News, Sentiment, and Inflation Expectations: Insights From Social Media Data and Experiments

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Abstract

News media serve as a primary information source for most people, with social media taking on a growing role in the way news is distributed and interacted. This paper investigates how households use information conveyed through media to form their inflation forecasts. Leveraging microdata, social media news data, and machine learning techniques, I show that households dynamically update the news topics they focus on when forming inflation expectations. However, the impact of news media on expectations is time varying — at times, it accounts for a significant portion of the variation in expectations, while at other times, its influence diminishes. Using social media reactions as a proxy for news-induced sentiment, I show that sentiment plays a central role in shaping expectations and can predict the direction of forecast revisions, even when the news is non-economic and unlikely to affect inflation through standard mechanisms. A novel information provision experiment, incorporating a sentiment elicitation method, further confirms the causal importance of sentiment in the expectations formation process. Moreover, I demonstrate that identical policy-related information, when framed with different tones, evokes distinct sentiment that lead to asymmetric effects on forecast revisions. I develop a simple Bayesian learning model in which sentiment distorts signal perception, explaining these results.

Keywords: survey, social media, expectations, machine learning
JEL Classification: E31, E52, E71

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1 Introduction

This paper seeks to assess how households use information from the media to form their expectations about future inflation. In economic theory, information plays a crucial role in shaping individuals' expectations, which in turn drive macroeconomic outcomes. The mechanism is straightforward: households form expectations about future economic conditions by processing the information available, which then influences their consumption, savings, and investment decisions. However, information is far from simple or uniform. It varies widely in form and quality and evolves over time, making it a complex phenomenon that requires careful study, particularly in the context of expectation formation. Despite the centrality of information in expectation formation, little is known about how households process diverse and evolving media signals. This study addresses this gap by combining micro-level expectations data, social media analysis, machine learning techniques, and a randomized controlled trial (RCT) experiment to investigate this crucial issue.

Recent technological advancements have made information even more accessible and widespread than ever before. The internet, social media, and mobile devices have lowered the cost and increased the speed of accessing information, transforming the landscape of expectation formation. As a result, the quantity of information has also increased, but not necessarily its quality. Yet, this increased availability has introduced new challenges: the abundance of information has made it more difficult for individuals to process and interpret it effectively.

Understanding how households navigate this complex information environment is essential to grasping the mechanisms that shape economic expectations. In this landscape of information overload and a growing number of alternatives, the news media still plays a central role as the primary source through which households receive updates on economic, political and social developments and which affects their beliefs and choices (Happer and Philo, 2013; DellaVigna and La Ferrara, 2015). What is even more important in the context of expectation formation is that media coverage not only informs the public about current events but also conveys signals about possible future trends. For example, during the COVID-19 pandemic, the media highlighted economic threats such as job losses, supply shortages, and long-term health challenges. Similarly, coverage of the war in Ukraine raised concerns about potential sanctions on Russia, leading to energy crises and rising energy prices. In another instance, the U.S. election coverage revealed insights into candidates' political and economic policies, influencing expectations about the economy's future direction.

While economic experts and policymakers have the tools to sift through this complex array of signals, search for relevant information, and form forecasts that broadly align with economic reasoning, the average household may struggle to process such a vast and often ambiguous volume of information. This paper explores how typical households without formal economic training digest the information presented by the media and form inflation expectations. By understanding this dynamic, we can gain insights into the broader mechanisms of expectation formation and their implications for economic stability and policy-making.

This paper leverages analysis based on both machine learning and experimental methods to explore the research question. The empirical analysis examines the dynamic relationship between news content and inflation expectations over time, capturing evolving patterns in public attention. Specifically, I construct a daily time series of news topics from social media posts using the Latent Dirichlet Allocation (LDA) model, combine this with daily inflation expectations from the Survey of Consumer Expecations (SCE) microdata, and analyze the relationships using rolling-LASSO regressions.

The results highlight the dynamic nature of public attention, showing that the topics households focus on when forming inflation expectations shift in response to major events. Additionally, the explanatory power of these topics fluctuates over time, reflecting the complex and context-dependent influence of media on expectations. To better understand the role of sentiment, I incorporate social media reactions — such as "Love," "Angry," and "Sad" — as proxies for the emotional responses generated by news topics.[1] This enables the construction of a panel dataset linking sentiment in the media environ-

[1]Throughout the paper, *sentiment* refers to the emotional attitude and feeling toward information delivered via news media. It is characterized by valence (positive or negative emotion) and arousal (intensity of the emotion), and can be expressed through a wide spectrum of complex emotions — from love to hate. Sentiment can be shaped by the language, presentation, and content of the news, which are interpreted through the filter of individuals' emotional reactions, personal experiences, and beliefs. This means that news media can affect sentiment toward information, but only to some extent, which is determined by unobservable characteristics of households, the study of which is beyond the scope of this paper.

ment to changes in individuals' inflation expectations. The analysis reveals that households frequently base their expectations not only on the factual content of news but also on the sentiment it generates. For instance, news associated with negative sentiment often leads to upward revision of inflation expectations, suggesting that sentiment plays a significant role in shaping economic perceptions. However, this analysis suffers from endogeneity concerns.

Thus, to confirm whether these findings hold more generally and establish a causal link, I conduct a survey experiment using the RCT methodology. I implement four treatments. One of them uses non-economic news that dominated media coverage and evoked negative reactions. This treatment provides additional evidence supporting the empirical finding that sentiment significantly influences economic expectations, even when the news driving that sentiment is not directly related to the economy.

The remaining three treatments involve economic news. While they are based on the same information about a Federal Reserve interest rate cut, they are presented with different tones, — positive, neutral, and negative. I find that media framing can influence households' emotional responses to economic information and, consequently, their interpretation of the information. These emotional responses significantly affect how households update their inflation expectations.

To rationalize the findings, I develop a Bayesian learning model in which sentiment distorts how households perceive a signal. Unlike standard frameworks that attribute signal bias solely to media framing, this model introduces bias through the subjective perception of the signal, shaped by sentiment. Specifically, when sentiment is strong (i.e., high in absolute value), it distorts the interpretation of the signal and enhances its perceived informativeness, leading consumers to place greater weight on the (biased) information and to exhibit reduced forecast uncertainty. This mechanism results in systematic deviations from rational expectations and helps explain why emotionally charged but informationally empty signals can still have an impact on inflation expectations.

The paper speaks directly to the growing literature that highlights the role of media in the expectations formation process. It builds on the work of Carroll (2003), Doms and Morin (2004), Pfajfar and Santoro (2013), Lamla and Lein (2014), and Dräger and Lamla (2017), but similar to Larsen et al. (2021) I use modern textual analysis and machine learning techniques to explore the research question. What distinguishes this study is the use of social media data, specifically users' reactions, which provides a more accurate measure of how individuals respond to the news. Unlike the traditional approach that focuses solely on the count and the tone of the news itself, this study incorporates user-generated responses to propose a sentiment-based mechanism that captures the direction of the effect of news topics on expectations. Additionally, by leveraging high-frequency data, this paper explores the dynamics of the expectations formation process. This approach offers a more granular view of how the significance of different news topics in shaping inflation expectations, and the role of media more broadly, evolves over time. In doing so, the study offers a fresh perspective on the evolving relationship between media, public sentiment, and economic expectations. It is worth noting that while some studies have used Twitter data to analyze central bank communication (Korhonen and Newby, 2019; Gorodnichenko et al., 2024), they focus exclusively on central banking topics. In contrast, this study examines a broader range of general media topics. Additionally, by using Facebook data, which offers a richer variety of user reactions compared to Twitter, this study broadens the scope of analysis and provides deeper insights into how individuals respond to news.

Similar to Kamdar and Ray (2024), this paper underscores the critical role that sentiment plays in the expectations formation process of households. A key contribution is the positioning of news media as a sentiment-generating factor. In addition to the empirical analysis, I provide support for the mechanisms driving my findings with a survey experiment. This experiment follows the framework of the widely used information provision experiments (Binder and Rodrigue, 2018; Armona et al., 2019; Coibion et al., 2023a; Haaland et al., 2023), but with a unique emphasis on capturing the sentiment generated by the information provided — a focus that, to my knowledge, is novel in the existing literature. This approach not only extends the empirical understanding of sentiment's role in expectation formation but also offers a methodological contribution to survey-based studies on inflation expectations. By capturing sentiment directly, my experiment advances survey techniques, allowing for more nuanced insights into how households emotionally process economic information and how this sentiment drives inflation expectations.

Finally, more broadly, this paper contributes to the literature that explores the determinants of inflation expectations and deviations from the Full Information Rational Expectations (FIRE) assumption proposed by Muth (1961). It engages with theories such as rational inattention (Sims, 2003), information stickiness (Mankiw and Reis, 2002), learning from experience (Malmendier and Nagel, 2016), and heuristics (Bordalo et al., 2016), among others.

The paper proceeds as follows. Section 2 focuses on the empirical analysis, introducing the data, examining the dynamics of news topics, and demonstrating the role of news-generated sentiment in the expectations formation process. Section 3 is dedicated to a survey experiment that provides additional causal evidence and new facts. Section 4 proposes a theoretical model. Then, section 5 concludes.

2 Empirical Analysis

I employ textual analysis and machine learning techniques on high-frequency data to uncover new evidence regarding the role of media in shaping household inflation expectations. The analysis reveals three key findings: (1) the list of news topics influencing household inflation expectations changes over time, (2) the magnitude of the effect of news media on expectation formation is dynamic, and (3) the sentiment generated by news stories help explain the forecast uncertainty and the direction in which inflation expectations move.

2.1 News and Expectations Data

The data for this study come from social media, collected through CrowdTangle, a tool that tracks and aggregates public content from social media platforms. Given the increasing influence of social networks in the dissemination of information, social media have become a vital instrument for shaping public opinion (Newman et al., 2023; Tandoc Jr et al., 2020; Hermida et al., 2012). Unlike traditional media, social media enables users to interact with news content through comments, shares, and reactions, providing valuable insights into audience sentiment and news popularity. This additional information makes social media an excellent substitute for conventional news datasets typically used in this area of research.

To leverage the unique characteristics of social media data, I collected news posts from the official Facebook pages of 64 major U.S. news outlets, including ABC News, Bloomberg, CNN, Fox News, and The New York Times. The data span from November 2013 to January 2024, covering approximately 7.9 million posts.

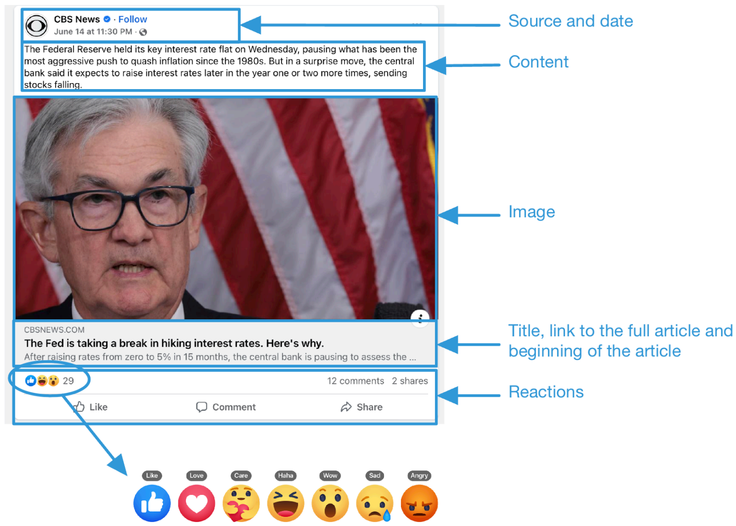

Figure 1: Facebook Post Example

The choice of Facebook as the source of news data was made with careful consideration. As Newman et al. (2023) highlighted, an increasing number of people are using social media as their primary source of news, with Facebook playing a central role in this trend. Mosquera et al. (2020) demonstrated through a field experiment that news consumption decreased significantly among those who abstained from using Facebook for a week. Despite its decline in popularity, Facebook remains the most widely used platform for news consumption in the U.S. Major media companies regularly post their content on Facebook, typically offering brief summaries along with links to full articles. This format makes news more accessible and often free, increasing the likelihood of reaching a broader audience.

Importantly, Facebook offers a unique mechanism for capturing user feedback through its reaction buttons — "Like," "Love," "Care," "Haha," "Wow," "Sad," and "Angry" — which provide rich insights into users' emotional responses to news content and the extent of its dissemination. Figure 1 shows an example of a Facebook post.

I processed the social media news posts for empirical analysis using standard Natural Language Processing (NLP) techniques.[2] Using the Latent

[2]Following Gentzkow et al. (2019), the text data were cleaned of punctuation, accents,

Dirichlet Allocation (LDA) model, the posts were algorithmically grouped into 80 distinct topics based on the dominant topic identified in the text. LDA operates on the premise that documents (or posts, in this case) are random mixtures of topics, with each topic consisting of a distribution of words. For example, the topic labeled "Pandemic" was defined by terms such as "covid19," "pandemic," "vaccine," "case," "test," "virus," "health," and so on. Each post was then assigned the topic that best described its content. These topics were further transformed into tone-adjusted time series based on their frequencies and balance of positive, negative, and neutral words. Detailed information on data cleaning and transformation can be found in Appendix A.

The time series of news topics is based on both the frequency and tone of the news, similar to previous literature (e.g., Larsen et al., 2021; Doms and Morin, 2004), rather than on social media metrics such as reactions. There are several reasons for this. First, using frequency and tone makes the results comparable to earlier studies. Second, Facebook reaction buttons were introduced only in 2016, which would significantly shorten the time series available for analysis. However, I do leverage social media metrics to construct a measure of the sentiment generated by the news and build a panel dataset, demonstrating that these sentiment can help predict the direction of changes in inflation expectations and forecast uncertainty.

To measure daily median household inflation expectations, I use micro-data from the Federal Reserve Bank of New York's SCE. Although the University of Michigan's Survey of Consumers (MSC) offers a longer time series, the SCE has distinct advantages for this study. With a sample size of approximately 1,300 respondents per month — more than twice the MSC's sample size — the SCE offers greater granularity and allows for the measurement of virtually daily inflation expectations, providing deeper insights into the dynamics of expectation formation. Additionally, as Armantier et al. (2017) noted, the SCE specifically asks respondents about "inflation" rather than "price changes," reducing ambiguity and ensuring a clearer understanding of the concept among respondents. Finally, respondents participate in the SCE survey up to twelve times, making it highly valuable for constructing the panel dataset that I use to study individuals' updating behavior.

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and stop words. An n-gram analysis was then applied to remove repetitive or irrelevant phrases (such as media names or advertisements) and to construct common bigrams and trigrams.

2.2 Dynamic Attention Toward News

In the following discussion, I extend the analysis of Larsen et al. (2021) by relaxing the assumption that the list of news topics influencing household inflation expectations is static over time. This dynamic view matters because, if shocks and shifting media salience do reorder which topics move expectations, treating the list as fixed risks misspecification and weaker policy inference.

Rather than relying on monthly data, I utilize rolling Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996) regressions on daily data with a rolling window of 90 days. This approach allows for a more dynamic understanding of how the relevance of different news topics evolves over time.

LASSO is particularly well-suited for this analysis because it not only identifies which variables (in this case, news topics) are most important, but it also shrinks the coefficients of less important variables to zero, effectively reducing the number of relevant topics. The regression model specification is as follows:

$$F_t \pi_{t+365} = \beta_0 + \sum_{n=1}^{N} \beta_n \cdot T_{n,t} + \epsilon_t, \tag{1}$$

In this model, $F_t \pi_{t+365}$ represents households' one year ahead (365 days) median forecast of inflation at time t, and N is the number of news topics $T_{n,t}$.[3] While LASSO does not explain the direction of the effect — since all variables are normalized — it highlights the news topics that correlate with the median inflation expectations of households. For each LASSO regression, I record which topics are selected, and I present the results in Figure 2, showing how the list of news topics that people are paying attention to evolves over time.

It is notable that topics related to politics are frequently selected, aligning with recent literature that highlights the role of political affiliation in shaping inflation expectations (Kamdar and Ray, 2023; Mian et al., 2023; Binder et al., 2024; Huseynov and Murad, 2024). Furthermore, the topics identified by LASSO reflect major global events such as the war in Ukraine and the COVID-19 pandemic, underscoring the relevance of media discourse in cap-

[3]To address outliers, I exclude all inflation forecasts outside the interval $[-38, 38]$. These bounds are those used by the Federal Reserve Bank of New York when fitting a generalized beta distribution to SCE respondents' density forecasts (Armantier et al., 2017). Each news topic time series is normalized as part of the LASSO methodology.

turing public attention (see Figure B1).[4] These results suggest that media coverage of significant events and politically salient issues likely plays a role in influencing public expectations over time.

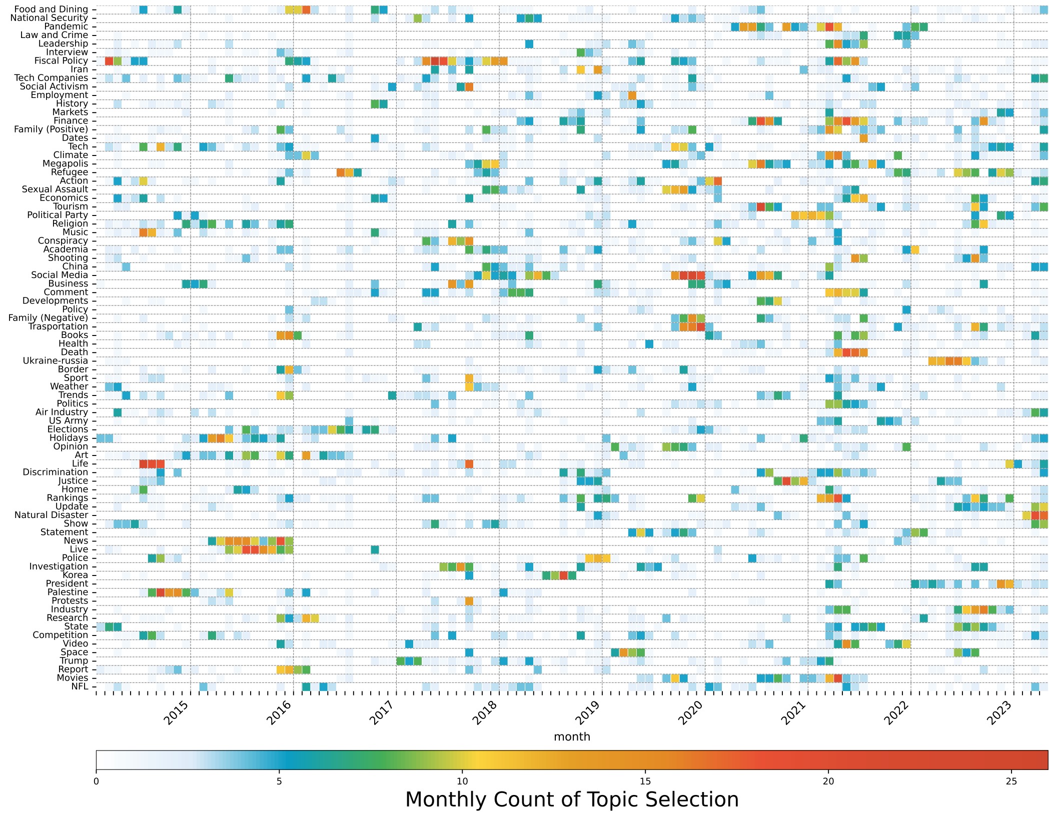


Figure 2: Inflation Expectations and Attention to the News Topics

Notes: The heatmap presents the results of rolling LASSO regressions using a 90-day window. The dependent variable is the daily median inflation expectations, while the independent variables consist of 80 tone-adjusted news topics. For each regression, I record the topics with non-zero coefficients and assign them to the latest day within the regression window. The heatmap displays the count of times each topic was selected by LASSO per month.

Additionally, the results indicate that certain topics attract public attention only temporarily, while others play a sustained role in shaping household inflation expectations over extended periods. This dynamic underscores the constantly evolving nature of the information environment, as public focus shifts between topics in response to changing circumstances. Notably, the

[4] It should be noted that the topic labels were assigned based on word clusters derived from the data, providing a systematic, albeit approximate, representation of the underlying themes.

coefficient of determination, R^2, illustrated in Figure 3, exhibits significant volatility. This variability suggests that while news media can occasionally be a dominant factor influencing inflation expectations, at other times, its explanatory power diminishes substantially, and other predictors play a more significant role.

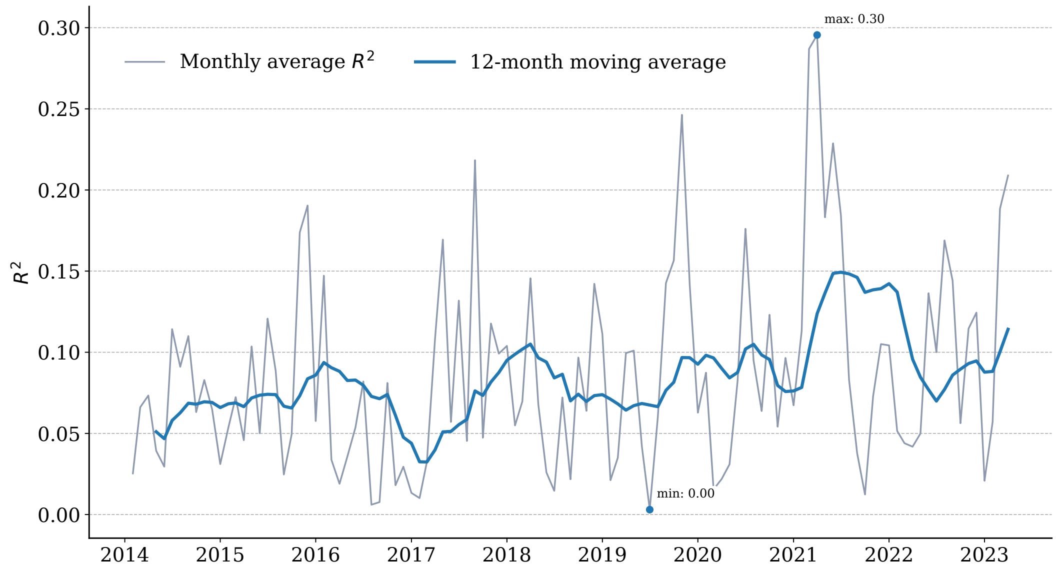


Figure 3: Rolling LASSO Coefficient of Determination

Notes: For each rolling LASSO regression, the coefficient of determination (R^2) is calculated and assigned to the last day within the regression window. The chart displays the monthly average of these R^2 values (blue line). Dark blue line is the 12-month moving average of monthly average R^2.

> **Finding 1:** *The relevance of news topics for inflation expectations changes over time.*

2.3 Sentiment-Driven Inflation Expectations

Next, I seek to uncover the mechanism through which media-reported news shapes household beliefs about future inflation. Specifically, I aim to understand how households transform complex and, in many cases, seemingly economically unrelated information from the news media into inflation forecasts. My hypothesis is that most households rely on a sentiment-based model, meaning that inflation expectations are driven by the sentiment (which reflects attitudes toward or feelings about the information) generated by news, alongside other factors.

To test this hypothesis, I exploit a unique feature of social media data — reactions — which are not available in conventional news media data sources. Unlike traditional sentiment measures based on textual analysis, Facebook data provide direct evidence of readers' attitudes toward news content.

Given that each respondent in the SCE is surveyed up to twelve times, I construct a panel dataset from the microdata, enabling an analysis of individuals' updating behavior. While reactions to news at the respondent level are not available in the SCE, Facebook data allow me to capture the prevailing reactions to news between consecutive survey waves in which a respondent participated, thereby providing an indication of the dominant sentiment generated by the media during that period.

To construct the individual specific sentiment measure, $\Delta\xi_i$, I calculate the aggregate number of media reactions (e.g., "Love," "Sad," "Angry") that occurred between the two survey dates for each respondent i.[5] The measure is individual-specific because it is based on the survey dates unique to each respondent i, but it reflects the aggregate number of media reactions observed during that period (or sentiment dominant in the media). However, it does not represent reactions made by respondent i since I merge two datasets (FB news and SCE expectations). The sentiment measure is defined by the following formula:

$$\Delta\xi_i = \underbrace{\frac{N_i}{100,000,000}}_{\text{Intensity}} \cdot \underbrace{\frac{n_i^{\text{love}} - n_i^{\text{sad}} - n_i^{\text{angry}}}{n_i^{\text{love}} + n_i^{\text{sad}} + n_i^{\text{angry}}}}_{\text{Polarity}}, \tag{2}$$

where N_i represents the total number of interactions with Facebook posts (including reactions, comments, shares, and reposts), and n_i^j denotes the total number of each reaction type $j \in \{$"Love," "Sad," and "Angry"$\}$. The first term reflects the intensity of information spread (a higher value indicates greater interaction with the news), while the second term captures the polarity of sentiment (positive versus negative). The division by 100,000,000 serves as a scaling factor to bring the measure to a tractable range, and it is based on the average number of total interactions.

To examine the role of sentiment in updating behavior, I regress the indi-

[5] I exclude the "Haha" and "Wow" reactions from the baseline sentiment balance, as they can convey both positive and negative sentiment, as confirmed in the subsequent survey experiment. Additionally, the "Care" reaction is excluded because it was introduced later, during the COVID-19 pandemic.

vidual revision of inflation expectations between two surveys, $\Delta\pi_i = \pi'_i - \pi_i$, on the constructed measure of sentiment, $\Delta\xi_i$. Specifically, I estimate the following regression,

$$\Delta\pi_i = \alpha + \beta \cdot \Delta\xi_i + \epsilon_i \tag{3}$$

This approach allows me to quantify the overall sentiment generated by the media during the period between surveys and assess its impact on changes in individuals' inflation expectations. By focusing on sentiment rather than the specific details of news stories, I aim to identify the emotional cues that households use to adjust their forecasts for future inflation.

Table 1: Forecast Revision, Uncertainty Change and Sentiment

	Forecast Revision					Uncertainty	
	I	II	III	IV	V	VI	VII
$\Delta\xi$	-0.060***	-0.124***	-0.056	-0.826*	-0.173*		
	(0.021)	(0.028)	(0.157)	(0.481)	(0.099)		
$\lvert\Delta\xi\rvert$						-1.558***	-1.380***
						(0.088)	(0.126)
Estimator	Huber	Huber	Huber	Huber	Huber	Huber	Huber
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	72,881	47,139	2,679	2,679	7,630	72,207	46,688
Sample	Full	Full	Full	Full	FB Users	Full	Full
Topics	All	All	All	LASSO	All	All	All
Period	Jan.18–Jan.24	Jan.20–Jan.24	Apr.20–Jun.20	Apr.20–Jun.20	Jan.20–Jan.24	Jan.18–Jan.24	Jan.20–Jan.24

Notes: Columns (I)–(V) report estimates of regression model (3) using Huber robust regression. Column (I) presents the baseline specification for the full sample from January 2018 through January 2024. Column (II) reports results for the post-COVID period. Columns (III) and (IV) present a case study of the pandemic onset; the last one restricts regressors to topics selected by LASSO. Column (V) reports results for the subsample of survey participants who resemble typical Facebook news consumers. In all specifications, I filter outliers by retaining observations whose change in inflation expectations lies within three standard deviations of the mean (based on Z-scores). Columns (VI) and (VII) report estimates of model (3) with the density-forecast variance as the dependent variable and with the absolute value of the sentiment measure included as a regressor. Robust sandard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 columns (I)-(V) present the results of the regression model (3). Across all specifications, the slope coefficient is negative, indicating that when news generates predominantly negative sentiment (i.e., accumulates negative reactions), inflation expectations are tend to be revised upward. For example, according to the model (I), a 1-unit increase in negative sentiment is associated with a 0.060 percentage point increase in inflation expectations, holding other factors constant. This finding supports my hypothesis based on a heuristic expectation formation model, where individuals project negative sentiment from the news onto their expectations for future inflation, which they also perceive unfavorably (Shiller, 1997; Stantcheva, 2024).

Finding 2: *Households revise their inflation expectations in response to media-generated sentiment.*

The effect of sentiment is stronger in the post-COVID period (column (II)), most likely reflecting increased news consumption and greater reliance on social media for news (Casero-Ripollés, 2020). As a case study, I examine the onset of the pandemic (April–June 2020), and focus exclusively on the news topics selected by the prior LASSO analysis. As shown in column (IV) of Table 1, the impact of sentiment is substantially stronger during this time interval. This period is especially noteworthy because it coincides with a pronounced divergence between household and professional forecasters' inflation expectations (Figure B2). Given the strong and statistically significant effect of the sentiment measure, this divergence likely stems from households reliance on news-driven sentiment, while professional forecasters continued to ground their expectations in observed inflation and the Phillips curve, anticipating an increase in unemployment. To assess whether this result is specific to the selected topics rather than the period, I re-estimate the same regression over April–June 2020 without filtering topics. The results, reported in column (III), are statistically insignificant, indicating that only a subset of topics transmitted sentiment into expectations during this episode.

The sentiment effect is slightly larger but less precisely estimated when the sample is restricted to respondents whose demographics match typical U.S. Facebook news consumers — primarily white women aged 30–49, according to the Pew Research Center.[6] This pattern suggests that the news channel mediates expectation formation. In a similar vein, recent work by Couture and Owen (2025) finds that social-media advertising (particularly on Meta) primarily influences the inflation expectations of the same demographic group, providing convergent external validity.[7]

Psychological research has shown that strong emotions, whether positive such as happiness or negative such as anger, can reduce individuals' perceived uncertainty in their forecasts (Tiedens and Linton, 2001). The SCE data offer a unique opportunity to test whether this result also applies in the context of

[6] Pew Research Social Media and News Fact Sheet (September 2024).

[7] Meta Platforms, Inc. owns Facebook, Instagram, Threads, Messenger, and WhatsApp.

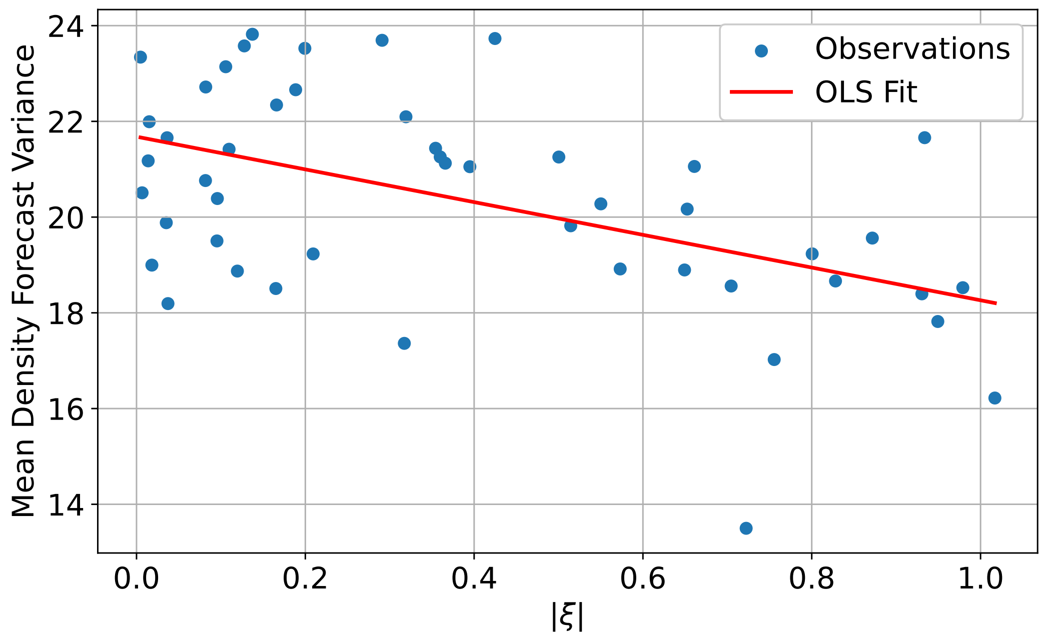


Figure 4: Sentiment and Inflation Forecast Uncertainty

Note: The figure displays the relationship between the monthly mean density forecast variance and the monthly absolute value of sentiment measure calculated using equation (2). The red line represents the linear fit.

inflation forecasting, since the survey includes respondents' density forecasts. These density forecasts make it possible to estimate forecast variance, which provides a direct measure of individuals' uncertainty.

To explore this relationship, I begin with the aggregate level. I compute the monthly mean forecast variance and the monthly sentiment measure for the period from January 2020 to January 2024.[8] Figure B3 indicates that the relationship can be described by a concave function that peaks around zero, suggesting that stronger sentiment, whether positive or negative, is associated with lower forecast uncertainty. Consistent with this result, Figure 4 demonstrates a strong negative linear relationship between the mean forecast variance and the absolute value of the sentiment measure. Finally, Table 1, columns (VI)-(VII), confirm that these relationships also hold at the micro

[8] I use the New York Fed's estimates of respondents' density-forecast variance to compute the monthly average variance (see details in Armantier et al., 2017). To calculate the monthly sentiment measure, I use equation (2), replacing individual-specific survey intervals with the beginning and end of each calendar month in the sample period. I focus on the post-COVID period because 2018–2019 exhibit limited month-to-month variation in sentiment and uncertainty, which weakens identification of the effect. Importantly, the micro-level analysis shows that the results are robust when 2018–2019 are included.

level by regressing individual posterior forecast uncertainty on the sentiment measure defined in equation (2).[9]

> **Finding 3:** *Stronger sentiment generated by the media is associated with lower forecast uncertainty.*

These results suggest that media-generated sentiment influences not only the direction of inflation expectations but also the degree of confidence individuals attach to them. Stronger sentiment, whether positive or negative, is associated with lower forecast uncertainty, consistent with psychological evidence that emotions reduce perceived uncertainty. The fact that this relationship holds both at the aggregate and individual levels highlights the role of sentiment as a heuristic in shaping how households form and update their inflation expectations. From a policy perspective, this implies that sentiment-laden media coverage can amplify or dampen the effectiveness of central bank communication by affecting not just expectations but also the certainty with which they are held.

3 Information Treatment Experiment

A critical limitation of the empirical analysis is that it only provides correlational evidence. To establish causality and explore relationships between sentiment and expectations more deeply, I collect data in a controlled environment, such as a survey experiment. Specifically, to study the causal effect of news on inflation expectations, I conduct an information provision experiment using a Randomized Control Trial (RCT), a methodology that has recently gained popularity in macroeconomics (Haaland et al., 2023). In the RCT, respondents are randomly divided into control and treatment groups. Since only the treatment groups receive information interventions, any statistically significant differences between the groups can be attributed to the effect of the information. This methodology also allows me to isolate sentiment's effect on inflation expectations by providing an uninformative signal.

The primary objective of the survey is to demonstrate that the news media plays an important role in shaping household inflation expectations by gener-

[9] I find no statistically significant effect on revisions in uncertainty, likely because the density-forecast variance is highly persistent. Part of this persistence is mechanical: unlike point forecasts, uncertainty is derived from a binned probability question with limited support (bins from -12 to $+12$, with open-ended tails), which compresses short-run variation.

ating sentiment through the information they convey. Based on the insights from the empirical analysis, I formulate the following key hypotheses to test in the experiment:

Hypothesis 1. Sentiment-Driven Expectations
Sentiment generated by general media news, even without direct economic information, can influence inflation expectations.

Hypothesis 2. Sentiment Shape Perception of Economic Signal
Sentiment generated by economic news influence how individuals perceive the economic signal it conveys.

3.1 Survey Design

To maintain consistency with the empirical analysis, many survey questions are based on the SCE instrument.[10] To elicit inflation expectations before the information treatment, I use a probabilistic question, where respondents assign probabilities to a range of inflation and deflation bins. They are then randomly assigned to one of five groups: a control group with no information, a *SentimentOnly* group, and three economic treatment groups categorized as *Negative*, *Neutral*, and *Positive*.

The *SentimentOnly* treatment incorporates five real Facebook posts collected from the official page of the New York Times that have recently triggered negative reactions but cannot be considered economic news. I focus on negative news, as previous studies, such as Nguyen and Claus (2013), have shown that consumer sentiment is more responsive to bad news. This treatment assesses whether the sentiment generated by these posts can move inflation expectations even though they are unrelated to economic conditions.

All economic treatments present the same news about a Federal Reserve interest rate cut that was recent at the time the survey was conducted, providing an opportunity to examine how indirect yet closely related economic signals in the media influence inflation expectations. Research by Coibion et al. (2023b) demonstrates that information about interest rates can prompt households to revise their inflation expectations, making this a particularly relevant and impactful choice for the information treatment. Importantly, at the time of the experiment, the recent shift toward monetary easing by the Fed offered a timely opportunity to examine how interest rate announcements

[10] Link to the instrument of this paper is here.

influence inflation expectations and how these communications can be made more effective.

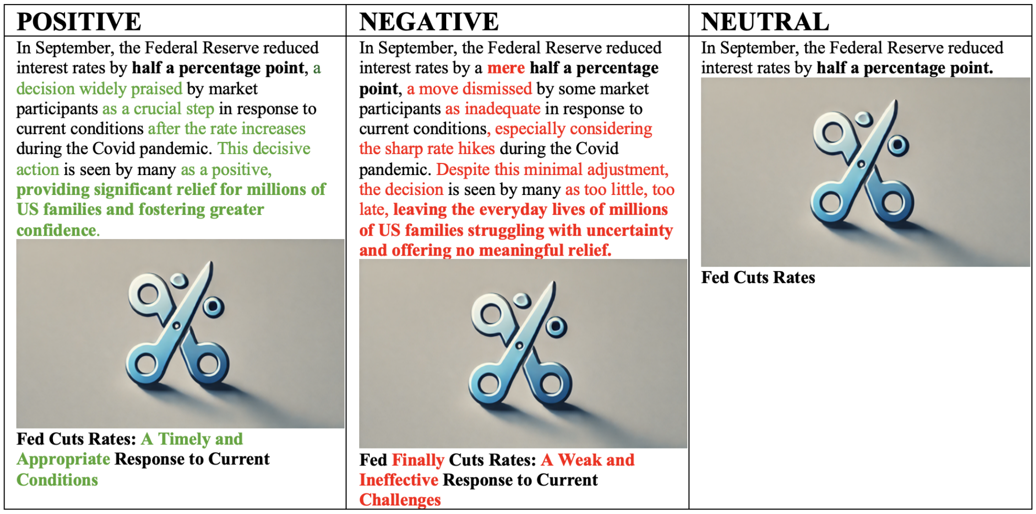


Figure 5: Economic Treatments

Notes: Green and red indicate the differences between treatments. All treatments are designed to mimic the format of a Facebook post. Right below the information treatment, respondents are asked to select one of the following reactions to the information presented: "Love," "Haha," "Wow," "Sad," "Angry," or "Care."

Each economic treatment is presented in a Facebook-style post with identical information about the rate cut but varying in tone — either positive, neutral, or negative. Crucially, none of the treatments include additional economic data or imply future economic developments. This design ensures that any observed effects on expectations are due to tone of the news and sentiment generated by it rather than content differences. To ensure comparability across treatments, I use a pre-trained Word2Vec model based on Google News to calculate the Cosine Similarity between the *Positive* and *Negative* treatments, yielding a score of 0.92 (where 1 indicates identical texts). Sentiment analysis indicates a polarity score of -0.12 for the *Negative* treatment and 0.18 for the *Positive* treatment, reflecting a clear difference in tone.

A novel feature of this survey experiment is that respondents react directly to the treatment, akin to engaging with an actual Facebook post. Respondents are asked to select a reaction that best reflects their feelings after reading the news. This approach not only verifies whether the treatment generated the intended sentiment but also allows for comparisons among respondents who reacted differently within the same treatment group, addressing concerns about varying interpretations of the treatments.

After each information treatment, all respondents, including those in the control group who receive no information, are asked again about their inflation forecast, but this time in the form of a point estimate question. This change in question format avoids asking the same question twice, helps measure forecast revision after the treatment while reducing the risk of demand effects, following current best practices in the literature (Coibion et al., 2023a).

To account for respondents' prior knowledge of interest rates and their understanding of the relationship between interest rates and inflation, additional questions are included after gathering their updated beliefs. Furthermore, data on demographic characteristics, news consumption, numerical literacy, and other data is collected.

3.2 Survey Data

The survey, conducted on November 1-2, 2024 via the Prolific platform, collected responses from 986 individuals representative of the U.S. population. The demographic composition of the sample is relatively balanced across treatment groups, though Democrats are notably overrepresented compared to Republicans. The average perceived inflation over the past 12 months was higher than the actual inflation rate, reflecting both the lasting impact of elevated prices during COVID-19 and households' general tendency to overestimate inflation (D'Acunto et al., 2023).

To compare prior and posterior inflation expectations, I estimate the implied mean for responses to the density forecast question, following Engelberg et al. (2009). Consistent with Armantier et al. (2017), I first fit a generalized beta distribution to the responses and then calculate the mean based on the estimated parameters. However, if a respondent assigns probability to an open interval, assumptions about boundary values are necessary.[11] This, combined with the differing question formats, leads to noticeably different standard deviations for prior and posterior expectations — a common outcome in this type of analysis (see, e.g., Coibion et al., 2023b). Additionally, the higher variability in posterior expectations across treatment groups compared to control group serves as a preliminary indication that the information provision had an impact on expectations. The descriptive statistics are presented in Table C1.

[11] Similar to the New York Fed's SCE methodology, I set boundary values at -38 and $+38$.

3.3 Results

Figures C1a and C1b show that the treatments successfully induced the intended sentiment. In the *SentimentOnly* and *Negative* arms, over 70% of reactions were negative, whereas reactions in the *Positive* and *Neutral* arms tended to be positive. This confirms that media framing shapes how information is perceived, at least in terms of sentiment. That said, the framing effect is not absolute given that even in the *Negative* treatment arm, a sizable share of respondents interpreted the information positively.

Because the economic treatments rely on how respondents connect inflation and interest rates, I document those beliefs as well (Figure C2). Only 10% of respondents believe that lower interest rates lead to higher inflation, while 22% think higher interest rates cause inflation to rise. These views may be related to the 41% who endorse the reverse causal link — that higher inflation leads to higher interest rates. I also find that most respondents assign a low probability to a rate change within the next 12 months (Figure C3), and fewer than 20% expect such a change to meaningfully affect inflation (Figure C4). Moreover, about half had already heard the rate-cut news on which the information treatment was based, further limiting the impact of the information treatment (Figure C5).

Attitudes toward inflation are similarly telling (see Figure C6). Respondents tend to view lower inflation as good for the economy, and the relationship is monotonic: many even perceive deflation positively. Using unemployment expectations, I also find heterogeneous updating behavior. In Figure C7 we can see that many respondents do not exhibit Phillips curve-consistent reasoning, though some do.

Taken together, these facts imply that analysis based on simple averages of forecast revisions may be uninformative. Differences in the location of priors relative to the signal and heterogeneity in updating models can attenuate average effects. Instead, I follow Coibion et al. (2022; hereafter CGW) and test whether beliefs are converging. Specifically, I estimate the following model:

$$\pi_i' = \alpha \cdot \pi_i + \sum_{k=2}^{5} \beta_k \cdot T_i^{(k)} + \sum_{k=2}^{5} \gamma_k \cdot T_i^{(k)} \cdot \pi_i + \epsilon_i \tag{4}$$

where π_i is the prior inflation forecast of respondent i, $T_i^{(k)}$ is an indicator variable for individual i and treatment $k \in \{Control, SentimentOnly,$

Negative, *Neutral*, *Positive*$\}$.

Table 2: Effect of Information Treatments on Posterior Inflation Expectations

	CGW Model		Reactions-Augmented CGW Model			
	Intercept (β) (I)	Slope (γ) (II)	Intercept (β) (III)	Intercept (ρ) (IV)	Slope (γ) (V)	Slope (τ) (VI)
Control	1.139***	0.691***	1.147***		0.689***	
	(0.346)	(0.065)	(0.347)		(0.065)	
SentimentOnly	−0.893*	0.212**	−0.617	−0.447	0.168	0.079
	(0.478)	(0.091)	(0.720)	(0.744)	(0.130)	(0.138)
Negative	−0.694	0.185**	0.975	−1.988***	−0.236	0.484***
	(0.485)	(0.094)	(0.738)	(0.766)	(0.156)	(0.163)
Neutral	−0.801	0.178**	−0.863*	0.221	0.092	0.278*
	(0.490)	(0.089)	(0.521)	(0.886)	(0.096)	(0.146)
Positive	−0.631	0.071	−0.399	−0.540	−0.001	0.154
	(0.498)	(0.089)	(0.565)	(0.762)	(0.103)	(0.125)
R^2	0.468		0.467			
Observations	964		964			

Notes: The table reports the slopes and intercepts from the regression models in equations (4) and (5), respectively — the CGW model and the Reactions-Augmented CGW model. Models are estimated via Huber robust regression with biweight iterations to mitigate the influence of outliers and influential observations. Robust standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01.

The results are presented in Table 2 columns (I)-(II). Theoretically, α should be equal to 1, as in the absence of any new information, respondents would not update their beliefs. However, $\alpha < 1$ (slope coefficient for the *Control* group), consistent with measurement differences introduced by eliciting priors and posteriors with different question formats. Thus, value of α serves as a benchmark to measure the weight assigned to different signals.

Under Bayesian updating, $\gamma_k \in [-1, 0]$ because posterior expectations are a weighted average of priors and the signal. For instance, equation (4) implies that in the presence of an information treatment:

$$\pi_i' = (\alpha + \gamma_k) \cdot \pi_i + \beta_k$$

When $\alpha + \gamma_k = 0$, households place full weight on the signal (β_k), disregarding their prior beliefs. Conversely, when $\alpha + \gamma_k = 1$, $\pi_i' = \pi_i$, indicating that households do not update their beliefs.

The results from the baseline CGW specification present a puzzle. First, consider the effect of non-economic news (the *SentimentOnly* treatment) on inflation expectations. The estimated slope is statistically significant and positive, indicating that the treatment effected beliefs but in a way that departs from a standard Bayesian model, — respondents appear to place more weight on their prior beliefs than the control group, effectively amplifying the role of their initial belief. A similar pattern obtains for the *Negative* and *Neutral* economic treatments: coefficients are statistically significant and positive, again consistent with an overweighting of priors rather than a pure pull toward the informational signal. Interestingly, this remains robust even after trimming extreme observations (see Table C2). This counterintuitive result suggests that a simple model of belief convergence may be overlooking a key psychological mechanism: the individual's subjective emotional reaction to the news.

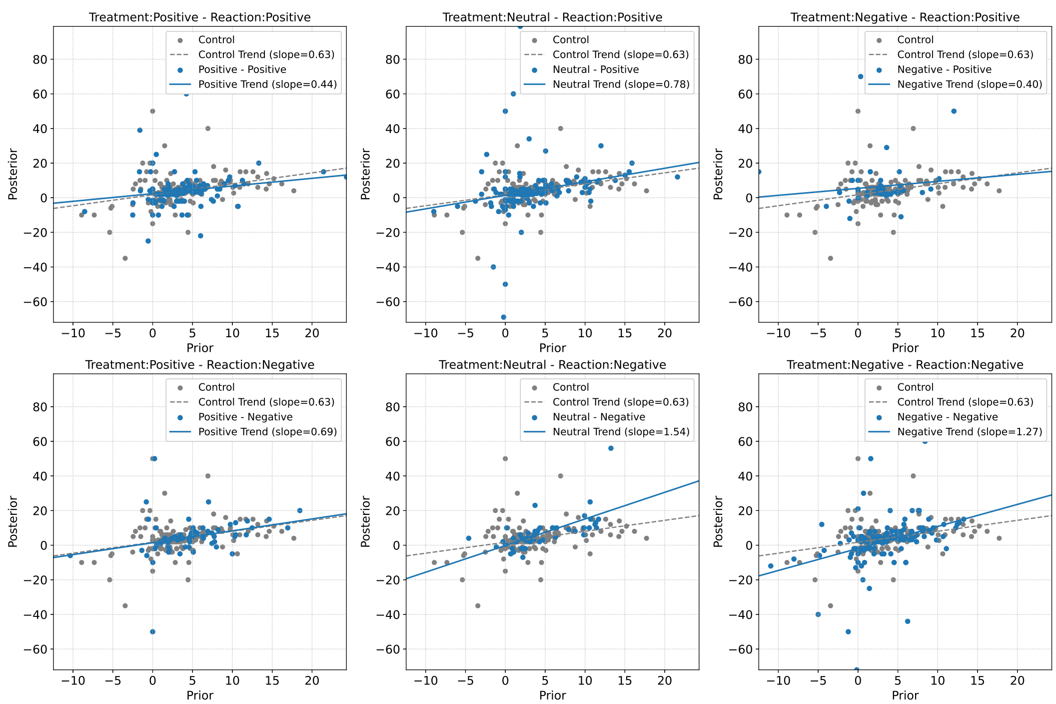


Figure 6: Treatment and Reaction Effects on Forecast Revision

Notes: This figure illustrates the relationship between prior and posterior inflation beliefs across different treatment groups (*Positive*, *Neutral*, *Negative*) and the *Control* group. Each subplot displays regression trend lines for both the *Control* group (gray line) and treatment-specific subgroups (blue line), organized by different reaction types. The *Control* group serves as a baseline, enabling comparisons of treatment effects on inflation forecast revisions.

By contrast, the *Positive* treatment, despite providing the same information about interest rates change, exhibits no notable effect on expectations.

Taken together, these findings point to a clear asymmetry: negatively framed news and news that deliver information without any frame are more attention-grabbing, whereas positively framed news is discounted. This is consistent with well-documented negativity bias (Baumeister et al., 2001; Soroka, 2006) and limited-attention mechanisms (Sims, 2003), and with the empirical evidence documented in previous part of the paper that respondents lean on sentiment rather than fully incorporating economic signal when updating.[12]

To investigate whether this puzzling result is driven by heterogeneous emotional responses, I leverage a unique feature of the experimental design: respondents' reactions to the information. I observe that forecast revisions across different groups and reactions, as shown in Figure 6, reveal distinct patterns. Respondents' reactions to economic treatments significantly influence both the weight assigned to new information and the direction of belief adjustments. Those who exhibit negative reactions to treatments tend to discount their prior beliefs and revise expectations upward relative to control group, suggesting that negative sentiment amplify pessimism, leading to higher inflation forecasts. In contrast, respondents with positive reactions display a stronger anchoring effect, assigning greater weight to prior beliefs and adjusting their expectations slightly downward. This pattern may reflect that positive sentiment reinforces confidence in existing beliefs, or simply that positive emotional responses are weaker than negative ones. In any case, this pattern warrants explicitly accounting for emotional responses to information in the regression analysis. To capture this effect, I extend the regression model (4) to the following (reactions-augmented CGW):

$$\begin{aligned}\pi_i' = \alpha \cdot \pi_i + \sum_{k=2}^{5} \beta_k \cdot T_i^{(k)} + \sum_{k=2}^{5} \gamma_k \cdot T_i^{(k)} \cdot \pi_i + \sum_{k=2}^{5} \rho_k \cdot T_i^{(k)} \cdot R_i^{(-)} + \\ + \sum_{k=2}^{5} \tau_k \cdot T_i^{(k)} \cdot R_i^{(-)} \cdot \pi_i + \epsilon_i\end{aligned} \tag{5}$$

where $R_i^{(-)}$ is indicator variable that equal to 1 if respondent i selected a negative reaction after the information treatment.[13] By incorporating sentiment-

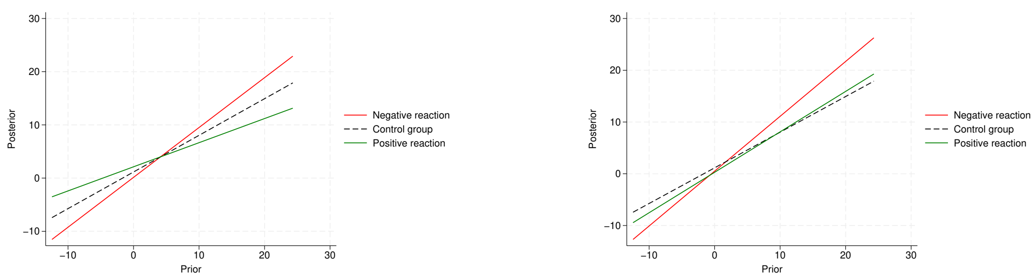
[12] Additionally, negatively framed information may alert respondents to risks and incentivize them to pay closer attention to the survey and the information provided. Drobot et al. (2024) underscores the importance of incentives in information-provision experiments and macroeconomic surveys in general.

[13] At the end of the survey, I ask respondents to classify each Facebook-type reaction as

based interaction terms, equation (5) allows for a more nuanced understanding of how emotional responses shape belief updating processes.

Table 2 columns (III)-(VI) indicate that reactions are the primary driver of deviations from a standard Bayesian updating. In particular, the positive and statistically significant slopes for the *Negative* and *Neutral* treatments observed in the CGW regression specification appear to be driven by the negative reactions (the slope τ is positive and statistically significant).

Given the complexity of model (6), Figure 7 visualizes the model's predictions for the *Negative* and *Neutral* treatments. In both cases, a negative reaction leads respondents to place greater weight on new information and to revise expectations upward (a steeper slope relative to the *Control* group). By contrast, a positive reaction yields downward revisions when the information is negatively framed (a flatter slope relative to *Control*) and essentially no revision when information is presented in neutral way.



(a) Negative Treatment (b) Neutral Treatment

Figure 7: Predictions of the Reactions-Augmented CGW Regression Model

Notes: The figure displays predictions from regression (5) for the *Negative* and *Neutral* arms in comparison to the *Control* group (black dashed line). Red line is prediction for the negative reaction to the information treatment, while green line is the positive reaction to the information treatment.

Taken together, these results indicate that the emotional perception of information, or sentiment, plays a key role in how households form expectations. Sentiment determines both the weight they place on a signal and the direction of their forecast updates. This finding highlights the importance of accounting for the sentiment generated by information when designing RCTs.

positive or negative. Thus, I match their reaction to the information with their own perception of that reaction's sentiment. For the *SentimentOnly* group, given that the information treatment included five Facebook posts, for each post I assign a score of +1 if the reaction is positive and −1 if it is negative. I then sum the scores, and if the total value is negative, I define a negative reaction indicator, $R_i^{(-)}$, to be equal to 1.

Finding 4: *The same information signal generates different sentiment across individuals, leading to heterogeneous updating behavior.*

4 Theoretical Framework

To rationalize the empirical results, I develop a behavioral model based on a standard Bayesian learning framework, similar to Lamla and Lein (2014). I simplify their setup to a single-signal case to isolate the novel mechanism I propose: sentiment-driven perception bias.

I begin by outlining the benchmark rational model. A representative consumer forms expectations about next-period inflation, denoted π_{t+1}. Her prior belief is that inflation is normally distributed around the current perceived inflation rate π_t, with a variance σ_a: $\Pi_t \sim \mathcal{N}(\pi_t, \sigma_a)$. She then observes a noisy signal from the media, ψ_t, which is centered around the true future inflation rate π_{t+1} with variance σ_ψ: $\psi_t \sim \mathcal{N}(\pi_{t+1}, \sigma_\psi)$.

Following Bayes' rule:

$$k(\pi_{t+1} \mid \psi_t) \propto f(\psi_t \mid \pi_t) \cdot h(\pi_t).$$

Since both distributions are normal, the posterior is also normally distributed:

$$\pi_{t+1} \mid \psi_t \sim \mathcal{N}\left(\frac{\sigma_a\psi_t + \sigma_\psi\pi_t}{\sigma_a + \sigma_\psi}, \frac{\sigma_\psi\sigma_a}{\sigma_a + \sigma_\psi}\right).$$

Thus, the forecast, or posterior mean, can be expressed as a linear combination of the prior and the signal:

$$\mathbb{E}(\pi_{t+1} \mid \psi_t) = \rho_t\pi_t + (1 - \rho_t)\psi_t, \tag{6}$$

where the weight on the prior, $\rho_t = \sigma_\psi/(\sigma_a + \sigma_\psi)$, depends on the relative precision of the signal versus the prior. A more precise (less noisy) signal (lower σ_ψ) reduces the weight on the prior and causes the agent to update her beliefs more strongly toward the new information.

Sentiment-Driven Distortion of Signal Perception

The experimental evidence presented in this paper shows that the same piece of information can trigger different emotional reactions — or sentiment — across individuals, leading to heterogeneous updating of their inflation expectations. This suggests that the standard model is missing a crucial channel: the subjective perception of the signal itself.

To capture this, I depart from the benchmark model by allowing media-generated sentiment, denoted ξ_t, to distort how the household perceives the signal. I model this distortion through two channels: a bias in the signal's level and a bias in the signal's perceived precision. The household does not observe the true signal ψ_t, but rather a subjectively perceived signal ψ_t^p:

$$\psi_t^p = \psi_t + \lambda \xi_t \quad \text{and} \quad \sigma_\psi(\xi_t) = \sigma_\psi e^{-\delta|\xi_t|}.$$

The first equation introduces a **level bias** where sentiment ξ_t pushes the perceived signal away from the true signal. The parameter λ captures the direction and magnitude of this push, allowing for heterogeneity in how sentiment affects beliefs (e.g., negative sentiment leading to higher inflation expectations for one person and lower for another).

The second equation introduces a perceived **precision bias**. Here, the strength of sentiment, $|\xi_t|$, reduces the perceived variance of the signal, where $\delta > 0$ governs the intensity of this effect. This formalizes the idea that emotionally charged information appears more salient and certain, regardless of whether the emotion is positive or negative.

This framework distinguishes between media bias (an objective property of the signal ψ_t) and perception bias (a subjective distortion by the household). My model focuses on the latter, contrasting with literature that typically assumes bias originates from the media source (Lamla and Lein, 2014; Larsen et al., 2021). For tractability, I assume sentiment ξ_t is exogenous, an assumption justified in the context of this study given that I show that sentiment can be empirically measured using social media data and elicited in controlled experimental settings.

The agent, observing the distorted signal ψ_t^p and its distorted variance $\sigma_\psi(\xi_t)$, forms a posterior expectations:

$$\mathbb{E}(\pi_{t+1} \mid \psi_t^p) = \rho_t^* \pi_t + (1 - \rho_t^*)(\psi_t + \lambda \xi_t), \tag{7}$$

where the new weight on the prior is $\rho_t^* = \frac{\sigma_\psi(\xi_t)}{\sigma_a + \sigma_\psi(\xi_t)}$.

The posterior variance, which represents the consumer's forecast uncertainty, is:

$$\mathrm{Var}(\pi_{t+1} \mid \psi_t^p) = \frac{\sigma_\psi(\xi_t)\sigma_a}{\sigma_a + \sigma_\psi(\xi_t)}.$$

This setup generates three testable propositions that explain the empirical findings of the paper.

Proposition 1: Stronger sentiment increases the weight on the new information.

Intuition and Proof: This proposition states that as sentiment becomes stronger (i.e., $|\xi_t|$ increases), agents rely less on their prior beliefs and more on the new signal they receive. To prove this, I show that the derivative of the weight on the prior, ρ_t^*, with respect to the absolute value of sentiment is negative:

$$\frac{\partial \rho_t^*}{\partial |\xi_t|} = -\delta \cdot \frac{\sigma_\psi \sigma_a e^{-\delta|\xi_t|}}{(\sigma_a + \sigma_\psi e^{-\delta|\xi_t|})^2} < 0.$$

The inequality holds because all parameters (δ, σ_a, σ_ψ) are positive, and the exponential term and the squared denominator are also positive. Thus, the derivative is negative. As $|\xi_t|$ increases, ρ_t^* decreases, which means the weight on the signal, $(1 - \rho_t^*)$, increases. This mechanism is consistent with the availability heuristic (Tversky and Kahneman, 1973), where emotionally salient information is perceived as more relevant, leading consumers to overweight it.

Proposition 2: Stronger sentiment reduces forecast uncertainty.

Intuition and Proof: This proposition formalizes the idea that when information feels more salient, people become more confident in their forecast. To show this, I take the derivative of the posterior variance with respect to the strength of sentiment, $|\xi_t|$:

$$\frac{d\mathrm{Var}(.)}{d|\xi_t|} = -\delta \cdot \frac{\sigma_a^2 \sigma_\psi e^{-\delta|\xi_t|}}{(\sigma_a + \sigma_\psi e^{-\delta|\xi_t|})^2} < 0.$$

The inequality holds because all terms are positive, and the expression is multiplied by $-\delta$. Therefore, an increase in the intensity of sentiment, $|\xi_t|$, leads to a decrease in the posterior variance. This provides a theoretical explanation for Finding 3 from the empirical section of the paper.

Proposition 3: Sentiment causes systematic deviation from the rational forecast.

Intuition and Proof: This proposition shows how perception bias leads to forecasts that are systematically different from those of a fully rational agent. The deviation is the difference between the forecast of an agent with sentiment and a rational agent observing the same true signal ψ_t:

$$\mathbb{E}(\pi_{t+1} \mid \psi_t^p) - \mathbb{E}(\pi_{t+1} \mid \psi_t) = (\rho_t^* - \rho_t)(\pi_t - \psi_t) + (1 - \rho_t^*)\lambda\xi_t.$$

This deviation has two components. The first term, $(\rho_t^* - \rho_t)(\pi_t - \psi_t)$, captures the effect of overweighting the signal due to perceived precision. The second term, $(1-\rho_t^*)\lambda\xi_t$, captures the direct effect of the level bias in the signal. Because both ρ_t^* and the bias term are functions of ξ_t, sentiment introduces a systematic, predictable wedge between the behavioral forecast and the rational benchmark.

Jointly, these propositions provide a unified theoretical explanation for the key empirical findings documented in this paper. The framework explains why even economically irrelevant news can cause significant forecast revisions if it is sufficiently sentiment-laden, as observed in the *SentimentOnly* treatment. Furthermore, it provides a clear mechanism for the heterogeneous updating behavior documented in Finding 4, showing how the same objective signal can lead to divergent forecast revisions as the sentiment it generates differs across individuals.

This framework also offers clear implications for central bank communication, suggesting that managing the emotional framing of announcements is as critical as the content itself. Proposition 1 suggests that a statement delivered with strong negative sentiment could cause households to overreact to the information, potentially leading to an outsized shift in inflation expectations. Moreover, Proposition 2 implies this communication doesn't just shift expectations; it can also make households overconfident in their new, potentially biased, beliefs, making those expectations harder to re-anchor later. Therefore, effective communication requires a deliberate approach to managing the public sentiment that policy announcements are likely to generate.

Addressing the RCT Puzzle

The empirical results from the information treatment experiment reveal a puzzle inconsistent with standard learning model. For the *SentimentOnly*, *Negative*, and *Neutral* treatments, the estimated interaction coefficient, γ_k, is positive, indicating prior reinforcement — a phenomenon where agents rely more heavily on their prior beliefs than a classical learning model would suggest. The baseline "perceived precision" mechanism outlined in Proposition 1 cannot account for this finding, as it only predicts a flatter slope ($\gamma_k \leq 0$).

To resolve this puzzle, I introduce an *assimilation effect* into the model, which captures the tendency for individuals to interpret new information through the lens of their existing beliefs. This extension is motivated by a large literature on motivated reasoning, which finds that individuals often subconsciously interpret new information in a way that confirms their existing worldview (Kunda, 1990). This defensive processing can be particularly strong when information is framed negatively, challenges a deeply held belief or simply difficult to process.

Mathematically, we can formalize this by allowing the perceived signal, ψ_t^p, to be pulled toward the agent's prior, π_t, governed by an assimilation parameter (assimilation elasticity), α:

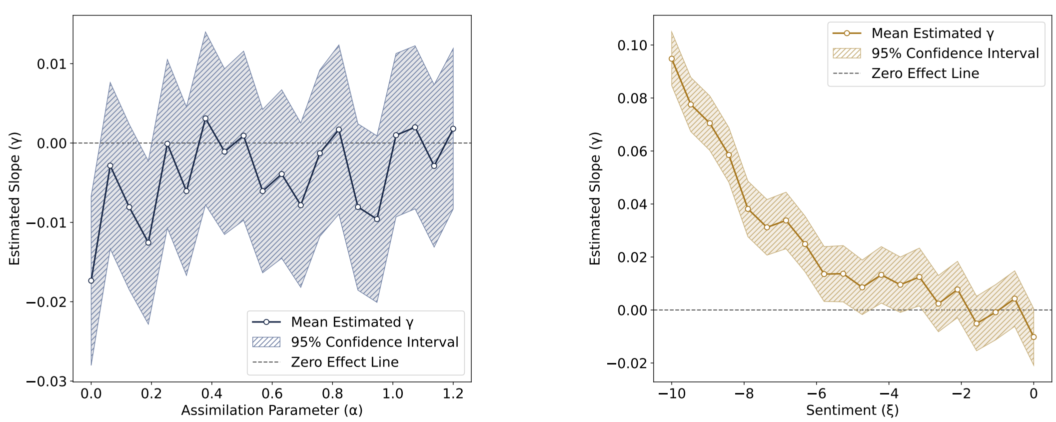
$$\psi_t^p = \psi_t + \alpha(\pi_t - \psi_t) + \lambda\xi_t,$$

where $\alpha = 0$ represents the case with no assimilation, at which point the model collapses to the baseline framework outlined previously. Crucially, this framework allows for the possibility of $\alpha > 1$, which represents a "backfire effect." This is not merely assimilation; it is a defensive overreaction where conflicting evidence causes an agent to double down and become even more entrenched in their initial belief. Mathematically, their perception of the signal is pushed beyond their prior, away from the new information.

To demonstrate quantitatively how this specification can produce $\gamma_k > 0$, I conduct a simulation exercise with 2,000 agents whose priors are drawn from a normal distribution (parameters are presented in Table C3). The agents are split into a control group and a treatment group. The control group receives no information, and their posterior is set equal to their prior plus a small amount of noise, implying an update slope of approximately 1. The treatment group is exposed to an extremely noisy or "uninformative" signal (variance $\sigma_\psi = 700.0$ vs. prior variance $\sigma_a = 4.0$) which mimics *SentimentOnly* treatment. Their posteriors are generated using the model described above, including the precision bias, level bias, and assimilation effects. I then estimate the CGW regression model (4) on this simulated data.

The results, shown in Figure 8, illustrate the crucial role of the assimilation mechanism. The first exercise (Figure 8a) fixes the sentiment at 0 and varies the assimilation parameter α from 0 to 1.2. In the absence of sentiment, the γ is not statistically significant, indicating that there is no updating behavior.

The second exercise (Figure 8b) fixes assimilation at a high level ($\alpha = 1.2$) and varies the strength of negative sentiment, ξ, from 0 to -10. The results show that when assimilation is strong, the γ coefficient becomes consistently positive and statistically significant if the sentiment is strong enough too. Together, these simulations provide strong quantitative support that a sentiment combined with an assimilation effect, particularly one strong enough to induce a backfire effect ($\alpha > 1$), can fully account for the puzzle of prior reinforcement found in the experimental data.



(a) Slope vs. Assimilation

(b) Slope vs. Sentiment

Figure 8: Simulation Results

Notes: This figure plots the estimated CGW interaction coefficient (γ) with 95% confidence intervals based on simulations. Panel (a) varies the assimilation elasticity (α) holding sentiment fixed at 0-level. Panel (b) varies sentiment (ξ) holding $\alpha = 1.2$.

5 Discussion

This study offers new insights into how news media shape households' inflation expectations by leveraging Facebook data to analyze emotional responses to news, captured through users' reactions and interactions. Unlike traditional datasets, which often focus solely on the content and tone of news articles, Facebook data provides a direct measure of user reactions. These interactions offer a valuable window into the emotional mechanisms driving expectation formation, allowing to link sentiment to forecast revisions in ways that traditional approaches cannot.

Facebook news data helped to reveal several important lessons. First, the dynamic nature of topic attention demonstrates that households are not passive consumers of information. Instead, they actively shift focus to different economic and social issues depending on media coverage. This highlights the volatility of media influence on expectations and underscores the need to study expectation formation as a process embedded in evolving information environments.

Second, sentiment analysis based on Facebook reactions highlights the significant role of media-generated sentiment in shaping inflation expectations. Negative reactions associated with negative sentiment, for example, often push inflation expectations upward. In addition, there is evidence that sentiment effects forecast uncertainty.

The survey experiment, designed to mimic Facebook's interactive dynamics, further validated the importance of sentiment-driven mechanisms, and proves a causal link. By integrating sentiment elicitation directly into the experimental design, I show that emotional responses to news are not peripheral but central to how households process and update their economic beliefs. The findings reveal that identical policy-related news, when framed with different tones, can evoke distinct sentiments, leading to asymmetrical effects on forecast revisions. This underscores the role of media not only as disseminators of information but also as generators of sentiment that influence public perceptions.

The theoretical framework developed in this paper formalizes how sentiment distorts the perception of economic signals through two channels: by biasing the perceived content of the signal and by increasing its perceived precision. These distortions arise not from the media itself but from how individuals emotionally respond to information. As a result, strong sentiment leads to systematic deviations from rational Bayesian updating and can lower forecast uncertainty. These dynamics help explain the experimental findings and highlight the aggregate implications of sentiment-driven expectations in macroeconomic settings. Furthermore, the model also explains the seemingly paradoxical finding that signals can cause households to rely more on their priors than the control group, a result likely driven by an assimilation effect.

This paper emphasizes the dual role of media as both an information source and a sentiment-shaping agent. It calls for a fresh look at Bernanke's famous statement that "monetary policy is 98 percent talk and only two percent action" (Bernanke, 2015): when media shape the sentiment generated by that talk (through headlines, framing, and coverage) expectations move accordingly. Incorporating sentiment-aware media intermediation into policy models can potentially improve the effectiveness of monetary policy.

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Appendix A: Data and Methods

A1. News Data

The news data consists of Facebook posts from the official pages of 64 major U.S. media outlets, covering a wide range of topics. The historical data was collected using CrowdTangle, a platform provided by Meta Platforms, Inc., that aggregates publicly available content from social media (Facebook, Twitter, Instagram, and Reddit). CrowdTangle tracks verified accounts and profiles, excluding personal information and private or restricted accounts.

A2. Data Cleaning

To focus on textual news, all posts containing only videos or photos were removed. The remaining posts, classified as "Link" by CrowdTangle, included a title, a description, a link to the news provider's official page, and occasionally, an image or video. To ensure all posts were in English, the Python library `langdetect` was used to identify and exclude non-English content. The textual components of each post (title, description, and link text) were combined into a single text entry.

Standard Natural Language Processing (NLP) steps were applied for data preparation, following Gentzkow et al. (2019). Text was converted to lowercase, and punctuation, accents, and stop-words (e.g., "is," "the," "and") were removed. N-gram analysis eliminated repetitive and irrelevant phrases (e.g., media names). Bigrams (two-word phrases) and trigrams (three-word phrases) were created to preserve meaning. Lemmatization reduced words to their root forms (e.g., "running," "runs," and "ran" became "run"). Only informative parts of speech (nouns, adjectives, verbs, adverbs) were retained. Short tokens and any remaining stop-words were removed.

A dictionary was created to map each unique word to a numeric ID, enabling conversion of posts into a "bag-of-words" format: a list of tuples where each tuple contains a word ID and its frequency in the post. Words appearing in fewer than ten posts or more than 50% of posts were removed for additional cleaning. The final dataset contained 7.9 million posts spanning November 2013 to January 2024.

A3. Topic Modeling

Topics were extracted using the Latent Dirichlet Allocation (LDA) model (Blei et al. (2003)), a widely used technique in NLP and economics. LDA treats each document as a mixture of topics and each topic as a collection of words, assuming Dirichlet distributions for both. For each post, LDA identifies a mixture of topics, assigning probabilities to words within each topic. The final output includes word distributions for topics and topic distributions for documents.

The LDA model was implemented using MALLET (Machine Learning for Language Toolkit, McCallum (2002)). The dictionary and "bag-of-words" representation were used as inputs. Following Larsen et al. (2021), the number of topics was set to 80. Labels for the topics were assigned based on the associated word lists and a random sample of posts linked to each topic.

A4. Topic Time Series

The trained LDA model was applied to the entire dataset to create topic time series. Each post was assigned a dominant topic based on the highest probability. For each day, the frequency of each dominant topic was calculated. Sentiment analysis was performed daily using the Harvard IV-4 dictionary, scoring texts for positive and negative sentiment. For days with multiple posts on a topic, the post contributing most to the topic (as determined by LDA) was used for sentiment scoring.

Sentiment scores were calculated as the difference between the number of positive and negative words, divided by their total. These scores were used to adjust daily topic frequencies. Finally, the daily time series were standardized, and monthly averages were computed for use in LASSO analysis.

Appendix B: Empirical Part

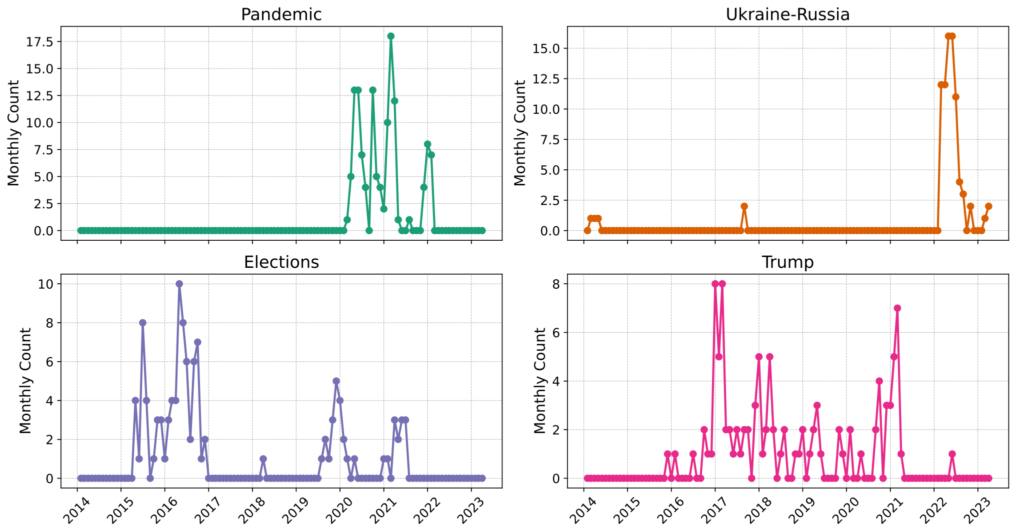


Figure B1: Inflation Expectations and Attention to Selected News Topics

Notes: The figure shows the monthly frequency with which the rolling LASSO selected each topic.

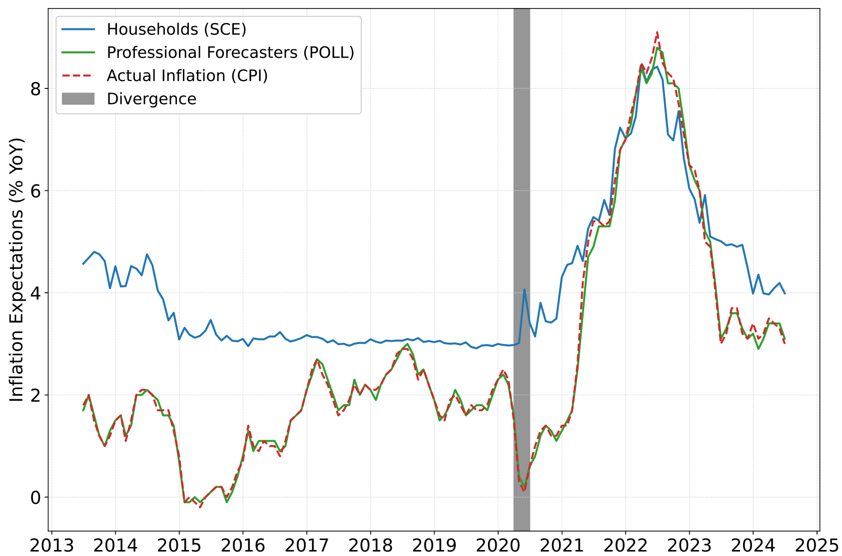


Figure B2: Inflation Expectations of Households and Professionals

Notes: The blue line represents the median one-year-ahead inflation expectations from the SCE. The green line shows the median inflation expectations of professional forecasters from the Reuters Poll. The red dashed line indicates the actual inflation (core CPI).

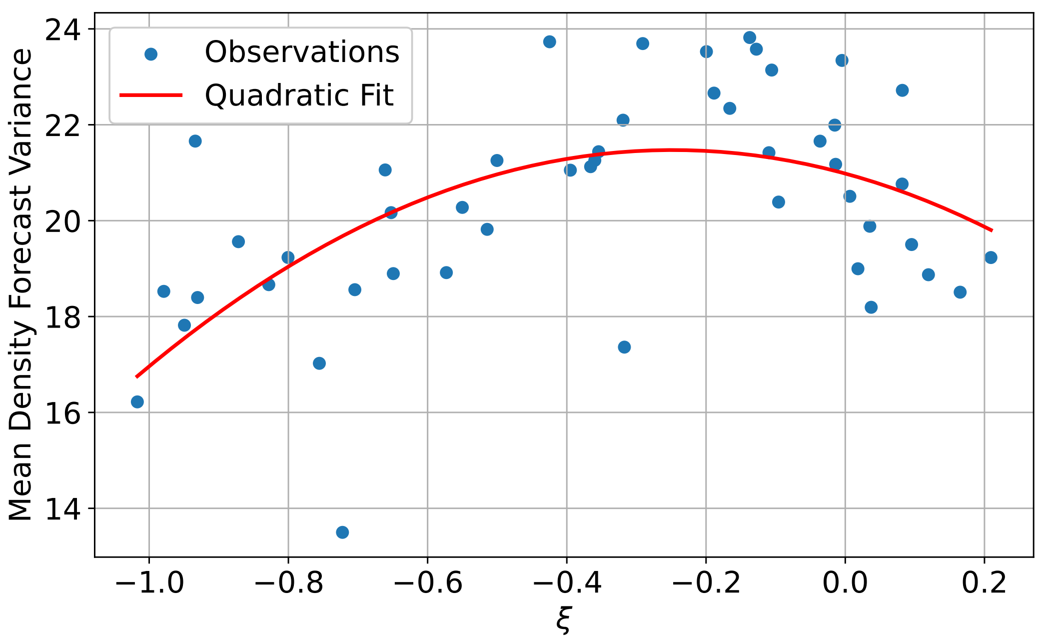


Figure B3: Sentiment and Inflation Forecast Uncertainty

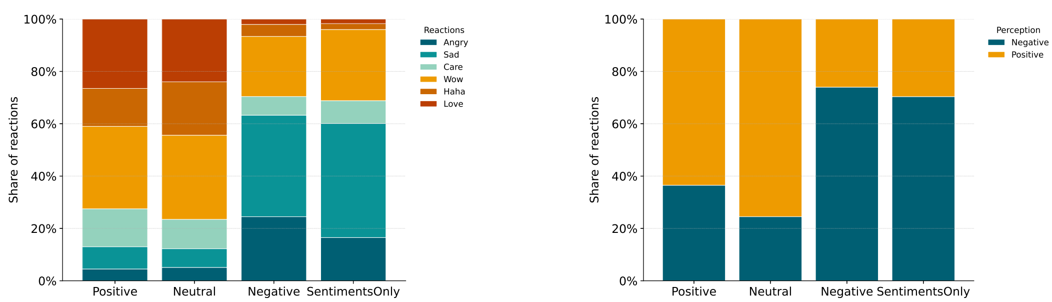
Notes: The figure displays the relationship between the monthly mean density forecast variance and the monthly sentiment measure calculated using equation (2). The red line represents the quadratic fit.

Appendix C: RCT Experiment

Table C1: Descriptive Statistics

Variable	Total (# obs = 986)	Control (# obs = 199)	Negative (# obs = 196)	Neutral (# obs = 196)	Positive (# obs = 200)	SentimentOnly (# obs = 195)
Demographics						
Age	44.57 (15.91)	44.48 (16.22)	45.75 (15.39)	43.83 (16.16)	44.07 (15.20)	44.72 (16.63)
Female	50.61%	50.25%	55.61%	48.47%	49.00%	49.74%
White	68.15%	64.32%	63.27%	70.92%	73.50%	68.72%
Democrat	49.09%	45.73%	54.59%	49.48%	44.72%	52.33%
Republican	36.41%	37.19%	36.22%	38.14%	36.68%	34.72%
Employed (part/full)	68.66%	71.86%	69.90%	65.82%	72.00%	63.59%
College	51.42%	49.75%	54.08%	53.57%	52.00%	47.69%
Less than 30K	28.70%	32.66%	28.57%	29.59%	22.50%	30.26%
30-100K	54.26%	50.75%	56.12%	53.57%	60.50%	50.26%
Inflation						
Prior Expectations	3.66 (4.23)	3.62 (4.18)	3.34 (3.92)	3.95 (4.54)	4.16 (4.25)	3.21 (4.22)
Posterior Expectations	4.46 (12.03)	4.16 (9.16)	3.53 (13.35)	4.84 (13.63)	4.73 (10.95)	5.03 (12.60)
Personal Inflation	11.93 (22.47)	10.53 (13.01)	11.56 (16.61)	12.87 (15.78)	10.71 (14.13)	14.06 (40.39)
Perceived Inflation	7.36 (14.39)	7.39 (10.47)	6.40 (10.68)	7.96 (11.06)	6.62 (12.43)	8.44 (23.23)

Notes: Values represent percentages/shares (indicated by %) or means with standard deviations in parentheses. Groups correspond to different treatments in the study. Sample sizes for each group are provided in parentheses in the header row.



(a) Reaction

(b) Reaction Perception

Figure C1: Analysis of respondents' reactions and associated sentiment

Notes: Figure (a) illustrates the share of respondents in each treatment group who selected one of the available reactions. Figure (b) depicts the perception (positive or negative) associated with the selected reactions.

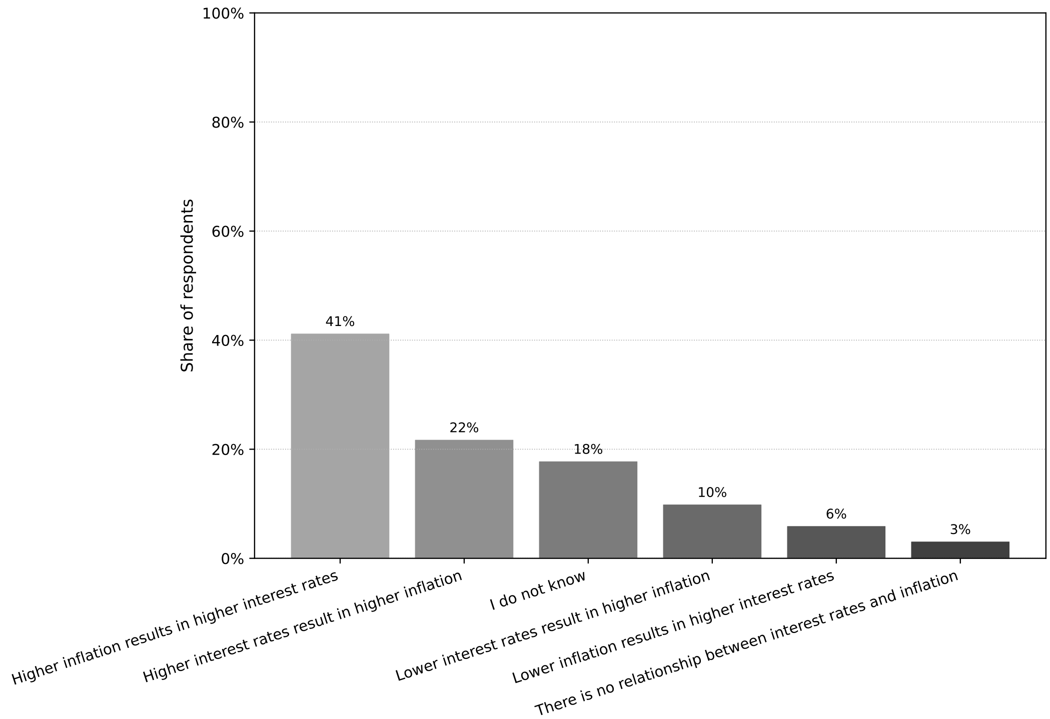
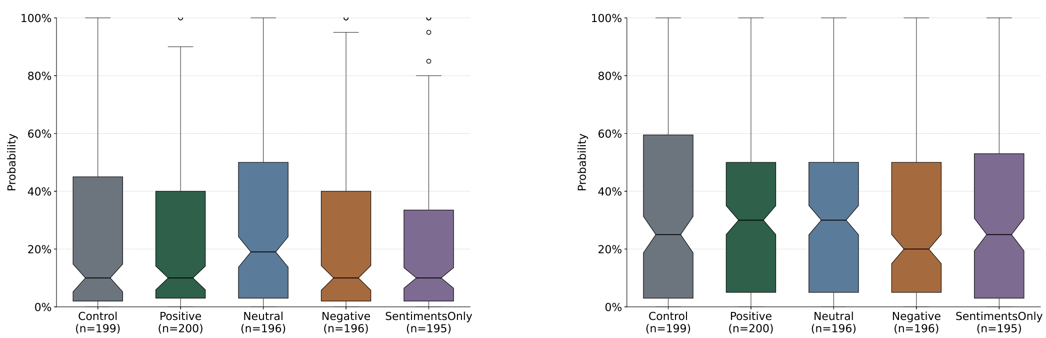


Figure C2: “In general, what do you think is the relationship between interest rates and inflation?”



(a) Rates Up

(b) Rates Down

Figure C3: “What do you think is the percent chance that the Federal Reserve will increase/decrease interest rates in the next 12 months?”

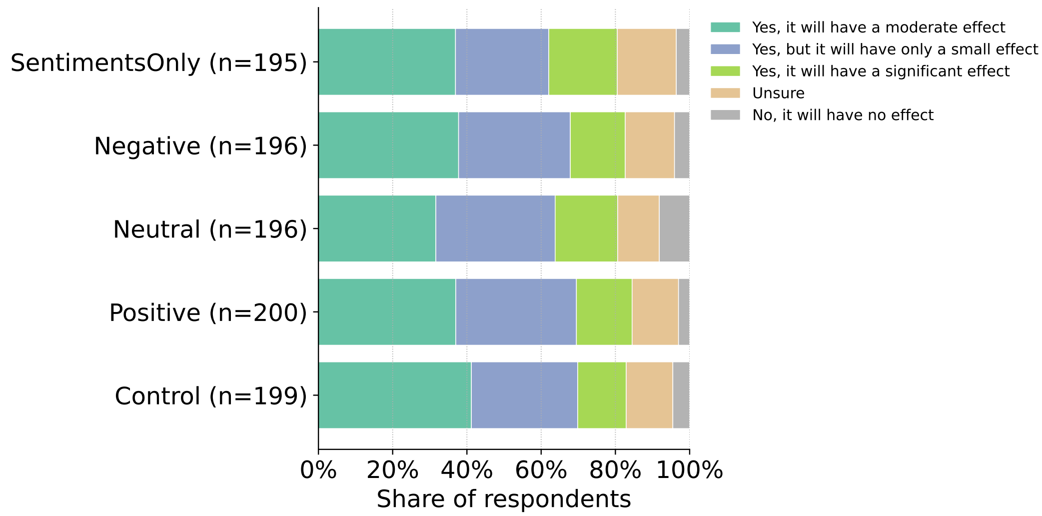


Figure C4: "Do you think the Federal Reserve's future change in interest rates will affect inflation in the next 12 months?"

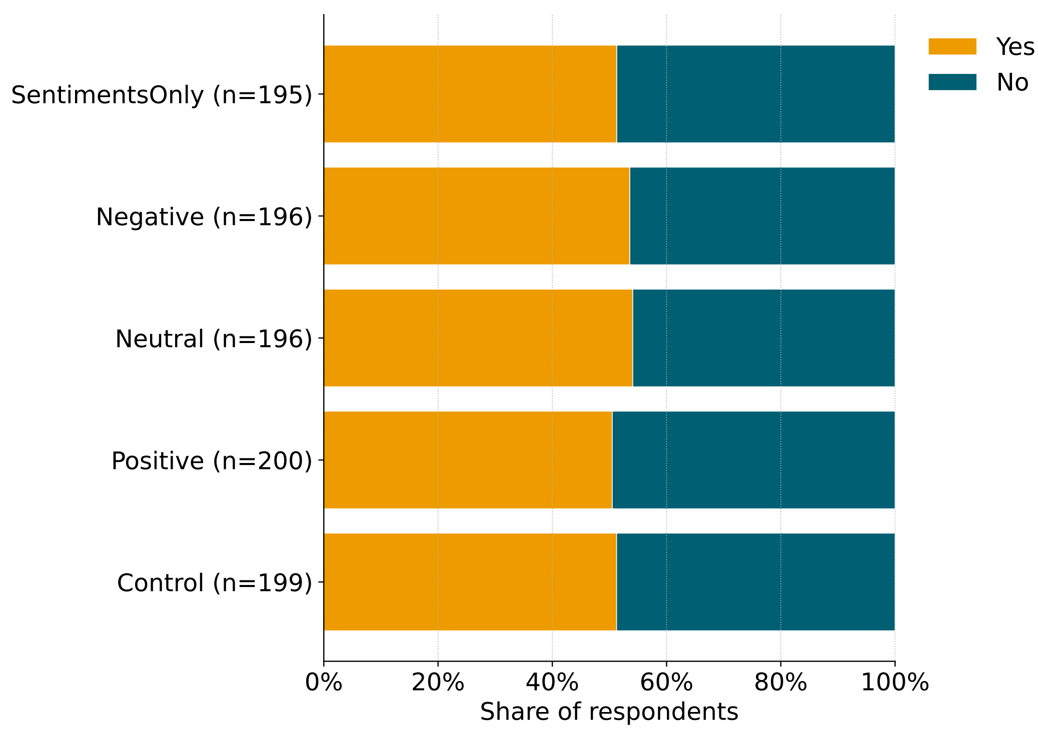


Figure C5: "Were you aware that the Federal Reserve cut interest rates in September, prior to taking this survey?'

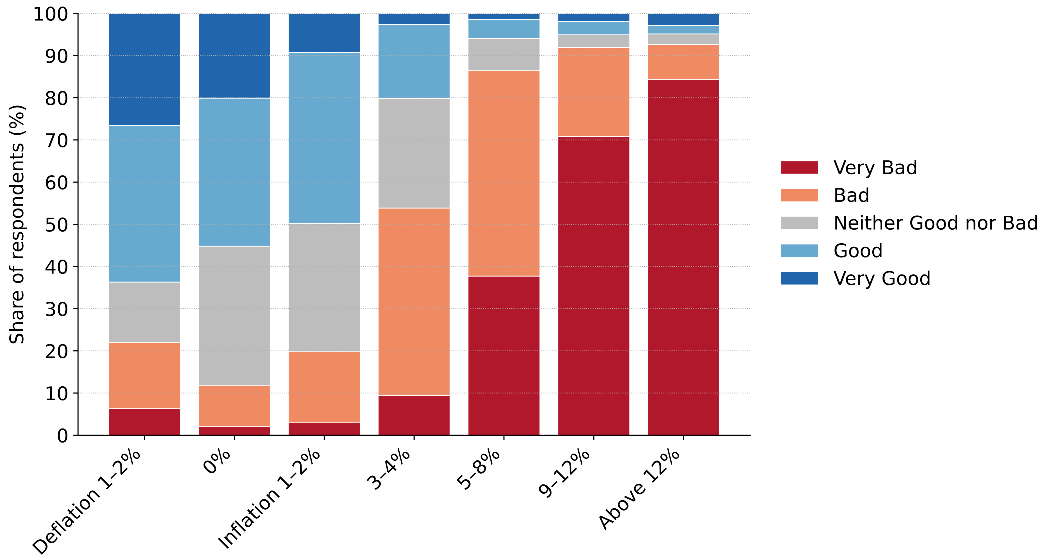


Figure C6: Perceptions of Inflation Levels for the Economy

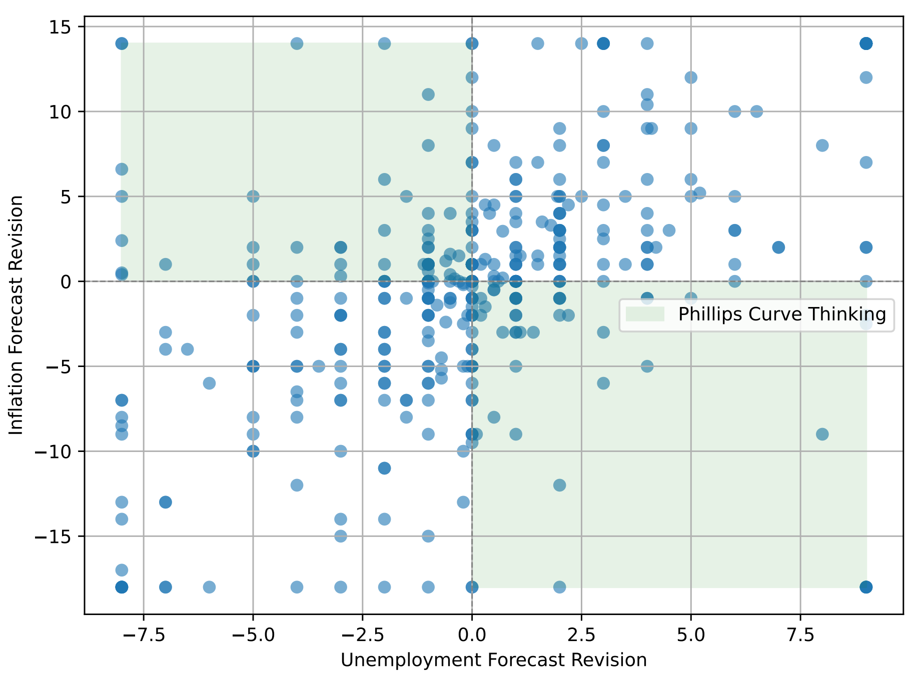


Figure C7: Inflation and Unemployment Forecast Revisions

Notes: The plot displays point forecast revisions the morning after the Election 2024. The data is winsorized at the 5th and 95th percentiles to reduce the influence of outliers.

Table C2: Effect of Information Treatments on (Trimmed) Posterior Inflation Expectations

	CGW Model		Reactions-Augmented CGW Model			
	Intercept (β) (I)	Slope (γ) (II)	Intercept (β) (III)	Intercept (ρ) (IV)	Slope (γ) (V)	Slope (τ) (VI)
Control	2.108***	0.507***	2.068***		0.513***	
	(0.316)	(0.058)	(0.311)		(0.057)	
SentimentOnly	−1.105**	0.280***	−1.312**	0.316	0.310***	−0.057
	(0.441)	(0.083)	(0.642)	(0.669)	(0.114)	(0.122)
Negative	−0.539	0.164*	0.429	−1.078	−0.219	0.443***
	(0.463)	(0.088)	(0.632)	(0.691)	(0.138)	(0.148)
Neutral	−0.876*	0.254***	−0.762	−0.240	0.139*	0.344***
	(0.451)	(0.080)	(0.476)	(0.751)	(0.084)	(0.125)
Positive	−0.591	0.119	−0.312	−0.859	0.031	0.269**
	(0.463)	(0.080)	(0.507)	(0.725)	(0.090)	(0.113)
R^2	0.462		0.480			
Observations	808		808			

Notes: The table reports the slopes and intercepts from the regression models in equations (4) and (5), respectively — the CGW model and the Reactions-Augmented CGW model. The analysis includes only observations where point forecast (posterior) lies in a range of $[-2, 20]$. Models are estimated via Huber robust regression with biweight iterations to mitigate the influence of outliers and influential observations. Robust standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01.

Table C3: Simulation Parameters

Parameter	**Value**
A. Prior Beliefs	
Prior Beliefs (π)	$\sim \mathcal{N}(3.6, 4.2)$
B. Signal	
Signal (ψ)	$\sim \mathcal{N}(2.0, 700)$
C. Updating Model Parameters (Treatment Group)	
Sentiment (ξ)	from -10 to 0
Precision Parameter (δ)	0.5
Level Bias Parameter (λ)	1.0
Assimilation Parameter (α)	from 0 to 1.2
Number of Observations	2,000

Note: The control group's posterior is modeled as their prior plus idiosyncratic noise ($\pi_i' = \pi_i + \epsilon_i$), implying a theoretical slope of 1. Parameters of prior distribution are selected based on Table C1 (distribution from survey responses).