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Abstract

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JEL Classification: E31, E58, G12, D84

Keywords: monetary policy, communication, voice, Emotion, text sentiment, Stock market, Bond market

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"How can a president not be an actor?" *Ronald Reagan (1980)*

"As Chairman, I hope to foster a public conversation about what the Fed is doing to support a strong and resilient economy. And one practical step in doing so is to have a press conference like this after every one of our scheduled FOMC meetings. ... [This] is only about improving communications." *Jerome Powell (2018)*[1]

1 Introduction

In a famous analysis, Mehrabian (1971) posited a 7-55-38 rule of communication: the words convey 7 percent of a message, the body language (gestures, facial expressions, etc.) accounts for 55 percent, and the tone delivers 38 percent. While the debate on exact percentages for each channel is far from settled, it is clear that effective communication has to rely on more than just the text. Central banks have been increasingly relying on communication-based tools (e.g., forward guidance) to manage the public's expectations, but do central bankers utilize communication to its full potential?

Textual analyses of policy statements, minutes, and transcripts (e.g., Rozkrut et al., 2007; Hansen and McMahon, 2016, Hansen et al., 2018, Cieslak et al., 2019, Ehrmann and Talmi, 2020) suggest that central bankers' words carry a lot of weight,[2] but little is known about the effects of their non-verbal communication. To shed more light on this issue, we use deep learning methods to quantify tone (vocal emotions) embedded in the answers given by Federal Reserve Chairs during press conferences. To the best of our knowledge, our study is the first to examine the effects of central bank communications through the vocal dimension. In other words, we move beyond text analysis and study *how* policy messages are voiced and whether emotions in voice tone can move financial markets.

We focus on policy communication during press conferences for several reasons. First, press conferences have been commonly used as an important communication tool.[3] As suggested by Ehrmann and Fratzche (2007) and emphasized by Powell (2018), press conferences, particularly the Q&A sessions, play a key role in helping financial markets and the general public to understand policy outlook and interpretation of current economic conditions. Especially during

[1] https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20180613.pdf

[2] More generally, central banks have significant power to influence the macroeconomy and expectations. For example, a large number of studies have documented the effectiveness of policy announcements in moving financial markets (e.g., Kuttner, 2001, Gurkaynak et al., 2005) or shaping firm and household inflation expectations (e.g., Coibion et al., 2019; Enders et al., 2019; Lamla and Vinogradov, 2019).

[3] See Kedan and Stuart (2014) for a review of central banks which use press conferences as a communication tool.

times of high uncertainty, market participants tend to seek further guidance/clarification through press conferences' Q&A sessions. Second, press conferences allow policymakers to go off script and communicate soft information via non-verbal channels and thus, influence investors' decision making.[4] Finally, because video/audio recordings of press conferences are available in a consistent format,[5] we can measure the tone of communication in a consistent manner and hence, provide a systematic analysis of how voice tone can influence economic outcomes.

Specifically, we split a given press conference into audio segments corresponding to each question raised during the event and the response of the speaker. The split audios are then run through a machine-learning procedure which is trained to recognize emotions from voice variations. Each answer is rated in terms of three emotions: positive (happy or pleasantly surprised emotions), negative (sad or angry emotions), and neutral. After aggregating the tone of answers for a given press conference, we examine how the tone of the press conference affects a variety of financial variables at high frequencies. We find that the tone can materially move the financial markets. For example, switching the tone of the press conference from negative (-1) to positive (+1) could raise S&P 500 returns by approximately 200 basis points. This order of magnitude is comparable to the magnitudes one can observe after a two-standard deviation shock to forward guidance. In other words, the voice component can generate economically large effects on the stock market. We also find that inflation expectations and exchange rates respond to the variation in voice tone, e.g., a more positive tone leads to a decrease in expected inflation. At the same time, there is no evidence of bond market reactions to voice variations in our sample. These results suggest that policy communication is more nuanced than reading and/or posting prepared remarks and speeches. It appears that a certain level of acting skill may be helpful to ensure that the public receives the policy message fully and correctly.

In addition to the vast literature on policy communication (see Blinder et al., 2008 and Coenen et al., 2017 for comprehensive surveys) and high-frequency analyses of monetary policy shocks (e.g., Kuttner, 2001, Gurkaynak et al., 2005, and many others), our study relates to research investigating the economic impacts of vocal cues. Using a sample of CEOs' speeches during

[4] Caffi and Janney (1994), Visschedijk et al. (2013), Dricu et al. (2017), and others document that voice conveys information beyond the verbal content and that information contained in voice can affect decision making.

[5] Video recordings can be used to study body language (e.g., facial expressions, gestures). However, videos are harder to analyze because cameras are moving (different speakers, different angles). In this respect, audio tracks offer a more consistent measurement. As a result, we focus on variation in voice tone.

earnings conference calls, Hobson et al. (2012) find that the vocal markers of cognitive dissonance can predict the likelihood of irregularity restatements. In a related study, Mayew and Venkatachalam (2012) show that market participants and analysts react to the affective states of managers expressed through vocal cues, e.g., happy/unhappy voices. For example, positive affect is positively related to changes in stock recommendations and future unexpected earnings. These results suggest that the affective states contain useful information about firms' fundamentals. In a more recent study, Hu and Ma (2020) find that positivity about a startup shown through the visual, verbal, and vocal dimensions increases the likelihood of being funded even if the startup's quality is low. Apart from having a different focus (central banking communication vs. CEO/manager communication), we differ in the tools employed to quantify the variation in tone. Earlier studies use commercial software or pre-trained machine learning algorithms for voice analysis, while we develop a customized deep learning model for detecting speech emotion. Our approach offers several advantages in terms of flexibility, room for further development, and implementations. For example, we can fine-tune the model's parameters to achieve a higher accuracy rate, which is not a feature available to commercial software. Similarly, the customized model allows us to adjust the number and/or the class of emotions, which also cannot be done with the commercial software and pre-trained algorithms.

The rest of this paper is organized as follows. In the next section, we describe the financial, text, and speech data used in the analysis and how the data are analyzed. Section 3 presents our empirical analyses and results. Section 4 concludes and discusses implications.

2 FOMC speeches: voice and linguistic analysis

Our sample runs from 2011 (when the first press conference was held) to June 2019. During this period, 67 meetings and 36 press conferences were held. For each meeting, the FOMC statement and the transcript of the press conference are collected from the Federal Reserve (Fed) website. The press conferences' videos are downloaded from the Fed's official Youtube channel. We use only the audio component of these videos. Because the Q&A session is the only part of the press conference that is not scripted, our analysis focuses on the answers of the Chair during the Q&A. Our audio sample contains 692 answers of 3 speakers (Ben Bernanke, Janet Yellen, and Jerome Powell).

2.1 *Voice Tone*

In this section, we describe how we train a neural network model (a deep learning algorithm) to recognize emotions. We also explain the mechanism of the neural network algorithm and how it is applied to predict voice emotion.

2.1.1 <u>Emotion Detection Using Neural Networks</u>

Voice can be characterized by various parameters such as pitch (indicating the level of highness/lowness of a tone) and frequency (indicating the variation in the pitch) which are useful in determining the mood/emotion of a speaker. Building on earlier research on voice recognition (e.g., Pan et al., 2012; Gao et al., 2017; Likitha et al., 2017; Bhavan et al., 2019), we use Librosa, a Python package, to extract the following vocal features: 40 Mel-frequency cepstral coefficients (MFCCs), 12 Chroma coefficients (Chromagram), and 128 Mel Spectrogram Frequencies (Mel). These features are later used as inputs for our deep learning model.

We use two data sets to train and validate our model. The first is the Ryson Audio-Visual Database of Emotional Speech and Song (RAVDESS). To create these data, 12 actors and 12 actresses speak two statements in a neutral North American accent and 8 emotions (calm, happy, sad, angry, fearful, surprised, disgust, neutral). The second data set is the Toronto Emotional Speech Set (TESS). To create these data, 2 actresses speak a set of 200 words in 7 emotions (happy, sad, angry, fearful, pleasantly surprised, disgust, neutral). These data sets are widely used in the computer science literature to build the speech emotion/expression systems (see, e.g., Verma and Mukhopadhyay, 2016, Gao et al., 2017, Choudhury et al., 2018, Bhavan et al., 2019, Andersson, 2020). Because fearful/disgust emotions are unlikely to arise during the Q&A sessions, we only use audios for 5 emotions: happy, (pleasantly) surprised, neutral, sad, and angry.

After extracting the vocal features from each recording in RAVDESS and TESS, we build a neural network model, i.e., a computing system consisting of different layers where each layer is a collection of different neurons (nodes). The output of one layer is used as the input for the proceeding layer. We illustrate the mechanism behind a neural work comprised of three fully connected layers in Figure 1. The first layer in this network is the input layer with three nodes and each node is a feature of the training audio data. The second layer is a hidden layer consisting of four nodes (HK_k, k=[1;4]) which are the activation functions of the input features IN_i (i=[1;3]). Particularly, a node HK_k is connected with the input through weight ($w_{k,i}$) and bias (b_k): $\sum_{i=1}^{3} IN_i \times w_{k,i} + b_k$. The weighted summations are passed on an activation function such as a binary step function, linear activation function, or non-linear activation function, to obtain the outputs O_k (k=[1;4]). Applying the same procedure on these outputs gives us the final output (i.e., the classification of emotion). We use 80% of RAVDESS and TESS as the training sample and the remaining 20% are used for validation.

After experimenting with different hyper-parameters of the neural network, e.g., using different types of layers, different combinations of those layers, and different activation functions, we obtain a network containing 3 fully connected (dense) layers (i.e., 1 hidden layer) with 200 units (200 nodes) and the softmax activation function.[6] This trained model gives us an accuracy score of 84%. The accuracy in predicting angry, sad, neutral, surprised, and happy emotion is 87%, 84%, 74%, 87%, and 80%, respectively.

2.1.2 Emotion Detection Output

After training the neural network to recognize emotions from variations in vocal features (MFCCs, Chromagram, and Mel Spectrogram), we feed the audio tracks of the policymakers' answers into the neural network and classify the answer into positive ("happy" or "pleasantly surprised" emotion), negative ("sad" or "angry" emotion), or neutral. We measure the tone of responses for a given Q&A session as follows:

$$VoiceTone = \frac{Positive\ answers - Negative\ answers}{Positive\ answers + Negative\ answers} \tag{1}$$

where $VoiceTone$ ranges from -1 (negative emotions) to +1 (positive emotions). We report descriptive statistics in Panel A of Table 1 and scores for each Q&A session in Appendix Table 1.

We find that Ben Bernanke on average had more positive emotions in his voice than Janet Yellen, who in turn had generally more positive emotions in her voice than Jerome Powell. Bernanke had five Q&A sessions with only positive emotions in his voice. In contrast, Jerome Powell had five

[6] Softmax is a mathematical function that translates a vector of inputs into a vector of probabilities. The softmax function normalizes the outputs so that the resulting probabilities sum to one.

Q&A sessions with only negative emotions. Janet Yellen's sessions always had a mix of positive and negative emotions. The average tone across these central bankers is close to zero. There is considerable within-speaker variation in the tone, with Jerome Powell exhibiting the largest variation.

2.2 Textual Analysis

Similar to Apel and Grimaldi (2014) and Neuhierl and Weber (2019), we use a "search and count" approach to classify the text sentiment into hawkish versus dovish sentiment. In particular, we build four lists of nouns, adjectives, and verbs of which combinations will indicate either tight monetary policy/strong economic outlook (i.e., hawkish) or expansionary monetary policy/weak economic outlook (i.e., dovish). As indicated in Table 2, a phrase combined of (1) A1 and A2 or (2) B1 and B2 is classified as "dovish" while a phrase combined of (1) A1 and B2 or (2) B1 and A2 is classified as "hawkish". To increase the accuracy of our classification, the search and count approach is performed on each part of a sentence then aggregated over the whole document.[7] Since negations such as "won't"', "aren't" can alter the meaning of the text, for each part of a text, a hawkish (dovish) phrase is only counted as hawkish (dovish) if the text does not contain a negation word/phrase. In contrast, if a hawkish phrase is accompanied by a negation word/phrase, then it is counted as dovish and vice versa.[8] The number of dovish and hawkish phrases detected in FOMC press releases and press conferences' transcripts are reported in Panel B of Table 1. The dovish phrases are generally used more often in FOMC communications during the examined period.

We use the following formula to measure the aggregate sentiment of the text of an FOMC statement/remarks/Q&A:

$$TextSentiment = \frac{Dovish\ phrases - Hawkish\ phrases}{Dovish\ phrases + Hawkish\ phrases} \qquad (2)$$

where $Dovish\ phrases$ and $Hawkish\ phrases$ are the counts of respective phrases in the FOMC statements as well as press conferences' transcripts when a press conference is held.

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[7] For example, the sentence "With inflation running persistently below this longer-run goal, the Committee will aim to achieve inflation moderately above 2 percent for some time so that inflation averages 2 percent over time and longer-term inflation expectations remain well anchored at 2 percent" contains 2 parts, "With inflation running persistently below this longer-run goal" and "the Committee will aim to…2 percent". Search and count is performed on each part separately, then aggregated over the whole sentence, and latter aggregated over the whole document.

[8] A similar approach was applied in Cieslak and Vissing-Jorgensen (2020) where a negative word accompanied by "not" is considered positive.

$TextSentiment$ is in the range of [-1;1]. A positive value of $TextSentiment$ indicates an expansionary monetary policy or that expansionary monetary policy is expected.

We find (Panel B of Table 1) that the sentiment of texts during the terms of Bernanke and Yellen was generally more dovish than Powell's.[9] This pattern likely reflects that policy rate increases dominated during Powell's period in our sample. The within-speaker variation in the text sentiment is broadly similar across the Fed Chairs. Note that the variation in text sentiment during Q&A sessions is larger than the variation in the text sentiment for statements and remarks, which likely reflects the less scripted nature of Q&A sessions relative to other communication types. The correlation of sentiment for statement and remarks is discernibly positive ($\rho = 0.4$), while the text sentiment of responses during Q&A sessions is approximately uncorrelated with the text sentiment of statements ($\rho = 0.06$). At the same time, the text sentiments for Q&A and remarks are correlated at $\rho = 0.32$. To measure the totality of the sentiment, we compute $TextSentiment$ using all three sources (statement, remarks, and Q&A responses). Given that we have a limited number of events in our sample, this approach allows us to save degrees of freedom but our results are robust to using $TextSentiment$ measured for each source separately or in other combinations.

2.3 Co-movement in Policy Actions and Word

How much do text sentiment and voice tone co-move? Although one might think that text and voice should be highly congruent, Figure 2 demonstrates that the relationship between these two channels of communication is more nuanced. Specifically, the positive messages conveyed in the tonality of voice are associated with more dovish statements in the accompanying texts, but this relationship is fairly weak. For example, the correlation between the text sentiment in statements and the voice tone in the corresponding Q&A sessions is $\rho = 0.35$. The correlation for Q&A tone with the text sentiment in remarks or Q&A is even lower: 0.16 and 0.24, respectively. In fact, Figure 2 shows that it is not uncommon to observe dovish texts and negative tonality. These results suggest that the tone of Q&A responses may generate variation in policy communication that is unrelated to what is contained in the texts of policymakers' statements, remarks, or even Q&A responses themselves.

[9] Text sentiment scores for each meeting are listed in Appendix Table 2.

In a similar spirit, the variation in tone appears to be only weakly correlated with actual policy shocks (panels A-C in Figure 3) identified as in Swanson (2020): a shock to the policy rate (FFR shock), a forward guidance (FG) shock, or an asset purchase (AP) shock. There is a stronger correlation between voice tone and the stage of the policy cycle. Specifically, the correlation between the shadow rate (measured as in Wu and Xia, 2016)[10] and voice tone is -0.29 (for comparison, the correlation with FFR shocks is -0.17), i.e., voice tone becomes more negative as the policy rate increases. We conclude that voice tone has variations unrelated to the Fed's actions and verbal (text) communication.

3 Empirical analysis

In this section, we investigate whether voice tone can move various financial indicators. In particular, we estimate the following specification in the spirit of Jordà (2005):

$$\begin{aligned} Outcome_{t,t+h} = b_0^{(h)} &+ b_1^{(h)} VoiceTone_t + b_2^{(h)} TextSentiment_t \\ &+ b_3^{(h)} FFRShock_t + b_4^{(h)} FGShock_t + b_5^{(h)} APShock_t \\ &+ b_6^{(h)} ShadowRate_t + error_t^{(h)} \end{aligned} \tag{3}$$

where t dates FOMC meetings. $VoiceTone_t$ measures voice tone of the Q&A session at date t. $TextSentiment_t$ indicates the sentiment in the policy statement, remarks, and Q&A responses. $FFRShock_t$, $FGShock_t$, and $APShock_t$ are policy shocks identified using intraday data by Swanson (2020). These policy shocks are normalized to have unit variance over a "typical" period (e.g., the FFR shock is normalized to have unit variance for the period that excludes zero lower bound). $ShadowRate_t$ is the shadow policy rate from Wu and Xia (2016). Policy shocks and the shadow rate control for "actions" of the Fed so that we can identify more cleanly the effects of voice tone on outcome variables.[11] Note that we code $VoiceTone$ equal to zero for FOMC meetings without Q&A sessions. Our results are robust to focusing only on meetings with Q&A sessions.

[10] The updated series of the shadow rate are available at https://sites.google.com/view/jingcynthiawu/shadow-rates.

[11] To check the robustness of our findings, we control for releases of macroeconomic data (unemployment rate, non-farm payroll, and GDP growth) in a version of specification (3). While most of the FOMC announcements were not overlapped with the releases of other macro data releases over the examined period, there are few exceptions. In particular, five FOMC announcements were released on the same day as the release of gross domestic product (GDP) data but none of these five were accompanied by a press conference. At the same time, seven FOMC announcements (six of which were followed by a press conference) were made on the same day as consumer price index data releases.

We estimate specification (3) for each horizon h separately and plot the estimated coefficients, e.g., $\left\{\hat{b}_2^{(h)}\right\}_{h=0}^{H}$, to illustrate the dynamics of the response to a form of policy action or communication. Note that while high-frequency analyses tend to find clear responses to policy announcements at the intraday frequencies (e.g., Kuttner, 2001, Swanson, 2020), we use the daily frequency which, given dramatic volatility for some financial indicators, often yields statistically insignificant estimates (see, e.g., Gorodnichenko and Weber, 2016). However, one could expect that the response may build over time, consistent with the notion of "slow- moving" capital proposed by Fleckenstein et al. (2014). Hence, using daily series offers an opportunity to examine responses at longer horizons, which may be important for identifying policy actions and communication tools with durable effects.

The outcome variables are daily financial indicators available from Thomson Reuters and other popular sources including Yahoo Finance and Tiingo. We generally use prices of exchange-traded funds (ETFs) that track popular indices. For example, we use the SPY, an ETF fund that tracks the S&P 500 index, to measure reactions of the stock market to policy shocks. We measure returns on ETF funds or similar securities as the log close price at date $t + h$ minus log open price at date t. Hence, the return on the day of an FOMC meeting is the log difference between close and open prices.

Because the sample is relatively small (67 FOMC meetings), we estimate specification (3) using bootstrap methods to correct for possible biases in the estimates as well as to construct confidence intervals with good coverage. Specifically, 90 percent confidence intervals are based on the 5th and 95th percentiles of the estimates generated in bootstrap draws. As a robustness check, we also estimate specification (3) with $VoiceTone$ as the only regressor.

3.1 Stock market reactions

When we use the SPY ETF to measure the reactions of the stock market to policy actions and communications, we find (Panel B of Figure 4) that a more positive voice tone leads to an increase in share prices. Specifically, the impact response (i.e., $h = 0$) of the stock market is weak and not significant statistically. Over time, the response builds up and after five days, the return on SPY

We found that controlling for the releases of macroeconomic news does not have a materially important effect on the reported estimates.

reaches approximately 100 basis points for a unit increase in voice tone. The response levels off after the first few days and stays statistically significant at 10 percent. We observe this pattern irrespective of whether we include controls (Panel B) or not (Panel A) in specification (3).

On the other hand, the sentiment of the policy texts does not appear to have a statistically discernible effect on the SPY in our sample, although the point estimates are positive, suggesting that more dovish sentiment leads to a boom in the stock market. This finding is qualitatively in line with the results documented in the literature. For example, employing the high-frequency event study approach, Rosa (2011b) shows that surprise hawkish FOMC statements lead to a reduction in equity returns. However, using monthly data over the 1998 – 2014 period, Hansen and McMahon (2016) find a statistically insignificant reaction of stock markets to FOMC statements talking more about strong economic conditions.

The FFR shock does not have a statistically significant effect on the stock market, which likely reflects the fact that the sample period is dominated by the zero-lower bound and changes in the short-term policy rate probably provided a rather limited outlook for the stance of monetary policy. Changes in the pace of asset purchases by the central bank (AP shock) also do not have a clear effect on the stock market, a finding consistent with Swanson (2020). Note that our sample does not include the first round of quantitative easing in 2009, which led to a strong reaction of the stock market (see, e.g., Chodorow-Reich, 2004, Krishnamurthy and Vissing-Jorgensen, 2011). For this sample period, however, a forward guidance shock leads to a persistent decrease in stock prices, in line with the intra-day responses estimated by Swanson (2020). This response is consistent with the signaling effect suggested by Campbell et al. (2012), i.e., an FG shock reveals that the Fed could be pessimistic about the state of the economy. Note that the magnitude of the stock market response to a unit decrease in voice tone is approximately equal to the response we observe after a one-standard-deviation forward-guidance shock. Thus, the variation in voice tone has economically significant effects.

To further understand the reaction of the stock market to policy actions and messages, we examine the response of the CBOE Volatility Index VIX (Figure 5), a popular measure of the stock market's expectations about future volatility. We also study the responses of futures on the VIX to have a more refined sense of how policy can influence outlook for volatility. Specifically, we use VIXY (Figure 6; VIX Short-Term Futures) and VIXM (Appendix Figure 7; VIX Mid-Term

Futures ETF) ETFs. We find that Fed actions (FFR/FG/AP shocks) tend to raise the volatility in the stock market. The sentiment in the texts does not lead to an apparent response in the volatility indices. In contrast, a positive voice tone tends to decrease current and anticipated volatility. This result is consistent with the notion that central banks can shape uncertainty about future economic conditions (Hansen et al., 2019). The variation in voice tone has economically significant effects: a unit decrease in the tone increases the volatility by the amount that is roughly equal to the increase after a one-standard-deviation shock to forward guidance.

Relatedly, monetary policy can convey information about the path of interest rates and thus reduce the interest rate risk (Hattori et al., 2016). To quantify the importance of this channel, we measure the interest rate risk with the following spread: $Outcome_{t,t+h} = log\left(\frac{P^{LQD}_{t+h,close}}{P^{LQD}_{t,open}}\right) - log\left(\frac{P^{LQDH}_{t+h,close}}{P^{LQDH}_{t,open}}\right)$, where P^{LQD} is the price of LQD ETF (investment grade corporate bonds) and P^{LQHD} is the price of interest-rate-hedged corporate bond LQDH ETF. A decrease in this measure indicates a decline in the perceived interest rate risk. Our results (Figure 7) suggest that a more positive tone leads to a reduction in investors' expectation about interest rate risk. Consistent with this interpretation and in line with the existing studies which document the impact of policy actions on bond risk premia (e.g., Hattori et al., 2016), we find that a forward guidance shock reduces uncertainty about the future path of interest rate. Note that a unit decrease in voice tone and a one-standard-deviation increase in the FG shock generate similar responses of the spread, again pointing to economic significance of voice tone. In contrast, an AP shock could signal the lower amount of interest rate risk in investor portfolio in the future, and thus, increase the perceived current interest rate risk, which is consistent with the analysis in Gorodnichenko and Ray (2017). Intuitively, asset purchases are a form of discretionary policy and deployment of such a tool increases uncertainty about the future path of policy.

3.2 Bond market reactions

Kuttner (2001), Swanson (2020), and many others document a strong reaction of the bond market to monetary policy shocks. Consistent with these earlier works, we find (Figure 8) that the price of GOVT ETF (a fund covering U.S. government nominal debt) decreases in response to a forward guidance shock (i.e., yields rise) and increases in response to an asset-purchase shock (i.e., yields fall). FFR shocks do not lead to a statistically significant response in GOVT prices, which likely reflects the prominence of the zero lower bound in our sample. In contrast to the strong responses of the stock market, responses of the bond market to voice tone are not statistically significant. Similarly, text sentiment does not move GOVT prices materially. These findings are consistent with Cieslak and Pang (2020) or Ehrmann and Talmi (2020), who document that bond market reaction to Fed communications is weak. Using ETFs for government debt with different maturities, we also examine if there could be a differential response across the maturity space. We find qualitatively similar responses for all maturities (Appendix Figure 1 through Appendix Figure 6) although the magnitudes of the responses to FFR/FG/AP shocks tend to be smaller for shorter maturities.

An important dimension of monetary policy transmission is how policy can influence interest rates faced by the corporate sector. While the bond market is highly integrated, the pass-through from U.S. government debt to corporate debt may be limited and nuanced. As a first stab at this question, we use the LQD ETF (a fund covering investment grade corporate bonds) and find (Figure 9) that policy actions (FFR/FG/AP shocks) tend to move yields in the same direction they move yields for U.S. government debt. Text sentiment does not have a statistically significant effect on LQD prices. A positive voice tone appears to elevate LQD prices (i.e., yields fall) for a few days after an FOMC meeting but this effect is short-lived and statistically insignificant. The results are broadly similar when we use the IVR ETF (real estate investment trust; Figure 10) to gauge the responses of the real estate sector, although a more dovish text sentiment appears to raise the IVR price after about a week.

3.3 Inflation Expectations

Management of inflation expectations is a key element of monetary policy (see Coibion et al., 2020 for a survey). To evaluate the success of policymakers in this matter we use two popular metrics. The first one is the spread between nominal and inflation-protected U.S. government bonds. Specifically, we use $Outcome_{t,t+h} = log\left(\frac{P^{GOVT}_{t+h,close}}{P^{GOTV}_{t,open}}\right) - \ log\left(\frac{P^{TIP}_{t+h,close}}{P^{TIP}_{t,open}}\right)$ as a measure of the spread, where P^{GOVT} is the price of GOVT ETF (nominal bonds) and P^{TIP} is the price of TIP ETF (inflation-protected bonds). An increase in this spread can be interpreted as signalling a decrease in expected inflation. The second one is the GLD ETF, a fund that tracks the gold spot price. This ETF is used as a hedge against inflation: an increase in the price of GLD signals a higher expected inflation. Although neither of these measures is perfect (e.g., the spread varies not only due to changes in inflation expectations but also with changes in liquidity conditions; gold prices can move for reasons unrelated to inflation), these two measures are consistently available and are based on reasonably deep markets.

We find that the responses of the GOVT-TIP spread (Figure 11) and GLD (Figure 12) paint a similar picture. As before, the FFR shock does not have a clear impact. The FG shock lowers inflation expectations, while the AP shock raises inflation expectations. More dovish text sentiment appears to raise inflation expectations (the GLD price increases), but this response is not statistically significant. Moreover, it does not seem to have support from the GOVT-TIP spread, which appears to decrease (i.e., expected inflation is lower), although again the estimates are not statistically significant. The impact response of the GOVT-TIP spread to a positive voice tone is close to zero, but the spread gradually increases (thus, signaling lower expected inflation) and peaks after about 10 days. The GLD price has similar dynamics (i.e., lower expected inflation) but the estimates are less precise. Hence, voice tone seems to have an independent effect on inflation expectations. One may conjecture that positive tone plays a signaling role: a happy tone of the Fed Chair indicates satisfaction with future inflation dynamics.

3.4 Exchange Rate

Exchange rate is an important channel for monetary policy transmission in the increasingly globalized economy. To shed more light on how policy actions and communication can work via this channel, we examine the responses of two key exchange rates: yen/dollar (JPY; Figure 13) and euro/dollar (EURO; Figure 14).[12] We find that policy actions generally lead to mixed reactions across currencies in our sample. For example, after an FFR shock (monetary tightening), the dollar depreciates against the euro (although the effect is not statistically significant) and appreciates against the yen.[13] In a similar spirit, after a more dovish text sentiment (opposite to monetary

[12] We also report results for the pound/dollar (GBP) exchange rate in Appendix Figure 8.

[13] Analyses using intraday data (e.g., Swanson, 2020) find that the dollar appreciates against the euro and yen after a FFR shock.

tightening), the dollar appreciates against the euro and depreciates against the yen. In contrast, a more positive voice tone leads to appreciation of the dollar against the euro but there is no statistically significant response for the yen/dollar exchange rate. While somewhat unexpected, the relatively lower level of reaction of the yen/dollar exchange rate to the monetary policy shocks has been also observed in other studies (e.g., Fatum and Scholnick, 2008, Rosa, 2011a).

3.5 Discussion

In general, our findings shed new light onto the effectiveness of press conferences as a central bank communication tool. We show that just as the actions of the Fed move financial markets so too does the vocal aspect of FOMC press conferences. In other words, the vocal dimension of the central bank communication conveys information beyond that in the text, and market participants form their expectations and make their decisions based on that information.

Why does non-verbal communication matter? One explanation is that due to asymmetric information between the public and the central bank, market participants tend to look for more information through the aspects which are not explicitly "scripted" such as the voice tone or body language of the Fed Chair. These non-verbal elements of communication can signal the Fed's perspective on current/future economic outlook and/or the course of future monetary policy. In fact, it is not uncommon that investors and media watch/listen to the FOMC press conference, analyze the Chair's voice, and attempt to interpret what it (i.e., the voice tone/emotion) means. In other words, the press and financial market investors appear to pay attention to the non-verbal communication.[14] For example, the Wall Street Journal[15] reported Ben Bernanke's voice as either shaky or quavering during the first FOMC press conference on 27 April 2011. In a similar spirit, the tone of Jerome Powell's voice at the press conference on 16 September 2020 was perceived to be consistent with the prior press conferences, which was then interpreted as a signal of downplaying his dovish position.[16]

[14] See, e.g., https://cutt.ly/FzbnCBo; https://cutt.ly/fzbn1le (Accessed on 10 March 2021)
[15] https://cutt.ly/3zbnQbe (Accessed on 10 March 2021)
[16] https://cutt.ly/RzbnAm5 (Accessed on 10 March 2021)

4 Concluding remarks

Press conferences are an important communication tool for delivering and explaining monetary policy decisions to the public. Unlike press releases, transcripts, or minutes, a press conference contains both verbal and non-verbal channels. The latter offers an opportunity to communicate "soft" information. Machine learning applied to text analysis allowed researchers to better measure messages in written policy documents and thus quantify the importance of soft information. Other parts of communication (emotions, moods, tones, body language) could be equally (if not more) important but these have proven to be particularly difficult to quantify. Building on recent advances in voice recognition and deep learning, we attempt to shed new light on the effects of non-verbal policy communication.

Our analysis of variation in the Fed Chairs' voice tone during Q&A sessions after FOMC meetings shows that the non-verbal communication can have a statistically and economically discernible effect on a variety of financial indicators. For example, our results suggest that the voice tone of policy communication may have a significant effect on the stock market above and beyond what is contained in the Fed's actions or actual words (texts). This reaction is consistent with the Fed communicating a more positive outlook for the economy and reducing uncertainty. Inflation expectations and exchange rates also respond to voice tone. In contrast, the bond market appears to take few vocal cues from the Fed Chairs.

Although future work should dig deeper into understanding nuances of using voice to communicate policy, our results clearly have important policy implications. *How* messages are said appears to be potentially as important as what is in the messages. This does not make the job of central bankers easier and possibly adds another qualification (voice control) to the job requirement. However, this could be a prerequisite for anybody interested in using a public arena for policy communication. Indeed, to paraphrase Ronald Reagan, how can a Fed Chair not be an actor?

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Table 1. FOMC meetings' statistics

	All	Bernanke	Yellen	Powell
	(1)	(2)	(3)	(4)
Meetings	67	25	31	11
Press conference	36	12	16	8
Panel A. Voice analysis of responses in Q&A during press conferences				
Answers (count)				
Positive	377	200	109	68
Negative	285	43	131	111
Neutral	30	0	28	2
Voice tone				
mean	0.09	0.64	-0.13	-0.30
standard deviation	0.75	0.58	0.61	0.82
Panel B. Textual analysis				
Statement				
Hawkish	182	76	79	27
Dovish	195	81	96	18
Text sentiment				
mean	-0.01	0.04	0.07	-0.23
standard deviation	0.21	0.11	0.17	0.23
Remarks				
Hawkish	335	108	156	71
Dovish	391	139	179	73
Text sentiment				
mean	0.07	0.11	0.06	0.02
standard deviation	0.19	0.22	0.17	0.17
Q&A				
Hawkish	442	155	203	84
Dovish	551	196	250	105
Text sentiment				
mean	0.13	0.12	0.12	0.16
standard deviation	0.26	0.29	0.23	0.32
Statement, Remarks, Q&A				
Text sentiment				
mean	0.09	0.12	0.09	0.06
standard deviation	0.16	0.17	0.15	0.20

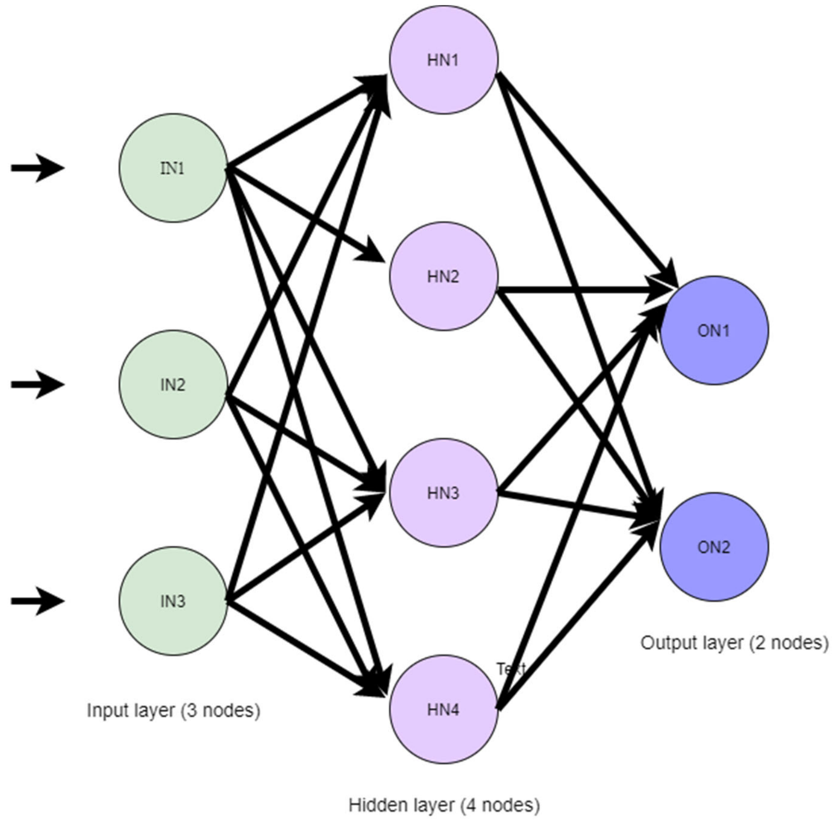
Notes: This table shows the statistics related to text and voice data of FOMC meetings and press conferences. Column (1) shows statistics for all FOMC meetings during the 2011 – July 2019 period. Columns (2)-(4) show the statistics for the FOMC meetings chaired by Ben Bernanke, Janet Yellen, and Jerome Powell, respectively. Positive, Negative, and Neutral indicate the number of answers expressed in the positive, negative, and neutral emotion, respectively. Voice tone is the average emotion for a given FOMC press conference ($VoiceTone = \frac{Positive\ answers - Negative\ answers}{Positive\ answers + Negative\ answers}$). Hawkish and Dovish are the number of hawkish and dovish phrases in the text, respectively. The average text sentiment is measured by $TextSentiment = \frac{Dovish\ phrases - Hawkish\ phrases}{Dovish\ phrases + Hawkish\ phrases}$.

Table 2. Dictionary for hawkish and dovish words.

Panel A1	Panel A2
inflation expectation, interest rate, bank rate, fund rate, price, economic activity, inflation, employment	anchor, cut, subdue, declin, decrease, reduc, low, drop, fall, fell, decelarat, slow, pause, pausing, stable, non-accelerating, downward, tighten
Panel B1	Panel B2
unemployment, growth, exchange rate, productivity, deficit, demand, job market, monetary policy	ease, easing, rise, rising, increase, expand, improv, strong, upward, raise, high, rapid
Panel C	
weren't, were not, wasn't, was not, did not, didn't, do not, don't, will not, won't	

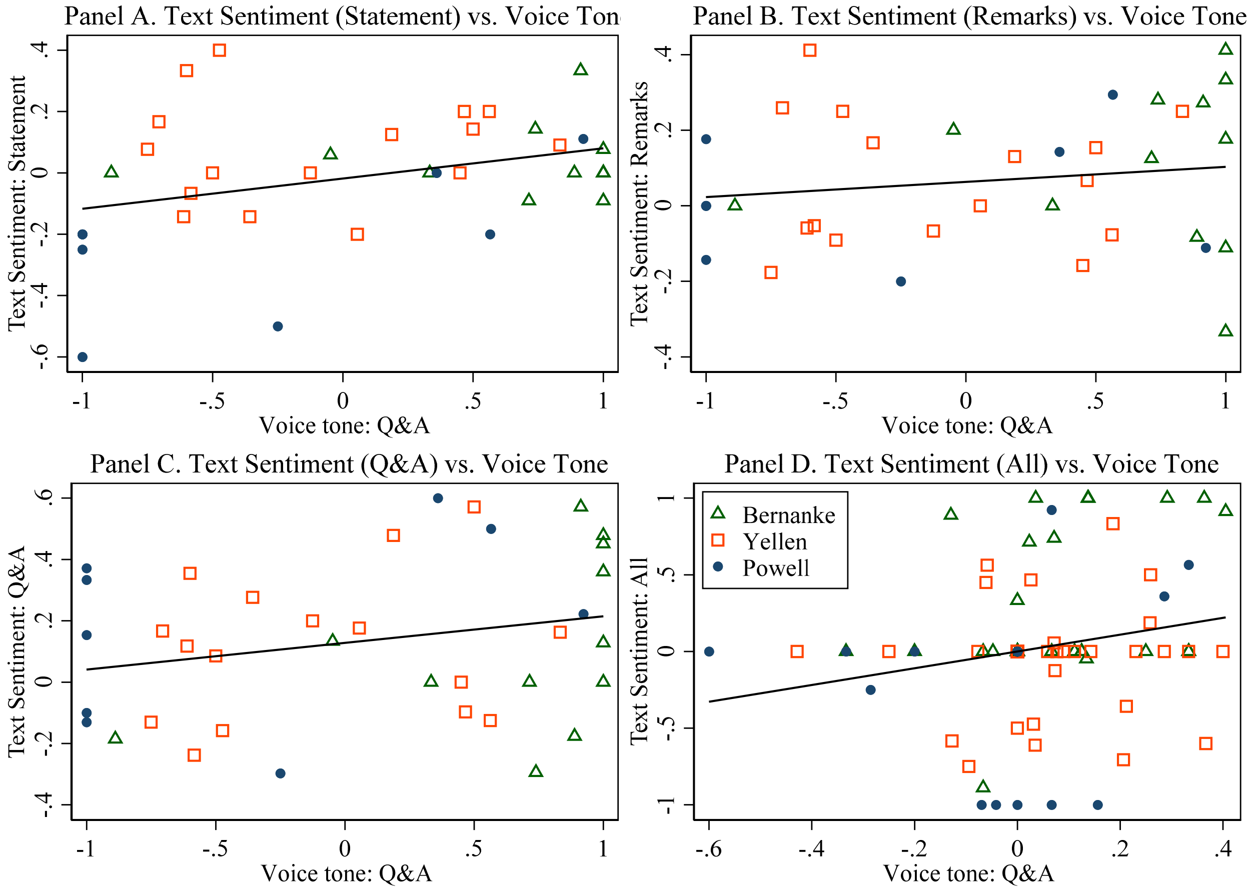
Notes: This table shows the words/phrases used to classify text into dovish/hawkish.

Figure 1. Conceptual neural network



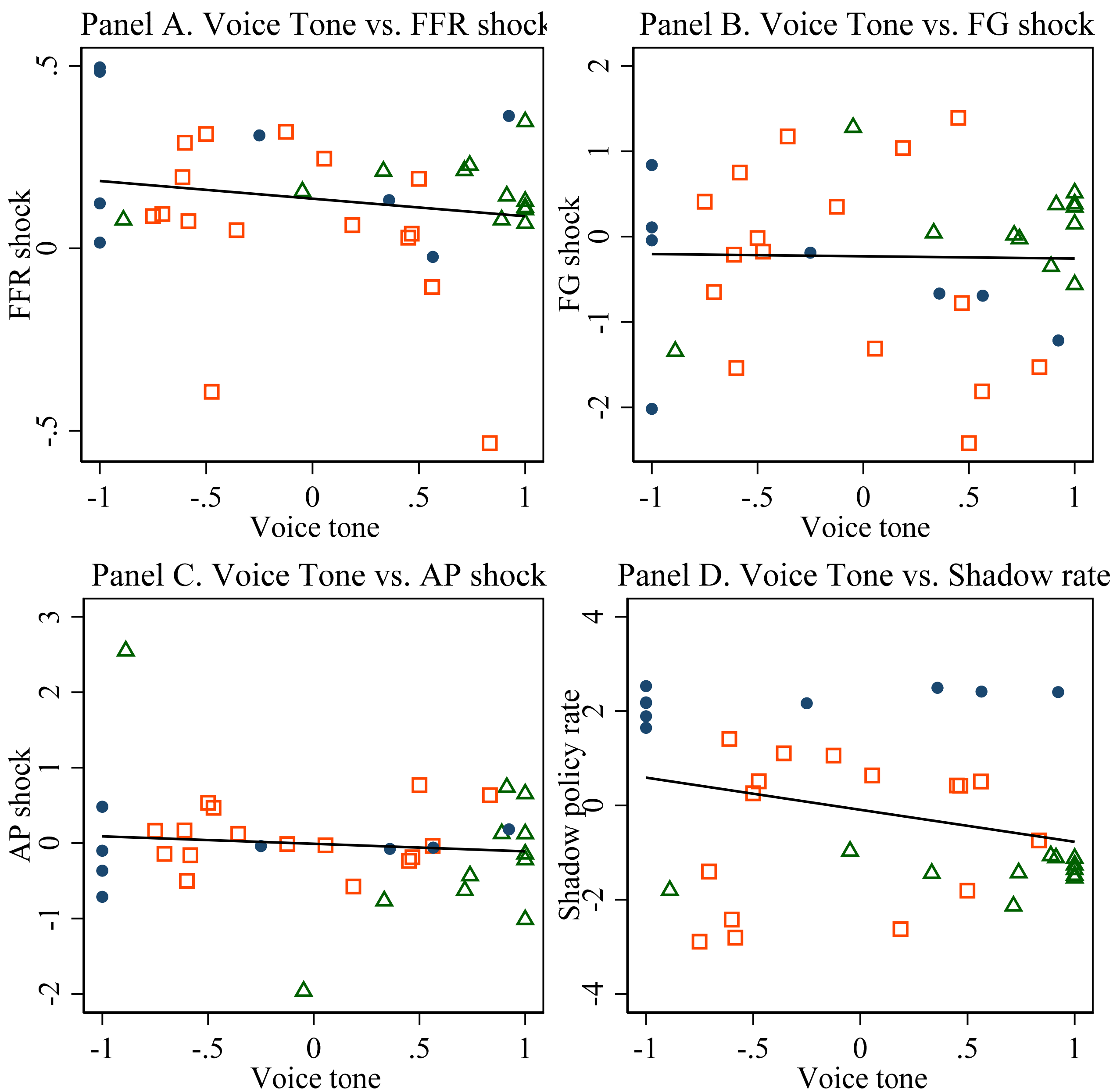
Notes: This figure shows a conceptual neural network with 3 layers for classifying voice features into emotions. The left layer is the input layer with three nodes and each node is a feature of the training audio data. The middle layer is a hidden layer consisting of four nodes (HK_k, k=[1;4]) which are the activation functions of the input features IN_i (i=[1;3]). A node HK_k is connected with the input the through weight ($w_{k,i}$) and bias (b_k): $\sum_{i=1}^{3} IN_i \times w_{k,i} + b_k$. The weighted summations are passed on the softmax activation function to obtain the outputs O_k (k=[1;4]). The right layer is the output layer.

Figure 2. Voice tone vs. Text sentiment.



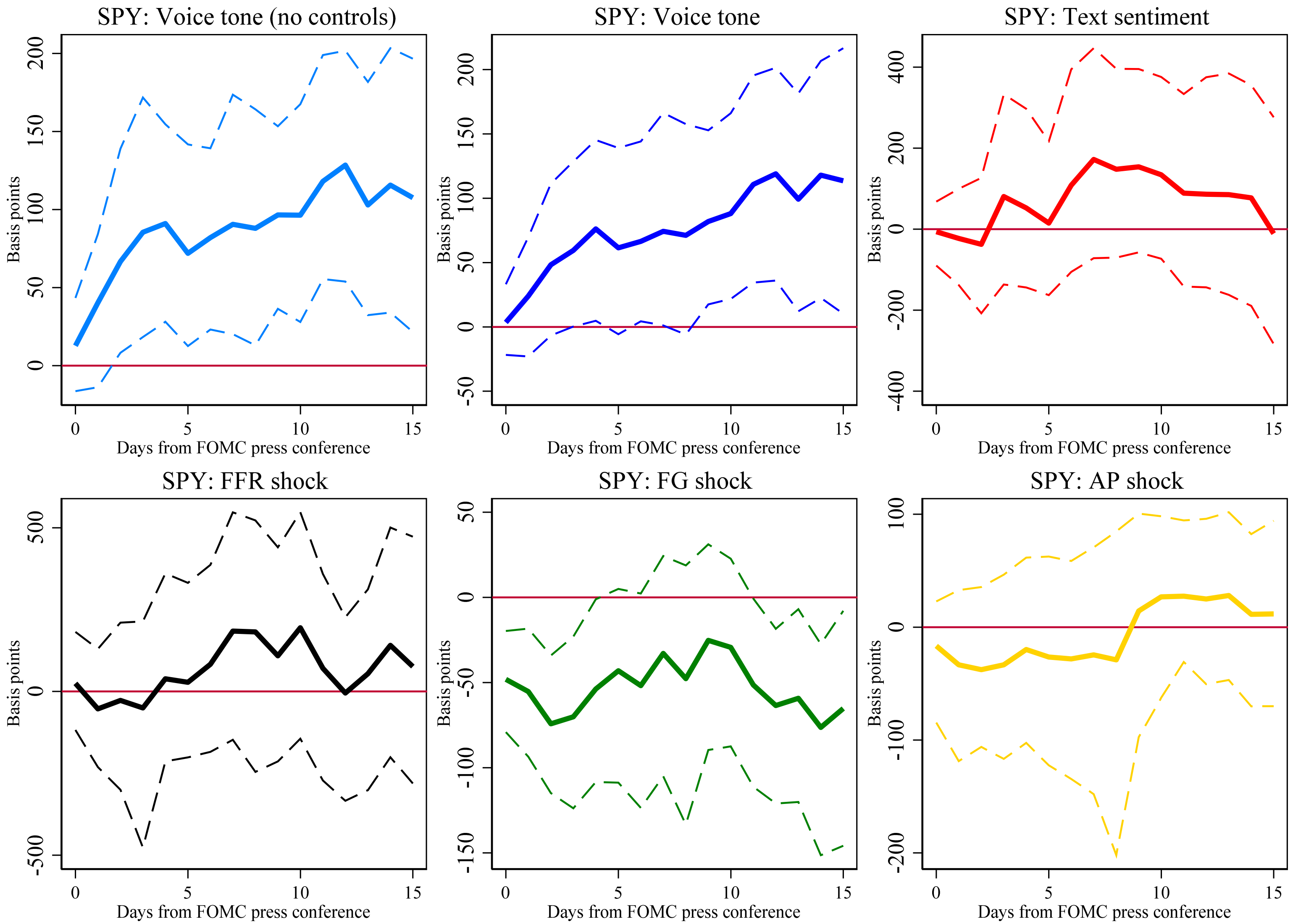
Notes: The figure shows the joint distribution of voice tone and text sentiment across FOMC meetings.

Figure 3. Policy Words vs. Actions.



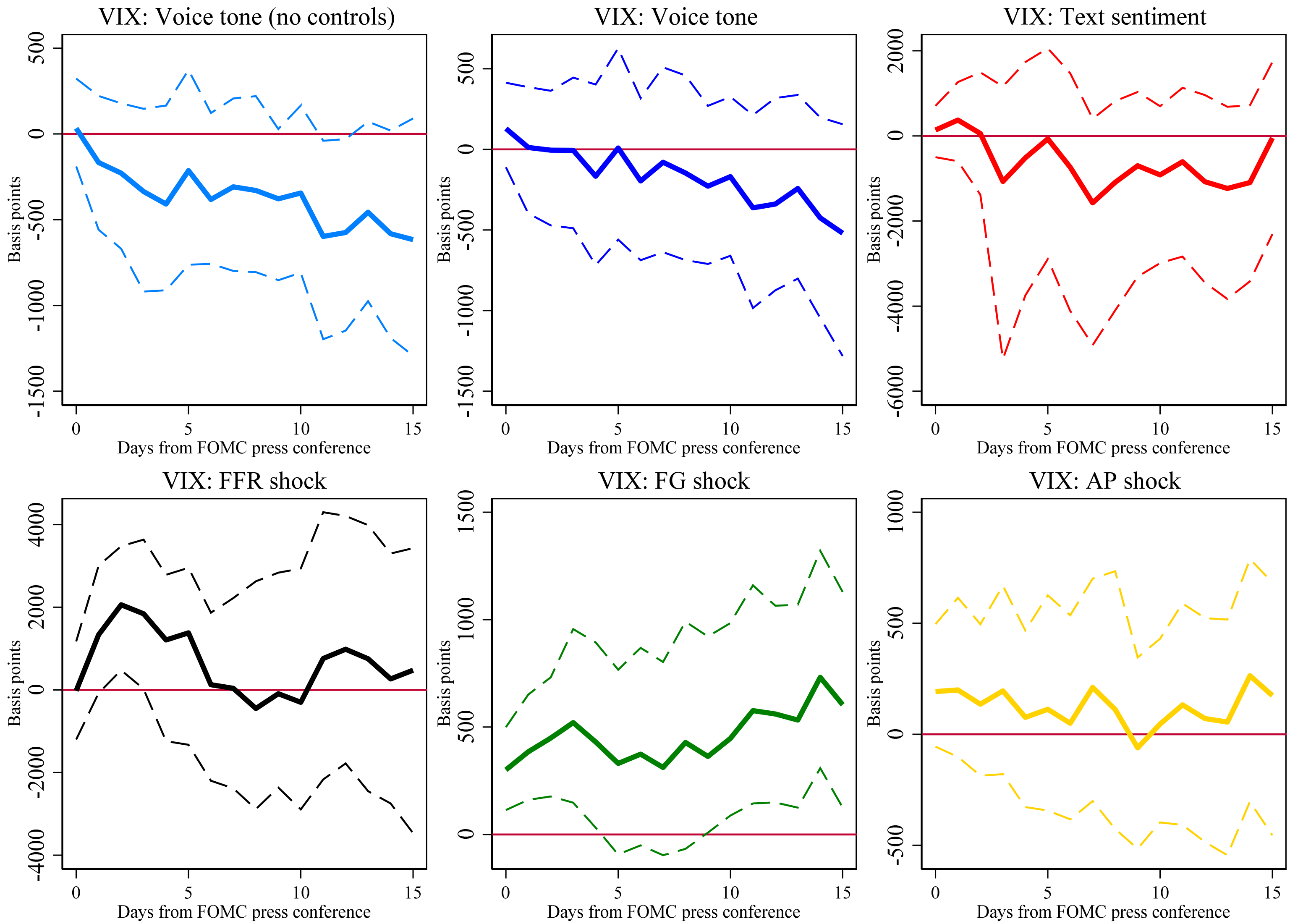
Notes: The figure shows the joint distribution of voice tone and policy actions/stance. Federal Funds Rate (FFR), forward guidance (FG), and asset purchase (AP) shocks are from Swanson (2020). The shadow policy rate is from Wu and Xia (2016).

Figure 4. Response of SPY ETF (S&P 500) to policy actions and messages.



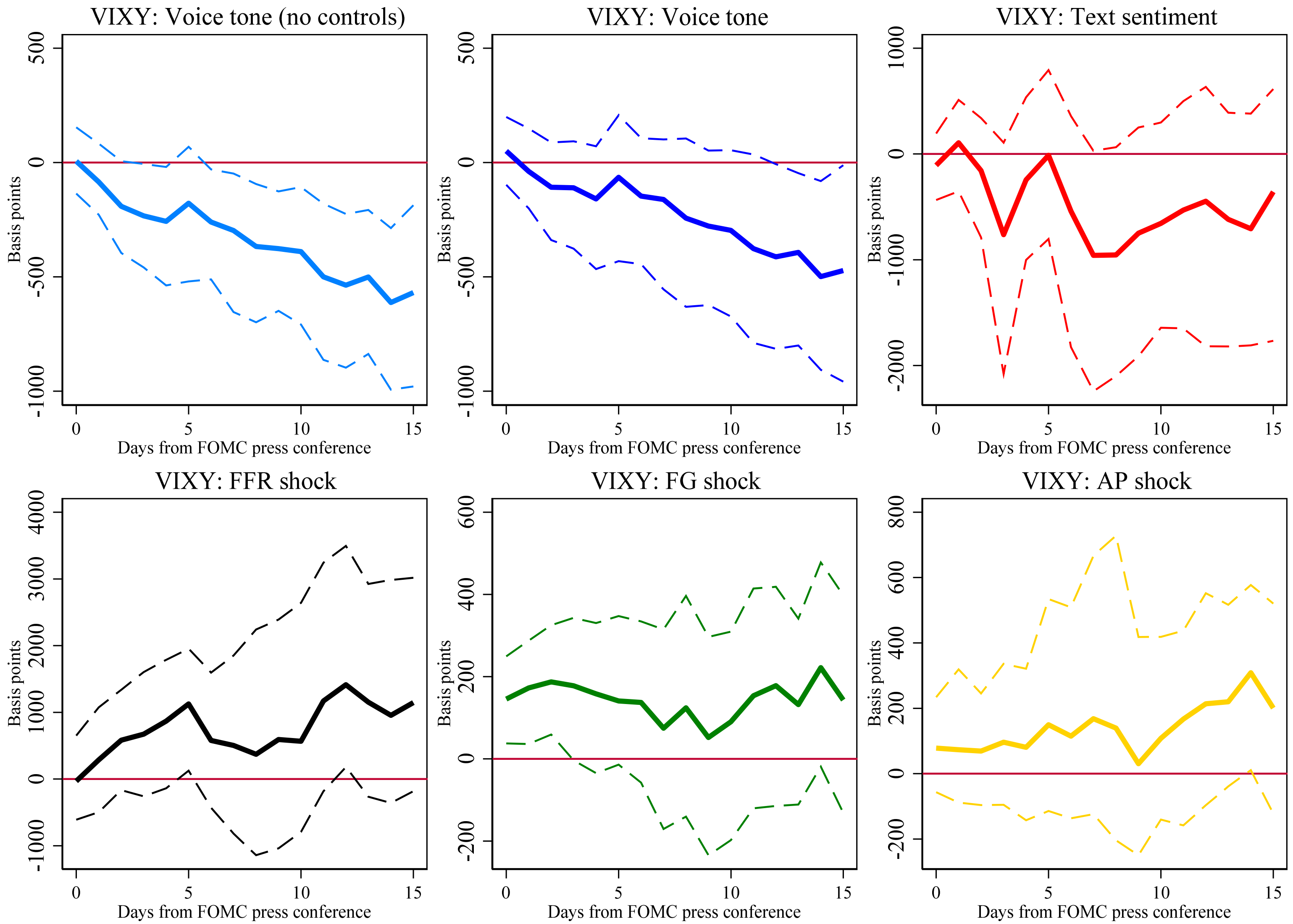
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 5. Response of VIX (CBOE Volatility Index) to policy actions and messages.



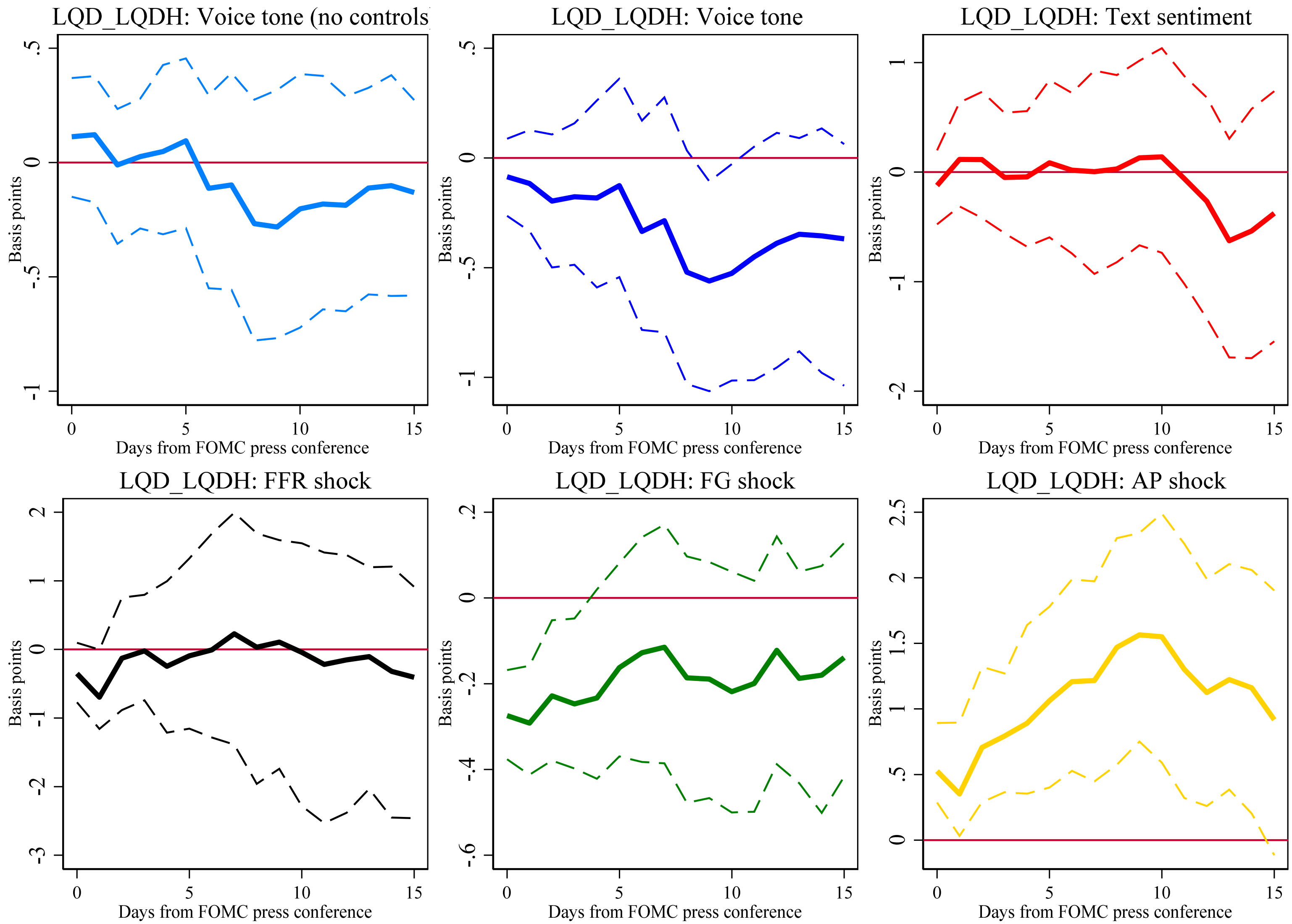
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 6. Response of VIXY ETF (VIX Short-Term Futures) to policy actions and messages.



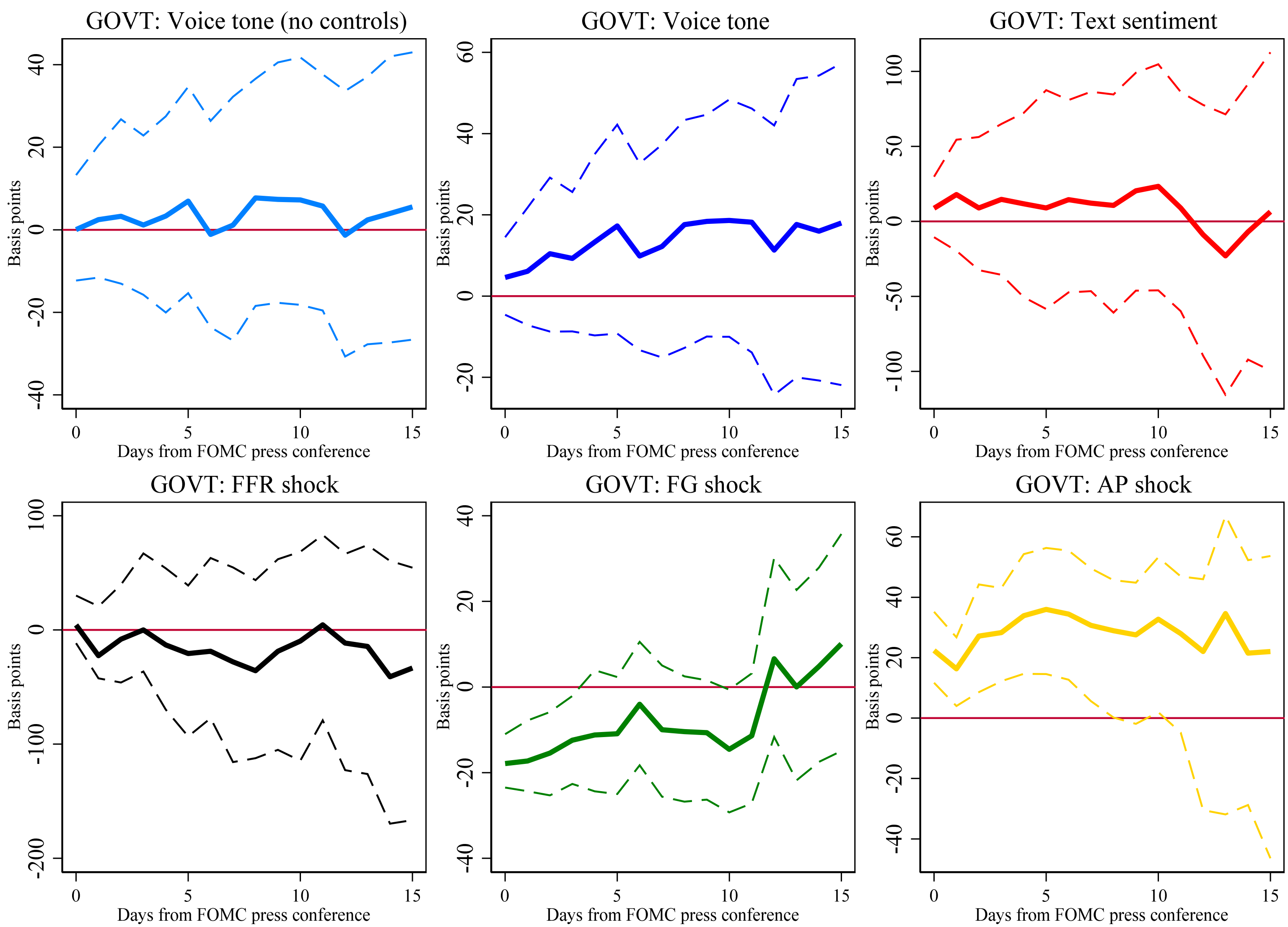
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 7. Response of LQD ETF (investment grade corporate bond) minus LQDH EFT (interest rate hedged corporate bond) to policy actions and messages.



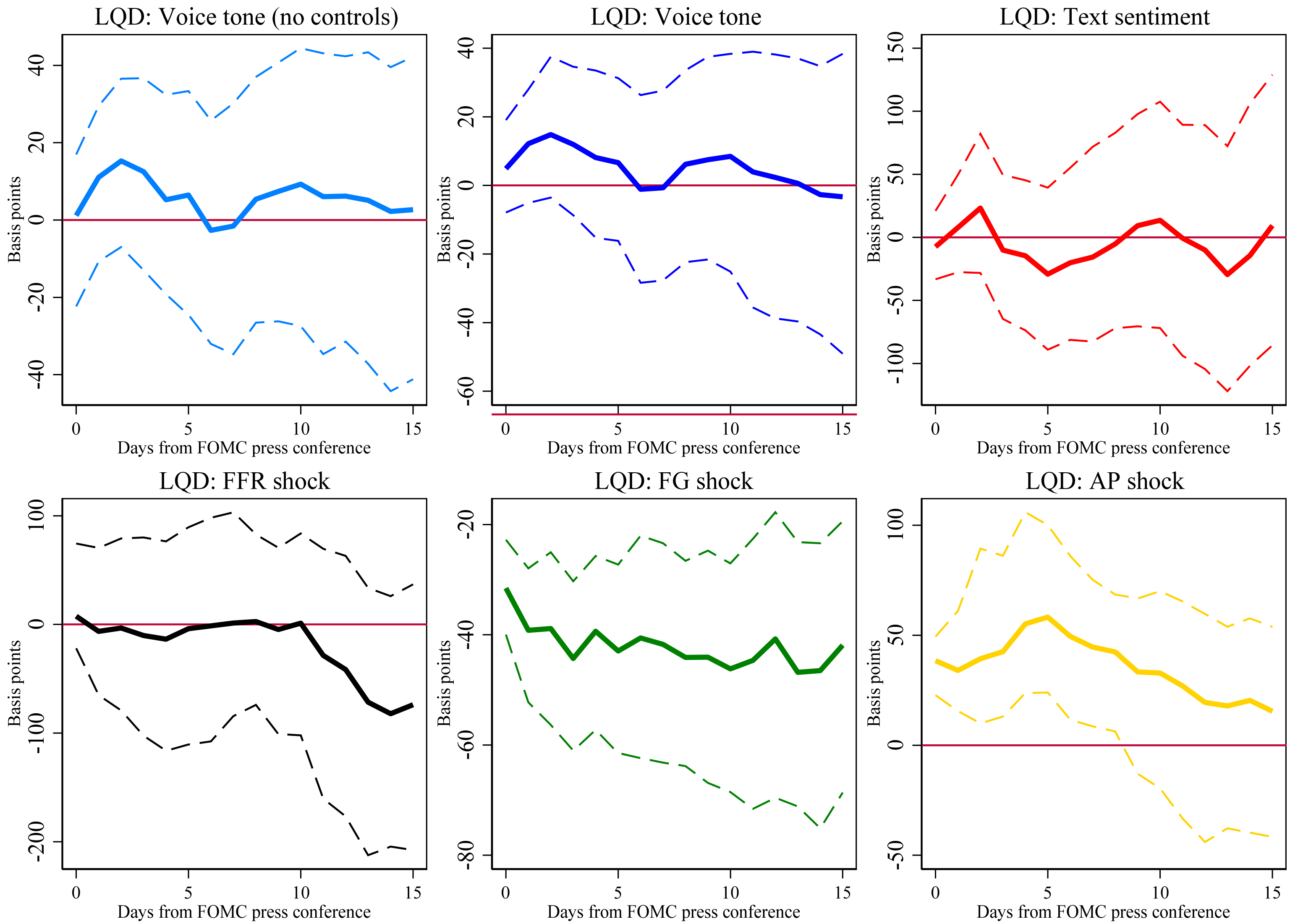
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 8. Response of GOVT ETF (U.S. government debt) to policy actions and messages.



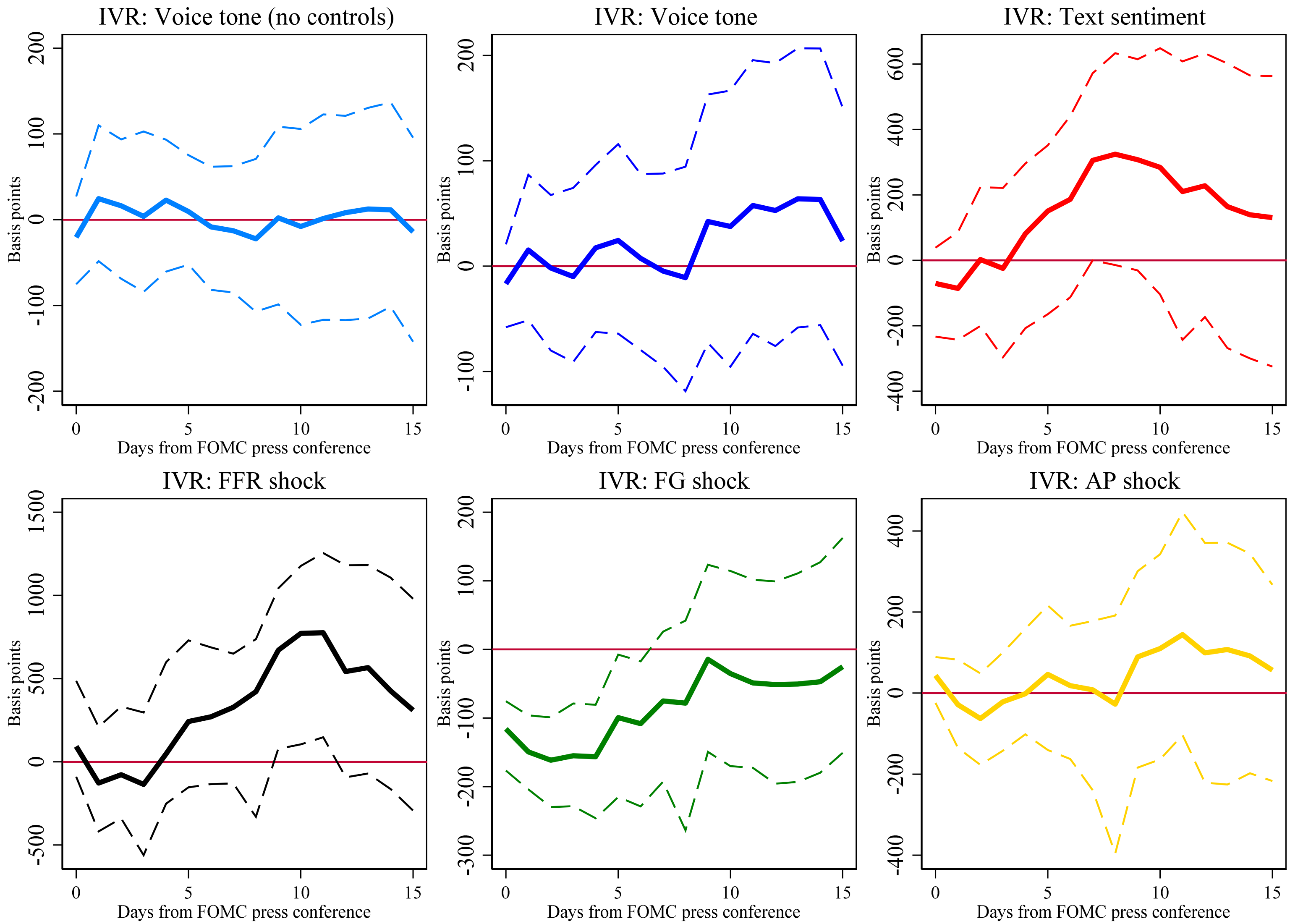
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 9. Response of LQD ETF (corporate debt) to policy actions and messages.



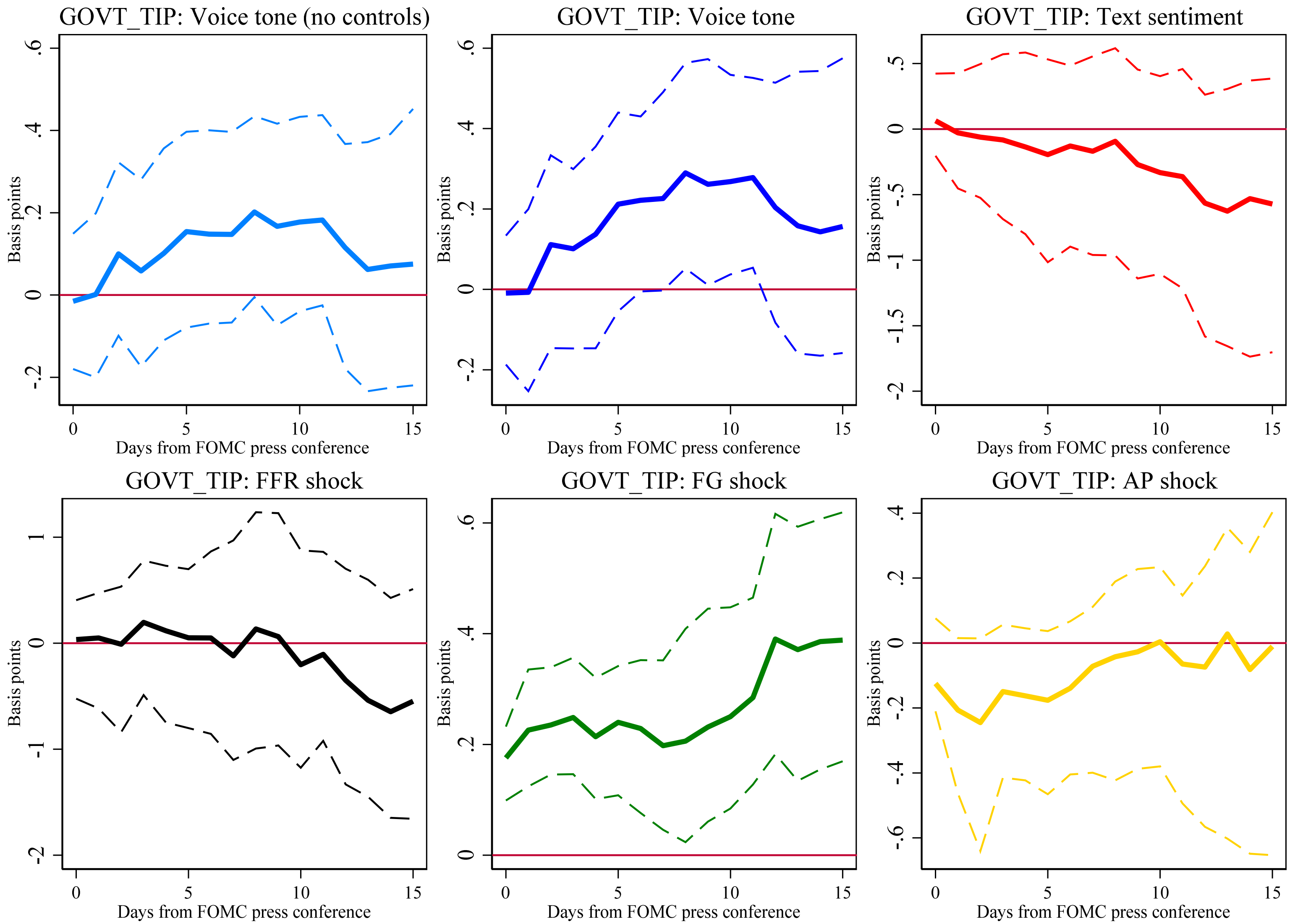
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 10. Response of IVR ETF (debt for the real estate sector) to policy actions and messages.



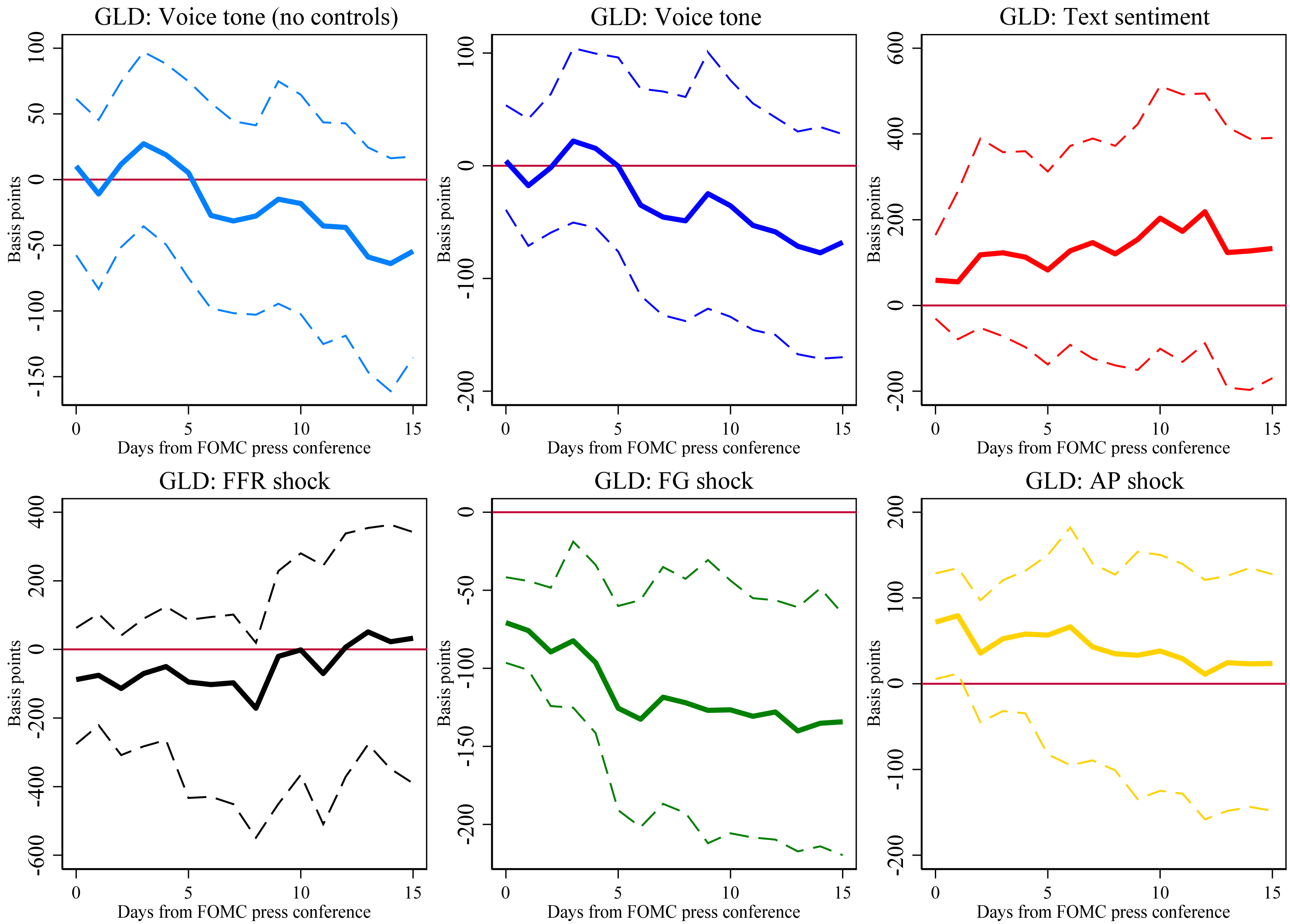
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 11. Response of GOVT ETF (nominal U.S. government debt) minus TIP EFT (inflation-protected U.S. government debt) to policy actions and messages.



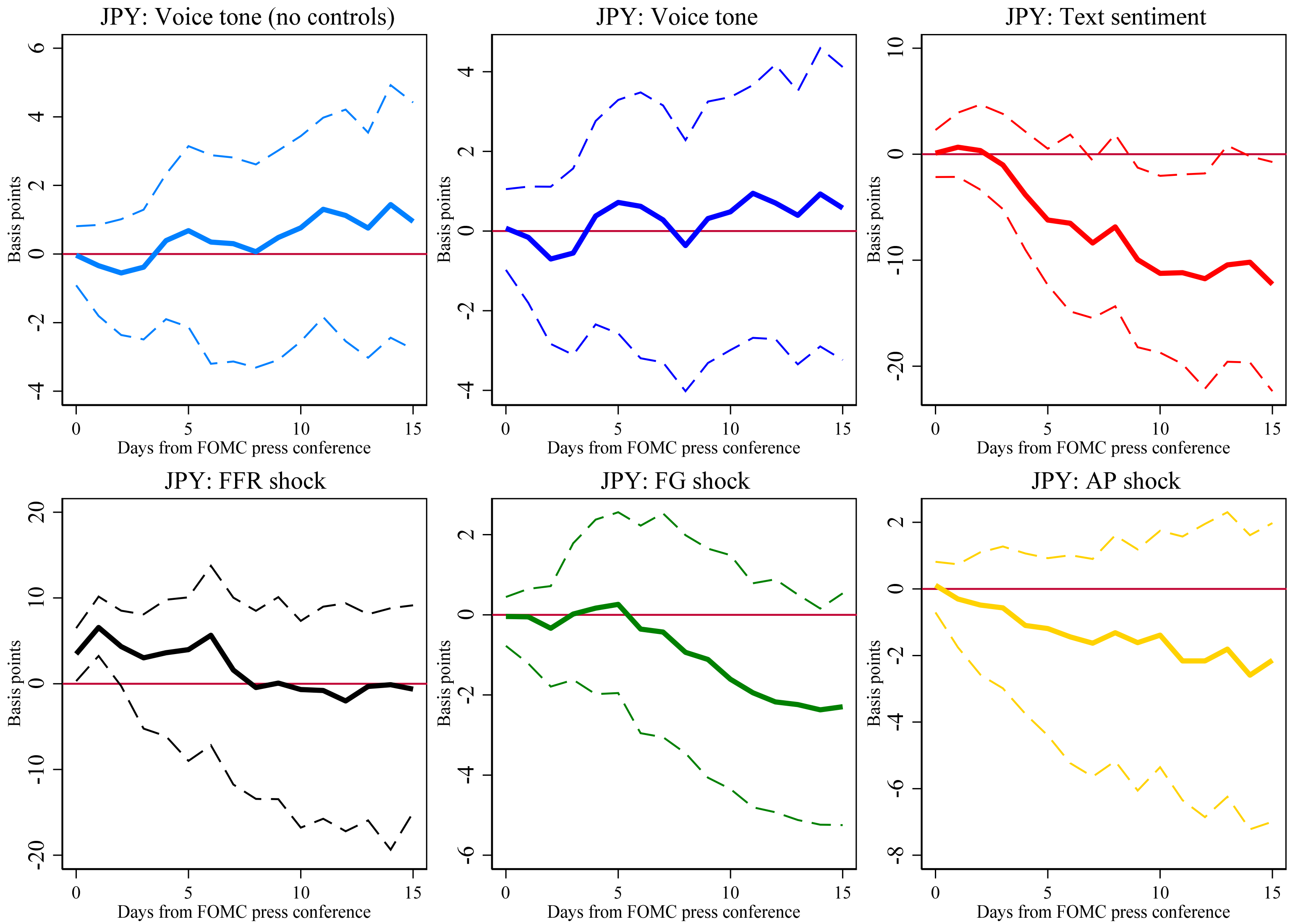
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 12. Response of GLD ETF (gold) to policy actions and messages.



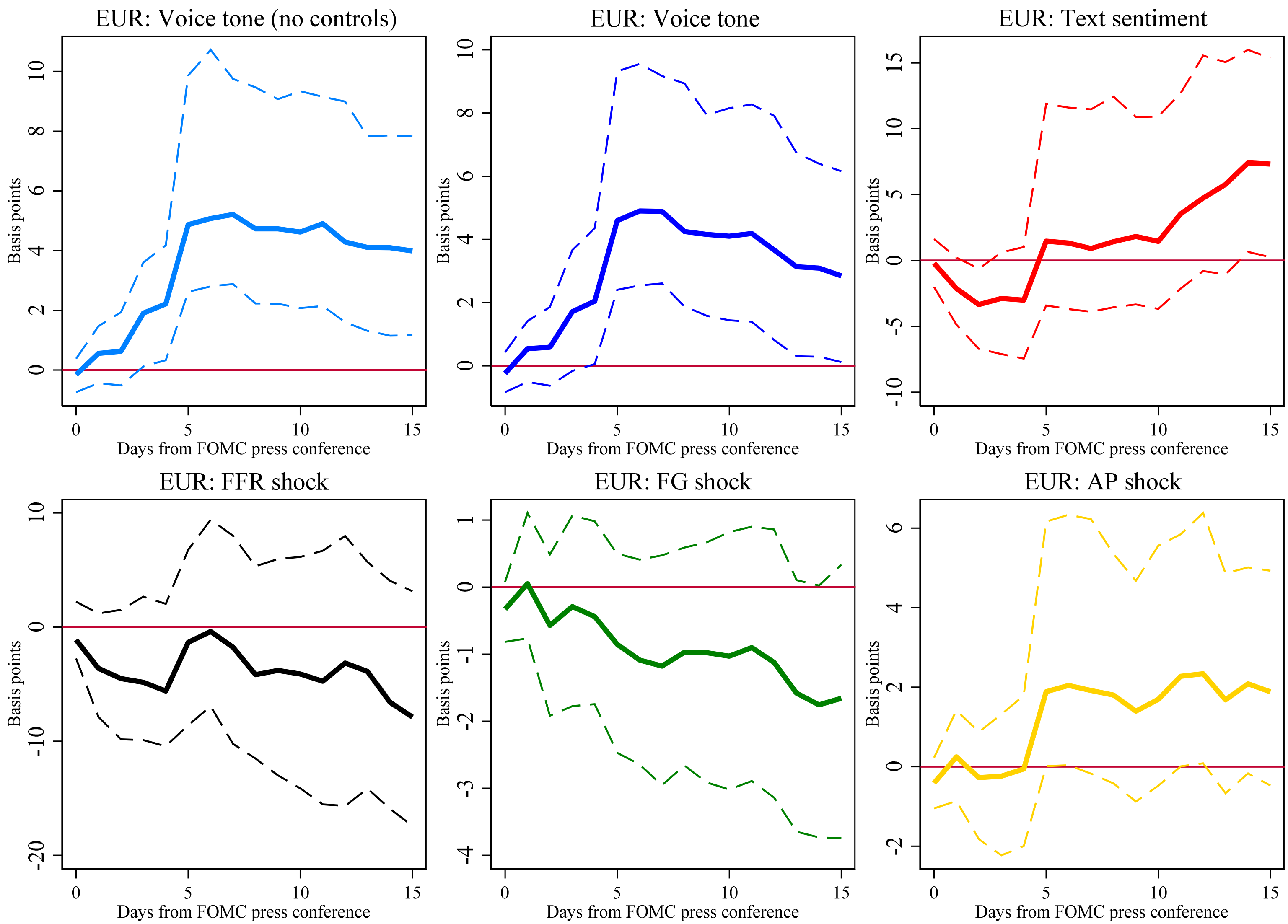
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 13. Response of the Japanese Yen to one U.S. Dollar (yen/dollar) exchange rate to policy actions and messages.



Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Figure 14. Response of the Euro to one U.S. Dollar (euro/dollar) exchange rate to policy actions and messages.



Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Online Appendix

Additional Tables and Figures

Appendix Table 1. Voice tone for responses during Q&A sessions.

Press conference date	Speaker	Positive responses	Neutral response	Negative responses	Tone
April 27, 2011	Bernanke	17	0	1	0.89
June 22, 2011	Bernanke	19	0	0	1.00
November 2, 2011	Bernanke	19	0	0	1.00
January 25, 2012	Bernanke	18	0	0	1.00
April 25, 2012	Bernanke	19	0	0	1.00
June 20, 2012	Bernanke	22	0	1	0.91
September 13, 2012	Bernanke	23	0	0	1.00
December 12, 2012	Bernanke	20	0	3	0.74
March 20, 2013	Bernanke	14	0	7	0.33
June 19, 2013	Bernanke	10	0	11	-0.05
September 18, 2013	Bernanke	1	0	17	-0.89
December 18, 2013	Bernanke	18	0	3	0.71
March 19, 2014	Yellen	7	5	4	0.19
June 18, 2014	Yellen	2	0	14	-0.75
September 17, 2014	Yellen	2	1	9	-0.58
December 17, 2014	Yellen	1	4	10	-0.60
March 18, 2015	Yellen	15	0	5	0.50
June 17, 2015	Yellen	1	3	13	-0.71
September 17, 2015	Yellen	16	1	1	0.83
December 16, 2015	Yellen	4	1	13	-0.50
March 16, 2016	Yellen	12	1	3	0.56
June 15, 2016	Yellen	11	0	4	0.47
September 21, 2016	Yellen	5	0	14	-0.47
December 14, 2016	Yellen	12	5	3	0.45
March 15, 2017	Yellen	9	1	8	0.06
June 14, 2017	Yellen	7	0	9	-0.13
September 20, 2017	Yellen	4	1	9	-0.36
December 13, 2017	Yellen	1	5	12	-0.61
March 21, 2018	Powell	0	0	20	-1.00
June 13, 2018	Powell	0	0	22	-1.00
September 26, 2018	Powell	9	0	15	-0.25
December 19, 2018	Powell	0	0	21	-1.00
January 30, 2019	Powell	16	2	7	0.36
March 20, 2019	Powell	25	0	1	0.92
May 1, 2019	Powell	18	0	5	0.57
June 19, 2019	Powell	0	0	20	-1.00
July 31, 2019	Powell	0	0	24	-1.00

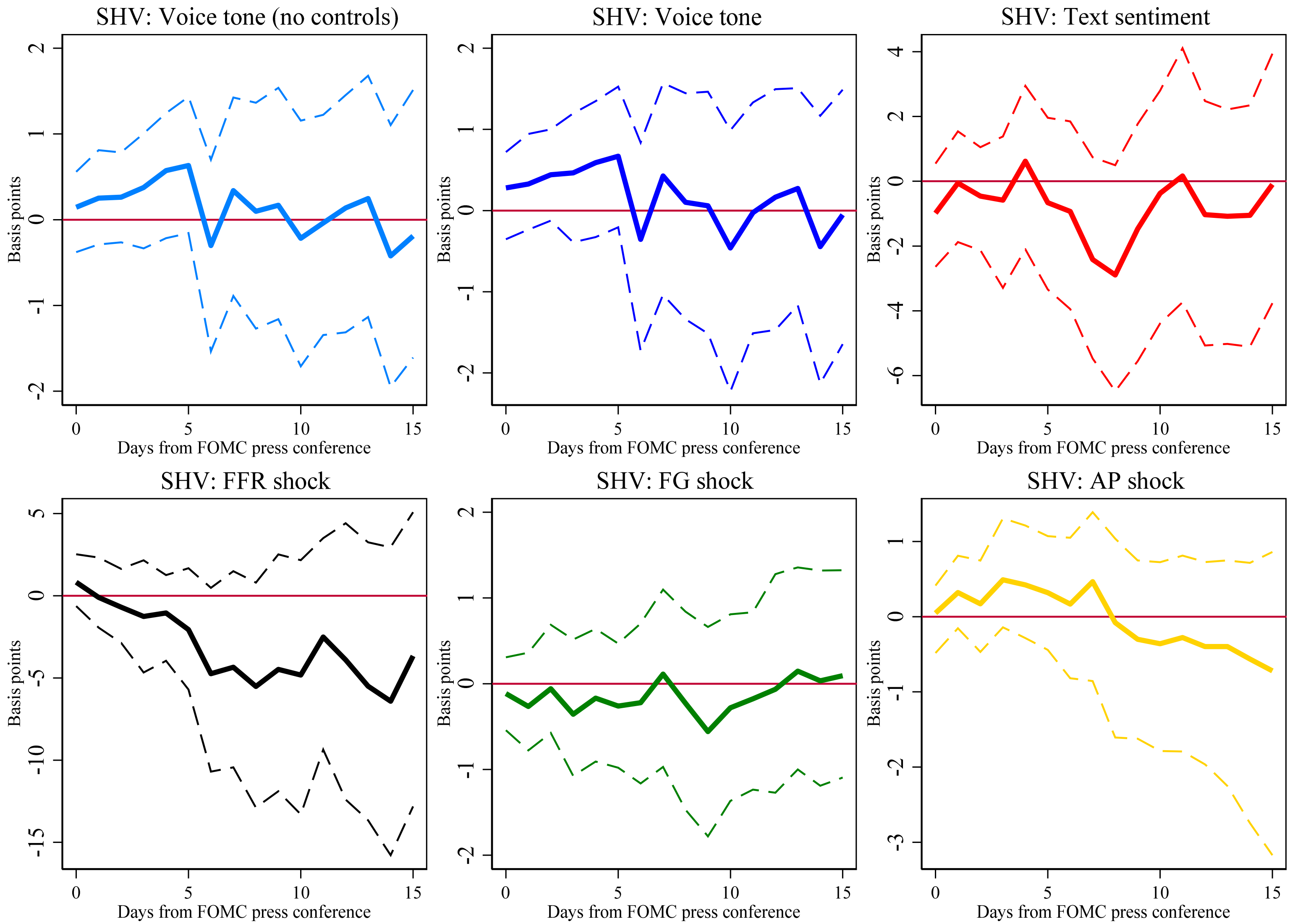
Notes: This table shows the number of positive, negative, and neutral responses as well as the aggregate voice tone for each press conference in the sample.

Appendix Table 2. Text sentiment for statement, remarks and Q&A.

Press conference date	Speaker	Text Sentiment	Press conference date	Speaker	Text Sentiment
January 26, 2011	Bernanke	0.333	September 17, 2015	Yellen	0.186
March 15, 2011	Bernanke	0.111	October 28, 2015	Yellen	0.000
April 27, 2011	Bernanke	-0.129	December 16, 2015	Yellen	0.000
June 22, 2011	Bernanke	0.137	January 27, 2016	Yellen	0.333
August 9, 2011	Bernanke	-0.200	March 16, 2016	Yellen	-0.059
September 21, 2011	Bernanke	0.000	April 27, 2016	Yellen	0.286
November 2, 2011	Bernanke	0.292	June 15, 2016	Yellen	0.026
December 13, 2011	Bernanke	-0.333	July 27, 2016	Yellen	0.231
January 25, 2012	Bernanke	0.364	September 21, 2016	Yellen	0.031
March 13, 2012	Bernanke	0.000	November 2, 2016	Yellen	0.111
April 25, 2012	Bernanke	0.036	December 14, 2016	Yellen	-0.061
June 20, 2012	Bernanke	0.405	February 1, 2017	Yellen	-0.250
August 1, 2012	Bernanke	0.333	March 15, 2017	Yellen	0.071
September 13, 2012	Bernanke	0.138	June 14, 2017	Yellen	0.073
October 24, 2012	Bernanke	0.125	July 26, 2017	Yellen	0.000
December 12, 2012	Bernanke	0.071	September 20, 2017	Yellen	0.212
January 30, 2013	Bernanke	0.250	November 1, 2017	Yellen	0.143
March 20, 2013	Bernanke	0.000	December 13, 2017	Yellen	0.034
May 1, 2013	Bernanke	0.067	January 31, 2018	Yellen	-0.429
June 19, 2013	Bernanke	0.134	March 21, 2018	Powell	-0.042
July 31, 2013	Bernanke	0.125	May 2, 2018	Powell	-0.333
September 18, 2013	Bernanke	-0.067	June 13, 2018	Powell	0.156
October 30, 2013	Bernanke	-0.067	August 1, 2018	Powell	-0.600
December 18, 2013	Bernanke	0.023	September 26, 2018	Powell	-0.286
January 29, 2014	Bernanke	-0.048	November 8, 2018	Powell	-0.200
March 19, 2014	Yellen	0.258	December 19, 2018	Powell	0.000
April 30, 2014	Yellen	0.077	January 30, 2019	Powell	0.286
June 18, 2014	Yellen	-0.094	March 20, 2019	Powell	0.067
July 30, 2014	Yellen	-0.077	May 1, 2019	Powell	0.333
September 17, 2014	Yellen	-0.127	June 19, 2019	Powell	-0.070
October 29, 2014	Yellen	0.400	July 31, 2019	Powell	0.067
December 17, 2014	Yellen	0.367			
January 28, 2015	Yellen	0.091			
March 18, 2015	Yellen	0.259			
April 29, 2015	Yellen	0.059			
June 17, 2015	Yellen	0.206			
July 29, 2015	Yellen	0.077			

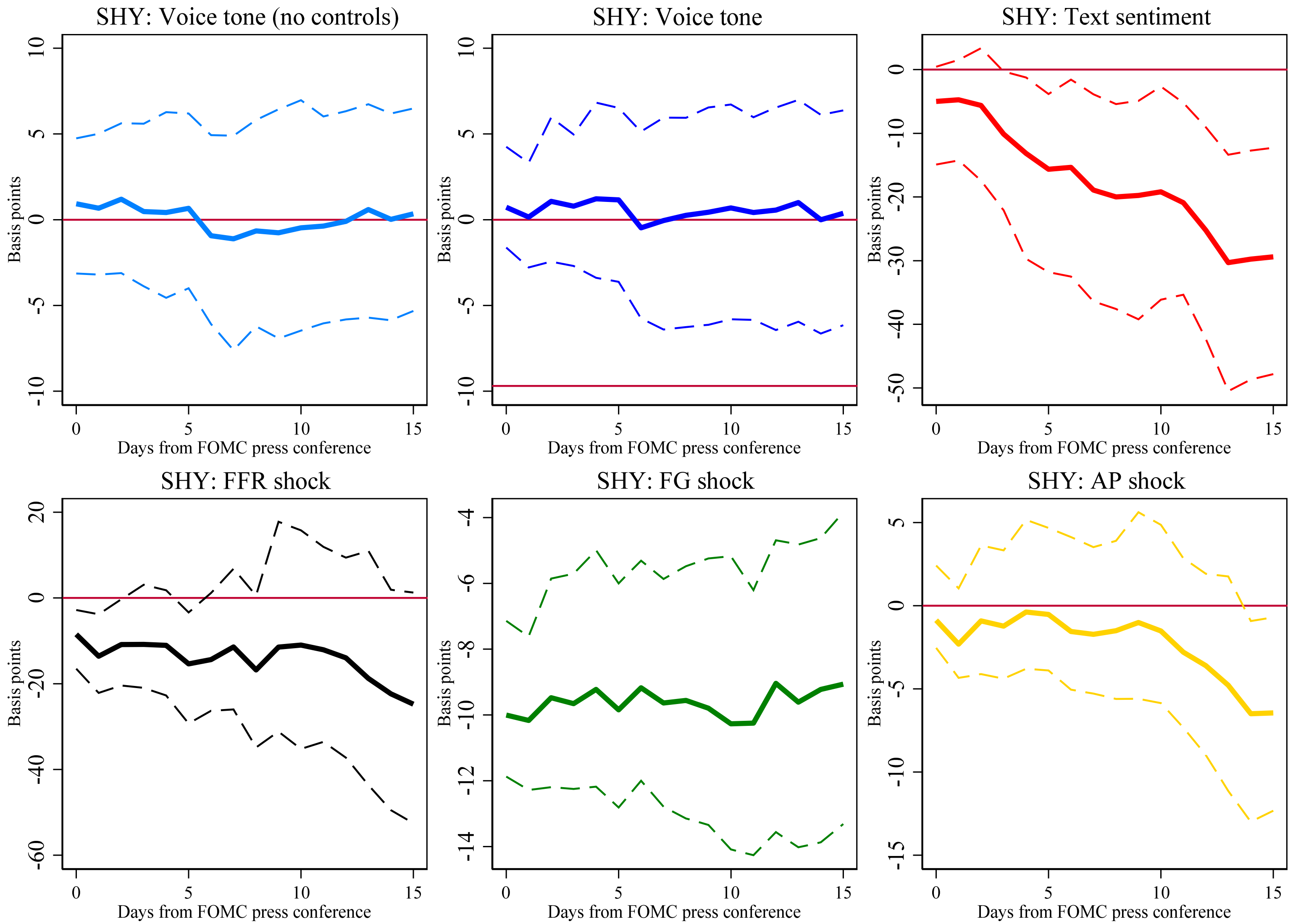
Notes: This table shows the aggregate text sentiment for each FOMC meeting in the sample.

Appendix Figure 1. Response of SHV ETF (Short Treasury Bond ETF; maturities one year or less) to policy actions and messages.



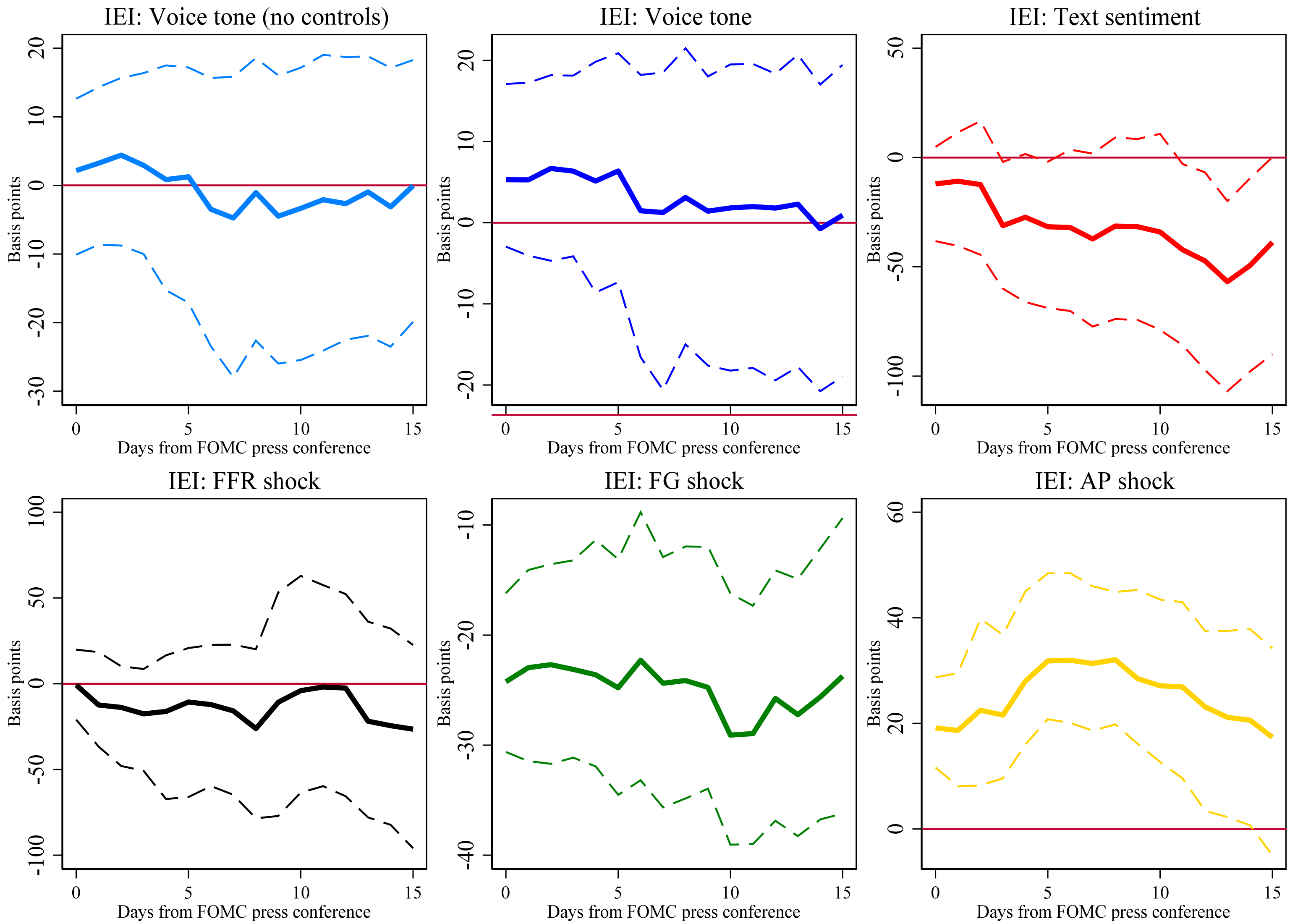
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 2. Response of SHY ETF (1-3 Year Treasury Bond ETF) to policy actions and messages.



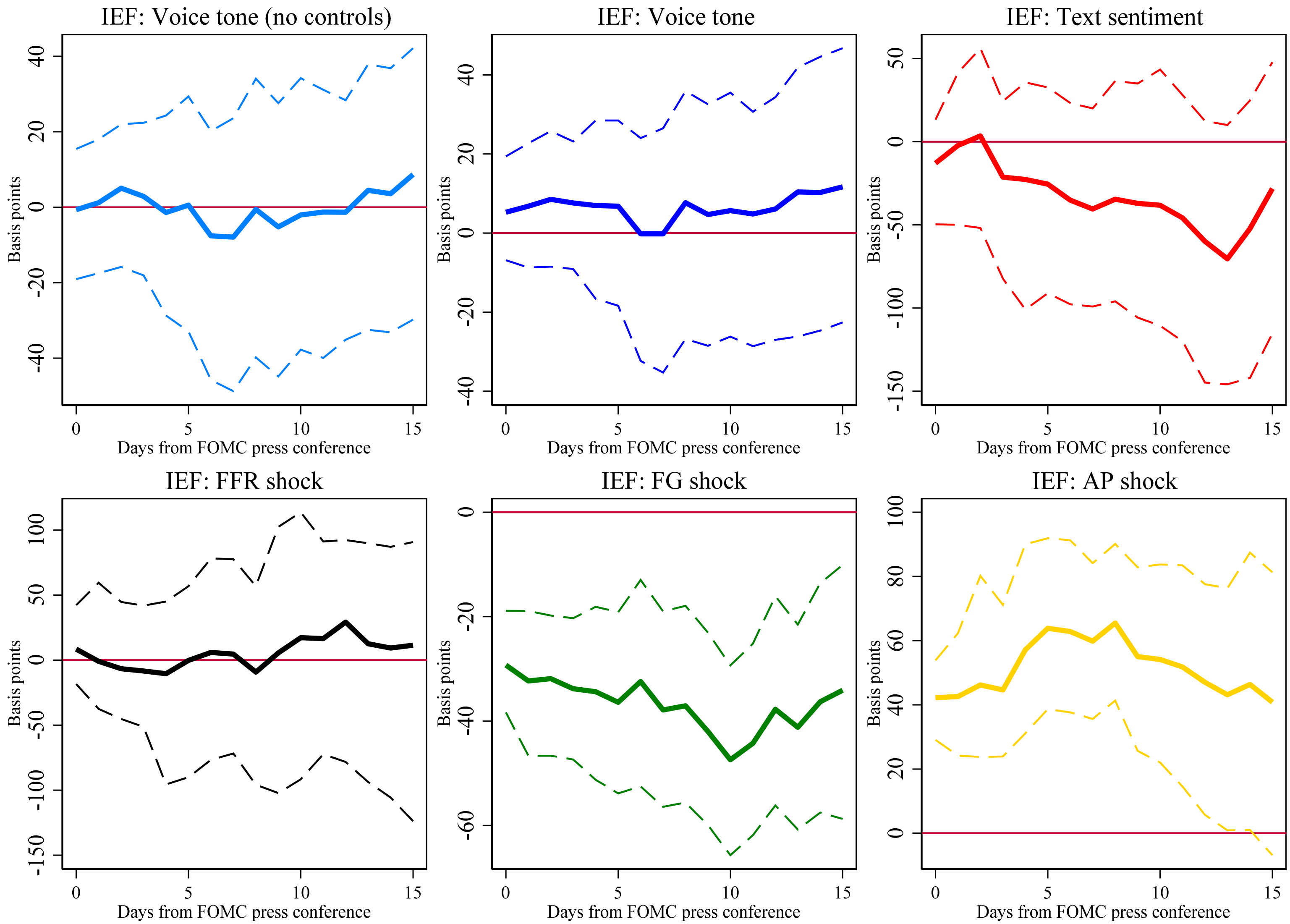
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 3. Response of IEI ETF (3-7 Year Treasury Bond ETF) to policy actions and messages.



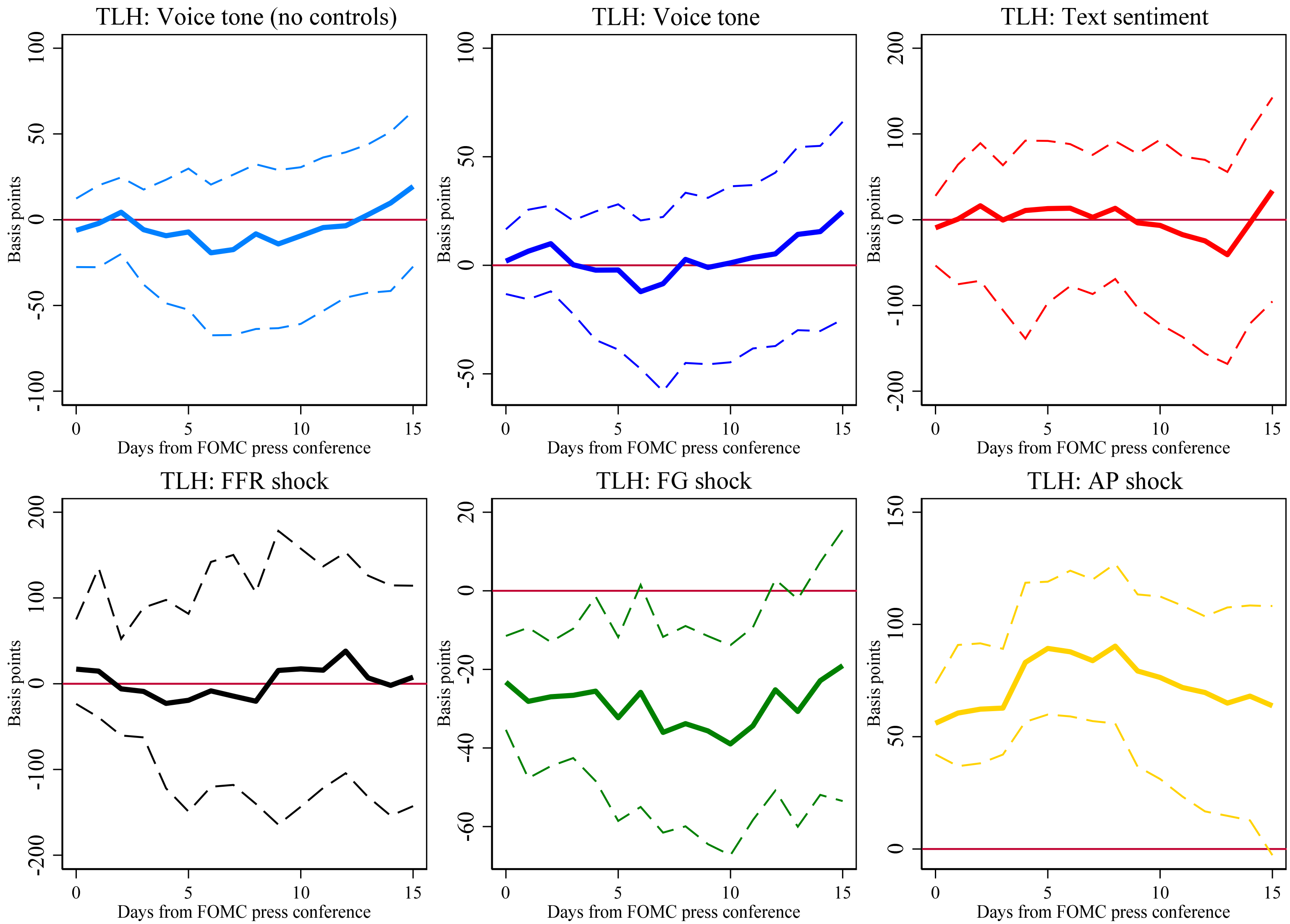
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 4. Response of IEF ETF (7-10 Year Treasury Bond ETF) to policy actions and messages.



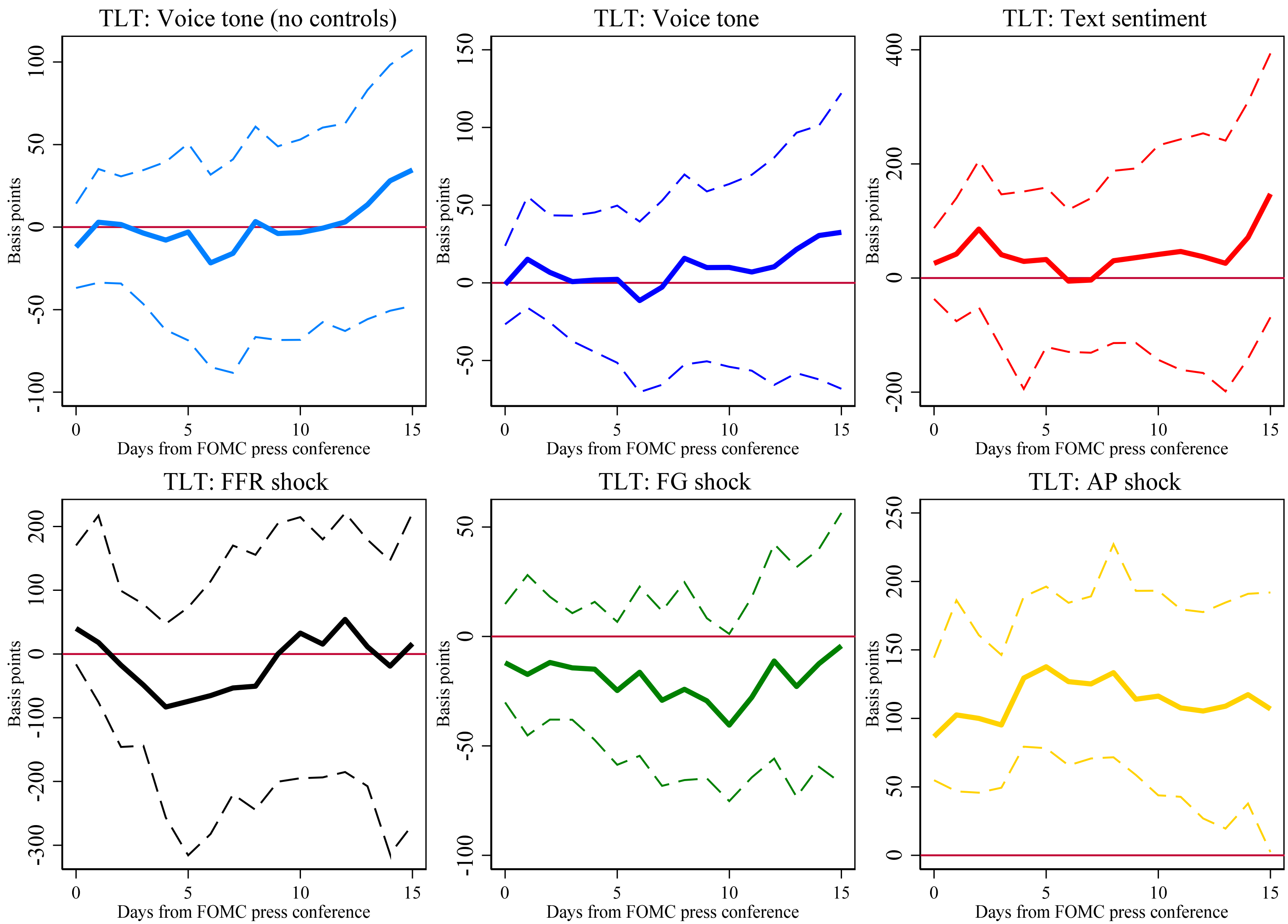
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 5. Response of TLH ETF (10-20 Year Treasury Bond) to policy actions and messages.



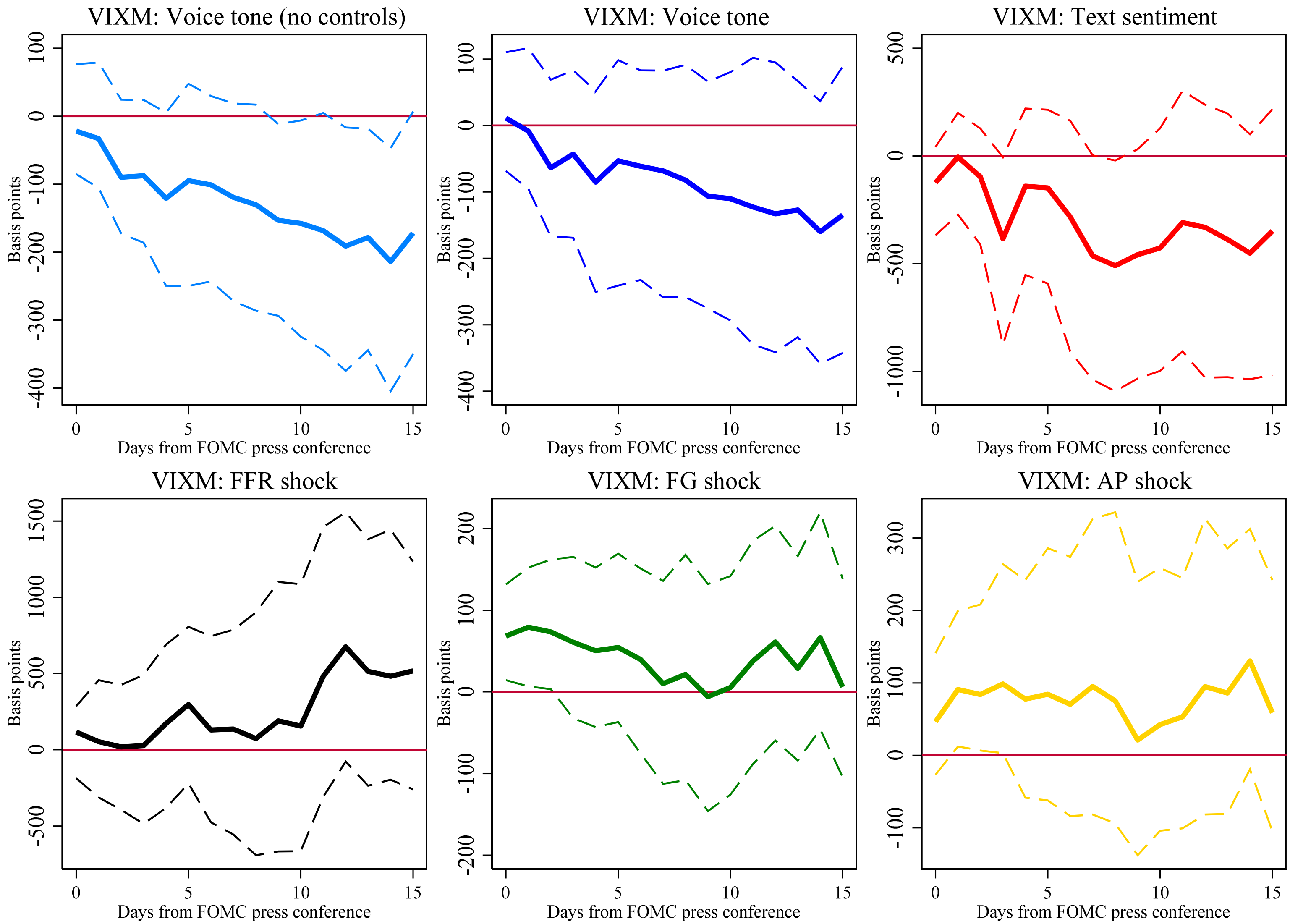
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 6. Response of TLT ETF (20+ Year Treasury Bond ETF) to policy actions and messages.



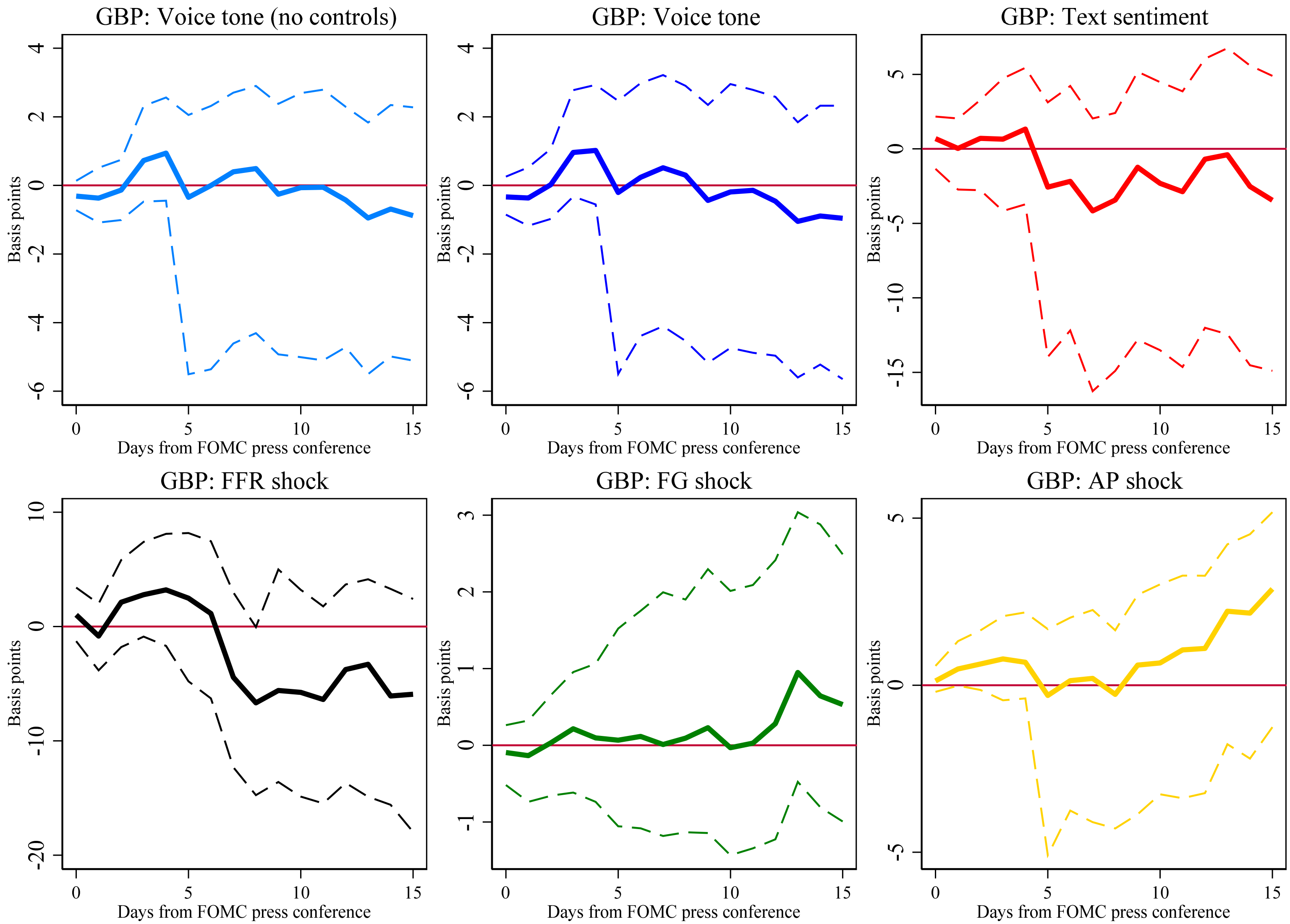
Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 7. Response of VIXM ETF (VIX Mid-Term Futures ETF) to policy actions and messages.



Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.

Appendix Figure 8. Response of the British Pound to one U.S. Dollar (pound/dollar) exchange rate to policy actions and messages.



Notes: the figure reports estimated slope coefficients *b* (Specification (3)) for policy communication/actions. Dashed lines show 90% bootstrap confidence intervals.