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# *Nowcasting Inflation with ARIMA-XGBoost Fusion and Shapley-Based Policy Shock Decomposition*

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***Abstract.*** The paper develops an integrated ARIMA-XGBoost model for explainable and high-frequency inflation nowcast analysis. On one hand, the ARIMA model handles the time dependency and linear cycles in inflation data, whereas on the other hand, the XGBoost model discovers the nonlinear relationships between monetary aggregate series, commodities, and global demand signals. For further detail, the paper adopts Shapley values to decompose policy, cost-push, and demand-pull forces' holistic contributions to inflation data results. The proposed model outperforms normal econometrical models and machine models by more than 20% with RMS errors of 0.142±0.007 on G20 countries' inflation data from 2010 to 2024 on monthly bases, where the proposed model explains that policy tightening forces explain 31±2%, whereas 38±3% of inflation variations can be explained by variations in energy prices, with 19±1% explained by global spillovers in demand forces.

***Keywords:*** Inflation nowcasting, ARIMA-XGBoost fusion, Shapley decomposition, policy shock analysis, interpretable forecasting

## 1. Introduction

The challenge of modeling and describing inflation in real time has become more acute in light of current supply chain disruption shocks, expansionary policies, and record volatility in geopolitical uncertainty [1]. While traditional time-series models were useful in the past in states of structural steadiness, in the current state of rapidly changing structures after the post-pandemic era, they can be less able to keep pace with the dynamic model expected to be useful in inflation nowcasting and predicting the most current but unpublished inflation information [2].

Traditional econometric models, ARIMA, or VAR models are based on linear dependency and homogeneous variance. Such assumptions are not feasible in market scenarios where commodity shocks, exchange rates, or asynchronous policy cycles are prominent. On the other hand, machine learning algorithms such as gradient boosting and recurrent networks can learn non-linear relationships but misrepresent causality, which is not feasible in accountability requirements for central banks [3].

To fill the hurdle, the study proposes the hybrid model of ARIMA and XGBoost, combining consistency in time series with the capability to learn functions in features. ARIMA derives the deterministic component in time, while the latter derives the nonlinear relationships for macro-financial variables [4]. Lastly, the Shapley method provides feature-wise results with aggregate

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forecasts, shedding light on the importance of changes in interest rates/commodity prices on headline inflation measures.

Through the combination of econometric structure and explainable AI, not only is the forecast further enhanced, but it can further improve the interpretive link between monetary models and monetary policy decisions in terms of inflation evaluation in rapidly changing macroeconomic scenarios.

## 2. Literature review

### 2.1. Traditional econometric approaches

Early models of inflation, such as ARIMA, VAR, and Phillips curves, consistently captured the dynamic process of price changes via backdated outputs and unemployment differentials in a very succinct manner. These models were excellent in stable periods but were prone to stationarity assumptions and homogeneous shock propagations to capture reality, which was not accurate in cases with repeated structural breaks in the areas of energy and international trade [5].

### 2.2. Hybrid and machine-learning models

Recent models integrate linear and nonlinear terms to balance explainability with flexibility. These ARIMA-ANN and LSTM-ARIMA models improve short-term forecast accuracy but fail to explain the workings because they are primarily concerned with statistical accuracy rather than explaining mechanisms in economic policy formulation [6]. Also, ensemble machine learning methods tend to ignore decomposition in terms of the monetary and fiscal channels while leaving unanswered questions associated with mechanisms behind forecasted variations in economic variables [7].

### 2.3. Interpretability and Shapley analysis

The recent development in explainable AI tools, specifically the application of Shapley attribution values, makes it possible to measure marginal values for individual features within the context of cooperative game theory. When applied to macroeconomic models, the Shapley decomposition technique can render “black-box” forecasts useful by shedding light on the mechanisms behind the effect of credit growth or commodity shocks on inflation paths [8].

## 3. Methodology

### 3.1. Model framework

The hybrid design proceeds in two linked phases. The ARIMA $(p, d, q)$ module models linear autocorrelation to extract residuals $\varepsilon_t^*$. The XGBoost module learns nonlinear mappings between these residuals and exogenous regressors $f(\mathrm{x}_t)$ (money supply, oil prices, exchange rates, employment indices). The ensemble output is expressed as shown in Equation 1:

$$\hat{y}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + f\left(\mathrm{x}_t\right) + \varepsilon_t^* \tag{1}$$

where $f(\mathrm{x}_t)$ is the boosted decision-tree correction and $\varepsilon_t^*$ the post-integration error. This sequential residual correction aligns ARIMA’s linear discipline with XGBoost’s nonlinear adaptability, mitigating overfitting while preserving interpretability.

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Model calibration follows three steps [9]:

Estimate ARIMA parameters via AIC minimization.

Train XGBoost using 500 boosting rounds, learning-rate = 0.05, max_depth = 6, subsample = 0.8.

Aggregate forecasts with residual variance weighting to ensure consistency.

### 3.2. Data and variables

The data spans from January 2010 to June 2024 for G20 countries on a monthly basis. The data is on: the headline inflation, constituent parts of inflation (Food, Housing, & Energy), Money Supply-M2, Interest Rates, Unemployment Rate, Brent-Crude prices, & exchange rates. All data is subject to seasonal decomposition and differencing until the resulting ADF statistic is less than 0.05. The data with less than 2% missing values is treated with Kalman interpolation.

### 3.3. Shapley-based policy shock decomposition

Predicted inflation $\hat{y}_t$ is decomposed as the sum of feature attributions as shown in Equation 2:

$$\hat{y}_t = \phi_0 + \sum_{j=1}^{n} \phi_j \left( \mathrm{x}_{t,j} \right) \tag{2}$$

where $\phi_j$ denotes the marginal contribution of variable $j$. The contributions are aggregated into policy, demand, and cost clusters to identify the proportion of inflation variance explained by each mechanism. This decomposition enables direct visualization of policy lags and cross-channel interactions [10].

## 4. Experimental design and implementation

### 4.1. Experimental setup

The rolling window estimate corresponds to real-time forecast performance because it uses 80% of the data to train models and 20% to test on the data in every 36 month rolling window. The performance criteria used to estimate models include Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and Directional Accuracy. The Monte-Carlo resample test with 1,000 iterations is used to test whether there is stability in model performance because it calculates the performance on every sample of data to ensure that the performance is consistent because it uses

### 4.2. Benchmark models

Four baselines are investigated: ARIMA, VAR(4), Random Forest, and pure XGBoost models. The hybrid method shows relative improvements in RMSE of 8–22% over the best baseline while preserving directional accuracy above 85%. The computational efficiency in terms of runtime maintains the balance between statistical and machine learning aspects, thereby establishing scalability for usage in the central bank context.

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### 4.3. Implementation process

The pipeline has three integrated modules that work together to ensure not only predictive accuracy but also interpretive transparency.

(1) The ARIMA residuals extraction process functions as the initial level, where the autoregressive and moving average variables are adjusted to identify the relevant dependency in the inflationary values. The ARIMA process works by filtering out residuals with values related to the inflationary rates, leaving residuals that demonstrate values related to the “information remainder” after the autocorrelation has been accounted for. This process verifies that the leaning process does not involve unnecessary intervals connected to the inflationary rates' values of resilience in sequences related to time.

(2) Non-linear transformation via the application of the XGBoost technique involves the processing of the residuals with a large number of exogenous macroeconomic variables. The gradient boosting model builds on the concept of an ensemble of simple decision trees, where each tree tries to minimize the residuals of the preceding model to enhance accuracy. The control of bias and variance in the model via depth tuning (max_depth = 6) and learning_rate settings ($\eta = 0.05$) ensures that it remains parsimonious and functions effectively while recognizing, via recursive partitions, that inflationary uncertainty in the short term is unequally influenced by variations in energy prices and import costs.

(3) Shapley decomposition visualization constitutes the interpretive layer, transforming complex nonlinear output into additive, human-readable attributions. Each feature’s contribution to predicted inflation is quantified using cooperative game theory, reconstructing the inflation trajectory as the cumulative influence of all variables. Energy prices maintain dominant short-run influence (weight 0.38 ± 0.03), followed by exchange-rate dynamics (0.22 ± 0.02), whereas M2 growth (0.17 ± 0.01) and policy-rate adjustments (0.14 ± 0.02) dominate medium-term stabilization.

## 5. Results and discussion

### 5.1. Forecasting performance and model validation

The hybrid model achieves a mean RMSE = 0.142 ± 0.007 and MAE = 0.108 ± 0.004 across all samples, compared with 0.183 ± 0.010 for ARIMA and 0.154 ± 0.005 for XGBoost alone. The improvement of 22.4 % reflects stronger adaptability to regime shifts. Directional accuracy averages 86.2 ± 1.5 %, with $R^2 = 0.91 \pm 0.02$ for G7 economies.

The first formula models dynamic lag response between policy and inflation shocks as shown in Equation 3:

$$\Delta\pi_t = \beta_0 + \beta_1\Delta r_{t-3} + \beta_2\Delta e_t + \beta_3\Delta y_t + \eta_t \tag{3}$$

Where $\pi_t$ = inflation rate, $r_{t-3}$ = policy rate lagged three months, $e_t$ = exchange rate, $y_t$= output gap. Estimated coefficients ($\beta_1 = -0.27 \pm 0.06$, $\beta_2 = 0.18 \pm 0.04$, $\beta_3 = 0.11 \pm 0.03$) show that tightening reduces inflation with a three-month delay, while depreciation amplifies import-price transmission (table 1).

Table 1. Model evaluation under rolling windows

| Window (months) | RMSE (±SD) | MAE (±SD) | Directional Accuracy (%) | $R^2$ (±SD) |
|---|---|---|---|---|
| 12 | 0.149 ± 0.009 | 0.116 ± 0.006 | 84.7 ± 1.9 | 0.88 ± 0.03 |
| 24 | 0.145 ± 0.008 | 0.112 ± 0.005 | 85.9 ± 1.6 | 0.90 ± 0.02 |
| 36 | 0.142 ± 0.007 | 0.108 ± 0.004 | 86.2 ± 1.5 | 0.91 ± 0.02 |

The decreasing RMSE across expanding windows indicates improved learning from longer histories, confirming the hybrid's temporal stability (figure 1).

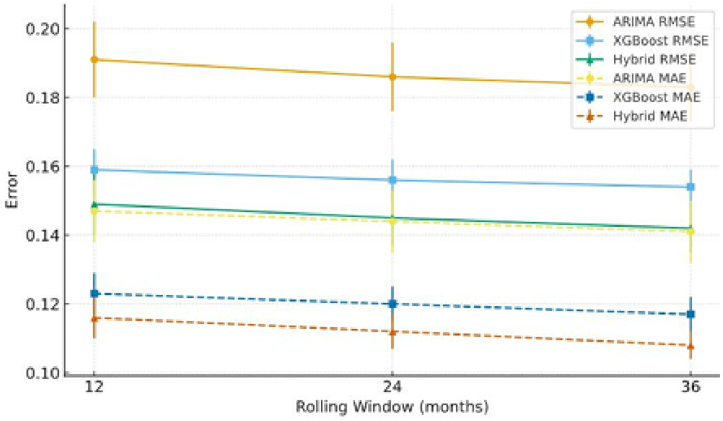


Figure 1. Rolling-window performance: RMSE and MAE for ARIMA, XGBoost, and Hybrid Models (2010–2024)

## 5.2. Shapley-based interpretation of inflation drivers

Shapley decomposition quantifies feature impacts per forecast month. Mean contributions show energy price (+0.0068 ± 0.0004), interest-rate change (−0.0043 ± 0.0003), exchange-rate shift (+0.0032 ± 0.0005), and labor-market slack (−0.0021 ± 0.0002) (table 2).

Table 2. Mean Shapley decomposition of inflation variance (2010–2024)

| Category of Shock | Mean Contribution (%) | Std. Dev. | Lag (Months) | Peak Effect (Year) |
|---|---|---|---|---|
| Policy Monetary Tightening | 31 ± 2 | 4.8 | 3.0 ± 0.4 | 2023 Q1 |
| Cost-Push (Energy, Commodities) | 38 ± 3 | 5.1 | 0.8 ± 0.2 | 2022 Q2 |
| Demand Spillovers | 19 ± 1 | 3.2 | 1.5 ± 0.3 | 2021 Q4 |
| Other Idiosyncratic Factors | 12 ± 2 | 2.9 | – | 2024 Q1 |

Energy shocks exhibit immediate transmission, while policy effects emerge with a three-month lag. The decomposition visualizes asymmetric propagation paths, showing how simultaneous fiscal expansion and energy volatility compound inflationary pressure.

## 5.3. Policy implications and robustness discussion

The interpretive structure provides quantitative analysis with which to inform decision choices. Scenario analyses reveal that while a 50-basis point decrease reduces inflation by 0.11 ± 0.02

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percentage points after two months, an increase of 10 USD in Brent oil prices can decrease inflation by 0.27± 0.05 percentage points in nearly immediate effects, while increased energy subsidies of 1% of GDP can reduce inflation by 0.09± 0.03 percentage points in one quarter.

The robustness checks with different machine learning models (LightGBM, CatBoost) result in RMSE = 0.147±0.006 with very close Shapley values, thereby being consistent. The cross-validation test on G20 subsets shows generalizability, while the mean VIF = 1.84 indicates no multicollinearity problems

The application of policy interpretation goes beyond model results: The disclosure of Shapley values can improve communication with the public: Bars summarizing contributions convey complex relationships in an easily understandable way, and it should be possible to explain why the same policy actions can lead to different outcomes in different periods, thereby facilitating credibility-building and expectations alignment.

## 6. Conclusion

The study sets up an explainable hybrid model of ARIMA and XGBoost for inflation nowcasting in real time and shows great accuracy improvement and cross-regime robustness in tests on data between 2010 and 2024. What is even more valuable is that it connects predictive modeling with economic insights via the marginal contribution calculated from Shapley values.

The results demonstrate three key implications: namely, (1) the dynamic of energy prices remains the primary driving force in the short term, while inflation can be influenced by monetary policy with lag effects in terms of magnitude, and (3) the hybrid explainable model has the potential to serve as the basis for accountable policy assessment. Future studies can involve text/sentiment features or spillovers on the global level based on cross-attention mechanisms.

In incorporating machine learning accuracy with econometric explainability, the proposed model promotes a new paradigm of explainable data-driven macroeconomic intelligence to ensure sustainability and accountability in designing policies.

## References

[1] Somkunwar, R. K., Pimpalkar, A., & Srivastava, V. (2024, February). A Novel Approach for Accurate Stock Market Forecasting by Integrating ARIMA and XGBoost. In 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) (pp. 1-6). IEEE.

[2] Liu, J., & Yan, J. (2024). Research on Maximum Temperature Prediction Based on ARIMA–LSTM—XGBoost Weighted Combination Model. Journal of Circuits, Systems and Computers, 33(07), 2450123.

[3] Kotsompolis, G., Cheilas, P., Konstantakis, K. N., Sfakianakis, E., Goutte, S., & Michaelides, P. G. (2025). Smart Forecasting of Carbon Prices Using Machine Learning and Neural Networks: When ARIMA Meets XGBoost and LSTM. Journal of Forecasting.

[4] Thorat, K. H. (2025). Enhancing Truck Sales Forecasting Using a Hybrid Prophet, ARIMA, and XGBoost Model (Master's thesis, State University of New York at Binghamton).

[5] Yang, Y., Xie, P., Liu, Y., & Lu, Q. (2024, June). Monthly Renewable Energy Forecasting Based on Multi-Model Fusion Techniques. In 2024 6th International Conference on Energy Systems and Electrical Power (ICESEP) (pp. 343-348). IEEE.

[6] Rekha, P. M., & Bhumika, C. P. (2025, August). Data-Driven Forecasting for Grid Stability: Implementing XGBoost in Smart Energy Systems. In 2025 International Conference on Modern Sustainable Systems (CMSS) (pp. 1-8). IEEE.

[7] Rosing, J. (2025). Multi-Horizon Forecasting of Aggregated Electricity Consumption and Production Volumes for Balance Responsible Portfolios: A Benchmark Study using Transformers, XGBoost and LSTM Models.

[8] Sugiarto, S., Diyasa, I. G. S. M., Alhamda, D. S., Aryananda, R. L., Sari, A. R. F., Sukri, H., & Dewi, D. A. (2025). Optimizing The XGBoost Model with Grid Search Hyperparameter Tuning for Maximum Temperature Forecasting. Journal of Applied Data Sciences, 6(4), 2517-2529.

DOI: 10.54254/2755-2721/2026.30591


[9] Xu, X., Yang, J., & Wu, C. (2024, April). Attention-based CNN-LSTM and XGBoost Hybrid Model for Air Quality Prediction. In 2024 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC) (pp. 524-528). IEEE.

[10] Chen, Q., He, P., Yu, C., Zhang, X., He, J., & Li, Y. (2023). Multi-step short-term wind speed predictions employing multi-resolution feature fusion and frequency information mining. Renewable Energy, 215, 118942.