# Monetary policy in the news: communication pass-through and inflation expectations*

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**Abstract**

We analyse how news media convey Federal Reserve communication to the public. Using large language models, we measure monetary policy sentiment in FOMC communications and media articles published by eight major news outlets between 1994 and 2023. We find a tight correspondence between FOMC communication and media coverage, with substantial variation over time. Communication pass-through weakened during the zero-lower-bound period but improved following the introduction of press conferences. Among the Fed's communication tools, the chair's answers during press conferences are most strongly associated with media coverage. Linking our sentiment measures to household survey data, we find that hawkish shifts in media sentiment reduce medium-term inflation expectations, particularly when inflation is high and volatile. By contrast, FOMC communication does not appear to have a direct impact. These findings underscore the media's crucial role in channelling central bank communication to the public.

**Keywords:** Central bank communication, media coverage, large language models, household expectations.
**JEL Codes**: E50, E52, E58.

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*"You know that the FOMC pays very close attention to what it says [...]. Getting this message out to the public depends a good deal on the work you do in reporting on the FOMC, analyzing its statements and actions, and explaining its role and objectives."— Janet Yellen (2012), remarks at the Society of American Business Editors and Writers*

# 1 Introduction

Over the past few decades, central banks have undergone a dramatic change in their approach to public communication (Blinder et al., 2008; Yellen, 2012). Prior to the 1990s, the prevailing strategy for central banks was to stir the economy by altering the short-term rate and disclose as little information as possible about monetary policy decisions. Explaining the rationale behind them or providing indications about future interest rates was considered inappropriate because it could trigger market overreactions or constrain future policy decisions. Much has changed since then. Central banks and academics have increasingly recognized that consumption and investment decisions depend not only on current returns to saving or borrowing costs but are also strongly influenced by expectations regarding future interest rates and inflation. Hence, monetary policy can considerably enhance its efficacy by leveraging public communication to influence expectations.

The importance of communication became particularly evident during the period after the 2007-08 global financial crisis (GFC) when many central banks in advanced economies found themselves constrained by the zero lower bound (ZLB), preventing deeper interest rate cuts. In those circumstances, central banks extensively relied on forward guidance to provide additional monetary stimulus, indicating their determination to keep interest rates low for a long period. Public communication also played a critical role during the post-pandemic inflation surge. To prevent a possible de-anchoring of inflation expectations, central banks went to great lengths to communicate their determination to regain control of inflation by keeping rates elevated for as long as needed to bring inflation firmly back to target.

Recent years have seen a flurry of research to understand how central bank communication affects financial markets and professional forecasters. Yet, far less is known about central banks' ability to influence the broader public. As discussed in Blinder et al. (2024), this is a critical area for research since effective public communication is essential to improve monetary policy transmission and support public confidence in central banks.

In this paper, we contribute to this research by studying the role of the media as a key intermediary between the Federal Reserve and households. Despite the rise of social

media, traditional media remain the main channel through which the general public acquires information about central banks (Hayo and Neuenkirch, 2015, 2018; Gardt et al., 2021; Conrad, Enders and Glas, 2022; D'Acunto et al., 2025). We make two contributions. First, we examine the degree of consistency between the Federal Reserve's official communication about monetary policy decisions and media coverage, which we also refer to as the pass-through of FOMC communication to the media. Second, we ask whether this media coverage affects households' inflation expectations. Together, these two steps allow us to assess not only whether the Fed's intended message survives media filtering, but also whether the media convey monetary policy information to the broader public beyond the reach of the Fed's direct communication.

To measure the pass-through of FOMC communication to the media, we leverage recent advances in textual analysis enabled by large language models (LLMs). Specifically, we use GPT-4 to classify the monetary policy stance conveyed in FOMC communication and newspaper articles as more hawkish or more dovish. We refer to this hawkish–dovish classification as monetary policy sentiment. We validate the GPT-4 classifications against human assessments of FOMC statements and compare their performance with that of RoBERTa, an established language model commonly used for text-classification tasks. Although the RoBERTa model has been specifically fine-tuned on central bank communication, we find that GPT-4 performs better in assessing the sentiment of FOMC communication. GPT-4 has also been shown to outperform RoBERTa when assessing longer texts (Gambacorta et al., 2024), an important advantage for measuring monetary policy sentiment in full newspaper articles.

We analyse around 14,000 articles from eight major news outlets, covering 224 FOMC announcements from 1994—when the FOMC released a first press statement—to 2023. We use these classifications to study the pass-through of FOMC communication to the media along three dimensions. First, we estimate the average degree of pass-through over the full sample. Second, we examine how pass-through has evolved over time. Third, we assess whether pass-through differs across communication tools, distinguishing between press statements, introductory remarks at press conferences, and the Fed chair's answers to journalists' questions.

Our first main finding is a high degree of consistency between the monetary policy sentiment expressed in FOMC communication and media coverage. Over the full sample, the correlation between FOMC and media sentiment is 0.83. To examine this relationship more systematically, we estimate regressions relating the sentiment of individual newspaper articles published after each meeting to FOMC sentiment. These estimates confirm a strong degree of pass-through, even when we control separately for changes in the fed-

eral funds rate target, the shadow rate, or monetary policy surprises. This suggests that the consistency between FOMC and media sentiment is not driven solely by the policy decision itself. We also find that pass-through is particularly high in the days immediately after the FOMC meetings, when most newspaper articles covering monetary policy are published.

The strength of this pass-through, however, varies considerably over time. It weakened substantially after the 2008 financial crisis, when monetary policy became constrained by the ZLB and the Fed increasingly relied on new tools to provide accommodation. These findings underscore the severe communication challenges associated with explaining how new tools would impact the economy and how they would be deployed.

Pass-through began to improve around 2011, coinciding with the introduction of the post-FOMC press conferences, which provided journalists with the opportunity to clarify their understanding of FOMC communication by directly posing questions to the Fed chair. Our results indicate that the chairs' answers exhibit the strongest relationship with media coverage among the communication tools considered. However, the analysis also provides a cautionary message about these tools. The sentiment expressed in the press conference answers is at times not fully aligned with the message conveyed in written FOMC communication. This discrepancy may partly stem from the chair's efforts to correct misinterpretations of the FOMC decisions that arise from journalists' questions. But it may also reflect the inherent communication challenges of addressing a wide range of questions under difficult circumstances. The press conferences are thus high-stakes events, which can strongly shape media coverage but may also provide a message not entirely consistent with written FOMC communication.

We then analyse whether media coverage influences household inflation expectations. To this end, we combine our media sentiment measures with microdata from the New York Fed's Survey of Consumer Expectations. Our empirical design compares survey responses collected before and after each FOMC meeting within alternative event windows and examines whether differences in inflation expectations vary with the change in media sentiment. Identification relies on the timing of survey interviews relative to FOMC meetings being quasi-random and on the absence of other contemporaneous shocks within the narrow event windows that affect household expectations and are correlated with media sentiment. The quasi-random timing assumption is discussed extensively in Binder, Campbell and Ryngaert (2024), while in a separate exercise we examine potential confounding effects from contemporaneous news by excluding meeting windows containing inflation and employment releases.

Our second main finding is that hawkish shifts in media sentiment lower house-

holds' medium-term inflation expectations. Across the different event windows, a one-standard-deviation hawkish shift in media sentiment lowers medium-term inflation expectations by around 0.18 percentage points. This response is particularly pronounced during the post-pandemic period, when the inflation surge likely increased households' attention to monetary policy news. Interestingly, we find little evidence that households respond directly to the sentiment expressed in FOMC communication. Together, these results corroborate the notion that media coverage of monetary policy decisions plays a crucial role in channelling FOMC communication to the public.

Finally, we explore whether this transmission is heterogeneous across households. Splitting respondents by education, mortgage status, and gender, our estimates suggest that the response of medium-term inflation expectations to media sentiment is particularly pronounced among households without a college degree, among households with mortgage debt, and, to a lesser extent, among male household heads. The education split also reveals a sharp contrast in the source of information to which households respond: college-educated households' expectations are more closely associated with FOMC sentiment, whereas households without a college degree respond primarily to media sentiment.

The paper is structured as follows. In Section 2, we provide a brief review of the literature. In Section 3, we present information about FOMC communication and media coverage. In Section 4, we describe the procedure to extract our sentiment indicators, and in Section 5, we examine the consistency between FOMC communication and the media. In Section 6, we examine the influence of media coverage on household inflation expectations. Section 7 concludes.

## 2 Literature review

The literature on central bank communication is vast. Most studies have focused on the impact of central bank communication on financial markets. A highly influential line of research has used event-study approaches to examine the reaction of asset prices in narrow time windows around central bank communication, including monetary policy statements, press conferences, and governors' speeches (Kuttner, 2001; Cochrane and Piazzesi, 2002; Bernanke and Kuttner, 2005; Gürkaynak, Sack and Swanson, 2005; Cieslak and Schrimpf, 2019; Andrade and Ferroni, 2021; Swanson, 2021). These papers document that central bank communication can strongly affect financial markets, impacting bond yields, stock prices, and exchange rates.

More recently, the literature has exploited technological advancements in language

processing tools to directly examine the content of central bank communication, rather than inferring it from market reactions. Much of this work has focused again on the impact of central bank communication on financial markets (Lucca and Trebbi, 2009; Hansen and McMahon, 2016; Neuhierl and Weber, 2019; Hansen, McMahon and Tong, 2019; Gardner, Scotti and Vega, 2022; Doh, Song and Yang, 2022; Cieslak and McMahon, 2023; Cieslak, McMahon and Pang, 2024). Leveraging computer-based techniques to analyze both textual and nonverbal aspects of communication, recent studies have documented that central bank governors also influence financial markets via their tone of voice and facial expressions (Gorodnichenko, Pham and Talavera, 2023; Curti and Kazinnik, 2023; Alexopoulos et al., 2024).

Rather than focusing on the impact of central bank communication on financial markets, our analysis examines the potential for central bank communication to reach the broader public via the media. This is a necessary condition for central banks to influence the public given that households still heavily rely on traditional media to learn about monetary policy (Hayo and Neuenkirch, 2018; Gardt et al., 2021; Conrad, Enders and Glas, 2022). However, two other conditions must also be satisfied.

First, people must be responsive to monetary policy news when provided with such information. Survey-based analyses using information provision experiments provide encouraging supportive evidence. For example, households tend to adjust their inflation expectations when informed about central banks' inflation targets and interest rate decisions (Coibion, Gorodnichenko and Weber, 2022; Coibion et al., 2023), especially if central banks use a simple narrative (Haldane and McMahon, 2018).

Second, people must be attentive to monetary policy announcements. The available evidence on this point is more mixed (see Binder, 2017, for an overview). Based on data from Australia, Claus and Nguyen (2020) document that households' expectations of economic conditions adjust following monetary policy shocks in line with theoretical predictions. Lewis, Makridis and Mertens (2019) find that US policy rate shocks affect households' confidence in the state of the economy. Using surveys conducted right before and after FOMC press conferences, Lamla and Vinogradov (2019) document an increase in the proportion of households that have heard about monetary policy news after the press conferences. However, they detect very little effect on households' expectations. Similarly, De Fiore, Lombardi and Schuffels (2026) examine responses from the NY Fed Survey of Consumer Expectations over the pre-pandemic period and find that households do not materially change inflation expectations around monetary policy announcements, suggesting that the general public pays limited attention to the FOMC communication of monetary policy decisions. Binder, Campbell and Ryngaert (2024) also document that, in

general, FOMC communication does not trigger changes in inflation expectations. However, they do find instances, especially during the Covid-19 pandemic, when households adjusted inflation expectations after FOMC announcements.[1]

Our study provides new evidence that, although households tend to be unresponsive to FOMC communication alone, they are sensitive to the media coverage. Specifically, households tend to lower medium-term inflation expectations when media coverage turns more hawkish. A few other papers also examine the role of media coverage in channelling information about monetary policy. Pinter and Kočenda (2023) manually assess the articles of the major French newspapers covering ECB policy decisions. They find that monetary policy shocks affect French firms' and consumers' expectations only when they are properly reported in the media. Schmanski et al. (2023) extract textual sentiment about monetary policy from FOMC communication and Dow Jones newswire articles using dictionary-based techniques. They find that media sentiment correlates more tightly with changes in bond yields and economic forecasts by professional analysts than FOMC sentiment. Our paper extracts textual sentiment by leveraging recent developments in LLMs. We study media coverage across a large set of newspapers and focus on its influence on households' inflation expectations.

Our paper is also related to several studies examining media coverage of central bank communication. Neuenkirch (2014) and Munday and Brookes (2021) investigate the textual features that might attract greater news coverage. Berger, Ehrmann and Fratzscher (2011) examine how favorably the media report about the monetary policy decisions by the ECB. Hayo and Neuenkirch (2012) and Hendry (2012) show that media coverage of communication by the Bank of Canada can influence equity markets and interest rates. Ter Ellen, Larsen and Thorsrud (2022) construct monetary policy shocks for Norway based on differences between the policy announcements and prior media coverage and show that they predict macroeconomic responses consistent with an information channel. Ehrmann and Wabitsch (2022) examine the role of Twitter in relaying information about the ECB's monetary policy communication.

# 3 FOMC communication and media coverage

We systematically examine FOMC communication and media coverage since February 1994, when the FOMC issued for the first time a press statement to announce a change

[1] A related literature shows that households' inflation expectations are sensitive to general media reporting, in particular when focused on inflation (Lamla and Lein, 2014; Dräger, 2015; Ehrmann, Pfajfar and Santoro, 2017; Larsen, Thorsrud and Zhulanova, 2021; Larsen, Maffei-Faccioli and Pagenhardt, 2025).

in the monetary policy stance. Before that, monetary policy decisions were implemented via market operations by the Fed, without being publicly announced. Press statements became more frequent in the second half of the 1990s and have been regularly released after every FOMC meeting since 2000. In April 2011, the Fed also started to use press conferences to provide additional information regarding monetary policy decisions and the future policy stance. The Fed chair opens press conferences by reading introductory remarks and then answers questions from journalists. Press conferences were initially held only after FOMC meetings when updated economic projections were released but have become regular events after every scheduled FOMC meeting since 2019.

In total, our analysis covers all press statements, introductory remarks at press conferences, and answers to journalists' questions for all the 224 FOMC meetings that took place between February 1994 and the end of 2023. Figure 1 illustrates several features of these data. The left panel shows the rising frequency of FOMC communication, captured by an increasing use of press statements and press conferences.[2] The growing emphasis on public communication is also reflected in the lengthening of communication, as illustrated in the middle panel. The average number of words in the statements increased from 131 in 1994 up to 821 in 2014. From that point onward, statements have become shorter but have been complemented with considerably longer introductory remarks (1326 words on average) and especially extensive answers provided during press conferences (4980 words on average).

Besides becoming more frequent and lengthy, FOMC communication has also adopted a simpler language over time, as measured by the Flesch-Kincaid readability score and illustrated in Figure 1c.[3] The readability score of press statements improved (as shown by an increase in the index) between 1994 and the eve of the 2008 financial crisis. Statements became more complex during the ensuing ZLB period as the Fed started to deploy new monetary policy tools, such as large-scale asset purchases and forward guidance. However, the introduction of press conferences allowed the Fed chair to communicate with the public using simpler language, especially when answering questions.

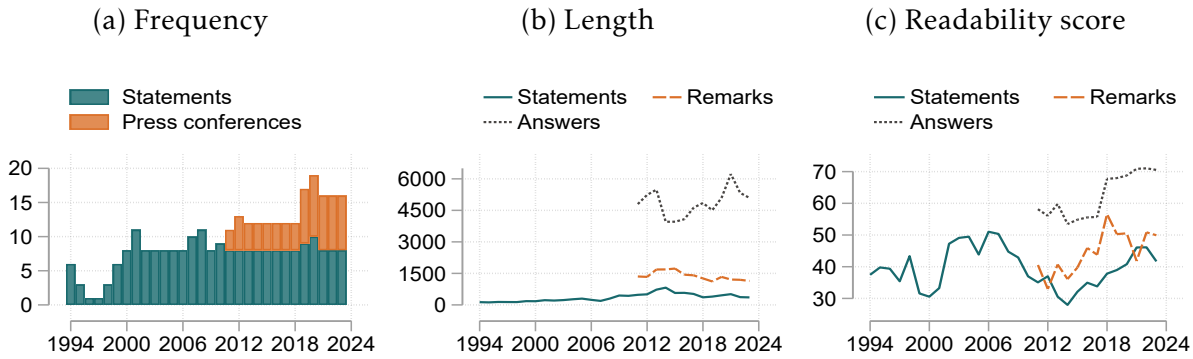
Turning to the media coverage of FOMC meetings, we collect articles published between two days before and seven days after the meeting from eight major media outlets: the Financial Times, Wall Street Journal, Washington Post, Los Angeles Times, CNN, USA Today, New York Post, and Fox News.[4] We select articles that include references to the

[2]FOMC meetings are generally held eight times per year. However, meetings can occur more frequently during crisis episodes, such as during the global financial crisis and the COVID-19 pandemic.

[3]The Flesch-Kincaid readability score captures complexity along two main dimensions, word length and sentence length.

[4]The selection of media outlets is based on readership in the US and considerations related to licensing

Figure 1: FOMC communication




*Notes:* The left panel shows the annual number of press statements and press conferences following FOMC meetings. The middle panel shows the yearly average number of words embedded in press statements, introductory remarks and the answers during press conferences. The right panel shows the Flesch–Kincaid readability score for each communication tool, where higher scores indicate greater ease of readability.

FOMC or the Fed and to interest rates or monetary policy decisions.[5] Our search criteria return 40,683 articles.

We then follow a 3-step data cleaning procedure to remove articles that are not relevant for our analysis. First, we eliminate transcripts of FOMC communication, for example distributed via newsletters and selected daily market articles. Second, we drop duplicate articles or very similar ones, for example, online articles that underwent minor changes. Third, we leverage the capabilities of GPT-4 to select articles that are sufficiently focused on monetary policy decisions by the Federal Reserve. Details of the data cleaning procedure are provided in Appendix A. The final analysis sample includes 14,021 articles whose distribution across media outlets is reported in Appendix Table A.1.

As illustrated in Figure 2a, the media coverage of the FOMC decisions remained broadly stable between 1994 and the 2008 financial crisis. Based on our sample of analysis – excluding the Financial Times for which we have data starting only in 2005 – FOMC meetings were covered on average in about 33 articles between 2 days prior and 7 days after the meeting. The media coverage of FOMC meetings increased considerably after the financial crisis, reaching about 54 articles per meeting.[6] Therefore, the increased frequency and length of FOMC communication were matched with larger media coverage.

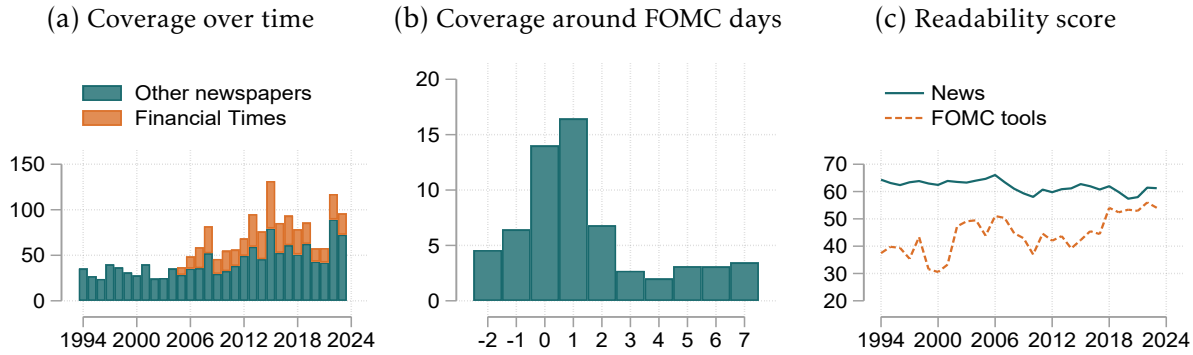
agreements required to process the articles using LLMs. Coverage of FT articles starts in 2005 because of licensing limitations. We retrieve articles from the Financial Times using its dedicated application programming interface (API) and we use the Factiva API for all other newspapers.

[5]More specifically, we select articles that include either the expressions "FOMC" or "Federal Open Market Committee" or "FED" or "Federal Reserve," as well as the word "interest rate" or "interest rates" or "monetary" or "federal funds rate" or "fed funds rate".

[6]The same figures including the FT are 53 for the period January 2005 - August 2008, and 80 for the period September 2008 - December 2023.

Regarding the distribution of articles around FOMC meetings, Figure 2b shows that the bulk of them are published the day of the meeting or the subsequent one.[7] Finally, in Figure 2c we observe that the readability score of media articles is considerably higher than the average readability of FOMC communication across all communication tools. This points to an important role played by the media in interpreting and simplifying Fed communication to reach the broad public.

Figure 2: Media coverage of FOMC meetings




*Notes:* The left panel shows the average number of articles per FOMC meeting per year. The middle panel shows the average number of articles published around the day of the FOMC meeting. The right panel shows the average Flesch–Kincaid readability score for the articles and FOMC communication tools, where higher scores indicate greater ease of readability.

# 4 Sentiment extraction

To examine the degree of consistency between FOMC communication and media coverage, we first need a common measure of the monetary policy stance. We refer to this stance as monetary policy sentiment and measure it using state-of-the-art LLMs.

## 4.1 Comparison of alternative LLMs

We consider two LLMs that have been used in the literature to analyze Fed communication: GPT-4 and RoBERTa (Hansen and Kazinnik, 2023). Regarding GPT, we use the most advanced version available at the time of our study, GPT-4. For RoBERTa, we use the version developed by Shah, Paturi and Chava (2023), which was trained on extracts

[7] To determine whether an article was published before or after the FOMC press statement, we used the timestamp of the article when available. When the timestamp was not available, we read and classified the articles as published pre- or post-FOMC based on their content.

from FOMC minutes, press conferences and speeches by Federal Reserve officials. We refer to this version as RoBERTa-SPC23. To select the most suitable LLM for the purpose of our analysis, we compare their performance in assessing the sentiment of sentences from FOMC statements against the interpretation of human research assistants made available by Gorodnichenko, Pham and Talavera (2023) (GoPhTA23) for all FOMC statements between 1997 and 2010. The authors asked research assistants to classify each sentence on a scale from -10 (very hawkish) to +10 (very dovish). They then averaged scores across the research assistants to classify each sentence as dovish ($\geq 0.5$), neutral (between $-0.5$ and 0.5), or hawkish ($\leq -0.5$).

RoBERTa-SPC23 has been fine-tuned to assess FOMC text on a three-point scale, including dovish, neutral or hawkish. For GPT-4, we use a finer 5-point scale to capture richer nuances in the text. Specifically, we provide GPT-4 with the following prompt:[8]

> *You're a research assistant working at the Fed. You have a Master degree in Economics. Your task is to understand and classify the monetary policy stance described in the text given to you into one of the following five categories: dovish, mostly dovish, neutral, mostly hawkish, hawkish. Dovish means that the central bank is more lenient towards higher inflation to support economic activity and employment, and hence is more likely to lower interest rates or keep them low for a period of time. Hawkish means the opposite. Neutral is neither one nor the other.*

To map GPT-4's 5-point scores to the 3-point scale used in GoPhTA23, we code "mostly dovish" as dovish and "mostly hawkish" as hawkish. This limits the number of neutral assessments in line with GoPhTA23's mapping of human scores into the 3-point scale which treats as neutral only those sentences with scores very close to zero (between -0.5 and 0.5) on a scale from -10 to 10.

Table 1 compares the aggregate performance of the models across different measures, while Table B.1 reports the underlying confusion matrices. GPT-4 outperforms RoBERTa-SPC23 on all three metrics. On average, GPT-4 correctly predicts sentiment in 74 percent of cases, compared with 68 percent for RoBERTa-SPC23. Because accuracy can mask uneven performance across sentiment categories, especially when some categories are more common than others, we also report the macro F1 score, the average of category-specific F1 scores. The category-specific F1 score is the harmonic mean of precision and recall, where precision measures the share of observations predicted to be in a given

[8] We tested different versions of this prompt and found that the results are similar. To ensure greater replicability of the results, we set the temperature in GPT (i.e. the degree of randomness in the model's output) to 0. In a few instances – about 0.3% of cases – GPT returns words that do not correspond to the dovish/hawkish categories. We re-classify these statements as neutral.

Table 1: Accuracy scores for FOMC statements across LLMs

| Measure | GPT-4 | RoBERTa-SPC23 |
|---|---|---|
| Accuracy | 0.74 | 0.68 |
| F1 | 0.74 | 0.68 |
| Quadratic-weighted $\kappa$ | 0.73 | 0.68 |

Notes: The table reports aggregate classification performance across different measures. Accuracy is the overall share of correctly classified observations. F1 is the equal-weighted average of class-specific F1 scores, where each class-specific F1 score is the harmonic mean of precision and recall for that class. Quadratic-weighted $\kappa$ measures agreement between predicted and actual labels while penalizing larger ordinal disagreements more heavily.

category that truly belong to that category, while recall measures the share of observations in that category that are correctly recovered by the model. GPT-4 again performs better, with a macro F1 score of 0.74 compared to 0.68 for RoBERTa-SPC23, indicating that its advantage is not driven solely by the most frequent category. Finally, neither accuracy nor the F1 score account for the ordinal structure of the sentiment labels: confusing dovish and neutral, for example, is treated the same as confusing dovish and hawkish. We therefore also report quadratic-weighted $\kappa$, which penalizes larger ordinal disagreements more heavily. GPT-4 attains a higher quadratic-weighted $\kappa$ of 0.73, compared with 0.68 for RoBERTa-SPC23, suggesting fewer severe classification errors.

The strong performance of GPT-4 is remarkable considering that GPT-4 was not subject to any specific training based on FOMC communication. Hence, GPT-4 is likely to perform even better relative to RoBERTa-SPC23 in the analysis of newspapers since RoBERTa-SPC23 has not been fine-tuned on media sources. Another important advantage of using GPT-4 rather than RoBERTa-SPC23 for our analysis is that the assessment of media sentiment is performed based on full articles rather than individual paragraphs since the Factiva API does not provide paragraph splits. As shown in Gambacorta et al. (2024), GPT-4 performs considerably better than RoBERTa-SPC23 in assessing longer texts. In light of these considerations, we conduct our analysis using GPT-4.

## 4.2 FOMC and media sentiment

Using GPT-4, we extract the sentiment of FOMC communication as expressed in press statements, introductory remarks to the press conference, and the Fed Chair's answers to journalists. The sentiment of FOMC statements and remarks is extracted based on the full text of these documents. This is consistent with the treatment of media articles

that are also analyzed at the full-text level, as described later on. We convert the sentiment classification into numerical values by assigning the dovish, mostly dovish, neutral, mostly hawkish, hawkish categories to $\{-1, -0.5, 0, 0.5, 1\}$ values, respectively. Regarding the press conference answers, we extract the sentiment of each answer and convert it to numerical values. We then construct an aggregate sentiment for the press conference answers as the average sentiment across the answers.[9]

We also construct an aggregate sentiment of the FOMC communication for each meeting by taking a simple average across the sentiment expressed in the press statement, the introductory remarks and the press conference answers. The sentiment of FOMC meetings that did not feature a press conference simply corresponds to the sentiment expressed in the press statement. Note that all sentiment indexes range between [-1,1], with higher values denoting more hawkish sentiment.

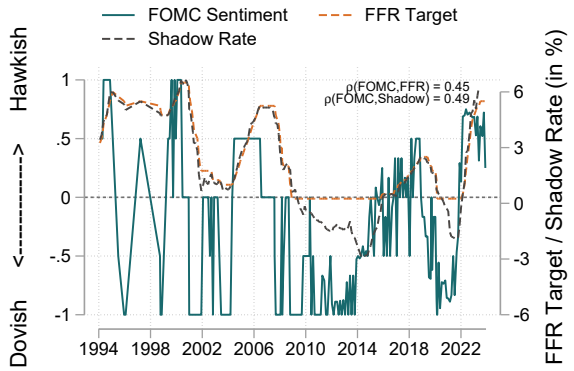
Figure 3a illustrates the evolution of the FOMC sentiment between 1994 and 2023, together with the dynamics of the federal funds rate and the shadow rate (Wu and Xia, 2016) to account for the ZLB period. Several observations stand out. First, the FOMC sentiment displays considerable variation over time, with sharp dovish shifts around economic downturns. For example, the FOMC sentiment turns rapidly dovish during the 2001, 2008, and 2020 recessions. We also see a rapid shift toward a hawkish sentiment in mid-2021, with the onset of the post-pandemic inflation surge. Second, sentiment dynamics align well with prevailing narratives about monetary policy phases. For example, the FOMC sentiment is characterized as persistently dovish in the years after the 2008 financial crisis, when the Fed engaged in several rounds of quantitative easing and used forward guidance to signal its intention to keep interest rates low for long. Third, fluctuations in FOMC sentiment correlate closely with the federal funds rate. We also see a tendency for changes in FOMC sentiment to anticipate interest rate adjustments, especially hiking cycles. For example, FOMC sentiment turned more hawkish in 2004 and 2015, right before interest rate hikes. Communication also turned sharply hawkish with the inflation surge in 2022, right before one of the sharpest tightening cycles in the history of the Fed.

Figure 3b illustrates the sentiments of individual communication tools. We see a tight comovement between the sentiment expressed in press statements (S) and in the introductory remarks (R) to the press conference, with a correlation coefficient of 0.86. This underscores how written texts are carefully drafted by the Fed to provide a consistent

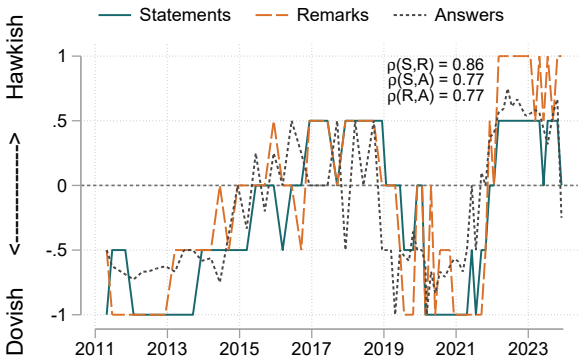
[9] We compute the average sentiment by excluding answers that are classified as neutral, following the aggregation in Gorodnichenko, Pham and Talavera (2023). The key results of the analysis are, in any case, robust to including neutral answers.

Figure 3: FOMC sentiment

(a) Aggregate




(b) By communication tool




*Notes:* Panel (a) compares the evolution of the sentiment of the aggregate FOMC official communication to that of the Federal Funds Rate target and the Shadow Rate. $\rho$ is the correlation coefficient between the indicated variables. Panel (b) plots the sentiment of each individual communication tool, i.e. statements (S), introductory remarks (R), and answers at press conferences (A). $\rho$ is the correlation coefficient between the two indicated tools.

message. The sentiment expressed in the answers during the press conference (A) is instead less tightly connected with the sentiment in written communication. The correlation between the sentiment of answers and remarks, as well as between answers and statements, is 0.77 in both cases. The smaller correlation between the sentiment of the answers and written statements may partly reflect the communication challenges arising during the press conferences, when the Fed Chair must address a broad range of questions from journalists on the spot. Discrepancies between these two communication tools may also result from attempts by the Fed Chair to push back against misinterpretations of FOMC decisions that may emerge during the press conference. For example, journalists may ask whether a dovish passage in the post-FOMC press statement rules out interest rate hikes in the near future, prompting the chair to clarify that the FOMC retains discretion to adjust the policy stance based on upcoming data.

Turning to the sentiment expressed in the media, we follow the same approach used to construct the sentiment of FOMC communication. Specifically, we ask the LLMs to assess the full text of each newspaper article along the five hawkish/dovish categories.[10] We then convert this classification into numerical values and average the scores across articles published after the FOMC announcement to obtain an aggregate media sentiment for each FOMC meeting.

[10]Note that since the Factiva API does not provide the split of newspaper articles in individual paragraphs, the analysis cannot be conducted at the paragraph level.

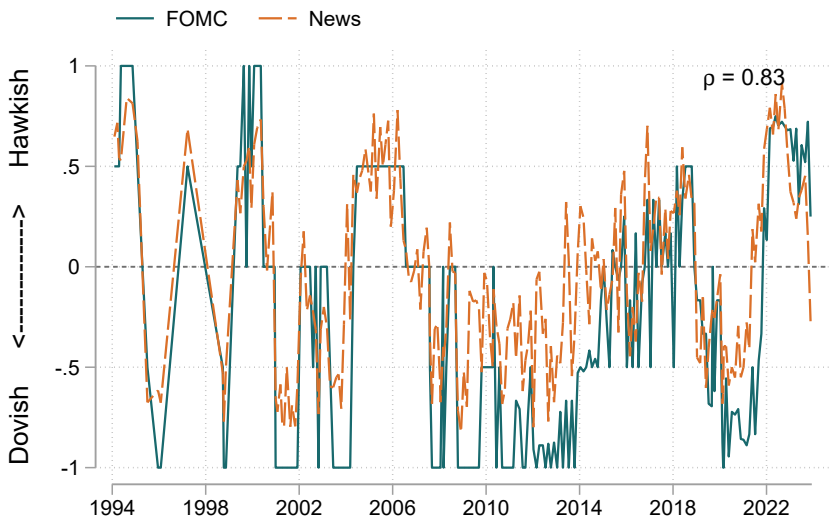
# 5 Consistency between FOMC and media sentiment

We now move on to examining the consistency between the sentiment extracted from Fed communication and its media coverage. In the next section, we start by assessing the average degree of consistency over the entire sample period and across all communication tools. We then examine in the subsequent section how the communication pass-through has varied over time and how it differs across communication tools.

## 5.1 Average degree of consistency

The analysis uncovers, on average, a strong degree of consistency between the FOMC communication and the media coverage. Figure 4 illustrates the evolution of the aggregate FOMC sentiment and the aggregate media sentiment based on all articles published up to 7 days after the FOMC meeting.[11] We see, in general, a strong comovement between these two series, with a correlation of 0.83.

Figure 4: FOMC and media sentiment




*Notes:* Green solid line denotes the aggregate FOMC sentiment. Orange dashed line denotes media sentiment. $\rho$ is the correlation coefficient.

To examine more systematically how changes in FOMC sentiment are reflected in media coverage, we estimate the following regression:

$$S^{Media}_{a,j,m} = \alpha_j + \beta_1 S^{FOMC}_m + \beta_2 \Delta r_m + u_{a,j,m} \tag{1}$$

[11] This excludes all articles that were published before the FOMC meeting.

Here, $S^{Media}_{a,j,m}$ denotes the sentiment of article $a$, published in newspaper $j$, within 7 days after the FOMC meeting $m$. The variable $S^{FOMC}_{m}$ is the aggregate sentiment of FOMC communication at meeting $m$, and $\Delta r_m$ denotes one of three alternative measures of the policy change associated with meeting $m$: i) the change in the target rate; ii) the change in the shadow rate from Wu and Xia (2016), which accounts for the ZLB period; and iii) the monetary policy surprise from Bauer and Swanson (2023).[12] The regression also includes newspaper-fixed effects, $\alpha_j$. Standard errors are clustered at the meeting- and newspaper-level.[13] The focus of the analysis is on the coefficient $\beta_1$, which captures the pass-through from FOMC communication to media sentiment. Controlling for $\Delta r_m$ allows us to examine whether media coverage responds to the sentiment of FOMC communication beyond the policy decision itself.

The first column in Table 2 reports the regression estimates without controls. The coefficient $\beta_1$ is positive and highly statistically significant, equal to 0.65, confirming a strong degree of consistency between FOMC communication and the media. This result is not driven by specific media outlets. In Appendix C, we re-estimate equation (1) for each media outlet separately and find a consistently strong degree of pass-through.

Columns (2)–(4) examine whether news sentiment responds to FOMC sentiment beyond the information contained in the Federal Reserve's policy decision. As expected, all three monetary policy measures are positively correlated with news sentiment. Importantly, even after controlling for these measures, the coefficient on FOMC sentiment remains positive, significant, and consistent in magnitude with the baseline estimation reported in column (1), ranging between 0.48 and 0.58. These findings show that the influence of FOMC communication on media coverage extends beyond the mere transmission of policy decisions.[14]

Besides assessing the average degree of pass-through, we also examine if the strength of the pass-through is influenced by the intensity or direction of FOMC sentiment. To this end, we extend the baseline regression equation (1) as follows:

$$S^{Media}_{a,j,m} = \alpha_j + \beta_1 S^{FOMC}_{m} + \beta_2 \Delta r_m + \beta_3 D_m + \beta_4 S^{FOMC}_{m} \times D_m + u_{a,j,m} \tag{2}$$

where $D_m$ is a dummy variable that takes value 1 if a certain criterion is satisfied. More specifically, we first differentiate the results based on the strength of the FOMC sentiment, namely whether it is particularly hawkish or dovish. In this case, the dummy $D_m$ captures

[12] Differently from the other monetary policy measures, the shadow rate is only available at monthly frequency.

[13] The results are overall robust to clustering only at the meeting-level.

[14] Appendix C shows that the estimates are similar when we only consider regular FOMC meetings.

Table 2: Sentiment pass-through and media coverage

| | (1) Base | (2) FFR | (3) Shadow rate | (4) MP surprise |
|---|---|---|---|---|
| FOMC sentiment | 0.651*** | 0.488*** | 0.563*** | 0.576*** |
| | (0.040) | (0.049) | (0.050) | (0.045) |
| Δ FFR | | 0.457*** | | |
| | | (0.081) | | |
| $\Delta r^{shadow}$ | | | 0.277*** | |
| | | | (0.064) | |
| MP surprise | | | | 1.811*** |
| | | | | (0.366) |
| Constant | 0.121*** | 0.077*** | 0.107*** | 0.109*** |
| | (0.020) | (0.019) | (0.020) | (0.019) |
| No. of meetings | 224 | 224 | 220 | 222 |
| Observations | 10472 | 10472 | 10214 | 10434 |
| $R^2$ | 0.38 | 0.40 | 0.41 | 0.41 |

Notes: The dependent variable is the sentiment of individual newspaper articles published after the FOMC announcement up to seven days after the meeting. All specifications include newspaper fixed effects. Δ FFR denotes the change in the Fed's target rate, $\Delta r^{shadow}$ the change in the shadow rate from Wu and Xia (2016) and MP surprise is the monetary policy surprise from Bauer and Swanson (2023). Standard errors are clustered at the meeting- and newspaper-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

FOMC meetings where the sentiment is within the top or bottom quartile of the sentiment distribution. The estimation results where $\Delta r_m$ measures changes in the shadow rate are reported in Table 3. The regression tables with alternative controls are delegated to Appendix C. The coefficient $\beta_4$ is positive, suggesting that meetings with more extreme FOMC sentiment tend to influence the media coverage more strongly, but not statistically significant at conventional levels.

We then examine whether the strength of pass-through differs depending on whether the FOMC sentiment is hawkish or dovish. To explore this issue, the dummy $D_m$ takes value 1 to denote meetings with dovish sentiment, i.e. meetings in which $S^{FOMC} < 0$, and value 0 for hawkish meetings. We drop meetings with neutral sentiment, i.e. $S^{FOMC} = 0$, to ensure a clean comparison between dovish and hawkish meetings. Column (3) shows that the interaction coefficient $\beta_4$ is negative, but again not statistically significant. Thus, the strength of pass-through does not appear to depend on whether FOMC sentiment is hawkish or dovish.

Table 3: Sentiment pass-through and media coverage – nonlinearities

| | Sentiment | | | Number of articles | | |
|---|---|---|---|---|---|---|
| | (1) Base | (2) Size | (3) Sign | (4) Base | (5) Size | (6) Sign |
| FOMC sentiment | 0.563*** | 0.456*** | 0.499*** | 0.725 | | |
| | (0.050) | (0.106) | (0.130) | (2.525) | | |
| $\Delta r^{shadow}$ | 0.277*** | 0.277*** | 0.267*** | 1.518 | 2.322 | 0.184 |
| | (0.064) | (0.064) | (0.069) | (7.152) | (6.099) | (7.284) |
| Strong sentiment | | 0.106* | | | -0.683 | |
| | | (0.047) | | | (2.710) | |
| FOMC X Strong sentiment | | 0.122 | | | | |
| | | (0.096) | | | | |
| Dovish sentiment | | | -0.264* | | | -2.750 |
| | | | (0.114) | | | (3.948) |
| FOMC X Dovish sentiment | | | -0.170 | | | |
| | | | (0.168) | | | |
| Constant | 0.107*** | 0.043 | 0.190* | 33.754*** | 33.912*** | 37.652*** |
| | (0.020) | (0.041) | (0.085) | (1.455) | (2.084) | (2.991) |
| No. of meetings | 220 | 220 | 180 | 220 | 220 | 180 |
| Observations | 10214 | 10214 | 8944 | 220 | 220 | 180 |
| $R^2$ | 0.41 | 0.41 | 0.43 | 0.00 | 0.00 | 0.00 |

Notes: The dependent variable in columns (1)–(3) is the sentiment of individual newspaper articles published after the FOMC announcement up to seven days after the meeting. These specifications include newspaper fixed effects. The dependent variable in columns (4)–(6) is the meeting-level number of articles, excluding the Financial Times. Strong sentiment denotes meetings in which FOMC sentiment is above the 75th percentile or below the 25th percentile of the sentiment distribution. Dovish sentiment denotes meetings in which FOMC sentiment is below 0. In columns (3) and (6), we drop meetings for which FOMC sentiment is neutral ($S^{FOMC} = 0$). $\Delta r^{shadow}$ denotes the change in the shadow rate from Wu and Xia (2016). In columns (1)-(3), standard errors are clustered at the meeting- and newspaper-level. In columns (4)–(6), standard errors are heteroskedasticity-robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Consistency between the FOMC and media sentiment is critical for an accurate transmission of monetary policy communication to the public. However, it is also important for the media to provide a balanced coverage of FOMC decisions. For example, if the FOMC and media sentiments are generally consistent but the media covers much more extensively hawkish FOMC meetings, this may create an overly hawkish perception about the FOMC. To assess this aspect, we regress the number of media articles for each FOMC meeting on the FOMC sentiment. As shown in column (4), we do not detect any correlation, implying that media coverage does not vary with FOMC sentiment. Furthermore, columns (5) and (6) show that the media coverage does not differ depending on whether the FOMC sentiment is strong or weak or on whether it is dovish or hawkish.

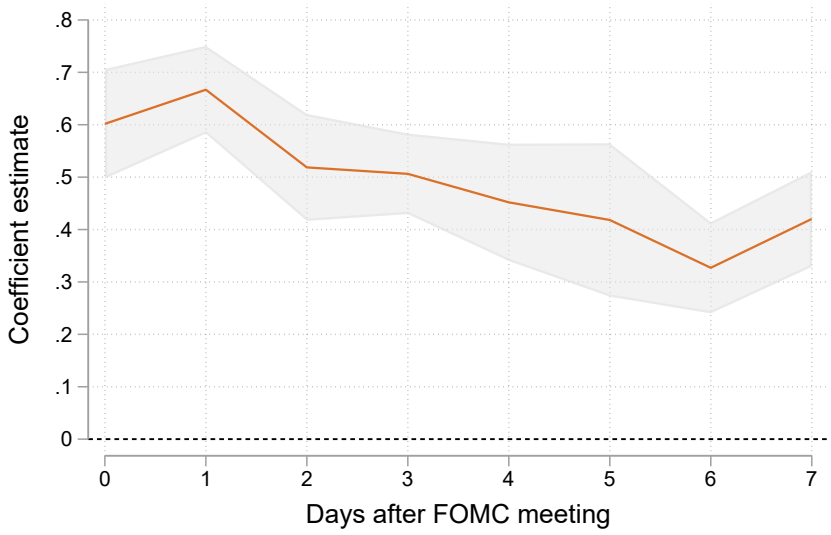
The analysis so far has focused on the average pass-through of the FOMC sentiment to articles published in the 7 days following the policy meeting. We now explore how the FOMC sentiment propagates over time in the media by differentiating articles based on

their publication dates. To this end, we estimate the following specification

$$S^{Media}_{a,j,m,h} = \alpha_j + \beta_{1,h} S^{FOMC}_m + \beta_{2,h} \Delta r_m + u_{a,j,m,h} \qquad \text{for} \quad h = 0, 1, ..., 7 \tag{3}$$

where the subscript $h$ captures the day of publication of each article relative to the FOMC meeting $m$. More precisely, $h = 0$ denotes the day of the meeting, $h = 1$ the day after and so on. Figure 5 shows the estimates of the $\beta_{1,h}$ coefficients. We see that the pass-through of the FOMC sentiment to the media coverage is particularly strong on the day following the meeting. As shown in Figure 2b, this is also the day with the highest number of articles covering the FOMC, thus arguably the most important one to shape public views. The strength of the pass-through declines modestly over the subsequent days as media coverage of FOMC decisions decreases.

Figure 5: Dynamic response of media sentiment




*Notes:* The figure reports estimates of the coefficient on FOMC sentiment from separate regressions for articles published on each day after the FOMC meeting. All regressions include newspaper fixed effects and control for the change in the shadow rate. Standard errors are clustered at the meeting- and newspaper level. 90 percent confidence bands in grey.

## 5.2 Differences across time and communication tools

The previous section has documented that the FOMC sentiment is, in general, well reflected in the media. We now explore whether the strength of the pass-through has varied over time and which types of FOMC communication tools generate the strongest pass-through to media coverage.

A closer inspection of Figure 4 already suggests that the correspondence between the FOMC and media sentiment varies over time. The two series comoved tightly during the pre-GFC period and during the hawkish turn triggered by the post-pandemic inflation surge. In contrast, the media sentiment did not track the FOMC sentiment that closely in the post-GFC period, when monetary policy was constrained by the zero lower bound. To examine these patterns more clearly, we assess the evolution of the pass-through over time by re-estimating our baseline equation (1) over rolling (overlapping) windows including 70 FOMC meetings, each covering about 10 years.[15] Figure 6 reports the estimates of the $\beta$ coefficient for each rolling window, with the horizontal axis denoting the date of the FOMC meeting in the middle of the window. We see a pronounced decline in the communication pass-through when monetary policy became constrained by the zero lower bound after the GFC. This underscores the communication challenges faced by the Fed at that time, reflecting the new uncharted conduct of unconventional monetary policy. The communication pass-through started to improve around the introduction of press conferences in 2011, consistent with the view that this communication tool proved effective in clarifying the stance of monetary policy. Finally, the strength of the pass-through has reached historical highs in the most recent period, when the rolling regression sample includes the sharp communication turns by the FOMC during the COVID-19 pandemic and the subsequent inflation surge.[16]

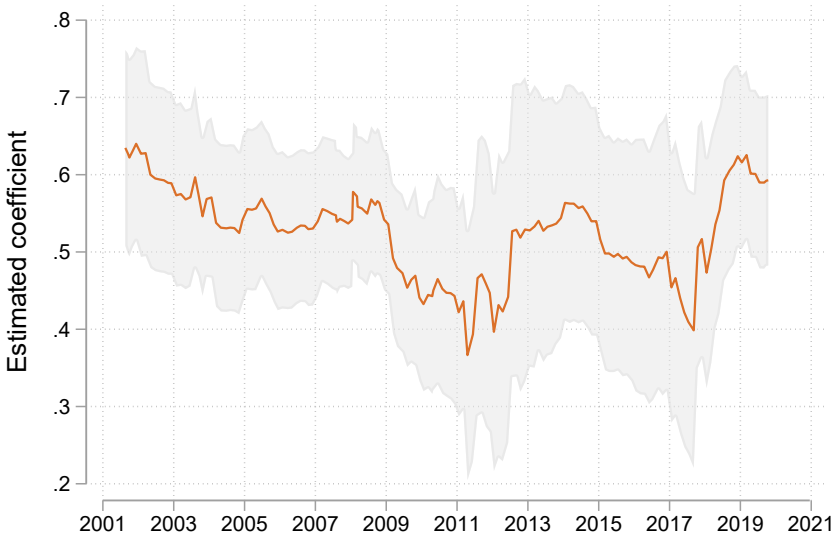
To further explore the role of press conferences in influencing media coverage, we assess whether the strength of pass-through differs depending on whether FOMC meetings are followed by a press conference. As previously discussed, press conferences were introduced in April 2011 and were held until 2019 only when updated economic projections were released. By focusing on the period between April 2011 and 2019 which saw FOMC meetings with and without press conferences, we estimate equation (2) where the dummy $D_m$ denotes FOMC meetings followed by a press conference. The results reported in column (1) of Table 4 suggest a larger pass-through for meetings with a press conference, although the difference is not statistically significant.

An additional approach to assess the importance of press conferences for media coverage is to examine the pass-through of each FOMC communication tool separately. To this end, we re-estimate our baseline equation by including as separate regressors the sentiment conveyed in the press statement, in the introductory remarks to the press con-

[15] Although FOMC meetings are now typically 8 per year, meetings were less frequent in the early part of our sample, resulting on average in around 7 meetings per year. Appendix C reports results for other window lengths. The overall pattern remains similar.

[16] In Appendix C, we also explore whether the strength of pass-through depends on the business cycle. We find suggestive evidence that pass-through is weaker in recessions.

Figure 6: Strength of the communication pass-through over time




*Notes:* The figure reports estimates of the coefficient on FOMC sentiment from regressions estimated over overlapping windows of 70 FOMC meetings. Each point on the x-axis corresponds to the date of the FOMC occurring in the middle of the rolling window. The grey area indicates the 90 percent confidence interval. Standard errors are clustered at the meeting- and newspaper level. All regressions include newspaper fixed effects and control for the change in the shadow rate.

ference, and in the answers provided by the Fed chair during the press conference. In this case, the regression includes all FOMC meetings featuring a press conference. The results are reported in column (2) of Table 4. The coefficient on the sentiment of the answers is the largest of the three and the only one that is statistically significant. These results provide suggestive evidence that the answers of the Fed chair play an important role in influencing media coverage, beyond the mere impact of policy decisions.

Table 4: Pass-through differences across time and tools

| | (1) April 2011-2018 | (2) Only meetings with press conference |
|---|---|---|
| FOMC sentiment | 0.480*** | |
| | (0.105) | |
| PressConf=1 | -0.128* | |
| | (0.065) | |
| PressConf=1 × FOMC sentiment | 0.139 | |
| | (0.128) | |
| $\Delta r^{shadow}$ | 0.291 | 0.268** |
| | (0.378) | (0.094) |
| Statements sentiment | | 0.181 |
| | | (0.127) |
| Remarks sentiment | | 0.158 |
| | | (0.099) |
| Answers sentiment | | 0.284** |
| | | (0.104) |
| Constant | 0.208*** | 0.097** |
| | (0.051) | (0.035) |
| No. of meetings | 62 | 69 |
| Observations | 3982 | 4921 |
| $R^2$ | 0.22 | 0.38 |

Notes: The dependent variable is the sentiment of individual newspaper articles published after the FOMC announcement up to seven days after the meeting. Column (1) uses meetings between April 2011 and the end of 2018 and interacts FOMC sentiment with an indicator for meetings followed by a press conference. Column (2) includes meetings featuring a press conference and separately considers the sentiment of the statement, introductory remarks, and answers. All specifications include newspaper fixed effects and control for the change in the shadow rate. $\Delta r^{shadow}$ denotes the change in the shadow rate from Wu and Xia (2016). Standard errors are clustered at the meeting- and newspaper level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 6 Media sentiment and households' expectations

The analysis has documented a high degree of consistency between the sentiment expressed in FOMC communication and media coverage. But does media sentiment in turn influence households, especially regarding their inflation expectations? A key goal of central bank communication with the public is indeed to manage inflation expectations.

To address this question, we examine the inflation expectations of US households collected by the New York Fed in the Survey of Consumer Expectations. The survey has been conducted since June 2013 and involves the participation of about 1,300 respondents each month. We use data up to September 2023, the last vintage available at the time of our study.

A useful feature of this survey for the purposes of our analysis is that participants sub-

mit their answers on different days. Building on Binder, Campbell and Ryngaert (2024) and De Fiore, Lombardi and Schuffels (2026), the empirical approach involves testing whether the inflation expectations collected a few days after FOMC meetings differ from those collected a few days before the meetings, and whether these differences are correlated with changes in media sentiment. Formally, we estimate the following regression

$$\pi_{it}^{e,T} = \alpha_i + \gamma_m + \left(\beta_1 + \beta_2 \Delta S_m^{News}\right) Post_{im} + u_{it} \tag{4}$$

The dependent variable $\pi_{it}^{e,T}$ denotes the inflation expectation of survey participant $i$ over the horizon $T$ on the day $t$. The regression controls for participant fixed effects, $\alpha_i$, as well as for FOMC-meeting fixed effects, $\gamma_m$. We include observations outside the event window in the estimation sample to improve the estimation of the participant fixed effect, although these observations do not directly contribute to the before-and-after comparisons around FOMC meetings. For observations within an event window, the $\gamma_m$ fixed effect absorbs meeting-specific differences in inflation expectations. The dummy variable $Post_{im}$ takes the value of one if inflation expectations are collected within $w$ days after the FOMC meeting $m$. Finally, the variable $\Delta S_m^{News}$ captures the change in media sentiment around the FOMC meeting $m$. This is computed as the difference in the average media sentiment from the FOMC announcement through the second day following meeting $m$ and from two days before the meeting up to the announcement.

The coefficient $\beta_1$ captures whether inflation expectations submitted within $w$ days after the meeting differ from those submitted within $w$ days prior to the meeting. The focus of the analysis is on the coefficient $\beta_2$. This coefficient captures whether changes in inflation expectations before and after the meeting are correlated with changes in the media coverage. Specifically, the $\beta_2$ coefficient should be negative if a hawkish turn in media sentiment reduces inflation expectations, as we would expect from a theoretical standpoint. We estimate equation (4) using alternative windows $w$ surrounding FOMC meetings. We start by setting $w = 3$, hence including only inflation expectations collected between 3 days before and 3 days after the meeting, and then increase this window up to 12 days. Shorter windows provide a cleaner identification of the effect of media sentiment on inflation expectations since inflation expectations are less likely to be contaminated by events unrelated to the FOMC. However, shorter windows also reduce the number of survey responses used to identify $\beta_2$.[17] In addition to 12-months ahead inflation

[17] We exclude respondents interviewed on the day of an FOMC meeting since we do not know whether they were interviewed before or after the FOMC decision. Furthermore, in a few instances, households fall within two FOMC meeting windows for longer window lengths. We exclude these responses from the analysis.

expectations, we consider also medium-term inflation expectations, defined as expected inflation over the 24- to 36-month period following the time of the survey. We refer to these expectations as 1- and 3-year-ahead inflation expectations.[18] The regression is estimated accounting for the survey weights and is based on the entire sample of inflation expectations from June 2013 to September 2023. Standard errors are clustered at the meeting-level.[19]

The causal interpretation of our estimates relies on two identification assumptions. First, it requires that the timing of survey responses relative to FOMC meetings must be quasi-random, as discussed extensively in Binder, Campbell and Ryngaert (2024). Second, within the narrow survey windows around FOMC meetings, there are no non-FOMC-related shocks that both affect household inflation expectations and are correlated with the change in FOMC-related media sentiment. Relatedly, our media sentiment measure must capture information and interpretation associated with the FOMC meeting, rather than unrelated news that independently shifts household expectations. We provide support for this restriction in Appendix D.5 by excluding FOMC meeting windows containing inflation and employment news releases. Under these assumptions, the specification in (4) estimates the effect of FOMC-related media coverage, which combines the pass-through of official FOMC communication with the media's own interpretation of the FOMC message. We later condition directly on a measure of FOMC communication to distinguish the role of media coverage from that of official FOMC communication.

Figure 7 shows the estimates of the coefficient $\beta_2$ for 1- and 3-year ahead inflation expectations, based on the alternative time windows surrounding FOMC meetings. The regression tables underlying the coefficient plots are delegated to Appendix D.1. The left chart shows that a hawkish shift in media sentiment reduces short-term inflation expectations over short windows. The estimates are negative and statistically significant for windows between 3 and 7 days, but become smaller and insignificant for longer windows. This somewhat moderate and temporary response is not surprising given that short-term inflation expectations tend to be highly affected by recent inflation developments. Central bank communication is more geared towards influencing medium-term inflation expectations rather than near-term expectations, also in light of the lags associated with

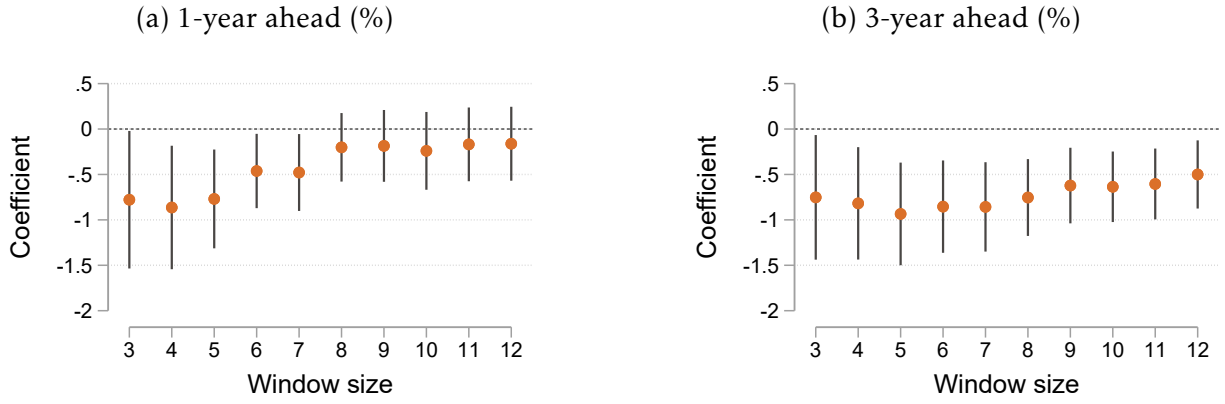
[18] For each month, we winsorize the tails of the distribution of inflation expectations at the 10 percent level to remove outliers. We also exclude the first six interview rounds for each respondent, since inflation expectations tend to be higher and more uncertain at the beginning of their survey participation (Kim and Binder, 2023; De Fiore, Lombardi and Schuffels, 2026). Appendix D.2 shows that the main regression results are similar if data are instead winsorized at the 5 percent level, or when we exclude alternative numbers of initial interview rounds.

[19] We also considered two-way clustering by respondent and meeting and obtained similar standard errors.

monetary policy transmission.

Media sentiment instead has a stronger impact on medium-term inflation expectations. The right chart shows that when media sentiment becomes more hawkish, households tend to revise down their expectations about the 3-year ahead inflation rate. The quantitative effects are sizeable across all windows. Using the average estimate across the different windows, a one-standard-deviation hawkish shift in media sentiment tends to lower 3-year ahead inflation expectations by about 0.18 percentage points. These results provide encouraging evidence about central banks' ability to affect households' inflation expectations via media coverage.

Figure 7: The impact of media sentiment on households' inflation expectations



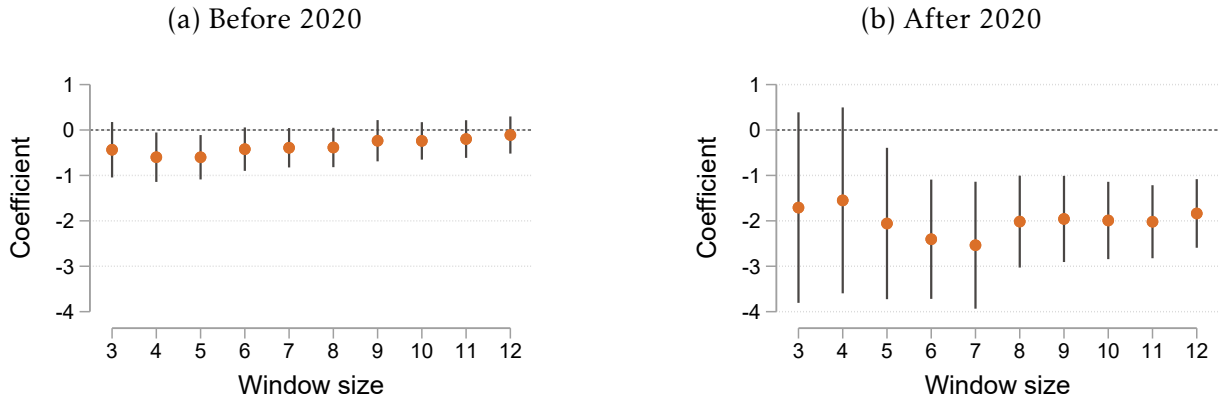

*Notes:* The figure reports estimates of the coefficient $\beta_2$ in equation (4) for different windows surrounding FOMC meetings, with 90% confidence intervals. The left and right panels consider inflation expectations over the next 12 months and between 24 and 36 months, respectively. Standard errors are clustered at the meeting-level.

We next examine whether the impact of media sentiment on households' expectations has varied over time. From June 2013, the start of our sample, until the onset of the COVID-19 pandemic, inflation rates remained persistently low and stable. As a result, households might have paid less attention to monetary policy news and have been less likely to revise inflation expectations based on such information. In contrast, the post-pandemic surge in inflation and central banks' explicit efforts to manage inflation expectations through public communications may have heightened households' attention to monetary policy news, thereby amplifying its influence on inflation expectations.

The econometric results support this hypothesis. Figure 8 shows estimates of the $\beta_2$ coefficient based on the sample before 2020 and from 2020 onwards for 3-year ahead inflation expectations, which are more closely aligned with the horizon relevant for monetary policy communication. The post-2020 estimates are considerably larger than those for the pre-2020 period, indicating that media coverage of monetary policy has stronger

effects on households' inflation expectations during times when inflation is high and volatile. This pattern is consistent with evidence that households pay greater attention to inflation in such periods (Pfäuti, 2023; Korenok, Munro and Chen, 2023; Bracha and Tang, 2025; Weber et al., 2025).

Figure 8: The impact of media sentiment on 3-year-ahead inflation expectations




*Notes:* The figure reports estimates of the coefficient $\beta_2$ in equation (4) for different windows surrounding FOMC meetings, with 90% confidence intervals, over different periods. The left panel considers the period up to 2020, while the right panel covers the period from 2020 onwards. Standard errors are clustered at the meeting-level.

A possible concern is that the changes in inflation expectations around FOMC meetings might be directly influenced by FOMC communication rather than by media coverage. To explore this issue, we estimate the following expanded version of equation (4):

$$\pi^e_{it} = \alpha_i + \gamma_m + \left(\beta_1 + \beta_2 \Delta S^{News}_m + \beta_3 \Delta S^{FOMC}_m\right) Post_{im} + u_{it} \tag{5}$$

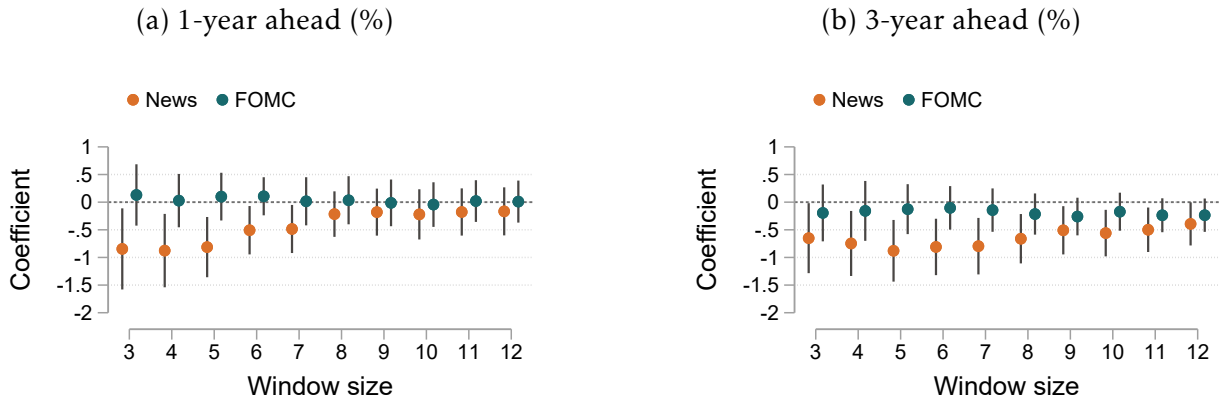
This specification allows expectations to respond separately to changes in media sentiment and to the sentiment conveyed by FOMC communication, denoted by $\Delta S^{FOMC}_m$. Since we do not have a measure of FOMC sentiment right before the meeting, we construct $\Delta S^{FOMC}_m$ as the difference between the FOMC sentiment of meeting $m$ and the media sentiment in the 2 days before the meeting, mirroring the procedure to construct the change in the media sentiment $\Delta S^{News}_m$. In this specification, $\beta_2$ captures the association between changes in media sentiment and households' inflation expectations, conditional on the measured sentiment of FOMC communication. Although the levels of FOMC and media sentiment are highly correlated, the corresponding sentiment changes are less correlated, allowing us to estimate their effects separately.

Figure 9 reports the estimates for the regression coefficients $\beta_2$ and $\beta_3$. The results paint a consistent picture across different regression windows. We continue to see that

a hawkish turn in media sentiment tends to reduce medium-term inflation expectations. In contrast, we do not detect any effect of the FOMC sentiment on inflation expectations, at both horizons.

Appendix D provides several robustness exercises. We show that our results are robust to replacing changes in FOMC sentiment with alternative measures of central bank actions, such as changes in the federal funds rate target, the shadow rate and monetary policy surprises. We also consider an alternative measure of the change in FOMC sentiment, computed relative to the previous FOMC meeting. This has the benefit of comparing sentiment across the same source of communication, but captures developments over the entire intermeeting period. We also show that the results hold in both the pre- and post-2020 samples. These findings are consistent with the premise of the analysis, namely that households do not directly read FOMC statements or listen to the press conferences. Therefore, the media plays a critical role in conveying monetary policy information to the public and, in turn, influencing households' inflation expectations.

Figure 9: Sensitivity of inflation expectations to media and FOMC sentiment




*Notes:* The figure reports estimates of the coefficient $\beta_2$ and $\beta_3$ in equation (5) for different windows surrounding FOMC meetings, with 90% confidence intervals. The left and right panels consider inflation expectations over the next 12 months and between 24 and 36 months, respectively. Standard errors are clustered at the meeting-level.

## 6.1 Heterogeneity in inflation expectation responses

Household inflation expectations are known to differ systematically across demographic, socioeconomic and financial characteristics, including gender, education, and homeownership status (D'Acunto et al., 2024; Coibion, Gorodnichenko and Weber, 2022; Piccolo and Gorodnichenko, 2025). These differences may also shape how households process monetary policy news. If some groups are more attentive to economic information, bet-

ter able to interpret central bank communication, or more exposed to media coverage of monetary policy, their expectations may respond more strongly to changes in news sentiment. Motivated by this evidence, we examine heterogeneity in the transmission from media sentiment to inflation expectations by re-estimating specification (5) separately by education, mortgage status, and gender.

We begin by splitting households by educational attainment, distinguishing between those with and without a college degree. Panels (a) and (b) of Figure 10 show a larger response of inflation expectations to news sentiment among households without a college degree. This pattern contrasts with the information-treatment evidence in Coibion, Gorodnichenko and Weber (2022), where less educated households exhibit weaker revisions in inflation expectations in response to information from USA Today. The difference may reflect that our analysis captures coverage across a broader set of articles and media outlets. In stark contrast, we find that the response to FOMC sentiment is statistically significant for households with a college degree, but not for those without. The evidence therefore suggests a sharp difference in the type of information to which households respond: less-educated households appear more responsive to news sentiment, whereas college-educated households' expectations are more closely associated with FOMC sentiment.

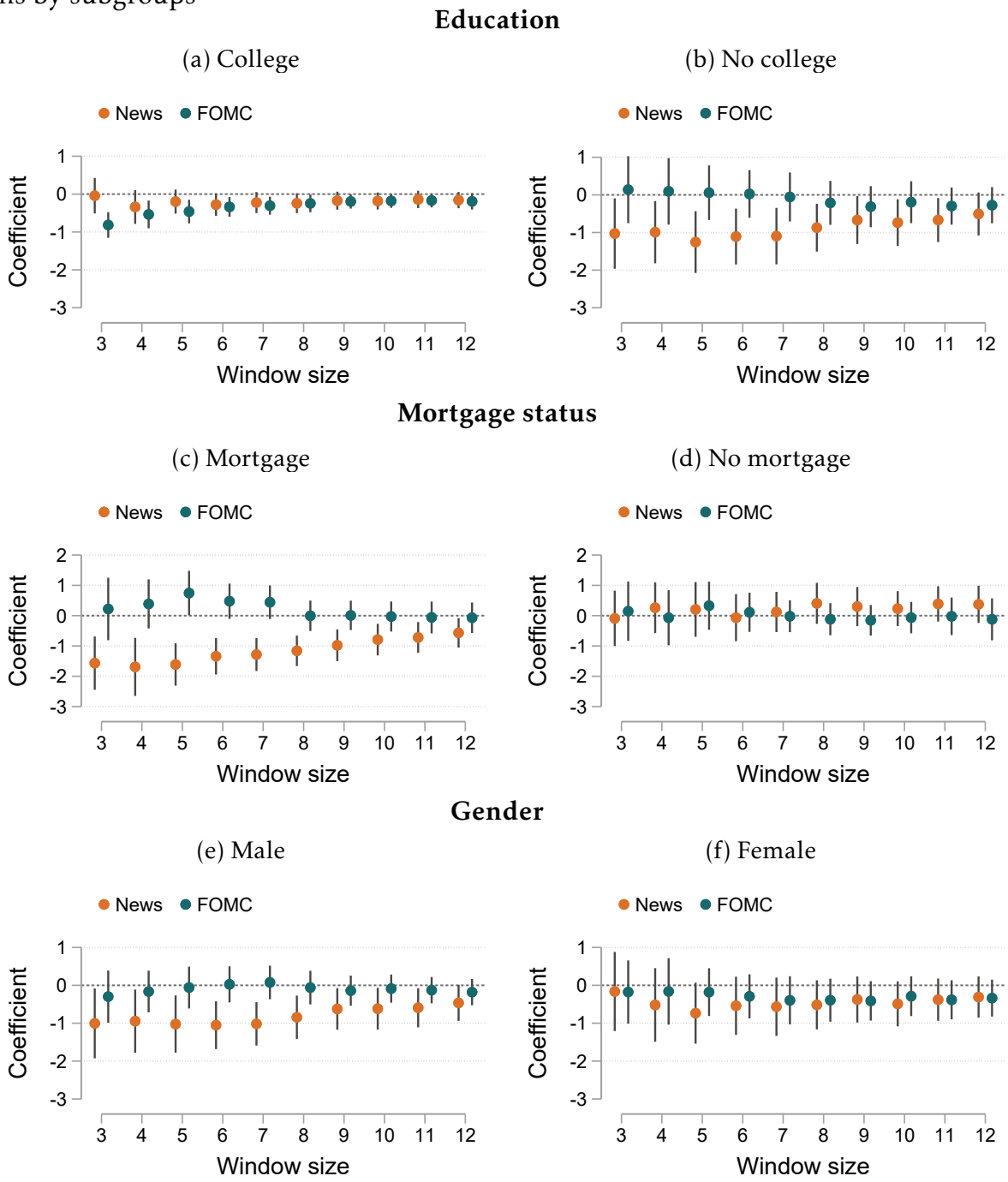
Next, we examine heterogeneity by mortgage status. Households with mortgages may be more sensitive to monetary policy because changes in interest rates directly affect their financial conditions, particularly when they have variable-rate loans. To obtain information on mortgage debt, we merge the core Survey of Consumer Expectations with the Household Finance Module. Since the Household Finance Module is available only through 2019 and is administered annually, the merge reduces the sample size. We classify households as mortgagors if they report positive outstanding loans against the value of the home and treat this status as fixed over the months in which they remain in the survey.[20]

Panels (c) and (d) of Figure 10 indicate that the response to news sentiment is concentrated among households with mortgage debt, while households without mortgage debt exhibit no statistically significant response. The response to FOMC sentiment, in contrast, is statistically insignificant, irrespective of mortgage status.

Finally, we investigate potential heterogeneity by gender. Overall, panels (e) and (f) show negative responses to news sentiment for both male and female household heads, although the estimates are only statistically significant across most windows for men.

[20]Outstanding loans against the value of the home could, in principle, also include home equity loans and lines of credit.

Figure 10: The impact of media and FOMC sentiment on 3-year-ahead inflation expectations by subgroups




*Notes:* The figure reports estimates of the coefficients $\beta_2$ and $\beta_3$ in equation (5) for different windows surrounding FOMC meetings, with 90% confidence intervals, for different subgroups. Standard errors are clustered at the meeting-level.

Neither group, however, exhibits a statistically significant response to FOMC sentiment.

# 7 Conclusion

Over the last decades, central banks have placed increasing emphasis on public communication by explaining the rationale for policy decisions and providing indications about the future policy stance. A key goal underpinning these efforts is to enhance the effectiveness of monetary policy and strengthen the anchoring of inflation expectations.

This paper sheds light on central banks' ability to influence the public by examining the degree of consistency between FOMC communication and media coverage. We focus on media coverage because survey evidence shows that households rely on the media to gather information on monetary policy and central bank decisions. Hence, a strong pass-through of FOMC communication to media coverage is a key pre-condition for central banks' ability to reach the public.

The analysis shows that FOMC communication is generally well portrayed by the media. However, there have been notable differences across time. The communication pass-through deteriorated considerably post-GFC, when the ZLB became binding and the Fed had to conduct monetary policy by deploying new tools. The pass-through then strengthened around the introduction of the post-FOMC press conferences. The answers provided by the Fed Chair during press conferences are particularly closely associated with media coverage. Finally, we show that when media coverage turns more hawkish, households tend to lower their medium-term inflation expectations. This response was particularly strong during the post-pandemic inflation surge, consistent with households paying more attention to monetary policy news when inflation is high and volatile and when central bank communication becomes more important. Instead, we detect no independent effect of the sentiment expressed in FOMC communication on household expectations, underscoring the critical role played by the media in channelling central bank communication to the public.

Future research could expand the analysis along various dimensions. First, it would be valuable to assess the role of governors' speeches in influencing media coverage, as these speeches also convey important indications about the monetary policy stance (Swanson, 2023). Second, the work could be extended to examine the consistency between central bank communication and media coverage concerning the economic outlook. In this context, it would be interesting to investigate potential differences in the coverage of the economic outlook across media outlets, which may reflect different editorial or political leanings. Finally, it would be worthwhile to examine the sentiment regarding monetary policy and the economic outlook portrayed on social media, given the growing use of these platforms among large segments of the population.

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# Appendix

## A Selection procedure for media articles

As described in the paper, we implement a 3-step cleaning procedure to eliminate articles that are not relevant for the analysis. First, we drop transcripts of FOMC communication, for example as distributed via newsletters. Second, we eliminate articles that are very similar to each other, for example as in the case of small revisions to articles posted online. We perform this step by measuring the "cosine similarity" between articles from the same newspaper covering the same FOMC meeting. This index quantifies the similarity between two texts by computing the cosine of the angle between their vector representations in a multi-dimensional space. For our purpose, these vectors represent the frequency of each word in each text. Articles with a similarity score exceeding 0.9 and with a length ratio below 1.5 are filtered out. If these articles are published on the same day, we keep the longest one. Otherwise, we keep the first one published. Note that we retain articles with a high similarity score but a length ratio exceeding 1.5 because these are more likely to reflect substantial revisions. Third, we use GPT-4 to select articles that are sufficiently focused on monetary policy decisions by the Federal Reserve. We do so by providing GPT-4 with the following prompt: "You're a research assistant working for the Fed. You have a Master's degree in Economics. Your task is to classify the following articles on a scale from 0 to 5 depending on the extent to which they focus on a monetary policy decision by the Federal Reserve. Specifically, 0 means that the article is unrelated to a monetary policy decision by the Federal Reserve. At the opposite end, 5 means that the article is squarely focused on a monetary policy decision by the Federal Reserve." We keep the articles that have a score of 4 or 5. This cleaning procedure leaves us with a final sample of 14,021 articles. Table A.1 shows the distribution of articles across media outlets.

Table A.1: Distribution of articles covering FOMC meetings across media outlets

| Newspaper | Number of articles | Percent |
|---|---|---|
| Wall Street Journal | 5,118 | 36.50 |
| Financial Times | 3,929 | 28.02 |
| Washington Post | 1,498 | 10.68 |
| USA Today | 1,083 | 7.72 |
| Los Angeles Times | 1,049 | 7.48 |
| CNN | 850 | 6.06 |
| New York Post | 456 | 3.25 |
| Fox News | 38 | 0.27 |
| Total | 14,021 | 100 |

# B LLM comparison

Table B.1 reports the confusion matrices for GPT-4 and RoBERTa that underlie the performance comparison in Table 1. GPT-4 outperforms RoBERTa on dovish (83% vs 71% correct classifications) and neutral statements (61% vs 53% correct classifications), but performs worse on hawkish statements (80% vs 95% correct classifications).

Table B.1: Confusion matrices for FOMC statements across LLMs

| Actual | Predictions | | | | | |
|---|---|---|---|---|---|---|
| | GPT-4 | | | RoBERTa-SPC23 | | |
| | Dovish | Neutral | Hawkish | Dovish | Neutral | Hawkish |
| Dovish | 0.83 | 0.15 | 0.02 | 0.71 | 0.22 | 0.07 |
| Neutral | 0.26 | 0.61 | 0.13 | 0.19 | 0.53 | 0.28 |
| Hawkish | 0.06 | 0.14 | 0.80 | 0.01 | 0.04 | 0.95 |
| No. statements | 511 | 489 | 243 | 511 | 489 | 243 |

Notes: The table reports confusion matrices, where each row corresponds to the true policy stance and entries denote the share of observations assigned to each predicted class.

# C Sentiment pass-through

This section reports various additional results regarding the sentiment pass-through from FOMC communication to the media.

**Newspaper heterogeneity.** Table C.1 reports the pass-through of FOMC sentiment to media sentiment by newspaper outlet based on estimating a variant of Equation 1 without newspaper fixed-effects for each newspaper individually. The estimated coefficients are large and statistically significant across all newspapers.

Table C.1: Sentiment pass-through by media outlet

| | (1) WSJ | (2) FT | (3) WP | (4) LAT | (5) CNN | (6) USAT | (7) NYP | (8) FOX |
|---|---|---|---|---|---|---|---|---|
| FOMC sentiment | 0.598*** | 0.586*** | 0.665*** | 0.729*** | 0.751*** | 0.798*** | 0.737*** | 0.770*** |
| | (0.033) | (0.049) | (0.032) | (0.034) | (0.055) | (0.034) | (0.039) | (0.215) |
| Constant | 0.107*** | 0.108*** | 0.110*** | 0.064** | 0.149*** | 0.083*** | 0.093*** | 0.180 |
| | (0.023) | (0.036) | (0.024) | (0.027) | (0.037) | (0.028) | (0.034) | (0.129) |
| No. of meetings | 224 | 161 | 223 | 210 | 104 | 213 | 173 | 13 |
| Observations | 3792 | 2903 | 1178 | 810 | 642 | 769 | 355 | 23 |
| $R^2$ | 0.32 | 0.27 | 0.48 | 0.57 | 0.48 | 0.56 | 0.45 | 0.48 |

Notes: Standard errors clustered at the meeting-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

**Regular vs irregular meetings.** Table C.2 shows the pass-through of FOMC sentiment to media sentiment for regular FOMC meetings only. The estimated coefficients are similar to those obtained from the full sample of FOMC meetings.

**Rolling window estimation.** Figure C.1 reports the rolling window estimation for alternative window lengths of 60 and 80 meetings. The pass-through variation is overall similar to the main specification with window length 70.

**State dependence of pass-through.** Table C.3 examines whether pass-through is state-dependent, specifically with respect to the interest rate level, the VIX, the state of the business cycle and inflation. Pass-through appears to be lower during recessions and periods of high uncertainty, but otherwise unaffected.

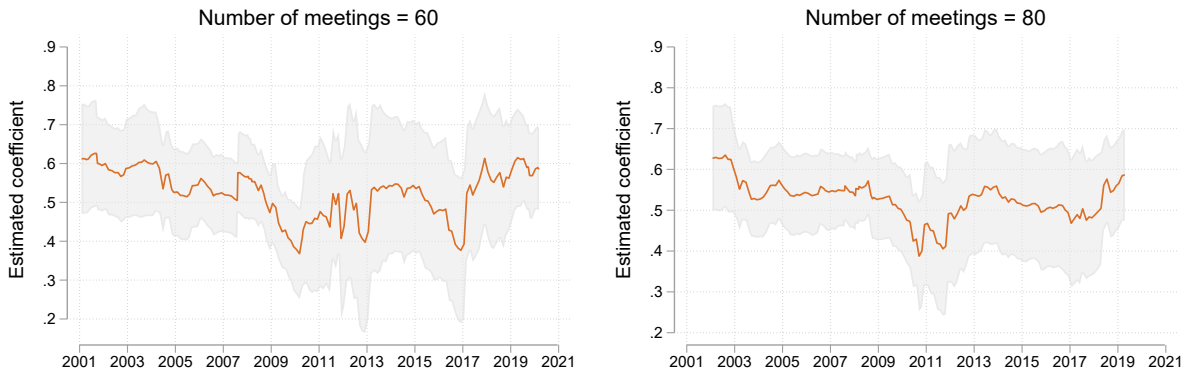
**Alternative interest rate controls.** The remainder of this section shows that the main figures and tables are robust to controlling for the change in the Federal Funds Target and the monetary policy surprise from Bauer and Swanson (2023) instead of the shadow rate.

Table C.2: Sentiment pass-through and media coverage – regular FOMC meetings

| | (1) Base | (2) FFR | (3) Shadow rate | (4) MP surprise |
|---|---|---|---|---|
| FOMC sentiment | 0.639*** | 0.471*** | 0.567*** | 0.579*** |
| | (0.040) | (0.050) | (0.049) | (0.045) |
| Δ FFR | | 0.537*** | | |
| | | (0.083) | | |
| $\Delta r^{shadow}$ | | | 0.281*** | |
| | | | (0.071) | |
| MP surprise | | | | 2.265*** |
| | | | | (0.395) |
| Constant | 0.127*** | 0.068** | 0.109*** | 0.110*** |
| | (0.020) | (0.020) | (0.021) | (0.019) |
| No. of meetings | 210 | 210 | 206 | 209 |
| Observations | 9605 | 9605 | 9347 | 9596 |
| $R^2$ | 0.37 | 0.39 | 0.39 | 0.41 |

Notes: Δ FFR denotes the change in the Fed's target rate, $\Delta r^{shadow}$ the change in the shadow rate from Wu and Xia (2016) and MP surprise is the monetary policy surprise from Bauer and Swanson (2023). Standard errors are clustered at the meeting- and newspaper-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

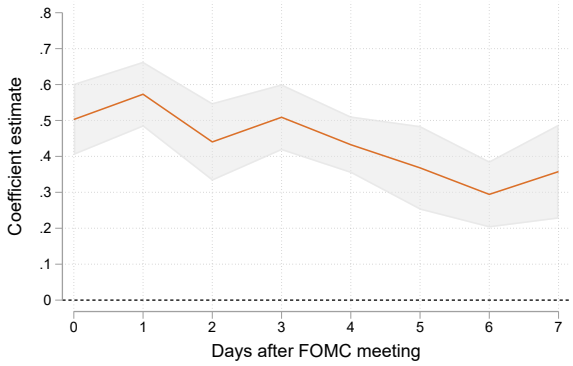
Figure C.1: Strength of communication pass-through over time – alternative windows



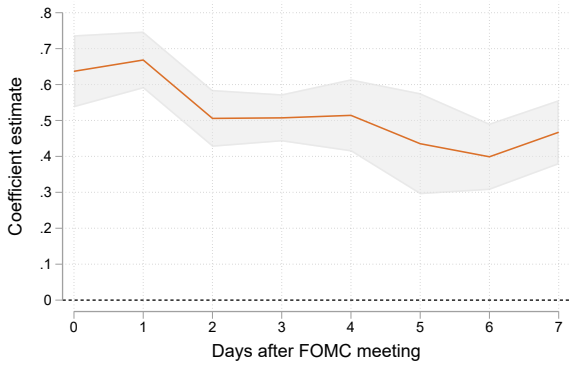

*Notes:* Estimated over overlapping windows. Each point on the x-axis corresponds to the date of the FOMC occurring in the middle of the rolling window. The grey area indicates the 90 percent confidence interval. Standard errors are clustered at the meeting- and newspaper level. The regression controls for the change in the shadow rate.

Figure C.2: Dynamic response of media sentiment – alternative controls

(a) FFR



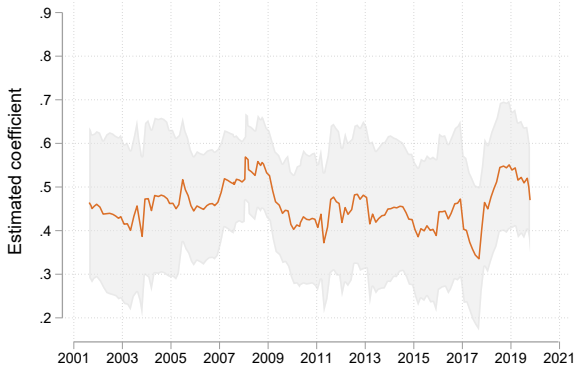

(b) MPS



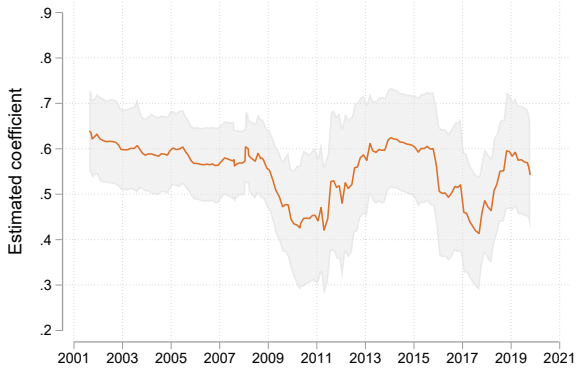

*Notes:* Standard errors are clustered at the meeting- and newspaper level. 90 percent confidence bands in grey. Controls include the change in the Fed Funds Target (a) and the monetary policy surprise (b).

Figure C.3: Strength of the communication pass-through over time – alternative controls

(a) FFR




(b) MPS




*Notes:* Estimated over overlapping 70-meeting windows. Each point on the x-axis corresponds to the date of the FOMC occurring in the middle of the rolling window. The grey area indicates the 90 percent confidence interval. Standard errors are clustered at the meeting- and newspaper level. Controls include the change in the Fed Funds Target (a) and the monetary policy surprise (b).

Table C.3: State-dependency of sentiment pass-through

| | (1) FFR | (2) Ygap | (3) VIX | (4) CPI | (5) Recession |
|---|---|---|---|---|---|
| FOMC sentiment | 0.487*** | 0.543*** | 0.670*** | 0.519*** | 0.548*** |
| | (0.072) | (0.056) | (0.081) | (0.078) | (0.059) |
| FedFunds | -0.031** | -0.034*** | -0.032** | -0.031** | -0.032** |
| | (0.010) | (0.009) | (0.009) | (0.010) | (0.009) |
| FOMC sentiment × FedFunds | 0.018 | | | | |
| | (0.014) | | | | |
| $\Delta r^{shadow}$ | 0.157** | 0.156** | 0.184** | 0.155* | 0.167** |
| | (0.064) | (0.064) | (0.066) | (0.066) | (0.068) |
| Output gap | 1.511 | 2.103 | 0.811 | 1.005 | 0.737 |
| | (1.053) | (1.639) | (1.166) | (1.206) | (1.170) |
| VIX | -0.004* | -0.004* | -0.009** | -0.004* | -0.005** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| CPI inflation | 4.277*** | 4.081*** | 4.988*** | 4.071*** | 4.504*** |
| | (1.042) | (0.969) | (1.151) | (1.018) | (0.998) |
| Recession=1 | -0.056 | -0.057 | -0.079 | -0.058 | -0.271** |
| | (0.062) | (0.062) | (0.059) | (0.060) | (0.096) |
| FOMC sentiment × Output gap | | 1.590 | | | |
| | | (1.986) | | | |
| FOMC sentiment × VIX | | | -0.007* | | |
| | | | (0.003) | | |
| FOMC sentiment × CPI inflation | | | | 0.586 | |
| | | | | (1.285) | |
| Recession=1 × FOMC sentiment | | | | | -0.319** |
| | | | | | (0.095) |
| Constant | 0.143** | 0.160*** | 0.205*** | 0.150** | 0.162*** |
| | (0.050) | (0.046) | (0.044) | (0.047) | (0.046) |
| N | 10214 | 10214 | 10214 | 10214 | 10214 |
| $R^2$ | 0.42 | 0.42 | 0.42 | 0.42 | 0.43 |

Notes: VIX is measured at daily frequency. Inflation is monthly y-o-y CPI inflation. The recession indicator and Fed Funds Rate are monthly. The output gap is quarterly. Standard errors are clustered at the meeting- and newspaper-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# D Media sentiment and inflation expectations

This section provides additional results regarding the effect of media sentiment on household inflation expectations.

## D.1 Regression tables

This subsection reports the regression tables underlying the coefficient plots of the main analysis in section 6.

## D.2 Alternative outlier correction schemes

We first examine the robustness of the household-expectations results to alternative treatments of outliers. Figure D.1 reports the main coefficient plots for one-year- and three-year-ahead inflation expectations when the dependent variable is winsorized at the 5 percent level, rather than at the 10 percent level used in the baseline specification. The results are similar to the baseline estimates.

Figure D.2 considers a second robustness exercise that varies the treatment of respondents' initial survey observations. In the baseline specification, we exclude the first six observations for each household to reduce the influence of initial reporting behavior and learning about the survey instrument. The figure shows that the estimated response of three-year-ahead inflation expectations is robust to excluding alternative numbers of initial observations.

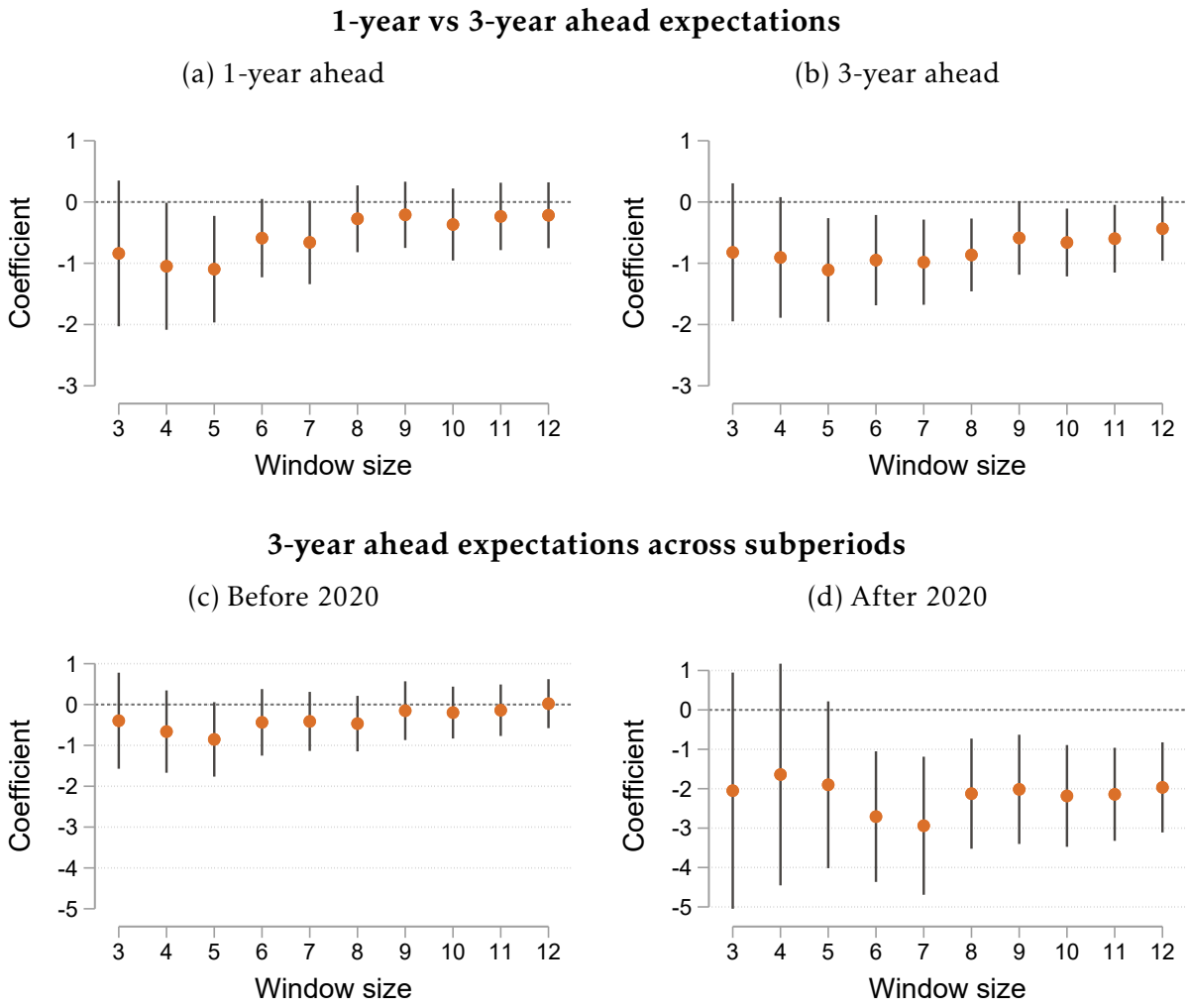
## D.3 Alternative measures of FOMC actions

Next, we examine whether our finding that household inflation expectations do not respond to FOMC sentiment changes is robust to alternative measures of FOMC actions. Table D.4 reports variants of regression Table D.3 replacing the control for FOMC sentiment with various alternative measures of FOMC actions: the change in the federal funds target, the change in the shadow rate, the high-frequency monetary policy surprise and an alternative measure of FOMC sentiment change where the change is computed relative to the FOMC sentiment of the previous FOMC meeting instead of the media sentiment preceding the FOMC meeting. Across all specifications, only the change in news sentiment yields a negative coefficient that is statistically significant at conventional levels.

## D.4 News vs FOMC sentiment across subperiods

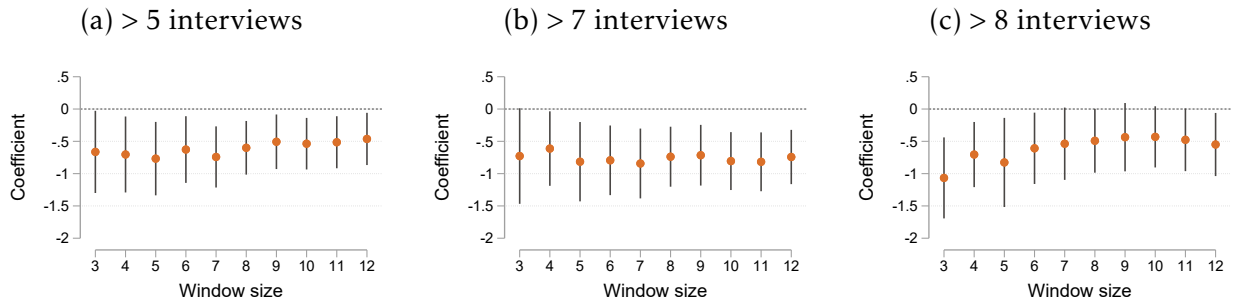
This subsection illustrates that household inflation expectations respond more strongly to news than to FOMC sentiment not only across the full sample, but also across subsamples. Specifically, Figure D.3 reports the sensitivity of 3-year-ahead inflation expectations to media and FOMC sentiment across the subsamples before 2020 and after 2020.

Figure D.1: Media sentiment and household inflation expectations – 5% winsorization



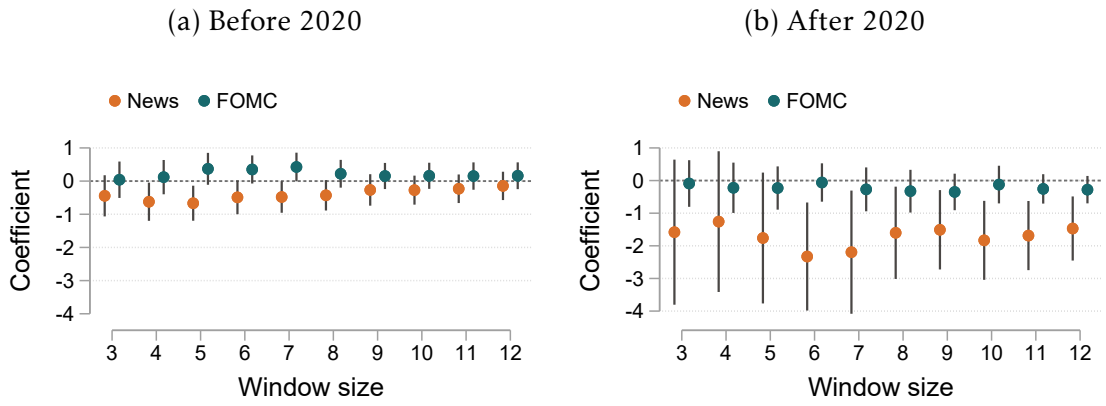

*Notes:* The figure reports estimates of the coefficient $\beta_2$ in equation (4) for different windows surrounding FOMC meetings, with 90% confidence intervals. Panels (a) and (b) consider inflation expectations over the next 12 months and between 24 and 36 months, respectively over the full sample. Panels (c) and (d) consider 3-year expectations for the period up to 2020, and the period from 2020 onwards, respectively. Inflation expectations are winsorized at the 5% level. Standard errors are clustered at the meeting-level.

Figure D.2: Media sentiment and households' inflation expectations – alternative samples




*Notes:* The figure reports estimates of the coefficient $\beta_2$ in equation (4) for different windows surrounding FOMC meetings, with 90% confidence intervals. The panels consider inflation expectations between 24 and 36 months. The left panel excludes the first 5 interview rounds of each respondent, the middle panel the first 7 and the right panel the first 8. Inflation expectations are winsorized at the 10% level. Standard errors are clustered at the meeting-level.

Figure D.3: Sensitivity of 3-year-ahead inflation expectations to media and FOMC sentiment across subperiods

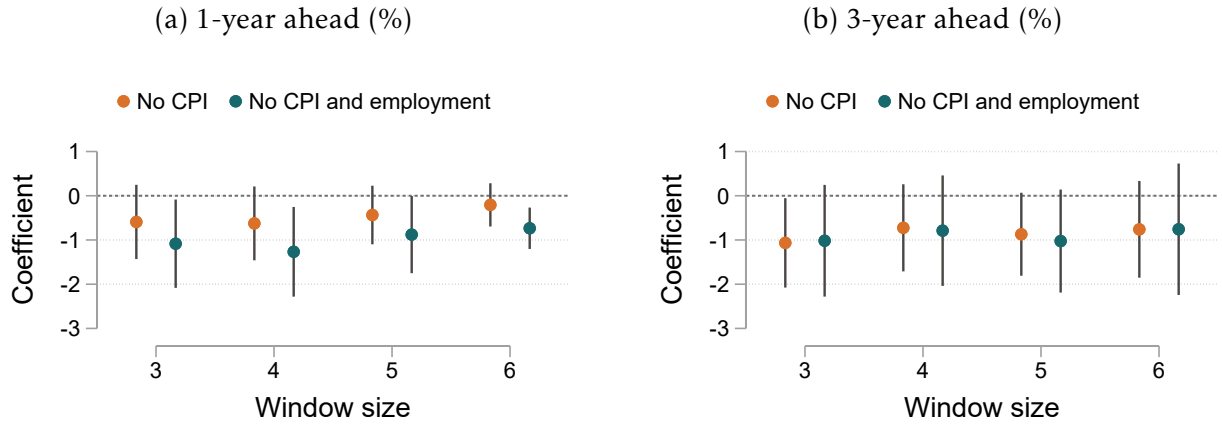



*Notes:* The figure reports estimates of the coefficients $\beta_2$ and $\beta_3$ in equation (5) for different windows surrounding FOMC meetings, with 90% confidence intervals. The left panel considers the period before 2020, while the right panel considers the period from 2020 onwards. Standard errors are clustered at the meeting level.

## D.5 Inflation and employment news releases

This subsection examines whether our baseline estimates are contaminated by the concurrent release of macroeconomic information. Figure D.4 reports the response of 1-year-ahead and 3-year ahead inflation expectations to changes in media sentiment for the subset of FOMC meetings around which there were no releases of CPI or employment reports by the U.S. Bureau of Labor Statistics. We report only coefficient estimates for windows of six days or less since for larger windows, we are left with fewer than 30 meetings after excluding those with concurrent macroeconomic news. Overall, the estimated coefficients are broadly similar in magnitude to the baseline estimates. The standard errors, however, are larger due to the smaller sample, in particular for the 3-year ahead estimates.

Figure D.4: Media sentiment and household inflation expectations – news releases




*Notes:* The figure reports estimates of the coefficient $\beta_2$ in equation (4) for different windows surrounding FOMC meetings, with 90% confidence intervals. The left and right panels consider inflation expectations over the next 12 months and between 24 and 36 months, respectively. The first series excludes meetings for which a CPI release falls within the estimation window. The second series additionally excludes meetings for which an employment report falls within the window. Standard errors are clustered at the meeting-level.

Table C.4: Sentiment pass-through and media coverage – nonlinearities under alternative policy controls

| **Panel A: Federal funds rate** | | | | | | |
|---|---|---|---|---|---|---|
| | Sentiment | | | Number of articles | | |
| | (1) Base | (2) Size | (3) Sign | (4) Base | (5) Size | (6) Sign |
| FOMC sentiment | 0.488*** | 0.428*** | 0.359** | 3.543 | | |
| | (0.049) | (0.105) | (0.148) | (3.021) | | |
| Δ FFR | 0.457*** | 0.435*** | 0.467*** | -6.950 | -0.599 | -9.167 |
| | (0.081) | (0.072) | (0.080) | (10.068) | (7.395) | (8.725) |
| Strong sentiment | | 0.081 | | | -0.620 | |
| | | (0.047) | | | (2.727) | |
| FOMC X Strong sentiment | | 0.074 | | | | |
| | | (0.101) | | | | |
| Dovish sentiment | | | -0.246* | | | -6.938 |
| | | | (0.120) | | | (4.211) |
| FOMC X Dovish sentiment | | | -0.066 | | | |
| | | | (0.170) | | | |
| No. of meetings | 224 | 224 | 184 | 224 | 224 | 184 |
| Observations | 10472 | 10472 | 9202 | 224 | 224 | 184 |
| $R^2$ | 0.40 | 0.40 | 0.43 | 0.01 | 0.00 | 0.02 |
| **Panel B: Monetary policy surprise** | | | | | | |
| | Sentiment | | | Number of articles | | |
| | (1) Base | (2) Size | (3) Sign | (4) Base | (5) Size | (6) Sign |
| FOMC sentiment | 0.576*** | 0.490*** | 0.555*** | 2.760 | | |
| | (0.045) | (0.102) | (0.136) | (2.135) | | |
| MP surprise | 1.811*** | 1.787*** | 1.930*** | -35.753 | -27.586 | -37.904 |
| | (0.366) | (0.339) | (0.350) | (22.933) | (22.887) | (23.342) |
| Strong sentiment | | 0.101* | | | -0.861 | |
| | | (0.045) | | | (2.682) | |
| FOMC X Strong sentiment | | 0.097 | | | | |
| | | (0.100) | | | | |
| Dovish sentiment | | | -0.162 | | | -5.068 |
| | | | (0.104) | | | (3.248) |
| FOMC X Dovish sentiment | | | -0.141 | | | |
| | | | (0.156) | | | |
| No. of meetings | 222 | 222 | 183 | 222 | 222 | 183 |
| Observations | 10434 | 10434 | 9173 | 222 | 222 | 183 |
| $R^2$ | 0.41 | 0.42 | 0.45 | 0.01 | 0.01 | 0.02 |

Notes: Strong sentiment denotes meetings in which FOMC sentiment is above the 75th percentile or below the 25th percentile of the sentiment distribution. Dovish sentiment denotes meetings in which FOMC sentiment is below 0. The dependent variable in columns (4)–(6) is the number of articles excluding the Financial Times. In columns (3) and (6), we drop meetings for which FOMC sentiment is neutral ($S^{FOMC} = 0$). In Columns (1)-(3), standard errors are clustered at the meeting- and newspaper-level. In columns (4)–(6), standard errors are heteroskedasticity-robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Pass-through differences across time and tools – alternative policy controls

| **Panel A: Federal funds rate** | | |
|---|---|---|
| | (1) | (2) |
| | April 2011–2018 | Only meetings with press conference |
| FOMC sentiment | 0.533*** | |
| | (0.083) | |
| PressConf=1 | -0.335*** | |
| | (0.081) | |
| PressConf=1 × FOMC sentiment | -0.222 | |
| | (0.192) | |
| Δ FFR | 1.755*** | 0.467** |
| | (0.473) | (0.162) |
| Statements sentiment | | 0.179 |
| | | (0.139) |
| Remarks sentiment | | 0.048 |
| | | (0.102) |
| Answers sentiment | | 0.335** |
| | | (0.102) |
| No. of meetings | 62 | 73 |
| Observations | 3982 | 5179 |
| $R^2$ | 0.25 | 0.37 |
| **Panel B: Monetary policy surprise** | | |
| | (1) | (2) |
| | April 2011–2018 | Only meetings with press conference |
| FOMC sentiment | 0.557*** | |
| | (0.103) | |
| PressConf=1 | -0.066 | |
| | (0.051) | |
| PressConf=1 × FOMC sentiment | 0.101 | |
| | (0.146) | |
| MP surprise | 4.701*** | 2.397** |
| | (0.936) | (0.729) |
| Statements sentiment | | 0.179 |
| | | (0.121) |
| Remarks sentiment | | 0.153 |
| | | (0.088) |
| Answers sentiment | | 0.280** |
| | | (0.092) |
| No. of meetings | 62 | 73 |
| Observations | 3982 | 5179 |
| $R^2$ | 0.28 | 0.39 |

Notes: Standard errors are clustered at the meeting- and newspaper level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Table D.1: Media sentiment and inflation expectations

| **Panel A: 1-year-ahead inflation expectations** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -0.778* | -0.864** | -0.770** | -0.462* | -0.479* | -0.201 | -0.186 | -0.240 | -0.169 | -0.162 |
| | (0.455) | (0.409) | (0.327) | (0.246) | (0.254) | (0.227) | (0.238) | (0.257) | (0.244) | (0.245) |
| Meetings | 81 | 81 | 82 | 82 | 81 | 81 | 81 | 81 | 81 | 81 |
| Respondents | 11702 | 11701 | 11701 | 11701 | 11698 | 11697 | 11697 | 11696 | 11695 | 11694 |
| Observations | 59487 | 59414 | 59369 | 59338 | 59304 | 59297 | 59244 | 59186 | 59139 | 59093 |
| R2 | 0.74 | 0.74 | 0.74 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 |
| **Panel B: 3-year-ahead inflation expectations** | | | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -0.752* | -0.818** | -0.935*** | -0.854*** | -0.857*** | -0.754*** | -0.622** | -0.636*** | -0.605** | -0.500** |
| | (0.412) | (0.372) | (0.340) | (0.305) | (0.296) | (0.254) | (0.250) | (0.233) | (0.234) | (0.226) |
| Meetings | 81 | 81 | 82 | 82 | 81 | 81 | 81 | 81 | 81 | 81 |
| Respondents | 11699 | 11698 | 11698 | 11698 | 11695 | 11694 | 11694 | 11693 | 11692 | 11691 |
| Observations | 59495 | 59422 | 59377 | 59347 | 59313 | 59306 | 59253 | 59195 | 59148 | 59102 |
| R2 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 |

Notes: The table reports the results from estimating Equation (4) with 1-year and 3-year ahead inflation expectations as the dependent variable. Each column corresponds to a different window length. Standard errors are clustered at the meeting-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## Table D.2: Media sentiment and 3-year ahead inflation expectations across subperiods

| **Panel A: Before 2020** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -0.435 | -0.599* | -0.600** | -0.422 | -0.391 | -0.385 | -0.236 | -0.240 | -0.199 | -0.111 |
| | (0.364) | (0.325) | (0.291) | (0.285) | (0.259) | (0.259) | (0.271) | (0.246) | (0.247) | (0.244) |
| Meetings | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 |
| Respondents | 7437 | 7437 | 7437 | 7437 | 7437 | 7436 | 7436 | 7435 | 7434 | 7433 |
| Observations | 36581 | 36581 | 36581 | 36581 | 36575 | 36568 | 36529 | 36479 | 36437 | 36400 |
| R2 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 | 0.72 |
| **Panel B: After 2020** | | | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -1.708 | -1.550 | -2.059** | -2.405*** | -2.537*** | -2.017*** | -1.958*** | -1.992*** | -2.020*** | -1.838*** |
| | (1.237) | (1.207) | (0.984) | (0.775) | (0.824) | (0.597) | (0.560) | (0.502) | (0.474) | (0.445) |
| Meetings | 31 | 31 | 32 | 32 | 31 | 31 | 31 | 31 | 31 | 31 |
| Respondents | 4478 | 4477 | 4477 | 4477 | 4474 | 4474 | 4474 | 4473 | 4473 | 4472 |
| Observations | 22689 | 22616 | 22573 | 22543 | 22515 | 22515 | 22501 | 22492 | 22487 | 22477 |
| R2 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 |

Notes: The table reports the results from estimating Equation (4) with 3-year ahead inflation expectations as the dependent variable for the subperiods before 2020 and from 2020 onwards. Each column corresponds to a different window length. Standard errors are clustered at the meeting-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Sensitivity of inflation expectations to media and FOMC sentiment

| **Panel A: 1-year-ahead inflation expectations** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -0.846* | -0.876** | -0.813** | -0.507* | -0.485* | -0.216 | -0.180 | -0.221 | -0.178 | -0.166 |
| | (0.441) | (0.399) | (0.328) | (0.263) | (0.261) | (0.247) | (0.256) | (0.273) | (0.257) | (0.261) |
| Post-FOMC X Δ FOMC Sentiment | 0.130 | 0.028 | 0.100 | 0.106 | 0.016 | 0.034 | -0.013 | -0.044 | 0.020 | 0.010 |
| | (0.333) | (0.290) | (0.259) | (0.207) | (0.262) | (0.261) | (0.254) | (0.242) | (0.227) | (0.228) |
| Meetings | 81 | 81 | 82 | 82 | 81 | 81 | 81 | 81 | 81 | 81 |
| Respondents | 11702 | 11701 | 11701 | 11701 | 11698 | 11697 | 11697 | 11696 | 11695 | 11694 |
| Observations | 59487 | 59414 | 59369 | 59338 | 59304 | 59297 | 59244 | 59186 | 59139 | 59093 |
| R2 | 0.74 | 0.74 | 0.74 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 |
| **Panel B: 3-year-ahead inflation expectations** | | | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Post-FOMC X Δ News Sentiment | -0.651* | -0.747** | -0.880** | -0.810*** | -0.796** | -0.661** | -0.509* | -0.560** | -0.499** | -0.393* |
| | (0.380) | (0.353) | (0.335) | (0.307) | (0.307) | (0.268) | (0.262) | (0.253) | (0.242) | (0.235) |
| Post-FOMC X Δ FOMC Sentiment | -0.195 | -0.158 | -0.127 | -0.103 | -0.144 | -0.215 | -0.260 | -0.172 | -0.237 | -0.236 |
| | (0.309) | (0.325) | (0.271) | (0.237) | (0.236) | (0.224) | (0.205) | (0.207) | (0.184) | (0.181) |
| Meetings | 81 | 81 | 82 | 82 | 81 | 81 | 81 | 81 | 81 | 81 |
| Respondents | 11699 | 11698 | 11698 | 11698 | 11695 | 11694 | 11694 | 11693 | 11692 | 11691 |
| Observations | 59495 | 59422 | 59377 | 59347 | 59313 | 59306 | 59253 | 59195 | 59148 | 59102 |
| R2 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 |

Notes: The table reports the results from estimating Equation (5) with 1-year and 3-year ahead inflation expectations as the dependent variable. Each column corresponds to a different window length. Standard errors are clustered at the meeting-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Sensitivity of inflation expectations to media and alternative measures of FOMC actions

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Federal funds rate** | | | | | | | | |
| | 1-year ahead (%) | | | | 3-year ahead (%) | | | |
| | (1) 3-day | (2) 5-day | (3) 7-day | (4) 9-day | (5) 3-day | (6) 5-day | (7) 7-day | (8) 9-day |
| Post-FOMC X Δ News Sentiment | -0.879* | -0.834** | -0.468* | -0.163 | -0.942** | -1.055*** | -0.931*** | -0.700*** |
| | (0.458) | (0.324) | (0.249) | (0.236) | (0.423) | (0.347) | (0.307) | (0.258) |
| Post-FOMC X Δ FFR | 0.665 | 0.445 | -0.080 | -0.172 | 1.255** | 0.830** | 0.566 | 0.596 |
| | (0.409) | (0.313) | (0.257) | (0.319) | (0.483) | (0.341) | (0.467) | (0.373) |
| Observations | 59487 | 59369 | 59304 | 59244 | 59495 | 59377 | 59313 | 59253 |
| R2 | 0.74 | 0.74 | 0.75 | 0.75 | 0.70 | 0.70 | 0.70 | 0.70 |
| **Panel B: Shadow rate** | | | | | | | | |
| | 1-year ahead (%) | | | | 3-year ahead (%) | | | |
| | (1) 3-day | (2) 5-day | (3) 7-day | (4) 9-day | (5) 3-day | (6) 5-day | (7) 7-day | (8) 9-day |
| Post-FOMC X Δ News Sentiment | -0.894* | -0.897** | -0.481* | -0.166 | -0.824** | -1.013*** | -0.775*** | -0.591** |
| | (0.459) | (0.347) | (0.256) | (0.233) | (0.390) | (0.337) | (0.283) | (0.248) |
| Post-FOMC X Δ Shadow Rate | 0.340 | 0.378** | 0.051 | -0.104 | 0.383 | 0.252 | -0.246 | -0.176 |
| | (0.289) | (0.177) | (0.150) | (0.162) | (0.544) | (0.279) | (0.190) | (0.190) |
| Observations | 58795 | 58677 | 58612 | 58552 | 58801 | 58683 | 58619 | 58559 |
| R2 | 0.74 | 0.75 | 0.75 | 0.75 | 0.70 | 0.70 | 0.70 | 0.70 |
| **Panel C: Monetary policy surprise** | | | | | | | | |
| | 1-year ahead (%) | | | | 3-year ahead (%) | | | |
| | (1) 3-day | (2) 5-day | (3) 7-day | (4) 9-day | (5) 3-day | (6) 5-day | (7) 7-day | (8) 9-day |
| Post-FOMC X Δ News Sentiment | -1.147** | -0.901** | -0.424 | -0.195 | -0.964* | -1.108** | -0.749* | -0.587* |
| | (0.498) | (0.416) | (0.332) | (0.301) | (0.498) | (0.437) | (0.388) | (0.323) |
| Post-FOMC X Δ MPS | 3.630 | 1.232 | -0.512 | 0.097 | 2.086 | 1.628 | -1.022 | -0.354 |
| | (2.291) | (2.838) | (2.031) | (1.529) | (2.880) | (2.442) | (1.842) | (1.754) |
| Observations | 59487 | 59369 | 59304 | 59244 | 59495 | 59377 | 59313 | 59253 |
| R2 | 0.74 | 0.74 | 0.75 | 0.75 | 0.70 | 0.70 | 0.70 | 0.70 |
| **Panel D: Alternative FOMC sentiment change** | | | | | | | | |
| | 1-year ahead (%) | | | | 3-year ahead (%) | | | |
| | (1) 3-day | (2) 5-day | (3) 7-day | (4) 9-day | (5) 3-day | (6) 5-day | (7) 7-day | (8) 9-day |
| Post-FOMC X Δ News Sentiment | -0.796* | -0.744** | -0.470* | -0.159 | -0.762* | -0.945*** | -0.844*** | -0.623** |
| | (0.464) | (0.333) | (0.266) | (0.237) | (0.410) | (0.344) | (0.300) | (0.255) |
| Post-FOMC X Δ FOMC Sentiment | -0.126 | 0.132 | 0.051 | 0.169 | -0.073 | -0.056 | 0.082 | -0.006 |
| | (0.262) | (0.241) | (0.190) | (0.138) | (0.258) | (0.215) | (0.190) | (0.145) |
| Observations | 59487 | 59369 | 59304 | 59244 | 59495 | 59377 | 59313 | 59253 |
| R2 | 0.74 | 0.74 | 0.75 | 0.75 | 0.70 | 0.70 | 0.70 | 0.70 |

Notes: Standard errors are clustered at the meeting-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For each window length, each column corresponds to a different measure of inflation expectations. Columns (1), (2), (3) and (4) refer to the 12m-ahead point estimate. Columns (5), (6), (7) and (8) refer to the point estimate for the inflation rate in 24/36 months. Δ FOMC sentiment denotes the change in FOMC sentiment between the current FOMC meeting and the previous FOMC meeting.