

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

The effects of annual reports on volatility: a European point of view

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The effects of Annual Reports on Volatility: A European Point of View

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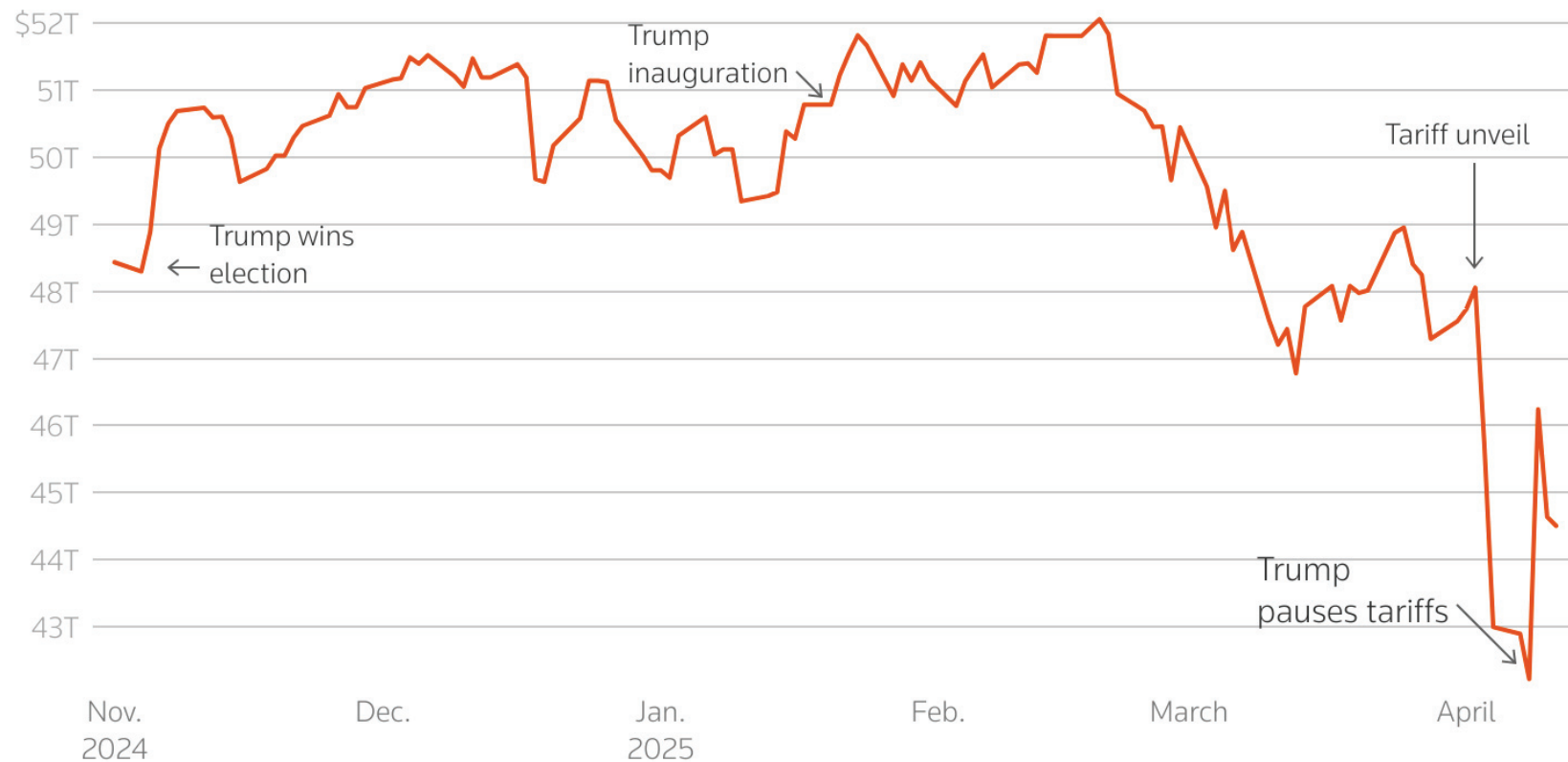
Babeş-Bolyai University,
Raiffeisen Bank International

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Motivation

Trump trade

— S&P 500 market capitalization



Source: LSEG
Created by Thomson Reuters / Noel Randewich

Assumptions and Research Question

- Financial Markets react **quickly** to events.
- Volatility cannot be entirely forecasted using historical data

Research Question

How much the emissions of annual reports affect the EURO STOXX 50 constituents?

From Keynes to FinBERT

The General Theory of Employment, Interest and Money, John Maynard Keynes (1936)

Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of **animal spirits** – of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.”

FinBERT

FinBERT is a pre-trained NLP model to analyze sentiment of financial text. It is fine-tuning it for financial sentiment classification.

Text Data

Algorithm: For each annual report $i \in \text{STOXX 50 of 2023}$, divide it in chunks (each one of 500 tokens), use FinBERT to label the chunks as positive, negative, or neutral. Then

$$a_i = \frac{\#neutral\ chunks}{\#total\ chunks},$$

$$b_i = \frac{\#positive\ chunks}{\#total\ chunks},$$

$$c_i = \frac{\#negative\ chunks}{\#total\ chunks}$$

Net Positivity Score

The *Net Positivity Score* x_i of a report i is defined as $x_i := b_i - c_i$.

Positive Tone

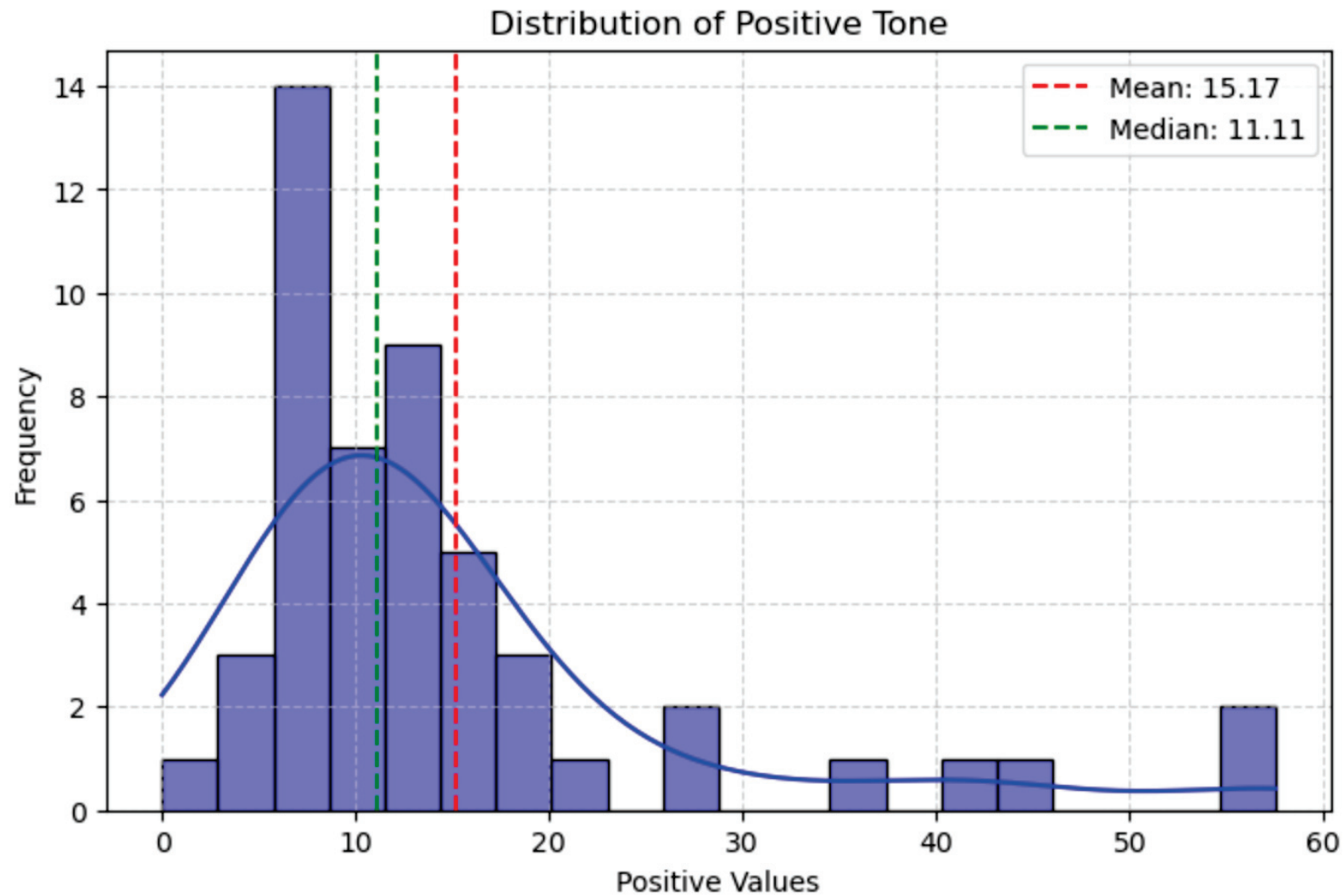


Figure: Histogram of Positive Tone across the reports

Negative Tone

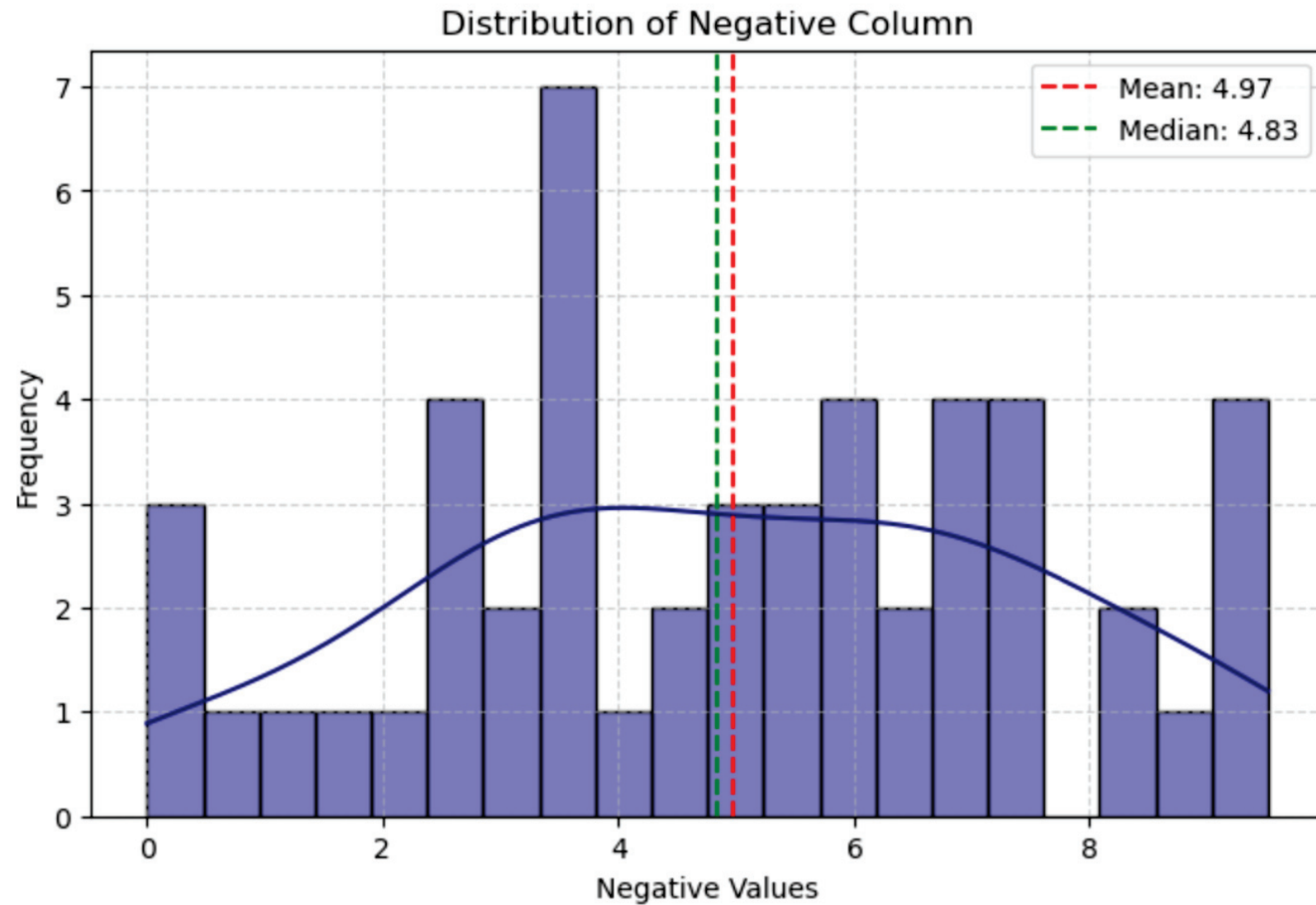


Figure: Histogram of Negative Tone across the reports

Neutral Tone

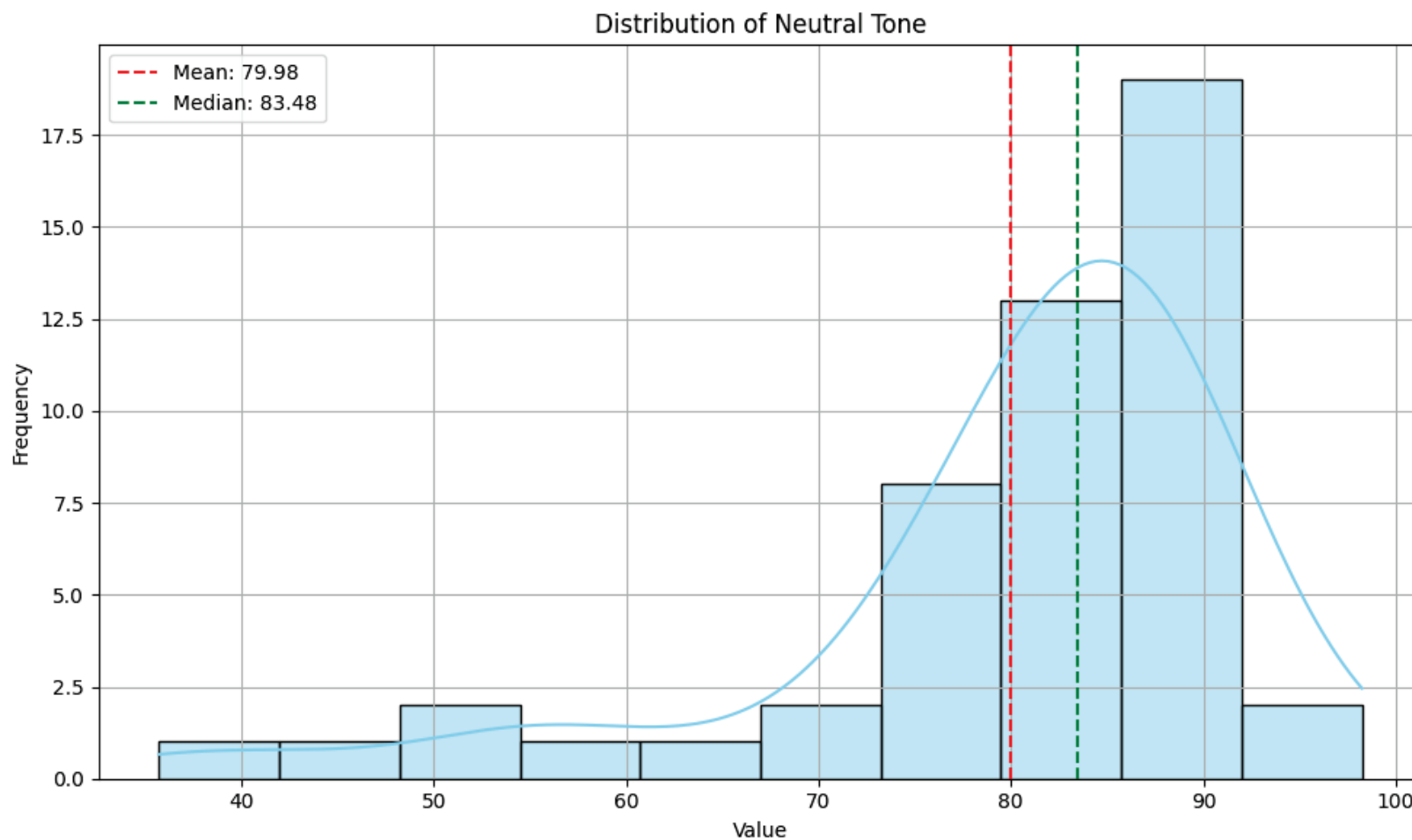


Figure: Histogram of Neutral Tone across the reports

Numerical Data and Model

Data: for each $i \in \text{STOXX 50}$ we collect the daily log return $r_i(t)$ for $t = 1, \dots, 7$, where $t = 1$ is the emission day of the annual report.

2-step EGARCH(1,1)

First step:

$$\log(\sigma_{t,i}^2) = \omega_i + \beta_i \log(\sigma_{t-1,i}^2) + \alpha_i \left(\left| \frac{\varepsilon_{t-1,i}}{\sigma_{t-1,i}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma_i \cdot \frac{\varepsilon_{t-1,i}}{\sigma_{t-1,i}}$$

Second step:

$$\hat{\sigma} = \beta_0 + \beta_1 x + u_t$$

where x is the net positivity score.

Results

	Const	Net Positivity Tone
coef	−8.3924	0.0151
std err	0.102	0.006
t	−82.462	2.448
P > t 	0.000	0.015
[0.025, 0.975]	[−8.592, −8.192]	[0.003, 0.027]

Table: Regression Output Summary

R²	95% Bootstrapped CI
0.015	[0.0021, 0.0308]

Table: R^2 and Bootstrapped Confidence Interval on the Tone

Conclusions

- ① Derived a variable called *net positivity* score from a collection of annual reports of 2023 regarding the STOXX 50 index.
- ② Used it to detect the local volatility after the emission dates.
- ③ There is a statistical contribution of the tone on explaining the local volatility, but it is not the main driver.

From Annual Report Sentiment to Market Risk

- Subtle deviations from neutral tone in annual reports influence market perception.
- Changes in report sentiment affect equity volatility.
- Increased volatility translates into CSPP/APP portfolio risk.

Policy Implications for CSPP/APP

- CSPP/APP portfolios are sensitive to sentiment-driven risk.
- Integrating sentiment analysis can complement traditional risk measures (ratings, spreads).
- Helps in managing portfolio risk proactively and sustainably.

Sentiment → Volatility → CSPP → Policy

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Thanks for your attention!