GENERALI ASSET MANAGEMENT

Core Matters

Machine Learning Strategies for Inflation Swaps Using News Sentiment

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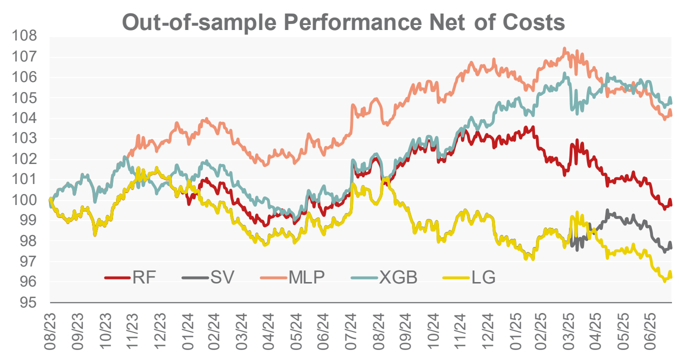
Our Core Matters series provides thematic research on macro, investment, and insurance topics

- While traditional financial data remains the primary input for assessing financial markets, alternative data is becoming an increasingly valuable complement. In particular, sentiment data has demonstrated strong potential for providing market insights that support investment decisions.
- Integrating quantitative techniques into the investment process as a complement to human expertise is essential for enriching decision-making.
- One of the initial applications of alternative data is the generation of proprietary market sentiment indicators. By leveraging these indicators, we applied machine learning and deep learning techniques to forecast US Inflation Swaps movements in a one-month horizon.
- This paper presents our ongoing development of expertise in analysing news using the Global Database of Events, Language, and Tone (GDELT) dataset. We construct indices and generate signals through machine learning (ML) and deep learning (DL) techniques, detailing the methodological framework adopted to process and model this high-dimensional data.
- Backtesting results pave the way for discussing practical applications. Further research could focus on different instruments and/or geographies. We recommend using XGB for its robustness and extremely high hit ratio. Note that 3/5 models generate negative returns, which is to be expected given high transaction costs and their lower hit ratio, for the reasons discussed in dedicated sections.



Source: GDELT, Bloomberg, GenAM own calculations

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1. Introduction

The Global Database of Events, Language, and Tone (GDELT) is one of the most comprehensive sources of alternative data openly available. It monitors news media from every country, enriched with sentiment and tone analysis via natural language processing (NLP) techniques. This vast and dynamic dataset offers a unique lens into global developments that traditional financial indicators alone cannot capture. For instance, it provides a wide range of sentiment-driven variables related to macroeconomics, geopolitics, monetary policy, growth, and employment, to name just a few.

The GDELT database has become part of our Research framework

The first use case involves constructing **in-house thematic sentiment-related indices** for several key categories available within the GDELT structure. For instance, the theme “economy” contains 8 equally weighted sub-themes that cover a total of 61 keywords existing in the GDELT classification.

The second use case is the generation of machine learning **(ML) forecasting signals** using financials data and alternative sentiment indices. Through this work, we illustrate how alternative data can be transformed into insights supporting investment strategies.

2. Understanding GDELT: Structure and Strategic Relevance

GDELT is a unique open-source initiative that systematically captures and codifies global news media into structured data. It consists of several interlinked datasets, each offering distinct analytical value.

GDELT's real-time ingestion pipeline processes news from over 100 languages across all countries, updating every 15 minutes -– making it one of the most responsive datasets available. News sentiment extraction through NLP now spans nearly a decade. We use data dating back to 2016.

For the financial industry, GDELT offers an opportunity to integrate non-financial signals into investment pro-cesses. Its coverage of media sentiment provides a complementary layer to traditional macroeconomic indicators. This is particularly relevant for fixed-income portfolios that are heavily exposed to macroeconomic and geopolitical risks. At GenAM Research, the GDELT dataset serves as a foundational alternative data source, enabling:

- The construction of sentiment indices within an interactive dashboard
- The feeding of ML/DL forecasting pipelines

Thus, we aim to develop and maintain a robust and innovative framework, capable of enriching our Research capabilities.

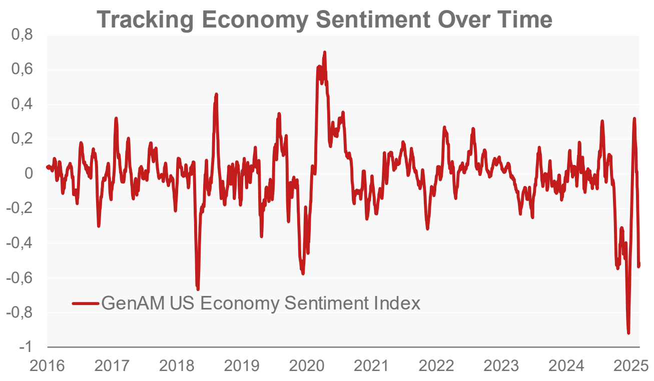
3. Sentiment Indices

We currently manage over 4.3 TB of raw data, with records starting in 2016

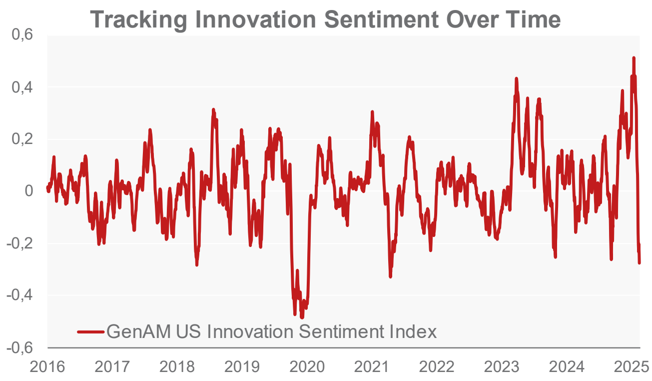
We have implemented a framework to extract, process, and analyse GDELT data on a daily basis (including weekends). This operational pipeline is designed to handle the scale and complexity of GDELT's high-frequency data. On average, a single day of GDELT can represent more than 1 GB of data.

Custom Indices: Thematic sentiment indicators constructed from selected subsets of GDELT data, aggregated and normalised to reflect trends across specific geographies or topics (e.g., economy, politics, geopolitical tensions).

These indices provide a synthetic view of sentiment evolution over time, enabling investment teams to monitor macro narratives and assess potential market impacts.



Source: GDELT, GenAM



Source: GDELT, GenAM

For example, our US Economy Sentiment Index aggregates sentiment from economic-related news sourced within the United States. A recent spike in volatility in this index clearly illustrates how disruptive (trade) policy announcements have influenced sentiment surrounding the US economic outlook. Going further back, the COVID crisis also appears in the US economic sentiment.

The GenAM US Innovation Sentiment Index shows a notable shift in tone over the past decade, with sentiment remaining relatively neutral until 2020, when it dropped sharply amid pandemic-related uncertainty. From 2021 onward, the index trends upward with pronounced peaks, reflecting growing optimism fuelled by breakthroughs in AI such as large language models and generative technologies.

Beyond these indices, we have developed a diverse set of sentiment indices based on GDELT topics, including Growth Slowdown, Geopolitics, Social, Economy, and Monetary Policy. These indices capture different dimensions of macroeconomic and market narratives.

4. GDELT and Statistical Learning

Another use case of GDELT as a data source involves its integration into machine learning pipelines. In this case, our objective is to forecast the one-month-ahead directional movement of inflation-linked swaps in the US market. This constitutes a classification problem. The following section introduces some preliminary definitions to support the modelling approach.

4.1 Instrument used

The analysis focuses on the generic 10-year US inflation swap zero-coupon. This derivative contract facilitates the transfer of inflation risk between two parties. In this structure, a single payment is made at maturity: one party pays a fixed rate on a notional principal amount, while the other pays a floating rate linked to the relevant inflation index.

4.2 Data setup

We derive dozens of features from markets and news

The input data combines both financial and alternative data. Financial data features include:

- Equities
- Commodities
- Government bonds and Nelson-Siegel coefficients
- US Federal Funds Effective Rate

Nelson-Siegel coefficients are estimated daily via a regression on the US Active Treasury Curve. Main factors include the curve's overall/long-term level - $\boldsymbol{\beta_0}$ -, its slope - $\boldsymbol{\beta_1}$ - and its curvature - $\boldsymbol{\beta_2}$ - associated to decay parameter $\boldsymbol{\lambda}$. Coefficients are computed using Ordinary Least Squares (OLS) applied to US Treasury yields, based on the parametric formula:

$$y(t,T) = \beta_0 + \beta_1 \frac{1 - e^{-\lambda^{-1}(T-t)}}{\lambda^{-1}(T-t)} + \beta_2 \left(\frac{1 - e^{-\lambda^{-1}(T-t)}}{\lambda^{-1}(T-t)} - e^{-\lambda^{-1}(T-t)} \right)$$

In addition, proprietary sentiment indices based on GDELT data, are incorporated, computed daily since 2016. As the objective is to forecast US instruments, only sentiment derived from US news sources is used. This approach reduces the dimensionality of the feature space while preserving targeted information. However, our broader database also includes sentiment data from other countries, allowing for future extensions. Custom indices are derived around key themes such as the economy, monetary policy, geopolitics, and growth, among others.

Instead of working directly with raw financial and alternative data — both of which are non-stationary time series — several pre-processing steps are applied to transform each feature into a meaningful representation of the market state.

At this stage, certain features may be manually discarded based on a correlation threshold or lack of stationarity. Removing variables simplifies the model, enhances interpretability, and can improve predictive performance. However, care must be taken to avoid excluding features that carry critical information.

The lesser the better?

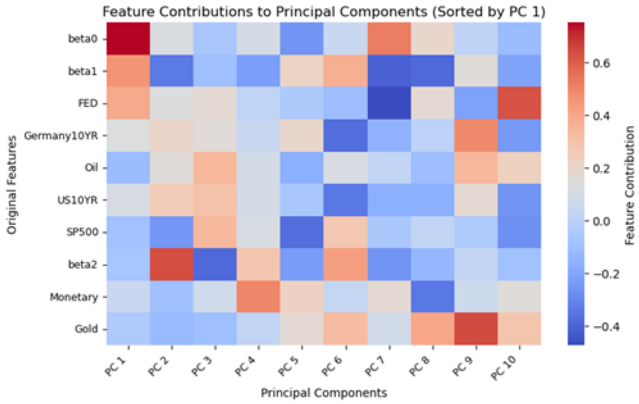
In financial timeseries forecasting, two problems often occur.

1/ The curse of dimensionality. As the number of features increases, significantly more data is required to train reliable models: the more space one has to search, the harder it gets.

2/ overfitting. When few data points are available, com-plex models, with numerous parameters, are able to memorize the whole dataset, instead of learning its patterns.

Less features and simpler models may be the solution. However, simplistic models may miss key patterns.

Once the data has been pre-processed, a machine learning pipeline is initiated. The first step involves performing Principal Component Analysis (PCA) to identify the main sources of variation within the dataset. Note that the components explaining the greatest variance do not necessarily correspond to the most predictive features. Below is an example illustrating the top 10 contributing features for the first principal component, based on a 10-component PCA.



Source: GDELT, Bloomberg, GenAM own calculations

Our dataset is divided into a training part and a testing part and contains around ~2400 days of data.

4.3 Models

ML, DL, AI: who's who?

Machine Learning (ML) and Deep Learning (DL) refer to statistical techniques used to uncover hidden relationships between an input variable X and a target variable y. Mathematically, this involves estimating a function $\hat{f}$ that approximates the true relationship f, such that:

$$y = f(X) \text{ and } \hat{f} \approx f$$

The term "model" refers to the general class to which $\hat{f}$ belongs—such as linear, polynomial, random forest, or deep neural networks.

ML broadly encompasses algorithmic statistical learning methods. DL is a subset of ML that applies complex neural architectures with multiple layers (e.g., large language models). ML is a form of artificial intelligence (AI) focused on algorithms that learn from data. DL, as a specialised category of ML, powers many AI tools, including LLMs, while other AI systems—such as rule-based chatbots—do not rely on it.

We tested different models, selected from the following classes:

- Logistic Regression (LG)
- Support Vector (SV)
- Random Forest (RF)

- XGBoost (XGB)
- Multilayer Perceptron (MLP)

The first four are considered machine learning models, while MLP falls under deep learning due to its structure. Deep learning models such as MLP are more prone to overfitting and variance. The rationale for employing more complex models lies in their ability to capture non-linear and subtle relationships within financial markets, as discussed in subsequent sections.

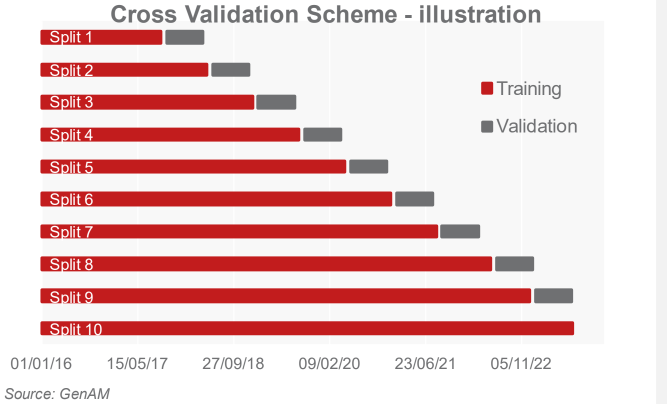
4.4 Cross Validation

To select each model's hyperparameters (i.e., parameters not learned during training), we use an expanding window cross-validation (CV) framework. This means we start with an initial training period and then progressively expand the window by adding new data over time, while testing on the next available segment. This approach mimics a real-world scenario where models are updated as more data becomes available.

This statistical method helps producing models that generalise as well as possible on unseen data.

To replicate the practical use of the model, we selected a cross-validation setup on increasing datasets. A gap is introduced between train and test periods to avoid data-leakage.

Cross-validation setup – illustration



Source: GenAM

Illustration for a cross-validation training set ranging from 2016 to 2023, with 10 splits. For instance, split 3 implies training from 01/2016 to 01/2019 and testing from 02/2019 to 09/2019 (with 1-month lag to avoid overlaps).

5. Results

This section presents the performance of the models, including results on a true out-of-sample test set. Each model class is analysed individually, and an ablation study is conducted to assess whether the inclusion of GDELT data enhances the predictive power of the framework.

How to evaluate models?

In this classification task, we use the following metrics.

Accuracy: Percentage of correct predictions.

Recall: Percentage of positive cases correctly identified by the model.

Precision: Percentage of positive predictions that are correct.

F1: Harmonic mean of precision and recall, providing a balanced measure of both metrics.

AUC-ROC: Measures the model's ability to distinguish between classes.

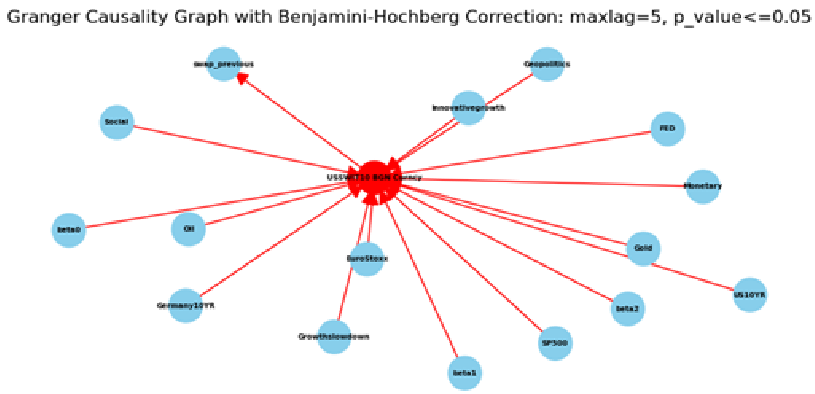
Confusion Matrix: A table summarizing the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

5.1 Machine Learning Task – Performance Metrics

We predict the direction of 1-month ahead swap rate.

Results are presented for US 10-year inflation swaps (zero coupon).

Dataset causality. Granger causality is examined be-tween the input variables and the target, with the Benja-mini–Hochberg procedure applied to ensure robust control of false positives. A total of 16 statistically significant relationships are identified, with a maximum of two false positives under a 5% false discovery rate (FDR).



Source: GDELT, Bloomberg, GenAM own calculations

The above graph provides a summary of directed causality. It should be interpreted as follows: an arrow from variable X to the target indicates that past values of X contain statistically significant information for predicting the target. The direction of the arrow encodes the temporal and predictive relationship, while the arrow length is purely for visualisation—it does not represent effect size, lag, or statistical strength.

Cross-Validation metrics

The following tables recap the CV metrics of each model on the whole dataset first, then focusing on the second part of the dataset.

10 fold	Accuracy	Precision	Recall	F1 Score	ROC-AUC
LG	**0.57**	**0.56**	**0.84**	**0.64**	**0.66**
SV	0.53	0.54	0.83	0.62	0.65
RF	0.55	0.49	0.67	0.54	0.62
XGB	0.52	0.51	0.51	0.43	0.57
MLP	0.54	0.51	0.64	0.53	0.56
5 last					
LG	0.58	**0.58**	**0.80**	**0.66**	0.57
SV	0.57	**0.58**	0.79	0.65	0.56
RF	0.58	0.49	0.56	0.51	**0.58**
XGB	0.59	0.48	0.46	0.47	0.56
MLP	**0.64**	0.57	0.71	0.62	**0.58**

Cross-Validation results. The following section presents model performance within the cross-validation (CV) framework. Summary tables below provide an overview of the results across different model classes.

OOS Metrics

The following table recaps the OOS metrics of each model.

OOS	Accuracy	Precision	Recall	F1 Score	ROC-AUC
LG	0.50	**1.00**	0.00	0.01	0.50
SV	0.55	0.82	0.14	0.23	0.55
RF	0.59	0.72	0.32	0.44	0.60
XGB	**0.67**	0.64	**0.77**	**0.70**	**0.66**
MLP	0.64	0.67	0.51	0.59	0.64

Out-of-Sample results. Once the models have been fitted to the training data, evaluation is performed on a true out-of-sample (OOS) dataset.

5.2 Key drivers of inflation swap rates

One of the most common criticisms of machine learning methods is the lack of an explicit formulation of the estimated relationships between input variables and the target. However, the absence of a closed-form expression does not imply that the model is not explainable. For example, financial interpretations can be derived by analysing SHAP values across different models.

SHAP values

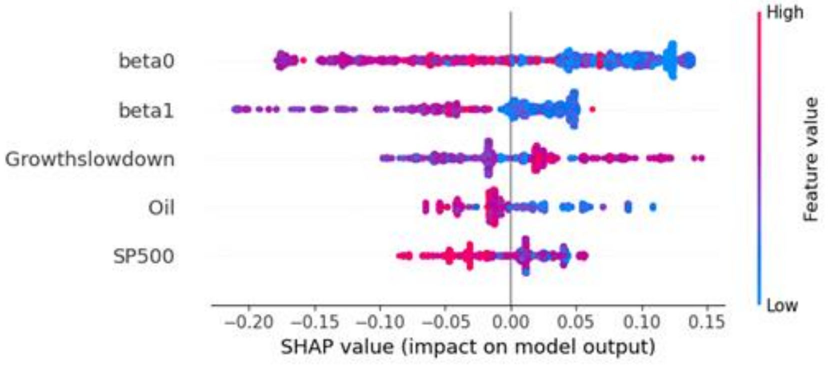
SHAP refer to the following method used to explain models that do not offer access to a closed-form equation between inputs and the target. Let φ_i be the SHAP value for feature i, then it is defined by:

$$\varphi_i := \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|S| - |N| - 1)!}{|N|!} . [f(S \cup \{i\}) - f(S)]$$

Where f is the model, N is the set of all input variables, and S is a subset of variables excluding i.

SHAP values provide a theoretically grounded method for interpreting individual predictions of machine learning models by attributing the output to each input feature. This methodology ensures that each feature's contribution is fairly assessed by computing its average marginal impact across all possible feature combinations.

Results are presented for the XGBoost (XGB) model, which demonstrated the highest accuracy on the out-of-sample (OOS) dataset. The following SHAP summary chart provides a structured interpretation of the model, highlighting the factors that most significantly influence variations in inflation swap yields.



Source: GDELT, Bloomberg, GenAM own calculations

Colour scheme: Pink points represent high feature values, while blue points represent low values. This allows us to see not only the impact but also the context (e.g., high oil prices vs. low oil prices).

X-axis (SHAP value): Indicates the direction and magnitude of each feature’s effect on the model output. Positive SHAP values push predictions toward higher inflation swap yields, while negative values push them toward lower yields.

It is normal for features to have both positive and negative contributions across observations—this reflects changing market regimes rather than model instability. For example, high oil prices (pink dots on the right) tend to increase yields, while low oil prices (blue dots on the left) tend to reduce them.

Why this matters: The chart makes the model's decision process transparent, identifies the most influential drivers (e.g., beta factors, growth slowdown, oil, SP500), and helps validate whether the model behaves consistently with economic intuition. This is critical for trust and interpretability in financial applications.

5.3 Ablation study

To further evaluate the contribution of GDELT, the experiment was repeated without including GDELT variables, while retaining all others. The model hyperparameters were slightly adjusted to reflect the reduced number of variables. The table below presents the out-of-sample results obtained without GDELT features. Additionally, McNemar's test statistics are provided to offer statistical evidence of the added value brought by GDELT.

OOS Metrics – Without GDELT

The following table recaps the OOS metrics of each model.

We also test if previous models were significantly better in terms of accuracy using McNemar's statistical test.

OOS	Accuracy	Precision	Recall	F1 Score	ROC-AUC
LG	0.50	**1.00**	0.00	0.01	0.50
SV	0.51	**1.00**	0.04	0.07	0.52
RF	0.53	0.63	0.19	0.29	0.54
XGB	**0.62**	0.58	0.85	**0.69**	**0.61**
MLP	0.53	0.52	**0.92**	0.67	0.53

McNemar	LG	**SV**	**RF**	**XGB**	**MLP**
p_value	1	**0,005**	**0,014**	**0,099**	**0,003**

Conclusion: GDELT demonstrably adds value with 90% confidence for four models, although not with 95% confidence in the case of XGB. It is worth noting that LG is overly simplistic; the inclusion or exclusion of GDELT features does not affect its predictions, resulting in a p-value of 1.

All models show more bias than before, meaning they tend to favour one outcome instead of adjusting to changes in the data. For example, XGB looks accurate overall, but that's mainly because it predicts the most common class (negative) rather than truly understanding the patterns.

5.4 Backtesting ML Signals

The models presented in this paper are intended to complement research expertise and will be extended to other asset classes. Systematic backtests demonstrate how the generated signals perform in practice.

Backtest portfolio. A portfolio is defined as holding a swap position – either on the payer or receiver side — with a maturity of $\boldsymbol{T}$. Let $\boldsymbol{V}(\boldsymbol{t})$ denote the value of this portfolio over time. At inception, $\boldsymbol{V}(\mathbf{0}) = \mathbf{0}$, regardless of the chosen swap side.

The portfolio is rolled monthly, with two separate approaches: one based on machine learning signals and another using a simple benchmark that always takes the inflation payer side. Under backtesting conditions without transaction costs, both payer and receiver systematic strategies exhibit comparable performance. The payer side is chosen to match the “naïve” approach offered by the LG model.

Value of the zero-coupon inflation swap. The swap rate $\boldsymbol{K}$ is defined to equate the present value (discounted via OIS) of both legs of the contract at maturity:

- Fixed leg: $\boldsymbol{N} \times [(\mathbf{1} + \boldsymbol{K})^{\boldsymbol{T}} - \mathbf{1}]$
- Floating leg: $\boldsymbol{N} \times \left[\frac{\boldsymbol{I}(\boldsymbol{T})}{\boldsymbol{I}(\mathbf{0})} - \mathbf{1}\right]$

where $\boldsymbol{N}$ is the notional and $\boldsymbol{I}$ is the inflation index. The swap rate reflects the market’s pricing of the average annual inflation rate over the next ten years.

Value of the portfolio. The present value of the portfolio after one month is calculated by evaluating both legs and taking the discounted difference between them. This represents the current value or P&L of the position.

Hypothesis: As the 9y11m maturity is non-standard, its fair value is estimated using log-linear interpolation between the 9-year and 10-year spot rates, both for the swap and the discount rate (OIS 10y). Trading costs are incorporated via a bid-ask spread of 2 basis points.

Key findings: The implemented strategies confirm that the models can be effectively used for tactical allocation. However, practical limitations such as trading costs and execution constraints may hinder real-world applicability and warrant further discussion.

Backtests Performance

The following table summarises the out-of-sample (OOS) performance metrics for the backtest strategy conducted from August 2023 to June 2025. All metrics are calculated per unit of notional, or assuming 100% of collateral is posted in a “risk-free” asset—i.e., without leverage.

Metric	RF	SV	**MLP**	**XGB**	LG/bench
SR	-0,02	-0,36	**0,69**	**0,77**	-0,59
TR	-0,2%	-2,4%	**4,1%**	**4,7%**	-3,8%
AR	1,6%	0,5%	**3,9%**	**4,1%**	-0,2%
Vol	3,2%	3,3%	**3,2%**	**3,2%**	3,3%

SR = Sharpe Ratio; TR = Total return; AR = Annualized return; Vol = Annualized volatility.

It is important to note that LG consistently predicts class 0, making it equivalent to the benchmark strategy of rolling an inflation payer swap each month. Given the decline in inflation since mid-2023, this strategy has yielded positive performance.

The MLP and XGB models achieve the strongest metrics overall, illustrating that reaching higher accuracy in predictions is the key to improve ML signals added value.

Note (see table below – excluding costs):

Bid-ask spread is a significant factor in determining P&L. Execution remains the primary limitation of the machine learning strategies.

Metric	RF	SV	**MLP**	**XGB**	LG/bench
SR	0,52	0,17	**1,24**	**1,32**	-0,06
TR	3,1%	0,9%	**7,5%**	**8,0%**	-0,5%
AR	1,6%	0,5%	**3,9%**	**4,1%**	-0,2%
Vol	3,2%	3,2%	**3,1%**	**3,1%**	3,2%

6. Conclusion

This study demonstrates the strategic value of integrating GDELT data into our pipelines, with a particular focus on US 10-year zero-coupon inflation swaps and in-house sentiment indices.

By incorporating sentiment indices derived from global news coverage, the modelling framework enables decision-making with real-time signals that carry strong predictive power.

Empirical results show that models incorporating GDELT variables consistently outperform those relying solely on traditional financial indicators. The ablation study confirms the incremental contribution of these features, while the backtest of systematic machine learning strategies highlights their practical relevance for asset allocation. In the case of inflation swaps, costs are nonetheless a key component to watch.

Beyond inflation-linked instruments, the framework presented here offers potential for wider application. It could support tactical asset allocation by helping investment teams adjust exposures in response to evolving sentiment and event-driven signals. Additionally, it may assist in assessing business cycle dynamics, providing early indications or confirmations of macroeconomic turning points.

In summary, this work underscores the potential of combining open-source sentiment data with advanced statistical learning techniques to improve tactical decision-making. Future research will extend the scope to broader asset classes and explore further causal relationships between news narratives and market behaviour.

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