**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”*

*Text

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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* *A picture containing chart

  Description automatically generated*
* 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*

Graphical user interface, text

Description automatically generated

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.” Graphical user interface, text

      Description automatically generated*
  + *Table

    Description automatically generated*

Other control variables are shown below:

*Text

Description automatically generated*

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>