Data summary for "Let's Face It: Quantifying the Impact of Nonverbal Communication in FOMC Press Conferences" of Curti and Kazinnik (2021)

Dependent variables

Financial asset data (minute-level, Jan2011-Sep2020)

- Equity (SPY): Price & volume
- Implied volatility
- Euro to US Dollar exchange rate futures: Price & volume

Dependent variables are *"percent changes within 3 minute intervals in SPY"* and *"average trading volume within 3 minute intervals during the time of the press conference in SPY and FX"*

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.

Composite score of facial expressions

- Youtube FOMC videos
- Pre-trained algorithm provided by Microsoft Azure Cognitive Services Emotion API https://azure.microsoft.com/en-us/products/cognitive-services/vision-services
- Extracts scores for eight facial emotions for each frame via CNN: *Anger, Contempt, Disgust, Fear, Happiness, Neutral, Sadness, and Surprise* (each retrieves a score between 0 and 1, all together adding up to 1)
- Frames extracted for 46 FOMC videos. Each frame is captured at the two second interval
- Scores aggregated to three-minute intervals
- The main independent variable is then composed by combining *Anger, Disgust, Fear*

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

- Alternative measures include PCA analysis of the emotion scores, and two scores that i) do not weigh the *Negative Emotions* score and ii) does consider the standard deviation of *Negative Emotions*

Key Independent Variables	
Negative Emotions	The Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.
Negative Emotions_{pca}	The Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative* $\textit{emotions}_{pca}$ intensity is the combination of the seven intensities (anger, contempt, disgust, fear, happiness, sadness, and surprise) as captured by the Microsoft Azure Cognitive Services Emotion API multiplied by the first principal component coefficients.
Negative Emotions_{std}	The standard deviation of the Chair's intensity of negative emotions averaged in the prior three minutes divided by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.
Negative Emotions_{dmd}	The Chair's intensity of negative emotions averaged in the prior three minutes subtracted by the average intensity of negative emotions across all FOMC meetings presided by the Chair. The *negative emotions* intensity is the sum of anger, disgust, and fear intensities as captured by the Microsoft Azure Cognitive Services Emotion API.

Control variables

- Text
  - Align time stamps of text with video
  - Manual text labeling: Dividing FOMC Q&A into Questions and answers, and *"classifying each text excerpt into a specific category"* (We may utilize the prepared data appendix of Gorodnichenko et al. (2023)
  - Quantify verbal components via pre-trained FinBERT, available via the Hugging Face, an open source library containing a wide range of pretrained models https://huggingface.co/ProsusAI/finbert
  - Classifies text as: *Positive, Negative,* or *Neutral.* This is then aggregated in two alternative measures:
    - "*Negative Tone"* - taking the "*total number of negative sentences, subtract the number of positive sentences, and divide it by the total number of sentences in that particular 3 minute interval*" and "*dividing it by its own standard deviation."*
    - "*Hawkishness"* - measures the prevalence of hawkish and dovish expressions using the stance dictionary in Hansen and McMahon (2016). This should be the Table A2 in that paper "*We do a search and count of words associated with this dictionary in each part of the sentence. These counts are then aggregated over the entire sentence to form the index in question."*

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

Table A2
Word lists and frequency across FOMC statements in sample.

Expansion words		Contraction words		Ambiguity words in sample	
Stemmed token	Frequency	Stemmed token	Frequency	Stemmed token	Frequency
Improv	55	Moder	82	Condit	91
Foster	52	Slow	35	Anticip	71
Increas	42	Low	33	Believ	20
Expand	38	Weak	27	Risk	14
Rise	27	Subdu	20	May	14
Higher	14	Lower	20	Appear	11
Risen	10	Fall	13	Conting	9
Gain	9	Slower	5	Suggest	9
Strong	5	Weaker	3	Seem	7
Acceler	1	Decreas	3	Somewhat	4
Faster	1	Weaken	2	Uncertainti	4
Strength	1	Contract	2	Uncertain	3
		Soften	2	Possibl	2
		Deceler	1	Destabil	2
		Cool	1	Volatil	1
				Tent	1
				Unusu	1
				Might	1
				Alter	1

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Other control variables are shown below:

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

References

Curti, F., & Kazinnik, S. (2021). Face It: Quantifying the Impact of Nonverbal Communication in FOMC Press Conferences. Working paper. https://doi.org/10.2139/ssrn.3782239

Gorodnichenko, Y., Pham, T., & Talavera, O. (2023). The Voice of Monetary Policy. American Economic Review (Vol. 113, Issue 2, pp. 548–584). https://doi.org/10.1257/aer.20220129

Hansen, S., & McMahon, M. (2016). Shocking language: Understanding the macroeconomic effects of central bank communication. Journal of International Economics (Vol. 99, pp. 114–133). https://doi.org/10.1016/j.jinteco.2015.12.008