Capturing international influences in US monetary policy through a NLP approach

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Introduction

- The United States: large, closed economy, with the world's dominant (and free-floating) reserve currency.
- US Federal Reserve generally considered to be more or less indifferent to the international environment.
- Translated in the dual mandate, comprising purely domestic objectives (full employment and price stability).

Yet, international situation is discussed (sometimes at lengths) in Federal Open Market Committee (*FOMC*) meeting minutes, and its influence is sometimes explicitly acknowledged:

"It is just not credible that the United States can remain an oasis of prosperity unaffected by a world that is experiencing greatly increased stress"

Alan Greenspan, 1998

The FOMC has to "consider [...] the influence of foreign economies on the U.S. economy as [they] reach [their] judgment on whether and how to change monetary policy"

Stanley Fisher, 2015

Research questions

We want to *quantitatively* study the the attention paid by the FOMC to the international environment and its effect on monetary policy decisions.

- **How to measure the Fed's attention to the international environment?**
- **What role does it play in shaping US monetary policy decisions?**

- *We use NLP techniques to build a FED International Attention Index*
- *We use this index to augment a Taylor Rule and show that a rise in this index entails a more accommodative monetary policy*

We contribute to two strands of the literature: the study of the effects of global factors on US monetary policy decisions and the quantitative study of central bank speech.

Literature review - The Fed and the rest of the world

Eichengreen, 2013 offers a very thorough history of this issue.

- In the 1960s, the Fed paid "considerable attention" to the balance of payments, resulting in a tighter monetary policy than what would have been expected from domestic considerations. This influence was drastically diminished after the late 1970s.
- Low attention to international environment has dominated ever since, despite increasing coordination with other central banks (meetings, coordinated interventions, dollar swap lines).
- The author contends that international considerations should be more explicitly taken into account by the FOMC in the future ("what happens abroad doesn't stay abroad").

In a more analytical work, Obstfeld, 2020 explores the way global economic situation can influence the US economy.

- Role of international prices (commodities for example) but also of international competition and *imported inflation* in shaping US inflation.
- Integration of global financial markets, which affects the determination of asset returns (including r^*, the natural real rate of interest) and domestic financial stability.
- Decisions made by policymakers which spill over to the outside world and can be spilled back onto the US economy (Breitenlechner, Georgiadis, and Schumann, 2022).

Literature review - NLP analysis of central bank communication

Researchers have used a large range of NLP techniques to study widely different monetary-policy related topics. Thorsrud, 2020: *Words are the new numbers*.

- Some apply unsupervised topic modeling techniques, such as *Latent Dirichlet Allocation*, for example Fligstein, Brundage, and Schultz, 2014 who analyze how FOMC members recognize financial crises or Hansen and McMahon, 2016 who study the effects of FOMC communication on both market and real economic variables. Some also use supervised topic modeling approaches (Ahrens and McMahon, 2021).
- Some count words in a pre-defined dictionary (Cieslak and Vissing-Jorgensen, 2021). Aruoba and Drechsel, 2022 build a novel method to identify monetary policy shocks and put forward a method to define their dictionary.
- Some use a supervised learning framework (Handlan, 2022 uses neural networks to predict change in fed funds futures) and classification (Kanakaraj and Guddeti, 2015 classify tweets between positive and negative based on different machine learning algorithms).

Many other topics studied: monetary policy surprises (TerEllen, Larsen, and Thorsrud, 2022) central banks communicate about climate change (Arseneau, Drexler, and Osada, 2022), reaction of asset prices (Lucca and Trebbi, 2009, Shibamoto, 2016), FOMC preferences (Shapiro and Wilson, 2021), expectations (Cai, Camara, and Capel, 2021).

Data

Federal Open Market Committee meeting minutes are published three weeks after each meeting.

- More complete, but less timely overview of the mechanisms behind monetary policy decisions than the statement published immediately after the meeting.
- Exist mainly as a tool of transparency and accountability policy of the Federal Reserve.
- Can have a sizeable impact on financial markets.

We retrieve text files of the minutes of FOMC meetings from the dedicated section on the Federal Reserve Board of Governors website.
Our dataset comprises 238 meetings, around 30,000 paragraphs and 60,000 sentences.

We use macroeconomic data from the Atlanta Fed's Taylor Rule Utility website.

Data Preprocessing

Necessary to pre-process our raw text to "normalize" it for computational textual analysis models.

- Stopwords (*the*, *a*), and numbers are removed.
- Words are lowercased, tokenized and stemmed, i.e. reduced to their root form (*dollars* transformed into *dollar* or *fairly* into *fair*). [1]

Since machine learning models are not capable of processing raw text but only numbers, we transform our sentences into vectors using two methods.

TF-IDF

- *tfidf(t, d, D)*, of each word. For a term t in a document d, in a corpus D, $tfidf(t, d, D) = tf(t, d) \times idf(t, D)$.
- $tf(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$ the relative frequency ($f_{t,d}$ raw count).
- $idf(t, D) = log \frac{|D|}{|\{d \in D : t \in d\}|}$ the inverse document frequency ($|D|$ total number of documents)

Word2Vec (Mikolov et al., 2013)

- Word embedding method: transforms words into vectors. Generates a vector space where words are positioned to be close in the space (cosine similarity) if they are close in meaning.
- Possible to substract or add vectors to each other (*king* - *man* + *woman* = *queen*).
- Word2Vec uses a neural network to infer word meanings from a corpus of text.

[1] We use the Snowball Stemmer (Porter, 2001).

Data Preprocessing

A meeting of the Federal Open Market Committee was held.	meeting Federal Open Market Committee held.	meet feder open market committe held

Table: Example of the 2-steps preprocessing of a sentence

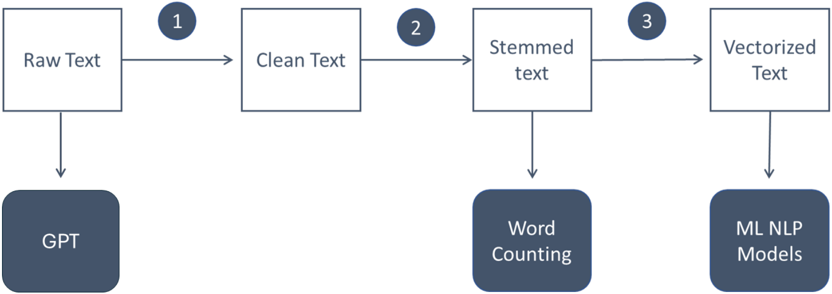


Figure: Preprocessing of our text data : (1) stopwords and numbers removal, (2) stemming (3) vectorization.

Dictionary Count - Methodology

We track simple counts of international-related phrases stored in a dictionary.

- Most of the literature on dictionary count use phrases in the dictionary chosen according to economic intuition.
- Algorithm put forward by Aruoba and Drechsel, 2022:
  - Sort all words, doubles and triples by their number of occurrences
  - Eliminate those not related to the global economic situation or contained in other phrases.
- Main world currencies and main trade partners of the United States are then added.

For each Fed minute, we count the total number of occurrences of the dictionary's words in the document and divide it by the total number of words. This ratio is our indicator of attention to foreign matters by the FOMC, **Fed IAI**.

Dictionary Count - Dictionary

	Number of Occurences		Number of Occurences
dollar	1415	global	693
currency	932	international	459
foreign exchange	488	abroad	377
foreign currencies	355	japan	363
euro	304	foreign economies	314
depreciation	206	china	278
pound	36	emerging market	262
renminbi	28	europe	201
sterling	17	EME	188
ruble	3	asia	147
imports	1782	world	111
exports	1207	russia	54
international trade	179	advanced economies	43
external sector	43	india	17

Table: Counts by phrase.

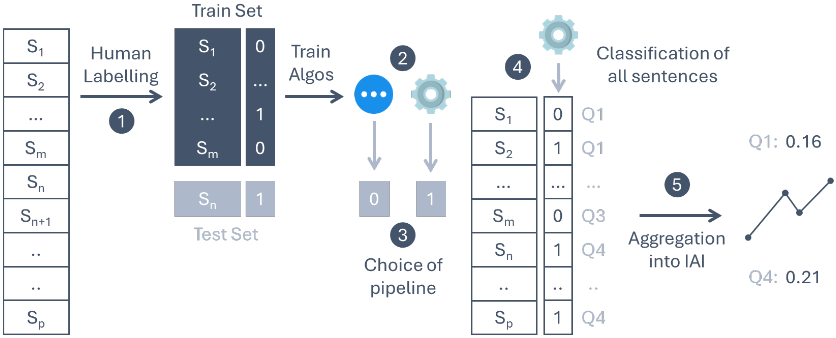
Classification models - Framework

We divide the text in sentences, which we then classify using Machine Learning models as either relating to international matters (1) or not (0).
Once sentences are classified, we compute the ratio of the number of words belonging to international-classified sentences on the total number of words in the text. This ratio is our International Attention Indicator for the minute considered.

Five steps:

1. Labeling data to train the algorithms: classify 4,300 (randomly-chosen) sentences between 0 and 1.
    - We obtain 90 % of 0, so we then rebalance the dataset.
2. Training algorithms on a *training set*.
    - Hyperparameters are determined via a *k-fold cross validation* and gridsearch.
3. Determining the most relevant pipelines (processing + algorithm) using a *test set*.
4. Computing the classification of all sentences
5. Computing the international environment index by taking the ratio of words in international-related sentences on total number of words.

Classification models - Framework



Classification models - Labeling example

2015-12-16	Participants generally agreed that the drag on U.S. economic activity from the appreciation of the dollar since the summer of 2014 and the slowdown in foreign economic growth, particularly in emerging market economies, was likely to continue to depress U.S. net exports for some time.	1
2015-12-16	Recent measures of the gains in labor compensation were mixed: Over the four quarters ending in the third quarter, compensation per hour in the business sector advanced at a strong 3-1/2 percent rate, while the employment cost index rose at a more moderate 2 percent pace.	0
2015-01-28	These participants further argued that the stability of survey-based measures of inflation expectations should not be taken as providing much reassurance; in particular, it was noted that in Japan in the late 1990s and early 2000s, survey-based measures of longer-term inflation expectations had not recorded major declines even as a disinflationary process had become entrenched.	0
2004-08-10	Available data indicated that major foreign industrial economies continued to expand at a solid pace in recent months.	1

Table: Example of labeling.

Classification models - Pipelines

We test the two vectorization methods, TF-IDF and Word2Vec, and three machine learning classifiers:

- Naive Bayes
- Logistic Regression
- Random Forest

We add a seventh pipeline: Dictionary-based naive classification, where we classify sentences as positive or negative based on whether or not they contain one of the phrases in the international dictionary described in table 2.

Classification models - Large Language Model

The state of the art in NLP research currently lies with Large Language Models. These multi-facted models are able to perform multiple tasks, including classification.
Such models (because of their size, number of parameters and training data) are extremely expensive and complex to develop and to run autonomously. We therefore decide to use an already existing model, **OpenAi's GPT 3.5**, though its API, to classify all our sentences.

The exact parameterization being out of our scope, the use of such a model, for our case, relies mainly on the prompt, i.e. the input we give it to explain what we want it to do and to return.
The prompt we use for this task is the following. We test three options which differ by the richness of the examples we provide in the prompt.

You are a macroeconomics expert.
Act as a classifier : classify if a sentence is about international macroeconomy or not, placing yourself in a US context and classifying as international macroeconomy all economic matters that are not specifically domestic to the US (including trade between the US and other countries, and events currently happening in other countries).
For example, "labor force participation rate and the employment-to-population ratio increased" **"financial markets downturn is affecting households"** *are not related to international, "inflation decreased in most major economies" or* **"disruptions in China impacted supply chains"** *are related to international.*

Classification models - Classification metrics

Vectorization	Algorithm	Precision	Recall	F1-Score
Word2Vec	Logistic Regression	0.3952	0.4749	0.3754
	Naive Bayes	0.2841	0.5000	0.3624
	Random Forest	0.2841	0.5000	0.3624
TF-IDF	Logistic Regression	0.8987	0.8843	0.8892
	Naive Bayes	0.8427	0.8378	0.8191
	Random Forest	0.9077	0.8971	**0.9011**
	Dictionary	0.8692	0.8532	0.8582
	GPT 3.5 Basic Prompt	0.8897	0.8841	0.8864
	GPT 3.5 Examples Prompt	0.8867	0.8882	0.8874
	GPT 3.5 Advanced Prompt	0.9057	0.9065	**0.9061**

Table: Results of the ten pipelines. In bold the models we retain for creating international attention indexes.

We proceed with creating Fed International Attention Indexes with 2 classification pipelines : Random Forest on TF-IDF and GPT 3.5 with example-rich prompting.

Fed International Attention Index - Dictionary-based

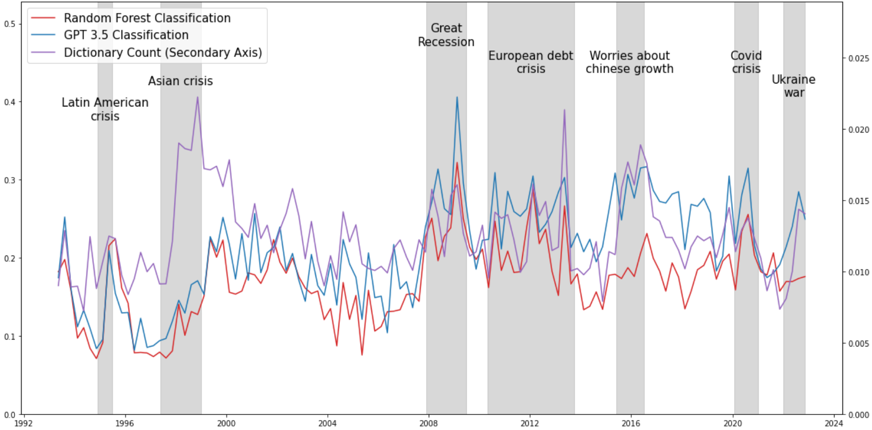


Figure: International Attention Indexes obtained with dictionary count and 2 classification methods (Random Forest and TF-IDF, GPT 3.5).

Fed International Attention Index - Discussion

Differences in values are more pronounced for the dictionary count index than for the sentence classification indexes (for example during the Asian Crisis of the late 90s).

- Might be explained by the fact that this index tracks the use of **precise words**.

Spikes in the indexes (periods of accrued international attention in FOMC minutes), correspond to major international events, and especially those outside of the US:

- Machine Learning based models better catch the Latin-American crisis, or the Covid crisis (a period for which our Random Forest model has seen no training data). The dictionary-based index experiences a stronger rise during the 1990s Asian crisis.
- The relatively small rise in dictionary-based index for the great recession period might come from a different type of attention in these years, not well captured in our dictionary.
- Similar moves for Eurozone crisis or 2015-2016 concerns about the Chinese economy (more pronounced in the case of dictionary count and GPT 3.5 classification).
- Stronger move for GPT index during the Russia-Ukraine war: the model has seen data from that period in its training.

Asymmetry in the indicator in both approaches: discussions about the international environment seem to take place more frequently when there is bad news in terms of foreign economic activity or markets.

Framework

Goal: measuring the influence of the attention to international environment on monetary policy decisions

- Estimate an augmented Taylor rule where our Fed International Attention Index (Fed IAI) augments traditional Taylor rule variables.
- Measure whether this addition provides significant information on Fed decisions.

Taylor rule (Taylor, 1993): response of interest rates to domestic macroeconomic conditions. Links Fed Funds Rate r_t, (core PCE) inflation rate π_t, inflation target π_t^* and output gap g_t.

$$r_t = \pi_t + R_t^* + \gamma(\pi_t - \pi_t^*) + \beta g_t \tag{1}$$

We use an other version of the Taylor Rule (Equation 2), which includes ρ, a smoothing term for the FFR, α, a constant playing the role of the neutral interest rate and add i_t, our *Fed IAI*.

$$r_t = \rho r_{t-1} + (1-\rho)(\alpha + \gamma(\pi_t - \pi_t^*) + \beta g_t + \delta i_t) \tag{2}$$

Estimation by Non-Linear Least Square.

Results

Dependent variable			FFR		
Model	(Cal)	(0)	(1)	(2)	(3)
r_{t-1}	0.85	0.915***	0.913***	0.903***	0.884***
		(0.024)	(0.024)	(0.023)	(0.026)
α	4.0	4.17***	4.191***	3.529***	3.63***
		(0.557)	(0.548)	(0.459)	(0.398)
$PCEGap_t$	1.5	1.285	0.889	0.922	0.692
		(0.794)	(0.777)	(0.615)	(0.521)
g_t	1.0	1.209***	1.251***	0.79***	0.865***
		(0.244)	(0.246)	(0.206)	(0.179)
i_t			-3.06	-8.149***	-5.443***
			(2.506)	(2.639)	(1.761)
Observations		115	115	115	115
Period		1994-2022	1994-2022	1994-2022	1994-2022
AIC		115.637	115.95	102.444	109.279
MSE		16.872	16.626	14.784	15.689

Table: Taylor rule regression results — Equation 2 specification

Note: The table shows Taylor Rule regression results for Non-Linear Least Squares Regression, with different inputs as the international attention index i_t: (0) is no international environment index, (1) the index derived from the dictionary count, (2) the index from random forest classification of sentences, (3) the index from GPT classification of sentences. The (Cal) column features the calibrated parameters (from the Atlanta Fed)
* p¡0.1; ** p¡0.05; *** p¡0.01.

Results

Our main findings are:

- The coefficients for domestic macroeconomic variables are of the expected sign and close to their calibration values (as provided by the Atlanta Fed) when the regression does not take i_t into account. Significativity issue for the PCE Gap.
- The version of the Fed IAI that yields the best results in terms of significativity, AIC and MSE is *(4)*, based on **Random Forest classification** (also best in class in terms of out-of-sample classification).
- The Fed IAI coefficient, $\hat{\delta}$ is -8.1. When the index is equal to 0.1, the FOMC tends to lower the Fed Funds Rate by an average of 8 basis points (all else being equal): a significant economic effect.
- These results hold for various robustness check, including substituting a shadow rate (Wu and Xia, 2016) for the FFR, using a Taylor Rule with time-varying R^* (Laubach and Williams, 2003), using the unemployment gap instead of the output gap or controlling for global financial or geopolitical stress (MSCI World (equity) index and the Geopolitical Risk index of Caldara and Iacoviello, 2022).
- Coefficient $\hat{\delta}$ varies in time if estimated on an expanding dataset, but retains significativity.

Sentiment

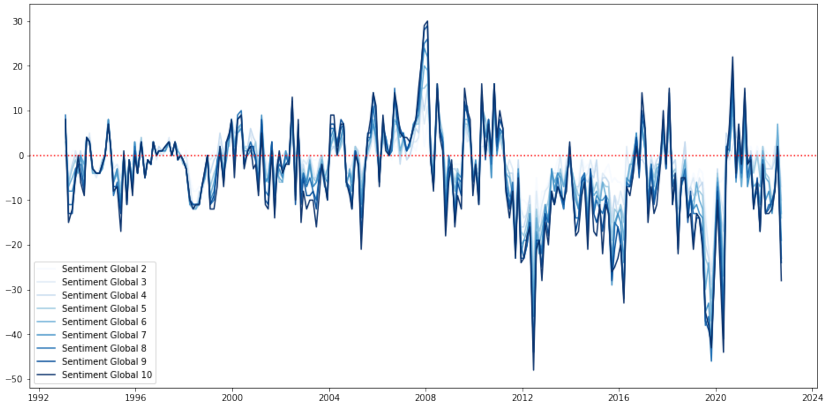


Figure: Sentiment around international-related words, for a given number of words before and after each word.

Robustness checks - Fed International Attention Index Channels

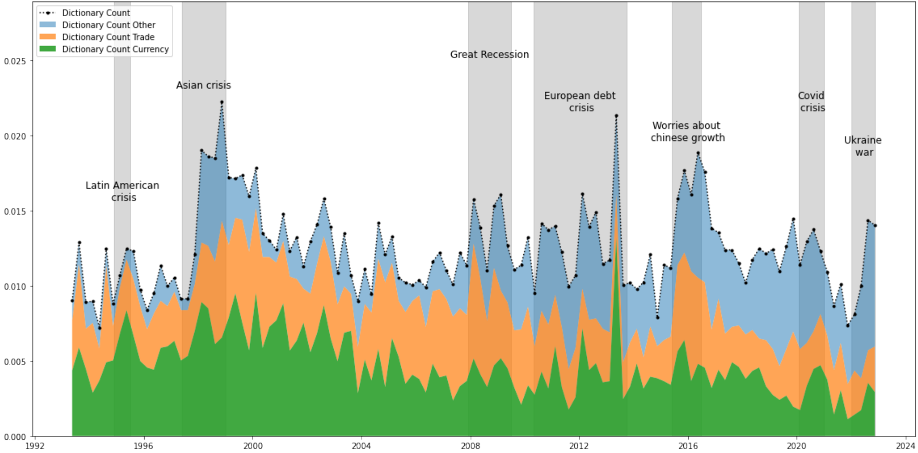


Figure: Value of the International Attention Index for dictionary count method and sub-dictionaries counts.

Robustness checks - Shadow Rates

Dependent variable		FFR			Shadow Rates		
Model	(Cal)	(0)	(2)	(3)	(0)	(2)	(3)
r_{t-1}	0.85	0.915***	0.903***	0.884***	0.921***	0.916***	0.905***
		(0.024)	(0.023)	(0.026)	(0.026)	(0.025)	(0.028)
α	4.0	4.17***	3.529***	3.63***	4.204***	3.421***	3.706***
		(0.557)	(0.459)	(0.398)	(0.856)	(0.76)	(0.723)
$PCEGap_t$	1.5	1.285	0.922	0.692	1.979	1.615	1.425
		(0.794)	(0.615)	(0.521)	(1.286)	(1.1)	(1.017)
g_t	1.0	1.209***	0.79***	0.865***	1.459***	0.945***	1.145***
		(0.244)	(0.206)	(0.179)	(0.374)	(0.34)	(0.328)
i_t			-8.149***	-5.443***		-10.483**	-5.101*
			(2.639)	(1.761)		(4.449)	(3.056)
Observations		115	115	115	115	115	115
Period		1994-2022	1994-2022	1994-2022	1994-2022	1994-2022	1994-2022
MSE		16.872	14.784	15.689	33.279	30.622	32.553

Table: Results of Taylor Rule Regression with Shadow Rates as the dependent variable

Note: The table shows Taylor Rule regression results for Non-Linear Least Squares Regression, with two possible dependent variables (Fed Funds Rates, Shadow Rates) and different inputs as the international attention index i_t: (0) is no international environment index, (2) the index from random forest classification of sentences, (3) the index from GPT classification of sentences. The (Cal) column features the calibrated parameters (from the Atlanta Fed).
* p¡0.1; ** p¡0.05; *** p¡0.01.

Robustness checks - Time varying R^*

Dependent variable Model	FFR (Cal)	FFR (TVR) (0)	 (2)
r_{t-1}	0.85	0.913*** (0.027)	0.919*** (0.025)
α	4.0		
$PCEGap_t$	1.5	0.567 (0.808)	0.537 (0.82)
g_t	1.0	0.828*** (0.191)	0.604*** (0.197)
i_t			-8.034** (3.569)
Observations		115	115
Period		1994-2022	1994-2022
AIC		117.029	107.8
MSE		17.377	15.76

Table: Taylor Rule regression results - Time-varying R^*

Note: The table shows time-varying R^* Taylor Rule regression, with different inputs as the international attention index i_t: (0) is no international environment index, (4) the index from random forest classification of sentences. The (Cal) column features the calibrated parameters (from the Atlanta Fed). * p¡0.1; ** p¡0.05; *** p¡0.01.

Robustness checks - Time varying R^*

Taylor Rule with time-varying R_t^*:

$$r_t = \rho r_{t-1} + (1-\rho)((R_t^* + \pi_t) + \gamma(\pi_t - \pi_t^*) + \beta g_t + \delta i_t) \tag{3}$$

We take as R_t^* the Laubach-Williams model 1-sided estimate, which is based on Laubach and Williams, 2003 and updated by the Federal Reserve Bank of New York (New-York, n.d.).

Robustness checks - Financial situation variables

Dependent variable				FFR		
Model	(Cal)	(2)	(2.1.1)	(2.1.2)	(2.2.1)	(2.2.2)
r_{t-1}	0.85	0.903***	0.912***	0.926***	0.909***	0.92***
		(0.023)	(0.023)	(0.024)	(0.022)	(0.023)
α	4.0	3.529***	3.397***	3.927***	3.657***	4.329***
		(0.459)	(0.507)	(0.618)	(0.476)	(0.594)
$PCEGap_t$	1.5	0.922	1.154	1.698*	1.161*	1.586*
		(0.615)	(0.722)	(1.004)	(0.672)	(0.882)
g_t	1.0	0.79***	0.769***	1.167***	0.774***	1.186***
		(0.206)	(0.224)	(0.27)	(0.211)	(0.248)
i_t		-8.149***	-8.111***		-8.115***	
		(2.639)	(2.862)		(2.707)	
$MSCI_t$			7.538	13.566*		
			(5.689)	(8.068)		
$Risk_t$					-1.619**	-2.062**
					(0.733)	(0.959)
Observations		115	115	115	115	115
Period		1994-2022	1994-2022	1994-2022	1994-2022	1994-2022
AIC		102.444	101.967	112.32	96.663	109.004
MSE		14.784	14.469	16.109	13.816	15.652

Table: Taylor rule regression results - Financial situation control variables

Note: The table shows Taylor Rule regression with additional variables to control for the global financial environment. All models use the same Fed IAI. Model (2) features no control, (2.1.1) and (2.1.2) the Quarter over Quarter evolution of the MSCI World Equity index, (4.2.1) and (4.2.2) the QoQ evolution of the GPR index. .1 and .2 versions are respectively with and without the IAI index included,. The (Cal) column features the calibrated parameters (from the Atlanta Fed). * p¡0.1; ** p¡0.05; *** p¡0.01.

Robustness checks - Variation of δ in time

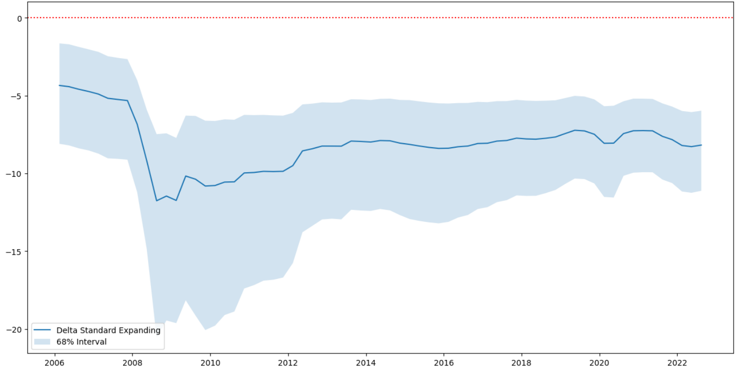


Figure: Value of $\hat{\delta}$, the IAI coefficient, and its 68% confidence interval in an expanding dataset.

Conclusion

- We develop a quantitative methodology to assess the attention paid by members of the FOMC to foreign economic conditions and its effect on policy decisions from 1993 to 2022.
- For that, we deploy multiple methods of computer-based textual analysis to construct Fed International Attention Indexes (*Fed AIA*) from the minutes of FOMC meetings.
- These indexes, coherent between them, reflect the main global economic events of the last decades. Coherence and economic relevance stress the fact that both state-of-the art and less sophisticated machine-learning models can perform well for a very specific economic task, with different strengths (time and ease of implementation for LLM, reproductibility and control for "traditional" Machine-Learning).
- We show that the *Fed AIA* indicator has a significant and negative impact on the fed funds rate in a Taylor rule model.
- We find evidence that the FOMC pays attention to the international situation and that this attention reinforces a dovish pattern with respect to a standard Taylor rule: all other macroeconomic conditions being equal, the more attentive the Fed is to global matters, the more dovish it is.

The End

Thank you for your attention!

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Appendix A - Vectorization methods - TF IDF

Sentence 1: Inflation today is very high and lasting.
Sentence 2: Inflation today is not high and is temporary.
Sentence 3: Inflation today is entrenched and dangerous.

Term	Count 1	Count 2	Count 3	TF 1	TF 2	TF 3
Inflation	1	1	1	1/7	1/8	1/6
today	1	1	1	1/7	1/8	1/6
is	1	2	1	1/7	1/4	1/6
very	1	0	0	1/7	0	0
high	1	1	0	1/7	1/8	0
and	1	1	1	1/7	1/8	1/6
lasting	1	0	0	1/7	0	0
not	0	1	0	0	1/8	0
temporary	0	1	0	0	1/8	0
entrenched	0	0	1	0	0	1/6
dangerous	0	0	1	0	0	1/6

Appendix B - Vectorization methods - Word2Vec

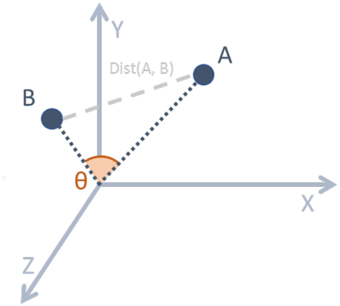


Figure: Distance between two vectors in Word2Vec representation: an example
Here, $\cos(\theta)$ is the distance between A and B.

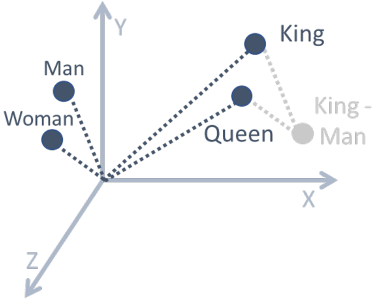


Figure: Vector composition in Word2Vec representation: an example

Appendix C - Machine Learning models - Naive Bayes

For y a class variable, and X a feature vector of size n.

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

$$P(y|x_1, ...x_n) = \frac{P(x_1|y)...P(x_n|y)P(y}{P(x_1)...P(x_n)}$$

(Independence assumption: hence "naive")

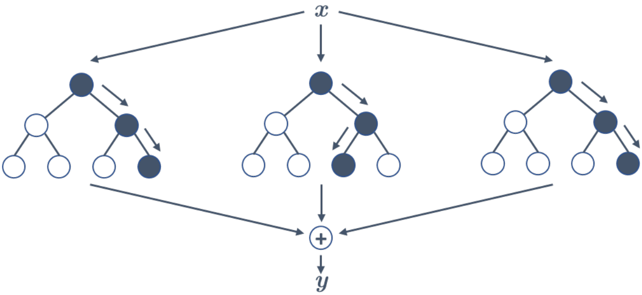
$$y = argmax_y P(y) \prod_{i=1}^{n} P(x_i|x)$$

Where $P(y)$ is the class probability and the $P(x_i|x)$ the conditional probabilities (in the case of a Gaussian Naive Bayes, gaussian assumption).

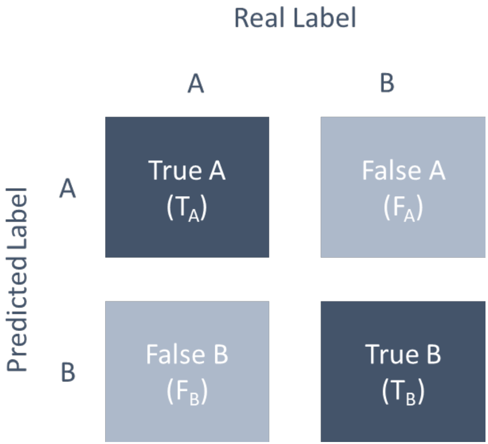
Appendix D - Machine Learning models - Random Forest

Random forest models are trained by applying bootstrap aggregating (bagging) to tree learners. Bagging selects a random sample of the training set (with replacement) and fits trees to the samples.

The different trees finally vote.



Appendix E - Classification Metrics



- Precision $= \frac{|T_A|}{|T_A+F_A|}$
- Recall $= \frac{|T_A|}{|T_A+F_B|}$
- F1 Score $= 2 \times \frac{precision \times recall}{precision + recall}$