How can a Fed Chair not be an actor?

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Készült az Egyetemi Kutatói Ösztöndíj Program keretében, a Kulturális és Innovációs Minisztérium Nemzeti Kutatási, Fejlesztési és Innovációs Alapjának támogatásával.

Motivation

- New policy tool since 2011: FOMC press conferences (PCs)
- Standard deviation of asset price changes are 2× larger during PCs than FOMC around statements
- What causes such movements? What kind of information is perceived? Less researched than FOMC statements (Bodilsen et al., 2021; De Pooter, 2021; Curti & Kazinnik, 2023; Gorodnichenko et al., 2023)

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- "Monetary policy is 98% talk and 2% action" – Ben Bernanke (2022).
- "When central bankers talk, financial markets listen" – Blinder et al. (2024)

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- Central bank texts can reveal signals beyond official numerical decisions.
- The **sentiment of FOMC releases** can trigger significant market reactions (Hansen & McMahon, 2016; Hansen et al., 2019; Doh et al., 2021; Hubert & Labondance, 2021; Chau et al., 2025)
- Fed Chair's **non-verbal communication** can influence financial markets (voice tone: Gorodnichenko et al. (2023); facial expressions: Curti and Kazinnik (2023))

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1. Measure multiple aspects of FOMC communication

- I propose a new Large Language Model (LLM) framework to construct multiple indicators of tone from FOMC statements and PCs
- Constructing a score from the emotional tone in the Fed Chair's voice

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2. Examine whether surprises in communication tone generate asset price changes in narrow windows around FOMC events (statement and PC

- Investigate the mechanism through which communication affects asset prices

Contribution

- Identifying the **causal effects** of multiple dimensions of communication
  - Most previous studies rely on one-dimensional indicator of tone (e.g. positive vs negative words) (e.g. Hubert and Labondance (2021) and Schmeling and Wagner (2025))
  - Measuring multiple components of communication using a **new algorithm building on fine-tuned LLMs**
  - Constructing "tone surprises" from tone indices for both statements and PCs

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- Investigating the **underlying transmission mechanism** of monetary policy communication, adding to Cieslak and McMahon (2023) and Cieslak et al. (2023)

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- Extending the recent literature on the effects of FOMC PCs (Bodilsen et al., 2021; De Pooter, 2021; Curti & Kazinnik, 2023; Gorodnichenko et al., 2023)
  - Fed Chairs have the ability to **move markets through verbal and non-verbal communication** at PCs

Textual Analysis - Data

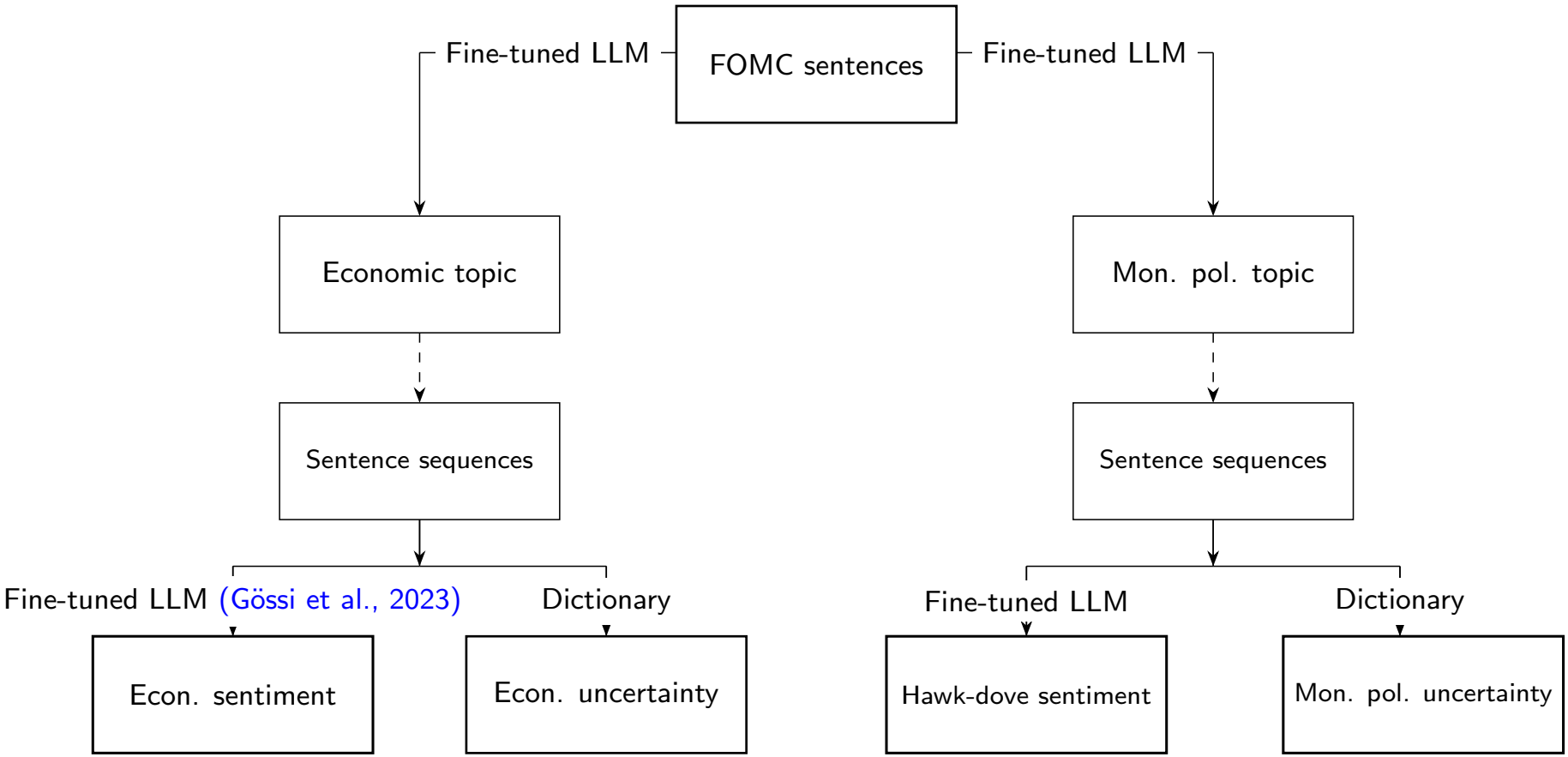
The textual data spans **from January 2011 to January 2025**, covering:

- FOMC Statements: 112 statements in total.
- FOMC Press Conferences: 80 press conferences in total

I download all FOMC statements and transcripts of FOMC press conferences from the Federal Reserve website in PDF format.

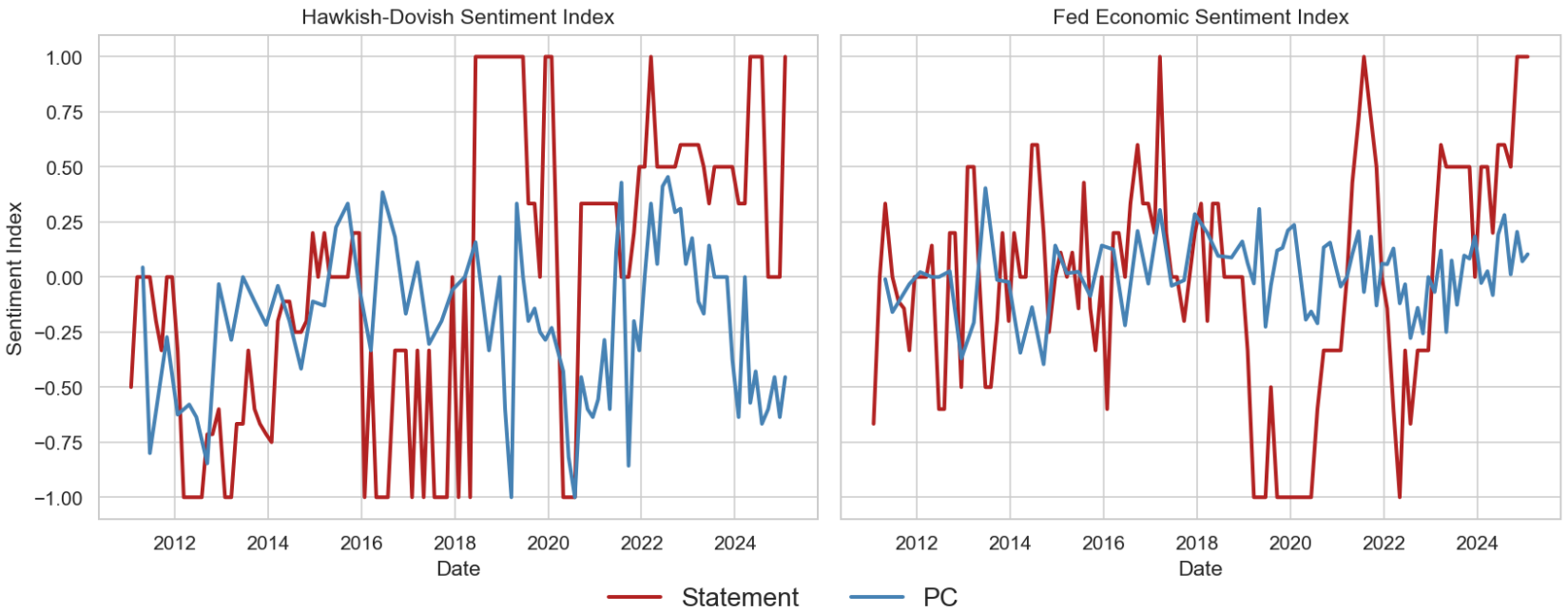
- I extract the paragraphs from each statement.
- For press conferences, I extract the Chair's introductory remarks and their responses to questions from the press
- I split the texts into sentences.

Textual Analysis - New framework



Appendix - Description of fine-tuned LLMs | Appendix - Textual indices

Textual indices



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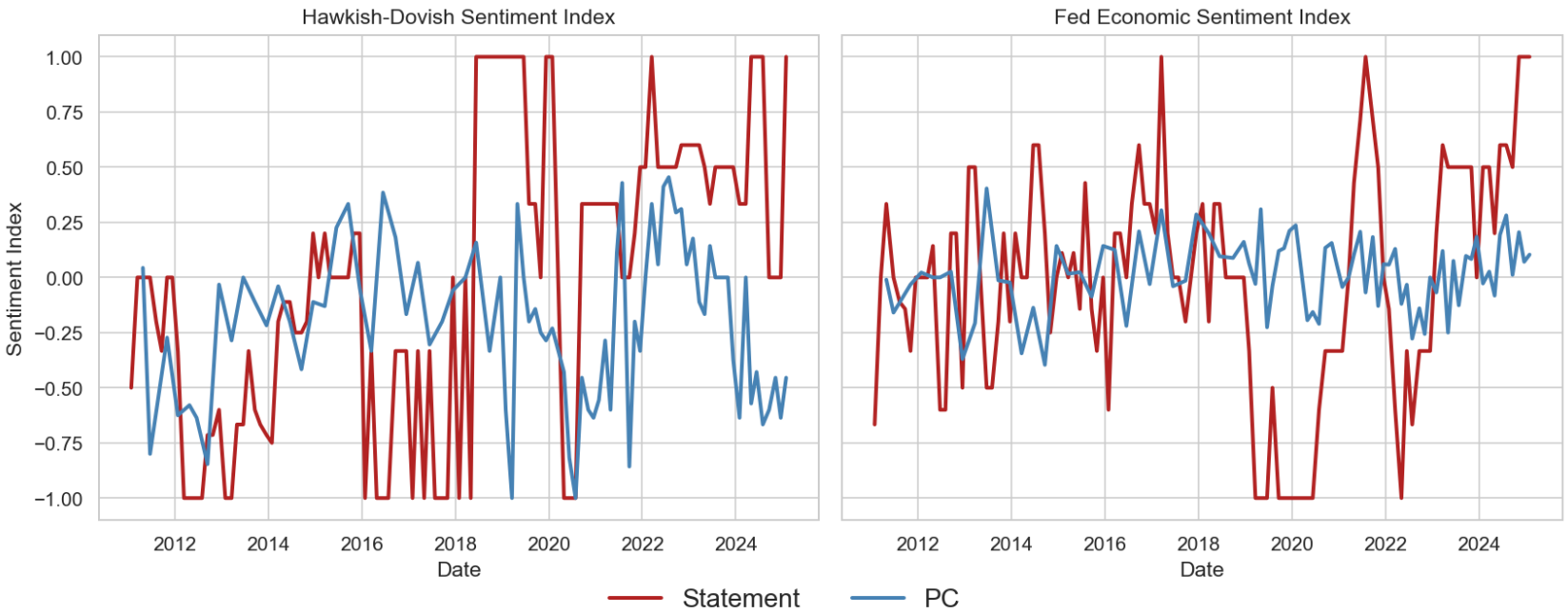

Correlations	$\Delta S\&P$	ΔFFR	FFR	$\Delta BCI_{t-1,t}$	$\Delta ENS_{t-1,t}$
HDS	-0,11	**0.31**	**0.54**	**-0.30**	**-0,21**
ESI	0,04	-0,08	-0,10	**0,22**	**0,19**

Sentiment indicators can be predicted by pre-announcement data and are correlated with announcement day changes. It is necessary to purge them of the expected part.

Voice tone analysis I

Inspiration: Gorodnichenko et al. (2023)
Extracting the voice of Chairs on FOMC press conferences

- Manually timestamping videos of FOMC Press Conferences: downloading each response given to press' question and the introductory remark.
- Answers last 5 - 300 seconds, we split longer answers into a maximum of 60 seconds long audio file

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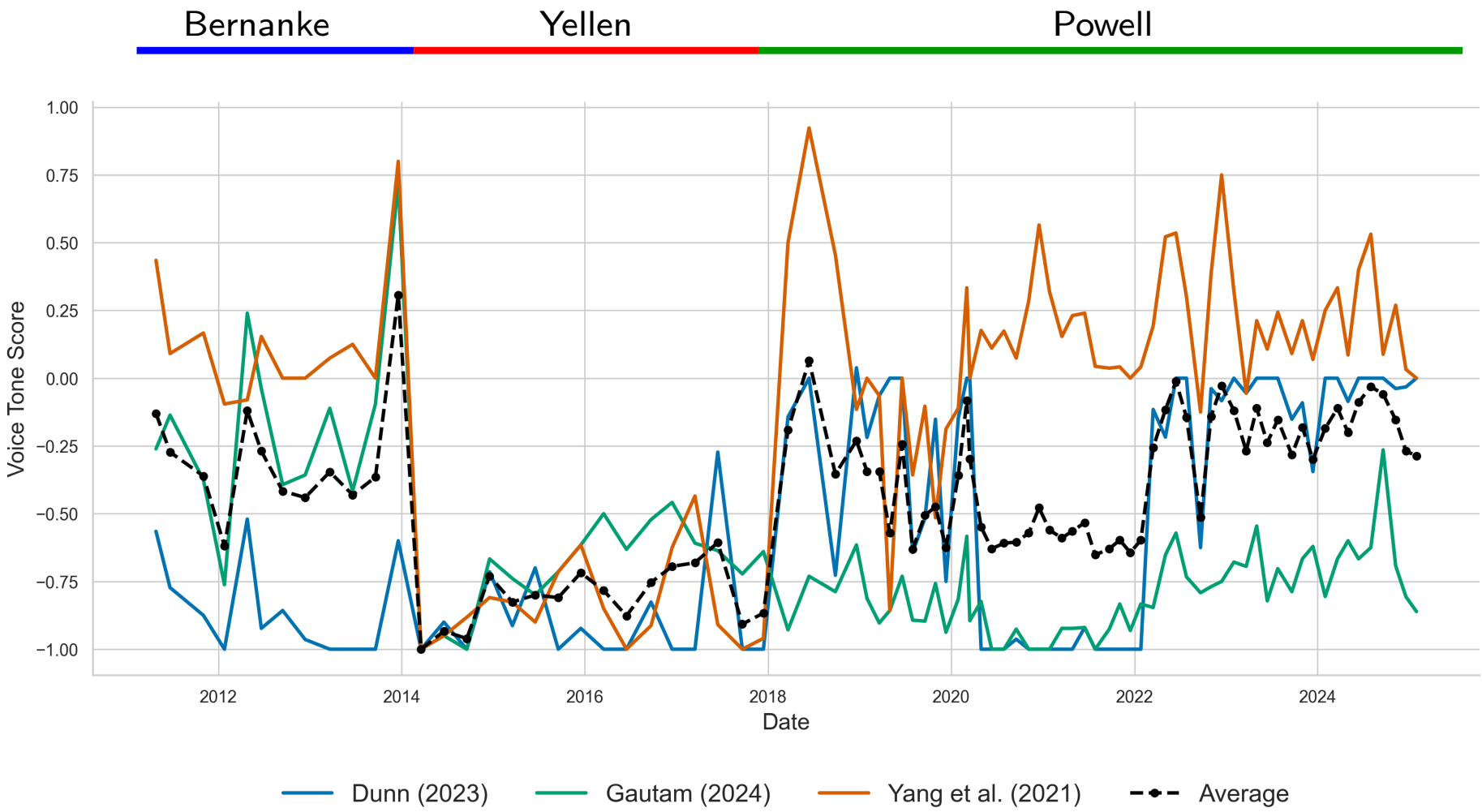
To avoid model selection bias we use three emotion recognition models available on the community platform HuggingFace.

- Each model is a fine-tuned version of the Wav2Wec2 model to recognize emotions.
  - For each model and press conferences we calculate the Voice Tone Score:

$$\text{VTS} = \frac{\#\text{Positive segments} - \#\text{Negative segments}}{\#\text{All segments}}$$

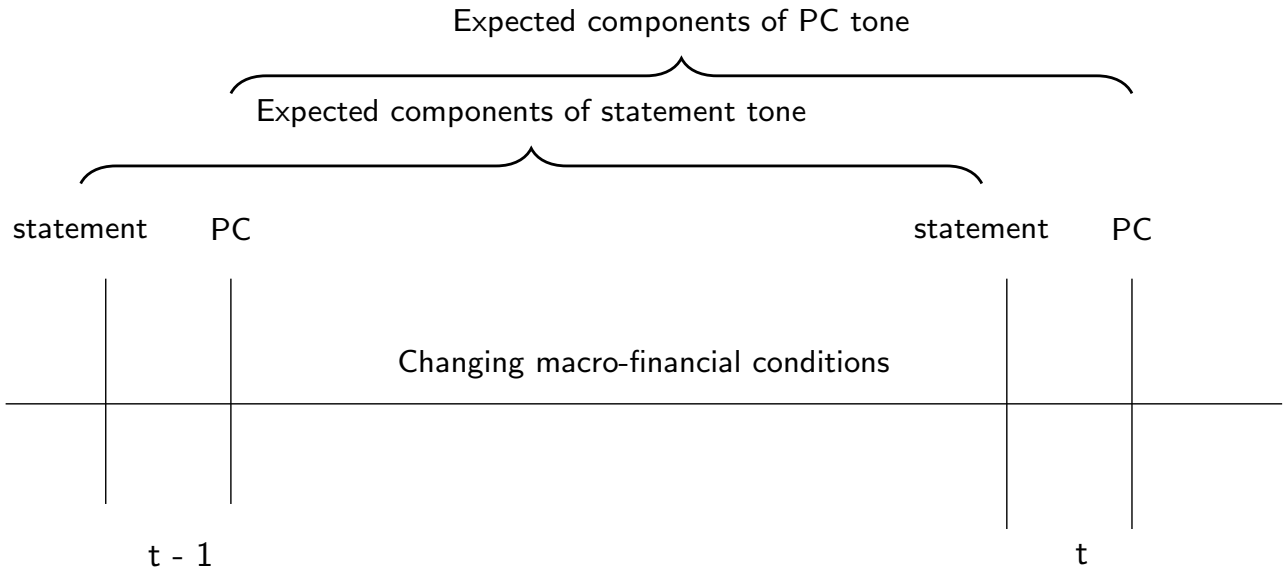
  - Averaging the Voice Tone Score of the three models

Voice tone analysis II



Constructing textual and voice tone surprises

Extending Hubert and Labondance (2021):



Running regressions to purge all tone indices of

- the change in financial and macroeconomic variables between $t-1$ and t.
- the monetary policy stance at $t-1$
- the FOMC tone at $t-1$
- in case of PC tone: the policy changes and tone at statement t

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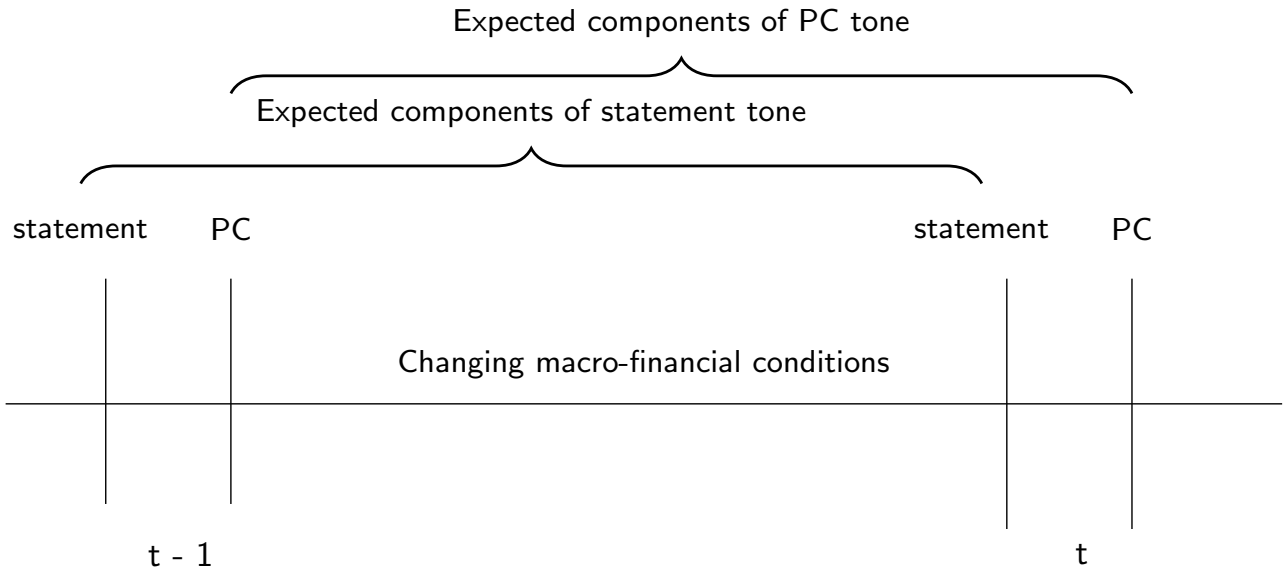

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R^2s: 40–90 %.

The residuals are the unexpected surprises in our textual/audio indices.

Asset price surprises

Yield changes in 2-, 5-, and 10-year Treasury note futures, and returns on E-mini S&P 500 futures, and VIX futures in narrow windows:

- Statements: changes from 10 minutes before to 20 minutes after the release
- PCs: 10 minutes before the start until 20 minutes after the end of the conference

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Decomposing Treasury yield changes and stock returns into four orthogonal components based on Cieslak and Pang (2021):

- **Monetary policy shocks** (short-term yields ↑ stocks ↓)
- **Growth shocks** (short- and mid- term yields ↑ stocks ↑)
- **Common** (discount-rate risk) **premia shocks** (long-term yields ↑ stocks ↓)
- **Hedging premia shocks** (long-term yields ↓ stocks ↓)

Sign-restricted SVAR(1) model with empirically and theoretically backed restrictions.

Appendix - Variance decompositions

Do textual and voice shocks generate monetary policy surprises?

Statements:

$$\Delta Y_t^{ST} = \alpha + \beta_1 \varepsilon^{ST}_{\text{HDS,t}} + \beta_2 \varepsilon^{ST}_{\text{FES,t}} + \beta_3 \varepsilon^{ST}_{\text{TMPU,t}} + \beta_4 \varepsilon^{ST}_{\text{TFEU,t}} + \beta_5 \mathbf{\Delta X_t} + \beta_6 \mathbf{\Omega_t} + \epsilon_t \quad (1)$$

- $\mathbf{\Delta X_t}$ includes changes in numerical policy indicators released in the statement
- $\mathbf{\Omega_t}$ includes controls for prevailing financial and economic conditions

Do textual and voice shocks generate monetary policy surprises?

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Press conferences:

$$\Delta Y_t^{PC} = \alpha + \beta_1 \varepsilon^{PC}_{\text{HDS,t}} + \beta_2 \varepsilon^{PC}_{\text{FES,t}} + \beta_3 \varepsilon^{PC}_{\text{TMPU,t}} + \beta_4 \varepsilon^{PC}_{\text{TFEU,t}} + \gamma \varepsilon^{PC}_{\text{VTS,t}} + \beta_5 \Delta \mathbf{X_t} + \beta_6 \mathbf{\Omega_t} + \epsilon_t \quad (2)$$

Results: statements I

	$\Delta 2Y$	$\Delta 5Y$	$\Delta 10Y$	$\Delta S\&P$	ΔVIX
Hawkish-dovish Sentiment shock ($\varepsilon^{ST}_{\text{HDS}}$)	-0.06	-0.10	-0.08	**0.11****	-0.05
	[0.06]	[0.07]	[0.06]	[0.05]	[0.06]
FED Economic Sentiment shock ($\varepsilon^{ST}_{\text{FES}}$)	**0.09***	**0.12***	**0.14***	**0.13****	**-0.12***
	[0.05]	[0.07]	[0.07]	[0.06]	[0.06]
Textual MPU shock ($\varepsilon^{ST}_{\text{TMPU}}$)	-0.03	-0.05	-0.05	0.05	-0.09
	[0.06]	[0.08]	[0.08]	[0.06]	[0.07]
Textual Economic Uncertainty shock ($\varepsilon^{ST}_{\text{TFEU}}$)	-0.02	-0.02	-0.01	0.02	0.02
	[0.04]	[0.08]	[0.03]	[0.02]	[0.04]

- A more positive economic tone raises bond yields and stocks and decreases risk aversion, in line with Hubert and Labondance (2021) and Chau et al. (2025)
- A one standard deviation positive FES shock increases S&P 500 futures by appr. 6 basis points

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	$\Delta 2Y$	$\Delta 5Y$	$\Delta 10Y$	$\Delta S\&P$	ΔVIX
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	[0.06]	[0.07]	[0.06]	[0.05]	[0.06]
FED Economic Sentiment shock ($\varepsilon^{ST}_{\text{FES}}$)	**0.09***	**0.12***	**0.14***	**0.13****	**-0.12***
	[0.05]	[0.07]	[0.07]	[0.06]	[0.06]
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- Hawkish surprises raise equity prices, as in Parle (2022) and Cieslak and McMahon (2023)
- Why?

Results: statements II

	ΔMP	ΔG	ΔCP	ΔHP
Hawkish-dovish Sentiment shock ($\varepsilon^{ST}_{\text{HDS}}$)	0.18	-0.01	**-0.19*** **	-0.11
	[0.11]	[0.11]	[0.07]	[0.08]
FED Economic Sentiment shock ($\varepsilon^{ST}_{\text{FES}}$)	-0.01	0.13	-0.00	**-0.24** **
	[0.07]	[0.10]	[0.09]	[0.11]
Textual MPU shock ($\varepsilon^{ST}_{\text{TMPU}}$)	-0.00	-0.01	-0.09	-0.03
	[0.10]	[0.10]	[0.09]	[0.11]
Textual Economic Uncertainty shock ($\varepsilon^{ST}_{\text{TFEU}}$)	0.01	-0.03	-0.03	-0.04
	[0.09]	[0.10]	[0.10]	[0.14]

- **Tone surprises act through risk premia!**
- Reaffirms Cieslak and McMahon (2023) and Caballero and Simsek (2022): the Fed's communication can signal intentions that can diverge from market expectations — **policy mistakes**
- When the tone is too dovish: this **misalignment** may lead to increased uncertainty and elevated risk premia
- A too hawkish tone can signal Fed's readiness to tighten, stabilizing risk premia
- **New result:** Signals of the economy also act through risk premia

Results: press conferences I

	$\Delta 2Y$	$\Delta 5Y$	$\Delta 10Y$	$\Delta S\&P$	ΔVIX
Hawkish-dovish Sentiment shock ($\varepsilon^{PC}_{\text{HDS}}$)	-0.08	-0.09	-0.10	**0.15***	**-0.15***
	[0.09]	[0.09]	[0.08]	[0.08]	[0.09]
FED Economic Sentiment shock ($\varepsilon^{PC}_{\text{FES}}$)	0.15	0.20	0.19	-0.16	0.12
	[0.12]	[0.13]	[0.13]	[0.12]	[0.12]
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	-0.16	-0.10	-0.06	0.10	-0.12
	[0.10]	[0.10]	[0.10]	[0.11]	[0.12]
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.13	-0.15	-0.14	0.06	0.10
	[0.16]	[0.16]	[0.17]	[0.14]	[0.10]
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	**-0.21****	**-0.19***	**-0.18***	**0.22****	**-0.26****
	[0.09]	[0.10]	[0.11]	[0.10]	[0.11]

- A hawkish surprise raises equity returns and lowers the VIX, consistently with Parle (2022) and Baranowski et al. (2023) for ECB press conferences

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	[0.12]	[0.13]	[0.13]	[0.12]	[0.12]
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	-0.16	-0.10	-0.06	0.10	-0.12
	[0.10]	[0.10]	[0.10]	[0.11]	[0.12]
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.13	-0.15	-0.14	0.06	0.10
	[0.16]	[0.16]	[0.17]	[0.14]	[0.10]
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- Voice tone surprises have **wide-ranging** effects on financial markets, in line with Gorodnichenko et al. (2023)
- A one std dev. voice tone surprise increases equity returns by appr. 17 basis points

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	[0.10]	[0.10]	[0.10]	[0.11]	[0.12]
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.13	-0.15	-0.14	0.06	0.10
	[0.16]	[0.16]	[0.17]	[0.14]	[0.10]
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	**-0.21****	**-0.19***	**-0.18***	**0.22****	**-0.26****
	[0.09]	[0.10]	[0.11]	[0.10]	[0.11]

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- A one std dev. voice tone surprise increases equity returns by appr. 17 basis points
- Gorodnichenko et al. (2023) suggest two possible explanations:
  - Tone of voice may act as **forward guidance**, signaling future policy direction - future easing or tightening
  - May reflect **information effects** — e.g., confidence in inflation and outlooks.

Results: press conferences II

	ΔMP	ΔG	ΔCP	ΔHP
Hawkish-dovish Sentiment shock ($\varepsilon^{PC}_{\text{HDS}}$)	-0.10	0.07	**-0.14***	-0.01
	[0.09]	[0.09]	[0.08]	[0.09]
FED Economic Sentiment shock ($\varepsilon^{PC}_{\text{FES}}$)	0.14	-0.00	0.17	-0.06
	[0.12]	[0.13]	[0.12]	[0.13]
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	-0.18	-0.12	0.05	-0.09
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Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.09	-0.12	-0.05	0.06
	[0.07]	[0.08]	[0.04]	[0.11]
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	**-0.23****	-0.01	-0.13	-0.02
	[0.09]	[0.09]	[0.11]	[0.13]

- A positive (negative) voice tone has similar effects to a monetary easing (tightening)
- This suggests that the chair's voice tone **carries information primarily about monetary policy stance** rather than the chair's perceived economic outlook

Results: Forecasting power of voice tone

Does voice tone work like forward guidance?
If yes, we expect voice tone surprises to predict future policy rate changes post-2014.

$$\Delta FFR_{t+j} = \alpha + \beta_1 \varepsilon^{PC}_{\text{VTS,t}} + \beta_2 \Delta \mathbf{X_t} + \beta_3 \Delta \mathbf{Z_{t/t-1}} + \beta_4 \mathbf{\Omega_t} + \epsilon_t \tag{3}$$

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	ΔFFR$_{t+1}$	ΔFFR$_{t+2}$	ΔFFR$_{t+3}$
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS,t}}$)	-**0.28****	0.02	-0.12
	[0.13]	[0.25]	[0.15]
Unemployment median forecast at t	-0.34**	-0.01	-0.16
	[0.15]	[0.24]	[0.21]
ΔFFR_t	0.73***	0.67***	0.43***
	[0.00]	[0.01]	[0.10]
VIX level at t	0.013***	0.01	0.02*
	[0.00]	[0.01]	[0.01]
BCI level at t	0.01**	0.00	0.01
	[0.00]	[0.01]	[0.01]
N	63	63	63
R^2	0.81	0.69	0.64

A positive (negative) tone is an indication of an increased likelihood of monetary easing (tightening).

Implications

1. **Multi-dimensional tone matters:** Economic sentiment and hawkish-dovish tone affect markets differently. One-dimensional measures may miss nuances and bias results.
2. **Text-based tone affects risk premia:** Sentiment surprises influence asset prices via the risk-taking channel of monetary policy (Borio & Zhu, 2012).
3. **Non-verbal tone as policy signal:** Voice tone contains information markets react to. Acts similarly to forward guidance; deep learning methods capture it.

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Practical lesson: Markets respond to both *what* the Fed says and *how* it is said. Tone surprises can shift risk premia and uncertainty—even without policy changes.

Further research: Why do markets react to information during PCs? (Gómez-Cram & Grotteria, 2022). Is tone used strategically? (Cieslak et al., 2023). The role of media and X in interpreting FOMC communication.

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Thank you for your attention!

Fine-tuning LLMs - topic classification

We face the challenge that FOMC texts cover multiple different topics.

- Within a single response from the Chair, multiple topics may be discussed, making sentence-level topic categorization essential.

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We leverage the structured format of the FOMC Minutes, which are published three weeks after each Federal Open Market Committee meeting. The documents cover discussions about three recurring topics:

- Economic Outlook (chapters Staff Review of the Economic Situation, Staff Economic Outlook, Participants' Views on Current Conditions and the Economic Outlook)
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We take a sample of 2,000 sentences from the FOMC Minutes dataset compiled by Acosta (2023) and label each sentence according to the section in which it appears.

- Two subsets: 80% to the training set, the remaining 20% to the test set.

How do we measure policy shocks from asset prices?

- Standard monetary policy shocks on FOMC announcement days affect the expected path of the policy rate and thus the short-rate
- A growing body of research documents that monetary policy acts through other channels beyond short-rate news.
- Monetary policy affects macroeconomic conditions by changing risk-taking and risk premia (the risk-taking channel of monetary transmission (Borio and Zhu 2012)
- Announcements reveal information not just about policy but also about the central bank's assessment of the economic outlook (Jarocisnki and Karádi 2020)
- The channels that have been examined can be broadly separated into information effects (e.g.,Campbell et al., 2012, Nakamura and Steinsson, 2018) and risk premium effects (e.g., Bernanke and Kuttner, 2005, Bekaert et al., 2013, Hanson and Stein, 2015)

How do we measure policy shocks from asset prices? II

- Cieslak and Pang (2021) create a framework to create orthogonal shocks that occur on FOMC announcement days from changes in Treasury yields and the S&P 500 index. They decompose announcement days market responses by ICA SVAR methodology into four independent components:

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- We follow Cieslak and Pang (2021) to create four types of shocks from financial data.
- We expect that different types of textual shocks contained in FOMC texts and the voice tone of the Chair generate different type of asset price shocks.

LLMs used

Fine tuning for topic classification using FOMC Minutes training dataset (Acosta, 2023)

Model	Train Loss	Val Loss	Test Loss	Accuracy	Macro F1
Fine-tuned RoBERTa Base	0.30	0.26	**0.36**	**90.18 %**	**0.87**
Fine-tuned BERT Base	**0.13**	0.22	0.37	88.92 %	0.84
Fine-tuned FinBERT	0.16	**0.19**	0.61	89.17 %	0.86
ChatGPT-4o mini	—	—	—	87.35 %	0.83

Fine tuning for hawkish-dovish-neutral classification (dataset: Gorodnichenko et al. (2023)

Model	Train Loss	Val Loss	Test Loss	Accuracy	Macro F1
Fine-tuned RoBERTa Base	0.69	0.65	0.62	73,1 %	0.71
Fine-tuned BERT Base	0.47	**0.58**	**0.60**	**80,8 %**	**0.81**
Fine-tuned FinBERT	**0.40**	0.63	0.61	77.9 %	0.78
FOMC RoBERTa (Shah et al. 2023)	—	—	0.62	67.5 %	0.68
ChatGPT-4o mini	—	—	—	77.1 %	0.79

Positive/negative economic sentiment: FOMC-FinBERT (Gössi et al., 2023)

Construction of textual indices

For each statement and press conference:
On monetary policy texts:

1. $$HDS = \frac{\#\text{Hawkish} - \#\text{Dovish}}{\#\text{Hawkish} + \#\text{Dovish}}$$

2. $$TMPU = \frac{\#\text{Uncertain Words}}{\#\text{All Words}}$$

based on the Loughran and McDonald (2011) dictionary

On economic texts:

3. $$FES = \frac{\#\text{Pos. sentiment} - \#\text{Neg. sentiment}}{\#\text{Pos. sentiment} + \#\text{Neg. sentiment}}$$

4. $$TFEU = \frac{\#\text{Uncertain Words}}{\#\text{All Words}}$$

Forecast error variance decompositions

(a) Statement changes

	ω_t^{mp}	ω_t^{g}	ω_t^{cp}	ω_t^{hp}
Δ2Y	0.62	0.25	0.11	0.02
Δ5Y	0.35	0.24	0.34	0.07
Δ10Y	0.29	0.14	0.38	0.20
ΔS&P	0.52	0.11	0.24	0.14

(b) Press conference changes

	ω_t^{mp}	ω_t^{g}	ω_t^{hp}	ω_t^{cp}
Δ2Y	0.63	0.24	0.09	0.04
Δ5Y	0.44	0.16	0.24	0.16
Δ10Y	0.33	0.13	0.32	0.22
ΔS&P	0.56	0.08	0.24	0.11

Notes: Each cell reports the share of explained variance in narrow window asset price changes on FOMC days attributable to each of the four structural shock dimensions: monetary policy (ω_t^{mp}), growth (ω_t^{g}), common premium (ω_t^{cp}), and hedging premium (ω_t^{hp}). Results are reported separately for statement and press conference windows. ChatGPT-4o was used in writing the LaTeX code that generates the layout of this table.