0.031)	(0.030)	(0.033)
ln(Other sectors)	0.028	−0.044	0.003	−0.040	−0.055
	(0.019)	(0.030)	(0.031)	(0.030)	(0.034)
ln(Banking sector)	0.024	0.008	0.033	−0.019	0.063*
	(0.021)	(0.030)	(0.032)	(0.033)	(0.036)
Sentiment	−0.144	−0.357	−0.059	−0.089	−0.343
	(0.177)	(0.266)	(0.282)	(0.284)	(0.312)
Economic sentiment	−0.194	−0.236	−0.050	−0.185	0.101
	(0.123)	(0.171)	(0.177)	(0.162)	(0.193)
ln(Fed accounts)	0.316***	0.118	0.147	0.022	−0.168*
	(0.054)	(0.081)	(0.090)	(0.079)	(0.101)
ln(Fed tweets)	0.386***	0.644***	0.266***	0.266***	0.250***
	(0.061)	(0.089)	(0.095)	(0.085)	(0.096)
Obs.	2,442	1,989	1,469	1,303	1,132
R-squared	0.696	0.329	0.401	0.296	0.177

Notes: This table reports the results for the indirect engagement with the Fed on the economic-related topics by user groups. *Public, Media, Economist, Finance*, and *Manager* is the natural log of unique users who mention the Fed and belong to the respective groups. $FOMC^{Unchange}$ equals to 1 for the FOMC days with no change in target rate and 0 otherwise. $FOMC^{Change}$ equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *ln(Monetary economics)* is the natural log of Fed tweets discussing monetary economic-related topics. *ln(Macroeconomics (Others))* is the natural log of Fed tweets discussing other macroeonomic-related topics. *ln (Banking sector)* is the natural log of Fed tweets discussing banking sector topics. *ln(Other sectors)* is the natural log of Fed tweets discussing topics related to other sectors. *ln(Fed tweets)* is the natural log of all Fed tweets on a given day. *ln(Fed accounts)* is the natural log of the number of Fed accounts tweeting on a given day. *Sentiment* is the daily weighted general sentiment of the Fed tweets. *Economic sentiment* is the daily weighted economic sentiment of the Fed tweets. In all estimations, a constant term as well as day of month, month of year, and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

example, when applied to a more appropriate/comprehensive dataset, the proposed approach can generate a good proxy of qualitative inflation expectations. Because inflation expectations appear to be driven mainly by the extensive margin (there is positive inflation vs. zero inflation rather than variations in the magnitude of positive inflation; see Andrade et al., 2023), such a proxy can provide a useful real-time diagnostic for central banks. Additionally, it can also be combined with the taxonomy construction framework discussed in Section 2.2.2 to elicit inflation expectations for different groups of economic agents (e.g., economic experts vs. non-experts).

Having documented that the Twitter-based measure can capture some inflation perceptions/expectation signals, we now turn our attention to investigating whether there is any link between the Fed's tweeting activities and the inflation expectation signals expressed in the Fed mentions. The results in Panel A of Table 9 suggest that Twitter users tend to express lower inflation perceptions/expectations on days when FOMC meetings take place and no policy changes are made. Given that the Twitter-based measures are constructed based on the subset of *Fed mentions*, this result can be interpreted as suggesting a larger impact of Fed "information" on inflation perceptions of more "Fed-attentive" agents. Thus, it lends some support to Lamla and Vinogradov (2019), who show that following FOMC announcements, informed economic agents tend to update their inflation perceptions downwards. In contrast, more (economic) positive Fed tweets, suggesting higher economic growth or improvement of economic conditions, correlate with more Fed mentions that indicate higher inflation expectations/perceptions.[15] This finding echoes a recent study by Pinter and Kočenda (2023), showing that negative sentiment of media reports on central bank announcements leads to a reduction in price expectations for both firms and consumers.

As expected, the inflation expectation signals expressed in the Fed mentions are highly responsive to the actual inflation rate. At the same time, the estimated coefficients for other Fed-activity indicators are in the expected direction but statistically insignificant. This is broadly in line with the existing studies, which show that central bank communication (news) has limited influence on households'

[15] We also regress the monthly survey-based inflation expectation measures on the monthly tweeting activities of the Fed and report the results in Appendix Table A4. The results for the link between Fed tweets' sentiment and inflation expectations are generally in line with those reported in the main text.

Table 7
Spread of engagement with the Fed on economic-related topics.

	Dependent variable:				
	$Spread^{Public}$ (1)	$Spread^{Media}$ (2)	$Spread^{Economist}$ (3)	$Spread^{Finance}$ (4)	$Spread^{Manager}$ (5)
$FOMC^{Unchange}$	0.633***	1.043***	0.755***	0.440*	−0.305
	(0.107)	(0.163)	(0.230)	(0.238)	(0.247)
$FOMC^{Change}$	1.028***	1.823***	1.239***	0.646*	0.536**
	(0.153)	(0.303)	(0.407)	(0.371)	(0.247)
ln(EPU)	0.055	0.095	0.192**	0.142	−0.079
	(0.037)	(0.066)	(0.077)	(0.094)	(0.107)
ln(Monetary economics)	0.056*	0.120**	−0.006	0.088	−0.048
	(0.029)	(0.053)	(0.062)	(0.064)	(0.077)
ln(Macroeconomics (Others))	0.010	0.028	−0.098	0.033	−0.068
	(0.038)	(0.066)	(0.088)	(0.086)	(0.104)
ln(Other sectors)	0.047	0.023	−0.143*	−0.029	−0.125
	(0.037)	(0.066)	(0.075)	(0.077)	(0.095)
ln(Banking sector)	0.073**	0.093	0.045	-0.043	0.050
	(0.037)	(0.071)	(0.081)	(0.088)	(0.106)
Sentiment	0.208	-0.494	-0.274	0.723	-1.134
	(0.306)	(0.637)	(0.642)	(0.731)	(1.001)
Economic sentiment	−0.320*	−0.628	−0.106	−0.213	0.880
	(0.192)	(0.426)	(0.451)	(0.506)	(0.615)
ln(Fed accounts)	0.328***	0.229	−0.444**	0.030	−0.093
	(0.101)	(0.199)	(0.222)	(0.245)	(0.284)
ln(Fed tweets)	0.410***	0.124	0.709***	0.147	0.435
	(0.108)	(0.189)	(0.230)	(0.256)	(0.283)
Obs.	2,331	1,676	1,103	829	757
R-squared	0.717	0.317	0.307	0.234	0.151

Notes: This table reports the results for the spread of engagement with the Fed on economic-related topics. In Columns (1)-(5), the dependent variable is the natural log of total number of reactions (likes, retweets, replies, and quotes) to Fed mentions which (1) talk about the economic-related topics and (2) are created by the general public accounts, media accounts, economists, finance accounts, and firm managers, respectively. $FOMC^{Unchange}$ equals to 1 for the FOMC days with no change in target rate and 0 otherwise. $FOMC^{Change}$ equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *ln(Monetary economics)* is the natural log of Fed tweets discussing monetary economic-related topics. *ln(Macroeconomics (Others))* is the natural log of Fed tweets discussing other macroeonomic-related topics. *ln(Banking sector)* is the natural log of Fed tweets discussing banking sector topics. *ln(Other sectors)* is the natural log of Fed tweets discussing topics related to other sectors. *ln(Fed tweets)* is the natural log of all Fed tweets on a given day. *ln(Fed accounts)* is the natural log of the number of Fed accounts tweeting on a given day. *Sentiment* is the daily weighted general sentiment of the Fed tweets. *Economic sentiment* is the daily weighted economic sentiment of the Fed tweets. In all estimations, a constant term as well as day of month, month of year, and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

inflation expectations (Lamla and Vinogradov, 2019; Coibion et al., 2020; Sheen and Wang, 2023).

We also look into the heterogeneous effects of the sentiment of the Fed tweets during periods of zero lower bound (ZLB) and no ZLB (Panel B of Table 9).[16] We find that the significant and positive link between the Fed tweets' economic sentiment and inflation expectations/perceptions is more discernable during the ZLB periods. One potential explanation is that during the prolonged ZLB periods, positive Fed tweets in the economic sense, in addition to indicating good economic conditions, could also imply that the Fed is satisfied with the current policy. Consequently, it could be a signal of the Fed's commitment to keeping nominal interest rates low, hence increasing inflation expectations/perceptions.

6. Conclusion

The need to improve central bank transparency has called for adopting new communication channels. Because communication via social media has become increasingly important given the rapid growth in social media usage generally and the use of social media as an information source particularly, it is vital to understand how central bank communication is conducted in social media and its effectiveness. In this study, we take up this task by examining the Federal Reserve System's communication on Twitter.

Analyzing the content of tweets posted by the Federal Reserve Board's and the regional Fed's Twitter accounts, we show that Twitter is used to disseminate and discuss both central banking business (e.g., monetary policy, the state of the economy) and other issues including financial risk, fiscal policy, or community-related issues. However, not all topics receive equal attention as Twitter users are more likely to react to (like or retweet) or engage with (reply to or quote) the content discussing macroeconomic-related issues. Among these, users pay the highest attention to the Fed tweets about monetary policy and economic conditions.

[16] We define the periods of negative shadow rate (Wu and Xia, 2016) as ZLB periods, i.e., January 2012 – November 2015 and November – December 2020.

Table 8
Correlations between Twitter-based and survey-based inflation expectation measures.

Row	Variables	$IE^{Twitter}$ (1)	$wIE^{Twitter}$ (2)
1	$Rate^{MICH}$	0.220*	0.230*
		(0.022)	(0.098)
2	IE^{MICH}	0.031	0.093
		(0.749)	(0.510)
3	ΔIE^{MICH}	0.067	0.193
		(0.495)	(0.166)
4	$Rate^{NY}$	0.032	0.084
		(0.764)	(0.553)
5	IE^{NY}	−0.025	0.124
		(0.812)	(0.382)
6	ΔIE^{NY}	0.188*	0.269*
		(0.076)	(0.053)
7	MoM^{Infl}	0.406*	0.485*
		(0.000)	(0.000)

Notes: This table reports the correlation coefficients between the Twitter-based inflation expectation measures and the survey-based measures. $IE^{Twitter}$ is the Twitter-based balance statistic calculated as $\frac{\sum Mentions^{Higher} - \sum Mentions^{Lower}}{All \text{ "}Price\text{" } mentions}$. $wIE^{Twitter}$ is the Twitter-based balance statistic weighted by probability. $Rate^{MICH}$ is the monthly expected inflation rate reported in the Michigan Survey of Consumers. $Rate^{NY}$ is the median of the monthly expected inflation rates reported in the Federal Reserve Bank of New York's Survey of Consumer Expectations. IE^{MICH} and IE^{NY} are the Michigan survey-based and Fed New York survey-based balance statistics. ΔIE^{MICH} and ΔIE^{NY} are the first difference of these balance statistics. MoM^{Infl} is the month-on-month inflation rate reported in the Michigan survey.

In the next part of the analysis, we classify Twitter users who retweeted a Fed's tweet or mentioned the Fed accounts into different groups. Most users are classified as the general public, as opposed to media, economists, non-economic-majored academics, individuals with financial knowledge, and firm managers. We find that media accounts are most active in engaging with the Fed (i.e., tagging the Fed accounts in their tweets), especially when discussing issues related to the macroeconomy. Their macroeconomic-related tweets are also more likely to be spread further to other users. These results suggest a few communication style strategies that can help attract more attention and engagement from the public. For example, central banks generally and the Fed particularly, should focus on discussing and disseminating information on the macroeconomy and especially central banking business. Additionally, instead of trying to engage with the general public directly, central banks could use the engagement with media on social media as an intermediary to engage with the general public.

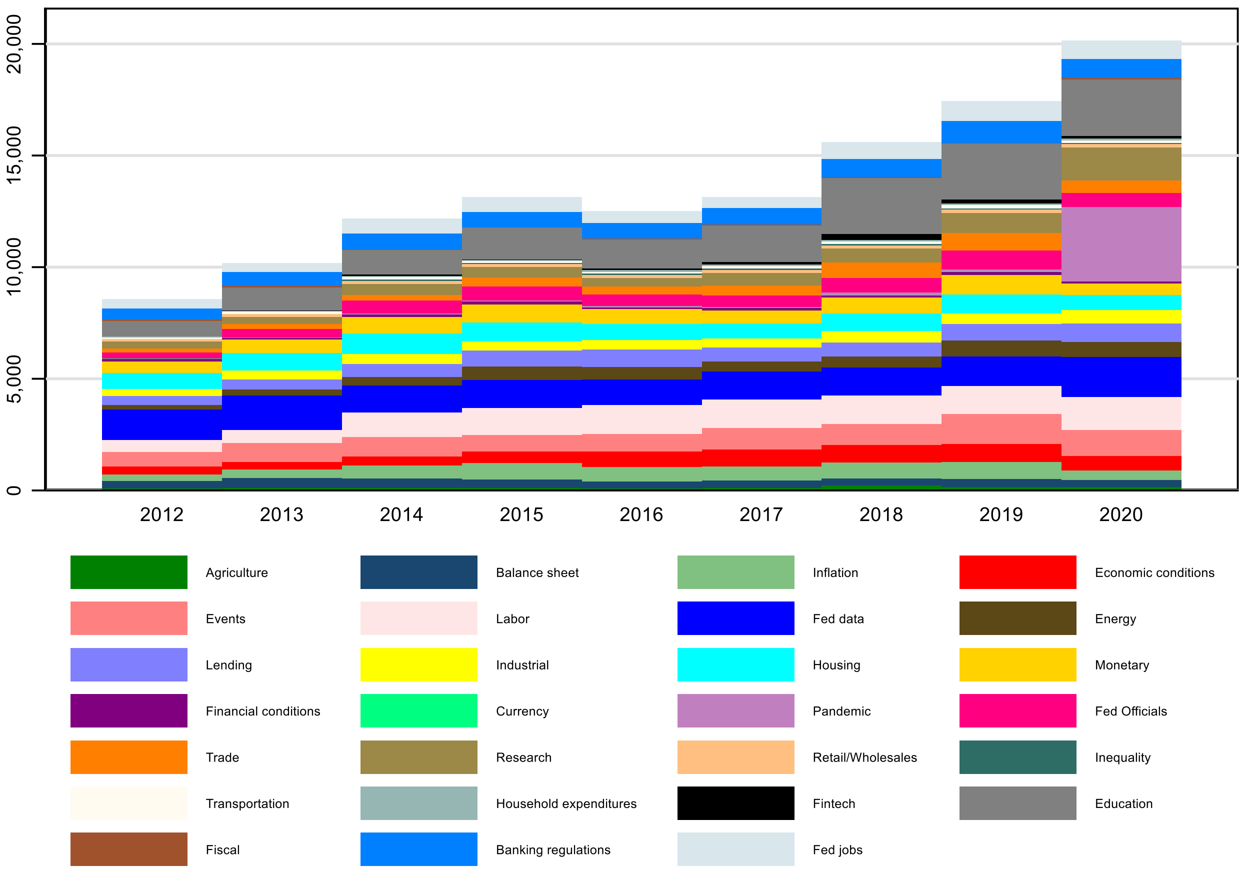
Finally, we elicit inflation expectation signals/inflation perceptions from the Fed mentions to examine the link between the Fed's tweeting activities and inflation expectations. Our results suggest that more Fed tweets with positive economic sentiment are associated with higher inflation expectations/perceptions expressed in Fed mentions, and this relationship is stronger during the zero lower bound periods (January 2012 – November 2015 and November – December 2020). This finding implies that social media communication could be used as an alternative unconventional tool to alter economic agents' expectations when the conventional policy tools cannot always be applied effectively (e.g., during the zero lower bound periods). That said, further research, ideally in a randomized control trial setup, is needed to understand the impacts of central bank communication on social media on inflation expectations.

Table 9
Impact on Twitter-based inflation expectations.

	Dependent variable:							
	$IE^{Twitter}$	$wIE^{Twitter}$	$Mentions^{Higher}$	$\mathrm{Mentions}^{\mathrm{Lower}}$	$IE^{Twitter}$	$wIE^{Twitter}$	$Mentions^{Higher}$	$Mentions^{Lower}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathrm{FOMC}^{\mathrm{Unchange}}$	−0.266***	−0.264***	−0.111***	0.059*	−0.259**	−0.256**	−0.108***	0.056
	(0.102)	(0.102)	(0.036)	(0.036)	(0.104)	(0.104)	(0.037)	(0.036)
$\mathrm{FOMC}^{\mathrm{Change}}$	0.043	0.073	0.006	−0.022	0.036	0.067	0.004	−0.019
	(0.123)	(0.123)	(0.047)	(0.042)	(0.122)	(0.122)	(0.047)	(0.042)
ln(EPU)	−0.016	−0.008	0.001	0.011	−0.021	−0.013	−0.001	0.012
	(0.057)	(0.056)	(0.020)	(0.019)	(0.058)	(0.056)	(0.020)	(0.020)
ln(Monetary economics)	0.037	0.035	0.004	−0.020*	0.038	0.037	0.004	−0.020*
	(0.033)	(0.033)	(0.012)	(0.011)	(0.033)	(0.032)	(0.012)	(0.011)
ln(Macroeconomics (Others))	0.050	0.052	0.019	−0.013	0.048	0.050	0.018	−0.012
	(0.051)	(0.050)	(0.018)	(0.017)	(0.050)	(0.050)	(0.018)	(0.017)
ln(Other sectors)	−0.064	−0.062	−0.020	0.021	−0.066	−0.064	−0.021	0.021
	(0.051)	(0.051)	(0.019)	(0.017)	(0.051)	(0.051)	(0.019)	(0.017)
ln(Banking sector)	0.013	0.017	0.003	−0.005	0.012	0.016	0.003	−0.005
	(0.047)	(0.047)	(0.017)	(0.015)	(0.047)	(0.047)	(0.017)	(0.015)
Sentiment	−0.246	−0.300	−0.146	0.011	−0.207	−0.262	−0.135	−0.003
	(0.393)	(0.376)	(0.138)	(0.130)	(0.394)	(0.375)	(0.138)	(0.130)
Economic sentiment	0.652**	0.754***	0.226**	−0.189**	0.359	0.457	0.140	−0.089
	(0.286)	(0.284)	(0.105)	(0.091)	(0.315)	(0.309)	(0.116)	(0.100)
ZLB					−0.116	−0.112	−0.032	0.042
					(0.116)	(0.115)	(0.041)	(0.037)
Economic sentiment × ZLB					1.194**	1.208**	0.352*	−0.408**
					(0.562)	(0.572)	(0.205)	(0.182)
ln(Fed accounts)	0.145	0.155	0.023	−0.069	0.147	0.157	0.024	−0.070
	(0.143)	(0.138)	(0.051)	(0.047)	(0.142)	(0.137)	(0.051)	(0.047)
ln(Fed tweets)	−0.201	−0.185	−0.056	0.072	−0.210	−0.195	−0.059	0.075*
	(0.137)	(0.134)	(0.050)	(0.045)	(0.135)	(0.132)	(0.049)	(0.044)
$\mathrm{MoM}^{\mathrm{Infl}}$	0.315***	0.314***	0.105***	−0.095***	0.347***	0.345***	0.114***	−0.107***
	(0.087)	(0.085)	(0.032)	(0.029)	(0.090)	(0.088)	(0.034)	(0.030)
Obs.	685	685	685	685	685	685	685	685
R-squared	0.168	0.169	0.155	0.158	0.175	0.176	0.159	0.166

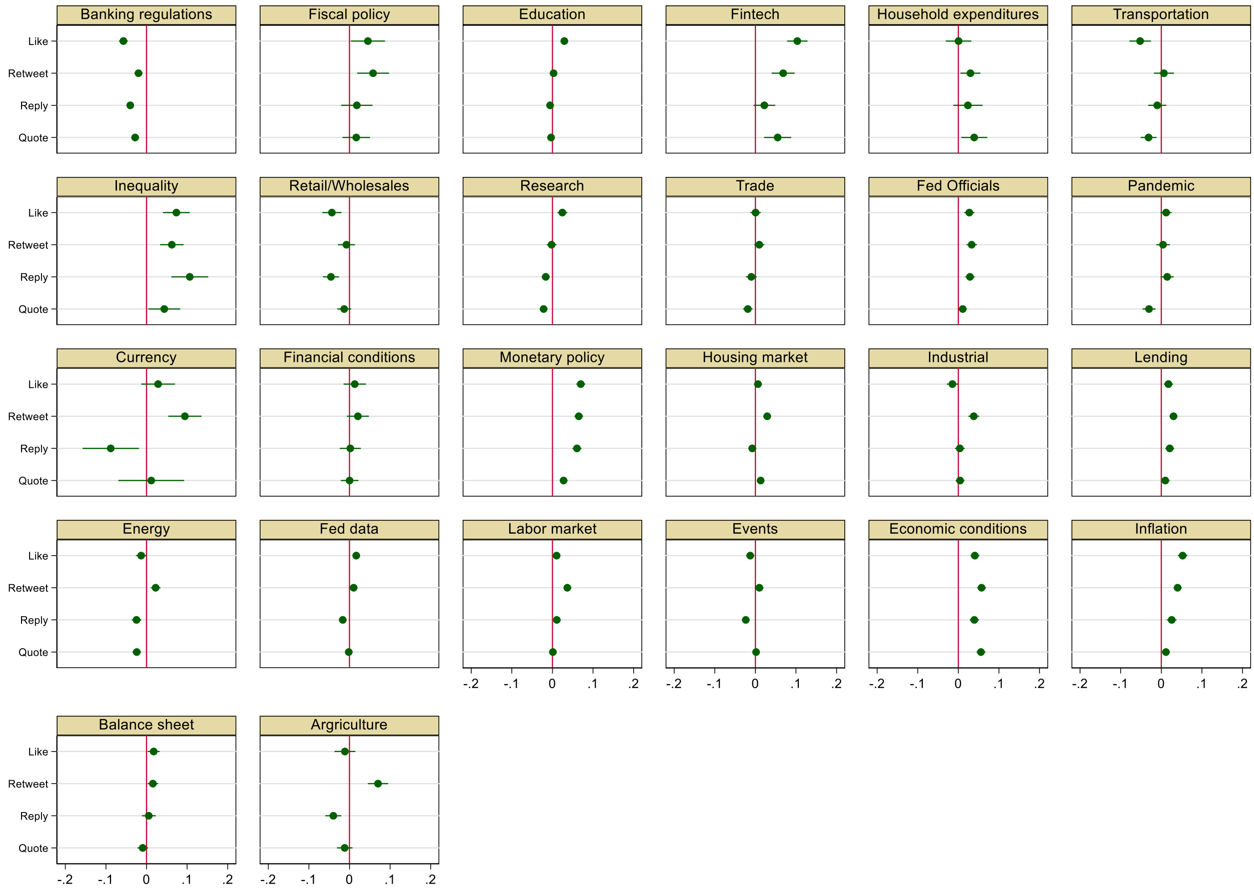
Notes: This table reports the results for the link between daily Fed's tweeting activities and daily Twitter-based inflation expectations expressed in the Fed mentions. $IE^{Twitter}$ is the Twitter-based balance statistic calculated as $\frac{\sum Mentions^{Higher} - \sum Mentions^{Lower}}{All\ ''Price''\ mentions}$. $wIE^{Twitter}$ is the Twitter-based balance statistic weighted by probability. $Mentions^{Higher}$ and $Mentions^{Lower}$ are the share of price-related Fed mentions indicating higher inflation perceptions and lower inflation perceptions, respectively. $FOMC^{Unchange}$ equals to 1 for the FOMC days with no change in target rate and 0 otherwise. $FOMC^{Change}$ equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *ln(Monetary economics)* is the natural log of Fed tweets discussing monetary economic-related topics. *ln(Macroeconomics (Others))* is the natural log of Fed tweets discussing other macroeonomic-related topics. *ln(Banking sector)* is the natural log of Fed tweets discussing banking sector topics. *ln(Other sectors)* is the natural log of Fed tweets discussing topics related to other sectors. *ln(Fed tweets)* is the natural log of all Fed tweets on a given day. *ln(Fed accounts)* is the natural log of the number of Fed accounts tweeting on a given day. *Sentiment* is the daily weighted general sentiment of the Fed tweets. *Economic sentiment* is the daily weighted economic sentiment of the Fed tweets. ZLB equals to 1 for the periods of negative shadow rates (Wu and Xia, 2016) and 0 otherwise. MoM^{Infl} is the month-on-month inflation rate reported in the Michigan survey. In all estimations, a constant term as well as day of month, month of year, and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

Appendix A. Data and Results



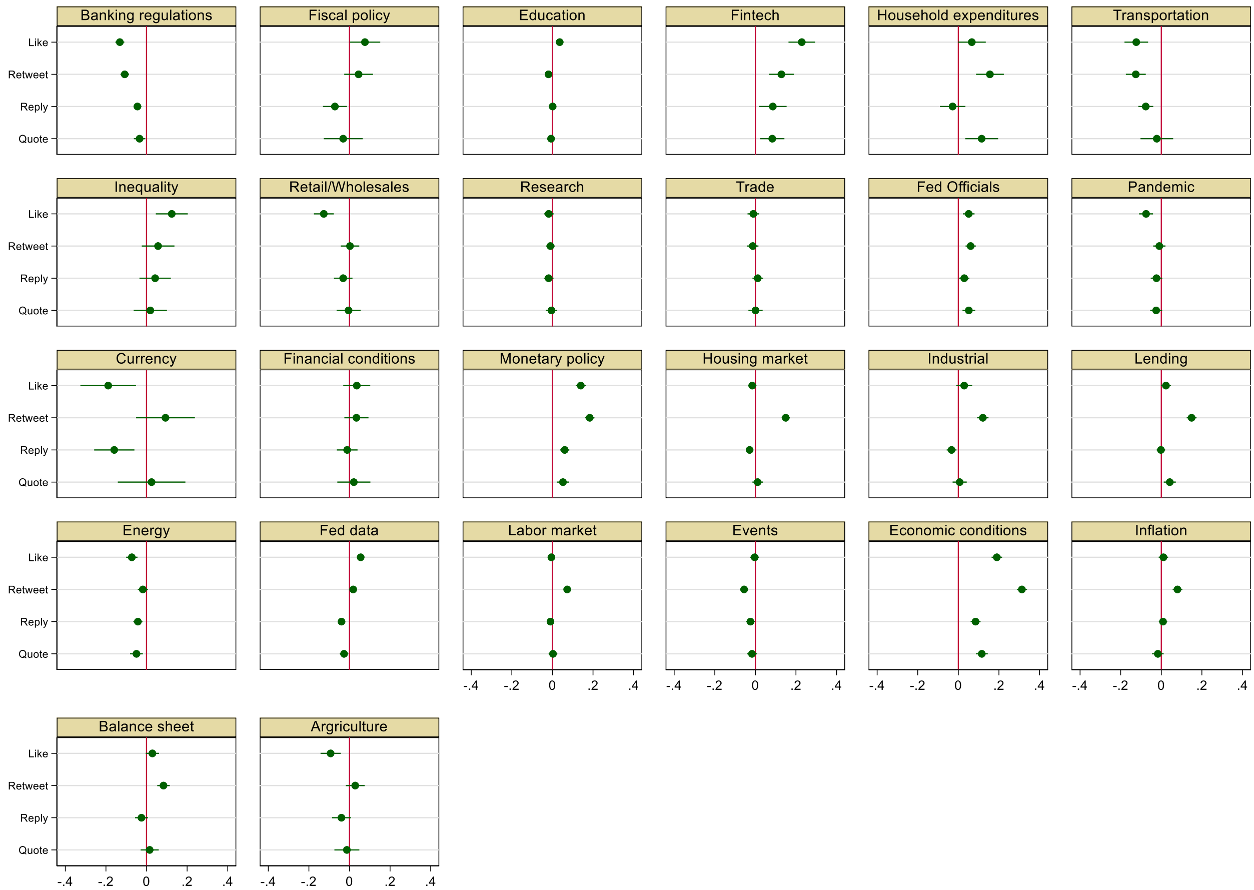
Appendix Figure A1.

Notes: This figure represents the number of all Fed tweets by 27 narrow topics. The tweet counts are not mutually exclusive across topics as one tweet can be counted multiple times if it belongs to multiple topics.



Appendix Figure A2. Extensive margin (narrow topics) - subsamples

Notes: This figure shows the estimates for 27 narrow topics in the extensive margin analysis of reactions to the Fed tweets. The extreme values (top 1 percentile) of the reaction count are excluded from the estimations.



Appendix Figure A3. Intensive margin (narrow topics) - subsamples
Notes: This figure shows the estimates for 27 narrow topics in the intensive margin analysis of reactions to the Fed tweets. The extreme values (top 1 percentile) of the reaction count are excluded from the estimations.

Appendix Table A1
Examples of viral tweets

In a possible future, cash disappears and central banks issue electronic money for all
What has no intrinsic value? Both bitcoin and the cash in your wallet. Learn other qualities they share
To honor Janet Yellen's extraordinary tenure & accomplishments at the federal reserve, her distinction as the first woman chair, & her inimitable style, we're sharing photos of our colleagues popping their collars–just like she does. #popyourcollar #womeninstem
Economics is awesome! economics is fun! economics helps good things happen! hooray for economics!#econome
Staff bids farewell to Chair Janet Yellen as she finishes her 4-year term
.@federalreserve seeks public comment on potential actions to facilitate real-time interbank settlement of faster payments:
Statement from federal reserve chair jerome h. powell:
Federal reserve announces extensive new measures to support the economy:
Dallas-fort worth economic indicators: in the labor market, employment rose an annualized 1.0 percent in may, and job growth in april was revised up to 1.8 percent. read more about business-cycle indexes and housing in #dfw ↘ʒ.
On june 27, the #gdpnow model estimate for real gdp growth in q2 2018 is 4.5 %

Notes: This table shows some examples of viral Fed tweets (the text was cleaned to remove urls).

Appendix Table A2
Extensive margin (broad topics) – subsamples

	Dependent variable:			
	Like^{D}	*Retweet*^{D}	*Reply*^{D}	*Quote*^{D}
	(1)	(2)	(3)	(4)
FOMC$^{\text{Unchange}}$	−0.016	0.011	−0.003	−0.009
	(0.011)	(0.012)	(0.008)	(0.010)
FOMC$^{\text{Change}}$	0.005	−0.032	−0.014	0.008
	(0.019)	(0.022)	(0.022)	(0.017)
Pandemic	0.012*	0.004	0.014*	−0.031***

(*continued on next page*)

Appendix Table A2 (*continued*)

	Dependent variable:			
	Like^D (1)	*Retweet^D* (2)	*Reply^D* (3)	*Quote^D* (4)
	(0.007)	(0.009)	(0.008)	(0.008)
Fed data	0.019***	0.010***	−0.016***	−0.002
	(0.004)	(0.003)	(0.004)	(0.003)
Monetary economics	0.064***	0.057***	0.045***	0.022***
	(0.004)	(0.004)	(0.004)	(0.003)
Macroeconomics (Others)	0.016***	0.040***	0.013***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Other sectors	−0.016***	0.029***	−0.018***	−0.005*
	(0.004)	(0.003)	(0.003)	(0.003)
Banking sector	−0.009**	0.010***	−0.009***	−0.008***
	(0.004)	(0.003)	(0.003)	(0.003)
Community	0.031***	0.005	−0.002	−0.002
	(0.004)	(0.004)	(0.003)	(0.003)
Fed	−0.003	0.010***	−0.008***	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment	0.042***	−0.046***	−0.017***	−0.025***
	(0.004)	(0.004)	(0.004)	(0.003)
Financial sentiment	−0.017***	0.003	−0.005**	−0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Is-retweet	−0.133***	−0.232***	−0.041***	0.009***
	(0.008)	(0.009)	(0.005)	(0.004)
Mention-Fed	0.032***	0.023***	−0.004	0.026***
	(0.006)	(0.007)	(0.005)	(0.005)
External-media	0.062***	0.094***	−0.028***	0.016***
	(0.007)	(0.010)	(0.005)	(0.005)
First-in-day	0.027***	0.026***	0.001	−0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Last-in-day	0.039***	0.029***	0.032***	−0.002
	(0.003)	(0.003)	(0.003)	(0.002)
First-in-Thread	0.104***	0.212***	0.028***	0.148***
	(0.008)	(0.009)	(0.006)	(0.008)
Last-in-Thread	−0.062***	−0.078***	−0.717***	−0.044***
	(0.007)	(0.008)	(0.007)	(0.008)
ln(EPU)	−0.001	0.004	−0.001	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)
Obs.	128,966	128,953	128,761	128,744
R-squared	0.260	0.168	0.274	0.169

Notes: This table shows the results for extensive margin. The extreme values (top 1 percentile) of the reaction count are excluded from the estimations. *Like^D, Retweet^D, Reply^D*, and *Quote^D* equal to 1 if the Fed retweet receives at least 1 like, retweet, reply, and quote, respectively and 0 otherwise. *FOMC^Unchange* equals to 1 for the FOMC days with no change in target rate and 0 otherwise. *FOMC^Change* equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *First-in-Day* equals to 1 if the tweet is the first tweet on a given day and 0 otherwise. *Last-in-Day* equals to 1 if the tweet the last tweet on a given day and 0 otherwise. *First-in-Thread* equals to 1 if the tweet is the beginning of a thread. *Last-inThread* equals to 1 if the tweet is the last tweet in a thread. *Is-retweet* equals to 1 if the tweet is a retweet and 0 otherwise. *Mention-Fed* equals to 1 if other Fed accounts were mentioned/tagged and 0 otherwise. *External-media* equals to 1 if the tweet contains photos, videos, or external URLs and 0 otherwise. *CentralBank* is a dummy variable which equals to 1 of the tweet mentions one of the following topics: *Pandemic, Fed data, Monetary economics, Macroeconomics (Others), Other sectors, Banking sector, Community,* and *Fed* equal to 1 if the tweet refers to the respective topic and 0 otherwise. *Sentiment* is the tweet's general sentiment weighted by the probability. *Economic sentiment* is the tweet's economic sentiment weighted by the probability. In all estimations, a constant as well as Fed account fixed effects, hour of day, day of week, day of month, month of year, and year fixed effects are included but not reported. The standard errors clustered by date of posting are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

Appendix Table A3
Intensive margin (broad topics) – subsamples.

	Dependent variable:			
	Like (1)	*Retweet* (2)	*Reply* (3)	*Quote* (4)
$FOMC^{Unchange}$	0.036	0.009	0.019	0.006
	(0.022)	(0.021)	(0.020)	(0.019)
$FOMC^{Change}$	0.014	0.073*	0.094***	0.063*
	(0.037)	(0.043)	(0.030)	(0.033)
Pandemic	−0.076***	−0.009	−0.023	−0.027*
	(0.018)	(0.015)	(0.014)	(0.015)
Fed data	0.059***	0.023***	−0.043***	−0.028***
	(0.009)	(0.008)	(0.008)	(0.011)

(*continued on next page*)

Appendix Table A3 (*continued*)

	Dependent variable:			
	Like (1)	*Retweet* (2)	*Reply* (3)	*Quote* (4)
Monetary economics	0.081***	0.145***	0.035***	0.032***
	(0.009)	(0.009)	(0.008)	(0.011)
Macroeconomics (Others)	0.049***	0.124***	0.015**	0.037***
	(0.007)	(0.007)	(0.007)	(0.009)
Other sectors	−0.045***	0.066***	−0.044***	−0.015*
	(0.008)	(0.007)	(0.006)	(0.009)
Banking sector	−0.021***	0.041***	−0.022***	0.014
	(0.008)	(0.008)	(0.007)	(0.009)
Community	0.039***	−0.014*	0.002	−0.008
	(0.008)	(0.008)	(0.008)	(0.009)
Fed	0.022***	−0.043***	−0.003	0.010
	(0.008)	(0.007)	(0.007)	(0.009)
Sentiment	0.110***	−0.094***	−0.008	−0.011
	(0.010)	(0.009)	(0.008)	(0.010)
Financial sentiment	−0.037***	−0.014***	−0.006	−0.007
	(0.005)	(0.005)	(0.004)	(0.006)
Is-retweet	−0.090***	−0.277***	0.013	−0.091***
	(0.016)	(0.015)	(0.016)	(0.030)
Mention-Fed	0.125***	0.048***	−0.013	−0.005
	(0.014)	(0.013)	(0.013)	(0.015)
External-media	0.139***	0.110***	−0.004	0.076***
	(0.018)	(0.014)	(0.009)	(0.015)
First-in-day	0.025***	0.041***	0.007	−0.015*
	(0.007)	(0.007)	(0.007)	(0.009)
Last-in-day	0.042***	0.058***	0.066***	0.015*
	(0.007)	(0.006)	(0.007)	(0.009)
First-in-Thread	0.509***	0.524***	0.181***	0.128***
	(0.020)	(0.020)	(0.012)	(0.018)
Last-in-Thread	−0.260***	−0.250***	−0.039***	−0.080***
	(0.016)	(0.016)	(0.011)	(0.016)
ln(EPU)	0.019***	0.017***	0.008	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
Obs.	88,171	99,484	34,066	19,199
R-squared	0.313	0.304	0.188	0.070

Notes: This table shows the results for intensive margin. The extreme values (top 1 percentile) of the reaction count are excluded from the estimations. *Like, Retweet, Reply*, and *Quote* are the natural log of the number of likes, retweets, replies, and quotes received by a Fed tweet, respectively. $FOMC^{Unchange}$ equals to 1 for the FOMC days with no change in target rate and 0 otherwise. $FOMC^{Change}$ equals to 1 on the FOMC days with changes in policy and 0 otherwise. *ln(EPU)* is the natural log of the economic policy uncertainty index (Baker et al., 2016). *First-in-Day* equals to 1 if the tweet is the first tweet on a given day and 0 otherwise. *Last-in-Day* equals to 1 if the tweet the last tweet on a given day and 0 otherwise. *First-in-Thread* equals to 1 if the tweet is the beginning of a thread. *Last-inThread* equals to 1 if the tweet is the last tweet in a thread. *Is-retweet* equals to 1 if the tweet is a retweet and 0 otherwise. *Mention-Fed* equals to 1 if other Fed accounts were mentioned/tagged and 0 otherwise. *External-media* equals to 1 if the tweet contains photos, videos, or external URLs and 0 otherwise. *CentralBank* is a dummy variable which equals to 1 of the tweet mentions one of the following topics: *Pandemic, Fed data, Monetary economics, Macroeconomics (Others), Other sectors, Banking sector, Community,* and *Fed* equal to 1 if the tweet refers to the respective topic and 0 otherwise. *Sentiment* is the tweet's general sentiment weighted by the probability. *Economic sentiment* is the tweet's economic sentiment weighted by the probability. In all estimations, a constant as well as Fed account fixed effects, hour of day, day of week, day of month, month of year, and year fixed effects are included but not reported. The standard errors clustered by date of posting are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

Appendix Table A4
Fed's tweeting activities and survey-based inflation expectations.

	Dependent variable:					
	$Rate^{MICH}$ (1)	IE^{MICH} (2)	ΔIE^{MICH} (3)	$Rate^{NY}$ (4)	IE^{NY} (5)	ΔIE^{NY} (6)
ln(Monetary economics)	−0.102	0.680***	−0.022	−0.153	0.098	−0.908***
	(0.091)	(0.251)	(0.359)	(0.153)	(0.346)	(0.327)
ln(Macroeconomics (Others))	−0.128	0.630	0.676	0.175	0.404	−0.248
	(0.161)	(0.491)	(0.569)	(0.400)	(0.630)	(0.552)
ln(Other sectors)	0.211	0.567	0.985	0.088	1.342*	0.841
	(0.154)	(0.423)	(0.605)	(0.225)	(0.687)	(0.908)
ln(Banking sector)	−0.245	−0.488	0.351	0.092	−0.706	−0.236
	(0.177)	(0.384)	(0.610)	(0.214)	(0.588)	(0.650)
Sentiment	−0.256	8.929***	2.685	-1.374	6.287*	-1.318
	(0.862)	(2.995)	(3.343)	(1.287)	(3.654)	(3.226)
Economic sentiment	-1.538*	2.984	-4.943	2.457*	4.351*	-3.492

(*continued on next page*)

Appendix Table A4 (*continued*)

	Dependent variable:					
	$Rate^{MICH}$	IE^{MICH}	ΔIE^{MICH}	$Rate^{NY}$	IE^{NY}	ΔIE^{NY}
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.788)	(1.902)	(3.742)	(1.274)	(2.508)	(3.462)
ln(Fed accounts)	−0.762***	0.270	−0.468	−0.419	2.024	1.854
	(0.274)	(0.787)	(1.139)	(0.687)	(1.246)	(1.381)
ln(Fed tweets)	0.816**	−0.149	−0.627	−0.557	−0.980	−0.227
	(0.328)	(0.699)	(1.015)	(0.653)	(1.529)	(1.583)
MoM^{Infl}	0.385***	1.192***	1.440***	0.085	1.372***	1.303***
	(0.073)	(0.228)	(0.338)	(0.092)	(0.330)	(0.458)
Obs.	108	108	107	91	91	90
R-squared	0.846	0.876	0.423	0.569	0.842	0.440

Notes: This table reports the results for the link between monthly Fed's tweeting activities and monthly survey-based inflation expectations. $Rate^{MICH}$ is the monthly expected inflation rate reported in the Michigan Survey of Consumers. $Rate^{NY}$ is the median of the monthly expected inflation rates reported in the Federal Reserve Bank of New York's Survey of Consumer Expectations. IE^{MICH} and IE^{NY} are the Michigan survey-based and Fed New York survey-based balance statistics. ΔIE^{MICH} and ΔIE^{NY} are the first difference of these balance statistics. MoM^{Infl} is the month-on-month inflation rate reported in the Michigan survey. ***ln(Monetary economics)*** is the natural log of Fed tweets discussing monetary economic-related topics. ***ln(Macroeconomics (Others))*** is the natural log of Fed tweets discussing other macroeonomic-related topics. ***ln(Banking sector)*** is the natural log of Fed tweets discussing banking sector topics. *ln(Other sectors)* is the natural log of Fed tweets discussing topics related to other sectors. *ln(Fed tweets)* is the natural log of all Fed tweets in a given month. *ln(Fed accounts)* is the natural log of the number of Fed accounts tweeting in a given month. *Sentiment* is the monthly weighted general sentiment of the Fed tweets. *Economic sentiment* is the monthly weighted economic sentiment of the Fed tweets. In all estimations, a constant term as well as month of year and year fixed effects are included but not reported. The standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate the significance level at 10 %, 5 %, and 1 %, respectively.

Appendix B. Methodology

Appendix Table B1
Examples of sentiment classification.

Text	Sentiment	Economic sentiment
After 15 years of growth, loans to small businesses by banks fell last year #banking	Neutral	Negative
St. Louis Fed President Bullard was on CNBC's squawk box this morning. Watch the video at urls	Neutral	Neutral
School improvements boost house prices more in better school districts than in other districts #stl	Positive	Positive
Unemployment rate declines to 9.5 percent from 9.7 percent	Negative	Positive
Sales of new homes fall to lowest level since at least 1963	Negative	Negative

Notes: This table shows some examples of general and economic sentiment classification. The urls are removed from texts.

Appendix Table B2
List of keywords to identify topics.

Topic level 1	Topic level 2	Keywords
	Covid	covid
	Covid	flu
	Covid	infection
	Covid	outbreak
	Covid	pandemic
	Covid	public health
	Covid	vaccine
	Fed data	chart
	Fed data	data series
	Fed data	database
	Fed data	economic data
	Fed data	economic database
	Fed data	economic indicator update
	Fed data	feddata
	Fed data	fred
	Fed data	graph
	Fed data	highlight page
	Fed data	interactive guide
	Fed data	update
	Fed data	weekly data
Banking sector	Balance sheet	asset
Banking sector	Balance sheet	balance sheet
Banking sector	Balance sheet	balancesheet
Banking sector	Balance sheet	liability

(*continued on next page*)

Appendix Table B2 (*continued*)

Topic level 1	Topic level 2	Keywords
Banking sector	Banking regulation	bank regs
Banking sector	Banking regulation	bankingregulation
Banking sector	Banking regulation	banking regulation
Banking sector	Banking regulation	dodd frank
Banking sector	Banking regulation	sec
Banking sector	Banking regulation	volcker rule
Banking sector	Financial condition	default
Banking sector	Financial condition	delinquency
Banking sector	Financial condition	financial condition
Banking sector	Financial condition	financial stress
Banking sector	Financial condition	nfci
Banking sector	Fintech	bitcoin
Banking sector	Fintech	blockchain
Banking sector	Fintech	crypto
Banking sector	Fintech	cryptocurrencies
Banking sector	Fintech	cryptocurrency
Banking sector	Fintech	financial technology
Banking sector	Fintech	fintech
Banking sector	Fintech	virtual currency
Banking sector	Lending	borrower
Banking sector	Lending	commercial paper
Banking sector	Lending	consumer borrowing
Banking sector	Lending	consumer credit
Banking sector	Lending	credit card
Banking sector	Lending	credit outstanding
Banking sector	Lending	debt
Banking sector	Lending	lending program
Banking sector	Lending	loan
Banking sector	Lending	main street lending
Banking sector	Lending	online lender
Banking sector	Lending	small business credit
Community	Education	child
Community	Education	classroom
Community	Education	econed
Community	Education	econlowdown
Community	Education	education
Community	Education	educator
Community	Education	financial literacy
Community	Education	finlit
Community	Education	learn
Community	Education	lesson
Community	Education	personal finance
Community	Education	personalfinance
Community	Education	resource
Community	Education	school
Community	Education	student
Community	Education	teach
Community	Education	teacher
Community	Education	workshop
Community	Inequality	income inequality
Community	Inequality	wealth gap
Community	Inequality	wealth inequality
Fed	Events	conference
Fed	Events	event
Fed	Events	keynote
Fed	Events	plenary session
Fed	Events	public engagement schedule
Fed	Events	speech
Fed	Events	summit
Fed	Events	symposium
Fed	Fed jobs	applynow
Fed	Fed jobs	atlantajobs
Fed	Fed jobs	careerfair
Fed	Fed jobs	employee
Fed	Fed jobs	hire
Fed	Fed jobs	hot job
Fed	Fed jobs	jobsearch
Fed	Fed jobs	intern
Fed	Fed officials	bernanke
Fed	Fed officials	chair janet

(*continued on next page*)

Appendix Table B2 (*continued*)

Topic level 1	Topic level 2	Keywords
Fed	Fed officials	chair yellen
Fed	Fed officials	chairman bernanke
Fed	Fed officials	dennis lockhart
Fed	Fed officials	fed president
Fed	Fed officials	fedchairman
Fed	Fed officials	feed president
Fed	Fed officials	fomc chair
Fed	Fed officials	governor
Fed	Fed officials	janet yellen
Fed	Fed officials	jeffrey lacker
Fed	Fed officials	jerome powell
Fed	Fed officials	jim bullard
Fed	Fed officials	john williams
Fed	Fed officials	lockhart
Fed	Fed officials	patrick harker
Fed	Fed officials	powell
Fed	Fed officials	pres rosengren
Fed	Fed officials	president bullard
Fed	Fed officials	president dudley
Fed	Fed officials	president eric
Fed	Fed officials	president harker
Fed	Fed officials	president jeffrey
Fed	Fed officials	president jim
Fed	Fed officials	president john
Fed	Fed officials	president lockhart
Fed	Fed officials	president mester
Fed	Fed officials	president richard
Fed	Fed officials	president rob
Fed	Fed officials	president rosengren
Fed	Fed officials	president tom barkin
Fed	Fed officials	president williams
Fed	Fed officials	richard fisher
Fed	Fed officials	rob kaplan
Fed	Fed officials	tom barkin
Fed	Fed officials	yellen
Fed	Research	research
Fed	Research	work paper
Macroeconomics (Others)	Currency	dollar currency
Macroeconomics (Others)	Currency	dollar index
Macroeconomics (Others)	Currency	dollar major currency
Macroeconomics (Others)	Currency	index value dollar
Macroeconomics (Others)	Economic condition	economic activity
Macroeconomics (Others)	Economic condition	economic condition
Macroeconomics (Others)	Economic condition	economic growth
Macroeconomics (Others)	Economic condition	economic outlook
Macroeconomics (Others)	Economic condition	gdp
Macroeconomics (Others)	Fiscal	fiscal
Macroeconomics (Others)	Labor market	compensation cost
Macroeconomics (Others)	Labor market	employment
Macroeconomics (Others)	Labor market	initial claim
Macroeconomics (Others)	Labor market	job data
Macroeconomics (Others)	Labor market	job growth
Macroeconomics (Others)	Labor market	job opening
Macroeconomics (Others)	Labor market	job posting
Macroeconomics (Others)	Labor market	labor force
Macroeconomics (Others)	Labor market	labor market condition
Macroeconomics (Others)	Labor market	labor productivity
Macroeconomics (Others)	Labor market	nonfarm payroll
Macroeconomics (Others)	Labor market	unemployment
Macroeconomics (Others)	Labor market	worker
Macroeconomics (Others)	Trade	export
Macroeconomics (Others)	Trade	export price
Macroeconomics (Others)	Trade	import
Macroeconomics (Others)	Trade	import price
Macroeconomics (Others)	Trade	net exporter
Macroeconomics (Others)	Trade	trade
Monetary economics	Household expenditure	consumption expenditure
Monetary economics	Household expenditure	disposable income
Monetary economics	Household expenditure	personal consumption
Monetary economics	Household expenditure	personal income

(*continued on next page*)

Appendix Table B2 (*continued*)

Topic level 1	Topic level 2	Keywords
Monetary economics	Household expenditure	personal saving rate
Monetary economics	Inflation	consumer expectation
Monetary economics	Inflation	cpi
Monetary economics	Inflation	disinflation
Monetary economics	Inflation	inflation
Monetary economics	Inflation	price change
Monetary economics	Inflation	price dynamic
Monetary economics	Inflation	price index
Monetary economics	Inflation	price pressure
Monetary economics	Inflation	sticky price
Monetary economics	Monetary	fomc
Monetary economics	Monetary	fund rate
Monetary economics	Monetary	monetary
Monetary economics	Monetary	policy rate
Monetary economics	Monetary	taylor rule
Other sectors	Agriculture	ag banker
Other sectors	Agriculture	ag credit
Other sectors	Agriculture	ag finance
Other sectors	Agriculture	agricultural
Other sectors	Agriculture	agriculture
Other sectors	Agriculture	crop
Other sectors	Agriculture	farm income
Other sectors	Agriculture	farm loan
Other sectors	Agriculture	farmer
Other sectors	Agriculture	farmland
Other sectors	Agriculture	land value
Other sectors	Agriculture	soybean
Other sectors	Energy	barrel
Other sectors	Energy	brent
Other sectors	Energy	crude oil
Other sectors	Energy	diesel
Other sectors	Energy	drilling
Other sectors	Energy	energy
Other sectors	Energy	fuel
Other sectors	Energy	gallon
Other sectors	Energy	gas
Other sectors	Energy	gasoline
Other sectors	Energy	oil price
Other sectors	Energy	oil production
Other sectors	Energy	petroleum
Other sectors	Energy	price gasoline
Other sectors	Energy	rig
Other sectors	Housing market	affordable housing
Other sectors	Housing market	build housing
Other sectors	Housing market	case shiller
Other sectors	Housing market	foreclosure
Other sectors	Housing market	home price
Other sectors	Housing market	home purchase
Other sectors	Housing market	home sell
Other sectors	Housing market	homeowner
Other sectors	Housing market	homeownership rate
Other sectors	Housing market	house price
Other sectors	Housing market	housing
Other sectors	Housing market	mortgage
Other sectors	Housing market	new home
Other sectors	Housing market	new house sell
Other sectors	Housing market	price new home
Other sectors	Housing market	price new house
Other sectors	Housing market	real estate market
Other sectors	Housing market	residential investment
Other sectors	Housing market	single family home
Other sectors	Industrial	capacity utilization
Other sectors	Industrial	capacityutilization
Other sectors	Industrial	construction project
Other sectors	Industrial	construction spending
Other sectors	Industrial	durable good
Other sectors	Industrial	factory activity
Other sectors	Industrial	industrial production
Other sectors	Industrial	industrial sector
Other sectors	Industrial	industrial sector

(*continued on next page*)

Appendix Table B2 (*continued*)

Topic level 1	Topic level 2	Keywords
Other sectors	Industrial	ism
Other sectors	Industrial	manufacture
Other sectors	Industrial	manufactured
Other sectors	Industrial	manufacturer
Other sectors	Industrial	manufacturing
Other sectors	Industrial	nonmanufacturing
Other sectors	Industrial	order index
Other sectors	Industrial	production index
Other sectors	Industrial	production total
Other sectors	Retail Wholesale	business inventory
Other sectors	Retail Wholesale	commerce sale
Other sectors	Retail Wholesale	inventory sale
Other sectors	Retail Wholesale	retail
Other sectors	Retail Wholesale	wholesaler
Other sectors	Transportation	freight
Other sectors	Transportation	passenger
Other sectors	Transportation	public transit
Other sectors	Transportation	rail
Other sectors	Transportation	shipment
Other sectors	Transportation	transportation

Notes: This table shows the hierarchical taxonomy. Level 2 topics are 27 narrow topics identified from the framework discussed in Section 2.2.2. Level 1 topics are the broader topics.

Appendix Table B3
Taxonomy for user classification.

Media	Manager	Finance	Academic	Economist
abacusnews	ceo	altcoin trader	adjunct professor	economist
bbc	cfo	asset management	assistant prof	chief economist
bloomberg	chairman	asset manager	assistant professor	economista
business insider	chairman board	bond trader	assoc professor	economics phd
businessinsider	chief operate	commodity trader	associate professor	economist phd
cbsnews	founder chairman	community banker	asst prof	phd econ
channel	president ceo	currency trader	asst professor	economista profesor
cnbc		derivative trader	distinguish fellow	environmental economist
cnn		economic analyst	distinguish professor	labor economist
financial times		equity trader	doctoral candidate	professor economics
fox news		financial advisor	doctoral student	senior economist
foxnews		financial analyst	phd candidate	
ft		forex trader	phd student	
media		fund manager	postdoc phd	
news		fx trader	postdoctoral fellow	
newyork times		hedgefund manager	profesor universidad	
nyt		intraday trader	profesor universitario	
techcrunch		investment banker	professor emeritus	
the economist		management firm	research associate	
wall street journal		mortgage banker	research fellow	
wsj		option trader	researcher	
theeconomist		portfolio management	postdoctoral fellow	
anchor		portfolio manager	profesor universidad	
correspondent		portfolio mgr	profesor universitario	
host podcast		prop trader	senior fellow	
journalist		proprietary trader	visiting professor	
commentator		purchase banker	professor	
podcast host		risk manager	fellow	
radio host		stir trader	postdoc	
reporter		stock picker	lecturer	
show host		stock trader		
contributor		trader investor		
columnist		wealth manager		
		banker		
		financial broker		
		cfa		
		msc economics		
		msc finance		

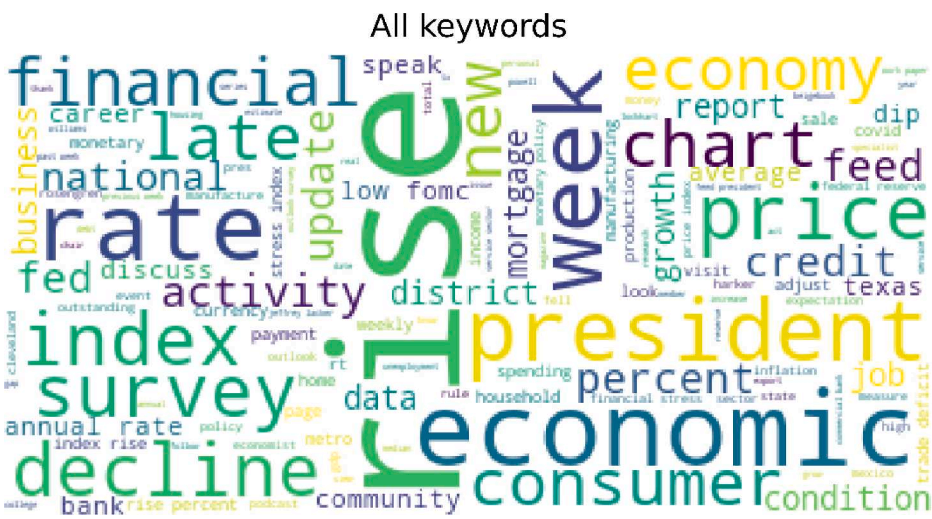
Notes: This table shows the list of keywords for each user group. The keywords are discovered using the taxonomy construction framework discussed in Section 2.2.3.

Appendix Table B4
Examples of inflation expectation classification.

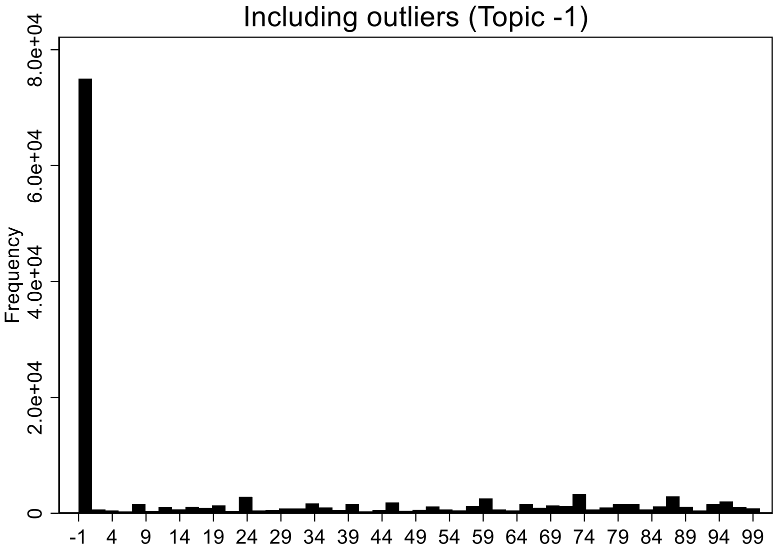
Text	Inflation expectation
the old #fed #trick is 2 create #inflation thinking ppl will rush to buy b4 prices go even higher.. good luck w/ that #idiots.. @stlouisfed	Higher
paying extra makes me appreciate gas more. qt @X: great job guys rt @stlouisfed: average price (cont)	Higher
relief ahead for econ? rt @stlouisfed: for third week in a row, gas prices drop; national average is $3.794 a gallon	Lower
#recovery - another + for consumers: rt@stlouisfed 1h chart: for the 2nd mo in a row, import prices down 0.6 percent	Lower
mt @stlouisfed: producer price index for finished goods was unchanged in august $fed $data #ppi	Unchanged
#us beige book watchword modest on virtually all fronts, wages and prices contained ht @stlouisfed	Unchanged

Notes: This table shows some examples of inflation expectation classification based on the approach discussed in Section 5.

Appendix Figure B1. Four most frequent topics.
Notes: This figure shows the keywords representing the four most frequent topics (out of 101 topics obtained from Components 2 and 3).



Appendix Figure B2. All keywords.
Notes: This figure shows all keywords representing 101 topics identified from the Components 2 and 3.



Appendix Figure B3. Distribution of topic frequencies.
Notes: This histogram shows the frequency of data points by topics. Topic -1 contains all points identified as outliers.

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