**Forecasting Inflation Trends with Interest Rates Using ARIMA Models**

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**Abstract:**

This study employs Vector Autoregressive (VAR) models to predict inflation dynamics through the lens of interest rates. By modeling the joint interactions between interest rates and inflation, the research seeks to enhance predictive accuracy. The VAR framework allows for a comprehensive analysis of the dynamic interplay between these economic indicators, providing valuable insights for policymakers and financial analysts. The findings aim to contribute to a nuanced understanding of how interest rate fluctuations influence inflation, offering a practical tool for forecasting inflation trends in a dynamic economic environment.

**Introduction:**

In the realm of economic forecasting, understanding the intricate relationship between interest rates and inflation is paramount for effective policymaking and financial decision-making. This study employs Vector Autoregressive (VAR) models to explore the dynamic interdependencies between interest rates and inflation, aiming to enhance our predictive capabilities in forecasting inflation trends. The VAR framework allows for a holistic analysis, capturing the simultaneous interactions and feedback loops between these key economic indicators. As we delve into this analysis, the goal is to uncover nuanced insights that contribute to a more nuanced understanding of how changes in interest rates shape inflationary trends, providing practical implications for policymakers and financial practitioners.

**Methodology**

This study aims to forecast inflation and interest rates using a Vector Autoregression (VAR) model, focusing solely on United States data. The methodology encompasses data preparation, stationarity testing, differencing transformation, and the application of the VAR model.

**Data Preparation:**

The dataset was curated to include only the relevant variables for the United States: inflation rates and interest rates. Prior to analysis, the data was rigorously cleaned to remove any inconsistencies or missing values. The dataset was then restricted to two columns, representing the inflation and interest rate time series, ensuring a focused approach.

**Stationarity Testing:**

To confirm the suitability of the time series data for the VAR model, an Augmented Dickey-Fuller (ADF) test was conducted on both variables. The ADF test is critical for identifying non-stationary data, which is a common feature in economic time series that can lead to spurious results if not addressed. The initial ADF tests indicated that both the inflation and interest rate series were non-stationary.

**Transformation for Stationarity:**

In response to the non-stationary nature of the data, a differencing transformation was applied. This process involves subtracting the previous observation from the current observation. Differencing was selected as it is a common method to induce stationarity in time series data, thereby facilitating more reliable and interpretable modeling.

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**VAR Model Specification:**

Following the transformation, the data was fitted to a VAR model. The VAR approach was chosen for its capacity to model the joint dynamics and interdependencies between multiple time series. In specifying the VAR model, the Akaike Information Criterion (AIC) was utilized to determine the optimal number of lags. The AIC helps in identifying the model that best balances goodness of fit with model simplicity. After applying the AIC, a lag length of 10 was identified as the optimal structure for our VAR model.

**Model Fitting and Diagnostics:**

The VAR model with the specified lag length was then estimated using the stationary differenced data. Post-estimation diagnostics included checking for serial correlation of residuals, ensuring model stability, and verifying the appropriateness of the chosen lag length. The model's adequacy was further confirmed through various tests, including the inspection of impulse response functions and forecast error variance decomposition, to understand the dynamic impact of the variables.

**A graph showing the growth of the rate of the stock market

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**Results:**

The impulse response function (IRF) show the reaction of both inflation and interest rates to shocks in each other over a period of time.

1. **Inflation → Inflation:**
   * Represents the response of inflation to its own shock. Initially, there's a spike, which quickly diminishes and oscillates around zero. This suggests that a shock to inflation has a temporary effect that fades over time, with the system returning towards stability.
2. **Interest → Inflation:**
   * Graph shows how inflation responds to a shock in interest rates. We can observe that the response is quite volatile and remains above zero for the duration observed. This may imply that a shock to interest rates has a persistent and positive effect on inflation.
3. **Inflation → Interest:**
   * Here we see the response of interest rates to a shock in inflation. The response is quite dynamic, showing fluctuations above and below zero. This suggests that the relationship between inflation shocks and interest rate changes is complex and the effects can be varied over time.
4. **Interest → Interest:**
   * This graph illustrates the response of interest rates to their own shock. Similar to the inflation self-response, we see a sharp initial reaction that decreases and continues to fluctuate around zero, indicating a return to equilibrium over time.

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For all graphs, the solid line represents the estimated response, and the dashed lines represent the confidence intervals. Confidence intervals that do not include zero suggest that the responses are statistically significant at the given point in time. Conversely, when the confidence intervals include zero, the responses are not statistically distinguishable from zero, which implies that the shocks have no significant effect at those points. The IRF plots do not display a clear pattern of decay back to zero for all variables, which may suggest the presence of complex dynamics in the time series. The confidence intervals are relatively wide, indicating a significant degree of uncertainty in the estimates. The system seems to exhibit some degree of inertia, given that the responses do not immediately drop back to zero but rather show some persistence. It's important to note that while IRF graphs provide insights into the dynamic interactions between variables, they do not imply causation. They simply describe how the variables react to each other's shocks based on the estimated model.

The autocorrelation function (ACF) plots show the autocorrelation of residuals at different lags for what appears to be a two-variable system, possibly the same inflation and interest rate variables from the impulse response function analysis.

1. **Inflation → Inflation:**
   * The fact that most bars are within the bounds suggests that there is little to no autocorrelation at those lags, which is a sign that the model is adequately capturing the time series structure for this variable.
2. **Interest → Inflation:**
   * Again, most autocorrelations are within the bounds, indicating a good model fit. However, there is a notable spike at lag 10, which might suggest some remaining pattern in the residuals at this lag that the model has not captured.
3. **Inflation → Interest:**
   * Here, there appears to be a significant negative autocorrelation at lag 3. This suggests that the residuals from one period may be negatively influencing the residuals of the following period for this variable.
4. **Interest → Interest:**
   * Again, most autocorrelations are within the bounds, indicating a good model fit.

The dashed lines represent the confidence bounds, which typically are set at plus or minus two standard errors (2/√T, where T is the number of observations). If the bars extend beyond these bounds, it indicates that the correlations are statistically significant at the corresponding lags.

The most part, these ACF plots suggest that the model is capturing the time series dynamics well, with most autocorrelations falling within the confidence bounds. The significant autocorrelations at certain lags indicate that there may be room for improvement in the model. This could involve adding additional lags or considering different model specifications. Ideally, we want the residuals of a model to be random, meaning that there should be no significant autocorrelation at any lag. This would suggest that all the information has been used by the model and the residuals are just white noise. Significant autocorrelation at any lag could be an indication of model misspecification.

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Forecast Error Variance Decomposition (FEVD) is used to assess how much of the forecast error variance of each variable in a vector autoregression (VAR) can be attributed to its own shocks versus shocks to the other variable in the system. It's a way to understand the magnitude of the impact of each variable on itself and on the other variable over time.

**FEVD for Inflation:**

* At lag 0, the variance in the forecast error for inflation is entirely due to its own shocks, which is expected since the initial shock is to inflation itself.
* As time goes on (from lag 1 to lag 9), the proportion of the forecast error variance for inflation due to its own shocks decreases from 96.1% to 74.8%, suggesting that over time, the impact of interest rate shocks on inflation forecast error variance becomes more pronounced.
* By lag 9, shocks to interest rates account for 25.1% of the forecast error variance in inflation. This indicates that, while inflation's own shocks are still the dominant source of variance, interest rate shocks have a noticeable influence on inflation variability.

**FEVD for Interest:**

* Initially (at lag 0), the majority of the forecast error variance for interest rates (71.2%) is due to its own shocks, and a smaller portion (28.7%) is due to shocks to inflation.
* Over time, the impact of inflation shocks on the variance of interest rate forecast errors increases, reaching a peak of 62.5% at lag 9.
* Notably, at lag 4, there is a significant shift in the contribution of shocks to inflation (54.5%) and interest (45.4%). This suggests that, at this point in time, inflation shocks become nearly as influential as interest rate shocks in driving the variability of interest rates.

**General Observations:**

* The results indicate that both inflation and interest rates are influenced by their own shocks as well as by the shocks to the other variable. However, the own-variable shocks are dominant in the short term, while cross-variable shocks grow in importance over time.
* The influence of inflation on interest rate variability increases over the period, suggesting that inflation is a key factor in interest rate forecast uncertainty.
* The variability in inflation due to interest rate shocks, while less than the variability due to its own shocks, is non-negligible, indicating interdependence between the two.
* The relatively high impact of inflation shocks on interest rate variance could be consistent with a monetary policy framework where central banks respond to inflation indicators by adjusting interest rates.

In summary, the FEVD results illustrate the dynamic interplay between inflation and interest rates, showing how shocks to each of these economic indicators can influence the other over different time horizons. These results can be particularly informative for policymakers and economists interested in understanding and predicting the effects of economic shocks.

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The Granger causality test is used to determine whether one time series can predict another time series. In other words, it tests whether past values of one variable help predict the future values of another.

**Null Hypothesis (H0):**

"Interest does not Granger-cause inflation." This means that past values of interest rates do not have predictive power over future values of inflation.

**Alternative Hypothesis (H1):**

"Interest Granger-causes inflation." This would mean that past values of interest rates do contain information that is useful in predicting future values of inflation.

The results of the Granger causality test are as follows:

* **Test Statistic (F-statistic):** 1.688. This is the calculated value from the test that will be compared to the critical value to decide whether to reject the null hypothesis.
* **Critical Value:** 2.412. This is the threshold value that the test statistic must exceed to reject the null hypothesis at the chosen significance level.
* **p-value:** 0.160. The p-value indicates the probability of observing the test results under the null hypothesis. In this context, there is a 16% probability of observing the test statistic of 1.688 or more if the null hypothesis is true.
* **Degrees of Freedom (df):** (10, 18). The first number represents the number of lags used in the test, and the second number represents the degrees of freedom of the model's error term.

**Conclusion:**

* Since the test statistic (1.688) is less than the critical value (2.412), we do not have enough evidence to reject the null hypothesis at the 5% significance level.
* The p-value of 0.160 is greater than the standard significance level of 0.05 (or 5%). This also indicates that we do not reject the null hypothesis.
* Therefore, based on the provided data and the Granger causality test, we cannot conclude that interest rates Granger-cause inflation. In other words, we fail to find statistical evidence that past values of interest rates provide any useful information in predicting future values of inflation.

It is important to note that failing to reject the null hypothesis does not prove that it is true. It simply means that there is not enough statistical evidence to conclude a Granger causal relationship in the sample data used for the test. Moreover, Granger causality is about predictability, not true causality in a philosophical or economic sense. Even if interest rates did Granger-cause inflation, this would not necessarily imply a direct causal relationship.