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More Than Words: Fed Chairs' Communication During Congressional Testimonies

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Abstract

We measure soft information contained in the congressional testimonies of U.S. Federal Reserve Chairs and analyze its effect on financial markets. Our measures of Fed Chairs' emotions expressed in words, voice and facial expressions are created using machine learning. Increases in the Chair's text-, voice-, or face-emotion indices during these testimonies generally raise the S&P500 index and lower the VIX—indicating that these cues help shape market responses to Fed communications. These effects add up and propagate after the testimony, reaching magnitudes comparable to those after a policy rate cut. Markets respond most to the Chair's emotions expressed about issues related to monetary policy.

Topics: Central bank research, Financial markets, Monetary policy communications

JEL codes: E52, E58, E7

“Unlike his predecessor Alan Greenspan, who was famous for convoluted public testimony, Bernanke was clear, concise and brief. He erased any doubts that he, as a longtime academic, could handle the political hot seat. He answered tough questions with confidence, authority and an occasional gentle smile.”

– *The Baltimore Sun (February 16, 2006)*¹

1 Introduction

Central bank leaders have the difficult task of communicating monetary policy to the public. Not only do they need to present complex information in simple and relatable terms, but they also need to be credible and convincing, all the while being at the center of the media’s spotlight. The literature has mostly studied *what* central bankers say, analyzing the content and design of central bank press releases, speeches, and policy reports.² But *how* central bankers deliver this content to the public, and the impact of the delivery itself, has received less attention. In this paper we address this gap, and instead of the message itself we study how it is delivered by the messenger.

It is well-known in psychology that communication is mainly transmitted via non-verbal cues, such as tone of voice, body language, and facial expressions (Mehrabian 1972). Moreover, humans are less adept at controlling their non-verbal cues than their words (Kahneman 2013). So when central bankers explain their policy during public events, “soft” information contained in their non-verbal or emotional signals may be as meaningful as their words. To study this hypothesis, we measure emotional cues of the Chairs of the U.S. Federal Reserve during congressional testimonies and analyze how they influence financial markets.

Our dataset of emotional cues is constructed using 32 semi-annual congressional testimonies between 2010 and 2017 that were given by two recent Fed Chairs, Ben Bernanke and Janet Yellen. Utilizing audio and video inputs from C-SPAN videos and text inputs from publicly available testimony transcripts, we apply machine learning and big data meth-

¹<https://www.baltimoresun.com/news/bs-xpm-2006-02-16-0602160182-story.html>

²Recent studies include Hansen & McMahon (2016), Bholat et al. (2019), Ehrmann & Talmi (2020), Fraccaroli et al. (2020), Cieslak & Vissing-Jorgensen (2021), Gómez-Cram & Grotteria (2022). Algaba et al. (2020) review econometric methodology for constructing quantitative sentiment variables from qualitative textual, audio, and visual data, and using them in an econometric analysis of the relationships between sentiment and economic variables.

ods to construct three distinct measures of each Fed Chair’s emotions expressed via his or her words, voice, and face. To measure stock market prices and their volatility, we use tick-by-tick prices for the S&P500 index and the VIX.

Our results highlight the salience of the soft information contained in the Fed Chair’s emotional signals for shaping market responses to Fed communications. In particular, we find that increases in the Chair’s text-, voice-, or face-emotion indices during both remarks and Q&A parts of the testimony raise the S&P500 index and lower stock market volatility as measured by the VIX, in most cases. To validate the estimated responses to voice- and face-emotion indices during the remarks, we design an alternative test that exploits a unique feature of semi-annual testimonies whereby the Chair delivers virtually identical results on both days, in front of the House and the Senate. This alternative identification of the effects of Chair’s vocal and facial emotions during the remarks corroborates our findings that positive emotional cues work to increase stock prices and decrease stock market volatility.

We provide evidence that market responses during the testimony are economically meaningful. First, we demonstrate that the responses during the testimony add up and propagate in days after the testimony, reaching magnitudes comparable to those after a policy rate cut. Second, during the testimony, market activity is elevated: asset prices are more volatile and trading volumes are higher. Finally, we use changes in the quantity of TV viewership and media coverage to demonstrate that semi-annual testimonies attract public attention, on par with FOMC press conferences.

The magnitudes of the financial market responses vary by the topics discussed during the Q&A rounds and by the Fed’s messenger. Discussions of issues directly related to monetary policy (the central bank’s reserves, balance sheet management, policy rate, and inflation) are the key drivers of financial asset responses. Markets are more sensitive to Bernanke’s emotions, with positive responses to all three of his indices, albeit voice responses are not significant. For Yellen, only the response to her voice-emotion is positive and significant, and it is only half the magnitude of the response to Bernanke’s vocal cues. There is no systematic link with other dimensions of the testimony. The responses to congressional members’ emotions are weaker, suggesting that markets mostly react to information reflected in the Fed Chair’s emotions. We also show that the results are only stronger when we explicitly control for market-wide news during testimonies.

Our paper is closely related to two recent papers that analyze the effects of Fed Chairs’

emotional cues on financial markets. [Gorodnichenko et al. \(2021\)](#) find that positive voice tone raises stock prices and lowers their volatility in the days following FOMC press conferences. [Let's Face It: Quantifying the Impact of Nonverbal Communication \(n.d.\)](#) estimate that the Chairs' negative facial expressions during FOMC press conferences lead to lower S&P500 and higher VIX levels. Similar to these papers, ours provides evidence that the Fed Chair's emotions carry meaningful information for stock prices and volatility, both during and after the testimony. While [Gorodnichenko et al. \(2021\)](#) and [Let's Face It: Quantifying the Impact of Nonverbal Communication \(n.d.\)](#) do not find significant evidence that voice or face emotions move interest rate expectations during or after FOMC press conferences, we find that positive textual, vocal, and facial expressions during congressional testimonies raise interest rate expectations, albeit by small magnitudes.

The analysis in our paper complements the analyses in [Gorodnichenko et al. \(2021\)](#) and [Let's Face It: Quantifying the Impact of Nonverbal Communication \(n.d.\)](#) along several new dimensions. While these papers study communications during FOMC press conferences, we study Fed Chair's congressional testimonies, which offer several advantages. Unlike press conferences ([Boguth et al. 2019](#)), testimonies do not normally accompany monetary policy announcements, and therefore communications during testimonies are not influenced by the announcement itself. In addition, unlike the tightly scripted and one-directional communication observed during relatively short press conferences, the testimony largely comprises an hours-long Q&A session between the Fed Chair and Congress members in an unscripted, two-directional, and sometimes contentious environment. Such a setting provides more time and scope for the Chair to express her-/himself in more ways than one. While post-FOMC press conferences were introduced in 2010, an examination of testimony coverage can also provide information on the effects of displayed emotions over a much longer time frame. Overall, our evidence suggests that the Fed Chair's emotional cues during testimonies exert similar influence on financial markets as during press conferences.

The second contribution of our analysis is that we consider Fed Chair's emotions jointly. How a person combines his/her words, voice, and face to express themselves, and how these emotions are distilled by others, remains an open research question. Therefore, focusing on only one or two emotions may omit some of soft information that could be inferred from the Chair's delivery. Indeed, in our sample, our three emotion indices are at best weakly correlated, suggesting that the Fed Chair may be using their emotional vehicles separately.

We also find that markets are twice as sensitive to a typical (one-standard-deviation) change in the Chair’s voice pitch than his/her text sentiment, and roughly five times more sensitive to the change in his/her facial expressions. These rankings are similar whether the Chair delivers the remarks or responds to questions on topics around monetary policy during Q&A. This evidence resonates with the view in psychology that communication is much more than words, and underscores the need for a holistic approach to central bank communication by both academics and practitioners.

Our work also relates to the voluminous finance literature that studies the effects of limited investor attention on financial market outcomes. Variations in investor attention are associated with market-wide news (Yuan 2015), news-searching and news-reading activity (Ben-Rephael et al. 2017), uncertainty about macroeconomic factors affecting the likely path of interest rates (Benamar et al. 2020), and fluctuations in trading volumes (Barber & Odean 2007, Dellavigna & Pollet 2009). We show that congressional testimonies are widely covered in the news and social media, both contemporaneously and in the days following the event. Moreover, they are associated with elevated trading volumes, which the literature would suggest is indicative of heightened investor attention. Emergent literature in behavioral finance uses advanced machine learning techniques to obtain evidence that sentiment indices constructed from audio and photo/video inputs can predict equity returns (Mayew & Venkatachalam 2012, Obaid & Pukthuanthong 2022, Edmans et al. 2022) and detect misreporting (Hobson et al. 2012). Hu & Ma (2021) show that visual, vocal, and verbal persuasiveness is effective during delivery of start-up pitches. We use similar techniques to construct sentiment indices for Fed Chairs.

Finally, our paper also relates to the literature that studies the effects of Fed announcements on financial markets using high-frequency data (Kuttner 2001, Gürkaynak et al. 2005, Nakamura & Steinsson 2018, Cieslak & Schrimpf 2019, Gürkaynak et al. 2021, Swanson 2021).³ These papers identify the effects of monetary policy surprises by analyzing market behavior within a narrow window around monetary news releases. We build on this approach by analyzing market responses within seconds and minutes after the Fed Chair registers soft information captured in text-, voice-, or face-emotion indices.

The remainder of the paper is organized as follows. Section 2 describes testimony and financial data and explains the construction of three emotion indices. Section 3 lays out

³Andrade & Ferroni (2021) and Altavilla et al. (2019) study the ECB announcements.

the estimation specifications and summarizes the main results. Section 4 discusses the factors that drive the results. Section 5 argues that the estimated responses are economically significant. Finally, Section 6 concludes.

2 Data and measurement

2.1 Testimony data

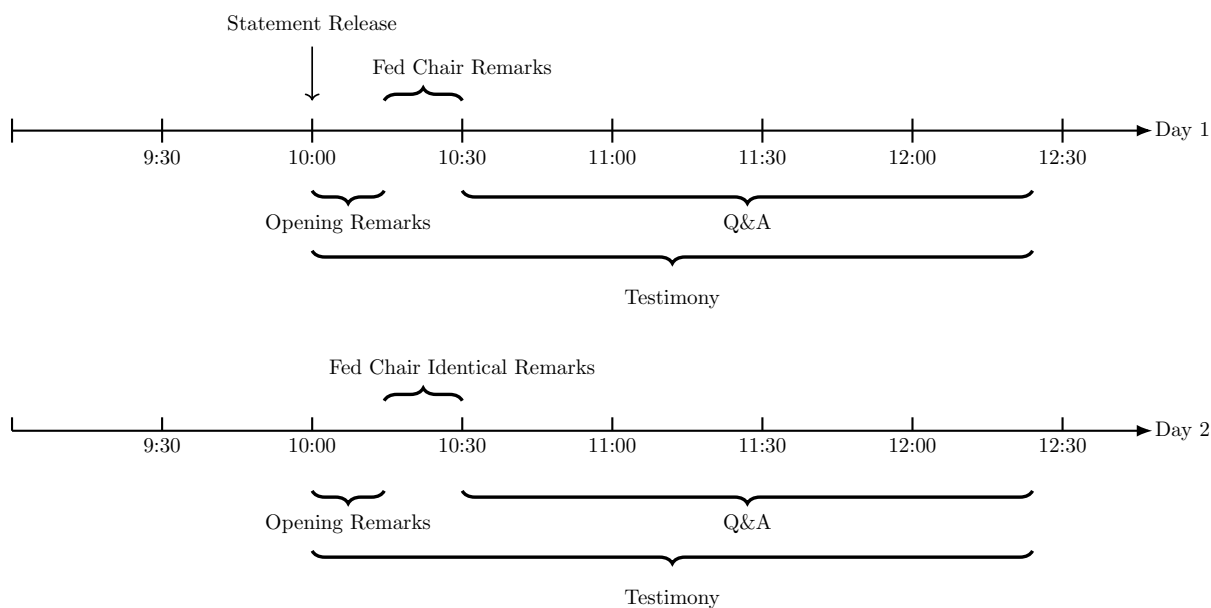


Figure 1. A typical testimony timeline.

Notes: The timeline of events around and during a two-day semi-annual testimony by the Chair of the Federal Reserve for House and Senate Chambers of the U.S. Congress.

To fulfill the requirements of the Humphrey–Hawkins Full Employment Act of 1978, the Federal Reserve issues two Monetary Policy Reports each year. In each, the Federal Reserve summarizes its past policy decisions along with their predicted impacts, as well as recent financial and economic developments for Congress. After each semi-annual report’s release, the Chair of the Federal Reserve delivers two congressional testimonies—one in front of the House Financial Services Committee and another in front of the Senate Banking, Housing,

and Urban Affairs Committee. The two testimonies normally take place within a day or two of each other, and the order of appearance before the Congress chambers alternates. The timing of events during a typical congressional testimony is depicted in Figure 1. The Fed Chair’s remarks are released at the beginning of the first day of these testimonies—usually at 10 a.m. The hearing, often starting at 10:00 a.m., begins with opening remarks by the Committee Chair and other high-ranking committee members and are followed by the prepared remarks of the Fed Chair. The Q&A session then begins upon the conclusion of the Fed Chair’s statement. The Q&A session consists of five-minute segments allotted to each committee member, in the order of their seniority, alternating by party affiliation (Congressional Research Service 2010). The testimony lasts several hours and ends with brief concluding remarks by the Committee Chair. The timeline of the second day of the testimony is similar, with the Fed Chair usually delivering precisely the same remarks.

Our data contain textual, vocal, and video inputs for 32 congressional testimonies by Fed Chairs that occurred between February 24, 2010, and July 13, 2017 (see Table 1). The sample covers 16 testimonies by Ben Bernanke (February 24, 2010–July 18, 2013) and 16 testimonies by Janet Yellen (February 11, 2014–July 13, 2017). The testimony transcripts we use were created by CQ transcriptions and obtained from LexisNexis’s Nexis-Uni online database.⁴ The videos of the C-SPAN broadcasted testimonies are mainly from Internet Archive’s TV News collection.⁵

We organize the data along the timeline in semantic blocks. The Fed Chair remarks part of each testimony is divided into blocks of 10 sentences, and the subsequent Q&A part is divided into blocks of Q&A rounds with each congress member. For each block, the text-emotion index reflects the sentiment of the language content in the block. Voice- and face-emotion indices are constructed with audio/video frames recorded within the block of sentences.

We opt to organize our data by blocks rather than by fixed-time windows because it pre-

⁴This source, available from <https://www.lexisnexis.com/en-us/professional/academic/nexis-uni.page>, is used for our analysis since these transcripts capture an unedited version of what was stated during the testimonies and often matched what was heard in the recordings more accurately than the official edited transcripts released with considerable lag.

⁵<https://archive.org/>. The House and Senate maintain general control over the footage that is recorded and broadcast. The Cable Satellite Public Affairs Network (C-SPAN) is a specialized nationwide television network that provides de facto exclusive video coverage of Congress proceedings (Eckman 2017).

	All testimonies	Bernanke testimonies	Yellen testimonies
Sample	24 Feb 2010– 13 Jul 2017	24 Feb 2010– 18 Jul 2013	11 Feb 2014– 13 Jul 2017
# of testimonies	32	16	16
Duration (mins)	154	146	161
<i>remarks</i>	15	15	14
<i>Q&A</i>	139	131	148
# of blocks			
<i>remarks</i>	217	127	90
<i>Q&A</i>	661	309	352

Table 1. Summary statistics.

Notes: The full sample includes 32 semi-annual monetary policy testimonies between 2010 and 2017. The remarks part of each testimony is divided into blocks of 10 sentences, and the subsequent Q&A part is divided into blocks of Q&A rounds with each congress member. The number of blocks reflects blocks included in the regression analysis.

vents breaking the natural flow of speech and speech-emotions mid-sentence in the remarks or in the middle of the Q&A round. The blocks’ lengths are long enough to allow time for accruing speech-emotions and financial market trades, and at the same time short enough to avoid washing out meaningful variation in emotions over the course of the testimony. On average, a sentence lasts 8 seconds, so a block of 10 sentences during prepared remarks lasts slightly more than a minute. A Q&A round, in contrast, is typically 5 minutes. Using this approach, a typical testimony has around 7 remarks blocks and 21 Q&A blocks, and it lasts around 2.5 hours.

2.2 Emotion indices

Based on the audio and video inputs from C-SPAN videos and the text inputs from publicly available testimony transcripts, we construct three distinct measures of each Fed Chair’s emotions expressed via his or her words, voice, and face. The details of data processing and construction of indices are provided in the Appendix.

The measure of emotions contained in text or words of the Fed Chair is based on the text-sentiment classifier trained by fine-tuning Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2018), a state-of-the-art natural language processing transformer model, with authors’ annotated testimony training data. The process of fine-

tuning allowed us to better capture the sentiment expressed during Congressional testimonies.

Experiments in psychology have demonstrated that increases in vocal pitch may reflect a variety of emotions.⁶ Therefore, following [Dietrich et al. \(2019\)](#), we utilize the changes of vocal pitch as our measure of vocal emotions. Using the vocal signal processing tool, *Praat* ([Boersma & Weenink 2001](#)), we extract the fundamental frequency ($F0$)⁷ at 0.015 second intervals. The vocal pitch is measured by calculating the mean $F0$ of each audio sentence.

For the face-emotion measure, we combine the video frame outputs from face recognition and facial expression analysis software⁸ to obtain facial muscle action values. Using upper facial actions and the Facial Action Coding System (FACS) created by [Ekman & Friesen \(1969\)](#), we then compute the Chair’s face-emotion score as the average of four basic negative emotions—*Sad*, *Angry*, *Fear*, and *Disgust*. We multiply this score by -1 so that high index values indicate less-negative face emotions.⁹

The emotion scores, *Scores*, are calculated at sentence level for text emotions, at 0.015 second intervals for voice, and at video frame level for facial expressions. We define three emotion indices $\text{TEXT}_{\tau,b}^i$, $\text{VOICE}_{\tau,b}^i$, $\text{FACE}_{\tau,b}^i$ for speaker i (or person on screen i), block b , testimony τ as the mean of corresponding emotion scores in that block, standardized by its standard deviation over all blocks in the Q&A:

$$\text{INDEX}_{\tau,b}^i = \text{mean}(\text{Scores}) / \text{sd}_{\text{INDEX}},$$

where $\text{INDEX} \in \{\text{TEXT}, \text{VOICE}, \text{FACE}\}$. Speaker superscript i denotes a chair or a congress member. We define a single index for congress members by pooling all Q&A blocks for different congress members. For the voice-emotion index, raw scores are de-meant for

⁶For example, the evidence presented in [Kamiloglu et al. \(2020\)](#) highlights that heightened pitch can be seen coinciding with positive emotions, even though other research commonly explores the relationship between high pitch and stress levels.

⁷ $F0$ corresponds to the rate of vocal fold vibrations: high pitch is associated with rapid vibrations and low pitch with slow vibrations

⁸We use Azure Video Indexer for face recognition and identification, and we use FaceReader for facial expression analysis. We process our videos with a frame rate of 29.97, i.e., 29.97 frames per second.

⁹We exclude muscles around the person’s mouth because they are activated when the person is speaking, introducing measurement error. We also do not include the basic emotion *Happy* in computation of the face-emotion score because it tends to imply counterintuitive and less significant results, especially for the remarks. We conjecture that because *Happy* is easier to control (e.g., by showing a smile), it is less informative about the speaker than the four negative emotions.

each speaker to remove differences in individuals’ average voice pitch. For the face-emotion index, we use data for the person on screen instead of the person speaking. By construction, positive index values indicate positive sentiment for text, higher pitch for voice, and less-negative face emotions.

The text-emotion index is different from the stance index used in the literature, which measures the degree of hawkish or dovish sentiment conveyed in the central banks’ communications (Ehrmann & Talmi 2020). Therefore, we also construct a stance index for each block of sentences using the dictionary in Gorodnichenko et al. (2021). We use the stance index as a control variable in our empirical analysis.

2.3 Time alignment of emotion and financial data

Synchronizing emotion indices with financial transactions is crucial for accurately identifying the effects of the Fed Chair’s communication on financial markets over the course of the congressional testimony. We synchronize the data in three steps. First, we derive corresponding timestamps at the block level for the three emotion indices. Next, we align the block level emotion indices with the time clock on the testimony day. Finally, time-stamped emotion data are matched with tick-by-tick financial market data for analysis. Figure 2 shows the organization of the testimony and financial market data.

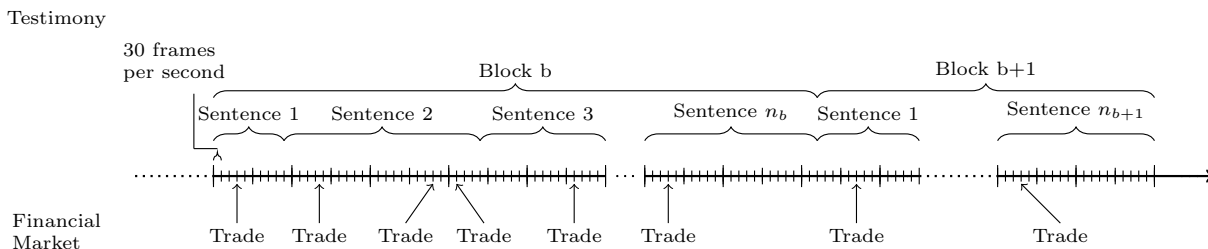


Figure 2. Time alignment of text, voice, video, and financial data.

Notes: The remarks part of each testimony is divided into blocks of 10 sentences, and the subsequent Q&A part is divided into blocks of Q&A rounds with each congress member. The emotion indices summarize the Chair’s emotions for each block.

Text sentiment is not correlated with either voice or face indices, whereas voice and face are related (see Appendix). Their relation, however, changes over the testimony. During

the remarks, voice and face emotions of the Chair are positively correlated, suggesting that the Chair is using them jointly to support the delivery of his or her remarks. By contrast, voice and face emotions are uncorrelated during the Q&A, suggesting they fulfill a somewhat different role during the Q&A, when the Chair responds to the questions from the congress members. Emotions of Chairs are positively correlated with respective emotions of congress members, suggesting that emotions of the Chair’s answers somewhat resonate with emotions of members’ questions.

3 Empirical analysis of financial market responses

We estimate financial market responses using high-frequency data for salient financial assets. We use the S&P500 index from TickData to measure stock market price responses, and the VIX from Refinitiv for stock market volatility. To measure U.S. interest rate expectations, we use five-quarter-ahead Eurodollar futures contracts from the Time and Sales database from Chicago Mercantile Exchange. These data are time-stamped by a second.

3.1 Financial market responses: Remarks

The dependent variable $Outcome_{\tau,b+h} - Outcome_{\tau,b}$ is a cumulative change in the outcome for the financial instrument over h minutes starting from the end of block b of testimony τ . For example, for the S&P500 index, $Outcome_{\tau,b+h} - Outcome_{\tau,b}$ denotes the h -minute change in the log price of the S&P500 after the end of block b in testimony τ . We restrict the data to regular trading hours, between 9:35 a.m. and 3:40 p.m.

We use the [Jordà \(2005\)](#) local projections method to estimate the effect of emotions by a Fed Chair in block b during the Chair’s remarks for testimony τ on financial market outcomes after h minutes, $h = 1, \dots, H$, using the following empirical specification:

$$Outcome_{\tau,b+h} - Outcome_{\tau,b} = \beta_{\text{TEXT}}^{(h)} \text{TEXT}_{\tau,b}^{\text{CHAIR}} + \beta_{\text{VOICE}}^{(h)} \text{VOICE}_{\tau,b}^{\text{CHAIR}} + \beta_{\text{FACE}}^{(h)} \text{FACE}_{\tau,b}^{\text{CHAIR}} + \text{controls} + \text{constant} + \varepsilon_{\tau,b}^{(h)}. \quad (1)$$

The set of controls includes testimony fixed effects and the stance index measuring dovish/hawkish statements. Because congressional testimonies are not accompanied by a policy announce-

ment, we do not need the controls for policy surprise, which were necessary in studies of FOMC press conferences (Gorodnichenko et al. 2021, *Let’s Face It: Quantifying the Impact of Nonverbal Communication* n.d.). Specification (1) is estimated by fixed-effects panel regression with Driscoll-Kraay standard errors (Driscoll & Kraay 1998). Estimated coefficients $\hat{\beta}_M^{(h)}$, $M \in \{\text{TEXT, VOICE, FACE}\}$, provide the responses of the left-hand variable to the emotion index M at the h -minute horizon. The null hypothesis for this regression is that variations in Fed Chair’s emotions captured by three indices are not influencing financial markets, i.e., $\beta_M^{(h)} = 0$.

Figure 3 provides the estimated responses of S&P500 and VIX to one-standard-deviation increases in text-, voice-, and face-emotion indices during the Chair’s prepared remarks. Positive changes in all three indices lead to positive S&P500 responses within minutes, and for text and face the responses are significant at 1 bp and 5 bps, respectively. The increases in the Chair’s text sentiment and voice pitch lower VIX by 3 and 12 bps, respectively. It is worth noting that the responses to changes in the degree of negative facial expressions are similar to those uncovered in *Let’s Face It: Quantifying the Impact of Nonverbal Communication* (n.d.), who focused on the impact of facial expressions on markets following FOMC press conference communications. However, our responses to a typical face-emotion shock appear somewhat larger even though we include the text-emotion and voice-emotion variables in our regressions. Moreover, at the aggregate level, the results suggest that increased pitch during the remarks section of the testimony is interpreted as a positive emotional cue resulting in an increase in the S&P500 and a corresponding decrease in the VIX.

The response of VIX to the Chair’s face emotion is counterintuitive, suggesting decreased market uncertainty when the Chair’s face emotion is negative. It is important to note that the measurement of the Chair’s face emotions during the remark period is potentially confounded by the fact that for more than half of the time during the remarks the Chair is moving his or her head down to read the remarks. When the Chair’s head is tilted down, it is more difficult for both the software and individuals watching the testimony to accurately identify all facial movements and related emotions. An examination of the responses by the Chair suggests that the counterfactual response for the VIX is only seen for Bernanke. Moreover, as indicated by the results from our alternate identification strategy discussed next, the counterintuitive result for the VIX’s response to facial emotions during remarks is not robust.

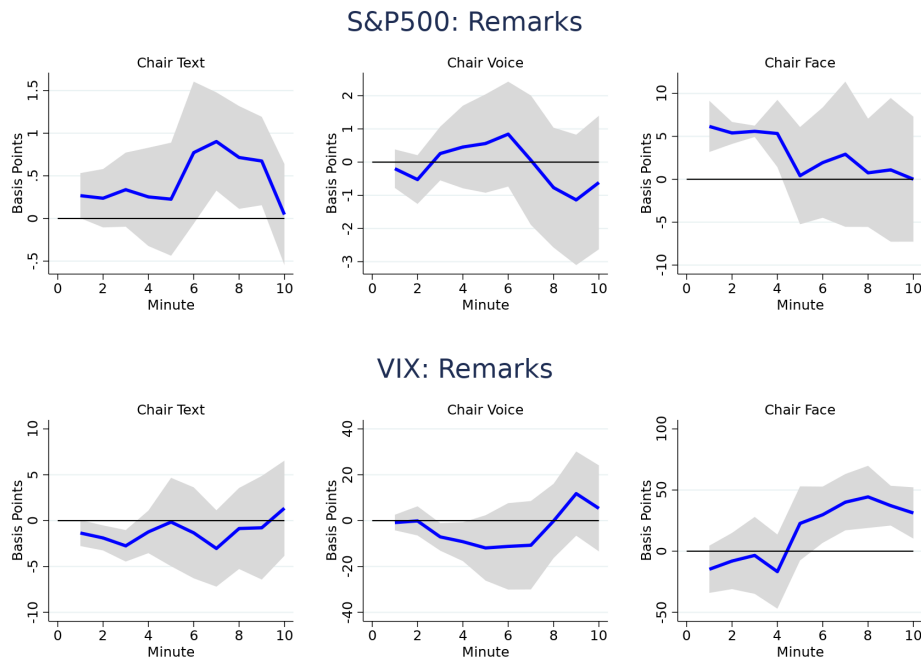


Figure 3. Responses during the remarks.

Notes: The figure provides responses of the change in log S&P500 (top) and the change of log VIX (bottom) to a one-standard-deviation positive impulse in the Fed Chair’s text-emotion index (left), voice-emotion index (middle), and face-emotion index (right) during remarks. Responses are estimated using specification (1). The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

3.2 Day 1 vs. Day 2: Fed Chair’s identical remarks

A unique feature of the semi-annual testimonies is that they take place on two separate days (to the House and to the Senate), and on both days the Chair delivers virtually identical remarks.¹⁰ This implies that the text-emotion index is identical between two days, and markets should respond to the Chair’s voice and face emotions only insofar as they differ from his or her voice and face emotions during Day 1’s remarks. We estimate the effect of these voice- and face-index differentials between Day 2 and Day 1 remarks using the following

¹⁰There are two exceptions. Bernanke delivered very different remarks on March 2, 2011 (Day 2) than on March 1 (Day 1). Yellen delivered remarks on July 12, 2017 (Day 1) while she delivered no remarks on July 13 (Day 2). We exclude these observations from this analysis. Among the remaining testimonies, three pairs of testimonies (February 2010, February 2013, and February 2014) contained minor differences in several sentences of the remarks. They do not influence the results.

specification:

$$\begin{aligned}
 Outcome_{\tau,b+h} - Outcome_{\tau,b} = & \beta_{VOICE}^{(h)} \Delta VOICE_{\tau,b}^{Chair} + \beta_{FACE}^{(h)} \Delta FACE_{\tau,b}^{Chair} \\
 & + \text{controls} + \text{constant} + \varepsilon_{\tau,b}^{(h)},
 \end{aligned} \tag{2}$$

where the dependent variable is the h -minute change in the outcome variable for the remarks on Day 2, and $\Delta VOICE_{\tau,b}^{Chair}$ and $\Delta FACE_{\tau,b}^{Chair}$ are the differences in voice- and face-emotion indices for block b of the remarks on Day 2 and same block b on Day 1.

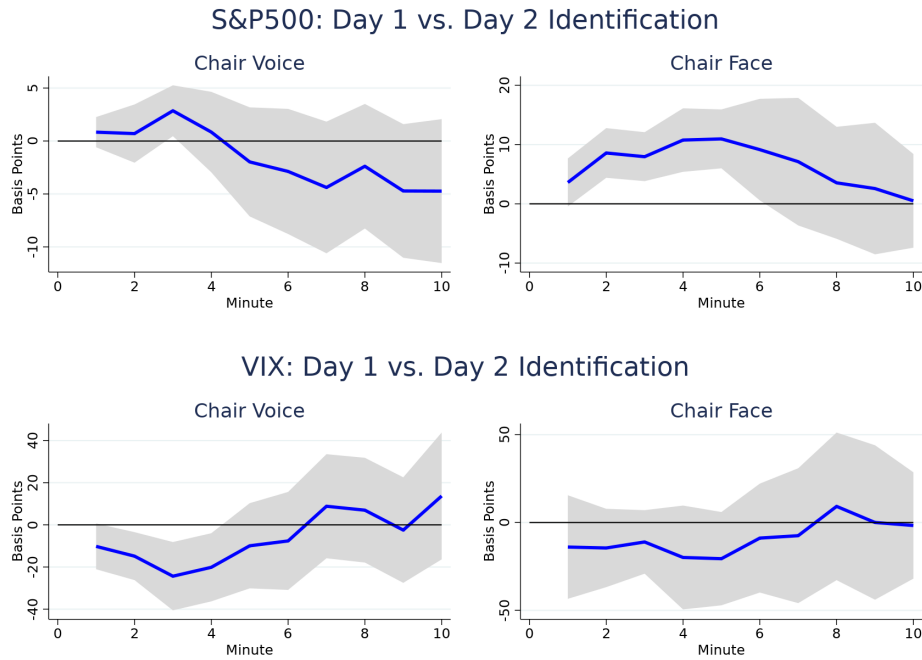


Figure 4. Responses: Day 1 vs. Day 2 testimonies.

Notes: The figure provides the responses of the changes in log S&P500 (top) and changes in log VIX (bottom) to a one-standard-deviation variation in the voice and face emotions of the Fed Chair between the Day 1 and Day 2 testimonies. Responses are estimated using specification (2). The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

The results are shown in Figure 4. S&P500 voice and face responses are in the same direction as in the first exercise, and they are quantitatively twice as large (and larger than *Let's Face It: Quantifying the Impact of Nonverbal Communication* (n.d.) find for FOMC press conferences). Both voice and face VIX responses are now negative, although VIX

responses to the Chair’s face emotion are not statistically significant. However, as we show in Section 5, they become larger and significant in days after the testimony. All in all, this alternative identification of the effects of the Chair’s vocal and facial emotions during the remarks corroborates positive responses of stock prices and negative responses of stock volatility obtained using specification (1).

3.3 Financial market responses: Q&A

To set up the analysis of Q&A data and focus on the effects of the Chairs’ responses to questions, we discard testimony blocks shorter than 10 sentences, blocks where the Chair speaks less than 20% of sentences, and blocks where the speaker’s face is recognized for less than 15% of the frames.¹¹ Out of total 741 Q&A rounds, we end up with 661 complete Q&A rounds between the Chair and the member, where the Chair has the opportunity to provide full answers.

We estimate the responses to variations in the Fed Chair’s emotion indices during Q&A using the baseline specification (1). In addition to controls used for the remarks, we include the following controls: three variables measuring the portion of each block containing the Chair’s speech, voice, or face, and three emotion indices and the stance index for congress members.

The estimated financial market’s responses to exchanges during the Q&A (Figure 5) are similar to responses we documented for the Chair’s prepared remarks. The S&P500 index increases after the Chair’s positive text- and voice-emotion indices change, and the responses are statistically significant at the 10% level. The VIX decreases in response to positive changes in all three indices, although not significantly for face emotions.

Quantitatively, stock market returns and stock volatility during Q&A are somewhat less sensitive than during the remarks, especially for face emotions. This is not very surprising. The Chair’s remarks are prepared, and the flow of speech—and associated emotions—is uninterrupted and one-sided, from the Chair to the audience. In contrast, during the Q&A section of the testimony, the Chair is responding to questions on a variety of topics, and his or her answers are mostly unscripted and frequently interrupted by a congress member. Therefore, what and how the Chair says during Q&A varies from round to round, which may

¹¹This could be due to a wide angle of the camera, the speaker’s head tilting down, or the camera being set from the side of the speaker so only the left or right part of the face is captured.

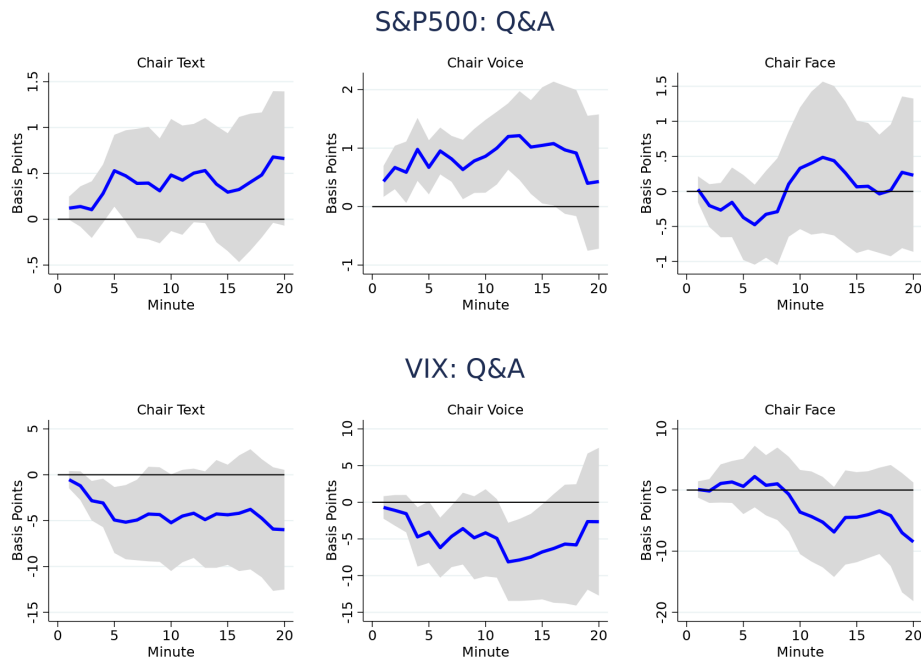


Figure 5. Responses during Q&A.

Notes: The figure provides responses of the changes in log S&P500 (top) and the changes in log VIX (bottom) to a one-standard-deviation positive impulse in the Fed Chair’s text-emotion index (left), voice-emotion index (middle), and face-emotion index (right) during Q&A. Responses are estimated using specification (1). The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

make it harder for the public and markets to distill. In the next section, we show that when the Chair discusses topics more relevant for financial markets, the responses to the Chair’s emotions are as large as the responses during the remarks.

The estimated responses of interest rate expectations, measured by five-quarter-ahead Eurodollar futures, are not as stark as stock market responses (Figure 6). All three of the Chair’s emotions have positive effects, albeit magnitudes are economically small. In the Appendix, we show that the responses tend to be positive for the remarks and also for longer yields (e.g., 10-year Treasury Note futures). Such responses suggest that markets associate the Chair’s positive emotions with a more hawkish monetary policy stance in the future.¹²

¹²The responses are indicative of the information channel of monetary policy, whereby interest rate surprises are interpreted as the Fed’s countercyclical responses to changes in economic outlook (Nakamura & Steinsson 2018, Cieslak & Schrimpf 2019, Jarociński & Karadi 2020)

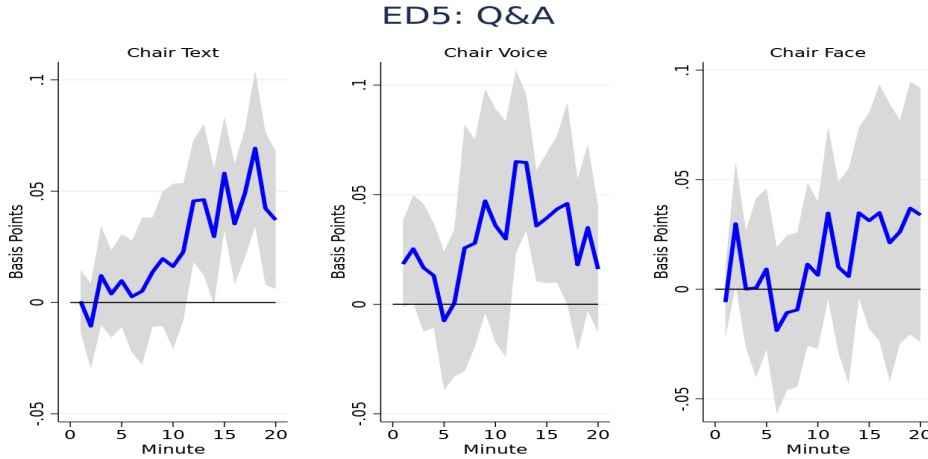


Figure 6. Interest rate expectation responses during Q&A.

Notes: The figure provides responses of the change in ED5 yields to a one-standard-deviation positive impulse in the Fed Chair’s text-emotion index (left), voice-emotion index (middle), and face-emotion index (right) during Q&A. Responses are estimated using specification (1). The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

In all, market responses to the Chair’s emotions during the delivery of the congressional testimonies have similar effects to those during or shortly after the Chair’s FOMC press conferences found elsewhere. [Gorodnichenko et al. \(2021\)](#) find that positive voice tone raises stock prices and lowers their volatility in the days following FOMC press conferences. [Let’s Face It: Quantifying the Impact of Nonverbal Communication \(n.d.\)](#) estimate that the Chair’s negative facial expressions during FOMC press conferences lead to lower S&P500 and higher VIX levels. We emphasize one difference in our results. We find that positive voice and facial expressions during congressional testimonies raise interest rate expectations. By contrast, [Gorodnichenko et al. \(2021\)](#) and [Let’s Face It: Quantifying the Impact of Nonverbal Communication \(n.d.\)](#) do not find significant evidence that voice and face emotions move interest rate expectations during/after FOMC press conferences.

Like these studies, our evidence indicates that soft information expressed by the Fed Chair during a public event influences financial markets. Our paper goes a step further, showing that such soft information is expressed via a combination of text, voice, and face variations. We demonstrate that all of these means of communication tend to move stock returns in the same direction, although their relative impacts may depend on the circumstances of the communication event. In the next section, we conduct additional analyses of these

circumstances to shed more light on the determinants of market reaction to the Fed Chair’s emotions.

4 Determinants of financial market responses

Our estimates show that financial markets react to soft information contained in the Chair’s discourse during the testimony, but do those responses depend on certain contexts or circumstances arising over the course of the testimony? Understanding these contexts or circumstances may help us discern some of the determinants of financial market reaction we document in the preceding section. In particular, we demonstrate that financial markets are somewhat differential to two key elements of the testimony—what was discussed and the Fed Chair person—while other elements seem less relevant.

4.1 Q&A topics

In the 32 testimonies of our study, there are a total of 741 Q&A rounds. Within each round, a congress member and the Fed Chair discuss several questions, six on average. In all testimonies, 4,323 questions and answers are covered. We use [Grootendorst \(2022\)](#)’s BERTopic algorithm to identify topics discussed in this set of question–answers. BERTopic leverages the word and sentence representations derived from the transformer model BERT as inputs, and creates dense clusters by using the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm ([Campello et al. 2013](#)).

The algorithm identifies 11 fairly narrow topics for two-thirds of 4,323 question–answer pairs in these testimonies (see Appendix). The remaining one-third are general and not associated with a narrow topic. For our analysis, we drop question–answers related to general pleasantries and those lasting less than 15 seconds to eliminate cross-talk, interruptions, platitudes, and introductions. This leaves us with 2,323 question–answer pairs. To estimate the responses conditional on topics discussed, we run specification (1) on a panel of question–answers, where blocks b are now question–answer pairs for each topic instead of the entire Q&A rounds we used above. We recompute emotion indices at a question–answer level, but leave normalization intact (i.e., dividing by standard deviations at the Q&A round level) for ease of comparison.

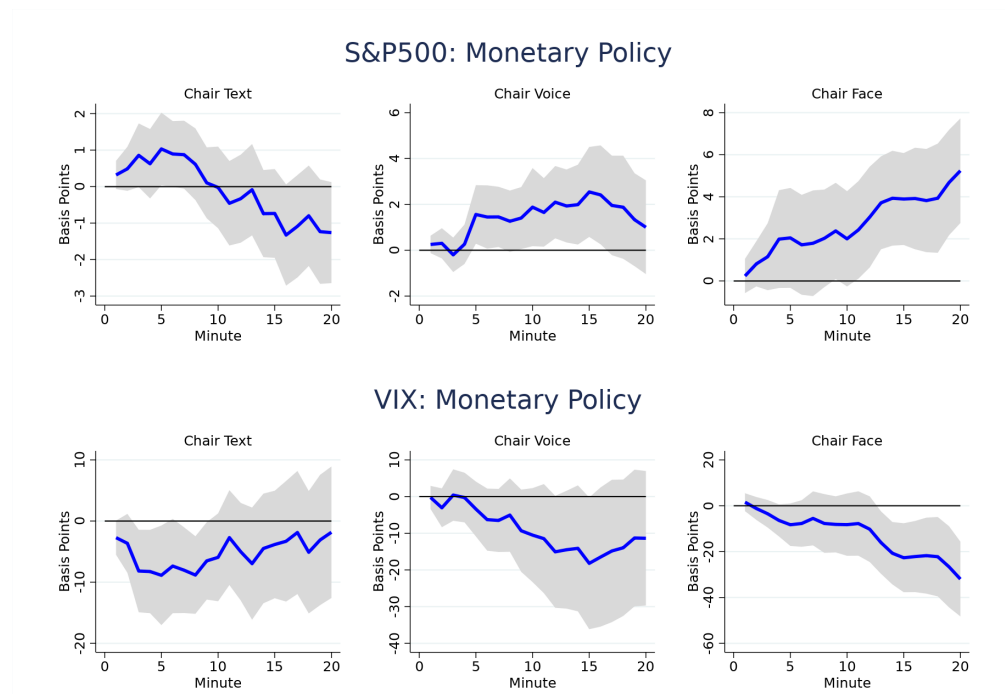


Figure 7. S&P500 and VIX responses to monetary policy topics during Q&A.

Notes: The figure provides the responses of the changes in log S&P500 (top) and log VIX (bottom) to a one-standard-deviation variation in the text-, voice-, and face-emotions of the Fed Chair conditional on discussing topics related to the Fed’s monetary policy. Responses are estimated using specification (1) on a panel of testimony blocks, where blocks b are question–answers for the selected topic, instead of entire Q&A rounds. The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

We find that the Q&A results in Section 3.3 are driven by discussions of issues directly related to monetary policy—the central bank’s reserves and balance sheet management, and the central bank’s policy rate and inflation. This topic was discussed 7% of time. Figure 7 shows that stock returns respond positively and significantly to positive changes in all three indices of the Fed Chair’s emotions during discussions of monetary policy, and VIX responses are negative and significant. Quantitatively, these responses have similar magnitudes to those we document for the remarks: by 1 bp (text), 2 bps (voice), and 5 bps (face) within 5 to 20 minutes.

These results are not surprising: markets are more likely to tune in to statements regarding the Fed’s interest rate and balance sheet policies. By contrast, the responses are either less systematic or less sensitive to discussions of bank regulations related to the Fed’s

regulatory mandate (35%) or discussions of other economic topics (fiscal policy 8%, housing and mortgage markets 5%, job market and unemployment 7%, trade and China 1%, growth and productivity 0.7%, unidentified topics 33%).

4.2 Bernanke and Yellen

The emotions measured by our indices, of course, reflect many idiosyncrasies of the “messenger”: cultural and educational background, previous work experience, demographic features such as age and gender, temperament, and mannerisms. We should not be surprised, therefore, if such differences between Fed Chairs translate into different market responses.

To this end, we repeat the estimations of remarks and Q&A responses separately for Bernanke and Yellen testimonies. In all, markets are more sensitive to Bernanke’s emotions, with positive responses of stock prices and negative responses of volatility to his positive cues in most cases. By contrast, the responses to Yellen’s emotions are less consistent and insignificant in many cases. For example, Figure 8 shows that the S&P500 response to Yellen’s voice emotion is half the magnitude of the response to Bernanke’s voice emotions, and the responses to her text sentiment and face emotion are insignificant or of the opposite sign.

These findings suggest that the market’s reaction to Fed messages is tightly linked to the messenger. With data for only two of the Fed’s Chairs, it is difficult to discern what it is about the messenger that markets are reacting to.¹³ Furthermore, different responses could also be associated with different states of the economy during each Chair’s respective tenures. Future work can draw firmer conclusions by adding testimony data for other Chairs and expanding the years covered by the analysis.

4.3 Other factors

Other dimensions of congressional testimonies appear less influential. In the Appendix we parse the responses by Day 1 versus Day 2 testimonies, the Senate versus the House testimonies, and the first versus the second halves of the Q&A of the same testimony. Although

¹³For example, individuals can interpret higher pitch in different ways. Sometimes high pitch is used to stress a point (like stressing a positive outcome in prepared remarks), in other instances high pitch may be interpreted as increased stress levels. Lausen & Schacht (2018) find that in some cases, when the speaker is a woman, men have a harder time accurately identifying emotions.

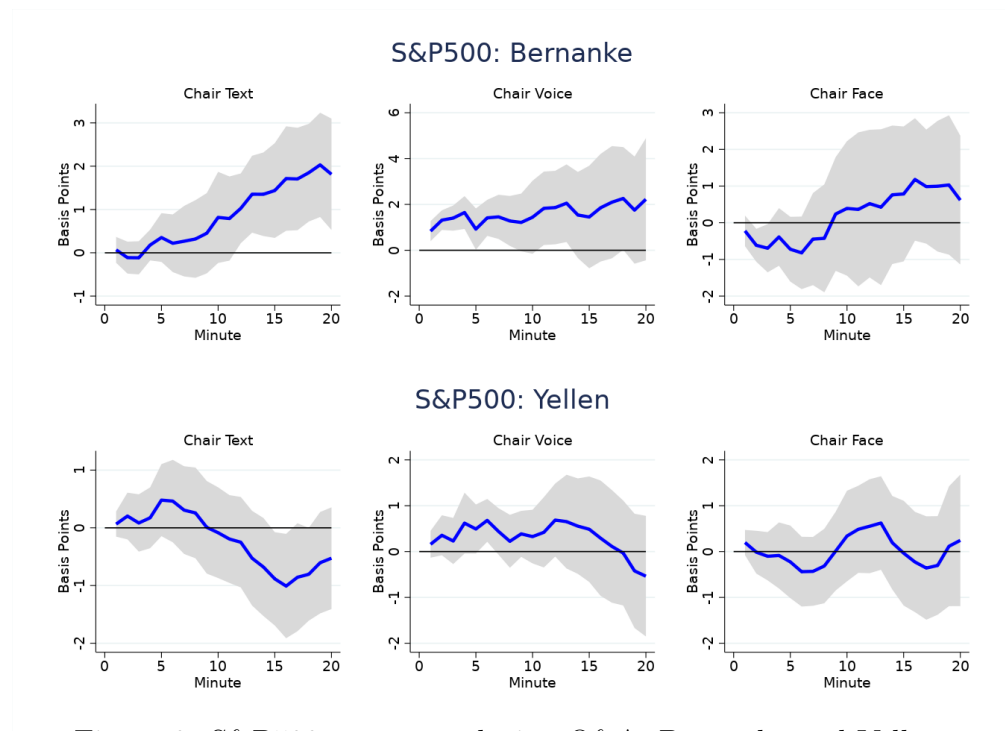


Figure 8. S&P500 responses during Q&A: Bernanke and Yellen.

Notes: The figure provides responses of changes in the log S&P500 to a one-standard-deviation positive impulse in the Fed Chair’s text-emotion index (left), voice-emotion index (middle), and face-emotion index (right) for Q&A during Bernanke testimonies (top) and Yellen testimonies (bottom). Responses are estimated using specification (1) and Q&A controls. The shaded areas represent the 90 percent confidence interval based on Driscoll-Kraay standard errors.

some of them show significant responses, there is no strong systematic link with the responses reported above. We find the responses to congressional members’ emotions are qualitatively similar but quantitatively weaker than the responses to the Chair’s emotions, suggesting that financial market activity during the testimony is associated mostly with information reflected in the Fed Chair’s emotions.

Furthermore, we also would like to rule out market-wide events that occur during the testimony and may influence the results. To identify such events, we mine information out of contemporaneous business news coverage from CNBC broadcasts, which are archived in the Internet Archives’ TV News collection (see Appendix). We assemble the breaking news segments that include macro news releases, political announcements, energy data releases, and other nation-wide news (e.g., hurricanes, terrorist attacks, federal government and regu-

latory announcements, worldwide events). Out of 661 blocks of testimony data, we identify 86 blocks that overlap with market-wide breaking news not related to the testimony. When we drop these blocks from the regression analysis, the estimated responses become somewhat stronger. Hence, market-wide events do not influence our results.

5 Discussion of the economic significance of estimated responses

In this section we argue that market responses during the testimony are economically meaningful. First, we provide evidence that the effects during the testimony add up and propagate in the days after the testimony, reaching magnitudes comparable to those after a policy rate cut. Second, during the testimony, we find evidence that market activity is elevated: asset prices are more volatile and trading volumes are higher. Finally, we show that semi-annual testimonies attract public attention, reflected in heightened viewership of live broadcasts and increased media coverage, similar to those around the FOMC press conferences. Below we elaborate on each of these points.

Financial market responses to the Chair’s three emotional cues are not only statistically significant, as we show above, but also economically significant. A one-standard-deviation change in the text-, voice-, or face-emotion indices during the remarks or relevant parts of the Q&A raises the S&P500 by 1 bp, 2 bps, and roughly 5 bps, respectively. If accumulated over the entire testimony, the effects of soft information from the Fed Chair may reach magnitudes comparable to those after an interest rate cut. For example, an unanticipated 25 bps cut in the Fed funds rate is associated with a roughly 100 bps increase in stock prices ([Bernanke & Kuttner 2005](#)).

Indeed, the effects that we document during the testimony appear to add up and persist in the days after the testimony. To determine the magnitudes, we estimate local projections at daily frequency:

$$\begin{aligned}
 Outcome_{\tau+h} - Outcome_{\tau-1} = & \beta_{\text{TEXT}}^{(h)} \text{TEXT}_{\tau}^{\text{CHAIR}} + \beta_{\text{VOICE}}^{(h)} \text{VOICE}_{\tau}^{\text{CHAIR}} + \beta_{\text{FACE}}^{(h)} \text{FACE}_{\tau}^{\text{CHAIR}} \\
 & + \text{controls} + \text{constant} + \varepsilon_{\tau}^{(h)}.
 \end{aligned} \tag{3}$$

where the dependent variable $Outcome_{\tau+h} - Outcome_{\tau-1}$ is the change in log close price between day $\tau - 1$ and day $\tau + h$, and index values are now the mean of corresponding the Chair’s emotion indices over the remarks and Q&A sessions of testimony τ , normalized by its own standard deviation across the 32 days (the data are provided in the Appendix). We include the three emotion indices of the members and the share of each block associated with the Chair’s speech as controls.

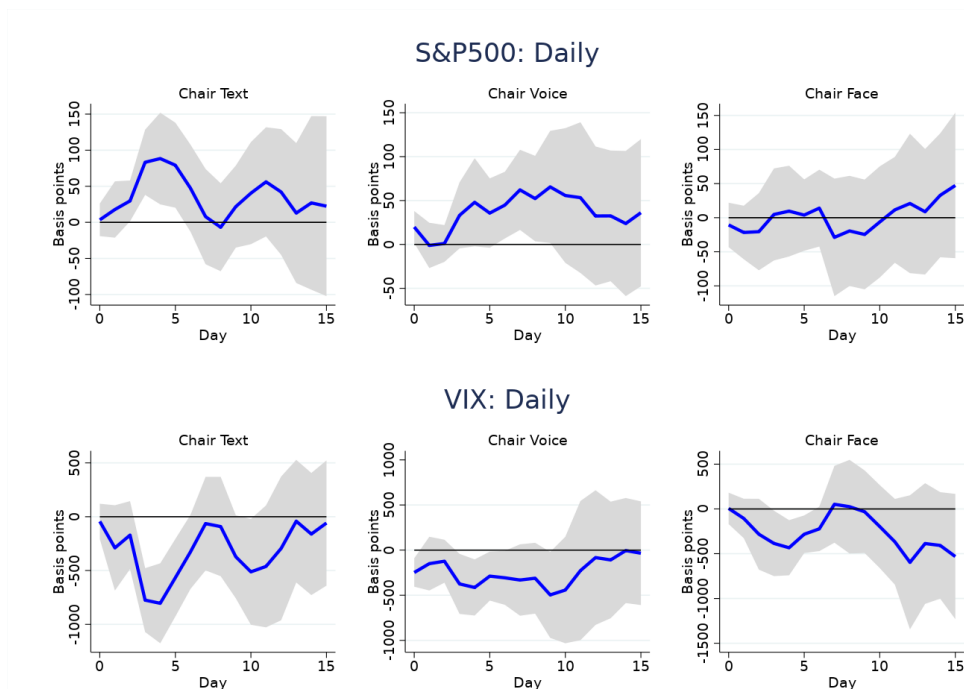


Figure 9. Responses at daily frequency.

Notes: The figure provides responses of the daily change in log S&P500 (top) and the daily change in log VIX (bottom) to a one-standard-deviation positive impulse in the Fed Chair’s average daily text-emotion index (left), voice-emotion index (middle), and face-emotion index (right). Responses are estimated using specification (3). The shaded areas represent the 90 percent confidence interval based on Newey-West standard errors.

Figure 9 shows that, for the most part, the S&P500 and VIX responses in days after the testimony have the same direction as responses during the testimony, although due to our small sample of 32 testimonies the responses are not always statistically significant. Note that response magnitudes are of the same order as those after a rate cut. The S&P500 responses to a testimony’s cumulative text and voice emotions reach 90 and 60 bps within one or two

weeks after the testimony. In particular, responses to vocal cues are similar in magnitude to those reported by [Gorodnichenko et al. \(2021\)](#) for the days after FOMC press conference. The responses to face emotion are around zero, suggesting that the market’s interpretation of the Chair’s facial emotions for stock prices are short-lived. The VIX responses are all negative and significant.

Second, congressional testimonies attract attention by the financial markets. We observe that, on average, 10,187 SPY trades (an ETF tracking the S&P500) are executed during one block in the Q&A, and 307,159 SPY trades are executed over the course of the whole testimony. [Rosa \(2018\)](#) finds that the Fed Chair’s FOMC press conferences and semi-annual testimonies between 2001 and 2012 significantly increase volatility of U.S. asset returns and trading volumes. We conduct our own related exercise and compute standard deviation of log changes and their trading volumes for SPY over 5-minute windows during each of 32 testimonies in our data. We compare these statistics with the day one week prior and one week after the day of each testimony. Even for such a small sample, we find that both price volatility and trade volumes are significantly higher during the testimony than seven days after, and they are also higher than seven days before the testimony, although for price volatility the difference is not statistically significant.

In addition to trading activity, the viewership of the televised or streamed testimonies and their coverage in the print and social media are also elevated. The testimonies are generally live-streamed by C-SPAN and on the Senate and House committees’ websites, as well as on the major business news networks, such as CNBC and Bloomberg. Hundreds of thousands of households, investors, and businesses are exposed to these broadcasts contemporaneously on cable TV, through Bloomberg’s terminals and TD Ameritrade, and on screens on the floor of the New York Stock Exchange.¹⁴ There is also significant information shared about the testimonies’ content in print and social media. We measure media coverage of the testimony by the daily number of related articles in the Dow Jones Factiva database (as a fraction

¹⁴See, e.g., [Comcast \(2011-2017\)](#) for Nielsen’s estimates of CNBC household penetration, [Stark \(1999\)](#) for a discussion of CNBC’s large daily audience outside of the home, and <https://ctv.kwayisi.org/networks/> for statistics on the viewership of CNBC’s programs typically airing the testimonies—Squawk on the Street, Power Lunch and Fast Money Halftime Report. See <https://www.bloomberg.com/professional/solution/bloomberg-terminal/> for evidence that there are over 325,000 terminals in use, and [Bloomberg Business Wire \(2010\)](#) and [Killam-Williams \(2005\)](#) for evidence on Bloomberg TV’s historical viewers in the United States and Europe based on reported data from Nielsen and the 2010 European Media and Marketing survey.

of total daily articles) and the daily number of related Twitter posts. The interest in a testimony builds over the days leading up to it and falls in the days following it, following a fairly standard news cycle pattern. Moreover, on the peak day, which usually corresponds to the first day of testimony, approximately 0.24%–0.75% of news articles and 0.00089%–0.00682% of Twitter posts cover the testimony, which is comparable to coverage of FOMC press conferences.

6 Conclusions

Central bankers are understandably restrained in what and how much they can say about monetary policy. Communications of monetary policy to the public need to be made in non-technical and relatable language (Bholat et al. 2019, Kryvtsov & Petersen 2021), but even simplified communications may not always get through to the audience (Coibion et al. 2020). Furthermore, it is not always desirable to disclose internal information, such as details of internal policy deliberations or staff views on the likely path of future interest rates (Natvik et al. 2020). When words are limited, how can central bank leaders present their institution’s policy as credible and be trusted to promote social welfare? Our evidence suggests central bankers do that with more than words.

Even if the sentiment is incorporated in the central bank’s written or verbal message, variations in voice pitch and facial expressions of the person delivering the message influence financial markets many times over. Positive emotional cues from the leader tend to be interpreted positively by financial markets. These effects do not disappear when the event is over, but rather they add up and propagate in the days after the event. Markets are more attentive when the central bank leader is speaking and when he or she is discussing monetary policy. These findings suggest that the delivery of central bank communications is potentially as influential for markets and the general public as is the content of these communications.

While the results demonstrate that the impacts of communications are linked to more than words, future research will help study the mechanisms of these effects and further clarify the most important channels. The impacts of soft forms of communication, for example, depend on both the messenger’s facial and vocal emotional expressions and the audience’s interpretation of these expressions. The messenger may choose to use the expressions in an

intentional way, such as to emphasize an important point, or the expressions may unintentionally reveal an emotional state, such as stress, through a wavering voice, nervous gestures, or momentary expressions of shock. The impacts on the audience may depend on the demographic makeup of the messengers (i.e., the Fed Chairs, senators, and the congressional representatives) and the attention levels and characteristics of the audience.

Therefore, future work will focus on three main sets of questions. First, how is the soft information obtained, interpreted, and used by different types of traders (i.e., high-frequency traders vs. others), and which groups are most affected by the emotional signals? Second, what is the role of conventional and social media coverage for disseminating soft information, and how do the emotional signals affect the topics discussed in the news? Finally, are there systematic differences in the interpretation of, and responses to, the communications by messengers that differ by demographic characteristics (including gender, age, cultural background) or political affiliation?

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