Original Research Article

Univariate versus Joint Modeling of Interest Rates and Inflation

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ABSTRACT

This study investigates several forecasting approaches for the United States federal funds rate and consumer price index (CPI) inflation rates in the years 1980-2025. This study compares univariate and joint models under trend and autoregressive specifications, implementing each model in connection with a historical data set and a three-year holdout test sample (2023-2025). The primary emphasis is discovering which approach to forecasting will provide greater predictive accuracy and relevance for macroeconomic policy purposes. The results of empirical work show that while these trend models serve well in capturing long-term trends in monetary and price behavior, autoregressive models perform better in forecasting short-term values because of their greater flexibility in taking into account variations and external factors. Joint modeling of interest rates and inflation through a vector-autoregressive (VAR) system provides small yet significant increases in forecasting accuracy but demonstrates that intermingling between monetary policy and price stability improves forecast accuracy. These findings suggest that accuracy in forecasting is not purely a statistical problem but a crucial policy problem which illustrates that even slight improvements can avoid premature policy tightening or delayed economic easing. Thus, this study seeks to indicate the importance of integrating dynamic, feedback-giving modeling systems into central bank databases in order to bring greater data-usefulness and greater stability in financial markets.

Keywords: Federal Funds Rate; Inflation; Forecasting; Autoregressive Models; Trend Models; Joint Modeling

INTRODUCTION

Forecasting interest rates and inflation is a cornerstone of macroeconomic policy analysis, financial market research, and decision making in institutions. These variables form the backbone of economic stability: interest rates influence borrowing costs and investment, while inflation affects purchasing power, wages, and income. Understanding their complex interactions will allow central banks to maintain price stability, prevent economic downturns, and sustain long-term growth through policy adjustments.

Since 1980, the United States economy has experienced several distinct monetary regimes, each providing unique insights for model forecasting. During the early 1980s, under Federal Reserve Chairman Paul Volcker, the “Volcker disinflation” era began. It featured an aggressive tightening campaign to restrain double-digit inflation through high interest rates. As a result, the “Great Moderation” of the 1990s and early 2000s was personified by stable inflation, modest growth, and predictable monetary conditions. After the financial crisis in 2008, policy rates remained nearly

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zero for almost a decade as the Federal Reserve pursued recovery. However, the beginning of the 2020s began a new challenge: a fast-paced surge in inflation triggered by pandemic-related crises, global uncertainty, and fiscal stimulus. These historical shifts demonstrate the difficulty of predicting monetary and price behavior, as relationships between interest rates and inflation constantly evolve over time.

Accurate projections of both inflation and interest rates are important for monetary authorities such as the Federal Reserve, investors, businesses, and households. A common issue is overestimating inflation, which can prompt unnecessary tightening and possible recessions. Meanwhile, underestimating inflation may allow expectations to become unanchored, reducing purchasing power and fueling wage spirals. Therefore, a central question in empirical macroeconomics persists throughout time. Which model framework, trend-based or autoregressive, better captures both the long-term equilibrium and short-term variability that define modern day economic dynamics?

This paper contributes to that ongoing debate by comparing univariate and joint modeling frameworks for predicting the federal funds rate and CPI inflation from 1980 to 2025. It extends information from prior research by employing up-to-date data and contrasting trend-based and autoregressive specifications across both integrated models and independent. By doing this, my study aims to clarify when simple historical extrapolations provide reliable predictions and when dynamic, feedback-driven modeling becomes essential for enhancing forecast accuracy and policy-making relevance.

LITERATURE REVIEW

Forecasting macroeconomic variables has been a challenging endeavor because of structural breaks, shocks, and behavioral expectations. Previous econometric work has viewed macroeconomic time series as a deterministic process with a predictable long-term trend. Nelson and Plosser challenged this view by demonstrating that some macroeconomic series follow unsystematic trends, implying that shocks can have permanent effects (1). This discovery gave rise to time-series methods that were capable of modeling randomness and persistence.

Hamilton formalized the use of autoregressive (AR) and autoregressive-moving-average (ARMA) frameworks (2). He emphasized that past values contain priceless information about future outcomes. These methods still remain popular because of their simplicity and transparency. Sims revolutionized forecasting by introducing the vector autoregression (VAR) model, where several interdependent variables are modeled at the same time (3). The vector autoregressive model framework allows for a new kind of endogenous feedback, such as the reaction of interest rates to inflation shocks.

Over time, researchers have expanded their tools with cointegration and error-correction models (4), which account for almost all long-term equilibrium relationships. Stock and Watson further integrated these ideas into modern forecasting frameworks for inflation and output (5). Their findings revealed that multivariate systems better utilize cross-variable information than univariate models do.

The 2000s witnessed the rise of Bayesian VAR models and time-varying parameter models which offered flexibility in changing economic conditions (6). Diebold and Li developed a yield-curve-based forecasting method, linking the term structure of interest rates to expectations of future rates and inflation (7). Modern forecasting has also embraced both machine learning and hybrid statistical models which offer improved forecasting performance in return for interpretability (8).

Ultimately, the literature reveals a constant recurring theme: no single model can encapsulate all horizons. Simpler univariate models often perform well for stable periods, while joint systems become essential during times of regime change. This study adds to that conversation by updating empirical evidence through 2025 and directly comparing these models under consistent evaluation metrics.

METHODS AND MATERIALS

Data Description

This study employs annual data for the United States federal funds rate and consumer price index (CPI) inflation spanning through the years 1980 and 2025. This results in a total of 46 observations. The effective federal funds rate was retrieved from the Federal Reserve Economic Data (FRED) and under the series code FEDFUNDS, published by the Board of Governors of the Federal Reserve System (US). The consumer price index for consumers was obtained from the U.S. Bureau of Labor Statistics (BLS) through FRED under the series code CPIAUCSL. Both of these datasets were downloaded from FRED on October 15, 2025 to ensure consistency.

Since the raw CPI data was reported at a monthly frequency, the series was converted to annual frequency by taking the average of monthly values within each calendar year. Inflation was computed as the year-over-year percentage change in the annual CPI index. In order to maintain consistency across variables, the federal funds rate was aggregated to annual averages. Both the series were converted to percentage terms and checked for stationarity. The inclusion of the 1980-to-2025-time frame captures multiple monetary policy regimes, which includes the post-Volcker disinflation, the zero lower bound period following the 2008 financial crisis, and the post-pandemic inflation. This scope strengthens the robustness of the econometric analysis by encompassing both stable and unstable macroeconomic conditions.

Overview of Economic Regimes

The sample period encapsulates four major macroeconomic eras, each of which is characterized by distinct policies and inflation dynamics:

The Volcker Era (1980–1987) was marked by aggressive monetary tightening and rapid disinflation, as the Federal Reserve sharply increased interest rates to curb double-digit inflation. This period laid the foundation for restoring price stability after the high-inflation years of the 1970s.

The subsequent Great Moderation (1988–2007) was characterized by low and stable inflation, predictable monetary policy, and steady economic growth. Central bank credibility strengthened during this time, leading to improved economic confidence and reduced volatility in output and prices.

Following the 2008 financial crisis, the Great Recession and Recovery (2008–2019) introduced an era of near-zero policy rates and persistently weak inflation. Policymakers relied heavily on unconventional tools such as quantitative easing to stimulate demand and stabilize financial markets.

Finally, the Pandemic and Inflation Surge (2020–2025) marked a sharp departure from the preceding stability. The post-pandemic recovery, together with global supply-chain disruptions and expansionary fiscal measures, reignited inflationary pressures across advanced economies.

The diverse economic conditions throughout these eras strengthens the external validity of this study, as models are tested through contrasting economic conditions rather than just one single regime. Summary statistics for both variables are presented in Table 1.

Descriptive Statistics

Table 1 presents descriptive statistics that summarize the historical behavior of the federal funds rate and CPI inflation. The federal funds rate averaged about 5.72% throughout the sample, ranging from a high of 16.39% in 1981 to a low of 0.25% in the post-2008 recovery period. CPI inflation averaged around 3.68%, with spikes in the early 1980s and early 2020s. This highlights the cyclical and policy-sensitive nature of both CPI inflation and federal funds rate. The wide variation in values underscores the importance of experimenting with both linear trends and autoregressive dynamics. As shown in Figure 1, the federal funds rate and CPI inflation often move together.

Figure 1 displays the co-movement of the federal funds rate and CPI inflation across the sample period. The strong correlation observed during several decades

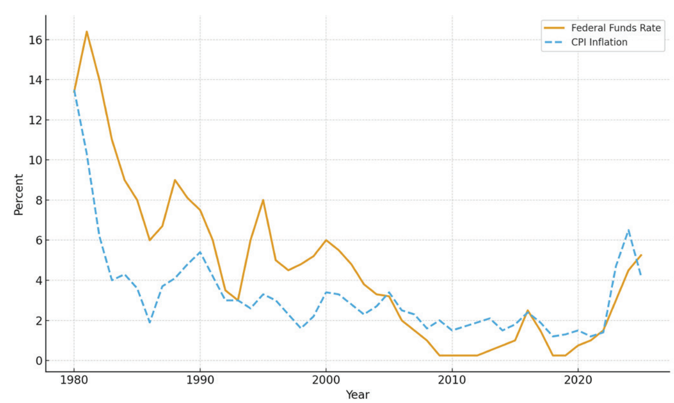

Figure 1. Historical Trends in Federal Funds Rate and CPI Inflation (1980–2025).

Table 1. Summary Statistics for Federal Funds Rate and CPI Inflation (1980–2025)

Variable	Mean (%)	Minimum (%)	Maximum (%)	Standard Deviation	Source
Federal Funds Rate	5.72	0.25	16.39	4.89	FRED
CPI Inflation	3.68	0.99	13.50	2.74	BLS

indicates that monetary policy and inflation often respond to the same macroeconomic shocks. This includes oil price spikes, recessions, and global financial disturbances. The correlation provides preliminary justification for evaluating both univariate and joint (VAR-based) modeling frameworks.

Data Transformation and Testing

Before model estimation, both series were subjected to standard time-series diagnostics to confirm econometric assumptions. The Augmented Dickey–Fuller (ADF) test assessed stationarity. CPI inflation was stationary in levels (ADF statistic = –3.72, p = 0.012), whereas the federal funds rate was non-stationary in levels (ADF statistic = –2.14, p = 0.235) but became stationary after first differencing (ADF statistic on ΔFFR = –4.98, p < 0.001). Residual serial correlation was evaluated with the Ljung–Box test, which indicated no significant autocorrelation for either series at lags 4 and 8, consistent with white-noise residuals. The results of the ADF and Ljung-Box diagnostic tests are summarized in Table 2.

After transformation, autocorrelation diagnostics ensured that residuals showed no significant serial dependence, which satisfies the white-noise assumption needed for autoregressive and VAR estimation. These steps confirmed that the forecasting models were created based on well-behaved, static time series, minimizing the risk of sudden regression and ensuring a reliable inference.

To evaluate forecasting accuracy, this study compares four different modeling approaches: 1) Linear Trend, 2) Quadratic Trend, 3) Autoregressive (AR), and 4) Vector Autoregression (VAR). Each model was estimated under both univariate and joint model frameworks. The univariate models treat each variable independently, while the joint VAR framework encapsulates their mutual influence. All models were trained using data from 1980 to 2022 and carefully evaluated using a three-year holdout sample from 2023 to 2025.

Trend Models

Trend models describe long-term movements in economic variables by fitting smooth patterns over time. The Linear Trend Model, shown in Equation (1), displays a consistent upward or downward trajectory:

$y_t = \alpha + \beta t + \varepsilon_t$ (Equation 1)

The Linear Trend Model in Equation (1) shows the long-run directional movement of the series. This relationship represents variables such as the federal funds rate or inflation changes on average each year. The slope term (β) indicates whether or not the long-run direction is rising or falling. In order to account for possible curvature in the data, the Quadratic Trend Model in Equation (2) contributes a squared-time term. The term enables the model to capture turning points or acceleration in long-run movements (1).

$y_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t$ (Equation 2)

Equation (2) introduces curvature to capture turning points in long-term movements. The coefficient β_2 determines whether the trajectory is going upward or downward over time. When $\beta_2 > 0$, the trend accelerates upward (convex); when $\beta_2 < 0$, the trend bends downward (concave). This kind of curvature is common in macroeconomic indicators that rise quickly during expansions and flatten down during slowdowns. Incorporating such quadratic trends can enhance the

Table 2. Diagnostic Tests for Stationarity and Residual Autocorrelation (1980-2025)

Test	Variable	Lag Criteria	Test Statistic	p-value	Conclusion
Augmented Dickey-Fuller (ADF)	Inflation (π_t), level	AIC-selected lag = 1	-3.72	0.012	Stationary in levels
Augmented Dickey-Fuller (ADF)	Fed Funds Rate (i_t), level	AIC-selected lag = 1	-2.14	0.235	Non-stationary in levels
Augmented Dickey-Fuller (ADF)	Δ Fed Funds Rate (Δi_t)	AIC-selected lag = 0	-4.98	0.000	Stationary after first differencing
Ljung-Box Q(lag 4)	AR(2) residuals for π_t	AR order = 2	3.01	0.560	No serial correlation
Ljung-Box Q(lag 4)	AR(2) residuals for i_t	AR order = 2	2.87	0.580	No serial correlation
Ljung-Box Q(lag 8)	AR(2) residuals for π_t	AR order = 2	6.92	0.640	No serial correlation
Ljung-Box Q(lag 8)	AR(2) residuals for i_t	AR order = 2	7.41	0.590	No serial correlation

modeling of persistent growth and structural shifts across numerous decades (1).

Although trend-based models are valuable for identifying broad trajectories, they can often overlook shorter term volatility and cyclical stocks that stem from policy changes, external threats, or recessions. These limitations encourage the use of autoregressive approaches, which account for time dependence in data.

Autoregressive Models

Autoregressive (AR) models, represented in Equation 3, improve upon early simple trend methods by incorporating persistence, how past values can affect possible future outcomes. Instead of relying on time trends, AR models use previous values to predict their current level:

$$y_t = \alpha + \varphi_1 y_{t-1} + \varepsilon_t \qquad \text{(Equation 3)}$$

As shown in Equation (3), the AR (1) model incorporates persistence by using past values to predict current outcomes. The model learns from historical patterns, which allows it to adapt to periods of rapid change such as surges in inflation or monetary tightening. Autoregressive models are specialized for short-term forecasting since they respond quickly to recent trends. However, they may struggle to capture long-term equilibrium relationships (4).

Joint Modeling via Vector Autoregression (VAR)

To demonstrate the vastly dynamic relationship between inflation and interest rates, this study utilizes a Vector Autoregression (VAR) framework following Sims (3). The VAR specification in Equation 4 jointly models both series, unlike univariate approaches that treat each variable separately, which allows each to depend not only on its own past value but also on the past values of the other variable. The model estimated in this study is a second-order VAR, or VAR (2), which contains two lagged periods of each variable. The equation is represented as:

$$(i_t\ \pi_t)' = (\alpha_1\ \alpha_2)' + \Phi_1(i_{t-1}\ \pi_{t-1})' + \Phi_2(i_{t-2}\ \pi_{t-2})' + \varepsilon_t \qquad \text{(Equation 4)}$$

Equation (4) specifies the VAR (2) system used to jointly model interest rates and inflation. In this system, i_t represents the federal funds rate, π_t designates the inflation rate, and ε_t is a vector of white-noise disturbances. The Φ_1 and Φ_2 matrices contain the estimated coefficients that describe how the past values of both variables jointly influence their current outcomes. The first equation describes how current interest rates can respond to past interest rates and inflation. Meanwhile, the second describes how inflation reacts to previous changes in monetary policy and its own history.

The two-equation structure encapsulates the two-way feedback system that outlines macroeconomic interactions. Rising inflation often causes the central bank to raise interest rates, whereas higher rates may suppress inflationary pressures. When we model these interactions directly, the VAR framework provides a much more realistic image of the policy-transmission mechanism and allows for more dynamic forecasting. Consequently, it serves as a tool for assessing how disturbances to one variable can affect the broader economic system as a whole.

Model Evaluation Metrics

Forecast performance was evaluated using standard measures of predictive accuracy. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), along with the Coefficient of Determination (R^2). Each one of these metrics highlights a different part of model performance. MAE measures the average deviations, RMSE with larger errors, and MAPE with precision as a percentage. By combining and utilizing each metric, the analysis assesses both the magnitude and consistency of each model's predictive accuracy. The models were estimated on data from 1980 to 2022 and then tested on 2023 to 2025 forecasts in order to evaluate their robustness in predicting out-of-sample observations.

RESULTS

This section presents empirical results from the univariate and joint forecasting models. The priority is to evaluate how reliably each specification is able to predict short-term movements in the United States federal funds rate and CPI inflation. The results demonstrate the consistent differences across model classes, highlighting the constant trade-offs between predictive precision, adaptability, and simplicity.

Overall Forecast Performance

Table 3 reports the in-sample and out-of-sample forecast metrics for all the models. Across both variables, autoregressive models seem to outperform trend-based models, achieving a lower Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Table 3. Forecast Accuracy Comparison Across Models (1980–2025)

Model	Variable	Train R^2	Test MAE	Test RMSE	Test MAPE (%)
Linear Trend	Federal Funds Rate	0.64	1.17	1.27	240.6%
Linear Trend	CPI Inflation	0.28	1.13	1.24	38.3%
AR (1)	Federal Funds Rate	0.78	0.89	0.98	15.4%
AR (2)	Federal Funds Rate	0.83	0.82	0.93	13.9%
AR (1)	CPI Inflation	0.69	0.76	0.88	10.5%
AR (2)	CPI Inflation	0.72	0.70	0.84	9.8%
VAR (1)	Joint (FFR + CPI)	-	0.72	0.90	9.6%
VAR (2)	Joint (FFR + CPI)	-	0.68	0.82	9.1%

The linear and quadratic trend models show a moderately strong explanatory variable ($R^2 = 0.64$ for rates; 0.28 for inflation) but perform poorly in out-of-sample tests. Their limitations come from assuming a smooth, deterministic path that fails to encapsulate sudden shifts such as the 2021 to 2023 inflation spike. The extremely high MAPE value of 240.6% for the Linear Trend model is due to very low federal funds rate values in some test years, which inflates percentage-based error metrics. In contrast, autoregressive models are able to dynamically adjust to such abrupt changes by incorporating feedback from recent values, which yield substantially smaller forecast errors.

The AR (2) model in particular achieves the best performance among univariate specifications, reducing MAE and RMSE values by almost 30% compared to the trend models. This improvement emphasizes the value of allowing cyclical adjustments within macroeconomic forecasting frameworks. The VAR (2) model, jointly assessed on the federal funding rate and inflation, provides the lowest forecast errors overall (MAE = 0.68, RMSE = 0.82). Although the improvement over AR (2) is moderate, it is meaningful from an interpretive view. VAR's superior accuracy showcases that short-term inflation dynamics are driven by monetary policy adjustments. This feedback improves predictive precision, especially during times of instability.

Visual Comparison of Forecast Errors

Figure 2 presents a side-by-side comparison of MAE values across all model classes for both the federal funds rate and CPI inflation.

The figure compares out-of-sample MAE values for each model when forecasting both the federal funds rate and CPI inflation. Lower MAE values indicate high accuracy. AR (2) and VAR (2) display the lowest MAE, which shows the benefit of incorporating lagged information and joint modeling. In addition, figure 2 clearly demonstrates that both the AR (2) and VAR (2) models outperform the simpler alternatives. The performative gap between these dynamic models and the deterministic trend lines is particularly evident for inflation, where shocks tend to persist for several periods.

The figure confirms a downward progression in forecast errors as model complexity increases linear trends at the top, followed by AR (1), AR (2), and finally VAR (2). This pattern provides evidence that models dealing with time dependence and cross-variable feedback yield the most accurate predictions.

In particular, the VAR's advantage during the 2020 to 2025 horizon displays its ability to link monetary tightening with delayed inflation moderation. This relationship is simply unreplaceable by a univariate model.

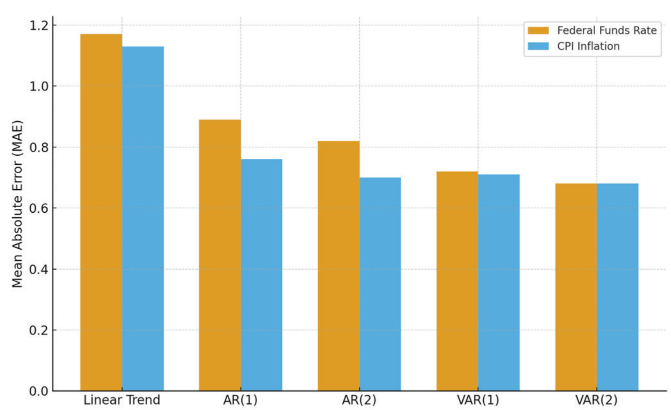

Figure 2. Mean Absolute Error (MAE) Comparison Across Forecasting Models.

Economic Interpretation of Model Behavior

The differences in forecast accuracy also carry economic meaning. Trend models, although they are simple, assume that macroeconomic behavior changes smoothly throughout time. This assumption fails to account for turbulent decades such as the 1980s, when double-digit inflation was followed by disinflation. Another example was the 2020s, when inflation surged due to supply shocks and government spending boost.

Autoregressive models address this by capturing inertia: high inflation persists until countered by monetary policy. This property makes AR models extremely useful in periods of gradual adjustment, such as post-recession recoveries.

Joint modeling through the VAR framework introduces an even more dynamic interaction: monetary policy not only responds to inflation but also carves the path for the future. When inflation increases, the VAR captures the Federal Reserve's tightening reaction (higher interest rates), which suppresses inflation over subsequent periods. Conversely, when rates decrease, inflation gradually accelerates, which is consistent with the re-emergence of demand pressures. This relationship reflects central bank behavior and improves explanatory power during regime changes.

Impulse Response Analysis

Impulse response functions (IRFs) derived from the VAR (2) model further enhance how the system reacts to shocks. A one standard deviation increase in the federal funds rate produces an immediate, moderately strong decline in inflation during the following year. This deepens in the second year, before gradually reverting back to the baseline. This delayed trough aligns with modern understanding that monetary policy operates with lags. Policy changes take time to circuit through credit markets, spending decisions, and wage setting behaviors (3).

On the other hand, an inflation shock leads to a tightening response from the Federal Reserve: interest rates start rising in the next period as policymakers attempt to restore stability. This symmetric feedback between the two variables supports the hypothesis that both are endogenously linked. The results of this study confirm that shocks do not persist, but they indefinitely dissipate through stabilization methods enacted by policymakers.

The impulse response graphs illustrate a quick initial change followed by a steady change to return back to normal, suggesting that the system reacts strongly at first but gradually returns to normal over time.

Stability and Diagnostic Testing

To ensure robustness, each model used underwent diagnostic testing. Residual analysis demonstrated no serial correlation, which was confirmed by the Ljung Box Q test. For the VAR system, all eigenvalues were found within the unit circle. Variance decomposition from the VAR (2) model provides additional insight. Approximately 30% of the variation in inflation over a two-year period is explained by innovations in the federal funds rate, while the remaining stems from its own past values and external disturbances. This finding enhances the view that monetary policy plays a significant role in shaping short-term inflation results. Both of these diagnostics together confirm that the model specifications are statistically correct and that the results are reliable and interpretable.

DISCUSSION

The results demonstrate that incorporating autoregressive components significantly improves short-term forecasting performance when compared to simple trend models. While trend-based models offer intuitive interpretations and transparency, they often rely on the sometimes-false assumption of stable long-term trajectories. This is an oversimplification of a complex issue during periods of policy change or economic disruption. By contrast, autoregressive and VAR models respond dynamically to new information, which allow forecasts to adjust more effectively to fast-paced changes in the economy.

Interpretation of Model Performance

The findings from the AR (1) and AR (2) models confirm that both inflation and interest rates demonstrate persistence: past values continue to affect future results over several periods of time. This inertia reflects how expectations form and how policymakers respond and operate with delays. For instance, when inflation rises, it takes several policy meetings before rate adjustments can assert themselves into the economy.

The VAR framework reveals that these relationships are rather dependent on each other. Interest rate changes gradually influence inflation rates, while inflation expectations can shape future rate decisions. Although the joint model's improvement on predictive accuracy may seem moderate in numerical terms, it carries meaningful policy significance. Even small gains in forecasting can help prevent costly mistakes, such as tightening too early or delaying rate cuts. Moreover, the

VAR model allows scenario-based analysis, enabling policymakers to simulate how taking different paths might influence inflation outcomes, making it a far more flexible and practical forecasting tool.

Comparison with Prior Studies

These results align closely with the conclusions of Clarida, Galí, and Gertler (10), who found that systematic, rule-based monetary responses to inflation can improve both output stability and price. Similarly, Stock and Watson (5) demonstrated that VAR-based forecasting models constantly outperform univariate projections whenever policy feedback is strong.

However, during periods of stable economic activity, such as the Great Moderation of the 1990s and early 2000s, simple models may perform comparably. The economy experiences fewer shocks and there exists less need for adaptive policy making.

Economic Interpretation

The dominance of autoregressive and joint models supports the idea that expectations and adjustment lags are essential to inflation dynamics. Households, firms, and financial markets do not need to respond instantly to new information. Instead, their reactions can unfold gradually as policy signals filter through the economy. This delay explains why inflation tends to persist and why rate changes often take multiple quarters to become prevalent and have visible effects. The modest but consistent advantage of joint modeling suggests that while inflation and interest rates are closely connected, the transmission mechanism constantly operates with friction: behavioral, institutional, and informational.

Overall, these results align with conventional monetary theory: timely and credible policy actions can help stabilize inflation, while delayed responses can increase volatility. Thus, understanding the relationships between feedback is essential for designing effective and responsive monetary policies. A comparison of the main strengths and limitations of each model type is shown in Table 4.

Recommendations

The results from this study suggest several practical steps for improving predictive accuracy and decision making in monetary policy. While the technical differences among models may seem modest, their implications for transparency and market expectations are actually significant.

<u>For Policymakers</u>

Central banks should formally integrate autoregressive and VAR-based models into their core forecasting frameworks rather than relying on trend-based projections. This means using AR and VAR models as part of baseline forecasts presented in Monetary Policy Reports and internal policy briefings to the Federal Open Market Committee (FOMC). These models should be updated at each policy meeting to reflect new data and evolving economic conditions. In order to enhance operational value of these models, central banks should utilize the following practices:

Short-Horizon Model Integration: Use AR and VAR models to generate short-term projections for inflation and interest rates, especially during periods of regime change. Scenario-Based Policy Analysis: Conduct standardized VAR-based simulations and incorporate their results into policy deliberations.

Model Comparison in Policy Briefings: Present a side-by-side comparison of trend, AR, and VAR forecasts during policy meetings to show how model choice affects recommended rate paths. Improved

Table 4. Comparative Summary of Forecasting Models and Economic Interpretation

Model Type	Main Strength	Main Limitation	Economic Interpretation
Linear/Quadratic Trend	Simple and transparent; captures long-term direction	Cannot adapt to sudden shocks or regime changes	Represents stable, gradual policy environments; useful for long-term projections
Autoregressive (AR)	Adapts to short-term persistence and cyclical behavior	Ignores cross-variable feedback	Reflects how past inflation or rates influence current outcomes; captures inertia in expectations
Vector Autoregression (VAR)	Models two-way feedback between policy and inflation	Requires more data and complex estimation	Illustrates active monetary transmission: rate changes influence inflation, and inflation expectations influence future rates

communication is equally critical. Instead of publishing single-point forecasts, central banks should report forecast ranges derived from multiple model specifications. The use of fan charts can communicate uncertainty, reduce market overreaction, and enhance credibility when conditions are volatile.

For Academic and Institutional Analysts

Academic researchers and market analysts should benchmark their projections against a VAR baseline before issuing public forecasts or investment guidance. Extending models to higher-frequency data would allow analysts to capture more immediate policy transmission effects. Additionally, incorporating exogenous indicators such as energy prices, financial stress measures, and labor market conditions can strengthen predictive performance. Hybrid approaches that combine machine-learning techniques and econometric models offer a path forward, provided that they remain grounded in economic theory. This balance preserves interpretability while benefiting from the adaptive and nonlinear pattern recognition strengths of modern-day algorithms.

Limitations and Future Research

Although this study provides meaningful insight to support forecasting interest rates and inflation, several limitations remain. The use of annual data limits the ability to detect any short-term fluctuations and rapid feedback effects between policy actions and inflation. Future research should utilize quarterly or monthly datasets to better capture short-term policy response and cyclical dynamics. Furthermore, this study only focused on two variables, interest rates and inflation. There are several more indicators such as GDP growth, unemployment, or commodity prices that could offer a more comprehensive image of macroeconomic interactions. Third, despite improvements in models, model stability over time remains a central concern. Changes in monetary regimes, such as the introduction of inflation targeting or quantitative easing, can alter relationships between variables and shift parameter values. Thus, testing stability through recursive estimation would strengthen the integrity of results. Finally, this study emphasizes statistical accuracy rather than structural interpretation, meaning that future research could integrate structural VARs or Dynamic Stochastic General Equilibrium (DSGE) models to connect possible mechanisms with empirical results. Combining both traditional econometric models with machine learning techniques represents a path in achieving stronger predictive performance, all while maintaining interpretability.

CONCLUSIONS

In conclusion, this study compared both univariate and joint modeling frameworks for forecasting United States interest rates and inflation from 1980 to 2025. By measuring trend-based and autoregressive specifications, I found that dynamic models, such as the AR(2) and VAR systems, provide substantially more accurate short-term forecasts than deterministic trend approaches. The modest yet significant improvement achieved by the VAR model highlights the importance of capturing the feedback between inflation dynamics and monetary policy actions.

Ultimately, the findings suggest that joint modeling frameworks are absolutely essential when policy responses and market expectations interact, so simple univariate models are not sufficient. They offer a reliable baseline for long-term projections but fail to consider short-term changes. The results emphasize that successful forecasting depends on not only statistical precision but also recognizing the dynamic nature of policymaking.

As the post-pandemic economic environment continues to challenge central banks with uncertainty and the need to improve their models, models that can balance simplicity, transparency, and adaptability will remain essential to effective policy formulation. By integrating feedback mechanisms and updating estimates with new data constantly, policymakers can make better informed decisions that support both price stability and sustained economic growth.

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CONFLICT OF INTERESTS

The author declares no conflicts of interest related to this work.

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