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Let's face it: Quantifying the impact of nonverbal communication in FOMC press conferences ☆

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ABSTRACT

When the Fed Chair speaks, investors not only listen, but also watch. To demonstrate this phenomenon, 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, even when controlling for the verbal component of the press conference and other explanatory variables.

1. Introduction

"...In the 1920s, the Governor's "eyebrows" famously became one of the Bank's 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

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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.[1] Conceptually, these changes 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 study, we examine the financial market's response to the nonverbal aspect of central bank communication. We use FOMC press conference videos to identify and quantify facial expressions of Fed Chairmen using facial recognition technology and machine learning algorithms. This way we capture the nonverbal cues alongside verbal messages, allowing us 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. (2023) 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. (2023) 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 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. 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. 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.

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 facial expressions.[2]

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 that 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.[4] 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.

[1] 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.

[2] Moreover, there is some anecdotal evidence that supports this reasoning. For example, according to MarketWatch.com, there are hedge funds already studying Jerome Powell's facial expressions and their impact on markets. See, for example: Goldstein (2018). Hedge funds are studying Jerome Powell's 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"".

[4] Our sample includes all of the existing post-FOMC press conferences, up to and including the one on September 16th 2020.

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 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 discussed, and when the tone of the discussion is more negative. We also note that display of negative facial expressions lowers trading volume in the subsequent three minute interval.[5]

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 equities (SPY index) during a given three minutes interval. The economic significance applies to the other asset classes too: the implied volatility index increases by 3.76 basis points and the Euro to US Dollar exchange rate decreases by 0.18 basis points.[6] These impacts are evaluated on a three-minute interval and can become substantial if the Chair displays negative

I will do my best to communicate the points that have been made here. END OF MEETING"" emotions for several minutes combined during a press conference. Finally, we explore possible explanations for our findings. We find some 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.

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, and Section 6 concludes.

2. Literature review

2.1. FOMC press conferences

The FOMC Committee holds eight scheduled meetings annually to discuss current and future monetary policy actions. Post-FOMC statements, which began in 1994, have been released after every meeting since May 1999, specifying target levels for the federal funds rate. After the federal funds rate hit its effective lower bound in December 2008, the importance of these statements grew. To enhance transparency, the then Chairman Ben Bernanke initiated press conferences after select meetings, and since 2019, every FOMC meeting has been followed by a press conference.

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.[7] 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 (e.g., 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 (e.g., 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)).

[5] Our results are robust to several alternative fixed effects specifications, as well as alternative approaches to capturing press conference content. We consider a number of alternative specifications that capture Chairs' negative facial expressions, and find that the adverse effect of Chairs' negative emotions on the markets increases at the extremes. We also show that the adverse effect of Chairs' negative emotions on the markets is not a function of how we construct the emotion based measure.

[6] For facial expressions above the 90th (99th) quantile of the aggregate distribution, a one standard deviation in the score is associated with a 1.11 (1.72) basis point change in SPY.

[7] We provide a detailed description of our data cleaning process in the Online Appendix.

The existing literature in finance applies this theory of human behavior to analyze nonverbal communication and its impact on market outcomes. Mayew and Venkatachalam (2012) examine the response of the capital market to manager's 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. (2017) develop a composite measure of investor perception using 30 s 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. Akansu et al. (2017) show that CEO displays of disgust or anger during media interviews lead to increased profit margins, sales growth, and return on assets, while expressions of happiness result in decreased profit margins, return on equity, and return on assets. Breaban and Noussair (2018) analyze facial expressions of traders and link expressed fear to negative movements in a firm's stock price, and positive emotional state with purchases and overpricing. Choudhury et al. (2019) analyze videos and transcripts of interviews with emerging market CEOs to identify distinct communication styles, incorporating both verbal and nonverbal elements, and examine their relationship with firms' mergers and acquisitions outcomes. Momtaz (2019) investigates the effect of CEOs' nonverbal communication on firm valuation during blockchain-based capital raising, revealing that negative emotions correlate with reduced underpricing deviations, while positive emotions have no significant impact. Mathur et al. (2022) construct a collection of public conference call videos, audio, and text for a set of central banks, and empirically demonstrate the potential benefits of integrating visual cues alongside audio and textual data for financial predictions.

The paper closest in methodology to ours is by Hu and Ma (2021). The authors employ machine learning algorithms to analyze visual, vocal, and verbal features from entrepreneur pitch videos, utilizing Face++ API and Microsoft Azure Cognitive Services for emotion scoring. They find that positivity across all dimensions boosts funding likelihood, even for low-quality startups.

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 section.

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 min) 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. Detailed definitions of these variables are listed in Table 1.

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.[8]

- 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.

[8] 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.

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.
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. *Negative Emotions*$_{pca}$ is a combination of the seven intensity scores (anger, contempt, disgust, fear, happiness, sadness, and surprise), captured by the Microsoft Azure Emotion API, and 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.
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.
...	
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	Hawkishness measures the stance of the words expressed by the Chairs in the prior three minutes, based on classification conducted using GPT-3 language model with embeddings.
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 min proceeding the beginning of the FOMC press conference, measured in basis points.
VIX Pre Drift	The *VIX* percent change in the 30 min proceeding the beginning of the FOMC press conference, measured in basis points.
EURUSD Pre Drift	The *EURUSD* percent change in the 30 min 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 minus the full sample average of articles about the FOMC 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.

Based on the above data we calculate percent changes within 3 min intervals in SPY, VIX, and FX prices, all measured in basis points. We calculate the average trading volume within 3 min 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.

The average price change for SPY over the course of 3 min 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 min 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 (e.g., 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.

Table 2
Descriptive Statistics. This table presents descriptive statistics. The sample includes 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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	2518	0.006	10.764	−4.116	0.401	5.081
%Δ VIX	2518	−2.093	105.124	−39.841	0.000	29.455
%Δ EURUSD	2518	−0.174	6.159	−3.147	0.077	3.052
%Δ ZN10	2518	0.085	4.058	−1.388	0.000	2.489
SPY Volume	2518	0.447	0.361	0.212	0.338	0.559
EURUSD Volume	2518	0.713	0.507	0.299	0.625	1.008
ZN10 Volume	2518	4.619	4.881	1.776	3.303	6.068
Panel B: Key Independent Variables						
	N	Mean	Std	P25	P50	P75
Negative Emotions	2518	0.944	1.060	0.225	0.533	1.196
Negative Emotions_{pca}	2518	1.007	1.043	0.416	0.937	1.559
Negative Emotions_{std}	2518	0.028	0.032	0.004	0.016	0.040
Negative Emotions_{dmd}	2518	−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	2518	−0.001	0.005	−0.003	−0.000	0.002
Hawkishness	2518	0.801	0.754	0.333	0.667	1.333
Δ FFR	2518	1.122	19.066	0.000	0.000	0.000
SPY Pre Drift	2518	10.975	41.414	−15.542	6.669	31.390
VIX Pre Drift	2518	−122.330	385.964	−202.247	−91.093	31.990
EURUSD Pre Drift	2518	3.479	37.110	−17.749	1.670	21.753
ZN10 Pre Drift	2518	5.489	27.639	−8.054	4.797	15.308
MPU	2518	1.395	0.767	0.919	1.095	1.562
Market Conditions	2518	0.190	0.369	0.006	0.123	0.379
Media Coverage	2518	15.111	5.509	12.000	14.000	18.000
Press Statement Surprise	2518	35.663	64.168	0.000	0.000	25.000
Status of Economy	2518	0.124	0.330	0.000	0.000	0.000
Forward Guidance	2518	0.174	0.379	0.000	0.000	0.000
Chair Tenure	2518	8.429	4.779	4.000	8.000	12.000

We rely on these advancements to capture nonverbal communication component in a standardized and dynamic fashion. We adopt an implementation of Microsoft Azure Cognitive Services Emotion API.[9] The underlying algorithm is trained, tested, and cross-checked by reputable providers using millions of human-rated training observations.[10] 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 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 employs a state-of-the-art convolutional neural network (CNN) to transform input images into weighted pixels, generate specific parameters like open mouth, contracted eyebrows, and smile width, and produce output values. The weights are optimized by minimizing a loss function, which measures the error between output values of facial expressions from input images and those with existing labels in the training set.

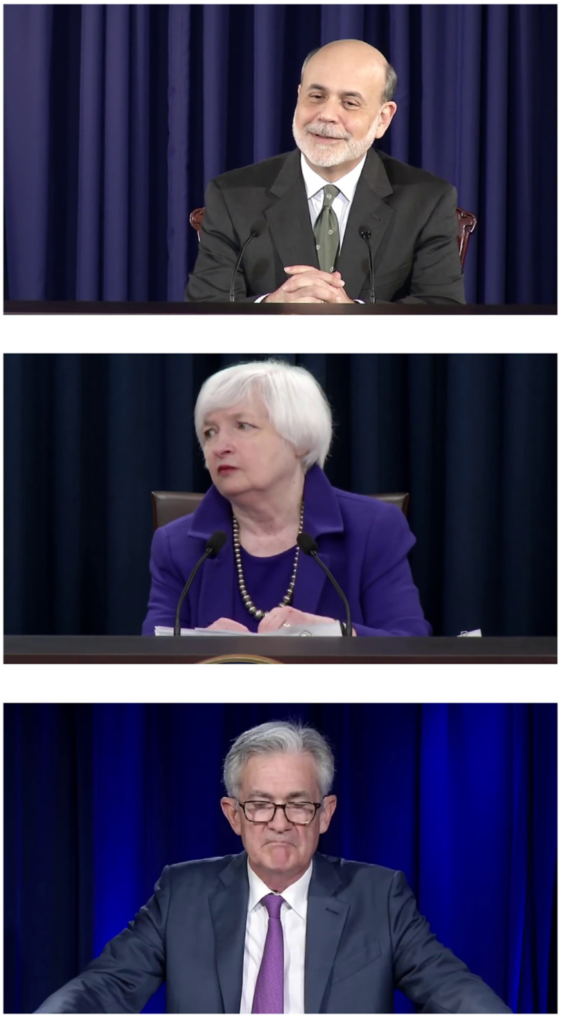
The API then returns emotion scores for the eight facial emotions (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Neutral*, *Sadness*, and *Surprise*), where each emotion receives a score between zero and one. These scores add up to 100%. Fig. 1 provides an example of the scored frames for the three Chairs in our sample.

In order to prepare the data for the API, we first decompose each of the 46 videos into a set of frames. The images are captured in a continuous manner, with each frame being captured at the two second interval.[11] 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

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

[10] 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. We acknowledge that our current results are based on Microsoft Azure's emotion detection engine. As with any analytical tool, the findings may be influenced by the specific algorithms and methodologies used. While Azure has proven to be a reliable tool for our current research, we bear in mind the possibility of varying results if different emotion detection engines are employed.

[11] 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 and Friesen, 2003).



Panel A: Ben Bernanke, March 20th 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 14th 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 30th 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

Fig. 1. 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 20th, 2013, Panel B shows Janet Yellen during the FOMC press conference held on December 14th, 2016, and Panel C shows Jerome Powell during the FOMC press conference held on January 30th, 2019.

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.[12]

This methodology yields a sample that includes 2518 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 min long, where the first 10 min 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

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

of negative emotions across all FOMC meetings presided by the Chair. The intensity scores of Anger, Disgust, and Fear are considered as negative emotions.[13]

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

In the above equation, as an example, Anger$_{i,k}$ represents the average intensity of anger expressed during a given 3 min interval i for Chair k. Correspondingly, 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 Eq. (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.[14]

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.[15]

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 Chair's average intensity of negative emotions in three minute intervals, with higher numbers denoting more negative emotions.

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 timestamping 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.[16]

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.[17] It is a deep learning model

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

[13] 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.

[14] We provide a visual description of these results in the Online Appendix. We show that 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.

[15] We report these robustness checks in the Online Appendix. Overall, our results hold under alternative specifications of our main explanatory variable.

[16] While we invest a great deal of effort into synchronization, it is challenging to perfectly align all the variables in question. If there were to be any cases of timing misalignment, it would mean a potential reduction in the likelihood of identifying significant findings.

[17] Bidirectional Encoder Representations from Transformers (BERT) is "designed to pre-train deep bidi-that has been trained on the entire English Wikipedia and BookCorpus, 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.

task, given its specific context. The FinBERT model is currently available for implementation through 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 (i.e., positive, negative, or neutral).[18] Based on this process, we create our main measure of tone, rectional representations from unlabeled text by jointly conditioning on both left and right context." (Devlin et al., 2018).

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 min interval. We then normalize this measure by dividing it by its own standard deviation.

In addition, we create a separate policy stance variable named *Hawkishness*, which measures the prevalence of hawkish and dovish language present in central banks' communications. We first tokenize our sentences, and then convert them into a sequence of numerical values (i.e., embeddings) using pre-trained GPT-3 model.[19] These embeddings capture the context that underlies each sentence. We then run a classification model that takes embeddings as input features and learns to classify the text based on the provided labels. We use this variable as an additional control variable in our empirical analysis. Table 2, Panel C presents descriptive statistics for both *Hawkishness* and *Negative Tone* variables.[20]

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 min 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 min 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. We create three dummy variables for each three minute interval, 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, 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.[21]

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

[18] 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.

[19] We use text-embedding-ada-002 model to embed our data. Hansen and Kazinnik (2023) demonstrate the ability of GPT models to classify FOMC language relative to a human benchmark.

[20] In 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 standardizing our main variable Negative Tone, and find no significant impact on our results. This analysis is available upon request.

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

Table 3
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 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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. 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 min 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 presented in parentheses, and are clustered at the FOMC meeting level. Variables definitions are reported in Table 1.

(1) %Δ SPY	(2) %Δ SPY	(3) %Δ SPY	(4) %Δ VIX	(5) %Δ VIX	(6) %Δ VIX	(7) %Δ EURUSD	(8) %Δ EURUSD	(9) %Δ EURUSD	
Negative Emotions	-0.463^{**}	-0.497^{**}	-0.500^{**}	3.180	3.313	3.557	-0.255^{**}	-0.247^{**}	-0.174^{*}
	(0.200)	(0.198)	(0.225)	(2.041)	(2.041)	(2.208)	(0.112)	(0.113)	(0.094)
Negative Tone	−0.391	−0.349	0.300	21.699	22.271	21.695	-2.796^{**}	-2.784^{**}	−3.125
	(1.845)	(1.855)	(1.851)	(19.059)	(19.066)	(19.419)	(1.311)	(1.313)	(2.009)
Hawkishness	−0.331	−0.296	0.095	12.600	12.650	11.762	-1.105^{**}	-1.106^{**}	−1.263
	(0.769)	(0.771)	(0.770)	(7.800)	(7.799)	(7.929)	(0.525)	(0.525)	(0.787)
Δ FFR	-0.033^{**}	-0.039^{***}		0.221^{*}	0.269^{**}		0.009	0.010^{*}	
	(0.014)	(0.014)		(0.115)	(0.117)		(0.006)	(0.006)	
SPY Pre Drift	0.023^{***}	0.022^{***}							
	(0.007)	(0.007)							
VIX Pre Drift				0.006	0.005				
				(0.006)	(0.006)				
EURUSD Pre Drift							0.010^{**}	0.010^{**}	
							(0.004)	(0.004)	
MPU	−0.503	0.090		1.415	0.059		0.305^{*}	0.215	
	(0.337)	(0.433)		(2.842)	(3.595)		(0.157)	(0.213)	
Market Conditions	−0.500	0.271		5.060	2.373		0.242	0.101	
	(0.846)	(0.916)		(5.950)	(6.320)		(0.399)	(0.406)	
Chair FE	No	Yes	No	No	Yes	No	No	Yes	No
Meeting FE	No	No	Yes	No	No	Yes	No	No	Yes
N	2518	2518	2518	2518	2518	2518	2518	2518	2518
Adj R^2	0.012	0.017	0.051	0.001	0.002	0.022	0.007	0.007	0.040

$*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level.

specification for each of our dependent variables:

$$\%\Delta Market_{t,me} = \alpha_{fe} + \beta_1 NegativeEmotions_{t-1} + \beta_k Ctrls_{t-1} + \epsilon_{t,me,fe} \tag{2}$$

where t indexes the minutes, me indexes the FOMC meeting, and fe indexes either the Chair or FOMC meeting.%ΔMarket 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 Sections 3.3 and 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 meeting level. Table 3 presents the results of our main specification under different fixed effect schemes.

Table 3, 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 5% 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 ($= 1.060 * (-0.5)$) for a three minutes interval.

Column (6) shows that the coefficient on *Negative Emotions* is positive but not statistically significant. Columns (4) and (5) are 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 3.76 basis point increase in VIX ($= 1.060 * 3.55$) 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 for Columns (7) and (8), 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

Table 4
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 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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 presented in parentheses, and are clustered at the FOMC meeting level. Variables definitions are reported in Table 1.

	(1)SPY Volume	(2)EURUSD Volume
Negative Emotions	−0.012**	−0.006
	(0.005)	(0.007)
Negative Tone	−0.035	0.172***
	(0.044)	(0.058)
Hawkishness	−0.002	0.124***
	(0.018)	(0.024)
Meeting FE	Yes	Yes
N	2518	2518
Adj R^2	0.566	0.621

∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level.

Negative Emotions is associated with a −0.18 basis point change in EURUSD ($= 1.060 * (-0.174)$) 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) posit that new information can impact trading volume by influencing disagreement among market participants. Increased disagreement may lead to higher trading volume, while reduced disagreement, reflecting converging beliefs, could result in lower volume. Cookson et al. (2022) attribute this phenomenon to the confirmation bias of market participants.

To investigate the relationship between trading volumes and *Negative Emotions* we perform a multivariate regression analysis in the spirit of Eq. (2), with dependent variables being the average trading volumes evaluated in the three minutes following the measurement of *Negative Emotions*. Table 4 presents the results.

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 both *Hawkishness* and *Negative Tone*, and EURUSD trading volume. A one standard deviation increase in *Hawkishness* is associated with a trading increase of 131,440 shares per minute for EURUSD ($= 1.060 * (0.124) * 1,000,000$). A one standard deviation increase in *Negative Tone* is associated with a trading increase of 182,320 shares per minute for EURUSD ($= 1.060 * (0.172) * 1,000,000$). Thus, *Hawkishness* and *Negative*

Tone variables 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.

Table 5
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 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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 minus the full sample average. Press Statement Surprise is the absolute change in ZQ (30 Day Fed Fund Futures) that occurred from 10 min 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 presented in parentheses, and are clustered at the FOMC meeting level. Variables definitions are reported in Table 1.

Panel A: Media Attention			
	(1)	(2)	(3)
	%Δ SPY	%Δ VIX	%Δ EURUSD
Negative Emotions	−0.456**	3.353	−0.153
	(0.213)	(2.198)	(0.108)
Media Coverage * Negative Emotions	−0.089**	0.405	−0.042**
	(0.037)	(0.338)	(0.018)
Negative Tone	0.335	21.540	−3.109**
	(1.858)	(22.305)	(1.319)
Hawkishness	0.093	11.773	−1.264**
	(0.773)	(9.123)	(0.530)
Meeting FE	Yes	Yes	Yes
N	2518	2518	2518
Adj R^2	0.053	0.022	0.042
Panel B: Press Statement Surprise			
	(1)	(2)	(3)
	%Δ SPY	%Δ VIX	%Δ EURUSD
Negative Emotions	−0.078	−2.190	−0.209*
	(0.217)	(2.113)	(0.112)
Press Statement Surprise * Negative Emotions	−0.015***	0.200**	0.001
	(0.005)	(0.086)	(0.002)
Negative Tone	0.685	16.463	−3.157**
	(1.812)	(21.138)	(1.318)
Hawkishness	0.244	9.736	−1.275**
	(0.754)	(8.710)	(0.529)
Meeting FE	Yes	Yes	Yes
N	2518	2518	2518
Adj R^2	0.056	0.033	0.040

*, **, and *** denote significance at the 10%, 5%, and 1% level.

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 min 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.

Table 5, 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 non-verbal 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 5, 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.

Table 6
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 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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 presented in parentheses, and are clustered at the FOMC meeting level. Variables definitions are reported in Table 1.

Panel A: Written Tone			
	(1)	(2)	(3)
	%Δ SPY	%Δ VIX	%Δ EURUSD
Negative Emotions	−0.769***	5.675*	−0.379**
	(0.070)	(2.957)	(0.156)
Negative Tone	3.723	−4.154	−0.630
	(5.131)	(16.994)	(2.694)
Negative Tone * Negative Emotions	−3.457**	26.060**	−2.515
	(1.451)	(11.807)	(2.021)
Hawkishness	1.322	4.106	−0.522
	(2.236)	(9.092)	(1.137)
Hawkishness * Negative Emotions	−1.230*	7.392	−0.716
	(0.630)	(4.718)	(1.000)
Meeting FE	Yes	Yes	Yes
N	2518	2518	2518
Adj R^2	0.051	0.022	0.042
Panel B: Discussion Theme			
	(1)	(2)	(3)
	%Δ SPY	%Δ VIX	%Δ EURUSD
Negative Emotions	−0.080	0.703	−0.012
	(0.244)	(2.755)	(0.127)
Negative Tone	0.183	21.551	−3.306**
	(1.851)	(22.667)	(1.308)
Hawkishness	0.130	10.826	−1.315**
	(0.769)	(9.345)	(0.525)
Status of Economy	1.396**	−7.998	−0.267
	(0.687)	(6.814)	(0.512)
Status of Economy * Negative Emotions	−0.525	2.771	−0.394
	(0.700)	(6.311)	(0.452)
Forward Guidance	0.915	−2.539	0.509
	(0.781)	(7.612)	(0.492)
Forward Guidance * Negative Emotions	−1.897***	13.633***	−0.756***
	(0.524)	(4.597)	(0.282)
Meeting FE	Yes	Yes	Yes
N	2518	2518	2518
Adj R^2	0.056	0.025	0.042

*, **, and *** denote significance at the 10%, 5%, and 1% level.

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.

Table 6, Panel A summarizes our findings with respect to the overall level of negative sentiment, captured by Negative Tone and Hawkishness. The coefficients on the interaction term for *Negative Tone* is negative and significant in Columns (1) and (2), revealing an amplification effect of the facial expressions with the negative tone of the message.

Table 6, 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, there is no amplification effect. 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

Central bank communication impacts financial asset prices through two primary mechanisms: the monetary effect, which involves unexpected policy measures, and the information effect, which conveys the bank's economic outlook (Romer and Romer, 2000). Recent studies, including Nakamura and Steinsson (2018), Cieslak and Schrimpf (2019), and Jarociński and Karadi (2020), emphasize the information effect's role and provide empirical evidence that market reactions are significantly influenced by the central bank's release of economic fundamentals.

One possible channel for the transmission of the information effect in our set-up is via belief-based channel.[22] 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. Next two sections lay out the results. And finally, we examine whether the effect of facial expressions reverses over time

5.1. FOMC minutes

We analyze FOMC meeting minutes to determine if emotions during press conferences are driven by genuine information. The minutes offer insights into economic conditions and policy decisions. Previous research focused on statements' impact on financial markets due to their timing and brevity. However, the minutes receive attention for their detail and nuance. They give an unfiltered view of the discussions, while decision announcements reflect the Committee's majority opinion. Rosa (2013) demonstrates that the minutes contain market-relevant information, as their release affects U.S. asset price volatility and 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 average level of negative emotions per meeting on a set of measures related to the negative tone and hawkishness of the Federal Open Market Committee (FOMC) minutes. We report the results in Table 7.

The results show that the tone of FOMC minutes has a statistically significant positive relationship with the average level of negative emotions exhibited during a press conference, as indicated by the coefficient values of 91.89 and 94.05 for Columns (1) and (2), respectively, both significant at the 5% level. This suggests that the more negative the tone in the FOMC minutes, the higher the level of negative emotions expressed. The results also shows that the relationship between the stance of FOMC minutes and the average level of negative emotions is not statistically significant. Overall, the findings suggest that the tone of the FOMC minutes has a significant impact on the average level of negative emotions expressed.

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 8.

Column (1) of Table 8 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.

[22] 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.

Table 7
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 27th, 2011 and September 16th, 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. Standard errors are presented in parentheses and are hetroskedasticity-robust.

	Negative Emotions*avg*	
	(1)	(2)
FOMC Minutes Negative Tone	91.895**	94.052**
	(37.158)	(42.816)
FOMC Minutes Hawkishness	2.451	2.237
	(1.834)	(1.755)
Negative Tone*avg*	6.551**	6.352*
	(3.312)	(3.258)
Hawkishness*avg*	2.299*	2.263*
	(1.276)	(1.283)
Chair FE	No	Yes
N	46	46
Adj R^2	0.145	0.108

*, **, and *** denote significance at the 10%, 5%, and 1% level.

Table 8
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 2518 observations at the minute level from 46 FOMC meetings chaired by Ben Bernake (12), Janet Yellen (16), and Jerome Powell (18) between April 27th, 2011 and September 16th, 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 presented in parentheses, and are clustered at the FOMC meeting level. Variables definitions are reported in Table 1.

	(1)%Δ SPY	(2)%Δ VIX	(3)%Δ EURUSD
Negative Emotions	0.188	1.675	0.061
	(0.444)	(4.030)	(0.226)
Chair Tenure * Negative Emotions	−0.092*	0.251	−0.031
	(0.050)	(0.412)	(0.024)
Negative Tone	0.291	21.721	−3.128**
	(1.854)	(22.341)	(1.322)
Hawkishness	0.045	11.898	−1.280**
	(0.770)	(9.131)	(0.532)
Meeting FE	Yes	Yes	Yes
N	2518	2518	2518
Adj R^2	0.051	0.022	0.040

*, **, and *** denote significance at the 10%, 5%, and 1% level.

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.

6. Conclusion

The expectations transmission channel of monetary policy has gained considerable importance in recent years. 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, such as forward guidance, which aims to influence expectations. However, asymmetrical information can cause Delphic pessimism among market participants. Our paper reveals that specific facial expressions during press conferences can exacerbate this effect, leading to market under-reaction or overreaction. This suggests that managing expectations is more complex than previously considered, as market participants both listen and watch Fed Chairs closely.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.06.007.

References

Akansu, A., Cicon, J., Ferris, S.P., Sun, Y., 2017. Firm performance in the face of fear: how CEO moods affect firm performance. J. Behav. Financ. 18 (4), 373–389.
Baccianella, S., Esuli, A., Sebastiani, F., 2010. Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In: Proceedings of the Conference on Language Resources and Evaluation, 10, pp. 2200–2204.
Bernanke, B. (2004). The great moderation. Board of Governors of the Federal Reserve System.
Bernanke, B., Reinhart, V., Sack, B., 2004. Monetary policy alternatives at the zero bound: an empirical assessment. Brook. Pap. Econ. Act. 2, 1–100.
Birdwhistell, R. (1970). Kinesics and context. Essays on body-motion communication.
Blankespoor, E., Hendricks, B.E., Miller, G.S., 2017. Perceptions and price: evidence from CEO presentations at IPO roadshows. J. Account. Res. 55 (2), 275–327.
Boguth, O., Grégoire, V., Martineau, C., 2019. Shaping expectations and coordinating attention: the unintended consequences of FOMC press conferences. J. Financ. Quant. Anal. 54 (6), 2327–2353.
Breaban, A., Noussair, C.N., 2018. Emotional state and market behavior. Rev. Financ. 22 (1), 279–309.
Choudhury, P., Wang, D., Carlson, N.A., Khanna, T., 2019. Machine learning approaches to facial and text analysis: discovering CEO oral communication styles. Strateg. Manag. J. 40 (11), 1705–1732.
Cieslak, A., Morse, A., Vissing-Jorgensen, A., 2019. Stock returns over the FOMC cycle. J. Financ. 74 (5), 2201–2248.
Cieslak, A., Schrimpf, A., 2019. Non-monetary news in central bank communication. J. Int. Econ. 118, 293–315.
Coibion, O., Gorodnichenko, Y., and Weber, M. (2019). Monetary policy communications and their effects on household inflation expectations. Working Paper.
Cookson, A.J., Engelberg, J., and Mullins, W. (2022). Echo Chambers. Working Paper.
Cortes, G., Sethuraman, M., Silva, F.B.G., 2021. Does wall street understand Fed speak? In: Proceedings of the Monetary Policy Communication and Corporate Conference Calls Working Paper.
Devlin, J., Chang, M.W., Lee, K., and Toutanova, K. (2018). BERT: pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.
Eggertsson, G.B., Woodford, M., 2003. Optimal Monetary Policy in a Liquidity Trap. National Bureau of Economic Research, p. w9968.
Ekman, P. and Friesen, W.W. (2003). Unmasking the face: a guide to recognizing emotions from facial clues, volume 10.
El Kaliouby, R., Robinson, P., 2004. Real-time inference of complex mental states from facial expressions and head gestures. In: Proceedings of the Conference on Computer Vision and Pattern Recognition Workshop.
Fleming, M.J. and Piazzesi, M. (2005). Monetary Policy Tick-by-Tick. Working Paper.
Gomez Cram, R., Grotteria, M., 2022. Real-time price discovery via verbal communication: method and application to fedspeak. J. Financ. Econ. 143 (3).
Gorodnichenko, Y., Pham, T., Talavera, O., 2023. The voice of monetary policy. Am. Econ. Rev. 113 (2), 548–584.
Gu¨rkaynak, R.S., Sack, B., Swanson, E., 2005. The sensitivity of long-term interest rates to economic news: evidence and implications for macroeconomic models. Am. Econ. Rev. 95 (1), 425–436.
Hansen, A.L. and Kazinnik, S. (2023). Can ChatGPT Decipher Fedspeak? SSRN Working Paper.
Hecht, M.A., Ambady, N., 1999. Nonverbal communication and psychology: past and future. Atl. J. Commun. 7 (2), 156–170.
Hill, A.D., Petrenko, O.V., Ridge, J.W., Aime, F., 2019. Videometric measurement of individual characteristics in difficult to access subject pools: demonstrating with CEOs. Res. Methodol. Strategy Manag. 11, 36–61.
Howard, A., Zhang, C., Horvitz, E., 2017. Addressing bias in machine learning algorithms: a pilot study on emotion recognition for intelligent systems. In: Proceedings of the IEEE Workshop on Advanced Robotics and its Social Impacts, 2, pp. 1–7.
Hu, A. and Ma, S. (2021). Persuading Investors: a Video-Based Study. Working Paper.
Husted, L., Rogers, J., Sun, B., 2020. Monetary policy uncertainty. J. Monet. Econ. 115, 20–36.
Jarociński, M., Karadi, P., 2020. Deconstructing monetary policy surprises-the role of information shocks. Am. Econ. J. Macroecon. 12 (2), 1–43.
Amato, J.D., Morris, S., Shin, H.S., 2002. Communication and monetary policy. Oxf. Rev. Econ. Policy 18 (4), 495–503.
Kim, O., Verrecchia, R.E., 1991. Trading volume and price reactions to public announcements. J. Account. Res. 29 (2), 302–321.
Kohn, D.L. and Sack, B. (2003). Central Bank talk: does it matter and why? Finance and Economics Discussion Series.
Kuttner, K.N. and Posen, A.S. (1999). Does Talk Matter After All? Inflation Targeting and Central Bank Behavior. Institute for International Economics Working Paper.
Leathers, D.G., Eaves, M., 2015. Successful Nonverbal Communication: Principles and Applications. Routledge.
Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. J. Financ. 66 (1), 35–65.
Lucca, D.O., Moench, E., 2015. The Pre-FOMC announcement drift. J Finance 70 (1), 329–371.
Lundqvist, L.O., Dimberg, U., 1995. Facial expressions are contagious. J. Psychophysiol. 9, 203 –203.
Malo, P., Sinha, A., Takala, P., Ahlgren, O., Lappalainen, I., 2013. Learning the roles of directional expressions and domain concepts in financial news analysis. In: Proceedings of the IEEE 13th International Conference on Data Mining Workshops, pp. 945–954 pages.
Manela, A., Moreira, A., 2017. News implied volatility and disaster concerns. J. Financ. Econ. 123 (1), 137–162.

Mathur, P., Neerkaje, A., Chhibber, M., Sawhney, R., Guo, F., Dernoncourt, F., Dutta, S., Manocha, D., 2022. Monopoly: financial prediction from monetary policy conference videos using multimodal cues. In: Proceedings of the 30th ACM International Conference on Multimedia, pp. 2276–2285 pages.
Mayew, W.J., Venkatachalam, M., 2012. The power of voice: managerial affective states and future firm performance. J. Financ. 67 (1), 1–43.
Momtaz, P.P. (2019). CEO emotions and underpricing in initial coin offerings. Working Paper.
Nakamura, E., Steinsson, J., 2018. Identification in macroeconomics. J. Econ. Perspect. 32 (3), 59–86.
Philpott, J.S. (1983). The relative contribution to meaning of verbal and nonverbal channels of communication: a meta-analysis. Working Paper.
Romer, C.D., Romer, D.H., 2000. Federal reserve information and the behavior of interest rates. Am. Econ. Rev. 90 (3), 429–457.
Rosa, C., 2013. The financial market effect of FOMC minutes. Econ. Policy Rev. 19 (2).
Rozin, P., Royzman, E.B., 2001. Negativity bias, negativity dominance, and contagion. Personal. Soc. Psychol. Rev. 5 (4), 296–320.
Shalen, C., 1993. Volume, volatility, and the dispersion of beliefs. Rev. Financ. Stud. 6 (2), 405–434.
Vaish, A., Grossmann, T., Woodward, A., 2008. Not all emotions are created equal: the negativity bias in social-emotional development. Psychol. Bull. 134 (4), 383.
Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., et al., 2020. Transformers: state-of-the-art natural language processing. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pp. 38–45 pages.
Woodford, M., 2001. Monetary Policy in the Information Economy. National Bureau of Economic Research, p. w8674.
Woodford, M., 2005. Central Bank Communication and Policy Effectiveness. National Bureau of Economic Research, p. w11898.
Yellen, J. (2013). Interconnectedness and systemic risk: lessons from the financial crisis and policy implications. Board of Governors of the Federal Reserve System.