Finance Research Letters 86 (2025) 108418

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

When the FED speaks their tone, do international financial markets respond?

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ARTICLE INFO

JEL classifications:
E31
E58
G12
D84

Keywords:
FED tone
International financial market
Determinants

ABSTRACT

This study aims to explore the question, "*When the FED speaks, do international financial markets respond?*" through an extended analysis using a two-step regression method. Initially, we perform a regression analysis on the tone of speeches by FED Chairpersons, based in the US, against the rate of return on major stock exchanges from over 60 countries. Subsequently, to account for the variability of these coefficients in the initial phase, we incorporate macroeconomic and financial indicators, such as proximity, GDP per capita, and lending interest rates, into our analysis to test our hypotheses. Our findings indicate that proximity negatively influences return changes, and other factors, including total reserves, lending interest rates, external debt of stock, and exchange rates, show a predictive capacity for these variations from the first estimate.

1. Introduction

Tone, body language, nuance, and facial expressions all play a significant role in our communication. Mehrabian (1981) suggested that only 7 % of feelings and attitudes are expressed through the words we use in spoken communications, 38 % through tone and voice, and the remaining 55 % through body language.

Former Bank of England governor Montagu Norman's initial stance of "Never apologize, never explain", epitomized the British take on central bank communication hundred years ago, which was shown to be less effective. Since then, the communication strategies of central banks have evolved considerably. Today, central banks, including the Federal Reserve, actively use various channels, such as reports, speeches, press conferences, in order to guide expectations. The Federal Reserve's influence on global markets is substantial, yet the role of tone in its communication has been less studied.

Research has examined how U.S. monetary policy affects global markets. Cuaresma et al. (2019) noted that countries integrated into global trade and finance networks experience stronger spillovers. The U.S. financial market, holding a third of EMDEs' portfolio assets and denominating 80 % of global bond issuance, plays a central role. Beyond trade, cross-border stock market co-movements have been observed (Kose et al., 2003), though regional variations exist (Bekaert et al., 2009, 2014). Beyond monetary policy shocks from both central banks, information shocks from the FED also played a role in driving the co-movement of interest rates across numerous countries (Hou et al., 2024).

U.S. monetary policy, largely governed by supply and demand, was occasionally steered by the Federal Open Market Committee (FOMC). Interest rate shifts could cause global ripple effects, with increased co-movements and financial volatility (Lastauskas &

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https://doi.org/10.1016/j.frl.2025.108418
Received 2 August 2025; Received in revised form 24 August 2025; Accepted 5 September 2025
Available online 10 September 2025

Nguyen, 2023). Researchers have explored how FOMC decisions influence asset prices (Patelis, 1997; Rigobon and Sack, 2004), noting that time sensitivity was crucial for investor response. Forecasting methods are evolving to detect monetary signals during FOMC meetings. Geographic spillover effects are also being studied. Mehl et al. (2024) used distance metrics, such as physical, linguistic, and digital, to assess transaction volatility. Results suggested that distant trade relationships were more exposed to demand shocks, though effects on stock returns remain unclear.

Recent interest rate hikes and FOMC announcements have not succeeded in re-anchoring short-term inflation expectations (Chibane & Kuhanathan, 2023). They found that both the likelihood and severity of expected inflation surges or crashes remained largely unaffected by policy announcements and short-term interest rate changes. In contrast, Gorodnichenko et al. (2021), using deep learning to assess the emotional tone in speeches by FED Chairs, showed that a more positive vocal tone is associated with significant increases in stock prices, while the bond market responded less strongly. Moreover, the tone of these speeches also influenced inflation expectations and exchange rates: more optimistic tones tended to be linked with lower inflation forecasts.

The study of tone and emotional content in speech has evolved significantly over recent decades. Early research focused on simple acoustic features such as pitch and frequency to infer speaker mood and attitude (Mehrabian, 1981). With advances in computational power and machine learning, researchers began to extract more sophisticated vocal. Recently, Ko (2024) analyzed the impact of the sentiment expressed in speeches by FED chairs on Treasury bond yields, using a finBERT model developed by Huang et al. (2022). Moreover, deep learning approaches, especially neural networks, have become prominent due to their ability to automatically learn complex representations from raw audio data, improving the accuracy of emotion recognition in speech (Gorodnichenko et al., 2021). These methodological advancements have enabled more precise measurement of emotional tone in policy communications, which is critical for understanding their impact on financial markets.

Expanding on these literatures and the previous study of Gorodnichenko et al. (2021), our study explores the global influence of FOMC tones by examining stock returns across 60 countries, while accounting for macroeconomic conditions and proximity to the U.S. We assess whether the emotional tone in FED communications affects international markets and whether this impact varies with countries' economic ties or similarities to the U.S.

The remainder of the paper is organized as follows. Section 2 describes the empirical strategy, including our identification approach and regression framework. Section 3 presents the data sources and variable information. Section 4 discusses the empirical results from both the first-stage and second-stage regressions, as well as robustness checks. Section 5 concludes with key findings, policy implications, and avenues for future research.

2. Empirical strategy

2.1. Identification strategy

Gorodnichenko et al. (2021) introduced an innovative methodology for assessing the impact of Federal Reserve communications on financial markets by employing a deep learning model to extract emotional content from press conferences following Federal Open Market Committee meetings. Their findings indicate that positive vocal tones expressed by Federal Reserve Chairs are significantly associated with statistically and economically meaningful increases in U.S. equity prices.

The authors trained a neural network model (a deep learning algorithm) to recognize voice emotions. For a specific Q&A session, the authors calculated the tone of responses as follows:

$$VoiceTone = \frac{Positive\ answers - Negative\ answers}{Positive\ answers + Negative\ answers}$$

In this context, 'Voice Tone' is a variable that ranges from -1 to +1, representing from the negative emotions to positive emotions.

For textual analysis, a "*search and count*" method are used to classify FOMC communications as hawkish or dovish. Gorodnichenko et al. (2021) constructed four words lists, including nouns, adjectives, and verbs, representing signals of either restrictive (hawkish) or accommodative (dovish) monetary policy. Sentiment is quantified using the following formula:

$$Text\ Sentiment = \frac{Dovish\ phrases - \ Hawkish\ phrases}{Dovish\ phrases + \ Hawkish\ phrases}$$

Motivated by these insights, the present study seeks to replicate and extend this approach to a global context. Specifically, we examine whether the emotional tone of FOMC communications exerts a comparable influence on international equity markets. In the present study, we directly use the voice and text sentiment measures provided in their dataset and merge these with international equity return data from 60 countries to analyze cross-country responses to FOMC communications.

Then in the second stage, building on these coefficients from the first stage, we formulated the research question: "*Which macroeconomic factors can explain the variation in the sensitivity of stock returns to FED sentiment across countries?*" To address this, we employed a second-stage linear regression, using the previously obtained coefficients as dependent variables and macroeconomic indicators as explanatory variables.

Table 1
First-step regression outcomes: countries with significant sentiment effects.

Variables	(1) Tunisia	(2) New Zealand	(3) Chile	(4) Ukraine
emo	-0.0024*	-0.0032*	-0.0047**	-0.0057**
	(0.0014)	(0.0018)	(0.0022)	(0.0029)
	0.0906	0.0685	0.0305	0.0483
S_QASR0	0.0008	-0.0047	0.0042	-0.0080**
	(0.0020)	(0.0043)	(0.0045)	(0.0040)
	0.6975	0.2746	0.3588	0.0447
ffr	-0.0050	-0.0045	0.0093	-0.0160
	(0.0058)	(0.0082)	(0.0135)	(0.0196)
	0.3869	0.5794	0.4919	0.4141
fg	0.0020	0.0009	-0.0036	0.0042
	(0.0015)	(0.0014)	(0.0024)	(0.0029)
	0.1791	0.5143	0.1252	0.1549
ap	-0.0011	0.0003	0.0008	-0.0012
	(0.0014)	(0.0015)	(0.0033)	(0.0028)
	0.4415	0.8637	0.8076	0.6766
shadowrate	0.0002	0.0001	-0.0013	-0.0005
	(0.0004)	(0.0006)	(0.0009)	(0.0010)
	0.6875	0.8178	0.1616	0.6051
nopress	-0.0004	0.0019	-0.0016	-0.0041
	(0.0013)	(0.0027)	(0.0031)	(0.0030)
	0.7462	0.4805	0.6155	0.1662
Constant	0.0000	0.0016	-0.0021	0.0097**
	(0.0015)	(0.0024)	(0.0033)	(0.0048)
	0.9959	0.5010	0.5231	0.0442
Observations	62	67	64	66
R-squared	0.1834	0.1354	0.1747	0.2358

Standard errors in parentheses
***$p < 0.01$
Note: This table presents the regression results for the effect of emotional sentiment (emo) and other control variables on equity returns (tun_er, nzl_er, chl_er, ukr_er) across Tunisia, New Zealand, Chile, and Ukraine, respectively. These are the only countries where the sentiment variable (emo) shows statistically significant effects. Results for countries without significant findings are presented in the Appendix (Appendix A6).
** $p < 0.05$
* $p < 0.1$

2.2. *Empirical model*

2.2.1. *First-step regression: bootstrapping with a foreach loop*

We use the stock returns of 60 countries to examine the response of international stock markets to the announcement of FED. We applied this model to 60 countries, then we extracted the coefficients of the regression models, the standard errors in order to study the linkages between FED announcements and the international stock returns. We apply the foreach method to extract the coefficients of 60 countries from the same regression model used in the previous study. Foreach runs the commands enclosed in braces and repeatedly sets the local macro name to each element of the list. To save more time, the loop is run zero or more times.

$$i\_ER_{t,t+h} = \beta_0^{(h)} + \beta_1^{(h)} VoiceTone_t + \beta_2^{(h)} TextSentiment_t + \beta_3^{(h)} FFRShock_t + \beta_4^{(h)} FGShock_t + \beta_5^{(h)} APShock_t + \beta_6^{(h)} ShadowRate_t + errors_t^{(h)} \tag{1}$$

The Eq. (1) is based on the model of Gorodnichenko et al. (2021) (Appendix C). In our study, we examine the stock returns ($i\_ER_{t,t+h}$) as the outcome variable over a future period has a function of several factors observed at time t. These include the tone of the FED's voice ($VoiceTone_t$), the sentiment of its textual communication ($TextSentiment_t$). It also controls for three types of monetary policy shocks ($FFRShock_t$, $FGShock_t$, $APShock_t$) based on intraday data from Swanson (2020), each normalized to ensure comparability. The $ShadowRate_t$ from Wu and Xia (2016) is included to account for FED policy stance when interest rates are near zero. By controlling for these "actions" of the FED, the model isolates the impact of tone and sentiment on equity rate movements. We apply this framework to a panel of 60 countries to examine the global transmission of U.S. monetary policy communication.

2.2.2. *Second-stage regression: macrofinancial indicators*

In the first stage, we consecutively estimated for each market to obtain the coefficients. Afterwards, we have one coefficient which captures the relationship between the voice of monetary policy and the stock returns movement. Furthermore, we also retrieved the standard error as the control variables. To come up with the research question "Which macroeconomic factors could predict the relationship between the FED sentiment and stock returns?", we continue to use the linear regression models to see the effects of macro variables on the coefficients of 60 countries based on the replicated results. The model with the following structure is built:

Table 2
The outcomes of which factors explained the variation of the return on FOMC voice-tone.

Variables	(1) coefficient	(2) coefficient	(3) coefficient	(4) coefficient	(5) coefficient	(6) coefficient	(7) coefficient	(8) coefficient	(9) coefficient	(10) coefficient
stderrors	0.7870***	0.7877***	0.7842***	0.8645***	0.8714***	0.8708***	0.8552***	0.8589***	0.8662***	0.7939***
	(10.4818)	(11.3743)	(12.0217)	(8.3168)	(8.5416)	(8.5779)	(7.3382)	(8.0779)	(8.2453)	(12.4975)
log_governmentdebt		-0.0000	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
		(-1.2962)	(-1.1255)	(-0.8944)	(-0.7557)	(-0.7520)	(-0.8912)	(-0.2922)	(-0.4487)	(-0.2563)
log_proximity			-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002	-0.0002**
			(-0.6307)	(-0.4917)	(-0.8984)	(-1.3018)	(-1.2804)	(-1.1966)	(-1.7270)	(-3.4334)
log_totalreserves x lendinginterest				-0.0000*	-0.0000**	-0.0000**	-0.0000**	-0.0000*	-0.0000**	-0.0000**
				(-2.6136)	(-3.1150)	(-2.9707)	(-3.6895)	(-2.5746)	(-2.9141)	(-3.7356)
exchangerate					0.0000***	0.0000***	0.0000	0.0000	0.0000	0.0000
					(7.6116)	(7.4763)	(1.1785)	(1.1858)	(1.1365)	(0.4603)
fdi						-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
						(-0.3667)	(-0.8496)	(-0.9736)	(-1.1581)	(-0.7423)
gdppcg							0.0002	0.0002	0.0002	0.0002
							(1.1133)	(1.2165)	(1.1676)	(1.0111)
inflation								-0.0002	-0.0002	-0.0003
								(-1.2973)	(-1.3024)	(-1.8822)
log_broadmoney									0.0000	-0.0000
									(0.6259)	(-0.1902)
log_externaldebt										0.0001**
										(3.4893)
Constant	-0.0017**	-0.0017**	-0.0011	-0.0011	-0.0010	-0.0008	-0.0006	-0.0003	-0.0002	0.0001
	(-3.6405)	(-4.0921)	(-1.6782)	(-1.7170)	(-2.0488)	(-1.2115)	(-0.6895)	(-0.3384)	(-0.2560)	(0.1609)
Observations	60	59	59	59	59	59	59	59	59	59
R-squared	0.3095	0.3200	0.3212	0.3746	0.3897	0.3899	0.4096	0.4424	0.4434	0.4800

Robust t-statistics in parentheses
*** $p < 0.01$
** $p < 0.05$
* $p < 0.1$

Note: In this table, we perform a second-stage regression by extracting the emo coefficient values of 60 countries which are represented in Table A6 above as dependent variable and add more economic factors: log_governmentdebt, proximity, log_totalreserves, lendinginterest, exchangerate, fdi, gdppcg (GDP per capital growth), inflation, log_broadmoney, log_externaldebt and stderrors. The regression is clustered by Continent, which denotes the twenty Asian-countries as 1, four African-countries as 2, two Oceania-countries as 3, twenty-five European-countries as 4, and nine Americas-countries as 5.

$$
\begin{aligned}
\textit{Coefficient of VoiceTone}_i = \; & \beta_0 + \beta_1 \textit{log\_proximity}_i + \beta_2(\textit{log\_totalreserve}_i \times \textit{lendinginterest}_i) + \beta_3 \textit{log\_externaldebt}_i + \beta_4 \textit{interestrate}_i \\
& + \beta_5 \textit{gdppc}_i + \beta_6 \textit{inflation}_i + \beta_7 \textit{fdi}_i + \beta_8 \textit{log\_governmentdebt}_i + \beta_9 \textit{log\_broadmoney}_i + \beta_{10} \textit{exchangerate}_i \\
& + \textit{stderrors}_i
\end{aligned}
\tag{2}
$$

Here, i, which represents each country in the dataset, varies from 1 to 60. For each country i, the residual effect not explained by the model is captured by the $stderrors_i$ term. The dependent variables if the coefficient of voicetone, which is from the first regression; the independent variables are proximity, external debt, GDP per capita, inflation, FDI, government debt, broad money, exchange rate. Variables denoted with the prefix "log_" are expressed in natural logarithms to reduce skewness and facilitate interpretation in terms of percentage changes. We also add the product of two continuous variables: logarithm of total reserve and lending interest rate to capture the combined effect on these two dependent variables on the coefficient and find how its interaction explains the coefficient of voice tone.

3. Data

For our study, we collected daily stock close price data from 60 countries from 1/2/2010 - 30/8/2019, from the Investing.com database. We will extend our study in the second stage by collecting macroeconomic data and using the coefficient in the previous stage in the regression model to see the relationship between these variables. The list of 60 countries and macroeconomic variables can be found in the Appendix (Appendix A.1 and A.2, respectively). In addition, the detail information of macroeconomic variables can be found in Appendix D.

4. Empirical results

4.1. First-stage regression

The first-step regression investigates the relationship between stock returns of 60 countries and variables inspired by Gorodnichenko et al. (2021). The results are summarized in Table 1, with detailed outputs in Table A6 (Appendix). Overall, most country-level regressions were statistically insignificant ($p > 0.1000$), except for Tunisia ($p = 0.0906$), New Zealand ($p = 0.0685$), Ukraine ($p = 0.0483$), and Chile ($p = 0.0305$).

These four cases show a negative relationship between FOMC voice tone and stock returns, with coefficients of -0.0024 (Tunisia), -0.0032 (New Zealand), -0.0047 (Ukraine), and -0.0057 (Chile). This means that a one-unit increase in negative tone is associated with a decline in stock returns of approximately 0.24 % in Tunisia, 0.32 % in New Zealand, 0.47 % in Ukraine, and 0.57 % in Chile.

The explanatory power also varies across countries: the R-squared for Ukraine is 0.2358 (indicating the model explains 23.58 % of the variance in returns), for Chile 0.1747 (17.47 %), for Tunisia 0.1834 (18.34 %), and for New Zealand 0.1354 (13.54 %). These values suggest that, while the effects are modest, changes in FOMC tone can meaningfully explain a portion of stock return movements in these markets.

4.2. Second-stage regression: the relationship between the emotion coefficient and the macro financial indicators

The second-stage regression aims to identify which macro financial indicators explain FOMC voice-tone's effects on stock returns. The results, presented in Table 2, show an R-squared of 0.4800, indicating 48 % of the variance in FOMC voice-tone coefficients is explained by this model. Most variables were statistically insignificant ($p > 0.05$), except for geography proximity ($p = 0.0260 < 0.05$), total reserves multiplied by lending interest ($p = 0.0200 < 0.05$), and external debt ($p = 0.0250 < 0.05$).

The results show geography proximity has a significant and negative relationship with FOMC voice-tone coefficients ($\beta = -1.8040$ basis points[1]), aligning with Anand et al. (2011). In practical terms, this means that for each unit increase in distance from the United States, the stock market's reaction to a one-standard-deviation increase in FOMC tone is weaker by about 1.8 basis points.

External debt has a positively significant relationship ($\beta = 0.5090$ basis points[2]), suggesting that countries with higher levels of external debt respond more strongly to FOMC signals. Specifically, a one-standard-deviation increase in tone could be associated with a rise of roughly 0.5 basis points in stock market returns for such countries.

Although GDP per capita and inflation are not statistically significant, their coefficients are positive, consistent with the hypothesized direction. This implies that, while not conclusive, higher GDP per capita or inflation may be linked to a slightly stronger market reaction to FOMC tone.

Meanwhile, FDI, government debt, broad money, and exchange rate are all insignificant with $p > 0.05$ and have negative coefficients, indicating these factors do not affect the FOMC voice-tone's impact on stock markets in this context.

The interaction term between total reserves and lending interest was negative ($\beta = -0.0259$ basis points[3]) and statistically significant

[1] Exact coefficient: -0.0001804 (1 basis point = 0.0001)

[2] Exact coefficient: 0.0000509 (1 basis point = 0.0001)

[3] Exact coefficient: -0.00000259 (1 basis point = 0.0001)

Table 3
Coefficient stability and selection bias from unobservable.

	log_proximity	log_externaldebt	log_totalreserves x lendinginterest
Oster's (2019) bound (β*, β)	[-0.00018, -0.00010]	[0.00005, 0.00003]	[-0.00000, -0.00000]
Oster's (2019) absolute δ for β= 0	12.07991	10.26246	-4.36062
Robustness effect	Yes	Yes	No

Note: This table provides regression estimates of the impact of macrofinancial indicators on the coefficient of FOMC voice-tone effect on a country's return, derived from the first-step regression (Table A6). It also showcases the outcomes of the coefficient stability test formulated by Oster (2019). The δ statistic signifies the relevance of unobserved confounders, compared to observed control variables, in accounting for the primary results. β^* represents the bias-adjusted coefficient, assuming that δ= 1 and $Rmax$= 1.3R. All regressions include an intercept, which is not mentioned for the sake of brevity. Heteroscedasticity-robust standard errors are given in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(p= 0.0200)**.** This suggests that when both total reserves and lending rates increase together, the influence of FOMC tone on stock returns weakens by about 0.026 basis points for each unit increase in the interaction term.

4.3. Robustness check

To account for potential bias from missing variables, additional controls were included in the regression. Table 3 reports these results alongside the Oster's (2019) test, which assesses robustness by estimating a bias-adjusted coefficient (β*) when δ= 1 and R_{max} = 1.3R (with R_{max}= 0.6240 and first-step R-squared= 0.4800 in Table 3).

The Oster test shows log_proximity (δ= 12.0800) and log_externaldebt (δ= 10.2600) are robust to omitted variable bias, while the interaction term between the total reserves and the lending interest rate has δ= -4.3600, indicating a lack of robustness. This negative value indicates that the coefficient for the interaction term is not stable across model specifications and could be affected by unobserved factors excluded from the analysis. The estimated coefficient for this interaction is extremely small, on the order of -0.2600 basis points, making its economic significance negligible even if statistically significant in some specifications. Given both the low magnitude and the sensitivity to controls, this result should be interpreted with caution, and no strong policy conclusions should be drawn from it.

5. Conclusion

This study shows most markets were unaffected, with only one country in America and one in Europe demonstrating a significant relationship. As financial markets become more interconnected, US policy signals can spill over globally. To account for this, we incorporated traditional economic indicators - FDI, external debt, exchange rate, central government debt, total reserves, lending interest, GDP per capita, and geographical proximity - into a second-step regression. The results show that geographically closer countries are more strongly affected by FOMC voice tone, while the interaction of total reserves and lending interest dampens this impact. Furthermore, higher external debt in advanced economies may amplify the effects of FOMC messages on their stock markets. Effective economic management, which is understanding central bank signals, managing international reserves, and borrowing prudently, is crucial to financial stability.

There is no co-movement between other macroeconomic factors and a country's stock return volatility in our research. Additionally, data limitations for some countries and the exclusion of the COVID-19 period (2020 - 2023), a time of significant political and economic upheaval, may affect the robustness of our findings. The FOMC chairman's voice signals and financial indicators remain new and underexplored in empirical research. Our 10-year sample may be too short to observe sustained effects of voice tone on markets. Nonetheless, these findings highlight the potential of this approach with music sentiment (Can et al., 2024).

Future research could integrate multimodal analysis that combines vocal tone with facial expression recognition or facial action coding. Such an approach would capture both auditory and visual emotional cues, potentially enhancing the accuracy and richness of central bank communication analysis.

CRediT authorship contribution statement

Thu Thanh Luu: Writing – review & editing, Writing – original draft, Resources, Methodology. **Minh Quang Tran:** Writing – review & editing, Writing – original draft, Software, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank the Editor and an anonymous referee for suggestions that improved the paper. We thank the 6th Asia Conference on

Business and Economic Studies (ACBES 2024) for helpful comments and suggestions. All errors are our own.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2025.108418.

Data availability

Data will be made available on request.

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