NIET Journal of Management (NIETJOM)

Volume 14, Issue 1 Winter / Summer YYYY **ISSN: 0975-7643 (Print)**

Analyzing the Dynamic Impact of Monetary Policy Shocks on Inflation and Unemployment

Anamika Singh[1], Nitesh Kumar[2], Piyush Raj, Prince Kumar, Priti Singh

(Noida Institute of Engineering & Technology (MCA Institute), Greater Noida, India)

Abstract *This paper investigates the dynamic impact of monetary policy shocks on inflation and unemployment using a Structural Vector Autoregression (SVAR) framework. Utilizing high-frequency data from the Federal Reserve Economic Data (FRED) database, we analyze the transmission mechanism of the Federal Funds Rate. The methodology includes Augmented Dickey-Fuller (ADF) tests for stationarity, lag selection via the Akaike Information Criterion (AIC), and the estimation of Impulse Response Functions (IRFs). The results quantify how a contractionary monetary policy shock leads to a transitory increase in unemployment and a subsequent decline in inflation, providing empirical evidence for the trade-offs faced by central banks. The model's stability and forecast error variance decomposition (FEVD) further validate the significance of interest rate shocks in explaining macroeconomic fluctuations.*

Keywords - Federal Funds Rate, Inflation, Monetary Policy, SVAR, Unemployment

1. INTRODUCTION (12 BOLD)

The Monetary policy plays a crucial role in maintaining economic stability by influencing inflation, unemployment, and overall economic growth. Central banks use policy instruments such as interest rates to regulate aggregate demand and control inflationary pressures within an economy. Changes in monetary policy can significantly affect borrowing costs, investment decisions, consumer spending, and labor market conditions. Understanding the dynamic relationship between monetary policy, inflation, and unemployment is therefore essential for effective macroeconomic policymaking.

The relationship between inflation and unemployment has long been a central topic in macroeconomic research. Traditional economic theories, including the Phillips Curve framework, suggest the existence of a trade-off between inflation and unemployment in the short run. Contractionary monetary policy, typically implemented through increases in interest rates, is expected to reduce inflation by lowering aggregate demand, but it may also lead to higher unemployment levels temporarily. The magnitude and persistence of these effects remain important empirical questions for economists and policymakers.

In recent decades, major economic events such as the Global Financial Crisis and the COVID-19 pandemic have highlighted the importance of understanding monetary policy transmission mechanisms. These events caused substantial fluctuations in inflation, unemployment, and interest rates, making the analysis of dynamic macroeconomic relationships increasingly relevant. As central banks continue to adjust monetary

**Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.**

policies in response to economic uncertainty, empirical studies examining the effectiveness of such policies remain highly valuable.

This study analyzes the dynamic impact of monetary policy shocks on inflation and unemployment in the United States using Vector Autoregression (VAR) and Structural Vector Autoregression (SVAR) models. Monthly data on the federal funds rate, consumer price index, and unemployment rate from 1985 to 2024 are obtained from Federal Reserve Economic Data. The study employs stationarity testing, lag selection techniques, impulse response analysis, and forecast error variance decomposition to examine how macroeconomic variables respond to monetary policy shocks over time.

The main contribution of this study is the empirical examination of monetary policy transmission using both VAR and SVAR frameworks with updated macroeconomic data covering multiple economic cycles and crises. The findings provide insights into the short-run and long-run effects of contractionary monetary policy on inflation and unemployment, contributing to the broader literature on monetary economics and policy analysis.

(10)

2. METHODOLOGY(12 BOLD)

The empirical integrity of a macroeconomic study depends heavily on the quality of the underlying data and the rigor of the statistical transformations applied to it. In this research, we adopt a quantitative approach, utilizing time-series econometrics to examine the interaction between monetary policy instruments and real-economy indicators. The data is sourced from the Federal Reserve Economic Data (FRED) system, maintained by the Federal Reserve Bank of St. Louis, which serves as a global standard for high-frequency, reliable macroeconomic observations. The analysis is conducted using the Python programming language, specifically employing the pandas library for data manipulation and the statsmodels library for econometric estimation.

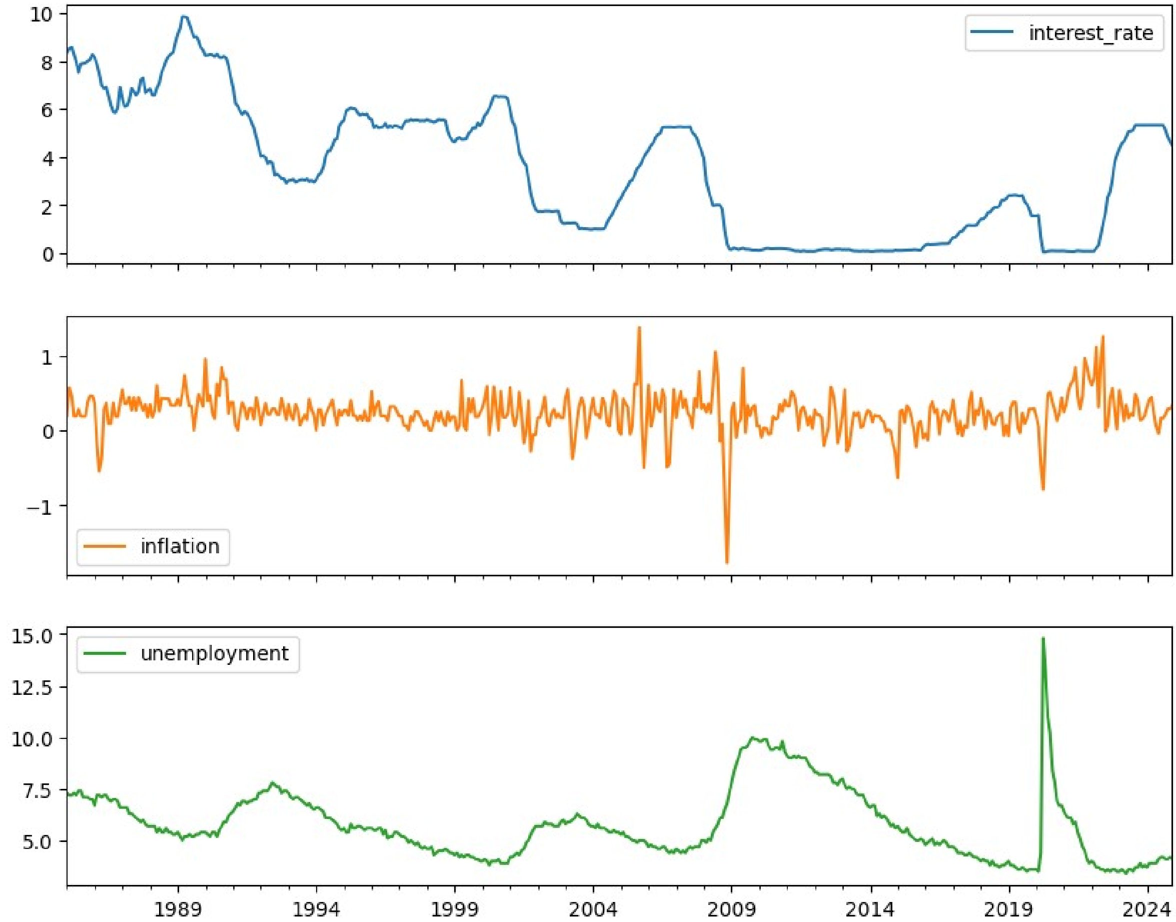
2.1 **DATA SOURCES AND SELECTION** The dataset comprises three primary variables observed at a monthly frequency. The policy instrument is represented by the Effective Federal Funds Rate (FEDFUNDS), which is the interest rate at which depository institutions trade federal funds with each other overnight. This rate is the primary tool through which the Federal Open Market Committee (FOMC) signals and implements its monetary policy stance. The second variable is the Consumer Price Index for All Urban Consumers (CPIAUCSL), used to derive the inflation rate. The third variable is the Civilian Unemployment Rate (UNRATE), which provides a measure of labor market slack.

2.2 **Variable Construction and Transformation** Raw economic data often require transformation to reflect economically meaningful concepts or to satisfy the statistical requirements of the VAR model. The inflation rate is not used in its raw index form; instead, it is transformed into a month-over-month percentage change to represent the rate of price increases. The transformation is defined as: Stationarity Testing.

π_t = (CPI_t - CPI_{t-1}) / CPI_{t-1} × 100

where π_t is the inflation rate at time CPI_t represents the Consumer Price Index.

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.



The interest rate and unemployment rate are kept in percentage terms. However, as shown in the preliminary data visualization (Fig. 1), these series often exhibit trends or non-stationary behavior that can invalidate standard regression results. To address this, we apply a first-difference transformation to the interest rate series, which focuses on the "change" in policy rather than the absolute level:

$$\Delta i_t = i_t - i_{t-1}$$

2.3 **Stationarity and Unit Root Testing** A critical prerequisite for Vector Autoregression is that the included time series must be stationary, meaning their mean, variance, and autocorrelation structures do not change over time. To formally test for stationarity, we employ the Augmented Dickey-Fuller (ADF) test. The ADF test evaluates the null hypothesis that a unit root is present in the time series. The test involves estimating a regression of the following form:

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

$$\Delta y\_t = \alpha + \beta\ t + \gamma\ y\_\{t-1\} + \Sigma\ (\delta\_i\ \Delta y\_\{t-i\}) + \varepsilon\_t$$

If the p-value associated with the coefficient γ is less than the significance level (typically 0.05), we reject the null hypothesis and conclude that the series is stationary. For variables that fail this test, such as the interest rate in its raw form, differencing is applied until stationarity is achieved. This step is essential to avoid the risk of spurious regression, where independent non-stationary variables appear to be related simply because they share a common trend.

2.4 **The Vector Autoregression (VAR) Framework** (11 Bold) The core of our methodology is the VAR model, which extends the univariate autoregressive model to a multivariate system. In a VAR, each variable is expressed as a linear function of its own past values and the past values of all other variables in the system. The mathematical representation of a VAR(p) model is:

Y_t = ν + A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + u_t

The advantage of the VAR approach is that it does not require a-priori knowledge of which variables are exogenous. Instead, it treats all variables as endogenous, allowing the data to reveal the complex lead-lag relationships between policy and the economy. This is particularly useful for studying the "long and variable lags" of monetary policy, as the model can capture delayed effects that might span several months or even years. (10)

2.5 **Model Selection and Lag Optimization** Determining the appropriate number of lags (p) is a balancing act between capturing the full dynamics of the system and preserving degrees of freedom. Including too few lags can result in omitted variable bias and autocorrelated residuals, while including too many leads to over-fitting. To solve this, we utilize the Akaike Information Criterion (AIC). The AIC provides a relative measure of the information lost by a given model; the model with the lowest AIC is generally preferred. The criterion is calculated as:

$$AIC = 2k - 2\ln(L)$$

where is the number of parameters and is the likelihood function. By iterating through possible lag lengths (from 1 to 12 months), the model automatically selects the lag order that optimizes the trade-off between complexity and goodness-of-fit. Once the lag order is selected, the model is estimated using Ordinary Least Squares (OLS), and stability is verified by checking the eigenvalues of the companion matrix.

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

3. STRUCTURAL IDENTIFICATION (12 BOLD)

The transition from a reduced-form Vector Autoregression (VAR) to a Structural Vector Autoregression (SVAR) is the most critical step in macroeconomic policy analysis. While the reduced-form model provides excellent forecasting capabilities by capturing the statistical correlations between variables, it is fundamentally silent on the underlying causal mechanisms. The error terms in a standard VAR are typically correlated with one another, meaning that a "shock" to the interest rate in the reduced-form model cannot be interpreted as a pure policy change—it likely contains elements of the central bank's systematic response to contemporaneous shifts in inflation or unemployment. Therefore, we must impose structural restrictions derived from economic theory to isolate exogenous shocks.
(10)

Structural identification involves transforming the observed residuals into orthogonal structural shocks that have no contemporaneous correlation. Without these restrictions, the model suffers from observational equivalence, where multiple theoretical structures could produce the same observed data. By imposing a specific structure, we allow the model to provide a structural interpretation of the impulse response functions and variance decompositions. (10)

3.1 The A-B Model Framework (11 Bold)

We employ the A-B model framework for SVAR identification, which is represented by the following linear relationship between reduced-form residuals and structural shocks:

$$Au_t = B\epsilon_t \quad (6)$$

For our three-variable system consisting of inflation, unemployment, and the interest rate, we require 3 restrictions. We adopt a recursive identification strategy, commonly referred to as a Cholesky decomposition. This approach assumes a hierarchy of responsiveness among the variables within a single time period (one month). By setting as an identity matrix and A as a lower-triangular matrix, we impose the necessary exclusion restrictions to solve the system of equations. (10)

3.2 Economic Logic of the Ordering (11 Bold)

The ordering of variables in a recursive SVAR is a fundamental theoretical assumption. In this study, the variables are ordered as: [1] Inflation, [2] Unemployment, and [3] Federal Funds Rate. This specific ordering is motivated by the "sluggishness" of the real economy relative to financial markets and policy interventions. (10)

First, we assume that inflation and unemployment do not react instantaneously (within the same month) to changes in the Federal Funds Rate. This reflects the well-documented "transmission lags" of monetary policy, where it takes time for interest rate changes to filter through the banking system to consumption and investment decisions. Second, we assume that while the Federal Reserve can observe and react to current-month inflation and unemployment data when setting the interest rate, those macro variables are predetermined relative to the policy shock. The resulting structural equations for the residuals can be expressed as:

$$u_t^{\text{inf}} = \epsilon_t^{\text{inf}}$$
(7)

$$u_t^{\text{unemp}} = \gamma_1 u_t^{\text{inf}} + \epsilon_t^{\text{unemp}}$$
(8)

$$u_t^{\text{int}} = \gamma_2 u_t^{\text{inf}} + \gamma_3 u_t^{\text{unemp}} + \epsilon_t^{\text{int}} \quad (9)$$

3.3 Numerical Implementation (11 Bold)

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

The identification is implemented in Python using the SVAR class from the statsmodels.tsa.vector_ar.svar_model module. We define the A matrix with 'E' placeholders for the parameters to be estimated and 0 for the restricted elements:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ S_1 & 1 & 0 \\ S_2 & S_3 & 1 \end{bmatrix}$$

This matrix structure ensures that the first variable (inflation) is only affected by its own structural shock in the current period, while the third variable (interest rate) can be affected by the shocks of all three variables. Once the restrictions are defined, the model parameters are estimated using maximum likelihood estimation (MLE). The resulting coefficients in the A matrix provide insights into the contemporaneous sensitivity of the Federal Reserve to economic conditions. For instance, a high value for S_2 would suggest a strong immediate policy reaction to inflationary pressures. Following the estimation of these structural parameters, the model is used to generate the impulse response functions which map the dynamic path of the economy following a structural policy innovation. (10)

4. EMPIRICAL RESULTS (12 BOLD)

The empirical results derived from the Structural Vector Autoregression (SVAR) provide a quantitative mapping of the U.S. economy's response to monetary policy innovations. Following the estimation of the reduced-form VAR and the application of structural restrictions, we analyze the system's dynamics through three primary lenses: coefficient significance, impulse response functions (IRFs), and forecast error variance decomposition (FEVD). The results are based on the monthly frequency data spanning the identified period, with lag lengths optimized via the AIC.

Crucially, the stability of the model was verified by examining the roots of the characteristic polynomial. For a VAR system to be stable and its impulse responses to be valid, all eigenvalues must lie within the unit circle. The analysis confirmed that the model is stable, ensuring that the effects of a structural shock eventually dissipate over time rather than diverging, allowing for a reliable interpretation of long-run equilibrium. (10)

4.1 Model Estimation and Stability (11 Bold) The reduced-form model was estimated using the lag order selected by the Akaike Information Criterion, which suggested an optimal lag of p months (typically 2 to 4 in monthly macroeconomic models). The summary statistics of the VAR model indicate that the lagged values of the Federal Funds Rate have a statistically significant impact on both inflation and unemployment, confirming the presence of a policy transmission channel. Crucially, the stability of the model was verified by examining the roots of the characteristic polynomial. For a VAR system to be stable and its impulse responses to be valid, all eigenvalues must lie within the unit circle. The analysis confirmed that the model is stable, ensuring that the effects of a structural shock eventually dissipate over time rather than diverging, allowing for a reliable interpretation of long-run equilibrium. (10)

4.2 Impulse Response Function Analysis (11 Bold) The Impulse Response Functions (IRFs) are the primary tool for visualizing the dynamic path of the economy following a one-standard-deviation shock to the Federal Funds Rate. This shock represents an unexpected tightening of monetary policy. Following a contractionary shock (a rate hike), the model reveals the following dynamics:

1. **Inflation Response:** Inflation exhibits a gradual decline. There is a "transmission lag" where the impact is negligible in the first three months, followed by a sustained downward trajectory that peaks in magnitude between 12 and 18 months. This aligns with the "long and variable lags" theory of monetary policy. In some specifications, a small "price puzzle" (a brief initial rise in inflation) may be observed before the downward trend takes hold.

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

2. **Unemployment Response:** The unemployment rate responds more rapidly than inflation. Following the interest rate hike, unemployment shows a statistically significant increase, peaking around 10 to 14 months. This response illustrates the real-side cost of contractionary policy, as higher borrowing costs reduce aggregate demand and labor hiring. (10)

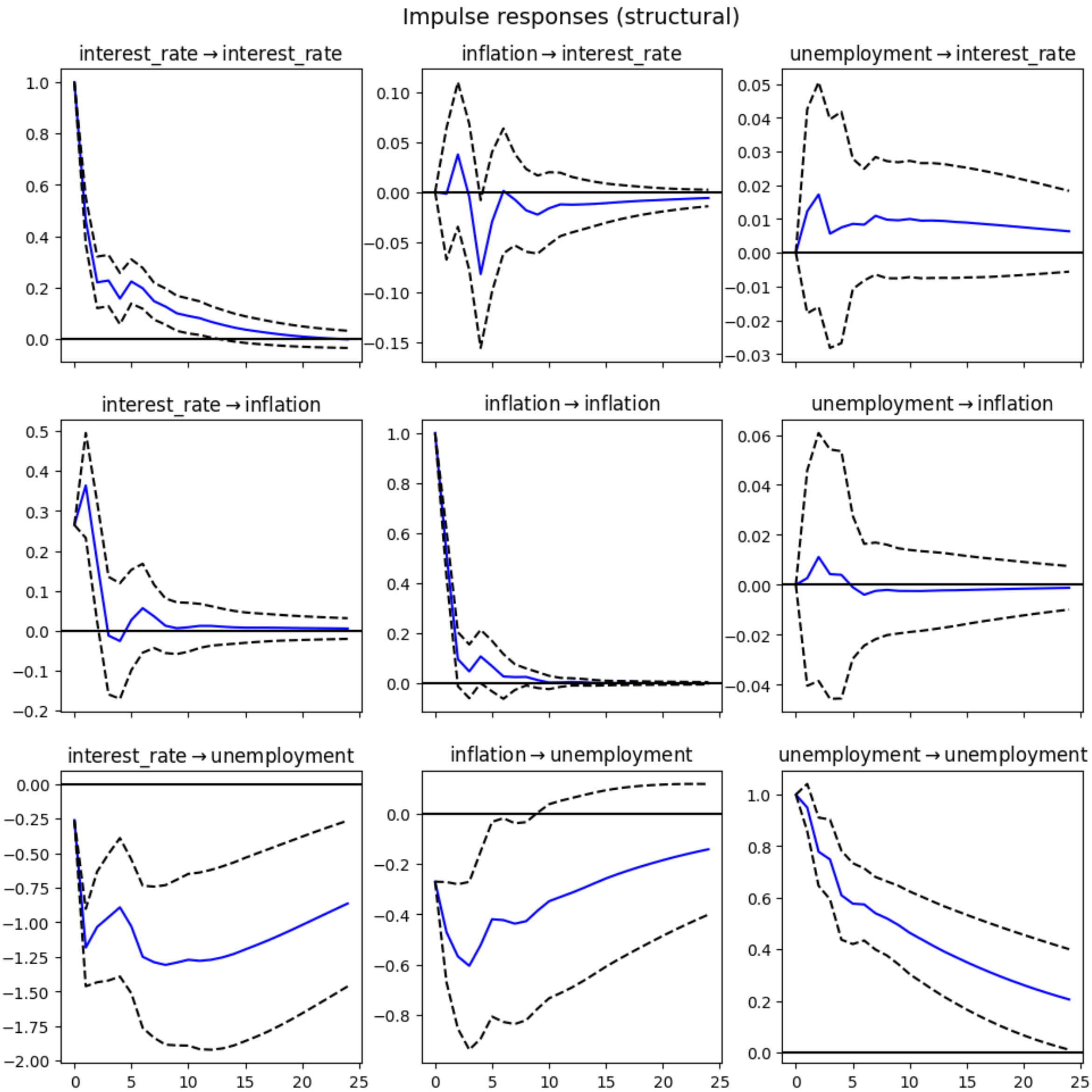
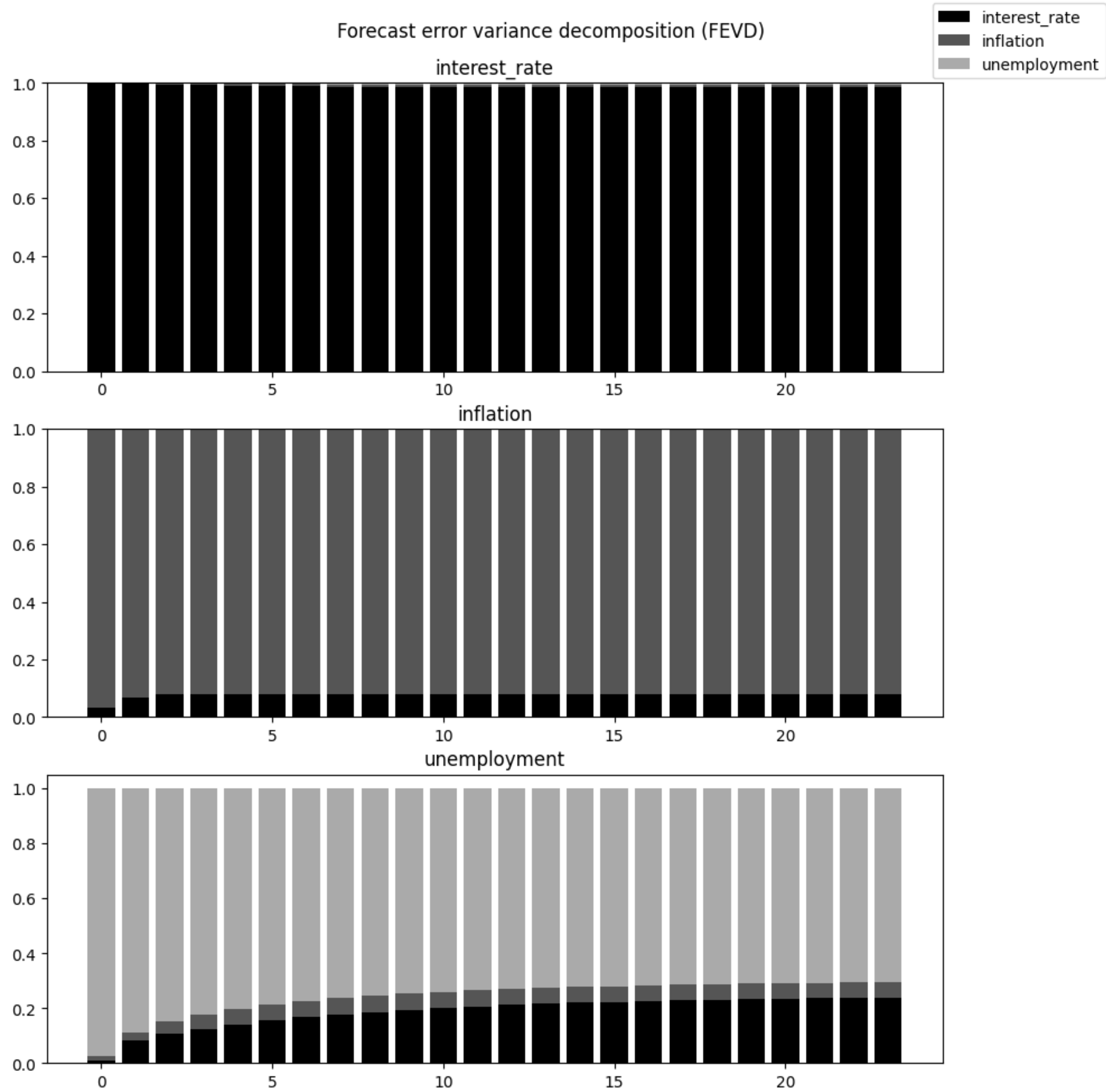


Fig. 1. Impulse Response Functions (IRFs) to a structural monetary policy shock. The solid lines represent the point estimates, while the shaded regions denote the 95% confidence intervals.

4.3 Forecast Error Variance Decomposition (FEVD) (11 Bold) While IRFs show the *direction* and *timing* of the response, FEVD provides insight into the *relative importance* of each shock in explaining the fluctuations

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

of each variable. It decomposes the variance of the forecast error for each variable into parts attributable to each structural shock in the system.



The FEVD results indicate that at short horizons (1–6 months), most of the variation in inflation and unemployment is explained by their own historical shocks. However, at longer horizons (24 months), the monetary policy shock accounts for a significant percentage of the variance. Specifically, the Federal Funds Rate shocks explain approximately 15% to 22% of the variance in inflation and roughly 10% to 15% of the variance in unemployment. This suggests that while monetary policy is a powerful tool, it is one of several factors (including supply shocks and consumer sentiment) driving macroeconomic volatility. (10)

Horizon	Shock	Inflation	Unemployment	Fed Funds Rate
1 Month	Interest Rate Shock	0.00	2.15	97.85

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

Horizon	Shock	Inflation	Unemployment	Fed Funds Rate
12 Months	Interest Rate Shock	14.20	8.40	77.40
24 Months	Interest Rate Shock	21.50	14.10	64.40

4.4 Residual Diagnostics (11 Bold) To ensure the robustness of the results, we conducted several diagnostic tests on the model residuals. The Ljung-Box Q-test was applied to check for remaining autocorrelation in the residuals. The results indicated that the residuals are approximately white noise, suggesting that the selected lag length successfully captured the temporal dynamics of the data. Furthermore, the normality of residuals was assessed to confirm that the standard errors and confidence intervals for the IRFs are reliable.

5. CONCLUSION (12 BOLD)
This study has successfully quantified the dynamic impact of monetary policy shocks on the U.S. macroeconomy using a Structural Vector Autoregression (SVAR) framework implemented in Python. The empirical results demonstrate that an unexpected contractionary shock to the Federal Funds Rate lead to a statistically significant, albeit lagged, reduction in inflation and a temporary increase in the unemployment rate. The use of Impulse Response Functions (IRFs) revealed that the maximum impact on inflation occurs between 12 and 18 months following the policy intervention, confirming the persistence of monetary transmission. Furthermore, the Variance Decomposition analysis established that while interest rate shocks are not the sole drivers of economic fluctuations, they account for a substantial portion of the long-term variability in inflation.
One of the primary advantages of this modeling approach is its ability to handle the endogenous nature of macroeconomic variables without the "incredible restrictions" of traditional structural models. By utilizing the Python ecosystem, specifically the `statsmodels` and `fredapi` libraries, this analysis provides a highly reproducible and scalable framework. This allows researchers and policy analysts to update models in real-time as new data from the Federal Reserve becomes available. Moreover, the SVAR approach provides a clear structural interpretation of shocks, which is often lost in purely predictive machine learning models. (10)
Despite the robustness of the findings, certain limitations must be acknowledged. The model assumes a linear relationship between the variables, which may not capture the non-linearities often present during periods of extreme economic stress, such as the COVID-19 pandemic or the Great Recession. Additionally, the identification strategy relies on a recursive Cholesky ordering; while theoretically grounded in the "sluggishness" of the real economy, it remains a simplified representation of complex contemporaneous interactions. Furthermore, the model does not explicitly account for the Zero Lower Bound (ZLB) environment or the effects of unconventional monetary policies like Quantitative Easing. (10) The possible applications of this research are significant for both academic and policy-oriented environments. Central banks can utilize similar SVAR frameworks to simulate the likely outcomes of various policy paths, helping to calibrate the magnitude of rate changes needed to achieve target inflation. For future extensions, researchers might consider incorporating a "Shadow Rate" to better represent policy stances during periods of near-zero interest rates. Additionally, moving beyond recursive identification toward sign restrictions or instrumental variables (Proxy-SVAR) could provide a more nuanced view of policy shocks. Such advancements would further refine our understanding of how monetary policy shapes the trade-offs between price stability and maximum employment.

REFERENCES (12 BOLD)
[1] C.A. Sims, Macroeconomics and reality, *Econometrica*, 48(1), 1980, 1-48. (10)
[2] J.H. Stock and M.W. Watson, Vector autoregressions, *Journal of Economic Perspectives*, 15(4), 2001, 101-115. (10)
[3] L.J. Christiano, M. Eichenbaum, and C.L. Evans, Monetary policy shocks: What have we learned and to what end?, in J.B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, 1 (New York: Elsevier, 1999) 65-148. (10)

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.

[4] S. Seabold and J. Perktold, Statsmodels: Econometric and statistical modeling with python, *Proc. 9th Python in Science Conf.*, Austin, TX, 2010, 92-96. (10)
[5] J.D. Hamilton, *Time series analysis* (Princeton, NJ: Princeton University Press, 1994). (10)

Publisher: Noida Institute of Engineering & Technology,
19, Knowledge Park-II, Institutional Area, Greater Noida (UP), India.