Unveiling Currency Market Dynamics: Leveraging Federal Reserve Communications for Strategic Investment Insights

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Abstract

The purpose of this paper is to extract market signals for the major currencies (EUR, USD, GBP, JPY, CNY) analyzing the Federal Reserve System (FED) minutes and speeches, and, consequently, making suggestions about going long/short or remaining neutral to investors thanks to the causal relationships between FED sentiment and currency exchange rates. To this purpose, we aim to verify the hypothesis that the currency market dynamics follow a trend that is subject to the sentiment of FED minutes and speeches related to specific relevant currencies. The proposed paper has highlighted two main findings: (1) the sentiment expressed in the FED minutes has a strong influence on financial market predictability on major currencies trend and (2) the sentiment over time Granger-causes the exchange rate of currencies not only immediately but also at increasing lags according to a monotonically decreasing impact.

Keywords: Federal Reserve Communications, Sentiment, Currency Exchange Rate

1. Introduction

Within the financial sector, the qualitative analysis of central bank communications, encompassing Federal Reserve (FED) minutes and speeches, has emerged as a crucial practice for investors to predict market trends, evaluate economic conditions, and guide strategic decision-making policies. The role of the FED has been recently investigated in (Benchimol et al., 2021) to study the changes across different communication types (Fed fund rate announcements, Federal Open Market Committee minutes, and Fed chairman speeches) during a few economic crises (Global Economic Crisis, Dot-Com Bubble and COVID-19) paying particular attention to financial stability and monetary policies. Additional evidence about the importance of the FED communications and the corresponding sentiment outlook can be grasped in (Wischnewsky et al., 2021), where the authors highlighted that a negative sentiment (estimated on the Humphrey–Hawkins hearings) matters to a greater extent than positive sentiment to the financial stability. A similar conclusion can be derived in (Tadle, 2022) where the FED document's sentiment has been shown as to proxy to predict interest rate tilt. Finally, a very recent investigation is reported in (Fischer et al., 2023) where the authors estimated the extent to which market-implied policy expectations could be improved with further information disclosure from the FED documents, highlighting that the forecasting of future monetary policy could be strongly affected by the sentiment of FED communications.

Although the above-mentioned investigations represent a fundamental step towards the understanding of the FED communications role to explain the general marked behaviours, they are focused on coarse-grained document sentiment (entire document or at most topics), do not pivoting on specific currencies, and on long-term impact on monetary policies, do not assessing the short term implications on the Forex market.

In this paper, we provide two main contributions:

1. FedSent Index: we introduce a metric to evaluate the content of FED meeting minutes and speeches. We create an index that proxies the sentiment expressed in the FED meetings, which has a strong influence on financial market predictability on major currency trends.
2. Forex Market Sentiment Impact: we demonstrate that the sentiments expressed in FED minutes have a significant influence on financial market predictability, especially on major currency trends.

2. Related Work

The literature about Natural Language Processing techniques related to the currency market dynamics has received several efforts in the last five years. The main contributions can be roughly distinguished in two main directions: (1) language models and tools for the broad-ranging financial sector and (2) investigations about specific currencies focusing on different sources of information to perform long-term predictions.

In the first area, the panorama is dominated by several models such as FinBERT (Liu et al., 2021), FLANG (Shah et al., 2022), InvestLM (Yang et al., 2023), FinMA (Xie et al., 2023), BloombergGPT

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(Wu et al., 2023) and FinGPT(Liu et al., 2023), where most of them require considerable computational resources to function optimally, making their implementation challenging. On the other hand, the investigations about specific currency are still in their infancy especially focusing on FED communications. While in (Seifollahi and Shajari, 2019), the authors proposed an NLP-based model employing news headlines to predict the upward and downward trends of a Forex currency pair, in (Lee et al., 2021) an interpretable and user-friendly Natural Language Processing (NLP) system has been developed to decode Federal Reserve communications providing tools to deal with sentiment analysis, topic modelling and summarization without deepening the relationships between the available communication and specific market behaviour. Additional investigations relate to the use of Deep Learning techniques for forecasting foreign exchange volatility (Jung and Choi, 2021). Notably, these approaches have been explored without incorporating exogenous variables, offering intriguing perspectives for central banks and financial institutions seeking to enhance their forecasting strategies.

In what follows, we will bridge the gap by extracting sentiment market signals for the major currencies (EUR, USD, GBP, JPY, CNY) analyzing the FED minutes and speeches, and consequently, making suggestions about going long/short or remaining neutral to investors.

3. Federal Reserve Communications

3.1. Data Collection

The datasets used in our paper were sourced from the official websites of the Federal Reserve to obtain distinct time series for speeches, statements, and minutes. Three separate datasets were compiled, each containing pertinent details regarding speeches, statements, or minutes. These datasets include information such as the URL link to access the data, title, date, text content, and associated paragraphs. The datasets contain communications from 1993 to (September) 2023, obtaining 1.671 speeches, 252 minutes and 224 statements (details as reported in Appendix 1 (Table 4). From an initial overview of the collected communications, we can highlight two main aspects:

- publication of minutes and statements are almost constant over the years (∼8 per year per data source), starting from 1993 and 1994 for the minutes and statements respectively.
- publication of speeches is the most variable over time, due to the larger number of publications per year, starting from 1996.

Subsequently, we examined the lexical diversity within the text, encompassing all words present in the documents while excluding stopwords, for minutes, speeches, and statements individually. Our findings align closely with Zipf's Law (Piantadosi, 2014). For instance, when analysing the distribution of terms in the minute dataset, particularly on the left side where frequently occurring words can be observed, notable terms indicative of market trends and sentiment (such as *increase*, *decline*, *risk* and *rise*) emerged. This observation suggests the hypothesis that the currency market dynamics could be related to the sentiment embedded within the FED documents. Analogous observations can be drawn also for speeches and statements.

3.2. Forex Data

In this section we focus our attention to specific Forex data, considering only those minutes, speeches and statements which contain at least one keyword related to the following currency: EUR (euro, €, EUR), USD ($, USD, dollars), GBP (GBP, pounds, sterling), JPY (JPY, yens), CNY (CNY, yuan, renminbi), and general (fx, forex, currency, currencies).

We finally obtained the following datasets to be used in the subsequent analysis:

1. Minutes: all of them mention at least one FX $(100\% - 252/252)$, with a medium number of days between citations of ~ 44 days;
2. Speeches: almost half of them contain at least one FX $(47.34\% - 791/1'671)$, with a medium number of days between citations of ∼12 days;
3. Statements, in the last 30 years, quote in just 6 documents at least one FX keyword $(2.68\% - 6/224)$, with a medium number of days between citations of ∼880 days. Given the reduced number of available observations, the Statements dataset has been disregarded.

Given the Minutes and Speeches datasets, only those sentences containing the above-mentioned currencies have been considered (see the distributions reported in Appendix 1 Figure 4 and 5).

According to the resulting selection, minutes appear longer than speeches, being in line with what we expect. Minutes are published less frequently than speeches therefore containing more sentences mentioning the considered Forex. In the end, however, only a few sentences contain the considered FX keywords: only 4.60% of sentences contain at least one Forex in Minute documents, while for speeches the percentage is 1,62%.

4. Fed Sentiment Index

The core idea is to consider each sentence mentioning an FX and subsequently compute the corresponding overall sentiment index for the referenced FX. To this purpose, we exploited one of the most widely used language models known as *FinBERT* (Liu et al., 2021) to classify each sentence (mentioning a given FX) as positive, negative and neutral and obtain the corresponding probability distribution. To exemplify, we provide FinBERT's score of USD sentences of the Fed minute relative to September 21st 2022 in Table 1.

Let c be a given currency and S^t_{cd} the set of sentiments obtained from FinBert for those sentences in given FED document d at timestamp t that mentions c. At time stamp t the **FedSent Index (FSI)** can be estimated as mean or median aggregation of sentiment probabilities. In particular, $FSI_\mu(c,t)$ representing a mean aggregation of sentiment probabilities is computed as:

$$FSI_\mu(c,t,d) = \begin{cases} \dfrac{\sum_{i=1}^{n} p_i^{=} \times \epsilon}{n} & \text{if } \bigcup_{i=1}^{n} S^t_{cdi} = neutral \\ \dfrac{\sum_{i=1}^{k} p_i^{+} - \sum_{i=1}^{m} p_i^{-}}{k+m} & \text{otherwise} \end{cases} \quad (1)$$

where:

- $p_i^{=}$, p_i^{+} and p_i^{-} denotes the probability of a sentence i of being neutral, positive or negative respectively;
- $\bigcup_{i=1}^{n} S^t_{cdi}$ denotes the unique sentiment values obtained from FinBERT related to document d mentioning c at timestamp t (with $n = |S^t_{cdi}|$)
- k and m represent the number of sentences that are respectively predicted as positive and negative.

An analogous estimate could be computed similarly by adopting a median aggregation of sentiment probabilities. We will denote such median aggregation as $FSI_{\tilde{\mu}}(c,t,d)$.

In practice, for those documents containing only *neutral* sentences mentioning the given FX, we computed the FSI by median the mean scores multiplied by coefficient ϵ to obtain an aggregated score close to 0. For those documents containing at least polarized sentences all neutral probabilities are disregarded, computing the mean and the median of the residual non-neutral probabilities. In this way, for each document d (speech or minute) and for each FX (EUR, USD, GBP, JPY, CNH and general currencies), we get an overall sentiment index.

In order to take into account how specific a minute/speech is with respect to a given FX, we computed a **specificity coefficient**. Such coefficient μ is estimated as the ratio between the number of sentences mentioning an FX and the total number of sentences in the considered minute/speech:

$$\beta_{ctd} = \frac{r_{ctd}}{r_{dt}} \quad (2)$$

where r_{ctd} represents the number of sentences in document d at time stamp t that mention a currency c, while r_{dt} denotes the total number of sentences contained in document d at timestamp t. The specificity coefficient β_{ctd} tends to 1 where all sentences in a document mention an FX at least once.

The above-mentioned FedSent Indexes $FSI_\mu(c,t,d)$ and $FSI_{\tilde{\mu}}(c,t,d)$ can be finally smoothed according to the specificity coefficient β_{ctd} by simple multiplication. In Figure 1 and Figure 2 the time series computed as $FSI_\mu(c,t,d) \times \beta_{ctd}$ and $FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$ are reported for EUR and USD. The time series of all currencies are reported in Appendix 2.

(a) Smoothed (median) FedSent Index time series, i.e. $FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$, for USD and EUR.

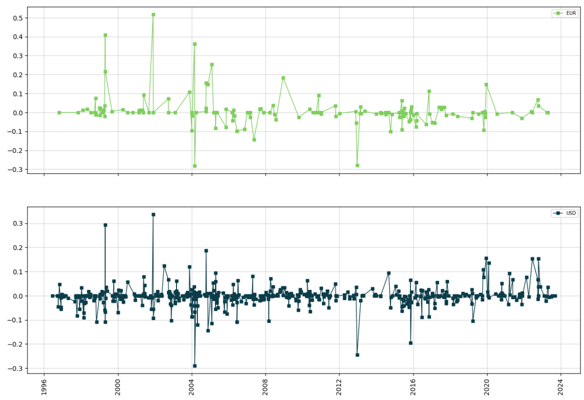
(b) Smoothed (mean) FedSent Index time series, i.e. $FSI_\mu(c,t,d) \times \beta_{ctd}$, for USD and EUR.

Figure 1: Smoothed FedSent Index on Minutes.

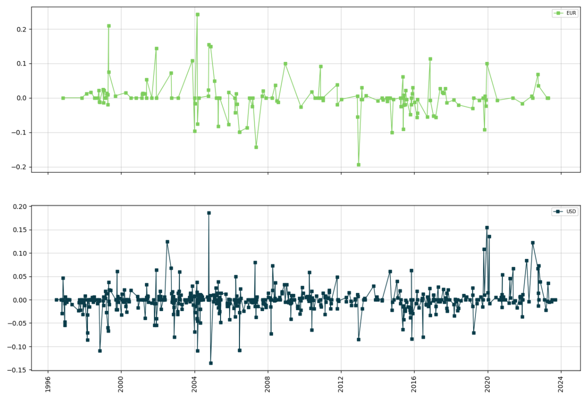
Analyzing the time series of Minutes and Speeches sentiment scores, we observe that:

SENTENCE	LABEL	PROBABILITY
The exchange value of the dollar appreciated notably, reaching multi-decade highs in real terms, as market participants perceived mounting economic challenges abroad.	positive	0.96
The U.S. dollar appreciated further against most major currencies, reaching multi-decade highs against the euro, the British pound, and the Japanese yen.	positive	0.94
The dollar's strength largely reflected increasing investor concerns about the global growth outlook as well as widening interest rate differentials between the United States and Japan.	positive	0.83

Table 1: Example of FinBERT sentiment across USD sentences in Fed minute of September 21st 2022.



(a) Smoothed (median) FedSent Index time series, i.e. $FSI_{\tilde{\mu}}(c, t, d) \times \beta_{ctd}$, for USD and EUR.



(b) Smoothed (mean) FedSent Index time series, i.e. $FSI_{\mu}(c, t, d) \times \beta_{ctd}$, for USD and EUR.

Figure 2: Smoothed FedSent Index on Speeches.

- CNH are rarely quoted in speeches (only 3 times in the whole dataset) and never mentioned in minutes;
- GBP and JPY are mentioned only a few times within the documents and there is a long time between signals: their score time series are discontinuous over time;
- the EUR and USD are the FX most mentioned by the FED's minutes and speeches.

Given the frequency and non-discontinuity of EUR and USD sentiment scores within the time series and the expected relevance of the FED communications with USD, we decided to focus on such currency in the subsequent analysis. In particular, from now onward, we focus on USD sentiment time series to check if there exists a relationship between the computed score with the exchange rate USD/EUR over time. To this purpose, we downloaded USD/EUR exchange rate time series from the official site of *Banca di Italia*, obtaining all the estimates available from January 1999 to September 2023. Since the historical USD currency has a daily frequency, it is necessary to have a comparable sentiment score time series at daily basis. For this purpose, the sentiment index between two subsequent communications has been estimated according to the following imputation methods:

- **Ffill**: we repeat the last available sentiment score until another value is found. From a financial point of view, we are considering that the sentiment between a minute/speech and the next one remains constant between two adjoining communications;
- **Exponential Decay**, with different decay rates: in particular we use 0.1, 0.05, 0.01 and 0.001. In this case, the sentiment score degrades over time representing a scenario where the sentiment index at the FED communication day has more relevance to the currency value on the corresponding day and then a decreasing impact;
- **Most Recent Value**: in this case our assumption is that we can estimate the sentiment index between two consecutive FED communications using the last available one associated with previous dates with a similar percentage change in currency;
- **Delta Median**: in this case, we replace the missing values of sentiment score with the median of previous ones associated at previous dates with a similar percentage change in currency.

5. Forex Market Sentiment Impact

We compute the percentage change of the USD currency with respect to the previous day, and then we shift this variation using 1-4 days lags, to verify if there exists a relationship over time with the sentiment indices previously introduced.

5.1. Correlations

As a first analysis, we computed the *Pearson correlation* (Pearson, 1895) coefficients, separately per minutes and speeches considering all the imputation methods but also non-filled sentiment scores. In Table 2, the most relevant results for minutes are shown. First of all, we can observe that the most important correlations are positive. This is in line with what we hypothesized: sentiment increases, the exchange is favourable and therefore the currency price increases, i.e. they are positively correlated.

Focusing on **minutes** correlations, in a nutshell, we find out that:

- all non-filled scores are positively correlated with 3-days shift of percentage variations ($\sim 20\%$ of correlation). In our analysis, we observe positive correlation on the day of the Federal Reserve minute. Subsequently, the following day displays an inclination towards a negative correlation. This discernible pattern resembles a characteristic behavior in financial markets, where, following a noteworthy event, initial days witness a depreciation in market value, followed by an attempt at rebounding on the subsequent day. It is important to note, that in the subsequent two and three days, the correlation consistently remains positive.
- Adopting imputation strategies on the FedSent Index time series, we obtain the highest correlation percentage between the daily percentage change and $FSI_{\mu}(c, t, d) \times \beta_{ctd}$, getting 26.45% of correlation, immediately followed by $FSI_{\mu}(c, t, d)$, which obtains 25.23%.

This is reflected in Figure 3, corresponding to the minute of September 21^{st} 2022 whose sentiment was positive (Table 1). In such a figure, we observe the rising trend of the USD over the next 5 days, which is strongly correlated with the sentiment previously estimated. Therefore, this example corroborates the hypothesis that the FedSent Index has a relevant impact on the USD.

Regarding **speeches**, where no relevant correlation coefficient has been found, we can hypothesize that, while mentioning the USD, the documents are not specific enough to influence the dollar's trend, and their impact may be overshadowed or moderated by other significant drivers, captured more specifically in the minutes.

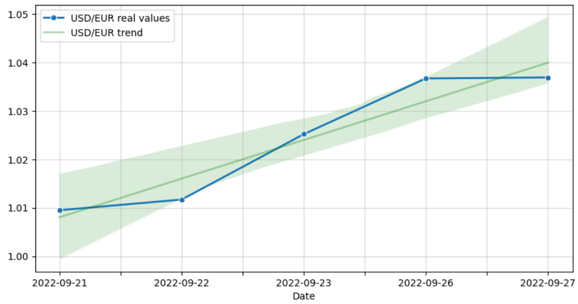


Figure 3: Trend of USD dollar

5.2. Granger Causality

In this section we approach the Granger causality test (Granger, 1969; Shojaie and Fox, 2022) to establish causation by predicting the actual state of a currency using past estimates. Specifically, in our case the sentiment index is the *Grangercause* of the currency exchange value (USD/EUR) if and only if the sentiment index of minutes uniquely improves the predictability of the currency exchange value. This implies that that when forecasting the future states of the currency exchange value (USD/EUR) based on its own past values can be improved when the past sentiment index is also included in the model. In particular, we aim to test the null hypothesis $H0$, i.e. the sentiment score time series does not Granger cause the percentage daily change of USD dollar. More specifically, Granger causality means that past values of the sentiment score have a statistically significant effect on the current value of percentage daily change. By rejecting the null hypothesis, we assume that sentiment score time series Granger causes a percentage daily change of USD dollar if the p-values (using F-Test) are below a given value (0.05).

We test all the sentiment index time series with percentage change of USD/EUR with different lag (from 1 to 4) focusing on those scenarios with the highest positive correlations highlighted in Table 2.

In Table 3 we present the p-values when comparing the sentiment time series identified within minutes with the USD series of LAG at 1-2-3 and 4-days. Focusing on Non-Filled sentiment time series, and in particular, on the mean sentiment index multiplied by specificity coefficient (i.e., $FSI_{\mu}(c, t, d) \times \beta_{ctd}$), we can observe that the p-values for all tests and lags (1, 2, 3, and 4) consistently register a estimation below the 0.05 threshold. Consequently, in such cases, we reject the null hypothesis suggesting that there is a Granger causality between the sentiment score and the lagged percentage change of USD/EUR time series. From a financial point of view, this means that when a minute is published, the corresponding sentiment index per currency has an impact on the subsequent four

Score type	Score	% Daily Change	Shift 1-day	Shift 2-days	Shift 3-days	Shift 4-days
Non-Filled	$FSI_{\tilde{\mu}}(c,t,d)$	10.46%	−1.70%	13.56%	**21.94%**	5.93%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	12.47%	−1.15%	15.41%	**22.18%**	3.27%
	$FSI_{\mu}(c,t,d)$	12.04%	−7.15%	12.67%	15.51%	5.07%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	12.22%	−5.80%	13.67%	**20.20%**	2.48%
Ffill	$FSI_{\tilde{\mu}}(c,t,d)$	0.94%	0.65%	0.92%	1.63%	2.00%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	0.76%	0.31%	0.80%	1.75%	2.05%
	$FSI_{\mu}(c,t,d)$	0.89%	0.41%	0.78%	1.23%	1.65%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	0.77%	0.22%	0.73%	1.70%	1.96%
Exponential Decay (0.1)	$FSI_{\tilde{\mu}}(c,t,d)$	2.65%	2.08%	3.05%	4.74%	4.51%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	2.21%	1.78%	2.91%	4.67%	4.34%
	$FSI_{\mu}(c,t,d)$	3.15%	2.03%	2.81%	3.91%	3.82%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	2.36%	1.47%	2.45%	4.12%	3.90%
Exponential Decay (0.05)	$FSI_{\tilde{\mu}}(c,t,d)$	2.28%	1.93%	2.65%	4.06%	4.07%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	1.98%	1.68%	2.54%	4.02%	3.95%
	$FSI_{\mu}(c,t,d)$	2.57%	1.83%	2.47%	3.42%	3.51%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	2.06%	1.44%	2.21%	3.62%	3.59%
Exponential Decay (0.01)	$FSI_{\tilde{\mu}}(c,t,d)$	1.28%	1.01%	1.40%	2.29%	2.59%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	1.11%	0.73%	1.31%	2.40%	2.63%
	$FSI_{\mu}(c,t,d)$	1.32%	0.82%	1.26%	1.85%	2.20%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	1.15%	0.63%	1.20%	2.29%	2.48%
Exponential Decay (0.001)	$FSI_{\tilde{\mu}}(c,t,d)$	0.97%	0.68%	0.97%	1.70%	2.06%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	0.80%	0.35%	0.85%	1.82%	2.12%
	$FSI_{\mu}(c,t,d)$	0.94%	0.45%	0.83%	1.30%	1.71%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	0.81%	0.27%	0.78%	1.77%	2.01%
Most Recent Value	$FSI_{\tilde{\mu}}(c,t,d)$	18.55%	−0.61%	−1.15%	1.07%	0.69%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	**21.38%**	0.76%	−1.62%	1.01%	0.74%
	$FSI_{\mu}(c,t,d)$	18.29%	−1.39%	−0.43%	1.25%	0.28%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	19.68%	0.41%	−0.78%	1.16%	0.69%
Delta Median	$FSI_{\tilde{\mu}}(c,t,d)$	19.29%	0.52%	−1.12%	1.33%	−1.23%
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	**22.76%**	2.35%	−0.48%	2.69%	−1.33%
	$FSI_{\mu}(c,t,d)$	**25.23%**	0.26%	−0.60%	1.09%	−1.27%
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	**26.45%**	2.43%	0.11%	2.84%	−1.59%

Table 2: Correlations related the USD currency. The coloured cells are those with the highest correlation found with daily percentage change and its shift by 1 to 4 days.

Score type	Score	LAG-1	LAG-2	LAG-3	LAG-4
Non-Filled	$FSI_{\tilde{\mu}}(c,t,d)$	0.2372	0.3962	0.3666	0.3789
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	0.0275*	0.0541	0.0328*	0.0681
	$FSI_{\mu}(c,t,d)$	0.0912	0.2507	0.3603	0.5632
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	0.002*	0.0118*	0.0251*	0.0389*
Most Recent Delta	$FSI_{\tilde{\mu}}(c,t,d)$	0.5209	0.199	0.1688	0.2325
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	0.0964	0.2236	0.3044	0.0562
	$FSI_{\mu}(c,t,d)$	0.85	0.3885	0.4897	0.4698
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	0.1351	0.3236	0.4654	0.0552
Delta Median	$FSI_{\tilde{\mu}}(c,t,d)$	0.9225	0.0688	0.0772	0.065
	$FSI_{\tilde{\mu}}(c,t,d) \times \beta_{ctd}$	0.3799	0.0962	0.1391	0.0127*
	$FSI_{\mu}(c,t,d)$	0.4652	0.1839	0.3333	0.2718
	$FSI_{\mu}(c,t,d) \times \beta_{ctd}$	0.3085	0.1902	0.3164	0.032*

Table 3: F-Test p-values of Granger causality to test whether USD sentiment score causes daily percentage change at different lags (1 to 4).

days. As expected, however, the p-values increase at increasing lags, denoting a decreasing impact of the sentiment extracted from the Fed Minutes.

Another important aspect to underline is the role of the specificity score when replacing the missing values according to the Delta Median strategy. In this case, the p-values (0.0127 and 0.032) at lag-4 suggest that the estimated sentiment index series can be used to forecast the USD/EUR exchange rate 4 days later than the availability of the FED minutes.

These considerations would help when making decisions about going short/long on currencies. If the sentiment is negative at a given timestamp t, then it implies that the exchange rate USD/EUR will decrease, suggesting to sell the USD currency at t, buying EUR. On the contrary, if the sentiment is positive at a given timestamp t, then it implies that the exchange rate USD/EUR will increase, suggesting buying the USD currency at t, selling EUR.

6. Conclusion

In conclusion, our analysis finds out a significant correlation between the sentiment expressed in Federal Reserve (FED) meeting minutes and the percentage change of the USD dollar. Through our investigation, we have demonstrated that shifts in sentiment reflected in these crucial documents tend to influence market perceptions and subsequently impact the value of the USD dollar. This correlation highlights the importance of carefully monitoring FED communications and sentiment analysis as integral components of currency market analysis and forecasting. Understanding the nuanced implications embedded within FED minutes can offer valuable insights for investors, policymakers, and financial institutions navigating the complexities of the global economy: it becomes increasingly evident that sentiment analysis remains a pivotal tool for deciphering market movements and informing strategic decision-making in the realm of international finance. Although this study provides valuable insights, further in-depth investigations into additional determining factors influencing currency markets are necessary to enrich the breadth of analysis. Factors such as GDP, inflation rates, and unemployment levels of countries utilizing the currencies may have an impact on currency exchange rates. Furthermore, currency market trends may also be influenced by speeches or communications issued by other central banks (e.g., the European Central Bank), forecasts issued by other industry experts, specific social signals within the industry, financial agencies, and regulatory institutions pertaining to both currencies under consideration.

7. Additional material

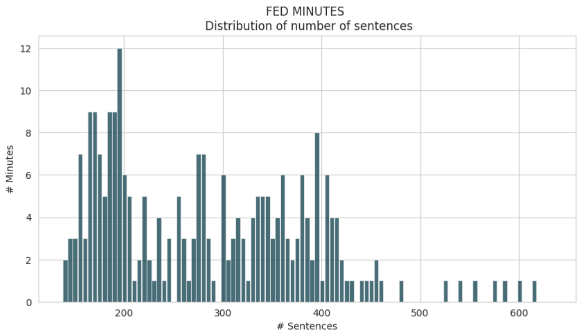
We report here, a set of statistics and distributions related to the available dataset gathered from the FED official site https://www.federalreserve.gov. In Table 4 the number of Minutes, Statements and Speeches from 1993 to 2023.

Year	#Minutes	#Statements	#Speeches
2023	5	6	57
2022	8	8	49
2021	8	8	69
2020	8	12	53
2019	8	9	81
2018	8	8	44
2017	8	8	59
2016	8	8	44
2015	8	8	54
2014	8	8	41
2013	8	8	53
2012	8	8	41
2011	8	8	48
2010	8	9	60
2009	8	8	55
2008	7	11	73
2007	10	10	72
2006	8	8	73
2005	8	8	87
2004	8	8	102
2003	8	8	71
2002	8	8	76
2001	12	11	58
2000	9	8	62
1999	8	6	68
1998	8	3	57
1997	8	1	45
1996	8	1	19
1995	8	3	0
1994	9	6	0
1993	8	0	0

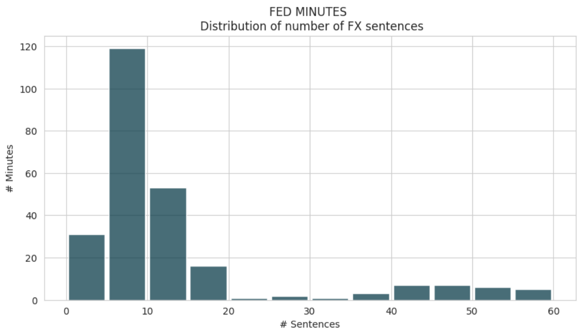
Table 4: Data available per year for each source.

Additionally, we depict in Figure 4 and 5 the overall distributions of the sentences and the corresponding distributions of sentences mentioning an FX, for Minutes and Speeches respectively.

In Figure 6, we report the time series of the smoothed FedSent Index related to Minutes and Speeches, considering both median and mean aggregation functions. As mentioned before, the time series concerned with GBP, JPY and CNY are discontinuous. Considering speeches, we can easily note that the time series of the FedSent Index is significant only for EUR and USD. This is because for GBP, CNY and JPY are rarely mentioned in the analyzed speeches.

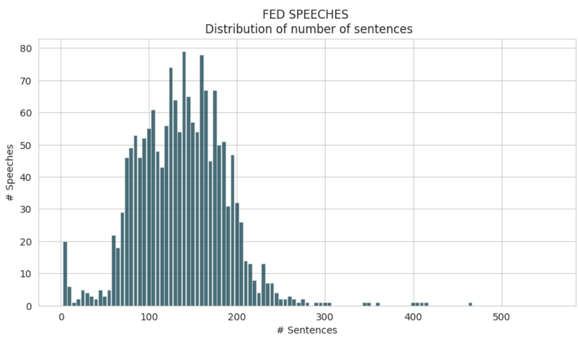


(a) Number of sentences

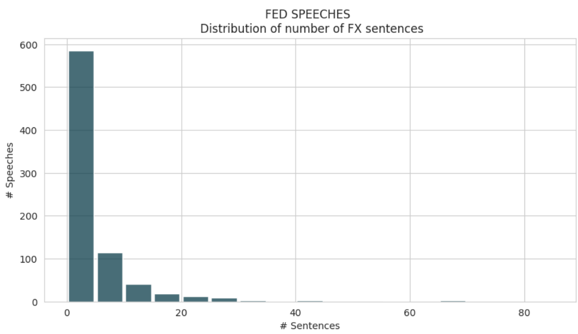


(b) Number of FX sentences

Figure 4: FED minutes distributions.

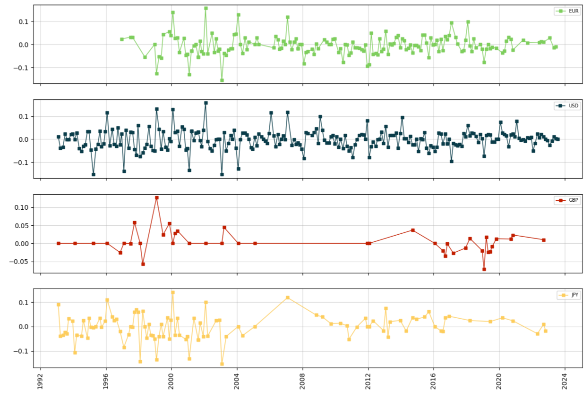


(a) Distribution of sentences

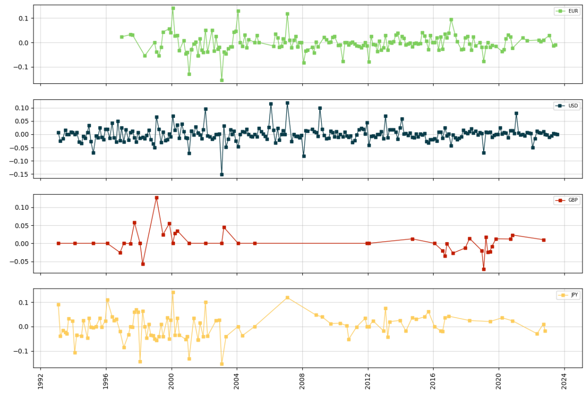


(b) Distribution of sentences mentioning currencies

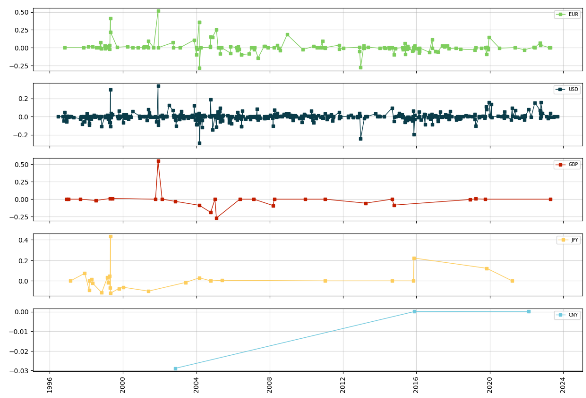
Figure 5: FED speech distributions.



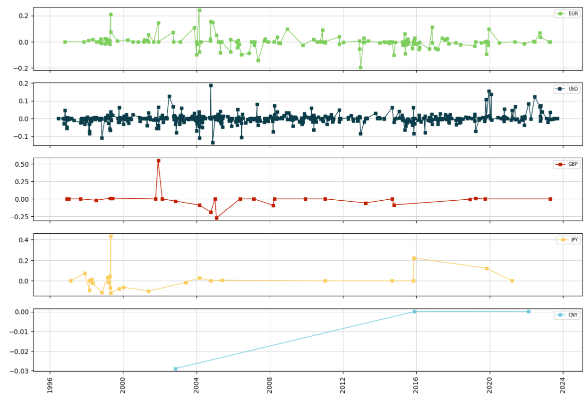
(a) Minutes - Smoothed (median) FedSent Index time series, i.e. $FSI_{\tilde{\mu}}(c, t, d) \times \beta_{ctd}$, for major currencies.



(b) Minutes - Smoothed (mean) FedSent Index time series, i.e. $FSI_{\mu}(c, t, d) \times \beta_{ctd}$, for major currencies.



(c) Speeches - Smoothed (median) FedSent Index time series, i.e. $FSI_{\tilde{\mu}}(c, t, d) \times \beta_{ctd}$, for major currencies.



(d) Speeches - Smoothed (mean) FedSent Index time series, i.e. $FSI_{\mu}(c, t, d) \times \beta_{ctd}$, for major currencies.

Figure 6: Smoothed FedSent Index.

8. Bibliographical References

Jonathan Benchimol, Sophia Kazinnik, and Yossi Saadon. 2021. Federal reserve communication and the covid-19 pandemic. *Covid Economics*, 79:218–256.

Eric Fischer, Rebecca McCaughrin, Saketh Prazad, and Mark Vandergon. 2023. Fed transparency and policy expectation errors: A text analysis approach. *FRB of New York Staff Report*, (1081).

Clive WJ Granger. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, pages 424–438.

Gunho Jung and Sun-Yong Choi. 2021. Forecasting foreign exchange volatility using deep learning autoencoder-lstm techniques. *Complexity*, 2021:1–16.

Jean Lee, Hoyoul Luis Youn, Nicholas Stevens, Josiah Poon, and Soyeon Caren Han. 2021. Fednlp: an interpretable nlp system to decode federal reserve communications. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2560–2564.

Xiao-Yang Liu, Guoxuan Wang, Hongyang Yang, and Daochen Zha. 2023. FinGPT: Democratizing internet-scale data for financial large language models. In *NeurIPS 2023 Workshop on Instruction Tuning and Instruction Following*.

Zhuang Liu, Degen Huang, Kaiyu Huang, Zhuang Li, and Jun Zhao. 2021. Finbert: a pre-trained financial language representation model for financial text mining. In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*, IJCAI'20.

Karl Pearson. 1895. Note on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London*, 58:240–242.

Steven T Piantadosi. 2014. Zipf's word frequency law in natural language: A critical review and future directions. *Psychonomic bulletin & review*, 21:1112–1130.

Saeed Seifollahi and Mehdi Shajari. 2019. Word sense disambiguation application in sentiment analysis of news headlines: an applied approach to forex market prediction. *Journal of Intelligent Information Systems*, 52:57–83.

Raj Shah, Kunal Chawla, Dheeraj Eidnani, Agam Shah, Wendi Du, Sudheer Chava, Natraj Raman, Charese Smiley, Jiaao Chen, and Diyi Yang. 2022. When flue meets flang: Benchmarks and large pretrained language model for financial domain. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 2322–2335.

Ali Shojaie and Emily B Fox. 2022. Granger causality: A review and recent advances. *Annual Review of Statistics and Its Application*, 9:289–319.

Raul Cruz Tadle. 2022. Fomc minutes sentiments and their impact on financial markets. *Journal of Economics and Business*, 118:106021.

Arina Wischnewsky, David-Jan Jansen, and Matthias Neuenkirch. 2021. Financial stability and the fed: evidence from congressional hearings. *Economic Inquiry*, 59(3):1192–1214.

Shijie Wu, Ozan Irsoy, Steven Lu, Vadim Dabravolski, Mark Dredze, Sebastian Gehrmann, Prabhanjan Kambadur, David Rosenberg, and Gideon Mann. 2023. Bloomberggpt: A large language model for finance. *arXiv preprint arXiv:2303.17564*.

Qianqian Xie, Weiguang Han, Xiao Zhang, Yanzhao Lai, Min Peng, Alejandro Lopez-Lira, and Jimin Huang. 2023. PIXIU: A comprehensive benchmark, instruction dataset and large language model for finance. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.

Yi Yang, Yixuan Tang, and Kar Yan Tam. 2023. Investlm: A large language model for investment using financial domain instruction tuning.