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Bachelor's Degree Course in

Digital Economics and Business

FORECASTING INFLATION DYNAMICS IN INDIA:

A DATA-DRIVEN APPROACH

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ABSTRACT

This study compares six models, ARIMA (5,0,3), ARIMA (3,0,5), VAR (1), Random Forest, XGBoost, and Support Vector Regression (SVR), for forecasting quarterly inflation in India, a task that has grown more important since the RBI adopted Flexible Inflation Targeting in 2016 but remains difficult given the nonlinear, structurally unstable nature of Indian price dynamics. Using quarterly data on inflation, interest rates, money supply, output, and the exchange rate, each model is evaluated out-of-sample over 2019 Q1–2022 Q3, a period that places the COVID-19 shock entirely outside the training data. SVR achieves the lowest forecast error across all three accuracy metrics, followed by Random Forest and XGBoost, with all three machine learning models clearly outperforming the econometric models. VAR (1) outperforms both ARIMA specifications by incorporating macroeconomic information, though its impulse responses are not statistically significant, likely reflecting the short, structurally disrupted sample. These results strongly support the hypothesis that machine learning improves on traditional forecasting, and partially support the hypothesis that VAR captures macroeconomic dynamics more effectively than univariate models.

CHAPTER I: INTRODUCTION

I.1 BACKGROUND OF THE STUDY

Inflation forecasting is a crucial macroeconomic tool that helps policymakers maintain economic stability, formulate effective monetary policies, and promote overall economic growth and health. In India, especially ever since RBI (Reserve Bank of India) has introduced Flexible Inflation Targeting (FIT) framework in 2016 which is a framework for fixing the target inflation at 4%, accurate inflation forecast has become a necessity [4]. A reliable inflation prediction of inflation plays a crucial role for RBI to plan monetary policy [19]. For instance, adjusting interest rates in advance. At the same time for businesses, accurate forecasts have become a necessity to make decisions about investment, savings and wages. Moreover, it is also important for the government to plan budgets, subsidies and expenditure on welfare programs. In short for almost every part of the Indian economy, inflation forecasting is essential for decision making.

Despite its importance, accurate forecasting inflation in India is very challenging, for example, the nonlinear and evolving nature of price movements, that is, inflation in India can be affected by various other factors like rainfall, and international oil prices. Also, complications like structural breaks due to COVID, changing policy frameworks, and interactions among multiple macroeconomic variables have contributed to the complexity of forecasting process [10].

I.2 STATEMENT OF THE PROBLEM

Even though traditional econometric models have widespread use, the have certain limitations when it is used for forecasting inflation, for instance, Univariate models like ARIMA do not consider multiple important macroeconomic variables but instead relies heavily on historic inflation and multivariate models like VAR uses multiple macroeconomic variables, however, they still depend on linear specifications [16].

However, machine learning models like Random Forest, XGBoost and SVR models tackle these issues by prioritizing predictive accuracy and flexibility. Despite these theoretical advantage machine learning models, applications of these models in India are relatively limited [16]. This thesis focuses on a systematic comparison of the traditional models and machine learning models by evaluating and comparing performances of both approaches.

I.3 OBJECTIVES OF THE STUDY

The primary objectives of this study are:

- To model and forecast inflation dynamics in India using traditional econometric approaches such as ARIMA and VAR.
- To examine the dynamic interactions between inflation and key macroeconomic variables like Interest rate using impulse response functions (IRFs).
- To apply machine learning models, including Random Forest, XGBoost, and Support Vector Regression, to inflation forecasting.
- To find the best model by comparing the forecasting performance of all models using RMSE, MAE, and MAPE as accuracy measures.

To answer the following research questions:

- Which forecasting model delivers the most accurate predictions for inflation in India?
- How do shocks to key macroeconomic variables affect inflation over time within a VAR framework?
- Do machine learning models offer measurable improvements over traditional econometric models in forecasting performance?

Based on objectives and research questions, the study tests the following hypotheses:

- Machine learning models outperform traditional time series models in forecasting Indian inflation.
- VAR and IRF analyses capture the dynamic relationships among macroeconomic variables more effectively than univariate ARIMA models.

CHAPTER II: LITERATURE REVIEW

II.1 CLASSICAL ECONOMETRIC MODELS

One of the most widely used univariate models for forecasting inflation is ARIMA (Autoregressive Integrated Moving Average) which consists of 3 components that are Auto Regression (AR), Moving Average (MA) and Integration (I). ARIMA model is based on inflations past values (AutoRegressive (AR) terms) and its past errors (Moving Average (MA) terms) to predict the inflation in future. This model is particularly useful when inflation exhibits strong persistence. Due to their simplicity and relatively stable performance in stable environments, it is being widely used by developed countries and emerging countries like India [13]

However, inflation is not usually driven by just one single variable, it is influenced by multiple variables. Multivariate models such as Vector Autoregression (VAR) allow the study to expand using multiple other macroeconomic variables that interact with inflation to forecast inflation [11]. An important analytical tool that is derived from VAR model is IRF (Impulse Response Function). IRF examines how a movement or sudden shock to one variable affects the future values of all the other variables like output gap. In inflation analysis, IRF could be particularly useful in understanding how policy intervention could affect inflation[18].

II.2 MACHINE LEARNING IN TIME SERIES FORECASTING

Despite the strengths, tradition model only relies on linear models and assumes parameter stability over time. For economies like India which experiences frequent structural changes these may lead to inaccurate forecasts. Unlike traditional models, machine learning models are designed specifically to optimize predictive performance and capture nonlinear relationships and complex interactions among variables [16].

Random forest is a common machine learning technique which is based on decision tree. It combines predictions of multiple decision trees built on different subsets of the data to improve forecasting accuracy. Random Forest technique is especially useful when the data set consists of many predictors [15].

XGBoost (Extreme Gradient Boosting) is another useful machine learning algorithm which builds models sequentially by correcting the errors from the previous errors[16]. XGBoost can handle complex patterns efficiently and reduce overfitting through regularization techniques [15].

Support Vector Regression (SVR) finds a function that best fits the data within a specified error margin it is especially effective in high-dimensional settings[16].

Despite having multiple theoretical advantages and usually outperforming traditional models [16], there have been times when Traditional model outperforms Machine learning models[9], moreover, due to its limited interpretability [15], in studies sometimes combine both econometric and machine learning techniques for the getting best out of both [16], [15].

II.3 MODEL EVALUATION METRICS

A forecast could only be meaningful if appropriate performance metrics measure the difference between predicted and actual values. Some most used evaluations methods are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) [8].

RMSE measures the square root of the average squared forecast errors and places greater weight on large deviations between forecasts and actual values. As a result, it is particularly sensitive to extreme errors and is useful when large forecasting mistakes are especially costly[8].

MAE calculates the average absolute difference between forecasted and actual inflation values. Unlike RMSE, MAE treats all errors equally, making it easier to interpret and less sensitive to outliers [8].

MAPE expresses forecast errors as percentages of actual values, allowing for intuitive comparisons across models and datasets. However, it can be sensitive when actual values are close to zero [8].

Using multiple evaluation metrics captures different aspects of forecasting accuracy which leads to more comprehensive assessment of model performance [3]

II.4 PAST STUDIES AND GAPS

A vast part of these researches have tried to forecast Inflation in India using Traditional econometric models usually using ARIMA [13] or Phillips curve based frameworks[10], some researches have also incorporated multivariate approaches such as VAR models to analyze the interaction between other macroeconomic variables including interest rates, output, money supply, and exchange rates there are a limited number of studies using machine learning techniques for forecasting inflation of India as well [19], [16], [15].

However, many studies focuses specifically on either traditional econometric models or machine learning approaches instead of conducting a meaningful and understandable comparison in the performance of these as a whole.

CHAPTER III: METHODOLOGY

III.1 DATA

Quarterly macroeconomic data was used throughout the study. The CPI was converted from monthly to quarterly and year-on-year inflation was calculated as $\pi_t = [(CPI_t - CPI_{t-4})/CPI_{t-4}] \times 100$. Since the domestic statistics portal (mospi.gov.in) provides CPI only from 2011, the IMF series was used to obtain a longer sample. The two sources' slight methodological variations are recognized as a drawback. The other variables are also included: the discount interest rate, broad money supply M3 real GDP, and the INR/USD exchange rate

Table III.1: Variables and Data Sources

Variable	Series Code	Source	Freq.
CPI Inflation	IND.CPI._T.IX.M	IMF Data Explorer	Monthly
Interest Rate	INTDSRINM193N	FRED	Monthly
Money Supply (M3)	MABMM301INQ189N	FRED	Quarterly
Real GDP	IMF.STA:QNEA	IMF Data Explorer	Quarterly
Exchange Rate (INR/USD)	IMF.STA:ER	IMF Data Explorer	Monthly

III.2 DATA PROCESSING

ADF test stated that quarterly inflation was stationary (I (0)), and the other variables were stationary (I (1)). Because of this: real GDP was replaced by an output gap series computed via the Hodrick-Prescott filter [7]; money supply was log-transformed and first-differenced to obtain a quarterly growth rate ($\Delta \ln M_t$); and the interest rate was first-differenced (ΔR_t). The exchange rate was collected but excluded from the final VAR system after specification testing, but it is retained as a feature variable in the machine learning models.

III.3 CLASSICAL ECONOMETRIC MODELS

For ARIMA since the inflation is stationary, the differencing parameter d=0. Using ACF and PACF plots as a guidance, few combinations of 'p' and 'q' were estimated and ranked by AIC and BIC, AIC was the lowest in ARIMA (5,0,3) and ARIMA (3,0,5) was consistently second. Both passed the Ljung-Box test as well.

For VAR, the lag length was selected using VARselect() which suggested 1,7 and 9, among which 7 and 9 had high correlation whereas 1, however VAR (1) still failed Normality and Heteroskedasticity tests. This may be due to the Covid-19 structural break, but this does not invalidate the forecast completely. IRFs were derived from VAR (1) using Cholesky decomposition, computed over 10 quarters with 95% bootstrap confidence bands.

III.4 MACHINE LEARNING MODELS

The feature matrix consists of 4 lags, 1 for each variable. The sample was split at 2018 Q4: observations up to that point form the training set (~87 observations) and 2019 Q1 onwards forms the test set (~16 quarters), placing the COVID-19 period entirely out-of-sample. RF (Random Forest) was trained with ntree = 500 and default settings. XGBoost used fixed parameters (max_depth = 6, eta = 0.1, nrounds = 100). SVR used an RBF kernel with inflation lags 1–4 as features, tuned via grid search over, $\gamma \in \{0.01, 0.05, 0.1, 0.2\}$, and $\varepsilon \in \{0.001, 0.01, 0.1\}$ using tune.svm().

CHAPTER IV: RESULTS

The estimate findings, forecast accuracy, and comparative performance of the six models ARIMA (5,0,3), ARIMA (3,0,5), VAR (1), Random Forest, XGBoost, and SVR are presented in this chapter. The findings are presented in three sections: ARIMA, VAR, and machine learning. A cross-model comparison comes next.

Interpretation and discussion of these results, including their economic implications, theoretical context, and policy relevance, are presented separately in Chapter V.

IV.1 ARIMA RESULTS

Both ARIMA models were estimated and used to generate 16-quarter ahead forecasts. Out-of-sample accuracy data are shown in Table IV.1. In all three metrics-lower RMSE, MAE, and MAPE, ARIMA (3,0,5) perform better than ARIMA (5,0,3), even though ARIMA (5,0,3) achieves a slightly lower in-sample AIC. This suggests that the MA (5) specification is better for the test period.

Table IV.1: ARIMA Out-of-Sample Forecast Accuracy

Model	RMSE	MAE	MAPE (%)
ARIMA (5,0,3)	2.7113	2.3409	64.39
ARIMA (3,0,5)	**2.6208**	**2.1999**	**61.22**

Figure IV.1 shows the ARIMA (3,0,5) forecast with 80% and 95% confidence intervals. The model was estimated using data extending back to the 1950s, a sample that includes the extreme inflation volatility of the 1970s oil shock period.

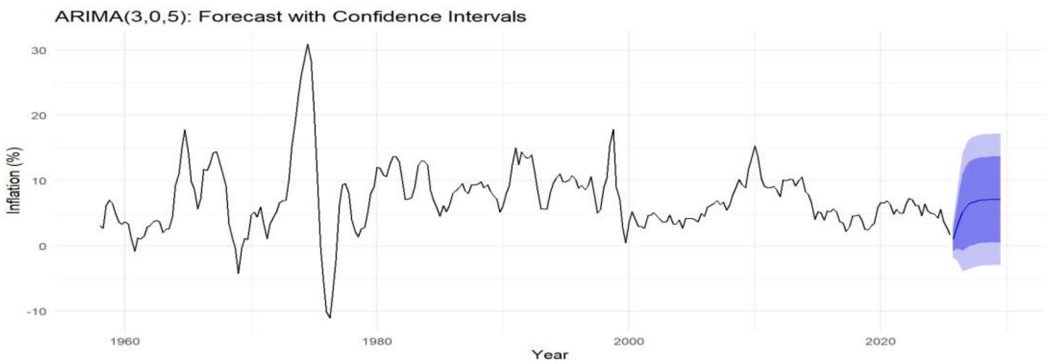

Figure IV.1: ARIMA (3,0,5) Forecast with 80% and 95% Confidence Intervals

IV.2 VAR RESULTS AND IMPULSE RESPONSE ANALYSIS

The VAR (1) model produced a 16-quarter ahead forecast. With RMSE, MAE and MAPE as given in Table IV.2

Table IV.2: VAR (1) Out-of-Sample Forecast Accuracy

Model	RMSE	MAE	MAPE (%)
VAR (1)	1.6713	1.2899	23.46

Figure IV.2 presents the three IRF panels derived from VAR (1), tracing the response of inflation to a one-unit shock in each explanatory variable over 10 quarters (95% bootstrap CI, 100 runs).

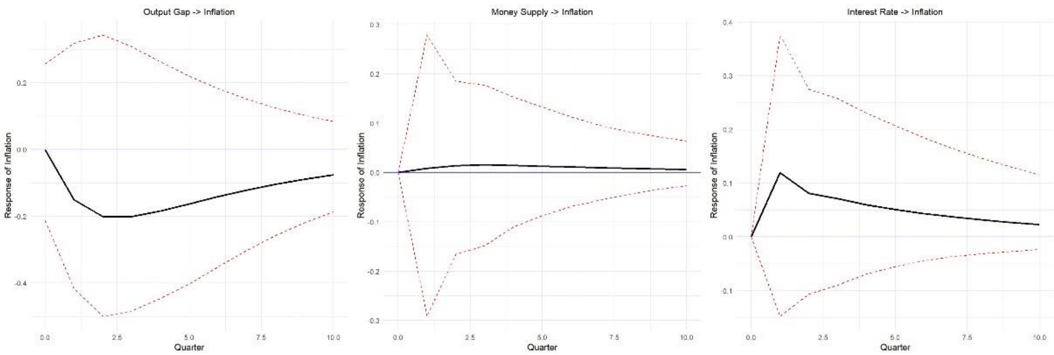

Figure IV.2: Impulse Response Functions - Response of Inflation to One-Unit Shocks (95% Bootstrap CI)

IV.3 MACHINE LEARNING RESULTS

Table IV.3 shows test-set accuracy for all three machine learning models. SVR achieves the best performance across all metrics, followed by Random Forest and XGBoost. Every ML model substantially outperforms both ARIMA and VAR on every metric.

Table IV.3: Machine Learning Out-of-Sample Forecast Accuracy

Model	RMSE	MAE	MAPE (%)
Random Forest	1.1851	1.0300	19.20
XGBoost	1.2027	1.0589	19.42
SVR	**0.9911**	**0.8432**	**17.45**

Figures IV.3, IV.4, and IV.5 display actual versus predicted inflation for SVR, Random Forest, and XGBoost respectively, over the test period (2019 Q1 – 2022 Q3).

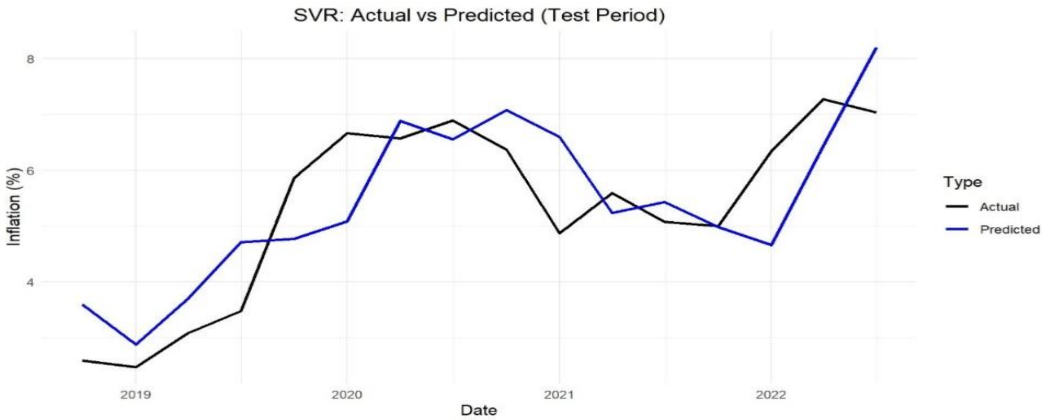

Figure IV.3: SVR- Actual vs Predicted Inflation (Test Period: 2019 Q1 – 2022 Q3)

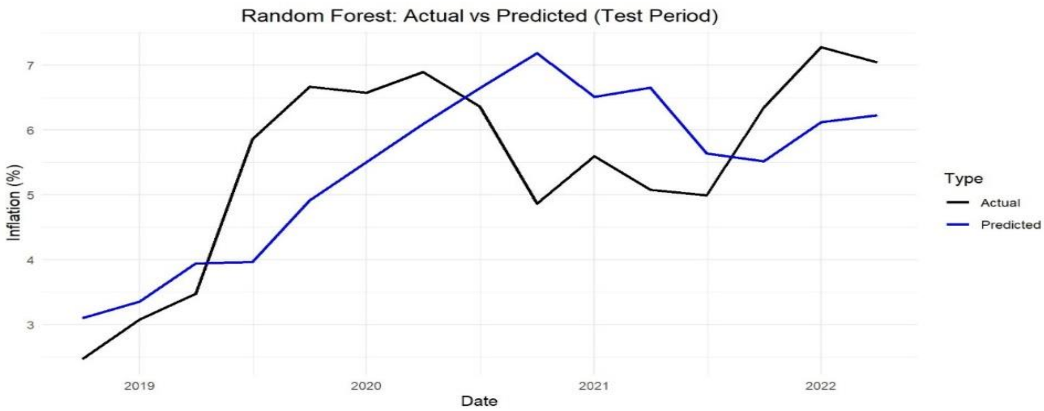

Figure IV.4: Random Forest - Actual vs Predicted Inflation (Test Period)

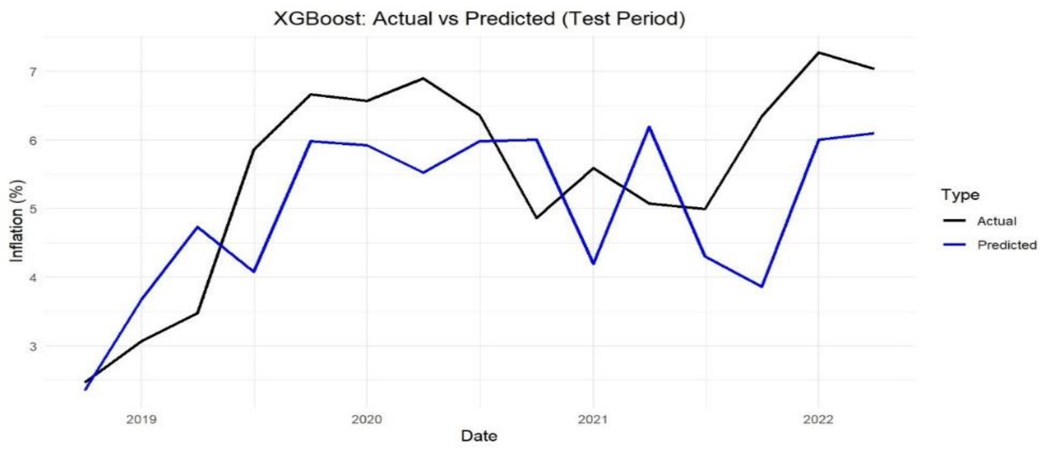

Figure IV.5: XGBoost - Actual vs Predicted Inflation (Test Period)

IV.4 CROSS-MODEL COMPARISON

Table IV.4 consolidates results for all six models ranked by RMSE, MAE and MAPE. SVR ranks first on all three criteria, making it the best-performing model in this study.

Table IV.4: Full Model Comparison - All Metrics (Test Set)

Model	RMSE	MAE	MAPE (%)	Rank
ARIMA (5,0,3)	2.7113	2.3409	64.39	6
ARIMA (3,0,5)	2.6208	2.1999	61.22	5
VAR (1)	1.6713	1.2899	23.46	4
Random Forest	1.1851	1.0300	19.20	2
XGBoost	1.2027	1.0589	19.42	3
SVR	**0.9911**	**0.8432**	**17.45**	**1**

CHAPTER V: INTERPRETATION AND ANALYSIS

While Chapter IV presented the empirical results in a descriptive form, this chapter provides an in-depth interpretation of these findings, links them within the theoretical and empirical literature reviewed in Chapter II. The limitations of the modelling approach used in this study is also well examined in this chapter.

V.1 INTERPRETATION OF ARIMA RESULTS

In all three metrics, ARIMA (3,0,5) performs better than ARIMA (5,0,3) even though ARIMA (5,0,3) achieves a marginally lower in-sample AIC. this divergence between in-sample and out-of-sample performance illustrates a well-known tension in model selection: information criteria such as AIC [1] are computed using in-sample residuals and therefore reward models that fit the training data closely, but a closer in-sample fit does not ensure better generalisation to unseen data. ARIMA (5,0,3), with two additional autoregressive terms relative to ARIMA (3,0,5), may be capturing noise specific to the training period rather than a persistent structural feature of Indian inflation, leading to a degree of overfitting that shows up as weaker test-set performance.

The model was fitted on data going back to the 1950s, which includes the extraordinary inflation volatility of the 1970s oil shock period. This significantly widens the confidence intervals shown in Figure IV.1.

Consistent with the model's inability to account for macroeconomic determinants of price dynamics, the forecast mean returns toward the long-run average and fails to anticipate the elevated inflation of 2020–2022.

V.2 INTERPRETATION OF VAR AND IRF RESULTS

VAR significantly outperforms both ARIMA specifications, confirming that the inclusion of the output gap, money supply growth, and interest rate changes provides meaningful predictive content beyond lagged inflation alone.

Compared with ARIMA (3,0,5), the VAR (1) model produces a clear improvement in forecasting performance. The RMSE falls from 2.62 to 1.67, representing a reduction of approximately 36%, while the MAPE decreases from 61.22% to 23.46%, cutting the average percentage forecast error by more than half. The fact that these gains are achieved with a relatively simple one-lag VAR specification is particularly noteworthy.

None of the impulse responses shown in Figure IV.2 are statistically significant at the 5% level, as the confidence bands in all three panels are wide and include zero at every horizon. This probably reflects the COVID-19 structural instability and the limited sample size.

Inflation responds negatively to a positive output gap shock, peaking at quarter 2 (IRF = −0.20). In India's structurally changing economy, this counterintuitive sign, which contradicts the standard Phillips curve [14], may represent supply-side dynamics captured by the HP-filtered output gap.

A shock to money supply growth produces a small positive inflation response peaking at quarter 3 (IRF = +0.016), consistent with the quantity theory of money [2] but negligible in magnitude, reflecting the weak monetary transmission documented in the Indian context [12]

Overall, the VAR results provide only partial support for the second hypothesis of this study. The fact that the VAR produced more accurate forecasts than the ARIMA model suggests that incorporating interactions among macroeconomic variables improves predictive performance. However, the impulse response analysis does not provide statistically significant evidence on how shocks are transmitted to inflation. Rather than showing that these relationships do not exist, the findings point to the practical difficulties of identifying them using a short quarterly sample that includes a major structural break. In this sense, the results are informative because they highlight the limitations of structural VAR analysis under these data conditions.

V.3 INTERPRETATION OF MACHINE LEARNING RESULTS

SVR's actual versus predicted inflation during the test period is shown in Figure IV.3. The model fits the overall course well, capturing the rise in 2019–2020 and the subsequent easing, though it diverges around the end of 2022 when inflation increased substantially. Its strong out-of-sample performance is attributable to the epsilon-insensitive loss function and the grid-searched RBF kernel.

One important difference between SVR and both Random Forest and XGBoost lies in the loss function used during training. SVR relies on the ε-insensitive loss function, which ignores prediction errors that fall within a predefined threshold (ε). Only errors that exceed this margin are penalised, and even then, the penalty increases linearly rather than quadratically.

Figure IV.4 shows Random Forest predictions. The model captures the general upward trend in inflation but lags actual values during the sharp COVID-19 rise in 2020 and fails to track the subsequent trough in mid-2021. The model produces predictions biased toward the training-set mean, which understates extreme movements.

This pattern can be explained by the way Random Forest produces its forecasts instead of relying on a single decision tree, the model combines the predictions from 500 different trees, each built using a bootstrapped sample of the training data.

The final forecast is simply the average of these individual predictions. While averaging helps reduce random variation and improves overall stability, it also makes the model less responsive to sudden changes in the data.

Figure IV.5 shows XGBoost predictions. Compared to Random Forest, the model is more volatile, overshooting in some quarters and undershooting in others, especially in 2021. This is probably because the fixed hyperparameters used without cross-validation tuning resulted in a degree of overfitting to the training data.

Overall, the machine learning results provide strong support for the first hypothesis of this study. All three machine learning models achieved better forecasting accuracy than both ARIMA specifications and the VAR (1) model across every evaluation metric. This is particularly noteworthy because the Random Forest and XGBoost models were trained using largely default hyperparameter settings rather than an extensive tuning process. The results suggest that the main advantage of these machine learning methods comes from their ability to combine information from multiple lagged macroeconomic variables and capture relationships that are difficult for traditional linear models to represent.

V.4 CROSS-MODEL COMPARISON AND DISCUSSION

The results reveal a clear hierarchy by model class. ARIMA performs worst, as univariate models cannot incorporate macroeconomic covariates or handle structural breaks. VAR (1) reduces RMSE by 36% relative to the best ARIMA model by exploiting cross-variable dynamics. The machine learning models improve further, with SVR reducing RMSE by an additional 41% relative to VAR (1), demonstrating that nonlinear functional forms add independent predictive value beyond the multivariate information already captured by VAR.

V.5 LIMITATIONS OF THE STUDY

There are Several limitations of this study that should be noted, as they affect how broadly the results can be interpreted and also suggest directions for improvement in future research.

Firstly, in the ARIMA models, which are estimated using a CPI series that extends back to the 1950s. This long historical coverage includes periods such as the high-inflation environment of the 1970s, which is very different from the modern inflation-targeting regime in India. Including these structural breaks in the estimation sample may increase noise in the fitted model and widen confidence intervals, ultimately reducing forecast accuracy for the more recent period of interest.

A second limitation relates to hyperparameter selection in the machine learning models. The Random Forest model was estimated using 500 trees and default mtry settings, while the XGBoost model was run with fixed parameters (max_depth = 6, eta = 0.1, nrounds = 100) without any cross-validation-based tuning. In contrast, the SVR model was carefully optimised using a grid-search approach via tune.svm(). This introduces an imbalance in the comparison, meaning that SVR's superior performance may partly reflect more careful calibration rather than a purely inherent advantage of the algorithm.

Third, there is an inconsistency in the input features used across models. The SVR model is estimated using only lagged inflation values (lags 1–4), whereas the Random Forest and XGBoost models use a wider set of 16 macroeconomic variables. This difference in feature design makes the comparison less uniform and means that SVR's performance could either be influenced by its simpler specification or, alternatively, that it might perform even better if it were given the same multivariate information as the other models.

A fourth limitation concerns the evaluation period, which runs from 2019 Q1 to 2022 Q3. This period includes the COVID-19 shock and the subsequent inflation spike, making it a particularly challenging and structurally unusual test environment. While this strengthens the evaluation in the sense that models are tested under stress conditions, it also means that the results may not be fully representative of more stable macroeconomic periods.

Finally, the VAR model is restricted to four variables. Although this restriction helps preserve parsimony given the limited sample size, it also excludes potentially important determinants of inflation in India, such as global commodity price movements, fiscal conditions, and inflation expectations. The omission of these variables may limit both the predictive performance of the model and the economic interpretation of the impulse response functions.

CHAPTER VI: CONCLUSION

VI.1 SUMMARY OF FINDINGS

The main objective of this study was to compare the forecasting performance of six different models-ARIMA (5,0,3), ARIMA (3,0,5), VAR (1), Random Forest, XGBoost, and Support Vector Regression (SVR) for quarterly inflation forecasting in India. In addition to comparing forecasting accuracy, the study also used impulse response functions from the VAR (1) model to examine how selected macroeconomic shocks influence inflation over time.

VI.2 RECOMMENDATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The findings of this study lead to several practical recommendations. First, machine learning methods, particularly SVR, could be used alongside traditional econometric models within the RBI's forecasting framework. Rather than replacing existing approaches, these models could provide an additional source of information, especially during periods of high economic uncertainty such as the COVID-19 pandemic.

Second, the weak and statistically insignificant impulse responses found in the VAR analysis suggest that inflation dynamics in India cannot be explained by monetary policy variables alone. This reinforces the importance of complementing monetary policy with supply-side measures, particularly in areas such as food and energy, which account for a substantial share of the Indian consumer price index.

Finally, future studies should apply the same level of hyperparameter tuning to all machine learning models. A consistent optimisation strategy would provide a fairer comparison of model performance and make it easier to identify whether differences in forecasting accuracy arise from the algorithms themselves or from the way they are calibrated.

There are also several opportunities to extend this research. One obvious improvement would be to use monthly data instead of quarterly observations, providing a larger sample for model estimation. Future work could also investigate hybrid forecasting approaches that combine the economic interpretability of VAR models with the predictive strengths of machine learning methods, including neural-network-based or LSTM architectures [6]. In addition, applying systematic time-series cross-validation to every machine learning model would make performance comparisons more robust. Finally, models that explicitly account for structural breaks, such as Markov-switching VAR [5] or time-varying parameter VAR [17], could provide a better understanding of inflation dynamics during periods of major economic disruption and potentially improve both forecasting accuracy and the interpretation of policy shocks

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