# Beyond Words: The Impact of Fed Chairs' Facial Cues on Global Stock Performance

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*Keywords*: International stock markets, Facial sentiment, Central bank communication, Machine learning

*JEL Classifications*: F42, E52, D83, G14

## 1. Introduction

Understanding how U.S. monetary policy affects other economies is central in international macroeconomics, reflecting the dollar's role as a global reserve currency and the Federal Reserve's broad influence on financial markets. Traditionally, the literature focuses on how changes in the Federal Reserve's policy rate and unconventional monetary policy are transmitted to international financial markets.[1] However, as Ben Bernanke noted, "Monetary policy is 98 percent talk and 2 percent action, and communication is a big part."[2] Central bank communication also has a significant influence on financial markets (Gorodnichenko, Pham, and Talavera, 2023; Curti and Kazinnik, 2023; Schmelingand and Wagner, 2025). For example, some hedge funds have analyzed Jerome Powell's facial expressions to predict interest rates.[3] Therefore, a research gap exists regarding the international effects of Federal Open Market Committee (FOMC) communication—a gap that this paper seeks to address. Specifically, we provide evidence that the Fed Chairs' facial expressions during FOMC press conferences represent a significant, yet previously unexplored, channel through which Federal Reserve signals are transmitted to international financial markets. To investigate this phenomenon, we examine the relationship between international stock market performance and the facial sentiment of Fed Chairs. In particular, we test whether positive facial expressions during FOMC press conferences are favorable signals for international markets.

The FOMC possesses significant informational advantages relative to public market participants (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). Recent empirical evidence suggests that positive sentiment—whether conveyed through textual content, vocal tone, or facial expressions during central bank press conferences—consistently signals favorable economic conditions to financial markets (Curti and Kazinnik, 2023; Gorodnichenko, Pham, and Talavera, 2023; Schmeling and Wagner, 2025). Moreover, U.S. monetary policy generates significant international spillovers through multinational firms, the central role of the dollar and the U.S. economy in international markets. (Albagli, Ceballos, Claro, and Romero, 2019; Brusa, Savor, and Wilson, 2020; Lakdawala, Moreland, and Schaffer, 2021). More specifically, Brusa, Savor, and Wilson (2020) find that, when aggregating across markets, the announcement premium

[1] For example, Svensson and Van Wijnbergen (1989), Obstfeld and Rogoff (1995), Betts and Devereux (2000), Wongswan (2006), Rey (2015), Albagli, Ceballos, Claro, and Romero (2019), Chari, Stedman, and Lundblad, 2021, Georgiadis and Jarocinski (2023), Camara (2025) and so on.

[2] https://www.brookings.edu/events/ben-bernanke-the-fed-from-the-great-inflation-to-covid-19/.

[3] https://www.marketwatch.com/story/hedge-funds-are-studying-jerome-powells-facial-expressions-to-predict-interest-rates-2018-03-22.

of the global market portfolio is significant only for FOMC meetings and not for any of the three central banks: the Bank of England, the Bank of Japan, or the European Central Bank. Given that FOMC press conferences allow policymakers to go off script and communicate soft information through nonverbal channels, they serve as a critical window for investors to assess the direction of U.S. monetary policy—particularly during the Q&A session (Gorodnichenko, Pham, and Talavera, 2023). Consequently, the facial sentiment of Fed Chairs can be seen as a partial reflection of the policy stance adopted by U.S. authorities. Based on these findings, we propose that the Fed Chairs' positive facial expressions can serve as a signal of robust policy stance and economic fundamentals, bolstering investor confidence and, in turn, leading to higher returns of international stock markets. Nevertheless, the underlying mechanisms remain underexplored, and there is still no empirical evidence regarding how the Fed Chairs' facial cues influence international stock markets or the channels through which this effect propagates.

To explore whether the international stock markets react to the facial expressions of the Fed Chairs during FOMC press conferences, we analyze two-day changes in the closing prices of international stock markets surrounding FOMC press conferences to assess the influence of the facial sentiment (Albagli, Ceballos, Claro, and Romero, 2019; Lakdawala, Morelan, and Schaffer, 2021).[4] Moreover, we extract the facial sentiment from the facial expressions of the Fed Chairs during FOMC press conferences. Specifically, we convert 70 FOMC press conference videos into frames and utilize an advanced machine learning algorithm to capture micro-expressions and subtle emotional signals of the Fed Chairs. Then, following Antweiler and Frank (2004), we construct a facial sentiment indicator to measure the emotional valence conveyed through the Fed Chairs' facial displays.

Using 50 economies and 70 FOMC press conferences from January 2011 to December 2023, we find that more positive facial sentiment is associated with higher international stock market returns even after we control the contemporary U.S. stock market return. More specifically, one-standard-deviation increase in facial sentiment is associated with an increase of 0.251% in *Ret*, approximately 14.855% of international stock market returns' standard deviation. This finding validates our initial hypothesis, demonstrating that the international stock markets boom when the

[4] Two-day window allows all international stock markets have sufficient time to respond to FOMC shocks. Moreover, we account for the time zone and trading hours differences for each when calculating the two-day changes, as shown in Appendix B.

Fed Chairs smile. To address concerns about potential differences in sentiment expression among the three Chairmen, we use either their sentiment during their first FOMC meeting or the average sentiment across all their past FOMC meetings as benchmarks. We then adjust the original sentiment measures based on these benchmarks and find that our results remain unchanged. Following Hu and Ma (2025), we employ Shapley-Owen decomposition (Shorrocks, 2013) to test the explanatory contribution of the Fed Chairs' facial sentiment and conclude that this factor accounts for 9.59% contribution of all variables, which is the third most important variable. In addition, to address the concern that panel model may enlarge the significance of results, we take time-series regressions for the whole stock markets and find that the effect of facial expressions holds.

We also conduct several robustness tests and find similar results. Firstly, we construct the facial sentiment measure based on alternative split frequency and find that the baseline results hold. Furthermore, we test whether the effect of facial sentiment is driven by several specific economies through a bootstrap that we randomly choose 10 economies from our sample for 1000 times and rerun the baseline regressions. The baseline results general for international stock markets. Moreover, our baseline results are based on event and economy cluster method, and we try alternative cluster methods to test the robustness. We find that the results are largely consistent. To eliminate the influence of outliers, we apply 99% trimming on continuous variables and find the results robust. Overall, these robustness tests strengthen the validity of our baseline results and provide additional confidence in the relationship between facial sentiment and international stock markets.

In addition, we decompose the FOMC press conference Q&A sessions into three parts based on the proportion of 30%, 30%, and 40% and find that the effect of facial expression is mainly in the first part. Utilizing the method of Curti and Kazinnik (2023), we construct and test the effects of positive and negative facial sentiment separately. The results reveal that the influence of facial expressions is largely driven by positive facial sentiment. To investigate whether there is reversal effect for facial sentiment; we take a long-run analysis and find that all impacts are absorbed in two-day window and there is no reversal phenomenon.

To further explore the influence of facial sentiment, we adopt several heterogeneity tests. First, when the FOMC press conferences Q&A session refers to global information more, these press conferences will be more related to global markets. Therefore, we expect that the effect of facial

sentiment will be more significant for these events, and our results align with this expectation. Moreover, not all investors are English native speakers, but they are all "Facial Expression" native speakers. If investors cannot effectively extract information from the text, the demand and importance of facial sentiment information will be larger. By testing the interaction between facial sentiment and language background, we discover a stronger result for economies that do not use English as the most-spoken language.

Moreover, we test several underlying channels for the effect of facial sentiment on international stock markets. Firstly, our findings suggest that when the Fed Chairs have more positive facial expressions, FOMC will be more confident about the monetary policy and have a higher-level monetary policy consistency, which lowers the uncertainty of global economies. Correspondingly, the positive facial sentiment is associated with a significant decrease in options-implied volatility and lowers the risk premium. In addition, we discover that when the FOMC members hold more positive attitude about future economic fundamentals, the Fed Chairs will be happier. Therefore, more positive facial sentiment may predict better economic conditions and results support this perspective.

Our paper contributes to two strands of literature. First, this paper extends the literature on nonverbal communication in financial markets. While prior studies have documented the impact of Fed Chairs' vocal tone (Gorodnichenko, Pham, and Talavera, 2023) and facial expressions (Curti and Kazinnik, 2023) on the U.S. markets, our research makes a distinct contribution by examining the cross-border transmission of these nonverbal signals. By focusing on international stock markets' responses to Fed Chairs' facial sentiment, we leverage variation across economies in language barriers and time zones to better isolate the marginal impact of nonverbal communication channels relative to traditional verbal policy signals.

Second, this paper is related to the research on the international effects of the U.S. monetary policy. Previous studies have documented the international effects of U.S. monetary policy surprise (Wongswan, 2009; Albagli, Ceballos, Claro, and Romero (2019)), quantitative easing (Chari, Stedman, and Lundblad, 2021), monetary policy uncertainty (Lakdawala, Moreland, and Schaffer, 2021), multidimensional monetary policy (Georgiadis and Jarocinski, 2023), and monetary information effects (Camara, 2025). Our paper is the first to focus on the relationship between U.S. Federal Reserve communication and the international stock markets.

The remainder of this paper is structured as follows. Section 2 describes the data and measures construction. Section 3 presents our main results. Section 4 shows the heterogeneity tests. Section 5 analyzes the underlying channels. Section 6 concludes.

## 2. Data and measures

### 2.1. Sample and data sources

Our paper focuses on global stock market returns associated with the facial sentiment of Chairs during the FOMC press conference Q&A session. Due to data availability, our tests cover stock markets in fifty economies, including 22 emerging economies and 28 advanced economies.[5] We include 70 scheduled FOMC meetings followed by a press conference from January 2011 to December 2023.[6] We choose 2011 as the starting year of our sample because it was the first year in which the FOMC held a press conference following the announcement.

We obtain daily equity return series (denominated in domestic currency) from the Datastream Global Equity Indices. One-year, two-year and ten-year government yields, exchange rate as well as volatility indices are also obtained from Datastream. We collect the dates, transcripts, and videos of FOMC press conferences from the website Federal Reserve.[7] We obtain the federal funds rate change for each FOMC meeting from the Archival Federal Reserve Economic Data (FRED).[8] We gather the measure of monetary policy uncertainty constructed by Bauer, Lakdawala, Mueller (2022) and monetary policy surprise proposed by Bauer and Swanson (2023). Consumer Price Index (CPI), unemployment rate, import and export are collected from the IMF's International Financial Statistics. Furthermore, we collect FOMC members' projection of unemployment from Federal Reserve Bank of ST. Louis (ALFRED)[9].

[5] Developed economies include Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, and UK. Emerging economies include Argentina, Brazil, Bulgaria, Chile, China, Colombia, Egypt, India, Indonesia, Jordan, Nigeria, Peru, Philippines, Poland, Romania, Russia, South Africa, Sri Lanka, Thailand, Turkey, Venezuela, Vietnam.

[6] We exclude the FOMC press conferences held on March 3 and March 15, 2020, because they are both unscheduled. We also exclude the FOMC press conference held on April 27, 2011, because the video quality is too poor for accurate machine learning recognition, making it impossible to extract precise facial information.

[7] https://www.federalreserve.gov.

[8] https://fred.stlouisfed.org/series/DFEDTARU.

[9] https://alfred.stlouisfed.org/. Compared with FRED, the summary of economic projection data in ALFRED is the version of initial data and not adjusted. This is more suitable for our event analysis.

## 2.2. Variables and measures

### *2.2.1. Stock return*

Following Hanson and Stein (2015), Albagli, Ceballos, Claro, and Romero (2019), and Lakdawala, Moreland, and Schaffer (2021), we focus on two-day changes in stock market indices surrounding each FOMC press conference. We use two-day changes to ensure that all international stock markets have sufficient time to respond to U.S. monetary policy shocks. The two-day change is calculated as the difference between the closing prices one trading day after and one trading day before an FOMC announcement.[10] Some markets are open when the FOMC press conferences end, while others are closed. We also account for the timing zone and stock exchange differences in calculating the two-day changes, as detailed in Appendix B.

### *2.2.2. Facial sentiment*

Recent advances in machine learning have enabled the precise recognition of facial micro-expressions and researchers have conducted extensive studies on facial expressions (Teixeira, Wedel, and Pieters, 2012; Yazdani, Chakravarty, and Inman, 2024; Jiang, Yin, and Liu, 2019). Artificial intelligence models employ feature extraction techniques to identify facial details from images—such as the jaw, eyes, nose, and mouth—and combine this information to infer sentiment conveyed by human facial expressions. Inadvertent micro-expressions often reveal a speaker's true thoughts. Therefore, we believe the facial expressions displayed by the Fed Chairs during FOMC press conference Q&A session, to some extent, reflect their genuine internal emotions, such as their level of confidence in the answers provided. To capture these facial micro-expressions inadvertently revealed by Fed Chairs during press conferences, we utilize the DeepFace model developed by Facebook AI Research (FAIR). DeepFace is an open-source facial analysis model that employs deep learning technology to efficiently perform tasks such as face detection and emotional analysis (Serengil and Ozpinar, 2020).

To construct the facial sentiment measure, we convert 70 videos into frames, enabling DeepFace to extract the Fed Chairs' facial muscle features. Research indicates that human micro-expressions typically last between 0.5 and 4 seconds (Ekman, 2003). Thus, following Curti and Kazinnik (2023), we continuously extract frames at two-second intervals for our analysis. Next, we perform the following four steps. First, for all videos, we use DeepFace for facial recognition

[10] The results hold the same if we use one-day event window as shown in Table 4.

to filter out valid frames showing clear and recognizable images of the Fed Chairs during press conference Q&A session. Second, for each frame in which the Fed Chairs are identified, we apply DeepFace's facial expression analysis module (Facenet512) to perform emotion recognition. Specifically, DeepFace can accurately identify various emotional states, including anger, disgust, fear, happiness, sadness, surprise, and neutral. For each frame in which the Fed Chairs appear, DeepFace computes scores based on facial features and classifies the expressed emotion accordingly. Figure 1 presents several examples of these classification results. Third, for each press conference, we aggregate all frames by emotional categories to obtain the overall emotion conveyed during that press conference. We classify anger, disgust, fear, and sadness as negative emotions; happiness and surprise as positive emotions; and neutral as neutral. Finally, we construct a facial sentiment indicator for each press conference. Specifically, building upon Antweiler and Frank (2004), we incorporate neutral sentiment into our scoring approach. For the Q&A session of each FOMC press conference, we construct the facial sentiment indicator as follows:

$$Facial\ Sentiment = \frac{positive\ frame - negative\ frame}{positive\ frame + negative\ frame} \quad (1)$$

where $positive\ frame$ and $positive\ frame$ represent the total number of frames classified as positive and negative, respectively, in the FOMC press conference. Higher values of the facial sentiment index indicate more positive emotions the Chair conveys during FOMC press conference Q&A session. Values closer to zero suggest neutral emotions, and lower values indicate the Chair conveys more negative emotions during the Q&A session.

[Insert Figure 1 about here]

*2.2.3. Control variables*

Sentiments are often conveyed to the public and markets through multiple channels. To isolate the specific effect of facial expressions, we control for the textual sentiment, vocal sentiment and other potential confounding factors.

We employ large language models (LLMs) to quantify the monetary-policy stance conveyed in the Fed Chairs' answers during press conferences. Gorodnichenko, Pham, and Talavera (2023) operationalize textual stance by classifying policy texts into dovish, hawkish, and neutral categories based on human-scored training data. While such supervised approaches can be

effective, they typically require costly manual labeling and non-trivial training and tuning of deep-learning models. Motivated by recent evidence that instruction-following LLMs can decode Fedspeak with strong performance, while requiring little to no task-specific training (i.e., zero-shot learning). Therefore, we follow Hansen and Kazinnik (2023) and adopt an instruction-based stance classification. Specifically, based on the official transcripts released by the Federal Reserve, we split each Q&A answer into sentences and employ Gemma3-Instruct—Google's state-of-the-art lightweight open-source large language model, to classify each sentence as dovish, mostly dovish, neutral, mostly hawkish, or hawkish. Based on the analysis results for each press conference's Q&A session, we treat dovish and mostly dovish as dovish, and mostly hawkish and hawkish as hawkish, then similarly construct a textual sentiment indicator as follows:

$$Textual\ Sentiment = \frac{dovish\ text - hawkish\ text}{dovish\ text + hawkish\ text}, \tag{2}$$

In addition to facial and textual sentiment, Gorodnichenko, Pham, and Talavera (2023) demonstrate that the voice tone of central bank communication significantly affects asset prices. To control the vocal sentiment in the Fed Chairs' voice, we manually perform a timestamping procedure by recording the timestamps of their remarks during the Q&A session. We utilize OpenAI's Whisper large-v3 model to segment the Fed Chairs' audio remarks at the sentence level. Whisper is a state-of-the-art model for automatic speech recognition (ASR), capable of precisely recognizing speech in audio and accurately dividing paragraphs into sentence-level audio segments.

Subsequently, we measure the Fed chairs' vocal sentiment by following the procedure in Gorodnichenko, Pham, and Talavera (2023). Specifically, for each audio segment obtained from the Q&A session, we extract a set of standard acoustic features that capture time-frequency content and tonal characteristics, including mel-spectrogram coefficients, mel-frequency cepstral coefficients (MFCCs), and chroma features. We then input these features into a supervised neural-network classifier trained on widely used emotional-speech datasets (RAVDESS and TESS). Because emotions such as fear and disgust are unlikely to arise in the context of FOMC press conferences, we focus on five emotions—happy, pleasantly surprised, neutral, sad, and angry.

Consistent with the facial sentiment, we classify 'happy' and 'pleasantly surprised' as the Fed Chairs' positive vocal sentiment and 'sad' and 'angry' as negative vocal sentiment. Based on the results of vocal sentiment analysis of each press conference, we similarly construct a vocal sentiment indicator as follows:

$$Vocal\ Sentiment = \frac{positive\ voice - negative\ voice}{positive\ voice + negative\ voice}, \quad (3)$$

In addition to the above sentiment control variables, we use the changes in federal funds rate and monetary policy surprise (Bauer and Swanson, 2023) to control the policy action of FOMC (Curti and Kazinnik, 2023; Gorodnichenko, Pham, and Talavera, 2023). Lakdawala, Morelan, and Schaffer (2021) find that there exists significantly negative international spillover effect of U.S. monetary policy uncertainty during FOMC meeting. Therefore, we control for changes in monetary policy uncertainty within the two-day window to ensure that the effect of facial sentiment extends beyond previously known factors. There is a significant lead-lag relationship between the U.S. stock market returns and those of other economies (Rapach, Strauss, and Zhou, 2013). Thus, there is a possibility that investors respond to movements in the U.S. stock market rather than to the Chairman's facial expressions. To address this concern, we control for the contemporaneous U.S. stock market return within the two-day window to isolate the direct effect of facial sentiment.

Cieslak and Vissing-Jorgensen (2021) find that policy makers pay attention to the stock market and negative stock returns comove with downgrades to the Fed's growth expectations and predict policy accommodations. Thus, an alternative explanation for the effect of facial sentiment is that positive U.S. stock market returns make the Chairman appear happy while simultaneously boosting international stock markets. To exclude this possibility, we control for the cumulative U.S. stock market return between the FOMC press conferences.

Moreover, to better identify the effect of facial sentiment and isolate the influence of nearby local events[11], following Schmelingand and Wagner (2025), we control for local market conditions before each FOMC meeting by including the cumulative local stock market returns, realized volatility of local stock markets, average yield to maturity of local two-year treasury bonds, and average difference of yield to maturity of local ten-year treasury bonds and two-year treasury bonds between FOMC press conferences. In addition, we also include lagged local stock returns

[11] Albagli, Ceballos, Claro, and Romero (2019) find that, in their sample, while Fed meetings are not always the sole events moving yields on a given day, this is the case much more often than not, with the overlap frequency between U.S. monetary policy meetings and events in other countries being only about 7%. Therefore, the identification problem of FOMC meetings is not significant. Furthermore, Column (1) in Table 4 shows that even we apply a narrower one-day event window, the results still hold.

to control for autocorrelation in price changes. All continuous variables are standardized to have a mean of 0 and a standard deviation of 1.

### 2.3. Summary statistics

Summary statistics for the main variables are presented in Table 1. There are 2,793 economy-meeting level observations in our sample. Detailed variable definitions are provided in Appendix A. The mean and standard deviation of stock market returns are -0.033% and 1.687%, respectively. The sample's average federal funds rate change is 9.076 bps, with a standard deviation of 20.633 bps. There exist some extreme values for several variables, but as revealed in Table A4, our results do not change if we remove the influence of outliers.

[Insert Table 1 about here]

Across all 70 FOMC press conferences from January 2011 to December 2023, we classify the FOMC press conferences with highest 10 facial sentiment as "Higher facial sentiment" events, while those with lowest 10 facial sentiment as "Lower facial sentiment" events. As indicated by Figure 2, no matter we apply equal-weighted or market-capitalization-weighted methods, the "Higher facial sentiment events" exhibits significantly superior average cumulative returns in and after the two-day window.

[Insert Figure 2 about here]

Figure 3 illustrates the relationship between changes in the federal funds rate and facial sentiment. We observe considerably more positive federal funds rate changes than negative changes during the sample period. Moreover, there is no clear relationship between changes in federal funds rate and facial sentiment.

[Insert Figure 3 about here]

## 3. Main results

### 3.1. Baseline results

In the baseline analysis, we examine the effects of the facial sentiment of Fed Chairs on the international stock markets using following equation:

$$Ret_{j,t} = \alpha + \beta Face_t + \gamma Control_{j,t} + \delta Year + \theta Month + \vartheta Economy + \varepsilon_{j,t}, \qquad (4)$$

where $Ret_{j,t}$ is the dependent variable representing the two-day stock market returns around the FOMC press conference. The independent variable, $Face_t$ is the facial sentiment extracted from facial expressions of Fed Chairs during FOMC press conferences. We control for several variables including textual sentiment (*Text*), vocal sentiment (*Voice*), federal funds rate changes (*FFR*), monetary policy surprise (*MPS*), monetary policy uncertainty (*MPU*), contemporary U.S. stock market returns (*USRET*), cumulative U.S. stock market returns (*MCUSRET*), cumulative local stock market returns (*MCRET*), realized volatility of local stock markets (*MCRV*), average yield to maturity of local two-year treasury bonds (*MCINTEREST*), and average difference of yield to maturity of local ten-year treasury bonds and two-year treasury bonds *(MCTS*), and lagged local stock market returns (*MCLAG*). To account for unobserved heterogeneity, we included economy, year, and month fixed effects in our model, and cluster standard errors at the event and economy level. If the facial sentiment of the Fed Chairs lead to higher international stock market returns, $\beta$ should be significantly positive.

[Insert Table 2 about here]

Table 2 presents the baseline regression results. Panel A reports the estimates from economy-meeting panel regressions. Column (1) examines the univariate relationship between facial sentiment and international stock returns, controlling only for fixed effects. The coefficient of Face is 0.3901 and statistically significant at the 1% level, providing preliminary evidence that positive facial expressions from Fed Chairs are associated with higher international equity returns. In Column (2), we utilize the full set of control variables to isolate the marginal effect of facial sentiment. Consistent with our hypothesis, the coefficient of Face in Column (2) remains positive and highly significant. This indicates that even after controlling for the content of the speech (*Text*), the tone of voice (*Voice*), and the reaction of the U.S. market (*USRET*), the nonverbal signals conveyed through the Chairs' facial expressions provide distinct and valuable information to global investors. Regarding control variables, *Text* and *Voice* also show positive coefficients. Notably, *MPU* exhibits a significantly negative coefficient.

To address concerns about potential differences in sentiment expression among the three Chairmen, we use their sentiment during their first FOMC meeting as a benchmark in Column (3) and the average sentiment across all their FOMC meetings as a benchmark in Column (4). We then

adjust the original sentiment measures based on these benchmarks and regress Equation (4) using the adjusted sentiment measures. The results remain robust, as shown in Columns (3) and (4).

A key finding regarding the economic magnitude of these variables is presented in Column (5), where we utilize a Shapley-Owen decomposition to quantify the relative contribution of each variable to the model's $R^2$. The analysis reveals that Face contributes approximately 9.59% to the explanatory power of the model. Importantly, facial sentiment emerges as the third most important predictor of international stock returns, surpassed only by U.S. stock market returns (*USRET*, 71.50%) and monetary policy uncertainty (*MPU*, 10.57%). The result reveals a distinction in how markets process different communication channels: nonverbal facial cues are a dominant channel of communication, possessing significantly higher explanatory power than textual sentiment (2.16%) or vocal tone (2.71%). This finding highlights a crucial distinction in how global markets process different communication channels. From a global perspective, facial expressions often serve as a "universal language" that transcends linguistic barriers, making them a more accessible and effective channel for international investors compared to verbal content.

Finally, there exists cross-sectional correlation in residuals across the 50 economies on each FOMC announcement date in our panel regressions. While Panel A regression addresses this issue by employing date clustering, we additionally conduct a time-series regression on facial sentiment as a robustness check. Panel B presents results from time-series regressions to further validate the aggregate market response. Across all specifications, the coefficient of Face remains stable at approximately 0.2490 and statistically significant2. This consistency between panel and time-series specifications reinforces the robustness of our findings. Overall, the coefficients associated with facial sentiment are positive and exhibit both statistical and economic significance, indicating that more positive facial expressions by Fed Chairs during FOMC press conferences are associated with increases in international stock market returns.

### 3.2. Robustness tests

We conduct several tests to demonstrate the robustness of the baseline results. First, to test if our results are driven by high-frequency noise or transitory facial ticks, we re-construct the facial sentiment index using a lower frequency of one frame per 2 seconds. The results are shown in Table A1. The results show that the coefficient of Face remains significantly positive. This

confirms that our findings capture the Fed Chairs' sustained emotional states and are robust to changes in sampling granularity.

Second, we examine the sensitivity of our results to different error clustering methods. While our baseline model clusters standard errors at the event and economy levels, we employ alternative clustering specifications, including Economy, Event, Year, and their combinations to account for various forms of dependence in the error structure. The results are shown in Table A2. The regression results show that the effect of facial sentiment remains robust regardless of different cluster methods.

Third, we investigate whether our results are driven by a specific subset of economies. To verify the global generalizability of the spillover effect, we conduct a resampling exercise where we randomly select 10 economies from our sample and re-estimate the baseline regression 1,000 times. The results are shown in Table A3. The consistently positive and significant coefficients reject the hypothesis, suggesting that the impact of facial sentiment on stock market returns is not driven by a specific economy sample.

Finally, we consider the potential influence of extreme market movements, which are common in financial data. To ensure that our estimates are not skewed by outliers, we apply a 99% trimming to all continuous variables. The results in Table A4 indicate that the coefficient of Face remains positive and highly significant even after removing extreme observations. This demonstrates that the positive spillover effect is driven by the general market response rather than rare, extreme events.

### 3.3. Decomposition of facial sentiment

Investors' attention is limited and as the FOMC press conferences proceed, investors may become more tired. Given that FOMC press conferences are information-dense events, we hypothesize that investors allocate the majority of their attention and energy to the initial stage of the conference, making the facial sentiment displayed during this period the most influential. To test this expectation, we split the Q&A session into three stages based on the proportion of 30%, 30%, and 40%. Then, we calculate the facial sentiment during each stage and test whether they have different impacts. The results are shown in Panel A of Table 3.

[Insert Table 3 about here]

In Columns (1), (2), and (3), we test the facial sentiment of three stages separately, and in Column (4), we utilize them all in one regression. We find that only the facial sentiment during the first stage has a significant influence in Column (4), which aligns with our expectation. This finding provides strong empirical support for the limited attention hypothesis, suggesting that global investors primarily anchor their market expectations on the nonverbal cues observed during the opening phase of the Q&A session, while subsequent expressions have a diminishing impact on asset prices.

Panel B of Table 3 further investigates the asymmetry of the market reaction by decomposing facial sentiment into positive and negative components, following Curti and Kazinnik (2023), we construct and test the effect of the positive and negative facial sentiment separately. Columns (1) and (2) examine these components individually. The results show that the positive sentiment extracted from facial expressions of the Fed Chairs (*FacePositive*) exerts a strong and statistically significant positive impact on returns. In contrast, negative sentiment (*FaceNegative*) shows only a marginally significant negative effect. When both components are included simultaneously in Column (3), the dominance of positive sentiment becomes evident. This finding suggests that international investors are primarily driven by "good news" signals; they interpret the Chairs' display of confidence and optimism as credible indicators of economic strength, whereas negative micro-expressions are treated with less weight in global asset pricing.

### 3.4. Long run analysis

Based on the relevant studies in the baseline regressions, we confirm the hypothesis that positive facial expressions by Fed Chairs during FOMC press conferences lead to increases in international stock market returns. However, the duration of this effect remains to be explored. Therefore, we test the long-run influence of facial sentiment on international stock market returns. Specifically, we examine returns over n trading days following the two-day window, T+N (N=0, 1, 2, 3, 4, 5). The results are shown in Table 4.

[Insert Table 4 about here]

The facial sentiment has a significant positive effect on the day of the press conference (T+0) and the immediately following day (T+1). These findings provide two key insights. First, they suggest that the international spillover effect of Fed Chairs' nonverbal cues is concentrated within

the first 48 hours. This indicates that global equity markets are efficient in processing soft information, rapidly incorporating the signals from facial expressions into asset prices. Second, the lack of significant reversal or continued drift after T+1 validates our methodological choice of using a two-day cumulative window ([T+0, T+1]) in the baseline analysis. This window effectively captures the full market reaction while minimizing noise from subsequent trading days.

### 3.5. Bond and currency market analysis

Besides international stock markets, we also test the influence of facial expressions of the Chairman on international bond and currency markets. The results are presented in Table A5.

We find that the facial sentiment can lower the yield of short-term government bond. This suggests that optimistic nonverbal cues lower near-term borrowing costs, likely by reducing immediate policy uncertainty and the associated risk premium in local markets. However, this "calming" effect does not extend to the medium-term, long-term government bond or exchange rates. Overall, Fed Chairs' facial sentiment appears to anchor near-term expectations without materially affecting long-run valuation or currency dynamics.

## 4. Heterogeneity tests

### 4.1. Global information

When the Chairman refers to more global information, the information underlying facial sentiment will be more related to international stock markets. We then expect the effect of facial expressions to be more pronounced if the Chairman discusses international situations in more detail. We calculate the term frequency-inverse document frequency (tf-idf) of words with stems "international" or "glob" for each Q&A text. We then analyze the interaction effect between facial sentiment and this global information measure, and the results are demonstrated in Table 5.

[Insert Table 5 about here]

Table 5 reveals a significantly positive coefficient for the interaction term. This indicates that the content of the speech acts as an amplifier: the positive spillover effect of the Fed Chairs' facial sentiment on international stock markets is substantially magnified when the discussion touches upon global topics. The results support the perspective that the FOMC press conferences is not

only related to the U.S. economy, but also global matters and the underlying information of facial expressions will have international influences.

### 4.2. Language background

Language differences create natural barriers to the transmission of verbal information. While the speech of Fed Chairs is delivered in English, facial expressions serve as a "universal language" that transcends linguistic boundaries and requires no translation. Moreover, if investors cannot extract information effectively from text, the demand for and importance of facial sentiment information will increase. Thus, we introduce an interaction term between facial sentiment and a dummy variable, *English*, which equals one if English is a primary official language of the economy. The results are shown in Table 6.

[Insert Table 6 about here]

We observe a statistically significant negative coefficient for the interaction term. This negative interaction implies that the sensitivity of stock returns to facial sentiment is significantly attenuated in English-speaking economies. Conversely, the effect is more pronounced in non-English speaking markets. This finding provides compelling evidence that nonverbal communication serves as a critical information bridge for global investors, particularly when linguistic frictions impede the immediate processing of traditional verbal signals.

## 5. Channel analyses

### 5.1. Risk premium

When people are more confident in their decisions, they show more positive facial expressions. Therefore, higher facial sentiment may signal Fed Chairs' more confidence in the monetary policy decisions and higher level of monetary policy consistency. To test this proposition, we construct monetary policy consistency (*MPC*) measure using a dummy that equals 1 if the federal funds rate change of next FOMC meeting has the same sign with current FOMC meeting, which means that the monetary policy stance doesn't change, and 0 otherwise. Then, we regress this measure on the Fed Chairs' facial sentiment and check whether the parameter of *Face* is significantly positive. Correspondingly, if monetary policy is more consistent, the uncertainty of global economy and

investors' risk premium will be lower. We apply the volatility indices[12] to measure the risk premium and test whether more positive facial sentiment will lower it. We use the log change of volatility indices in the two-day window to measure the risk premium level change. The results are presented in Table 7.

[Insert Table 7 about here]

As shown in Panel A of Table 7, no matter we use LPM, Probit or Logit models, the parameter of *Face* is significantly positive. More specifically, if the facial sentiment of the Fed Chairs is one-standard-deviation higher, there is higher probability of 12.03% for FOMC members to give a same monetary policy stance next FOMC meeting. In addition, as revealed in Panel B, when the Fed Charis smile more, investors are less worried about uncertain monetary policy and their risk premium will be significantly lower.

### 5.2. Economic fundamentals

Besides discount rate, the other factor influencing stock prices is future cash flow. For the entire stock markets of economies, the future cash flow is future economic fundamentals. Compared with common investors, FOMC members are more professional in analyzing economy and have information advantages. Thus, FOMC members' opinion on future economic fundamentals can correct investors perception about future economic fundamental and influence their trading behaviors. One the other hand, one of FOMC goals is to achieve better economic fundamentals and if FOMC members do have more positive opinion on future economy, they may have happier facial expressions. We collect the central tendency midpoint of unemployment rate projection proposed by FOMC members from Summary of Projection of FOMC meeting and regress the Fed Chairs' facial sentiment on it. We also use predictive regression to examine whether facial sentiment has significant predictive power for future economic fundamentals. We construct economic indicators such as price level (*CPIG*), unemployment rate (*UNEMPG*), and trade (TRADEG) and apply a logarithmic transformation to these variables when incorporating them into the model. *CPIG* reflects the inflation level, which typically affects consumer confidence and spending behavior. *UNEMPG* directly reflects the health of the labor market and affects consumer

[12] Due to data availability, we only get volatility indices for Australia, Canada, France, Germany, Hong Kong, India, Japan, Netherlands, Russia, South Africa, Korea, Sweden, Switzerland, and UK.

confidence and spending. *TRADEG* presents the economic benefits from international trade. The results are presented in Table 8.

[Insert Table 8 about here]

Based on Panel A, we can discover that no matter which cluster methods we choose, when the FOMC members expect lower future unemployment rate, the Fed Chairs will be happier. In addition, Panel B reveals that higher facial sentiment can predict better economic fundamentals. More specifically, Columns (1) to (4) represent the regression results for different forecasting periods: 3 months, 6 months, 9 months, and 12 months. The regression coefficients for *CPIG* are significantly positive in 3- month and 12-month horizons. This implies that markets may react strongly to anticipated price changes based on the Fed Chairs' facial sentiment during FOMC press conferences. In addition, there is a negative correlation between the unemployment rate and facial sentiment. The regression coefficients are all negative from 3 month to 12 months, and the magnitude of the negative correlation increases over longer forecasting periods, suggesting that the predictive effect of facial sentiment on the unemployment rate becomes more significant over time. Furthermore, higher facial sentiment also predicts more international trade. Therefore, we conclude that positive facial sentiment predicts better economic fundamentals and higher inflation in the future.

## 6. Conclusion

This paper demonstrates that the facial expressions of the Fed Chairs during FOMC press conferences constitute a significant and robust channel for international spillover effects of U.S. monetary policy. By employing machine learning techniques to quantify facial sentiment from video data, we show that positive nonverbal cues from the Fed Chairs are consistently associated with higher international stock market returns. This effect remains robust even after controlling for textual sentiment, tone, monetary policy indicators, monetary policy uncertainty, local market conditions, and contemporary U.S. stock market returns. In addition, we find that the effect of facial sentiment is mainly driven by the first part of the Q&A session and positive sentiment. Furthermore, the impact of facial expressions is totally absorbed in the two-day window and there is no reversal phenomenon.

Our analysis identifies several key dimensions of heterogeneity. The investors in non-English-speaking markets extract less information from text content and rely more on nonverbal information. Therefore, the effect of facial sentiment is more pronounced in these regions. In addition, the impact is also larger when the Fed Chairs refer to more global issue. Channel analyses reveal that positive facial sentiment signals that FOMC members are more confident in monetary policy and there exists a higher level of monetary policy consistency. Therefore, positive facial sentiment reduces the risk premium. Moreover, when the FOMC members hold more positive opinion for future economic fundamentals, the Fed Chairs has more positive facial sentiment. And higher facial sentiment indeed predicts better future economic fundamentals.

Overall, our findings highlight the crucial role of nonverbal communication in central bank signaling and its implications for global financial markets. Policymakers should recognize that their affective nonverbal cues can influence international markets. For investors, incorporating nonverbal sentiment analysis may provide an informational advantage. Future research should continue to explore the intersection of nonverbal cues and financial market behavior, further enriching the understanding of central bank communication in an increasingly interconnected world.

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**Figure 1. Facial sentiment analysis examples**

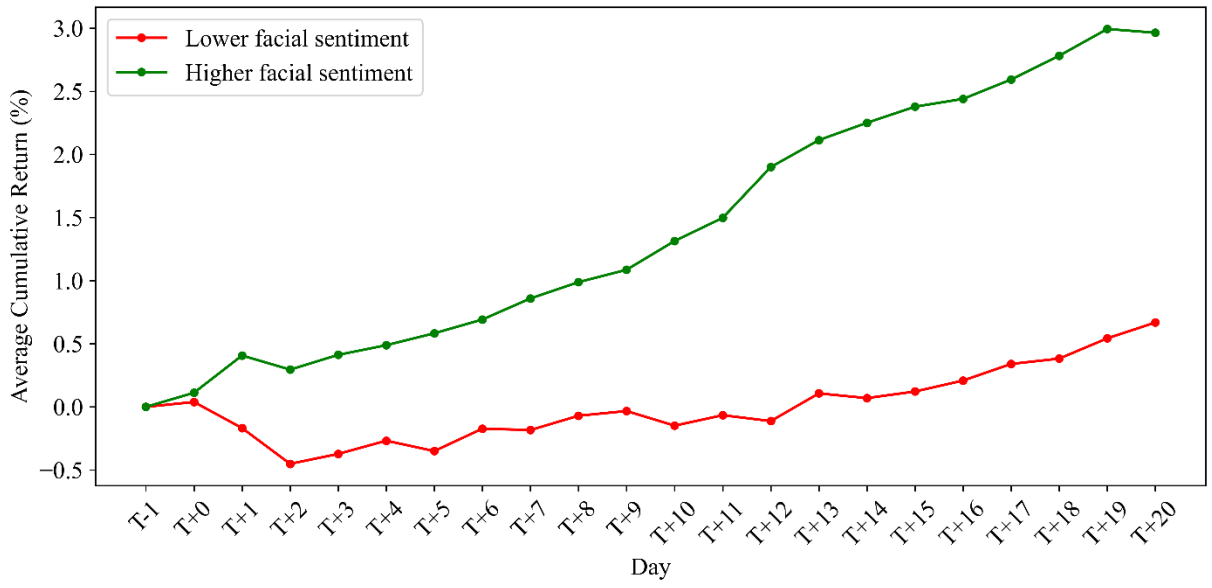
This figure provides frame examples classified by DeepFace, such as “Happy”, “Angry”, and “Sad”.



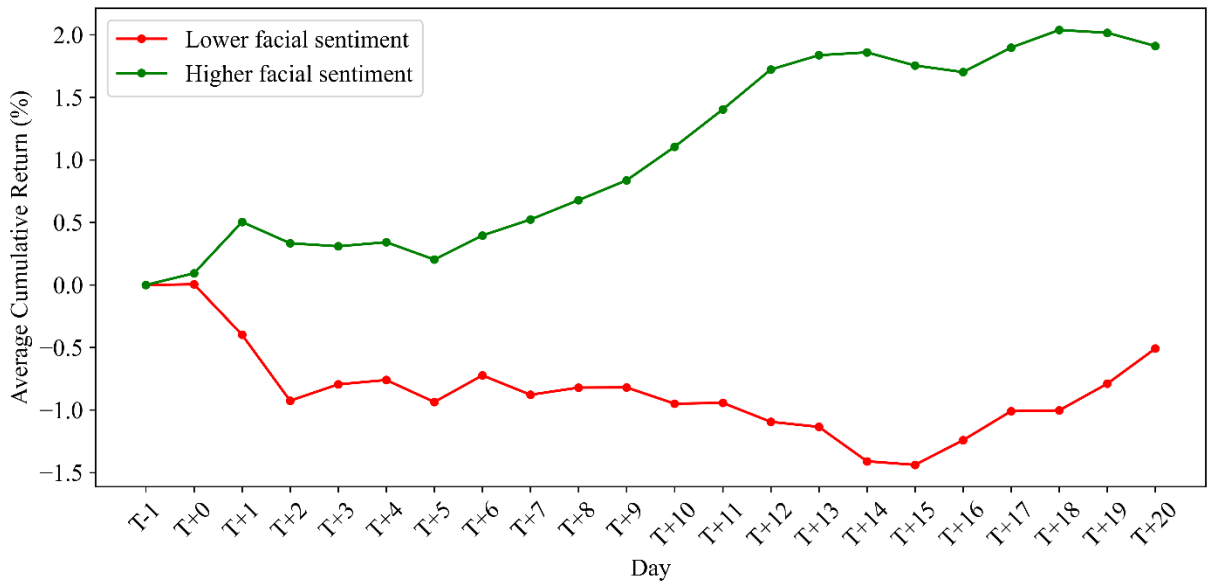
(a) Happy (b) Angry (c) Sad

**Figure 2. Average cumulative return after FOMC press conferences**

This figure plots the average cumulative daily international stock returns around FOMC press conferences, covering the period from January 2011 to December 2023. We classify the FOMC press conferences with highest 10 facial sentiment as "Higher facial sentiment" events, while those with lowest 10 facial sentiment as "Lower facial sentiment" events. Cumulative average international stock returns are shown in the [0, +20] day window of the FOMC press conferences. T+0 represents the day of FOMC press conference and the two-day window encompassing T+0 and T+1.



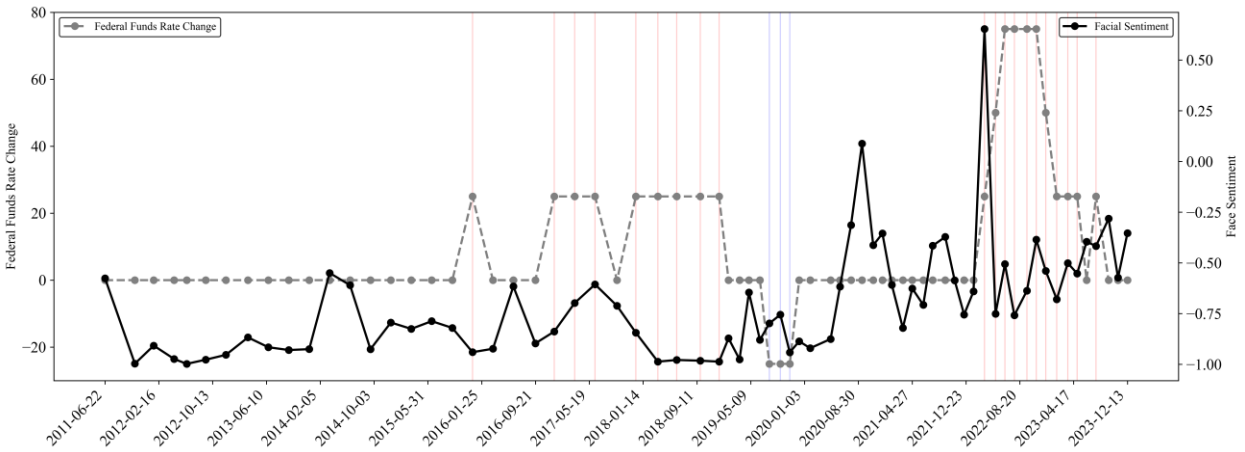

(a) Equal weighted




(b) Market capitalization (in dollar) weighted

## Figure 3. Federal funds rate changes and contemporary facial sentiment

This figure plots the facial sentiment and contemporary federal funds rate change for each FOMC meeting followed by a press conference, from January 2011 to December 2023. The facial sentiment has been standardized to have a mean of zero and a standard deviation of one across the full sample. Vertical bars are colored red for positive federal funds rate changes and green for negative changes.



## Table 1. Summary statistics

This table provides summary statistics for the data used in our empirical analysis, covering the period from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. Detailed variable definitions are provided in Appendix A.

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| *Ret (%)* | 2793 | -0.033 | 1.687 | -10.102 | 8.791 |
| *Face* | 2793 | 0.000 | 1.000 | -1.075 | 4.980 |
| *Text* | 2793 | 0.000 | 1.000 | -2.227 | 1.943 |
| *Voice* | 2793 | 0.000 | 1.000 | -0.588 | 2.358 |
| *FFR (bps)* | 2793 | 9.076 | 20.633 | -25.000 | 75.000 |
| *MPS* | 2793 | 0.000 | 1.000 | -2.062 | 2.989 |
| *MPU* | 2793 | 0.000 | 1.000 | -2.256 | 3.339 |
| *USRET* | 2793 | 0.000 | 1.000 | -3.409 | 2.178 |
| *MCUSRET* | 2793 | 0.000 | 1.000 | -3.170 | 2.816 |
| *MCRET* | 2793 | 0.000 | 1.000 | -8.120 | 7.924 |
| *MCRV* | 2793 | 0.000 | 1.000 | -1.618 | 9.078 |
| *MCINTEREST* | 2793 | 0.000 | 1.000 | -50.851 | 10.599 |
| *MCTS* | 2793 | 0.000 | 1.000 | -28.333 | 7.959 |
| *MCLAG* | 2793 | 0.000 | 1.000 | -9.611 | 6.409 |

## Table 2. Baseline results

This table presents regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. In Panel A, we use economy-meeting panel regressions. In Columns (1) and (2), the original sentiment measures are used. In Column (3), the sentiment during each Chairman's first FOMC press conference is used as a benchmark, and it is subtracted from the original sentiment measures. In Column (4), the average sentiment across all past FOMC press conferences for each Chairman serves as the benchmark. Economy, year, and month fixed effects are included, and standard errors are clustered at the event and economy level. In Column (5), we utilize a Shapley-Owen decomposition (Shorrocks, 2013) to get the contribution of each variable. In Panel B, we use time-series regressions. In Column (1), common OLS model is used and in Column (2), standard errors are computed using Newey–West correction up to 4 lags. In Column (3), we utilize nonparametric (accelerated) bootstrap methods to correct standard errors. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

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| **Panel A: Economy-meeting panel regressions** | | | | | |
|---|---|---|---|---|---|
| Benchmark methods | *No benchmark* | *No benchmark* | *Benchmark-first* | *Benchmark-last all* | *$R^2$ contribution* |
| | (1) | (2) | (3) | (4) | (5) |
| *Face* | 0.3901*** | 0.2506*** | 0.3322*** | 0.1922*** | 9.59% |
| | (0.126) | (0.070) | (0.109) | (0.068) | |
| *Text* | | 0.2559** | 0.2496** | 0.2125** | 2.16% |
| | | (0.111) | (0.098) | (0.091) | |
| *Voice* | | 0.2624** | 0.1366 | 0.1328 | 2.71% |
| | | (0.130) | (0.091) | (0.086) | |
| *FFR* | | -0.0010 | -0.0016 | -0.0025 | 1.03% |
| | | (0.006) | (0.006) | (0.006) | |
| *MPS* | | -0.1307* | -0.1179* | -0.1111 | 1.80% |
| | | (0.066) | (0.070) | (0.071) | |
| *MPU* | | -0.1959*** | -0.1857*** | -0.1821*** | 10.57% |
| | | (0.066) | (0.062) | (0.062) | |
| *USRET* | | 0.6543*** | 0.6785*** | 0.6873*** | 71.50% |
| | | (0.065) | (0.066) | (0.067) | |
| *MCUSRET* | | 0.0624 | 0.0782 | 0.0794 | 0.24% |
| | | (0.061) | (0.063) | (0.063) | |
| *MCRET* | | 0.0027 | 0.0039 | 0.0068 | -0.1%[13] |
| | | (0.071) | (0.073) | (0.073) | |
| *MCRV* | | -0.0503 | -0.0256 | -0.0307 | 0.33% |
| | | (0.067) | (0.074) | (0.076) | |
| *MCINTEREST* | | -0.0291*** | -0.0231* | -0.0247** | 0.03% |
| | | (0.010) | (0.012) | (0.012) | |
| *MCTS* | | -0.0310 | -0.0260 | -0.0245 | 0.20% |
| | | (0.036) | (0.038) | (0.038) | |
| *MCLAG* | | 0.0165 | 0.0134 | 0.0103 | -0.06% |
| | | (0.052) | (0.055) | (0.055) | |

[13] The contribution is based on adjust $R^2$ and it is possible that the contribution of one variable is negative.

| | | | | | |
|---|---|---|---|---|---|
| Economy FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES |
| Observations | 2793 | 2793 | 2668 | 2668 | 2793 |
| Adj. $R^2$ | 0.2107 | 0.3560 | 0.3591 | 0.3570 | 0.3560 |

**Panel B: Time-series regressions**

| Cluster methods | OLS | Newey-West | Bootstrap |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Face* | 0.2490*** | 0.2490*** | 0.2490** |
| | (0.090) | (0.090) | (0.125) |
| *Text* | 0.1459 | 0.1459 | 0.1459 |
| | (0.117) | (0.110) | (0.129) |
| *Voice* | 0.0817 | 0.0817 | 0.0817 |
| | (0.097) | (0.090) | (0.099) |
| *FFR* | 0.0057 | 0.0057 | 0.0057 |
| | (0.005) | (0.005) | (0.006) |
| *MPS* | -0.1761* | -0.1761* | -0.1761* |
| | (0.089) | (0.098) | (0.104) |
| *MPU* | -0.2048** | -0.2048** | -0.2048** |
| | (0.082) | (0.093) | (0.095) |
| *USRET* | 0.7795*** | 0.7795*** | 0.7795*** |
| | (0.086) | (0.064) | (0.090) |
| *MCUSRET* | -0.0775 | -0.0775 | -0.0775 |
| | (0.123) | (0.071) | (0.106) |
| *MCRET* | 0.0670 | 0.0670 | 0.0670 |
| | (0.230) | (0.142) | (0.188) |
| *MCRV* | -0.5275*** | -0.5275*** | -0.5275*** |
| | (0.135) | (0.121) | (0.203) |
| *MCINTEREST* | -0.1080 | -0.1080 | -0.1080 |
| | (0.578) | (0.244) | (1.366) |
| *MCTS* | 0.3289 | 0.3289 | 0.3289 |
| | (0.430) | (0.442) | (0.502) |
| *MCLAG* | 0.0563 | 0.0563 | 0.0563 |
| | (0.188) | (0.170) | (0.216) |
| Observations | 70 | 70 | 70 |
| Adj. $R^2$ | 0.6490 | 0.6490 | 0.6490 |

## Table 3. Decomposition of facial sentiment

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during three stages of FOMC press conferences. In Panel A, the Q&A session is split into three parts based on the proportion of 30%, 30%, and 40%. In Panel B, following Curti and Kazinnik (2023), we construct and test the effect of the positive and negative facial sentiment separately. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

**Panel A: Different parts**

| Dependent variable | *Ret* (1) | *Ret* (2) | *Ret* (3) | *Ret* (4) |
|---|---|---|---|---|
| *FacePart1* | 0.2903*** | | | 0.3580*** |
| | (0.068) | | | (0.113) |
| *FacePart2* | | 0.2039*** | | -0.0952 |
| | | (0.073) | | (0.180) |
| *FacePart3* | | | 0.2113*** | 0.0132 |
| | | | (0.067) | (0.160) |
| Controls | YES | YES | YES | YES |
| Economy FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |
| Observations | 2793 | 2793 | 2793 | 2793 |
| Adj. $R^2$ | 0.3584 | 0.3529 | 0.3543 | 0.3583 |

**Panel B: Positive vs. negative facial sentiment**

| Dependent variable | *Ret* (1) | *Ret* (2) | *Ret* (3) |
|---|---|---|---|
| *FacePositive* | 0.2407*** | | 0.2334*** |
| | (0.070) | | (0.078) |
| *FaceNegative* | | -0.1244* | -0.0162 |
| | | (0.069) | (0.071) |
| Controls | YES | YES | YES |
| Economy FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Observations | 2793 | 2793 | 2793 |
| Adj. $R^2$ | 0.3555 | 0.3492 | 0.3553 |

## Table 4. Long run analysis

This table presents economy-meeting panel regression results of long-run international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. T+N (N=0, 1, 2, 3, 4, 5) is international stock market returns on N trading days after FOMC press conferences. [T+0, T+1] is the two-day international stock market returns in the baseline regressions. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Horizon | [T+0, T+1] | T+0 | T+1 | T+2 | T+3 | T+4 | T+5 |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Face* | 0.2506*** | 0.1822*** | 0.2183*** | 0.0649 | 0.0339 | -0.0109 | -0.0090 |
| | (0.070) | (0.049) | (0.061) | (0.067) | (0.053) | (0.045) | (0.083) |
| Controls | YES | YES | YES | YES | YES | YES | YES |
| Economy FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2793 | 2793 | 2793 | 2793 | 2793 | 2793 | 2793 |
| Adj. $R^2$ | 0.3560 | 0.2737 | 0.2069 | 0.1163 | 0.1043 | 0.0934 | 0.0392 |

## Table 5. Heterogeneity analysis: Global information

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. We calculate the term frequency-inverse document frequency (tf-idf) of words with stems "international" or "glob" for each Q&A text and construct *Global*. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* |
|---|---|
| | (1) |
| *Face* | 0.4402*** |
| | (0.089) |
| *Face*×*Global* | 0.3017*** |
| | (0.095) |
| *Global* | 0.1366 |
| | (0.089) |
| Controls | YES |
| Economy FE | YES |
| Year FE | YES |
| Month FE | YES |
| Observations | 2793 |
| Adj. $R^2$ | 0.3619 |

## Table 6. Heterogeneity analysis: Language

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. *English* is a dummy variable that equals to 1 if one economy's most-spoken language is English and 0 otherwise. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* |
|---|---|
| | (1) |
| *Face* | 0.2716*** |
| | (0.075) |
| *Face*×*English* | -0.0868** |
| | (0.033) |
| Controls | YES |
| Economy FE | YES |
| Year FE | YES |
| Month FE | YES |
| Observations | 2793 |
| Adj. $R^2$ | 0.3562 |

## Table 7. Channel analysis: Risk premium

This table presents time-series regression results of monetary policy consistency and economy-meeting panel regression results of two-day change of volatility indices on facial sentiment of the Fed Chairs during FOMC press conferences. In Panel A, monetary policy consistency (*MPC*) is 1 if the federal funds rate change of next FOMC meeting has the same sign with current FOMC meeting, which means that the monetary policy stance doesn't change, and 0 otherwise. In Colum (1), we use linear probability model and correct standard errors through nonparametric (accelerated) bootstrap methods. In Columns (2) and (3), we employ Logit and Probit models separately. In Panel B, *Vol* is the two-day change of international volatility indices. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| **Panel A: Monetary policy consistency** | | | |
|---|---|---|---|
| Models | LPM-Bootstrap | Probit | Logit |
| | (1) | (2) | (3) |
| *Face* | 0.1203$^{*}$ | 0.9088$^{**}$ | 1.5309$^{**}$ |
| | (0.064) | (0.411) | (0.716) |
| Controls | YES | YES | YES |
| Observations | 69 | 69 | 69 |
| Adj./Pseudo $R^2$ | 0.0953 | 0.4026 | 0.4000 |
| **Panel B: Volatility indices** | | | |
| Dependent variable | *Vol* | | *Vol* |
| | (1) | | (2) |
| *Face* | -2.1986$^{**}$ | | -1.2442$^{*}$ |
| | (0.894) | | (0.678) |
| Controls | YES | | YES |
| Economy FE | YES | | YES |
| Year FE | YES | | YES |
| Month FE | YES | | YES |
| Observations | 671 | | 671 |
| Adj. $R^2$ | 0.2664 | | 0.4688 |

## Table 8. Channel analysis: Economic fundamentals

This table presents time-series regression results of facial sentiment on FOMC members' expectations about U.S. economic fundamentals and economy-meeting panel regression results of future international economic fundamentals on facial sentiment of the Fed Chairs during FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. In Panel A, expected unemployment rate (*EUME*) is the central tendency midpoint of unemployment rate projection proposed by FOMC members. In Column (1), common OLS model is used and in Column (2), standard errors are computed using Newey–West correction up to 4 lags. In Column (3), we utilize nonparametric (accelerated) bootstrap methods to correct standard errors. In Panel B, we consider log changes in price level (*CPIG*), unemployment (*UNEMPG*), and trade (*TRADEG*). We use forecast horizons in the range from one month to twelve months. In addition to control variables in equation (4), we control the log changes of economic fundamentals in the same month of FOMC press conference to consider the autocorrelation problem. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

**Panel A: Expected U.S. economic fundamental**

| Methods | OLS | Newey-West | Bootstrap |
|---|---|---|---|
| | (1) | (2) | (3) |
| *EUME* | -0.3968$^{*}$ | -0.3968$^{**}$ | -0.3968$^{*}$ |
| | (0.233) | (0.187) | (0.241) |
| Controls | YES | YES | YES |
| Observations | 50 | 50 | 50 |
| Adj./Pseudo R2 | 0.2553 | 0.2553 | 0.2553 |

**Panel B: Future international economic fundamentals**

| *Horizon* | 3M | 6M | 9M | 12M |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *CPIG* | 0.1366$^{***}$ | 0.1284 | 0.1893 | 0.2803$^{**}$ |
| | (0.042) | (0.099) | (0.120) | (0.126) |
| *UNEMPG* | -1.1785$^{**}$ | -2.8686$^{***}$ | -2.8630$^{*}$ | -3.1541$^{*}$ |
| | (0.460) | (1.036) | (1.410) | (1.747) |
| *TRADEG* | 1.8794 | 2.1961$^{***}$ | 3.1778$^{***}$ | 1.6469 |
| | (1.356) | (0.815) | (1.010) | (1.137) |
| Controls | YES | YES | YES | YES |
| Economy FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |

## Appendix A. Variable definitions

| Variable | Definition |
|---|---|
| *Ret* | The two-day change of stock market close prices around FOMC press conferences |
| *Face* | The sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences |
| *Text* | The sentiment extracted from text of FOMC press conferences |
| *Voice* | The sentiment extracted from voice of the Fed Chairs during FOMC press conferences |
| *FFR* | The change of federal funds rate announced in FOMC meetings |
| *MPS* | Monetary policy surprise constructed by Bauer and Swanson (2023) |
| *MPU* | The two-day change of monetary policy uncertainty constructed by Bauer, Lakdawala, Mueller (2022) |
| *USRET* | The two-day change of U.S. stock market close prices around FOMC press conferences |
| *MCUSRET* | The cumulative US stock market return between two FOMC press conferences |
| *MCRET* | The cumulative local stock market returns between two FOMC press conferences |
| *MCRV* | The realized volatility of local stock markets between two FOMC press conferences |
| *MCINTEREST* | The average short-term interest rate measured in the yield to maturity of local two-year treasury bonds between two FOMC press conferences |
| *MCTS* | The average difference of yield to maturity of local ten-year treasury bonds and two-year treasury bonds between two FOMC press conferences |
| *MCLAG* | Local stock market returns before FOMC press conferences |
| *FacePart1* | The sentiment extracted from facial expressions of the Fed Chairs during the first 30% part of FOMC press conferences |
| *FacePart2* | The sentiment extracted from facial expressions of the Fed Chairs during the second 30% part of FOMC press conferences |
| *FacePart3* | The sentiment extracted from facial expressions of the Fed Chairs during the last 40% part of FOMC press conferences |
| *FacePositive* | The positive sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences |
| *FaceNegative* | The negative sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences |
| *Global* | The term frequency-inverse document frequency (tf-idf) of words with stems "international" or "glob" for each FOMC press conference Q&A text |
| *English* | A dummy variable that equals to 1 if one economy's most-spoken language is English and 0 otherwise |
| *MPC* | Monetary policy consistency that equals 1 if the federal funds rate change of next FOMC meeting has the same sign with current FOMC meeting |
| *Vol* | The two-day change of volatilities around FOMC press conferences |
| *EUME* | The central tendency midpoint of unemployment rate projection proposed by FOMC members |
| *CPIG* | The monthly log change of CPI for each economy |
| *UNEMPG* | The monthly log change of unemployment rate for each economy |
| *BCIG* | The monthly log change of trade (export plus import) for each economy |
| *STY* | The two-day yield changes of one-year government bond around FOMC press conferences |
| *MTY* | The two-day yield changes of two-year government bond around FOMC press conferences |

| | |
|---|---|
| *LTY* | The two-day yield changes of ten-year government bond around FOMC press conferences |
| *ER* | The two-day log change of exchange rate around FOMC press conferences |

## Appendix B. Economy trading hours

| Economy | Developed | Time zone | Stock exchange | Stock exchange begin time | Stock exchange close time |
|---|---|---|---|---|---|
| Argentina | 0 | America/Argentina/ Buenos Aires | Buenos Aires SE (MERVAL) to Bolsas y Mercados Argentinos | 11:00 | 17:00 |
| Australia | 1 | Australia/Sydney | Australian SE | 10:00 | 16:00 |
| Austria | 1 | Europe/Vienna | Vienna SE | 9:00 | 17:35 |
| Belgium | 1 | Europe/Brussels | Euronext Brussels | 9:00 | 17:35 |
| Brazil | 0 | America/Sao Paulo | Sao Paulo SE (BOVESPA) | 10:00 | 17:00 |
| Bulgaria | 0 | Europe/Sofia | Bulgarian SE | 10:10 | 17:00 |
| Canada | 1 | America/Toronto | Toronto SE | 9:30 | 16:00 |
| Chile | 0 | America/Santiago | Santiago SE | 9:30 | 16:00 |
| China | 0 | Asia/Shanghai | Shanghai & Shenzhen SE | 9:30 | 15:00 |
| Colombia | 0 | America/Bogota | Bolsa de Valores de Colombia | 8:30 | 15:00 |
| Croatia | 1 | Europe/Zagreb | Zagreb SE | 9:00 | 16:00 |
| Cyprus | 1 | Asia/Nicosia | Cyprus SE | 10:30 | 17:05 |
| Czech Republic | 1 | Europe/Prague | Prague SE | 9:00 | 16:15 |
| Denmark | 1 | Europe/Copenhagen | Copenhagen SE | 9:00 | 17:00 |
| Egypt | 0 | Africa/Cairo | Cairo SE | 10:00 | 14:25 |
| France | 1 | Europe/Paris | Euronext Paris | 9:00 | 17:35 |
| Germany | 1 | Europe/Berlin | XETRA & Frankfurt | 9:00 | 17:35 |
| Greece | 1 | Europe/Athens | Athens SE | 10:30 | 17:10 |
| Hong Kong | 1 | Asia/Hong_Kong | Hong Kong SE | 9:30 | 16:10 |
| India | 0 | Asia/Kolkata | Bombay SE & National SE | 9:15 | 15:30 |
| Indonesia | 0 | Asia/Jakarta | Indonesia SE/Jakarta SE | 9:00 | 16:00 |
| Ireland | 1 | Europe/Dublin | Irish SE | 8:00 | 16:30 |

| | | | | | |
|---|---|---|---|---|---|
| *Israel* | 1 | Asia/Jerusalem | Tel Aviv SE | 9:59 | 15:50 for Sunday, 17:25 from Monday to Thursday |
| *Italy* | 1 | Europe/Rome | Milan SE | 9:00 | 17:35 |
| *Japan* | 1 | Asia/Tokyo | JASDAQ SE & Tokyo SE | 9:00 | 15:30 |
| *Jordan* | 0 | Asia/Amman | Amman SE | 10:30 | 12:30 |
| *Korea* | 1 | Asia/Seoul | Korea SE & KOSDAQ SE | 9:00 | 15:30 |
| *Netherlands* | 1 | Europe/Amsterdam | Euronext Amsterdam | 9:00 | 17:35 |
| *New Zealand* | 1 | Pacific/Auckland | New Zealand SE | 10:00 | 17:00 |
| *Nigeria* | 0 | Africa/Lagos | Nigerian SE | 10:00 | 14:30 |
| *Norway* | 1 | Europe/Oslo | Oslo SE | 9:00 | 16:25 |
| *Peru* | 0 | America/Lima | Bolsa de Valores de Lima | 8:30 from the second Sunday of march to the first Sunday of November; 9:30 From the first Sunday in November to the second Sunday of march | 15:10 from the second Sunday of march to the first Sunday of November; 16:10 From the first Sunday in November to the second Sunday of march |
| *Philippines* | 0 | Asia/Manila | Philippines SE | 9:30 | 14:50 |
| *Poland* | 0 | Europe/Warsaw | Warsaw SE | 9:05 | 16:50 |
| *Portugal* | 1 | Europe/Lisbon | Euronext Lisbon | 8:00 | 16:35 |
| *Romania* | 0 | Europe/Bucharest | Bucharest SE | 10:00 | 17:50 |
| *Russia* | 0 | Europe/Moscow | MICEX | 10:00 | 18:50 |
| *Singapore* | 1 | Asia/Singapore | Singapore SE | 9:00 | 17:05 |
| *Slovakia* | 1 | Europe/Bratislava | Bratislava SE | 11:00 | 15:30 |
| *Slovenia* | 1 | Europe/Ljubljana | Ljubljana SE | 9:15 | 15:30 |
| *South Africa* | 0 | Africa/Johannesburg | Johannesburg SE | 9:00 | 17:00 |

| | | | | | |
|---|---|---|---|---|---|
| *Spain* | 1 | Europe/Madrid | Madrid SE/SIBE | 9:00 | 17:35 |
| *Sri Lanka* | 0 | Asia/Colombo | Colombo SE | 9:30 | 14:30 |
| *Sweden* | 1 | Europe/Stockholm | Stockholm SE | 9:00 | 17:30 |
| *Switzerland* | 1 | Europe/Zurich | Six Swiss SE | 9:00 | 17:30 |
| *Thailand* | 0 | Asia/Bangkok | SE of Thailand | 10:00 | 16:40 |
| *Turkey* | 0 | Europe/Istanbul | Istanbul SE | 10:00 | 18:05 |
| *UK* | 1 | Europe/London | London SE | 8:00 | 16:30 |
| *Venezuela* | 0 | America/Caracas | Bolsa de Valores de Caracas | 9:00 | 13:00 |
| *Vietnam* | 0 | Asia/Ho Chi Minh | Ho Chi Minh City SE | 9:15 | 14:45 |

## Table A1. Alternative frequency

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences at a frequency of one frame per 2 seconds and standardized to one-unit standard deviation and zero mean in the full sample. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* | *Ret* |
|---|---|---|
| | (1) | (2) |
| *Face* | 0.3721*** | 0.2370*** |
| | (0.124) | (0.070) |
| Controls | NO | YES |
| Economy FE | YES | YES |
| Year FE | YES | YES |
| Month FE | YES | YES |
| Observations | 2793 | 2793 |
| Adj. $R^2$ | 0.2093 | 0.3552 |

## Table A2. Alternative cluster methods

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. For different columns, we use different cluster methods. Economy, year and month effects are included. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* (1) | *Ret* (2) | *Ret* (3) | *Ret* (4) | *Ret* (5) |
|---|---|---|---|---|---|
| *Face* | 0.2506*** | 0.2506*** | 0.2506*** | 0.2506*** | 0.2506*** |
| | (0.046) | (0.067) | (0.030) | (0.039) | (0.055) |
| Cluster methods | Economy | Event | Year | Economy, Year | Economy, Year, Month |
| Controls | YES | YES | YES | YES | YES |
| Economy FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES |
| Observations | 2793 | 2793 | 2793 | 2793 | 2793 |
| Adj. $R^2$ | 0.3560 | 0.3560 | 0.3560 | 0.3557 | 0.3555 |

## Table A3. Alternative sample

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. We randomly choose 10 economies from our sample and run the baseline regression for 1000 times. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* | *Ret* |
|---|---|---|
| | (1) | (2) |
| *Face* | 0.3922*** | 0.2514*** |
| | (0.081) | (0.089) |
| Controls | NO | YES |
| Economy FE | YES | YES |
| Year FE | YES | YES |
| Month FE | YES | YES |

## Table A4. Exclude outliers

This table presents economy-meeting panel regression results of two-day international stock market returns on facial sentiment of the Fed Chairs during FOMC press conferences. *Ret* is the two-day change of stock market close prices around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. We apply 99% trimming on continuous variables to remove the impact of outliers. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *Ret* | *Ret* |
|---|---|---|
| | (1) | (2) |
| *Face* | 0.3901*** | 0.2069*** |
| | (0.126) | (0.071) |
| Controls | NO | YES |
| Economy FE | YES | YES |
| Year FE | YES | YES |
| Month FE | YES | YES |
| Observations | 2793 | 2572 |
| Adj. $R^2$ | 0.2107 | 0.3760 |

## Table A5. Bond and currency analysis

This table presents economy-meeting panel regression results of two-day government bond yield changes and exchange rate returns on facial sentiment of the Fed Chairs during FOMC press conferences. *STY, MTY, and LTY* is the two-day yield changes of one-year, two-year, and ten-year government bond separately.*ER* is the two-day log change of exchange rate around FOMC press conferences. *Face* is the sentiment extracted from facial expressions of the Fed Chairs during FOMC press conferences and standardized to one-unit standard deviation and zero mean in the full sample. Economy, year and month fixed effects are included, and standard errors are clustered at the event and economy level. The sample period is from January 2011 to December 2023. During this period, there are 70 FOMC meetings followed by a press conference. The sample consists of 50 economies, which include 28 advanced and 22 emerging economies. Standard errors are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

| Dependent variable | *STY* | *MTY* | *LTY* | *ER* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Face* | -0.0044$^{*}$ | -0.0015 | 0.0028 | -0.0166 |
| | (0.002) | (0.003) | (0.003) | (0.055) |
| Controls | YES | YES | YES | YES |
| Economy FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |
| Observations | 2787 | 2791 | 2792 | 2506 |
| Adj. $R^2$ | 0.0451 | 0.0993 | 0.1728 | 0.1866 |