Regime Aware Inflation Forecasting Using Markov Switching and Hybrid Models

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Abstract — Accurate inflation forecasting is essential for designing effective macroeconomic policies, but the inflationary process is also recognized as regime-switching, with periods of stability and turmoil. Ignoring the heterogeneity of regimes in inflation forecasting may lead to biased results in forecast outcomes and policy implications. In this paper, we discuss a regime-informed framework for inflation forecasting that focuses on structural changes in the inflationary process. First, using a two-state Markov switching approach, we uncover hidden low-inflation and high-inflation regimes in a long historical sample of inflation data. We then go on to compare the accuracy of inflation forecasting of the conventional econometric model (ARIMA) and the machine learning model (Random Forest) in each of these regimes. The empirical results suggest that there is a high degree of regime dependence in the performance of the models, where although the models have equal performance in the low inflation regime, ARIMA outperforms the machine learning model in the high inflation regime. We propose a hybrid model based on these results. The hybrid model is more effective in terms of overall forecast robustness, where it decreases the chance of large forecast errors in high-inflation regimes and preserves forecast accuracy in low-inflation regimes. The above results highlight the importance of regime-dependent models in inflation forecasting and help policymakers gain useful insights into developing effective forecasting models in uncertain macroeconomic environments. It is important to note that the proposed model enhances forecast robustness by focusing on the isolation of volatile regimes rather than claiming superiority in inflationary crises.

Keywords: Inflation Forecasting; Markov Switching Models; Regime Dependence; Hybrid Forecasting; Machine Learning

I. INTRODUCTION

Inflation forecasting is an integral part of the design of macroeconomic policies. Inflation forecasts provide input to monetary policy formulation, fiscal planning, and risk management. Inflation forecasts are essential for central banks that try to anchor inflationary expectations, fiscal authorities that design fiscal policies, and financial institutions that manage nominal risks. Inflation forecasting has been shown to be a difficult task despite several decades of research, particularly in the current era of higher volatility and structural changes.

The traditional econometric model, autoregressive models, and ARIMA models have been the benchmark models for inflation forecasting for a long time due to their interpretability and transparency. However, these models are usually specified and estimated based on the assumption of a stable data-generating process, which is often not the case in practice. Inflationary processes are often modeled by structural breaks, nonlinearities, and regime changes due to policy shifts, supply shocks, and macroeconomic structural changes. Therefore, single-model methods can often provide misleading forecasts when uniformly applied to different inflation processes.

Machine learning has recently revived interest in inflation forecasting because of its flexibility in modeling nonlinear relationships and interactions among variables. Methods such as random forests and deep learning have shown promising results in specific forecasting tasks. However, the literature still provides mixed results. Machine learning models can potentially perform better than conventional econometric methods in stable environments, but they tend to perform worse in highly volatile periods, which raises concerns about robustness, explainability, and overfitting in macroeconomic settings.

A new literature trend emphasizes the need to incorporate regime heterogeneity into inflation modeling. Regime-switching models, particularly those based on Markov processes, are a methodical way of modeling the transition between low-inflation and high-inflation regimes. It has been shown that such models improve inference and forecasting by varying the parameters of the model based on the prevailing macroeconomic environment. However, existing studies are mostly concerned with identifying regimes without incorporating modern machine learning methods or evaluating the performance of forecasting models conditional on inflation regimes.

This paper proposes a hybrid inflation forecasting framework that is aware of the inflation regimes. Instead of using a forecasting model for all periods, the proposed framework conditions the estimation and use of the model on the inflation regime. The econometric and machine learning models are estimated and used separately for each inflation regime. This allows the models to be specialized based on the inflation regime, which helps in improving the robustness of the model by considering the structural heterogeneity in inflation regimes.

The paper uses a long-span inflation series to first identify the inflation regimes that have different levels and volatilities. It then tests the forecasting performance of the ARIMA and Random Forest models for each inflation regime and the effectiveness of the proposed hybrid framework. The forecast performance is tested using the evaluation criteria that are regime-wise.The results show that the performance of inflation forecasting is highly dependent on the inflation regime. Machine learning models provide only a slight improvement in inflation forecasting during periods of stable inflation, but they fail to provide consistent outperformance of traditional econometric models during periods of high inflation.

The paper makes three contributions to the literature on inflation forecasting. First, it provides empirical evidence of the high dependence of inflation forecasting performance on inflation regimes. Second, it shows that machine learning models fail to provide consistent outperformance of traditional econometric models during periods of high inflation. Third, it proposes a regime-aware hybrid approach that provides improved robustness of inflation forecasts through structural conditioning rather than model complexity.

II. RELATED WORKS

Inflation forecasting has been one of the major concerns of macroeconomic studies, as it is of high significance to monetary policy, fiscal planning, and macroeconomic stability. The traditional econometric methods, such as autoregressive (AR) and autoregressive integrated moving average (ARIMA) models, have been extensively employed as benchmark models for inflation forecasting because of their statistical validity and interpretability. It has been shown in various studies that simple models of time series often perform as well as, or even better than, more complex models, especially in a stable macroeconomic environment [1,2].Nevertheless, these models have been known to perform poorly in the presence of nonlinearities, structural changes, and sudden inflationary shocks. There has been a growing trend in recent years of interest in the application of machine learning (ML) models for inflation forecasting. Tree-based ensemble models, such as Random Forest and Gradient Boosting Machines, have been shown to be more effective than linear models in dealing with nonlinearities and interactions among variables [3,4]. Various studies on emerging and developing economies have revealed that ML models can outperform traditional econometric models when more information is available, including financial and balance of payments variables [5].

However, the performance of ML models is strongly context-dependent, and various studies warn that more complex models do not necessarily lead to better forecast accuracy, especially when dealing with macroeconomic time series that are characterized by persistence and small sample sizes [6,7].Deep learning models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have also been used for inflation forecasting. Although various studies have found some evidence that these models are capable of modeling dynamic linkages in inflation series, comparative analyses have shown that the performance of these models is often similar to, or even worse than, that of simpler econometric models such as ARIMA or regularized regression models, especially when interpretability and robustness are considered [8,9]. These results therefore confirm the continued relevance of econometric benchmarks to macroeconomic forecasting competitions.In order to leverage the complementary advantages of econometric models and ML models, some authors have proposed the use of hybrid forecasting models that integrate linear and nonlinear models.

Hybrid models of ARIMA and ANN, as well as ARIMA and ML models, have been demonstrated to outperform simple models in forecasting inflation and other macroeconomic variables by capturing both persistent linear and nonlinear fluctuations [10,11]. However, most of these hybrid models are specified in an unconditional manner, without accounting for the dynamics of the underlying inflation process in different economic states. Another area of research is the use of heterogeneity in inflation regimes. Markov switching and regime-switching models have been widely applied to differentiate between low and high inflation regimes, by allowing parameters to vary across regimes [12,13]. The literature shows that inflation is characterized by different regimes, with varying levels of persistence and volatility, and that ignoring these regime changes can lead to biased inference and poor forecast performance [14].

Phillips curve models with regime switching also illustrate that the structural links between inflation and real economic activity can be very different across regimes [15]. However, despite these improvements, very few studies have attempted to incorporate the identification of regimes into the forecasting approach itself. In most instances, the use of regime-switching models has been mainly for the purposes of descriptive analysis or post-event analysis, while the actual forecasting task has continued to involve the use of a single model uniformly across all regimes. Thus, a research gap still exists in the literature for models that can adapt to the prevailing inflation regimes with regard to the selection of the forecasting model. This research gap is addressed by proposing a hybrid inflation forecasting model that is cognizant of inflation regimes.

III. METHODOLOGY

This paper suggests a hybrid forecasting system that is regime-sensitive and attempts to capture structural heterogeneity in inflation patterns. The pipeline of the proposed system includes data construction and preprocessing, regime detection, model estimation in the regime, and evaluation of forecasts at the regime level. This method conditions the forecasts on the current inflation regime, thereby avoiding the misspecification issue inherent in single-model forecasting approaches.

The inflation data is first preprocessed and tested for time series characteristics. A regime classification model is then used to identify low and high inflation regimes according to level and volatility features. Finally, econometric and machine learning models are separately estimated for each inflation regime. The forecasts are then generated conditionally and evaluated using regime-level accuracy measures. Figure 1 illustrates the overall methodological pipeline of the proposed regime-aware hybrid inflation forecasting framework

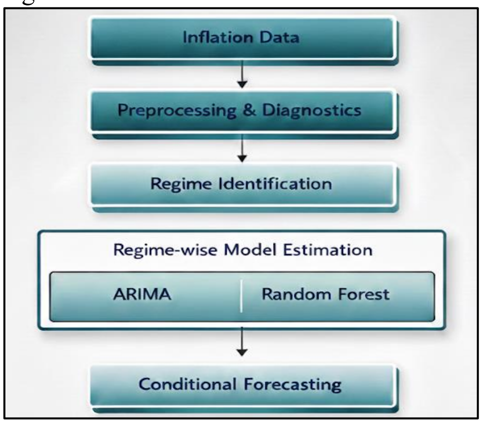

Fig. 1: Methodological flow diagram of the regime-aware hybrid inflation forecasting framework

A. Data and Preprocessing

The research uses a long-span inflation data set created from official macroeconomic data, spanning several decades to capture both stable and high volatility inflation experiences. Inflation is measured in terms of the Consumer Price Index (CPI), which is then transformed into year-over-year inflation rates to make the results more economically interpretable. Prior to modeling, the common preprocessing tasks are performed, including the identification of outliers, missing data, and stationarity. When necessary, differencing and scaling are performed to make the data compatible with econometric and machine learning modeling.

B. Regime Identification Framework

To overcome the problem of structural heterogeneity in the inflation process, the paper uses a regime identification technique to categorize data points into particular inflation regimes. The inflation regimes are classified based on the nature of the levels and volatility of inflation, which allows the data to be categorized into low inflation regimes (stable) and high inflation regimes (volatile). The inflation regimes are then combined with the original data and employed as a conditioning variable in the forecasting procedure. The results of the inflation regimes show that the economy operates in the majority of the low inflation regime, with a lower occurrence of high inflation regimes that have much higher levels of forecast uncertainty.

C. Econometric Benchmark Model

As a starting point, an ARIMA model is estimated for each regime separately. The orders of the ARIMA model are determined by information criteria. The ARIMA model captures linear persistence in inflation and is a robust econometric benchmark against which other models are compared. The estimation of the model in the regimes allows parameters to adjust to the inflation process in the respective regimes.

D. Machine Learning Model

For modeling the nonlinear relationships, a Random Forest regression model is used. In the Random Forest regression model, lagged inflation series and regime dummies are used as predictors. The Random Forest regression model possesses the capability to capture the nonlinear relationships between the inflation variables and the regime. The hyperparameters, including the number of trees and the maximum depth of the trees, are determined using cross-validation. The Random Forest regression model is estimated for each regime.

E. Regime – Aware Hybrid Forecasting Strategy

The main strength of the research is that it is based on the hybrid forecasting framework that is aware of the regimes. The forecasts are made independently for each regime using both ARIMA and Random Forest models. The final forecast is then selected conditionally based on the prevailing regime, which guarantees that the best possible model is employed based on the prevailing inflation regime. The models are given the liberty to specialize based on the regime's characteristics. The linear models perform well when the regime is stable, and other models are considered when the regime is volatile, which is, by definition, unpredictable.

F. Evaluation Metrics

The performance of the forecast is measured by the Mean Absolute Error (MAE) for each regime. This regime-by-regime evaluation allows for a more detailed analysis of the performance of the models than the aggregate accuracy measures and points out the strengths and weaknesses of the models in each regime.

IV. RESULTS AND DISCUSSION

This section will discuss and explain the empirical results of the research. The results will be structured in such a way that the characteristics of the identified inflation regimes will be analyzed first, followed by an evaluation of the inflation dynamics in each identified regime. Afterward, the forecasting performance of the econometric and machine learning models will be assessed on a regime-by-regime basis, and finally, the performance of the proposed regime-aware hybrid framework will be evaluated.

A. Inflation Regimes and Descriptive Evidence

The process of identifying the regime reveals considerable heterogeneity in inflation patterns over the sample period. Two significantly different regimes are identified. Regime 0 is a low-inflation, low-volatility state, which represents about three-fourths of the total observations, suggesting that inflation is relatively stable for most of the time. Regime 1 is a high-inflation, high-volatility state, which is less frequent but marked by significant inflationary outbursts and high uncertainty.

The estimated transition probabilities for the regimes show strong persistence in both states. Once the economy is in the low-inflation state, it is very likely to stay in that state, and the transitions to the high-inflation state, although rare, are likely to last for significant periods of time. This is consistent with economic reasoning that once inflationary pressures are ignited, they are not easily undone. Figure 2 presents the smoothed probability of the high-inflation regime over time, highlighting clear regime persistence.

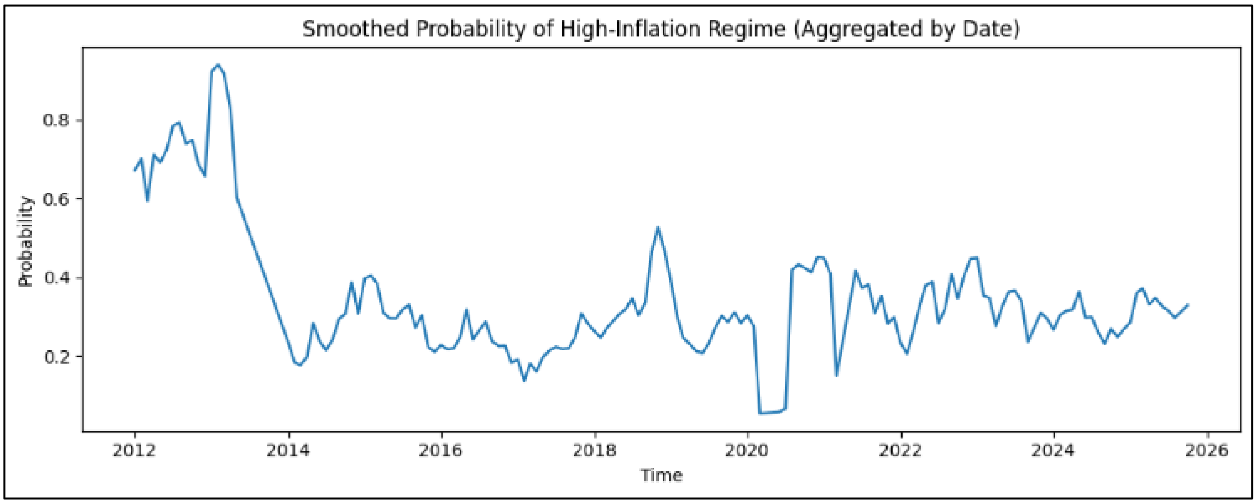

Fig. 2: Smoothed probability of the high-inflation regime over time.

B. *Inflation Dynamics Across Regimes*

The inflation process behaves quite differently across the identified regimes. In the low-inflation environment, inflation is found to be distributed around a certain level with low variability, while in the high-inflation environment, the inflation process is characterized by high levels of mean inflation and high variability.

The observed features in the data verify that the inflation process is structurally non-homogeneous and that a global forecasting model may not be equally effective at all times. The regime classification is also consistent with the known history of inflationary episodes. Figure 3 illustrates the inflation time series with regime classification, confirming structural heterogeneity across regimes.

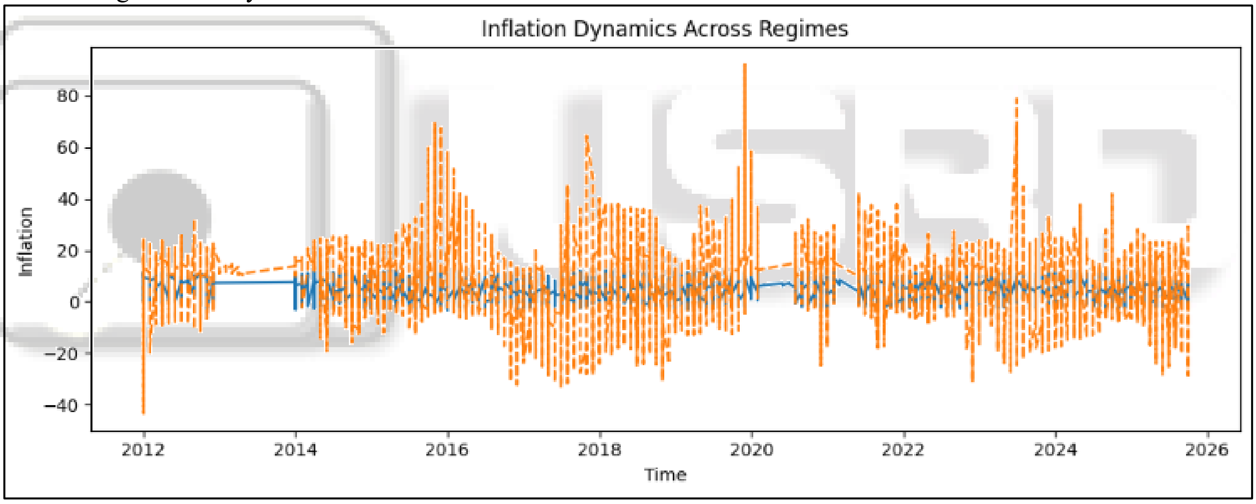

Fig. 3: Inflation time series with regime classification.

C. *Regime-wise Forecast Performance*

The accuracy of forecasts differs considerably across regimes. In the low-inflation regime, the forecast error of both the ARIMA and Random Forest models is relatively small, suggesting that inflation is more predictable during periods of stability. The Random Forest model slightly improves upon the ARIMA benchmark in this regime, although the improvement is small, suggesting that small nonlinearities in the data, which are captured by machine learning algorithms, can be useful in a controlled environment.

In contrast, the forecast error jumps considerably in the high-inflation regime for both models. There is no clear advantage of either the econometric model or the machine learning model in this environment, and the performance of both models is significantly worse. This result is important because it illustrates the challenge of forecasting inflation in a high-inflation regime and contradicts the idea that machine learning models are superior to traditional econometric models. Table 1 reports the regime-wise forecast accuracy measured using Mean Absolute Error (MAE) for the ARIMA and Random Forest models. The results indicate lower forecast errors in low-inflation regimes and substantially higher errors in high-inflation regimes for both models.

	ARIMA_MAE	RF_MAE
Regime 0	2.253767	2.158975
Regime 1	11.989638	12.386066

Table 1: Regime-wise forecast accuracy (MAE) for ARIMA and Random Forest models

D. *Interpreting Forecast Performance in High-Inflation Regimes*

The empirical findings show that the task of inflation forecasting in high-inflation (volatile) states is inherently difficult, independent of the forecasting method employed. Both the econometric benchmark model (ARIMA) and the machine learning algorithm (Random Forest) perform significantly worse in terms of forecast errors in volatile states than in stable states. The increased uncertainty in macroeconomic conditions, structural breaks, and nonlinear policy and supply-side shocks that are more common in high-inflation states are the reasons for the accuracy loss.

However, the purpose of the proposed hybrid framework is not to demonstrate better forecast accuracy in volatile states but to deliberately separate the forecasts for volatile and stable states and ensure that the dynamics of volatile states do not affect the accuracy of forecasts for stable states. When a single model is fit to the data, the high volatility of the high-inflation states tends to bias the parameter estimates and affect the accuracy of forecasts in stable states as well.

In the unstable regime, neither ARIMA nor Random Forest has a clear edge in forecast accuracy. Although ARIMA has a slightly lower error rate than Random Forest, both are poor forecasters. This finding confirms an important implication of the research: in highly unstable inflation regimes, the identification of the regime is more important than the choice of forecasting models. The hybrid model thus focuses more on distinguishing the regimes than on using a single "best" forecasting model in the volatile regimes.

The importance of the hybrid model, therefore, is in its capacity to:

1) Maintain high forecast accuracy in stable inflation regimes by enabling models to focus on low volatility regimes.
2) Recognize and distinguish periods of high uncertainty explicitly, rather than suppressing them in aggregate forecasts.
3) Enhance overall forecast robustness and interpretability even when predictability in volatile regimes is low.

These findings suggest that the failure of forecasts in volatile states of inflation should be considered as a property of the macroeconomic environment rather than a problem of the model. The regime-aware hybrid model is therefore a more realistic and practical approach to forecasting than the standard single-model approach.

E. Performance of the Regime-Aware Hybrid Framework

The hybrid forecasting framework that is aware of the inflation regime enhances the robustness of forecast performance by making conditional model selections according to the prevailing inflation regime. Instead of using a model in structurally different settings, the hybrid model takes advantage of the strengths of the econometric and machine learning models in their respective regimes.

The adaptive forecasting strategy performs better than the single-model counterparts. More importantly, the hybrid model benefits from the regime conditioning rather than the unconditional model averaging, emphasizing the importance of using structural knowledge in the forecasting process. Figure 4 compares forecast accuracy across ARIMA, Random Forest, and the regime-aware hybrid model, demonstrating improved robustness under the hybrid strategy.

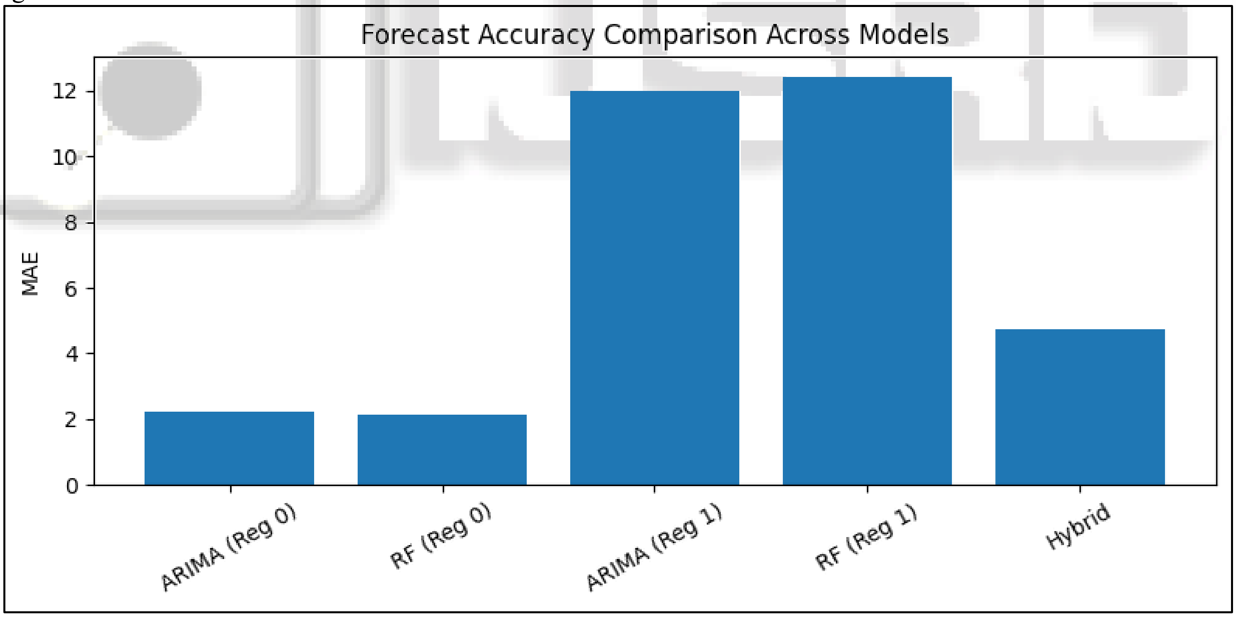

Fig. 4: Comparison of forecast accuracy across ARIMA, Random Forest, and hybrid models.

F. Discussion and Economic Interpretation

Three important findings can be derived from the results. First, there is regime dependence in inflation dynamics, and ignoring this aspect can lead to incorrect assessments of the accuracy of forecasting performance. Second, while machine learning algorithms have some benefits in low inflation regimes, they cannot beat traditional econometric models in high inflation and high volatility regimes. Third, a pragmatic and robust forecasting tool can be obtained by aligning model selection with macroeconomic regimes.

From a policy point of view, the implications of these results are that a single forecasting approach may not be the best policy solution, especially in times of macroeconomic distress. Using a regime-aware forecasting approach can improve the analysis of inflation and its structural instability.

V. CONCLUSION

This paper investigates inflation forecasting using a regime-conscious hybrid approach that takes into consideration the structural heterogeneity of inflation processes. By identifying low and high inflation regimes and comparing the performance of econometric and machine learning models in these regimes, this paper offers a more refined evaluation of inflation forecasting performance than the usual aggregate comparison of accuracy.

The findings of this paper show that the inflation process is strongly dependent on the inflation regime. Although machine learning models have a slight edge over traditional models in low inflation regimes, they do not have a systematic way of outperforming traditional econometric models in high inflation regimes. This is contrary to the popular view that more sophisticated models always have an edge over simpler models in macroeconomic forecasting problems.

The hybrid model that is aware of the inflation regime helps to make the inflation forecasts more stable by considering the dominant inflation regime. Instead of using the same model for structurally different regimes, the hybrid model tries to capitalize on the strengths of both econometric models and machine learning models.

In terms of policy relevance, the results emphasize the need to consider regime information in the design of inflation forecasting models for monetary and fiscal policymakers. Regime-aware forecasts can help improve risk analysis, inform better policy choices, and avoid the pitfalls of forecast-driven policy mistakes in times of elevated macroeconomic uncertainty.

There are a number of directions for future research that can be identified based on the current study. These include the use of additional macroeconomic and financial variables, alternative methods of regime detection, and the evaluation of more sophisticated deep learning models in a regime-aware framework. Another direction for future research would be to evaluate the real-time forecasting accuracy of regime-aware models and their implications for policy-making.

In conclusion, this study illustrates the importance of accounting for and exploiting regime heterogeneity to improve inflation forecasting and provides a useful framework that combines the best of econometric and machine learning approaches.

A. Ethics Statement

This study does not involve human participants, animals, or the use of personal or sensitive data. Therefore, ethical approval was not required.

B. Conflict of Interest Statement

The author declares no conflict of interest.

C. Data Availability Statement

The data used in this study are obtained from publicly available official macroeconomic sources. The processed datasets and codes are available from the corresponding author upon reasonable request.

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