Let's Face It: Quantifying the Impact of Nonverbal Communication in FOMC Press Conferences ☆

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Abstract

We apply facial recognition analysis to FOMC press conference videos and quantify one of the most important aspects of nonverbal communication — facial expressions. Using minute-level data, we align our nonverbal communication measure with a set of financial assets to estimate the impact of the Fed Chairs' facial expressions on investor expectations. We find that investors adversely react to negative expressions revealed during the press conference. Furthermore, we show that additional information is provided through the non-verbal channel. This work sets forth a new way of capturing soft information embedded in central bank communication and quantifying its impact on financial markets.

Keywords: Central Bank Communication; Market Expectations; Behavioral Finance; Facial Recognition; Video Data; Machine Learning

JEL Classification: E52, E58, F33, G12

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1. Introduction

> *"...In the 1920s, the Governor's "eyebrows" famously became one of the Banks means of communicating. The eyebrows were, in a way, a primitive form of emoji: sterling crisis - sad face.."*
>
> Speech by Andrew G. Haldane, 31 March 2017

The appreciation for central bank communication has increased dramatically in the past two decades. We now know that central bank communication affects employment, income, and inflation (Kuttner and Posen (1999); Woodford (2001); Amato et al. (2002); Kohn and Sack (2003); Coibion et al. (2019)). In times when the standard monetary policy toolkit has limited impact, communication becomes one of the most important tools at the disposal of policymakers (Eggertsson and Woodford (2003); Bernanke (2004); Bernanke et al. (2004); Woodford (2005); Yellen (2013)). Nominal interest rates have been at the zero lower bound for the main part of the last ten years, and, not surprisingly, attention to central bank communication during this period has been heightened.

Communication releases by the Federal Reserve (henceforth, the Fed), and the Federal Open Market Committee (FOMC) in particular, get a lot of attention from market participants. The FOMC has been shown to be an important mover of markets, with both equities and interest rates reacting when FOMC communication is released (Gürkaynak et al. (2005); Rosa (2013); Cieslak et al. (2019)). Arguably, the most important component of Fed communication is the product of the FOMC meeting deliberations.

In 2011, as part of the effort to further enhance the clarity of Fed communication, post-FOMC press conferences were introduced. This development introduced some changes into how the markets react to post-FOMC information. For example, Boguth et al. (2019) show that the implementation of post-FOMC press conferences skewed expectations of important monetary policy decisions towards meetings with press conferences. Gomez Cram and Grotteria (2022) show that for the days in which the FOMC has a scheduled meeting, for a wide range of financial assets, there is a strong positive correlation between price changes in the narrow window around the statement release and those during the subsequent press conference. Conceptually, these results can be explained by the fact that a press conference helps clarify the underlying motivation for the policy decision, and thereby provides news to investors.

In this paper, we study the reaction of financial market participants to a nonverbal component of central bank communication. We leverage existing FOMC press conference videos to identify and quantify facial expressions exhibited by Fed Chairmen during those press conferences. We use facial recognition technology and machine learning to create a composite score that summarizes these facial expressions quantitatively. Effective communication relies on more than just words, and by studying facial expressions exhibited during the press conference in conjunction with verbal messages, we are able to measure not only what is said, but also how it is said.

To the best of our knowledge, our paper is the first to study the impact of facial expressions in central bank communication. A contemporaneous paper by Gorodnichenko et al. (2021) uses a machine learning model to quantify the tone of voice embedded in FOMC press conferences and examines its impact on financial markets. The authors find a significant effect of tone of voice on the stock market. Similar to what we find in our paper, Gorodnichenko et al. (2021) provide evidence that nonverbal communication contributes meaningful information to market participants. In general, this emerging strand of literature sets forth a new way of identifying and capturing *soft* information embedded in central bank communication, with the goal of helping policymakers utilize communication tools at their disposal to their fullest.

Our paper adds to the literature on the signaling channel of monetary policy. Our hypothesis is that the market participants are impacted by information beyond that expressed verbally during the FOMC press conferences. We examine whether market participants notice and act on nonverbal signals expressed by Fed Chairmen during the FOMC press conferences. In order to properly capture market response, we use high frequency price and trading volume data for a set of financial asset classes, in the spirit of Gürkaynak et al. (2005) and Nakamura and Steinsson (2018), and use intensity of facial expressions as a proxy for how Chairs' expressed emotions are perceived by market participants. Specifically, we empirically document how market participants react to nonverbal communication signals in real time by relating a composite intensity score based on facial expressions to minute-level market responses.

Our paper also adds to the finance literature that leverages unstructured data and machine learning techniques. This is a new and growing literature, with a number of recent papers utilizing text-, image-, audio-, and video data (e.g., Bholat et al. (2015); Hansen et al. (2019); Jha et al. (2020); Ehrmann and Talmi (2020); Obaid and Pukthuanthong (2021); Hu and Ma (2021); Doerr et al. (2021); Gorodnichenko et al. (2021); Gardner et al. (2021); Gomez Cram and Grotteria (2022), and others). In this paper, we utilize machine learning algorithms to quantify video data at a high frequency along the facial expressions dimension.

Unstructured data creates value if it can capture meaningful signals that cannot be otherwise captured (Goldstein et al. (2021)). There are several types of unstructured data that can be derived from raw videos. First, there is the verbal component that can be captured in the form of text. The progress in textual data usage in economics and finance has matured considerably in the past decade. Textual analysis methods have been applied in various research settings, such as constructing text-based indices (e.g., (Manela and Moreira, 2017); Calomiris and Mamaysky (2019); Shapiro et al. (2020))); measuring financial constraints (e.g., Buehlmaier and Whited (2018)); and capturing linguistic tone (e.g. Garcıa et al. (2020)). Loughran and McDonald (2016) and Gentzkow et al. (2019) provide comprehensive review and discuss specific nuances of these methods. In this paper, we quantify the verbal component (text) of the press conferences by using a transformers-based machine learning model called FinBERT (Yang et al. (2020)), as well as a hawkish-dovish term frequency measure. We discuss these measures in detail is Section 3.3. Second, there is the visual dimension of the videos. There are currently several papers in financial literature that quantify static images or frames extracted from videos in various contexts (e.g., Graham et al. (2010); Blankespoor et al. (2017a); Obaid and Pukthuanthong (2021); Hu and Ma (2021)). The main goal of using images in financial research is to extract sentiment and/or embedded image labels and relate that information to pertinent economic indicators. In this paper, we decompose a set of press conference videos into a set of frames and use Microsoft Azure Emotion API to score each frame along the facial expressions dimension. We discuss this process in Section 3.2. Finally, there is the audio data. There is an existing line of research that uses speech-derived waveform data in financial research (e.g., Hobson et al. (2012), Mayew and Venkatachalam (2012), Gorodnichenko et al. (2021) and Hu and Ma (2021)). While, without doubt, the voice dimension plays an important role in nonverbal communication (e.g., Mehrabian (1971)), our study focuses on the facial expressions channel given its prevalence in our setting.[1] The interplay between these two communication channels is certainly an interesting question to investigate empirically, and perhaps grants its own specific study.

Why should market participants be impacted by Chairs' facial expressions? It's been shown that facial expressions are a key channel through which emotional contagion occurs (Lundqvist and Dimberg (1995)). Observed emotions may be taken as cues of deeper motives, and interpreted as additional information by market participants. We reason that market participants not only pay attention to, but also act upon information derived from Chair's

[1]In discussions with industry experts, it was noted to us that professional traders usually work in environments that are not conducive to receiving messages delivered through the spoken words. See, for example, the NYSE trading floor picture in: Schneider, H., Saphir, A., and Randall, D. (2021). Powell says Fed likely to taper asset purchases 'at the same time'. *Reuters*.

facial expressions. Moreover, there is some anecdotal evidence that supports this reasoning.[2] Nonverbal cues do get noticed and reported by the press, and we offer a way to study them systematically and objectively.

In our analysis, we focus on a set of negative facial expressions. Research shows that adults display an asymmetry in the way they process negative versus positive information, a phenomenon called negativity bias. Specifically, adults tend to take disproportionate note of negative information (e.g., Rozin and Royzman (2001), Vaish et al. (2008)). We hypothesize that market participants observing Chair's negative facial expressions during the FOMC press conference may associate similar negative feelings with the discussed topic. While we include positive emotions in our robustness checks, the amount of positive facial expressions in our sample is marginal. This is consistent with the post-FOMC press conference setting, given it is a high stakes interaction.[3]

We argue that given the presence of inherent information asymmetry between the Chair and the market participants, the latter might interpret excessive intensity in certain facial expressions as a signal beyond what is expressed verbally during the press conference. To formally examine this assertion, we analyze price and volume changes of several financial asset classes over the course of each FOMC press conference. Our sample includes all of the existing post-FOMC press conferences, up to and including the one on September 16th 2020. In our analysis, we control for the press conference content, general market conditions, meeting level characteristics, as well as other relevant controls described later in the paper.

We find that investors adversely react to Chairs' negative facial expressions exhibited during the press conference. This effect is statistically significant across asset classes and

[2]According to MarketWatch.com, there are hedge funds already studying Jerome Powells facial expressions and their impact on markets. See, for example: Goldstein S. (2018). Hedge funds are studying Jerome Powells facial expressions to predict interest rates. *MarketWatch*

[3]"Yellen (Dec 16, 2015 FOMC meeting minutes): *Okay. Boxed lunches will be available. If anybody wants to watch TV in the Special Library and see me get skewered at the press conference, please feel free. I will do my best to communicate the points that have been made here. END OF MEETING"*

specifications. Furthermore, we document that the impact of Chairs' negative facial expressions on the markets is heightened when there is increased media attention prior to the FOMC meeting, when forward guidance is being discussed, when the tone of the discussion is more negative, and when the policy stance is more hawkish. We also note that display of negative facial expressions lowers trading volume in the subsequent three minute interval. Our results are robust to several alternative fixed effects specifications, as well as alternative approaches to capturing press conference content.

Our results are both statistically and economically significant. A standard deviation increase in our negative emotions score is associated with a 0.53 basis point decrease in SPY index during a given three minutes interval. The economic significance applies to the other asset classes too: the implied volatility index increases by 3.75 basis points and the Euro to US Dollar exchange rate decreases by 0.18 basis points. While the impacts may look marginal in absolute terms, these are evaluated on a three-minute interval making them quite substantial if evaluated on longer horizons.

Lastly, we investigate potential explanations of our results. We find evidence for the nonverbal pass-through of information. Specifically, we show that the negative emotions expressed during the press conferences correlate significantly with the negative tone in FOMC meeting minutes transcripts. Conversely, we do not find evidence of overreaction to information as the short term returns reversal is insignificant.

The rest of the paper is organized as follows. We discuss relevant literature in Section 2, data in Section 3, and present empirical results in Section 4. Section 5 discusses potential channels for these results, Section 6 presents robustness checks, and Section 7 concludes.

2. Literature Review

2.1. FOMC Press Conferences

The FOMC Committee holds eight regularly scheduled meetings during a calendar year. During each meeting, there is a discussion of monetary policy actions at hand, as well as its likely future course. Policy decisions have been announced to the public via the post-FOMC statement releases starting in 1994, if the policy rate was changed. Since May 1999, the FOMC has issued a post-FOMC statement after every scheduled meeting. Starting June 1999, the statements began referring to specific target levels for the federal funds rate. Also in 1999, the FOMC Committee began to issue forward guidance in the form of an assessment of the perceived risks going forward.

The post-FOMC statements has been growing in both size and importance after the federal funds rate was lowered to its effective lower bound in December 2008. Given the increase in the level of complexity of Fed actions during that period, and in an effort to further increase transparency, the then Chairman Ben Bernanke began to hold press conferences following some, but not all, FOMC meetings. Starting 2019, all FOMC meetings have been followed by a press conference. Figure 1 visually presents the timeline of FOMC meeting set-up.

[Insert Figure 1 about here]

Market response to post-FOMC statements has changed since the introduction of press conferences. For example, Lucca and Moench (2015) show that there has been a large risk premium and stock price drift ahead of a post-FOMC statement announcement (the so called pre-FOMC drift). Boguth et al. (2019) show that this price drift occurs only when the Federal Reserve Chair holds a press conference after the FOMC announcement. They show that markets have adjusted to expect more important decisions on days with press conferences, and so the media and investors concentrate most of their attention on those meetings.

At the same time, Gomez Cram and Grotteria (2022) show a strong positive correlation between price changes around the post-FOMC statement releases and the subsequent press conferences. The authors hypothesize that there is an ongoing learning process during the press conference, with journalists asking for clarifications and explanations. They show how the messages communicated during the post-FOMC press conference form investors expectations, and specifically document the importance of those moments in which the Fed Chairman answers questions related to the interpretation of the post-meeting statement.

In this paper, we argue that the aforementioned learning process is based on the information supplied by both verbal and nonverbal communication components. We hypothesize that market participants derive information from nonverbal communication expressed by Fed Chairmen to decipher verbal communication, and subsequently form expectations regarding the state of the economy. We disaggregate press conference information into verbal and nonverbal components by considering both the text and the images of each conference. We then estimate the impact of nonverbal communication on the markets, while controlling for the verbal component and other explanatory variables. As previously discussed, the expectations transmission channel of monetary policy has gained considerable importance during the recent decades. Therefore, factors that potentially impact investor expectations will impact the transmission of monetary policy. This paper ultimately links the reaction of market participants to Chairs' nonverbal communication with monetary policy transmission.

2.2. Nonverbal Communication in Finance

Nonverbal communication plays a large role in all human interactions (Birdwhistell (1970); Philpott (1983)). Impressions about other people, as well as interpretations of what they say, are largely based on factors other than the verbal content (Hecht and Ambady (1999);

Leathers and Eaves (2015)). Facial expressions in particular play an important role in conveying nonverbal communication (e.g., El Kaliouby and Robinson (2004)). Moreover, humans react to nonverbal communication based on a thin slice of behavioral evidence. Research in psychology indicates that humans routinely make rapid evaluations based on one-time interactions (Ambady et al. (2000)). Overall, its been shown that brief judgments based on thin-slicing are similar to those judgments based on much more information. This is consistent with the rational inattention theory, where humans lack the ability to quickly absorb all available information, and base their decisions on select bits of data.

The existing literature in finance applies this theory of human behavior to analyze nonverbal communication and its impact on market outcomes. For example, Mayew and Venkatachalam (2012) examine the response of the capital market to managers nonverbal communication as expressed by the stress in the manage's voice during conference calls. They show that the stressed voice indicator is often a better predictor of future firm performance than is the content of manager's speech. Blankespoor et al. (2017b) develop a composite measure of investor perception using 30-second video clips of initial public offering (IPO) roadshow presentations. They provide evidence that investors' perception of management is incorporated into their assessments of firm value. Hill et al. (2019) use third-party ratings of video samples to assess positive and negative communication signals expressed by chief executive officers (CEOs), as well as their overall perceived appeal.

Within this literature, several works have specifically investigated the role of facial expressions. Breaban and Noussair (2018) analyze facial expressions of traders and link expressed fear to negative movements in a firms stock price, and positive emotional state with purchases and overpricing. Choudhury et al. (2019) use both the videos and the corresponding transcripts of interviews with emerging market CEOs to establish their communication styles. They synthesize the videos and transcripts and produce distinct communication styles that incorporate both verbal and nonverbal aspects of the conducted interviews. They then relate

CEO communication styles to firms mergers and acquisitions outcomes. Akansu et al. (2017) show that if a CEO shows disgust or anger during a media interview, there is a subsequent increase in the firm profit margin, sales growth, and return on assets, and when a CEO shows happiness in their face, there is a subsequent decrease in profit margin, return on equity, and return on assets. Momtaz (2019) examines how nonverbal communication expressed by CEOs impacts rm valuation in blockchain-based issuance of cryptocurrency tokens to raise growth capital. The paper shows that negative emotions expressed by CEOs are associated with lower absolute-value deviations from market's average underpricing level. Positive emotions, on the other hand, do not signicantly influence underpricing behavior.

The paper closest in methodology to ours is by Hu and Ma (2021). Hu and Ma (2021) use machine learning algorithms to quantify features along visual, vocal, and verbal dimensions extracted from a series of entrepreneur pitch videos. They identify human faces embedded in each video image using face detection algorithms. To score emotions, they use the Face++ API platform through which they input image frames and receive a set of face-related measures constructed by the algorithm, and use Microsoft Azure Cognitive Services as a robustness check. Hu and Ma (2021) 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.

Overall, this strand of literature provides strong evidence that nonverbal communication by executives impacts firm outcomes. While close in methodology to some of this work, our paper considers a new important context: central bank communication. Using a high-frequency setting, we provide evidence that Fed Chair's emotions carry meaningful information.

3. Data

Our data comes from three main sources. First, to proxy for market responses, we look at minute-level changes in prices of several financial asset classes. Second, to measure nonverbal communication, we build a composite score that captures the intensity of negative facial expressions conveyed by the Fed Chairs during the FOMC press conferences. And third, to control for other aspects related to market environment and meeting characteristics, we include a set of additional control variables. We highlight controls for the verbal content of the conference in a separate subsection.

3.1. Market Responses

We proxy for changes in market expectations with high-frequency changes in asset prices and volumes. Nakamura and Steinsson (2018) show that this type of identification addresses both endogeneity issues and omitted variables bias. Using high frequency data and very narrow time windows decreases the likelihood that other information, such as relevant macroeconomic news, is released around policy announcements, thus impacting the markets. This approach removes the possibility that it is the monetary policy that is reacting to movements in asset prices, and not the other way around.

Monetary policy announcements impact a wide range of financial assets. Because we look at very narrow (3 minute) time windows, we can assume changes in price are due to FOMC communication, and not due to a response to other events that occurred when markets are actively traded. We construct price changes around the post-FOMC statement release, as well as the subsequent press conference using a set of market instruments. Specifically, we use equity, implied volatility, and Euro to US Dollar exchange rate futures to measure the market reaction to the nonverbal component expressed during the press conference.[4]

[4]In an earlier version of the paper we considered an additional asset class, 10-year U.S. Treasury (T-Note) futures. Given our focus on short-term assets, we have excluded the results from this version of the draft, but they are available upon request.

Detailed definitions of these variables are listed in Table 1.

[Insert Table 1 about here]

- SPDR S&P 500 (SPY): We use a historical dataset of SPY prices at one-minute frequency, spanning January 2011 to September 2020. We also use the SPY trading volume, measured in number of individual shares traded.

- CBOE Volatility Index (VIX): The Chicago Board Options Exchange Market Volatility Index (VIX) is an implied volatility index. We use the option-implied volatility of the S&P 500, as measured by the VIX index, to proxy for uncertainty associated with monetary policy. The time series spans January 2011 to September 2020.

- Euro-to-USD Exchange Rate (EURUSD): We use historical market data for deal-able interbank Euro-to-USD exchange rates for each minute. The time series spans January 2011 to September 2020. We also use the Euro-to-USD trading volume, measured in millions of base currency.

Based on the above data we calculate percent changes within 3 minute intervals in SPY, VIX, and FX prices, all measured in basis points. We calculate the average trading volume within 3 minute intervals during the time of the press conference in SPY and FX. Table 2, Panel A reports the number of observations, mean value, standard deviation, and percentile distribution for the three minute interval price changes.

[Insert Table 2 about here]

The average price change for SPY over the course of 3 minutes is around zero, with a median of 0.40 basis points. The FX instrument fluctuates comparably to SPY during the press conference, with a mean of -0.17 basis points, and a median of 0.07 basis points. The average change for VIX over the course of 3 minutes is -2.09 basis points, with a median of 0.00.

Trading volumes for SPY and FX during the FOMC press conferences are higher than on FOMC announcement days without the press conference, as documented by Gomez Cram and Grotteria (2022). In our sample there are, on a average, 447,000 SPY shares, and 713 million of EURUSD base currency, traded per minute over the course of the conference.

3.2. Facial Expressions

Recent advances in computer vision and machine learning methods has made automatic recognition of facial expressions scalable. With precision greatly improved over the past decade, these algorithms now perform on par with human evaluators (Howard et al. (2017)). Besides scalability, accuracy, and speed, this method is easily reproducible, allowing for greater replication and transparency, as well as the reduction of computational burden for researchers.

For our purpose, we rely on these advancements to capture a component of nonverbal communication in a standardized and dynamic fashion. We adopt an implementation of Microsoft Azure Cognitive Services Emotion API.[5] The underlying algorithm is trained, tested, and cross-checked by reputable providers using millions of human-rated training observations. The reason for choosing this specific API for our analysis is because it uses the largest number of key points on the face compared to other available technologies. The number of users of the Microsoft Azure Emotion API is one of the largest in comparison with other similar services.

The process works as follows. The Azure platform provides an API through which we feed our set of images derived from press conference videos into the Microsoft cloud computing system. We receive a set of face-related measures constructed by Microsoft's computer vision

[5]The API can be accessed at https://azure.microsoft.com/en-us/services/cognitive-services/face/

and machine learning algorithms. First, via a face detection algorithm, the locations of facial landmarks are extracted from our set of images. Following that, an emotion recognition algorithm characterizes a facial expression for each frame.

The algorithm used is a state-of-the-art convolutional neural network (CNN) method. Conceptually, the algorithm transforms each input image into a set of weighted pixels using a neural network. Then, using these weights, specific parameters are generated (such as, degree of: open mouth, contracted eyebrows, smile width, and so on.) These parameters are then used to generate output values for input images. Finally, the weights are optimized based on minimizing a loss function, where the error is coded based on the difference between the output values of facial expressions derived from input images and "output values" of same facial expressions with existing labels (the training set).

The API then returns emotion scores for the eight facial emotions (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Neutral*, *Sadness*, and *Surprise*), where each emotion receives a score between zero and one. These scores add up to 100%.[6]

There are several existing papers that use Emotion API to analyze facial expressions. For example, Choudhury et al. (2019) use both the videos and the corresponding transcripts of interviews with emerging market CEOs to establish their communication styles. They synthesize the videos and transcripts and produce distinct communication styles that incorporate both verbal and nonverbal aspects of the conducted interviews. They then relate CEO communication styles to firms merger and acquisition outcomes.

In order to prepare the data for the API, we first decompose each of the 46 videos into a set of frames. Our images are continuous and extracted from videos. Each frame is captured at the two second interval. We consider this interval to be adequate for our analysis because it's been shown that most facial expressions typically last between 0.5 to 4 seconds (Ekman

[6]Figure A1 in Appendix A provides an example of the scored frames for the three Chairs in our sample.

and Friesen (2003)).

Once the set of frames is scored, we aggregate these scores to a three minute level, in line with how we aggregate the market response variables described in the previous section. The interpretation for the aggregates here is the following. If we take the average score of $Fear$, for example, expressed during a specific three minute interval, we would get an extent to which the individual on camera expressed fear during those three minutes.[7]

This methodology yields a sample that includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 26^{th}, 2011 and September 16^{th}, 2020. On average, the duration of each press conference video is about 55 minutes long, where the first 10 minutes on average correspond to the opening statement made by the Fed Chair. The sample contains press conferences of the three Federal Reserve Chairs to serve between years 2011 and 2020: Ben Bernanke, Janet Yellen, and Jerome Powell. The structure of each press conference has stayed consistent throughout the years. Each press conference starts with the Chair reading an opening statement that provides more details on the current FOMC decision, and follows with a Q&A portion, with journalists asking the Chair questions ranging from the current state of the economy to the future direction of interest rates.

Using these intensity scores, we construct our main independent variable called *Negative Emotions*. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over three minute intervals, scaled by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The intensity scores of $Anger$, $Disgust$, and $Fear$

[7]Robustness checks with 1-, 5-, and 10-minute intervals are available upon request.

are considered as negative emotions.[8]

$$Negative\ Emotions_{i,k} = \frac{(Anger_{i,k} + Disgust_{i,k} + Fear_{i,k})}{(\overline{Anger_k} + \overline{Disgust_k} + \overline{Fear_k})} \tag{1}$$

In the above equation, as an example, $Anger_{i,k}$ represents the average intensity of anger expressed during a given 3 minute interval i for Chair k. Correspondingly, $\overline{Anger_k}$ represents the average intensity of anger expressed across the sample by Chair k.

As discussed, we are focusing on negative emotions because we want to explore whether in the presence of information asymmetry market participants would interpret excessive intensity in negative facial expressions as a signal for worse economic outlook.

In an effort to provide further evidence to the effect of Chairs' emotions on market participants and demonstrate that our main independent variable is robust, we create several alternative measures of negative emotions. First, we build a measure that leverages all seven emotion scores by employing Principal Component Analysis (PCA), a dimensionality reduction technique. $Negative\ Emotions_{pca}$ score is created in the same fashion as our main measure in Equation 1, but uses the combination of all seven intensity scores (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Sadness*, and *Surprise*) multiplied by their first principal component coefficients. Figure 2 visualizes the first two principal component scores. Higher values of the first principal component are associated with more negative emotions as *Fear*, *Disgust*, and *Anger* are the emotions with the largest positive coefficients and *Happiness* is the only sentiment with a negative coefficient. The figure also indirectly supports our selection of emotions for the main measure of *Negative Emotions*.

[Insert Figure 2 about here]

[8]In an unreported analysis (available upon request), we add *Sadness* as a negative emotion and our results are unchanged. We decided to not include *Sadness* as a negative emotion in our main measure of *Negative Emotions*, as it may not necessarily reflect a strong negative sentiment, as, for example, anger.

Next, we build a measure *Negative Emotions*$_{dmd}$, estimating negative emotions in an absolute way instead of a relative way, with respect to the Chairs' average intensity of emotions. Specifically, instead of taking the ratio of Chairs' negative emotions to their averages, we subtract them. This measure considers the difference between negative emotions expressed in a three minute interval and the Chairs' averages in the same manner across Chairs. Lastly, *Negative Emotions*$_{std}$ measure is based on the standard deviation of negative emotions expressed in three minute intervals. This variable captures pronounced swings in expressed emotions. We report our results in Section 6 (Robustness Checks). Overall, our results hold under alternative specifications of our main explanatory variable.

The definitions for *Negative Emotions* and its alternatives are presented in Table 1. Descriptive statistics for these variables are presented in Table 2, Panel B. *Negative Emotions* accounts for each Chairs average intensity of negative emotions in three minute intervals, with higher numbers denoting more negative emotions. Figure 3 shows the *Negative Emotions* average score, within a FOMC meeting, by each Chair. As can be seen, the *Negative Emotions* meeting average differs greatly across meetings and all Chairs' exhibit variation.

[Insert Figure 3 about here]

3.3. Press Conference Content

In order to identify the effect of facial expressions, we first must properly control for the verbal content of the press conference. We conduct the following analysis to correctly identify, capture, and account for what is being said.

Our first step is text synchronization. Since our analysis is so granular, we need to make sure that what is being said aligns perfectly with the facial expressions. We perform the time-stamping procedure manually, where we time-stamp the text and make sure it is perfectly aligned with the conference video feed. We also manually conduct several text labeling tasks, such as dividing the Q&A portion of the press conference into questions (journalists) and answers (Chair), and classifying each text excerpt into a specific category.

We then take the following steps to quantify the verbal component of the press conference. In order to derive text sentiment, we employ BERT, a state-of-the-art natural language processing model based on an algorithm developed by Google AI.[9] It is a deep learning model that has been trained on the entire English Wikipedia and BookCorpus (Zhu et al. (2020)), and has displayed state-of-the-art performance on a number of general natural language understanding tasks. An additional advantage of BERT is that it is a bidirectional language model, meaning that it considers order of the words in a sentence in both directions, thus better capturing its context. This model and its variations significantly outperform bag-of-words algorithms in NLP tasks, such as language translation, named entity recognition, and sentiment classification of general texts (Devlin et al. (2018)). We therefore use this model instead of the more common dictionary-based methods because the degree of precision matters a lot in our task. In general, Manela and Moreira (2017) show that machine learning based methods are far superior to the dictionary-based ones.

To account for finance-specific content of press conferences, we employ a modified version of BERT model called FinBERT. FinBERT is a natural language processing model pretrained on financial communication text in order to enhance its ability to classify financial texts (Malo et al. (2013)). FinBERT is pretrained on the Financial Phrase-Bank dataset, consisting of 4846 English sentences selected randomly from financial news and annotated by 16 subject matter experts with a background in finance and business. The purpose of using an augmented BERT model is to allow for more precision in our text classification task, given its specific context. The FinBERT model is currently available for implementation through

[9] Bidirectional Encoder Representations from Transformers (BERT) is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context. (Devlin et al. (2018)

the Hugging Face, an open source library containing a wide range of pretrained models (Wolf et al. (2020)).

We use FinBERT to assign each sentence spoken by the Fed Chair an emotion score (positive, negative, or neutral).[10] Based on this process, we create our main measure of tone, *Negative Tone*. We take the total number of negative sentences, subtract the number of positive sentences, and divide it by the total number of sentences in that particular 3 minute interval. We then normalize this measure by dividing it by its own standard deviation.

In addition, we create a separate policy stance index named *Hawkishness*, which separately measures the prevalence of hawkish and dovish expressions present in central banks communications. We create this index for each text excerpt in our sample using the stance dictionary in Hansen and McMahon (2016). We do a search and count of words associated with this dictionary in each part of the sentence. These counts are then aggregated over the entire sentence to form the index in question. Our stance index is defined as:

$$Hawkishness_{i,k} = \frac{(HawkishTerms_{i,k} - DovishTerms_{i,k})}{(ExcerptLength_{i,k})} \tag{2}$$

where $Hawkish(Dovish)Terms$ is the number of times a term classified as hawkish (dovish) based on our dictionary appears during a given 3 minute interval i for Chair k, and *ExcerptLength* is the total number of words spoken during a given 3 minute interval i for Chair k. We use the stance index as an additional control variable in our empirical analysis. The logic behind this indicator is that hawkish terms would signal improving economic outlook and heightened inflationary pressures. Therefore, it would also indirectly signal a higher likelihood of monetary policy tightening.

Table 2, Panel C presents descriptive statistics for *Hawkishness* and *Negative Tone*. In

[10] Specifically, we get softmax outputs for three labels: positive, negative or neutral. The output is a vector that represents the probability distributions over these three outcomes. Training parameters and other details are available upon request.

addition, we test alternative vocabularies (financial sentiment dictionary based on Loughran and McDonald (2011), and generic sentiment dictionary SentiWordNet, based on Baccianella et al. (2010)), both at the word and sentence levels, as well as z-standardizing our main variable *Negative Tone*, and find no significant impact on our results. This analysis is available upon request. Figure 4 shows our data processing and merging procedure.

[Insert Figure 4 about here]

3.4. Other Control Variables

To control for aspects related to the state of the economy, and to the environment surrounding each meeting, we include a set of additional control variables in our analysis. Table 1 presents definitions of these variables. Table 2, Panel C presents descriptive statistics.

First, we include the change in the Federal Funds Rate (FFR) for the current FOMC meeting, measured in basis points, ΔFFR, to control for the actual change in the key rate. Then, we include a set of so called pre-drift variables. We include these variables to control for autocorrelation in prices changes. SPY, *VIX*, and *EURUSD* pre drift variables measure the percent change in the relevant asset price within the 30 minutes preceding the start of an FOMC press conference, measured in basis points. We specifically control for these variable given that the reaction from the publication of the FOMC statements carries forward, as shown by Lucca and Moench (2015) and Gomez Cram and Grotteria (2022).

We also include a measure of monetary policy uncertainty, *MPU*, developed by Husted et al. (2020). *MPU* is an index that captures the degree of uncertainty the public hold regarding the Federal Reserve policy actions and its consequences. This index tracks the frequency of newspaper articles related to monetary policy uncertainty in major news outlets. The last control variable is *Market Conditions*, included to reflect current market conditions. This variable is based on the cumulative return of S&P 500, calculated across all trading days, starting from the Monday following a previous FOMC meeting and ending three days before the current FOMC meeting.

In investigating heterogeneity effects, we first include *Media Coverage* and *Press Statement Surprise* as interaction variables. Both variables measure the degree of attention each FOMC press conference receives. *Media Coverage* is based on the daily number of articles related to the Federal Reserve and published in the Wall Street Journal and the New York Times. This variable thus captures the ex-ante interest in the meeting. We follow Boguth et al. (2019) to construct the relevant search query. *Press Statement Surprise* is derived from 30 Day Fed Fund Futures data, and is measured as the absolute change, in basis points, of 30 Day Fed Fund Futures occurring from 10 minutes prior to the FOMC announcement (1:50pm EST) and up until the start of the FOMC press conference (2:30pm EST). This variable captures the element of surprise the FOMC announcement delivered to the market.

Finally, we label each sentence in the press conference transcript as either one discussing the status of the economy, forward guidance, or other. Specifically, for each three minute interval, we create three dummy variables taking the value of one if either the status of the economy (*Status of Economy*), forward guidance (*Forward Guidance*) or other topics (*Other*) are discussed for the majority of the time, and zero otherwise. Table 2, Panel C shows that, on average, status of the economy is discussed for about 12% of the total conference time, and topics related to forward guidance are discussed for about 17% of the total conference time.[11]

3.5. Variable Correlations

Table 3 describes variable correlations. Panel A reports correlations between our set of market responses and our main measure of negative sentiment, *Negative Emotions*. Panel B reports correlations between negative emotions variables and the two text measures, *Negative*

[11] Appendix B provides examples of how transcript excerpts are assigned into these three categories.

Tone and *Hawkishness*.

[Insert Table 3 about here]

Panel A reports correlations between our dependent variables *SPY*, *EURUSD*, *VIX*, and our key explanatory variable, *Negative Emotions*. The correlations between these variables are as expected: negative, and of similar magnitude for *SPY*, *EURUSD*, and positive for *VIX*. For *SPY*, *EURUSD*, the correlations are at -0.047, and -0.040 respectively. The correlation is at 0.028 for *VIX*. We also note that the relation between the *Negative Emotions* and the asset price changes is significant, with the exception of *VIX*, which isn't significant at conventional levels.

Panel B reports correlations between our set of negative emotions variables and the two text measures, *Negative Tone* and *Hawkishness*. The correlations between the main independent variable and the text measures are not statistically significant, while the correlation between the two text measures is negative and statistically significant. The latter finding is consistent with Gorodnichenko et al. (2021).

4. Regression Results

4.1. Market Reaction

In order to examine whether Chairs' negative emotions are related to the changes in the stock and currency markets we employ a set of multivariate regressions that enable us to control for confounding effects. We estimate the following main specification for each of our dependent variables:

$$\%\Delta Market_{t,me} = \alpha_{fe} + \beta_1 Negative\ Emotions_{t-1} + \beta_k Ctrls_{t-1} + \epsilon_{t,me,fe} \quad (3)$$

where t indexes the minutes, me indexes the FOMC meeting, and fe indexes either the Chair or FOMC meeting. $\%\Delta Market$ is the percent change in price, in the following three minutes, for one of our three market measures: SPY, VIX, and $EURUSD$. *Negative Emotions* variable represents Chair's intensity of negative emotions averaged in the prior three minutes, and divided by the average intensity of negative emotions across all FOMC meetings presided by the same Chair. $Ctrls$ represents a vector of control variables described in Section 3.3 and Section 3.4. α_{fe} represents either Chair or FOMC meeting fixed effects, which absorbs potentially different levels of markets' percent changes and negative emotions at the Chair or FOMC meeting levels. We cluster standard errors at the Chair level to account for within-Chair correlation of the error terms. Table 4 presents the results of our main specification under different fixed effect schemes.

[Insert Table 4 about here]

Table 4, Columns (1)-(9), examines the impact of Chairs' negative emotions on percent changes in SPY, VIX, and EURUSD.

For SPY, Column (1) starts with a pooled regression specification with no fixed effects. The coefficient on *Negative Emotions* is negative and statistically significant at the 1% level. Columns (2)-(3) further suggest that the negative association in Column (1) is robust to the introduction of either Chair or FOMC meeting fixed effects. Based on the specification in Column (3), with meeting fixed effects, a one standard deviation increase in *Negative Emotions* is associated with a 0.53 basis point change in SPY ($= 1.060 * (-0.501)$) for a three minutes interval.

Column (5) shows that the coefficient on *Negative Emotions* is positive and statistically significant at the 10% level for the specification with Chair fixed effect. Column (4) and (6) are also close to being statistically significant suggesting that more intense negative emotions increase stock market volatility, as captured by VIX. Based on the specification in Column (6), with meeting fixed effects, a one standard deviation increase in *Negative Emotions* is associated with a 3.75 basis point increase in VIX ($= 1.060*3.54$) for a three minutes interval.

Columns (7)-(9) examine the impact of Chairs' negative emotions on percent changes in EURUSD exchange rate, and show that the coefficient on *Negative Emotions* is negative and statistically significant at the 5% level, suggesting that more intense negative emotions decrease the change in EUR-to-USD exchange rate. Columns (8)-(9) further suggest that the negative association in Column (7) is robust to the introduction of either Chair or FOMC Meeting fixed effects. Based on the specification in Column (9), with meeting fixed effects, a one standard deviation increase in *Negative Emotions* is associated with a -0.18 basis point change in EURUSD ($= 1.060 * (-0.173)$) for an interval of three minutes.

Overall, these results indicate that negative facial expressions, as captured by the variable *Negative Emotions*, adversely impact the financial markets. In the next section we investigate whether *Negative Emotions* variable impacts trading volumes.

4.2. Trading Volumes

Its been shown that both the trading volume and market depth increase during the FOMC announcement days, and, in particular, during minutes surrounding the statement release (Fleming and Piazzesi (2005)) or the press conference (Gomez Cram and Grotteria (2022)). Kim and Verrecchia (1991) and Shalen (1993) theoretical frameworks predict that new information may generate trading by impacting the extent of disagreement between market participants. Specifically, those frameworks predict that an increased disagreement among agents on new information would lead to an increase in trading volume. Cookson et al. (2022) posit that the underlying reason for the disagreement, i.e., slow belief updating, is confirmation bias of market participants. Conversely, a decrease in trading volume should reflect a convergence in agents beliefs about new information.

To investigate the relationship between trading volumes and *Negative Emotions* we perform a multivariate regression analysis in the spirit of Equation (3), with dependent variables being the average trading volumes evaluated in the three minutes following the measurement of *Negative Emotions*. Table 5 presents the results.

[Insert Table 5 about here]

Column (1) shows that the there is a statistically significant negative relation between SPY trading volume and Chair's *Negative Emotions*. Based on the specification in Column (1), a one standard deviation increase in *Negative Emotions* is associated with a trading decrease of 12,702 shares per minute ($= 1.060 * (-0.012) * 1,000,000$), which represent a 2.85% decrease with respect to the unconditional SPY trading volume mean. In Column (2), the estimated coefficient sign remains negative, but shows no statistically significant relationship between *Negative Emotions* and EURUSD trading volumes.

Overall, our results show that *Negative Emotions* reduces trading volume only for SPY, suggesting a convergence in agents' belief. At the same time, there is a positive, statistically significant relation between *Hawkishness* and both SPY and EURUSD trading volume. A one standard deviation increase in *Hawkishness* is associated with a trading increase of 30,740 shares per minute ($= 1.060 * (0.029) * 1,000,000$) for SPY, and a trading increase of 53,000 shares per minute for EURUSD ($= 1.060 * (0.05) * 1,000,000$). The *Hawkishness* variable might carry new information about the state of economy, hence introducing the disagreement between market participants and the subsequent trading volume increase.

4.3. Heterogeneous Effects

4.3.1. Media Attention and Press Statement Surprise

In this section we test whether increased media attention prior to the meeting exacerbates the reaction of market participants to negative emotions expressed by the Chair. Why would increased media attention matter? In general, increased media attention might be an indication of importance for the upcoming meeting. This, in turn, would lead to stronger investors' expectations, and more attention to the actual press conference.

We include two measures of market attention in our analysis, *Media Coverage* and *Press Statement Surprise*. *Media Coverage* is based on the daily number of articles covering the Federal Reserve and published in Wall Street Journal and New York Times, thus capturing ex-ante interest in the upcoming meeting. *Press Statement Surprise* is constructed by taking an absolute change, in basis points, of 30 Day Fed Fund Futures occurring from 10 minutes prior to the FOMC announcement and up until the start of the FOMC press conference. This variable captures the element of surprise the FOMC announcement delivered to the market.

[Insert Table 6 about here]

Table 6, Panel A summarizes our findings with respect to the amount of media coverage of an upcoming FOMC meeting using *Media Coverage* variable. Column (1) shows that increased media attention provides an amplification effect to nonverbal communication for SPY. Columns (1) and (3) show that there is a statistically significant effect of increased media attention on the reaction of market participants to negative emotions expressed during the press conference. While there is no statistical significance for columns (2), the coefficient sign remains positive for *VIX*.

Table 6, Panel B presents results related to the alternative measure of attention, *Press Statement Surprise*. Columns (1) and (2) show that there is a statistically significant effect of FOMC announcement surprise on the reaction of market participants to negative emotions expressed during the press conference. Column (3) shows no statistically significant response.

Overall, we find some evidence that the effect of the Chairs' *Negative Emotions* on the markets is amplified by investors' increased attention to the meeting.

4.3.2. Verbal Tone and Discussion Theme

In this section, we examine the interaction between the negative emotions expressed by the Chair with the tone, stance, and topic of the discussion. While the tone (*Negative Tone*) and stance (*Hawkishness*) variables are already used in our prior specifications to control for the general tone of the message, we use them in this section as interaction terms in order to test whether there is an amplification effect between the verbal and nonverbal communication instances.

The topic of the verbal component controls for the content of the message, and specifically captures whether the discussion was geared towards forward guidance or economic conditions. We create discussion theme indicator variables, *Status of Economy* and *Forward Guidance*, by manually labeling each excerpt within the press conference transcripts. We examine the interaction between the topics of the discussion and the negative emotions expressed in order to capture any interplay between the two variables.

[Insert Table 7 about here]

Table 7, Panel A summarizes our findings with respect to the overall level of negative sentiment, captured by *Negative Tone* and *Hawkishness*. Columns (1)-(3) show that the coefficients on the interaction term for *Negative Tone* and *Negative Tone* are negative and significant at least at the 10% level, revealing an amplification effect of the facial expressions with the negative tone of the message. The coefficient significance holds for the interaction term with *Hawkishness* for Column (1) and (2), further suggesting an amplification effect of facial expressions with a more hawkish stance of the message.

Table 7, Panel B considers interactions with our labeled discussion theme indicator variables, *Status of Economy* and *Forward Guidance*, while controlling for the *Negative Tone* and *Hawkishness* variables. Results in Columns (1)-(3) show that the adverse effect of *Negative Emotions* on markets is amplified when forward guidance is discussed during the conference. This result suggests that market participants consider negative facial expressions in the context of what is being discussed. At the same time, when status of the economy is discussed, the amplification effect only holds for SPY. This might signal that the bulk of the discussion on current economic activity is already priced in, and the markets are reacting mostly to forward looking information, as signified by the *Forward Guidance* indicator.

5. Potential Explanations

There is a number of possible mechanisms linking central bank communication with financial asset prices. In general, central bank communication affects agents' expectations for two main reasons: by communicating the implementation of unexpected monetary policy measures (the monetary effect), and by communicating its assessment of the economic outlook (the information effect). Essentially, central bank announcements involve a policy component and an information component (Romer and Romer (2000)). Recent literature highlights the role of the information effect, such as Nakamura and Steinsson (2018), Cieslak and Schrimpf (2019), and Jarociński and Karadi (2020). These studies provide empirical evidence that the release of information (or beliefs) about the fundamentals of the economy by the central bank is an important component of market reactions to monetary policy announcements.

One possible channel for the transmission of the information effect in our set-up is via belief-based channel. For example, Cortes et al. (2021) find this channel to be present in manager-analyst conference call dialogues by showing that the tone of monetary policy announcements directly spills over to the tones of macroeconomic dialogues in subsequent conference calls, which in turn affects market prices contemporaneously.

This section tests a set of potential explanations for the presence of this mechanism. First, we look at whether exhibited facial expressions reflect genuine information conveyed by the Fed. Then, we look at the length of Chair tenure, arguing that if facial expressions do provide genuine information, we should expect tenure to matter, with investors becoming more familiar with Chairs' facial expressions over time. And finally, we examine whether the effect of facial expressions reverses over time. Next three subsections lay out the results.

5.1. *FOMC Minutes*

In this section, we turn our attention to the FOMC meeting minutes to examine whether the expressed emotions during the press conference were driven by genuine information. Released three weeks after each policy decision, the FOMC minutes include summary of staff and committee views on economic conditions as well as deliberations behind the policy decision.

Much of the previous research has focused on the effect of statements on financial markets because of the timing of their release and their shorter length. As Rosa (2013) explains, the minutes, however, still receive a significant amount of attention because they are longer and contain more information and nuances about the policy meetings. The texts of decision announcements have to be agreed upon by a majority of the voting members of the committee and outlines the Committee's view on current and prospective economic conditions and appropriate monetary policy actions. The minutes, on the other hand, provide an unaltered overview of the discussion taking place at the meeting. Rosa (2013) examines to what extent the FOMC minutes contain market-relevant information by looking at asset price volatility and trading volume in a narrow window around the release of the minutes. The results show that the release significantly affects both the volatility of U.S. asset prices and their trading volume.

We take all of the relevant minute transcripts, spanning March 2011 to September 2020, and create two text measures (*FOMC Minutes Negative Tone* and *FOMC Minutes Hawkishness*), using the same technique we applied to quantify the tone and stance of the press conferences. We then regress the text measures derived from the meeting minutes on the same text variables and facial expressions measure derived from the press conferences. We report the results in Table 8.

[Insert 8 about here]

Columns (1) and (2) of Table 8 show a small, but statistically significant positive correlation between press conference-level average of *Negative Emotions* and FOMC meeting minutes average of *Negative Tone*. In Columns (3) and (4), the relation between negative facial expression and the policy stance in FOMC minutes, as captured by *Hawkishness* variable, is not significant. At the same time, there is a strong, positive, statistically significant correlation between the meeting-level average of tone hawkishness, and tone hawkishness of FOMC minutes.

Overall, our results suggests that the emotions expressed by the Chairs during the press conferences do capture the tone of the FOMC meeting minutes better than the tone of the conference itself, thus potentially providing market participants additional information through the non-verbal channel.

5.2. Chair Tenure

Given the findings in the previous section, we investigate whether Chairs' tenure significantly affects results. With time, market participants should develop the ability to more accurately perceive exhibited facial expressions. At the same time, if there is any intentional use of facial expressions on the side of the Chair, the ability to command those should increase over time as well. To test these notions, we look at the Chair tenure in order to study whether market response to Chairs' nonverbal communication changes over time. We create a variable called *Chair Tenure*. It represents the number of FOMC meetings chaired by the Chair at the time of the FOMC press conference. We consider this variable in Table 9.

[Insert 9 about here]

Column (1) of Table 9 shows that coefficient on the interaction term is negative and significant for SPY at the 10% level, with point estimate of -0.092. This indicates that the impact of Chairs' negative facial expressions on the market increases as the tenure of the

Chair, in terms of FOMC meetings, increases. Columns (2) and (3) show consistent patterns but the coefficients are not significant at conventional levels.

Overall, this result weakly supports the view that market participants learn to better decipher Chair's facial expressions with time, and/or that the Chairs' ability to communicate non-verbally improves with time as well.

5.3. Reversal

In this section we examine whether the observed reaction to Chair's facial expressions is driven by dissemination of genuine information or by non-fundamental sentiment. To do that, we study whether the effect of negative facial expressions reverses in the minutes following the identified effect, as an indication of non-fundamental changes. We acknowledge that we cannot conclusively test for it, as there are a potentially infinite set of "reversal" windows, as well as there might be an interplay of both behavioral and information channels in place. Nevertheless, we try to shed more light on the possible underlying mechanism by running a set of regressions on the return reversals. Specifically, we test whether there is a reversal in returns in the minutes following our identified effect. Table 10 presents our results.

[Insert 10 about here]

Column (1), (4), and (7) focus on percent changes for SPY, VIX, and EURUSD prices, from minute 3 to minute 5. Column (2), (5), and (8) focus on at percent changes for SPY, VIX, and EURUSD prices, from minute 3 to minute 10 while column (3), (6), and (9) focus on the changes between minute 5 to minute 15. Results in Columns (1)-(3) correspond to changes in SPY prices, Columns (4)-(6) correspond to VIX, and Columns (7)-(9) correspond to EURUSD.

None of the *Negative Emotions* coefficients are statistically significant, suggesting no evidence of return reversal related to our main independent variable. However, we note a strong, statistically significant reversal for SPY and VIX for *Negative Tone*, with a point estimate of 1.10 and 2.14 for the 3 to 5 and 3 to 10 minute intervals for SPY, and -14.4 and -28.08 for the 3 to 5 and 3 to 10 minute intervals for VIX, respectively.

There could be a number of explanations for this result. We hypothesise that market participants are likely accustomed to trading on deciphered Fed's verbal cues, which may explain the observed return reversal. At the same time, the usage of non-verbal cues is not necessarily a mainstream trading strategy, at least as of now. Furthermore, there might be elements of both behavioral and informational effects present which does not allow us to cleanly identify the channel.

6. Robustness Checks

6.1. Alternative Specifications of Negative Emotions

In this section, we re-estimate Equation 3 using a set of alternative measures for our main explanatory variable, *Negative Emotions*. Specifically, we consider three alternatives: *Negative Emotions*$_{pca}$, *Negative Emotions*$_{dmd}$, and *Negative Emotions*$_{std}$. *Negative Emotions*$_{pca}$ is a measure that leverages all seven intensity scores (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Sadness*, and *Surprise*) and is derived using principal component analysis. To construct the measure, the intensity scores of each emotion are multiplied by the first principal component coefficients estimated using 75,540 frames at the two-seconds level from the 46 the FOMC meetings analyzed in this study. As can be seen on the x-axis of Figure 2, negative emotions are associated with a positive principal component coefficient, while *happiness* is associated with a negative principal component coefficient, keeping the same interpretation as our main measure. *Negative Emotions*$_{dmd}$ estimates negative emotions in an absolute way instead of a relative way, with respect to the Chairs' average intensity of emotions. Specifically, to construct the measure we subtract the Chairs' averages from the Chairs' negative emotion in the prior three minutes instead of dividing the Chairs' negative emotions by their averages. Finally, to investigate whether changes in emotions also have an effects on the markets, we construct *Negative Emotions*$_{std}$ a measure based on the standard deviation of negative emotions expressed in the prior three minutes, or ninety frames.

[Insert Table 11 about here]

Table 11 considers the alternative measures of negative emotions and their impact on *SPY*, *VIX*, and *EURUSD*. Columns (1) through (3) show that the coefficients of all three alternative measures have the same sign and similar statistical significance with respect to our main explanatory variable, *Negative Emotions*. The coefficients in Columns (4)-(6) are of expected sign and statistically significant at the 10% (or very close to that). Columns (7) through (9) show that the coefficients for the negative emotions alternative variables are of expected sign and mostly significant as per our main specification.

Overall, Table 11 results show that the adverse effect of Chairs' negative emotions on the markets, as documented in our main specification, is not a function of how we construct the emotion based measure, and is robust to: 1) estimating Chairs' negative emotions considering all the emotions identified by the Microsoft Emotion API instead of considering only the negative ones; 2) estimating Chairs' negative emotions in an absolute manner instead of relative manner, with respect to the Chairs' negative emotions average, and; 3) estimating Chairs' negative emotions using a measure that captures the variability of emotions within the three minute interval.

7. Conclusion

The expectations transmission channel of monetary policy has gained considerable importance during the past two decades. Our paper contributes to the literature on this channel by uncovering a new dimension of central bank communication. Given the ever-increasing reliance of central banks on communication-based tools, this emerging line of work can help policymakers improve the effectiveness of these tools.

In this paper, we capture and quantify the nonverbal part of policy communication. We start with a premise that nonverbal communication reveals information about the state and trajectory of the economy to market participants. We confirm this premise empirically, and show that nonverbal communication plays a role in influencing investors' beliefs.

Nakamura and Steinsson (2018) underscore the "information effect" of monetary policy communication, i.e., the information delivered to market participants about the probable future state of monetary policy, otherwise known as forward guidance. The purpose of forward guidance is to influence expectations. The common understanding is that forward guidance is either a form of commitment ("Odyssean"), or a way of conveying information to the public ("Delphic") (Campbell et al. (2012)). Given the issue of asymmetrical information that divides market participants and policymakers, communication related to forward guidance might be, at any given time, perceived as an indicator of deterioration in macroeconomic fundamentals, and result in Delphic pessimism among market participants.

Our paper shows that certain facial expressions exhibited during the press conference could, in fact, exacerbate the Delphic effect. We provide evidence that certain aspects of press conference discourse have a potential to cause market under-reaction or overreaction. With this insight in mind, it seems that shaping expectations becomes even more of an intricate game than previously thought. When Fed Chairs speak, the market not only listens, but also watches.

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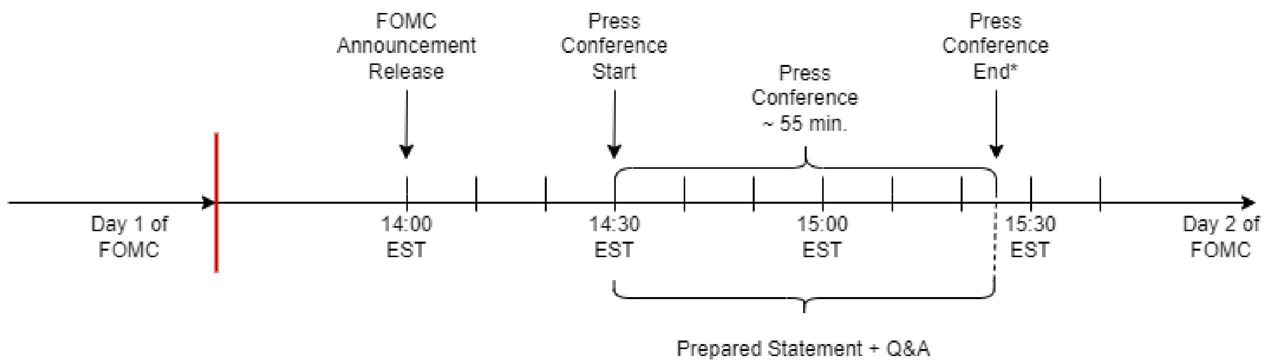


Figure 1: **FOMC Timeline**
This figure presents the structure of the timeline around FOMC meetings, starting in 2011.

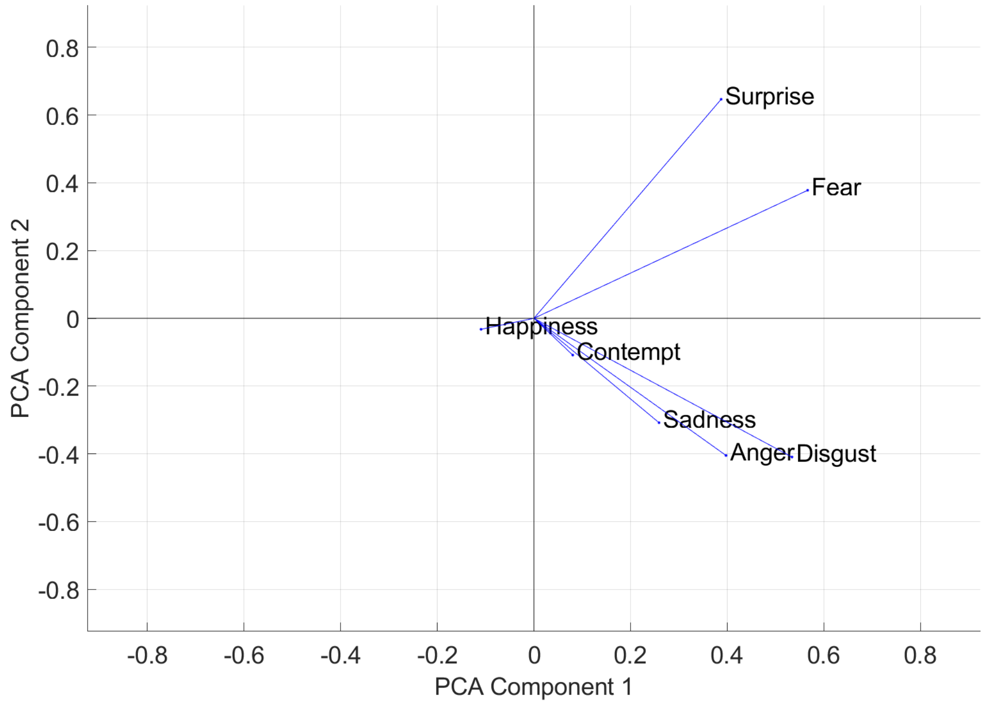


Figure 2: **Emotion Intensity Scores and Principal Component Analysis**
This figure presents the first two principal components of the emotion intensity scores as captured by the Microsoft Azure Cognitive Services Emotion API. The estimation sample includes 75,540 frames at the two-seconds level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020.

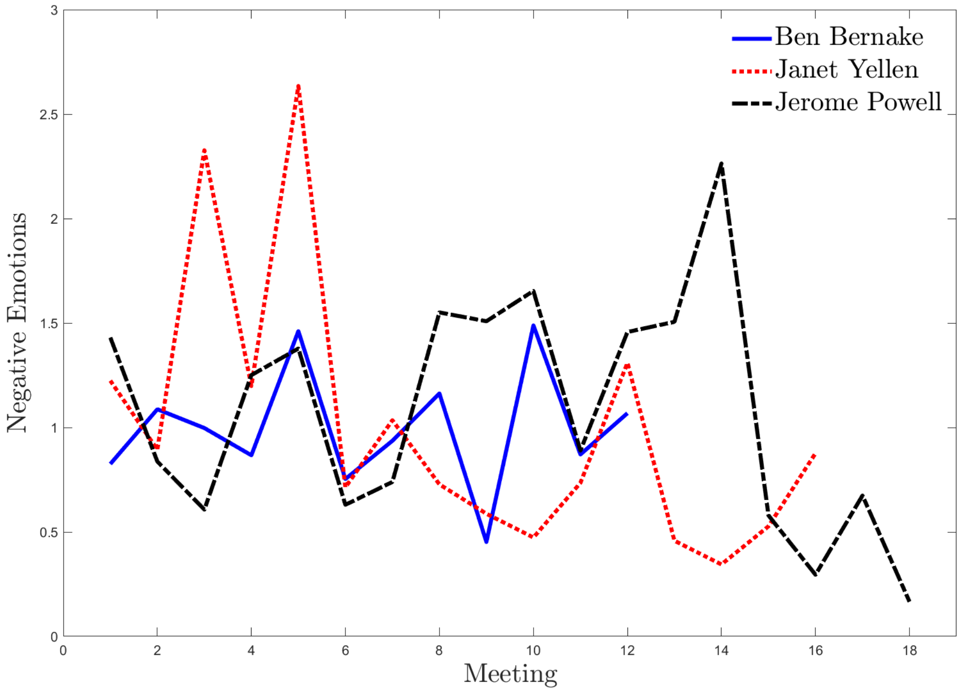


Figure 3: **Negative Emotions and FOMC Meetings**
This figure presents the relation between the equally averaged *Negative Emotions* score and the meetings presided by each of the Chairs of the Federal Reserve System. The sample comprises 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020.

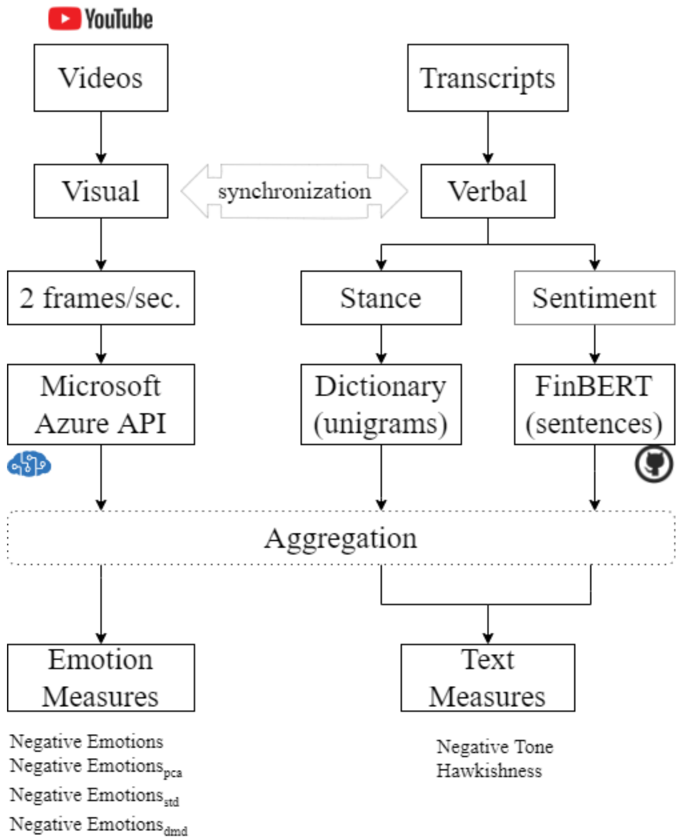


Figure 4: **Data Diagram**
This figure presents the data processing workflow for the image- and text-based measures.

Table 1: **Variable Definitions**

This table presents definitions of dependent variables, key independent variables, meeting characteristics variables, and other variables.

Dependent Variables	
%Δ SPY	The percent change in SPY (SPDR S&P 500), measured in basis points.
%Δ VIX	The percent change in VIX (Cboe Volatility Index), measured in basis points.
%Δ EURUSD	The percent change in EURUSD (EUR-to-USD) exchange rate, measured in basis points.
SPY Volume	The SPY trading volume, measured in number of individual shares traded divided by one million.
EURUSD Volume	The EURUSD trading volume, measured in millions of base currency divided by one thousand.
Key Independent Variables	
Negative Emotions	The Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.
Negative Emotions_{pca}	The Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative* $\textit{emotions}_{pca}$ intensity is the combination of the seven intensities (anger, contempt, disgust, fear, happiness, sadness, and surprise) as captured by the Microsoft Azure Cognitive Services Emotion API multiplied by the first principal component coefficients.
Negative Emotions_{std}	The standard deviation of the Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.
Negative Emotions_{dmd}	The Chair's intensity of negative emotions averaged in the prior three minutes subtracted by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.

Table Continued...

Meeting Characteristics and Other Variables	
Negative Tone	Negative Tone measures the tone of the words expressed by the Chairs in the prior three minutes, derived using the FinBERT NLP model Devlin et al. (2018) to capture the sentiment of each word and its context within the sentence.
Hawkishness	An indicator variable equal to 1 if the Chair's has expressed more hawkish words than dovish words in the prior three minutes, 0 otherwise. The identification of words as hawkish and dovish relies on the policy stance dictionary by Hansen and McMahon (2016).
Δ FFR	The change in the Federal Fund Rate (FFR) of the FOMC meeting, measured in basis points.
SPY Pre Drift	The *SPY* percent change in the 30 minutes proceeding the beginning of the FOMC press conference, measured in basis points.
VIX Pre Drift	The *VIX* percent change in the 30 minutes proceeding the beginning of the FOMC press conference, measured in basis points.
EURUSD Pre Drift	The *EURUSD* percent change in the 30 minutes proceeding the beginning of the FOMC press conference, measured in basis points.
MPU	The value of the Monetary Policy Uncertainty (MPU) index measured prior to the FOMC meeting as per Husted et al. (2020)
Market Conditions	The *SPY* percent change in the period between the Monday following the prior FOMC meeting and the Friday before the FOMC meeting of interest, measured in percentage points.
Media Coverage	The number of articles about the FOMC meeting appeared in the Wall Street Journal and New York Times the day before the FOMC meeting.
Press Statement Surprise	The absolute change in ZQ (30 Day Fed Fund Futures) occurred from 10 minutes before the FOMC Press Statement (1:50pm) and the beginning of the FOMC Press Conference (2:30pm), measured in basis points.
Status of Economy	An indicator variable equal to 1 if the Chair's has discussed the status of the economy for the majority of the time interval when *Negative Emotions* are estimated, 0 otherwise.
Forward Guidance	An indicator variable equal to 1 if the Chair's has discussed the forward guidance for the majority of the time interval when *Negative Emotions* are estimated, 0 otherwise.
Chair Tenure	The number of FOMC meetings chaired by the Chair at the time of the FOMC press conference.

Table 2: **Descriptive Statistics**

This table presents descriptive statistics. The sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. Panel A reports descriptive statistics on the dependent variables. Panel B reports descriptive statistics on the key independent variables. Meeting characteristics and other variables are reported in Panel C. Variable definitions are reported in Table 1.

Panel A: Dependent Variables

	N	Mean	Std	P25	P50	P75
%Δ SPY	2,518	0.006	10.764	-4.116	0.401	5.081
%Δ VIX	2,518	-2.093	105.124	-39.841	0.000	29.455
%Δ EURUSD	2,518	-0.174	6.159	-3.147	0.077	3.052
SPY Volume	2,518	0.447	0.361	0.212	0.338	0.559
EURUSD Volume	2,518	0.713	0.507	0.299	0.625	1.008

Panel B: Key Independent Variables

	N	Mean	Std	P25	P50	P75
Negative Emotions	2,518	0.944	1.060	0.225	0.533	1.196
Negative Emotions$_{pca}$	2,518	1.007	1.043	0.416	0.937	1.559
Negative Emotions$_{std}$	2,518	0.028	0.032	0.004	0.016	0.040
Negative Emotions$_{dmd}$	2,518	-0.000	0.014	-0.010	-0.002	0.002

Panel C: Meeting Characteristics and Other Variables

	N	Mean	Std	P25	P50	P75
Negative Tone	2,518	-0.054	0.275	-0.229	-0.042	0.109
Hawkishness	2,518	0.459	0.498	0.000	0.000	1.000
Δ FFR	2,518	1.122	19.066	0.000	0.000	0.000
SPY Pre Drift	2,518	10.975	41.414	-15.542	6.669	31.390
VIX Pre Drift	2,518	-122.330	385.964	-202.247	-91.093	31.990
EURUSD Pre Drift	2,518	3.479	37.110	-17.749	1.670	21.753
MPU	2,518	1.395	0.767	0.919	1.095	1.562
Market Conditions	2,518	0.190	0.369	0.006	0.123	0.379
Media Coverage	2,518	15.111	5.509	12.000	14.000	18.000
Press Statement Surprise	2,518	35.663	64.168	0.000	0.000	25.000
Status of Economy	2,518	0.124	0.330	0.000	0.000	0.000
Forward Guidance	2,518	0.174	0.379	0.000	0.000	0.000
Chair Tenure	2,518	8.429	4.779	4.000	8.000	12.000

Table 3: **Variable Correlations**

This table presents variable correlations. The sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. Panel A reports correlation between different dependent variables and our main measure of negative sentiment. Panel B reports correlations between different negative emotions measures and the sentiment measure. Variable definitions are reported in Table 1. p-values are presented in parentheses.

Panel A: Dependent Variables and Negative Emotions Correlation

	%Δ SPY	%Δ VIX	%Δ EURUSD	Negative Emotions
%Δ SPY	1.000			
%Δ VIX	-0.746	1.000		
	(0.000)			
%Δ EURUSD	0.275	-0.197	1.000	
	(0.000)	(0.000)		
Negative Emotions	-0.047	0.028	-0.040	1.000
	(0.018)	(0.155)	(0.044)	

Panel B: Negative Emotions and Sentiment Variables Correlation

	Negative Emotions	Negative Emotions_{pca}	Negative Emotions_{std}	Negative Emotions_{dmd}	Negative Tone	Hawkishness
Negative Emotions	1.000					
Negative Emotions_{pca}	0.416	1.000				
	(0.000)					
Negative Emotions_{std}	0.805	0.306	1.000			
	(0.000)	(0.000)				
Negative Emotions_{dmd}	0.875	0.364	0.850	1.000		
	(0.000)	(0.000)	(0.000)			
Negative Tone	0.026	0.004	0.060	0.047	1.000	
	(0.191)	(0.826)	(0.002)	(0.018)		
Hawkishness	-0.026	0.037	-0.043	-0.049	-0.196	1.000
	(0.184)	(0.062)	(0.031)	(0.015)	(0.000)	

Table 4: **Market Reactions and Negative Emotions**

This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. $\%\Delta$ *SPY*, $\%\Delta$ *VIX*, and $\%\Delta$ *EURUSD* are the percent changes evaluated in the three minutes following the measurement of the independent variables for *SPY*, *VIX*, and *EURUSD*. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. Δ *FFR* is the FOMC meeting change in the Federal Funds Rate (FFR). *SPY Pre Drift*, *VIX Pre Drift*, and *EURUSD Pre Drift* capture the percent changes in the 30 minutes proceeding the beginning of the FOMC press conference for the *SPY*, *VIX*, and *EURUSD*, respectively. *MPU* is the value of the Monetary Policy Uncertainty (MPU) index measured prior to the FOMC meeting as per Husted et al. (2020). *Market Conditions* is the *SPY* percent change in the period between the Monday following the prior FOMC meeting and the Friday before the FOMC meeting of interest. Specifications in column (2), (5), and (8) include Chair fixed effects. Specifications in column (3), (6), and (9) include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	%Δ SPY			%Δ VIX			%Δ EURUSD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Negative Emotions	-0.465^{***}	-0.499^{***}	-0.501^{***}	3.228	3.359^{*}	3.540	-0.261^{**}	-0.253^{**}	-0.173^{**}
	(0.000)	(0.000)	(0.000)	(0.122)	(0.097)	(0.101)	(0.022)	(0.021)	(0.017)
Negative Tone	0.059	0.092	-0.124^{***}	−4.744	−4.635	−3.142	−0.447	−0.445	−0.422
	(0.834)	(0.778)	(0.000)	(0.126)	(0.172)	(0.313)	(0.438)	(0.424)	(0.328)
Hawkishness	−0.344	−0.266	−0.253	2.386	2.096	2.076	-0.392^{**}	-0.407^{**}	-0.425^{**}
	(0.525)	(0.584)	(0.638)	(0.286)	(0.298)	(0.356)	(0.025)	(0.013)	(0.029)
Δ FFR	-0.032^{***}	-0.039^{***}		0.215	0.262		0.009^{**}	0.011^{***}	
	(0.000)	(0.002)		(0.237)	(0.273)		(0.031)	(0.000)	
SPY Pre Drift	0.023^{***}	0.022^{***}							
	(0.004)	(0.001)							
VIX Pre Drift				0.006	0.005				
				(0.145)	(0.178)				
EURUSD Pre Drift							0.009^{***}	0.010^{***}	
							(0.004)	(0.001)	
MPU	-0.518^{***}	0.072		1.590	0.194		0.287^{***}	0.193	
	(0.000)	(0.830)		(0.676)	(0.977)		(0.005)	(0.264)	
Market Conditions	−0.519	0.252		5.093	2.362		0.230	0.082	
	(0.683)	(0.831)		(0.562)	(0.796)		(0.725)	(0.920)	
Chair FE	No	Yes	No	No	Yes	No	No	Yes	No
Meeting FE	No	No	Yes	No	No	Yes	No	No	Yes
N	2,518	2,518	2,518	2,518	2,518	2,518	2,518	2,518	2,518
Adj R^2	0.012	0.017	0.051	0.001	0.001	0.021	0.005	0.005	0.038

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: **Trading Volumes and Negative Emotions**

This table reports coefficients from OLS regressions of changes in the trading volume of the stock, currency and treasury markets on Chairs' negative emotions and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *SPY Volume*, and *EURUSD Volume* are the percent changes in average trading volumes evaluated in the three minutes following the measurement of the independent variables for *SPY*, and *EURUSD*, respectively. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. All specifications include Meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	(1) SPY Volume	(2) EURUSD Volume
Negative Emotions	-0.012^{**}	-0.006
	(0.023)	(0.294)
Negative Tone	-0.023	-0.106^{***}
	(0.171)	(0.000)
Hawkishness	0.029^{***}	0.050^{***}
	(0.004)	(0.000)
Meeting FE	Yes	Yes
N	2,518	2,518
Adj R^2	0.567	0.620

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: **Meeting Attention, Press Statement Surprise and Negative Emotions**
This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions, meeting attention measures and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *%Δ SPY*, *%Δ VIX*, and *%Δ EURUSD* are the percent changes evaluated in the three minutes following the measurement of the independent variables for *SPY*, *VIX*, and *EURUSD*, respectively. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. *Media Coverage* represents the number of articles about the FOMC meeting appeared in the Wall Street Journal and New York Times the day before the FOMC meeting. *Press Statement Surprise* is the absolute change in ZQ (30 Day Fed Fund Futures) that occurred from 10 minutes before the FOMC Press Statement (1:50pm) to the beginning of the FOMC Press Conference (2:30pm). Panel A presents results on *Negative Emotions* interactions with the *Media Coverage* measure. Panel B presents results on *Negative Emotions* interactions with the *Press Statement Surprise* measure. All specifications include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

Panel A: Media Attention

	(1) %Δ SPY	(2) %Δ VIX	(3) %Δ EURUSD
Negative Emotions	0.904***	−2.909	0.509*
	(0.004)	(0.574)	(0.076)
Media Coverage * Negative Emotions	−0.090***	0.413	−0.044**
	(0.000)	(0.372)	(0.043)
Negative Tone	−0.102**	−3.245	−0.411
	(0.039)	(0.288)	(0.336)
Hawkishness	−0.308	2.330	−0.452**
	(0.552)	(0.270)	(0.024)
Meeting FE	Yes	Yes	Yes
N	2,518	2,518	2,518
Adj R^2	0.053	0.021	0.040

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Press Statement Surprise

	(1) %Δ SPY	(2) %Δ VIX	(3) %Δ EURUSD
Negative Emotions	−0.079	−2.278	−0.197*
	(0.841)	(0.585)	(0.084)
Press Statement Surprise * Negative Emotions	−0.015**	0.202**	0.001
	(0.045)	(0.032)	(0.552)
Negative Tone	−0.094***	−3.556	−0.424
	(0.000)	(0.246)	(0.327)
Hawkishness	−0.306	2.799	−0.422**
	(0.514)	(0.195)	(0.024)
Meeting FE	Yes	Yes	Yes
N	2,518	2,518	2,518
Adj R^2	0.056	0.033	0.038

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: **Written Tone, Discussion Theme, and Negative Emotions**
This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions, meeting attention measures and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *%Δ SPY*, *%Δ VIX*, and *%Δ EURUSD* are the percent changes evaluated in the three minutes following the measurement of the independent variables for *SPY*, *VIX*, and *EURUSD*, respectively. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. *Status of Economy* is an indicator variable equal to 1 if the Chair's has discussed the status of the economy for the majority of the time interval when *Negative Emotions* are estimated, 0 otherwise. *Forward Guidance* is an indicator variable equal to 1 if the Chair's has discussed the forward guidance for the majority of the time interval when *Negative Emotions* are estimated, 0 otherwise. Panel A presents results on *Negative Emotions* interactions with the *Negative Tone* measure. Panel B presents results on *Negative Emotions* interactions with discussion theme measures. All specifications include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

Panel A: Written Tone

	(1) %Δ SPY	(2) %Δ VIX	(3) %Δ EURUSD
Negative Emotions	−0.019	−0.091	−0.166
	(0.944)	(0.977)	(0.299)
Negative Tone	0.981	−15.569*	0.472
	(0.294)	(0.092)	(0.514)
Negative Tone * Negative Emotions	−1.301*	14.495*	−1.023**
	(0.089)	(0.051)	(0.050)
Hawkishness	0.871	−6.952	−0.289
	(0.135)	(0.211)	(0.396)
Hawkishness * Negative Emotions	−1.213***	9.817**	−0.163
	(0.004)	(0.015)	(0.476)
Meeting FE	Yes	Yes	Yes
N	2,518	2,518	2,518
Adj R^2	0.053	0.023	0.040

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Discussion Theme

	(1) %Δ SPY	(2) %Δ VIX	(3) %Δ EURUSD
Negative Emotions	−0.078	0.750	−0.018
	(0.134)	(0.825)	(0.763)
Negative Tone	−0.320	−0.952	−0.507
	(0.148)	(0.851)	(0.171)
Hawkishness	−0.287	2.155	−0.389*
	(0.594)	(0.318)	(0.054)
Status of Economy	1.437	−8.468	−0.202
	(0.177)	(0.144)	(0.642)
Status of Economy * Negative Emotions	−0.537*	2.894	−0.409
	(0.078)	(0.677)	(0.161)
Forward Guidance	0.935	−1.190	0.347
	(0.274)	(0.854)	(0.595)
Forward Guidance * Negative Emotions	−1.902***	13.213*	−0.702***
	(0.003)	(0.065)	(0.008)
Meeting FE	Yes	Yes	Yes
N	2,518	2,518	2,518
Adj R^2	0.056	0.024	0.040

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: **FOMC Minutes and Negative Emotions**

This table reports coefficients from OLS regressions of FOMC Meeting Minutes' negative tone and hawkishness on Chairs' negative emotions during the press conference, and control variables. The estimation sample includes 46 observations at the meeting level from FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *FOMC Minutes Negative Tone* measures the tone of the words in the FOMC meeting minutes. *FOMC Minutes Hawkishness* measures the stance (hawkish or dovish) of the words in the FOMC meeting minutes. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over press conference. *Negative Tone* measures the tone of the words expressed by the Chairs averaged over the press conference. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs averaged over the press conference. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	FOMC Minutes Negative Tone		FOMC Minutes Hawkishness	
	(1)	(2)	(3)	(4)
Negative Emotions$_{avg}$	0.001**	0.001*	−0.021	−0.016
	(0.046)	(0.072)	(0.363)	(0.458)
Negative Tone$_{avg}$	−0.003	−0.004	−0.197	−0.188
	(0.576)	(0.383)	(0.279)	(0.265)
Hawkishness$_{avg}$	−0.003	−0.002	0.292***	0.280***
	(0.349)	(0.351)	(0.009)	(0.007)
Chair FE	No	Yes	No	Yes
N	46	46	46	46
Adj R^2	0.049	0.334	0.203	0.323

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: **Chair Tenure and Negative Emotions**

This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions, meeting attention measures and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *%Δ SPY*, *%Δ VIX*, and *%Δ EURUSD* are the percent changes evaluated in the three minutes following the measurement of the independent variables for *SPY*, *VIX*, and *EURUSD*, respectively. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. *Chair Tenure* is the number of FOMC meetings chaired by the Chair at the time of the FOMC press conference. All specifications include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	(1) %Δ SPY	(2) %Δ VIX	(3) %Δ EURUSD
Negative Emotions	0.186	1.877	0.044
	(0.677)	(0.643)	(0.847)
Chair Tenure * Negative Emotions	−0.092*	0.222	−0.029
	(0.066)	(0.589)	(0.223)
Negative Tone	−0.023	−3.388	−0.390
	(0.975)	(0.632)	(0.494)
Hawkishness	−0.262	2.098	−0.428*
	(0.556)	(0.639)	(0.088)
Meeting FE	Yes	Yes	Yes
N	2,518	2,518	2,518
Adj R^2	0.051	0.021	0.038

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 10: **Return Reversal and Negative Emotions**

This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. $\%\Delta^{t_1-t_2}$ *SPY*, $\%\Delta^{t_1-t_2}$ *VIX*, and $\%\Delta^{t_1-t_2}$ *EURUSD* are the percent changes for *SPY*, *VIX*, and *EURUSD*, from minute t_1 to minute t_2 respectively following the measurement of the independent variables. In column (1), (4), and (7) the percent changes are measured over the two minutes starting from the third minute following the measurement of the independent variables. In column (2), (5), and (8) the percent changes are measured over the seven minutes starting from the third minute following the measurement of the independent variables. In column (3), (6), and (9) the percent changes are measured over the ten minutes starting from the fifth minute following the measurement of the independent variables. *Negative Emotions* measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. All specifications include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	SPY			VIX			FX		
	(1) $\%\Delta^{3-5}$	(2) $\%\Delta^{3-10}$	(3) $\%\Delta^{5-15}$	(4) $\%\Delta^{3-5}$	(5) $\%\Delta^{3-10}$	(6) $\%\Delta^{5-15}$	(7) $\%\Delta^{3-5}$	(8) $\%\Delta^{3-10}$	(9) $\%\Delta^{5-15}$
Negative Emotions	−0.212	0.064	0.112	2.178	−1.095	1.736	0.195	0.354	0.178
	(0.190)	(0.863)	(0.884)	(0.354)	(0.771)	(0.842)	(0.138)	(0.225)	(0.208)
Negative Tone	1.100***	2.136*	3.034	−14.449***	−28.808**	−34.673*	0.130	−0.667	−2.852**
	(0.000)	(0.072)	(0.331)	(0.000)	(0.012)	(0.054)	(0.821)	(0.740)	(0.031)
Hawkishness	0.578	0.654	0.070	−0.998	1.559	3.831	−0.182	0.230**	−0.229
	(0.454)	(0.322)	(0.952)	(0.905)	(0.809)	(0.792)	(0.130)	(0.040)	(0.635)
Meeting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,518	2,518	2,518	2,518	2,518	2,517	2,518	2,518	2,518
Adj R^2	0.028	0.122	0.168	0.006	0.068	0.097	0.022	0.127	0.193

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

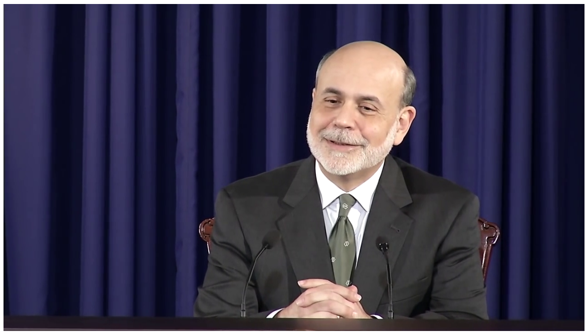
Table 11: **Alternative Measures of Negative Emotions**

This table reports coefficients from OLS regressions of changes in the stock, currency and treasury markets on Chairs' negative emotions and control variables. The estimation sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020. *%Δ SPY*, *%Δ VIX*, and *%Δ EURUSD* are the percent changes evaluated in the three minutes following the measurement of the independent variables for *SPY*, *VIX*, and *EURUSD*, respectively. $Negative\ Emotions_{pca}$ measures the Chairs' intensity of negative emotions averaged over the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair using all seven emotions, captured by the Microsoft Azure Cognitive Services Emotion API, multiplied by the coefficient of the principal component. $Negative\ Emotions_{std}$ measures standard deviation of the Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. $Negative\ Emotions_{dmd}$ measures the intensity of negative emotions averaged in the prior three minutes subtracted by the average intensity of negative emotions across all FOMC meetings presided by the Chair. *Negative Tone* measures the tone of the words expressed by the Chairs in the prior three minutes. *Hawkishness* measures the stance (hawkish or dovish) of the words expressed by the Chairs in the prior three minutes. Panel A reports regressions using measures from the stock market. Panel B reports regression from the FX and Treasury markets. All specifications include meeting fixed effects. Standard errors are clustered at the Chair level. Variables definitions are reported in Table 1. p-values are presented in parentheses.

	%Δ SPY			%Δ VIX			%Δ EURUSD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Negative Emotions_{pca}	-0.583^{**}			4.362			-0.192		
	(0.014)			(0.143)			(0.150)		
Negative Emotions_{std}		-15.219^{**}			75.134^{**}			-10.684^{***}	
		(0.032)			(0.038)			(0.000)	
Negative Emotions_{dmd}			-33.954^{***}			281.338			-19.831^{***}
			(0.000)			(0.133)			(0.000)
Negative Tone	-0.128	-0.097^{***}	-0.099^{**}	-3.121	-3.253	-3.363	-0.423	-0.399	-0.405
	(0.182)	(0.000)	(0.013)	(0.205)	(0.307)	(0.299)	(0.341)	(0.359)	(0.333)
Hawkishness	-0.203	-0.260	-0.267	1.703	2.095	2.204	-0.408^{**}	-0.433^{**}	-0.435^{**}
	(0.707)	(0.635)	(0.618)	(0.452)	(0.348)	(0.302)	(0.039)	(0.032)	(0.035)
Meeting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,518	2,518	2,518	2,518	2,518	2,518	2,518	2,518	2,518
Adj R^2	0.052	0.050	0.050	0.022	0.020	0.021	0.039	0.040	0.039

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix A: Emotion Intensity Scores



Panel A: Ben Bernanke, March 20^{th} 2013	
Emotion	Intensity Score
Anger	0.00
Contempt	0.00
Disgust	0.00
Fear	0.00
Happiness	1.00
Neutral	0.00
Sadness	0.00
Surprise	0.00

Panel B: Janet Yellen, December 14^{th} 2016	
Emotion	Intensity Score
Anger	0.02
Contempt	0.00
Disgust	0.00
Fear	0.00
Happiness	0.00
Neutral	0.98
Sadness	0.00
Surprise	0.00

Panel C: Jerome Powell, January 30^{th} 2019	
Emotion	Intensity Score
Anger	0.00
Contempt	0.05
Disgust	0.00
Fear	0.00
Happiness	0.00
Neutral	0.04
Sadness	0.91
Surprise	0.00

Figure A1: **Emotion Intensity Scores**
This figure presents emotion intensity scores as captured by the Microsoft Azure Cognitive Services Emotion API. Panel A shows Ben Bernanke during the FOMC press conference held on March 20^{th}, 2013, Panel B shows Janet Yellen during the FOMC press conference held on December 14^{th}, 2016, and Panel C shows Jerome Powell during the FOMC press conference held on January 30^{th}, 2019.

Appendix B: Statement Excerpts

In this appendix we provide examples of three categories of statements tagged in different ways. Each excerpts is tagged either as *Status of Economy*, *Forward Guidance* or *Other*.

1. Status of Economy

1.1. April 11th 2011

5 minutes, 41 seconds into the press conference, part of the opening statement:

"I turn now to the Committees economic outlook. As indicated in todays policy statement, the Committee sees the economic recovery as proceeding at a moderate pace. Household spending and investment in equipment and software continue to expand, supporting the recovery, but nonresidential investment is still weak and the housing sector is depressed. In the labor market, overall conditions continue to improve gradually. For example, the unemployment rate moved down a bit further and payroll employment increased in March; new claims for unemployment insurance and indicators of hiring plans are also consistent with continued improvement."

1.2. September 17th 2015

15 minutes, 42 seconds into the press conference, journalist question:

"Mr. Chairman, first, thanks for doing this. This is a tremendous development. There are critics who say that Fed policy has driven down the value of the dollar, and a lower value to the dollar reduces Americans standard of living. How do you respond to the criticism that, essentially, Fed policy has reduced Americans standard of living?"

1.3. June 13th 2018

22 minutes, 27 seconds into the press conference, journalist question:

"Hi, Chair Powell. Heather Long from the Washington Post. Can you give us an update on what the FOMC thinks about wages? Are we finally going to see that wage growth pickup this year? I know you're forecasting a little bit more inflation, but is that going to translate through to wage growth?"

24 minutes, 08 seconds into the press conference, Chair's answer:

"You know, wages have been gradually moving up. Earlier in the recovery, they were there are many different wage measures, of course, but so just but just to generalize, wages were running roughly around 2 percent and they've moved gradually up into between 2 to 3 percent as the labor market has become stronger and stronger. I think its fair to say that some of us and I certainly would have expected wages to react more to the very significant reduction in unemployment that weve had, as I mentioned, from 10 percent to 3.8 percent. Part of that can be explained by low productivity, which is something weve talked about at the Committee and elsewhere. But, nonetheless, I think we had anticipated, and many people have anticipated, that wages that in a world where were hearing lots and lots about labor shortages everywhere we go now, we hear about labor shortages but where is the wage reaction? So it's a bit of a puzzle. I wouldn't say its a mystery, but it's a bit of a puzzle. And, frankly, I do think

theres a lot to like about low unemployment. And one of the things isyou will see pretty much people who want to get jobs not everybody but people who want to get jobs, many of them will be able to get jobs. You will see wages go up. You'll see people at the, sort of, the margins of the labor force having an opportunity to get back in work. They benefit from that. Society benefits from that. So there are a lot of things to really like, including higher wages, as you asked. Our role, though, is also to, you know, to make sure that maximum employment happens in a context of price stability and financial stability, which is why we're gradually raising rates."

2. Forward Guidance

2.1. June 22nd 2011

8 minutes, 28 seconds into the press conference, journalist question:

"Jon Hilsenrath from the Wall Street Journal. Mr. Chairman, the FOMC says that it will maintain short-term interest rates at an exceptionally low level for an extended period. Does that policy or, does that guidance also apply for the Feds securities holdings? In other words, will they be maintained at a very high level for an extended period?"

8 minutes, 58 seconds into the press conference, Chair's answer:

"We haven't made any such commitment. It's true that when we begin to allow the portfolio to run off rather than reinvesting, that would be a first step in a process of exiting from our currently highly accommodative policies. But weve not yet chosen to make any particular commitment about the time frame. But well be looking at the outlook and trying to assess when the appropriate time is to take that step."

2.2. December 16th 2015

26 minutes, 6 seconds into the press conference, journalist question:

"Chair Yellen, Jon Hilsenrath from the Wall Street Journal. In the sentence in your statement about gradual increases, in that section, the Committee says that it will carefully monitor progress actual and expected progress on inflation. Thats going to read like some kind of code to a lot of people on Wall Street. Can you describe, what do you mean when you say carefully monitor? And, specifically, with regard to what you do next, do you need to see inflation actually rise at this point in order to raise interest rates again?"

28 minutes, 9 seconds into the press conference, Chair's answer:

"Well, we recognize that inflation is well below our 2 percent goal. The entire Committee is committed to achieving our 2 percent inflation objective over the medium term, just as we want to make sure that inflation doesn't persist at levels above our 2 percent objective. The Committee is equally committed, this is a symmetric goal, and the Committee is equally committed to not allowing inflation to persist below our 2 percent objective. Now, Ive tried to explain, and many of my colleagues have as well, why we have reasonable confidence that inflation will move up over time, and the Committee declared it had reasonable confidence. Nevertheless, that is a forecast, and we really need to monitor over time actual inflation performance to make sure that it is conforming, it is evolving, in the manner that we expect. So it doesn't mean that we need to see inflation reach 2 percent before moving again, but

we have expectations for how inflation will behave. And were we to find that the underlying theory is not bearing out, that it is not behaving in the manner that we expect, and that it doesn't look like the shortfall is transitory and disappearing with tighter labor markets, that would certainly give us pause. And we have indicated that we're reasonably close, not quite there, but reasonably closeto achieving our maximum employment objective, but we have a significant shortfall on inflation. And so were calling attention to the importance of verifying our that things evolve in line with our forecasts."

2.3. March 21st 2018

16 minutes, 50 seconds into the press conference, journalist question:

"Adam Shapiro with the Fox Business Network. You brought up the fiscal stimulus and the impact it's having, and I was curious, how is the change in the federal budget deficit, because the stimulus is coming with great debt, has it changed your approach to how many securities you're going to allow to roll off the balance sheet, and is there a level of Treasury supply at which the Fed would consider adjusting its balance sheet roll-off, given how much the U.S. governments going to have to borrow going forward? And, then a second question, things beyond your control, the President is expected to announce new tariffs against China, and does the Committee discuss what potential impacts that could have in regards to inflation? And do you have a timeline as to how you would respond to that?"

17 minutes, 17 seconds into the press conference, Chair's answer:

"So, in terms of the balance sheet, we've said that, you know, we carefully developed this plan. We carefully socialized it in a series of meetings last year. We announced it, and we said we wouldn't change it, really, unless there were a significant downturn that required, you know, meaningful reductions in interest rates. And I have no inclination to revisit that. We're going to use monetary policy as the principle tool of adjusting, you know, our policy."

3. Other

3.1. January 25th 2012

0 minutes, 43 seconds into the press conference, part of opening statement:

"In my opening remarks I will briefly review today's policy decision by the Federal Open Market Committee. And then I'll discuss next the consensus statement that has been distributed to you regarding the Committee's longer-run policy goals and strategy. And finally, I'll place today's policy decision in the context of our economic projections and our assessments of the appropriate path of monetary policy. And Ill then, of course, be glad to take your questions."

3.2. January 25th 2012

27 minutes, 35 seconds into the press conference, journalist question:

"Greg Robb, MarketWatch. Mr. Chairman, thank you. You haven't had a very good time in all the Republican presidential debates, and I was wondering if I could have your comment on what you've heard. And some of the analysts I talked to said that one of the reasons for this hostility, perhaps, is that a lot of the Republican primary voters are on fixed incomes

and have an inability to invest and make money with their funds. So could you talk to them as well? And one more thing, if Republicans take back the White House in November and ask you to resign, would you?"

28 minutes, 01 seconds into the press conference, Chair's answer:

"So I'm not going to get involved in political rhetoric. I'm just going to stay completely away from that. I have a job to do, and as long as I'm here, I will do everything I can to help the Federal Reserve achieve its dual mandate of price stability and maximum employment. That's my answer to the last part as well. I'm not going to be thinking about hypothetical situations in the future."

3.3. March 21st 2018

32 minutes, 58 seconds into the press conference, journalist question:

"Hi. Victoria Guida with Politico. More on the regulatory side, you know, the Fed might soon be getting more power to decide exactly which regulations, which stricter regulations to apply to banks with between 100 and 250 billion in assets. And so I had a couple of questions about that. So, for CCAR, those stress tests, since thats based around, you know, having a punitive penalty of potentially being able to restrict dividend payouts or stock buybacks, is there any kind of logistical challenge that could be posed if you dont have CCAR every year for certain banks? Is it possible to have CCAR not on an annual basis? And then, my other question is, you know, you've talked a lot about how size isnt the only thing that causes banks to pose systemic risk, and I was wondering, what other factors do you think would cause a bank to potentially pose a systemic risk?"

34 minutes, 01 seconds into the press conference, Chair's answer:

"Okay. So, this is a matter that Congress has under consideration. It's not something – so Congress is looking at raising the threshold for applying enhanced financial standards to – from 50 billion to 250 billion, while leaving us with the ability to reach below 250 billion and apply those standards where we think it's appropriate. And, you know, we havent been shy about doing that, because, of course, one of the eight SIFIs is below 250 already. So we are fully prepared to do that. But this is a decision that's in the hands of Congress. It's not something thats been taken. The version of the bill, I think, that passed the Senate did have, did give us the ability to do supervisory stress tests periodically, as opposed to annually, is the language. We haven't made any decision about that at all. We would want to think very carefully about that, and, you know, we would, whatever we do decide to do, we'd put that out for comment. Is it, you know, logistically possible? I would think it would be, but it's certainly not something that we've decided to do. And the second question you had was?"

Appendix C: FOMC Meetings

Table C1: **List of Scored FOMC Meetings**

This table presents the average scores of *Negative Emotions*, *Negative Tone*, Δ *FFR* for each meeting in our sample as well as the meeting type. The sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27^{th}, 2011 and September 16^{th}, 2020.

Date	Chair	Δ FFR	Negative Emotions	Negative Tone	Hawkishness	Type
April 27, 2011	Ben Bernanke	0	0.732	-0.109	0.081	Scheduled
June 22, 2011	Ben Bernanke	0	1.067	-0.093	0.069	Scheduled
November 2nd, 2011	Ben Bernanke	0	0.994	-0.067	0.099	Scheduled
January 25, 2012	Ben Bernanke	0	0.824	-0.131	0.132	Scheduled
April 25, 2012	Ben Bernanke	0	0.743	-0.129	0.099	Scheduled
June 20, 2012	Ben Bernanke	0	0.706	-0.067	0.110	Scheduled
September 13, 2012	Ben Bernanke	0	0.711	-0.128	0.138	Scheduled
December 12, 2012	Ben Bernanke	0	0.790	-0.129	0.115	Scheduled
March 20, 2013	Ben Bernanke	0	0.454	-0.009	0.072	Scheduled
June 19, 2013	Ben Bernanke	0	1.178	-0.111	0.110	Scheduled
September 18, 2013	Ben Bernanke	0	0.710	-0.098	0.124	Scheduled
December 18, 2013	Ben Bernanke	0	0.933	-0.098	0.117	Scheduled
March 19, 2014	Janet Yellen	0	1.206	-0.023	0.082	Scheduled
June 18, 2014	Janet Yellen	0	0.910	-0.065	0.104	Scheduled
September 17, 2014	Janet Yellen	0	2.342	0.013	0.102	Scheduled
December 17, 2014	Janet Yellen	0	1.169	-0.059	0.117	Scheduled
March 18, 2015	Janet Yellen	0	2.544	-0.017	0.086	Scheduled
June 17, 2015	Janet Yellen	0	0.692	-0.222	0.085	Scheduled
September 17, 2015	Janet Yellen	25	1.006	0.038	0.078	Scheduled
December 16, 2015	Janet Yellen	0	0.727	-0.078	0.064	Scheduled
March 16, 2016	Janet Yellen	0	0.592	-0.176	0.071	Scheduled
June 15, 2016	Janet Yellen	0	0.474	0.087	0.064	Scheduled
September 21, 2016	Janet Yellen	0	0.741	-0.047	0.090	Scheduled
December 14, 2016	Janet Yellen	25	1.303	-0.227	0.083	Scheduled
March 15, 2017	Janet Yellen	25	0.441	-0.229	0.122	Scheduled
June 14, 2017	Janet Yellen	25	0.351	-0.036	0.095	Scheduled
September 20, 2017	Janet Yellen	0	0.522	0.001	0.075	Scheduled
December 13, 2017	Janet Yellen	25	0.880	-0.138	0.083	Scheduled
March 21, 2018	Jerome Powell	25	1.511	-0.080	0.050	Scheduled
June 13, 2018	Jerome Powell	25	0.821	-0.084	0.072	Scheduled
September 26, 2018	Jerome Powell	25	0.605	-0.079	0.105	Scheduled
December 19, 2018	Jerome Powell	25	1.298	-0.084	0.100	Scheduled
January 30, 2019	Jerome Powell	0	1.332	-0.074	0.112	Scheduled
March 20, 2019	Jerome Powell	0	0.643	-0.050	0.099	Scheduled
May 01, 2019	Jerome Powell	0	0.755	-0.216	0.099	Scheduled
June 19, 2019	Jerome Powell	0	1.528	-0.002	0.086	Scheduled
July 31, 2019	Jerome Powell	-25	1.534	-0.133	0.084	Scheduled
September 18, 2019	Jerome Powell	-25	1.642	-0.078	0.100	Scheduled
October 30, 2019	Jerome Powell	-25	0.865	-0.077	0.114	Scheduled
December 11, 2019	Jerome Powell	0	1.533	0.029	0.080	Scheduled
January 29, 2020	Jerome Powell	0	1.282	-0.151	0.127	Scheduled
March 03, 2020	Jerome Powell	-50	2.485	-0.144	0.113	Unscheduled
April 29, 2020	Jerome Powell	0	0.580	-0.003	0.067	Scheduled
June 10, 2020	Jerome Powell	0	0.294	0.014	0.079	Scheduled
July 29, 2020	Jerome Powell	0	0.663	-0.026	0.091	Scheduled
September 16, 2020	Jerome Powell	0	0.170	-0.185	0.136	Scheduled

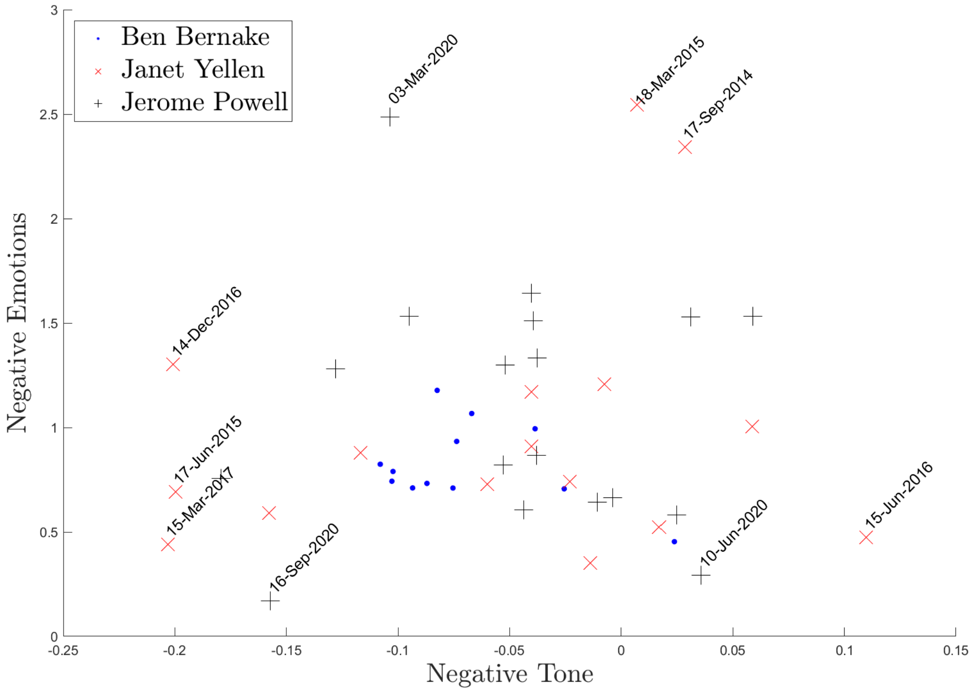


Figure D1: **Meetings' Negative Emotions and Tone**
This figure presents the average negative emotions and average negative tone for each meeting in our sample. The sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 26^{th}, 2011 and September 16^{th}, 2020.

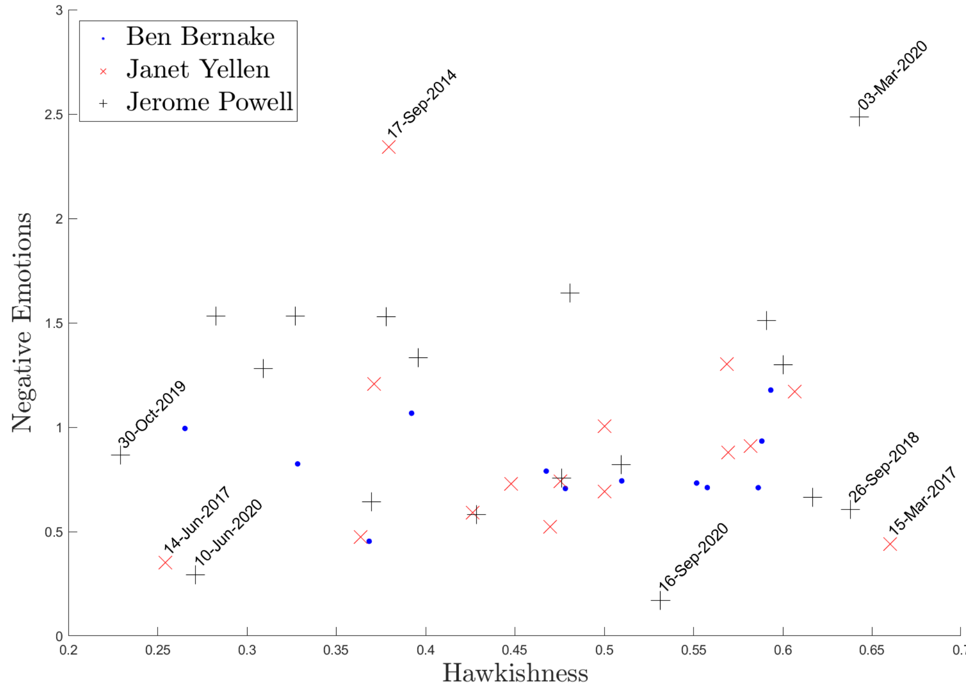


Figure E1: **Meetings' Negative Emotions and Hawkishness**
This figure presents the average negative emotions and average hawkishness for each meeting in our sample. The sample includes 2,518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 26^{th}, 2011 and September 16^{th}, 2020.