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Article

Inflation Dynamics in the U.S. Economy: A VAR-GARCH Analysis of Oil Prices, Money Supply, and Employment

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Abstract: Understanding the complex dynamics of inflation in the United States economy remains a critical challenge for policymakers, investors, and macroeconomic theorists. This study investigates the multifaceted drivers of U.S. inflation by employing an advanced Vector Autoregression (VAR) combined with a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. Specifically, the research examines the dynamic interplay and volatility spillovers among global oil prices, domestic money supply, employment levels, and the inflation rate over a comprehensive sample period. By integrating the VAR model to capture linear interdependencies and the GARCH model to account for time-varying volatility and risk, this paper provides a robust empirical analysis of macroeconomic shocks. The findings reveal significant Granger causality running from oil price fluctuations and money supply expansions to inflationary pressures, highlighting the vulnerability of the U.S. economy to both external energy shocks and internal monetary policy shifts. Furthermore, the employment data demonstrates a nuanced, lagged relationship with inflation, consistent with traditional Phillips curve expectations but complicated by recent structural economic changes. The volatility analysis underscores that uncertainty in oil markets disproportionately amplifies inflation variance compared to other macroeconomic indicators. Ultimately, this research contributes to the existing literature by offering a dual-layered perspective on both the directional impact and the volatility transmission mechanisms of key economic variables. The insights derived from this VAR-GARCH approach offer valuable implications for the Federal Reserve and other regulatory bodies in formulating more resilient monetary policies and stabilizing the macroeconomic environment against unforeseen exogenous and endogenous shocks.

Keywords: inflation dynamics; var model; garch model; oil prices; money supply; macroeconomics

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Abstract: In the face of ongoing inflation in the U.S. and fluctuating energy markets, understanding the drivers of inflation is essential. The effect on WTI crude oil prices, M2 money supply, nonfarm payroll employment, and the rate of inflation are analyzed based on monthly data from January 1990 to December 2025. This paper utilizes a joint Vector Autoregression (VAR) and GARCH (7,8) model to estimate linear interdependencies among the variables, alongside the strong conditional heteroskedasticity of the residuals. Three key findings are presented. Granger causality tests indicate that oil prices and M2 are significant predictors of inflation, while nonfarm payrolls are not, aligning with a flattened Phillips curve. Impulse responses show that oil shocks have a sudden, brief inflationary effect, whereas M2 shocks exhibit a lagged, enduring, multi-peak positive effect. The VAR-GARCH model provides a 24-month out-of-sample forecast, highlighting that purely statistical forecasts may be vulnerable to unexpected external shocks and structural breaks. These findings offer empirical evidence for inflation monitoring and suggest that energy prices and monetary aggregates may provide useful supplementary

information, while employment indicators should be interpreted in conjunction with broader labor-market and macroeconomic conditions.

1. Introduction

The U.S. economy has experienced renewed inflationary pressure in recent years, partly driven by energy-price fluctuations, monetary conditions, and post-pandemic labor-market adjustments. Inflation dynamics are closely related to household purchasing power, business costs, and monetary policy decisions [1]. Although the Federal Reserve aims to maintain price stability, inflation forecasting remains challenging because price movements are affected by multiple interacting macroeconomic factors. Understanding the relative predictive content of energy, monetary, and labor-market indicators is therefore important for short-run inflation monitoring.

The most frequently used analytic framework in the empirical literature of inflation dynamics is vector autoregression (VAR) models and their extensions. One study used the DSGE-VAR method, in which a small New Keynesian DSGE model provides background restrictions for a three-variable VAR including real GDP, the GDP deflator, and the federal funds rate. Using recursive estimation, the study found that U.S. inflation persistence declined structurally in the early 1980s, mainly due to changes in monetary policy stance rather than inherent inflation inertia. Another study proposed a semi-structural VAR incorporating Michigan Consumer Survey expectations, CPI, industrial output, and the federal funds rate to examine rational and sentiment shocks in inflation expectations. Additional research introduced micro-level behavioral variables into macroeconomic forecasting by using Google search indices to improve CPI inflation prediction [1]. Another approach used an MS-VAR framework with DSGE-based identification conditions to examine regime-dependent inflation responses. Further analysis found that M2 money supply growth has significant Granger predictive power for real oil prices under high-volatility regimes. Overall, VAR-class models have evolved into flexible empirical tools incorporating theoretical restrictions, regime changes, expectation decomposition, and behavioral indicators.

Taken together, the literature discusses U.S. inflation dynamics through three major channels: energy-price transmission, monetary expansion, and labor-market pressure. However, their relative short-run predictive content remains unsettled. Some studies emphasize oil-price shocks and cost-push transmission, whereas others focus on monetary aggregates, inflation expectations, or Phillips-curve mechanisms. Moreover, conditional mean dynamics and volatility dynamics are often examined separately. Therefore, the unresolved issue is how the relative predictive content of oil prices, money supply, and labor-market indicators can be compared within a unified and cautious empirical framework [2].

This paper focuses on three key macroeconomic indicators for the U.S. economy, crude oil prices, broad money supply (M2), and nonfarm payroll employment, and examines their predictive relationship with inflation. Rather than proposing a new structural theory of inflation, this study provides an empirical and integrative assessment of how energy, monetary, and labor-market indicators are associated with U.S. inflation dynamics within a unified VAR-GARCH framework. After stationarity processing, these three series, together with the month-over-month inflation rate, constitute the four core variables. A Vector Autoregression (VAR) model is used to capture dynamic interactions among them, while a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is introduced to characterize residual volatility [3].

This paper makes three main empirical contributions. First, Granger causality tests are used to evaluate the predictive relationships between inflation and crude oil prices, M2 money supply, and nonfarm payroll employment [4]. These tests are interpreted as evidence of predictive precedence rather than structural causality. They should not be understood as identifying true economic causal effects, because they may be affected by omitted variables, simultaneity, monetary policy endogeneity, and unobserved inflation expectations. Second, impulse response analysis examines the dynamic response path of inflation to shocks in oil prices, money supply, and employment. Third, the VAR-GARCH framework generates model-based inflation forecasts and assesses the role of conditional volatility in inflation uncertainty. Through this design, the paper provides comparative evidence on whether energy, monetary, or labor-market indicators contain stronger information for short-run inflation monitoring.

2. Methodology

The VAR-GARCH framework is utilized not as a novel econometric model but as an empirical tool for jointly analyzing the conditional mean dynamics and volatility structure of inflation-related macroeconomic variables [5]. The VAR component captures lagged predictive interactions among the variables, while the GARCH component models the time-varying volatility of the residuals.

2.1. VAR

The core of the VAR model lies in capturing the dynamic linear interactions among multiple endogenous variables as they evolve over time [6]. Specifically, this model treats every variable in the system as endogenous and allows the current value of any variable to be explained by its own lagged values as well as those of all other variables, thereby capturing the dynamic adjustment mechanism of mutual dependence and interaction among variables. The mathematical expression of VAR(p), a VAR model with $\text{lag} = \text{p}$, is as follows:

$$y_t = c + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \quad (1)$$

Where y_t is an $n \times 1$ vector of endogenous variables at time t, c is an $n \times 1$ vector of intercept terms, Φ_1 through Φ_p are $n \times n$ coefficient matrices capturing the dynamic relationships among variables across different lags, and ε_t is an $n \times 1$ white noise error vector with zero mean and constant covariance matrix. This specification indicates that the current state of each variable in the system is a linear function of its own past values and those of all other variables up to lag order p, plus a contemporaneous error term, thereby allowing for the estimation of mutual feedback and interdependencies over time [7].

One key feature of the VAR model is that it does not require a strict prior theoretical division between variables, as it treats all variables as endogenous, thereby avoiding the subjectivity of having to pre-specify which variables are exogenous or endogenous [8]. This characteristic makes the model particularly well suited for multivariate dynamic analysis, as it naturally captures the mutual influences and feedback effects among variables over time.

For impulse response analysis, this study uses orthogonalized impulse response functions based on Cholesky decomposition of the VAR residual covariance matrix. The baseline variable ordering is set as WTI crude oil prices, M2 money supply, nonfarm payroll employment, and inflation rate [9]. This ordering reflects the assumption that external energy price movements and monetary conditions may affect inflation with relatively short lags, while inflation is ordered last as the response variable of primary interest. The impulse responses should therefore be interpreted as conditional on this recursive identification scheme rather than as invariant structural causal effects.

2.2. Garch

Data involved in this paper, though already stationarized, exhibit volatility clustering, meaning that large changes tend to be followed by large changes (of either sign) and small changes by small changes. This empirical regularity implies that the conditional variance of the error term varies over time, rendering the traditional assumption of homoscedasticity (constant variance) inappropriate for modeling such series [10].

The GARCH (p, q) model specifies the dynamics of the conditional variance of a residual series ε_t. The conditional variance equation is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_j \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \quad (2)$$

Where $\omega > 0$ is a constant term, $\alpha_i \geq 0$ measure the impact of past squared residuals (the short-run or ARCH effect), and $\beta_j \geq 0$ capture the persistence of volatility by incorporating past conditional variances. To ensure covariance stationarity, the sum ($\sum_{i=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j$) is required to be strictly less than one [11].

The GARCH model naturally captures volatility clustering, meaning large changes tend to follow large changes and small changes follow small changes. When volatility persistence is high, shocks decay very slowly, exhibiting long-memory behavior. By allowing the conditional variance to evolve over time, the model better reflects real-world financial data [12]. Moreover, it achieves parsimony by using past conditional variances to capture long-run volatility dependence with few parameters.

In this study, the GARCH order is selected empirically rather than imposed a priori. Several alternative specifications, including lower-order GARCH models and asymmetric GARCH-type models, are considered during model selection. The GARCH(7,8) specification is retained because it provides a better empirical fit and more effectively removes remaining ARCH effects in the standardized residuals. Nevertheless, given its relatively high order, the possibility of overparameterization is acknowledged [11]. Therefore, the results based on GARCH(7,8) are interpreted cautiously, and the model is used mainly to characterize residual volatility rather than to claim a new volatility-generating mechanism.

2.3. Data Selection

Previous studies have demonstrated that fluctuations in crude oil prices and the M2 money supply significantly influence the inflation rate. Additionally, the Phillips curve relationship between employment and inflation remains a central topic in economics. Against this backdrop, this study utilizes the monthly time series of WTI crude oil prices, M2 money supply, total nonfarm payrolls, and the Consumer Price Index (CPI) for the United States from January 1990 to December 2025. All data are sourced from the FRED economic database maintained by the Federal Reserve Bank of St. Louis, with R employed for data retrieval and processing. The forecasting exercise is conducted after fixing the estimation sample, and a subsequent 24-month forecast is generated recursively using only information available within the estimation sample. No realized observations from the forecast horizon are incorporated into model estimation or parameter selection, thereby eliminating look-ahead bias.

To meet the stationarity requirement of the VAR model, the variables are appropriately transformed. It is observed that crude oil prices, M2 money supply, and CPI achieve stationarity through log-differencing, meaning their growth rate series are stationary. In contrast, the growth rate series of total nonfarm payrolls is non-stationary, necessitating an additional first difference to achieve stationarity. From the original time-series plots of the four variables, the distinct stationarity behavior of nonfarm payrolls compared to the other three variables appears to be linked to a sharp decline of over 10% during the COVID-19 pandemic, while remaining relatively stable in other periods. This extreme fluctuation suggests potential structural instability in the employment series, warranting cautious interpretation of the full-sample VAR results. Given that the sample period encompasses major macroeconomic disruptions, including the 2008 global financial crisis, the COVID-19 pandemic, and the post-pandemic inflation episode, the VAR-GARCH framework is employed as a linear benchmark model to summarize average full-sample predictive relationships rather than as a regime-specific structural model.

The variable selection is deliberately parsimonious, focusing on three representative channels: energy prices, monetary conditions, and labor-market quantity adjustments. Consequently, the model should be regarded as a four-variable benchmark system rather than a comprehensive structural model of U.S. inflation. Other relevant variables, such as the Federal Funds Rate, unemployment rate, wage growth, inflation expectations, exchange rates, fiscal policy shocks, and core inflation indicators, are excluded from the baseline specification and are discussed as limitations [13].

3. Results and Analysis

3.1. Fitting Performance of VAR Model

First, the historical fitting performance of the four-variable VAR model was evaluated. Table 1 reports the fitting performance metrics for each variable (all of which have been stabilized). The results show that the RMSE for the inflation rate is 0.1817, the MAE is 0.1286, the SMAPE is 0.7005, and the ME is close to zero, indicating no systematic bias in the model's fit for the inflation rate [14]. Additionally, the ACF1 for all variables is very close to zero (with a maximum of 0.0381), suggesting negligible first-order autocorrelation in the residuals. For each variable, both Theil's U1 and U2 are noticeably less than 1, indicating that the model's predictive performance outperforms the naive benchmark forecast.

Table 1. In-sample Fit Statistics in the VAR Model.

	Inflation Rate	**WTI oil price**	**M2 Money Supply**	**Nonfarm Payrolls**
ME	-1.823×10-19	-7.565×10-17	9.779×10-18	-5.724×10-18
RMSE	0.1817	7.242	0.3423	0.6339
MAE	0.1286	5.452	0.2201	0.3353
SMAPE	0.7005	1.159	0.5901	1.476
ACF1	0.0381	0.0243	2.638 ×10-4	5.059×10-5
Theil's U1	0.2878	0.4732	0.2536	0.3244
Theil's U2	0.5316	0.7732	0.4765	0.587

Further diagnostic tests were conducted on the VAR residuals, with the results presented in Table 2. The p-values for the Ljung-Box Q test are all 1 except for the inflation rate (0.9983), indicating no significant autocorrelation in the residual series. However, the McLeod-Li Q test results reveal that the test values for the inflation rate, WTI oil price, and M2 are all "close to zero," suggesting significant conditional heteroskedasticity (ARCH effects) in these residual series; only the McLeod-Li p-value for nonfarm payroll employment is 1, showing no obvious heteroskedasticity [15]. Moreover, the p-values for the Turning Points, Diff Signs, and Rank tests are mostly greater than 0.05, with no evidence of systematic structural bias in the residuals.

Table 2. Residual Diagnostic Tests in the VAR Model.

	Inflation Rate	**WTI oil price**	**M2 Money Supply**	**Nonfarm Payrolls**
Ljung-Box Q	0.9983	1	1	1
Mcleod-Li Q	Close to zero	Close to zero	Close to zero	1
Turning points T	0.289	0.0339	0.5558	0.0772
Diff signs S	0.3912	0.1227	0.6069	0.1227
Rank P	0.3333	0.3315	0.4392	0.9753

Additionally, the actual figure combining the real time series of inflation rate and the fitted one is shown in Figure 1, intuitively demonstrating the satisfying performance of the model.

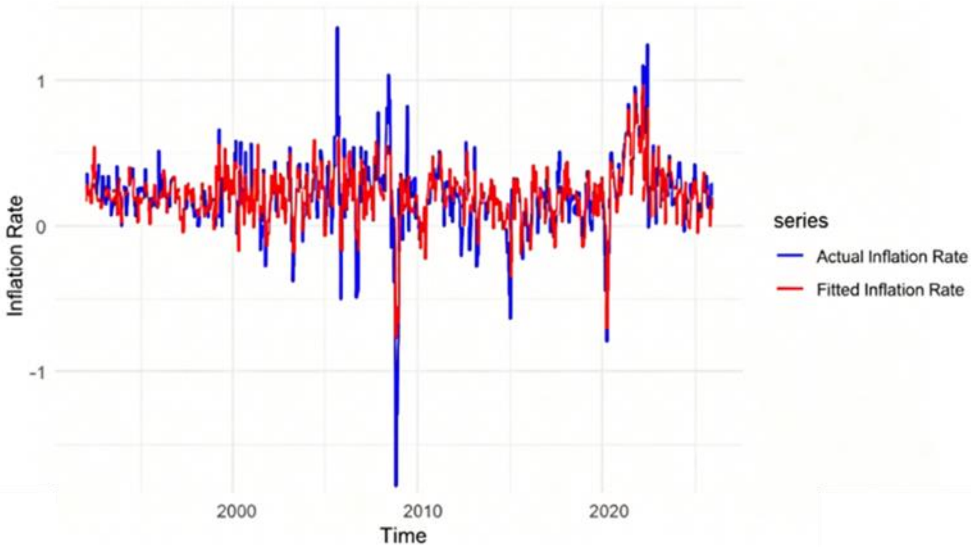

Figure 1. Comparison of Actual Vs. Fitted Inflation Rates

In summary, the VAR model demonstrates a good fit for all variables, with residuals free from autocorrelation but exhibiting significant conditional heteroskedasticity. This provides justification for introducing a GARCH model in subsequent steps to capture volatility dynamics.

3.2. Granger Causality Test

To examine the predictive power of various variables on the inflation rate, this study conducts Granger causality tests with a lag order of $p = 23$. The results are presented in Table 3.

Table 3. Granger Causality Test Results.

	F-statistic	p-value	Conclusion
	Panel A: Other Variables → Inflation Rate		
WTI Oil Price	2.962	9.284×10-6	Yes
M2 Money Supply	1.569	0.0476	Yes
Nonfarm Payrolls	0.8707	0.6387	No
	Panel B: Inflation Rate → Other Variables		
WTI Oil Price	1.279	0.1772	No
M2 Money Supply	1.6163	0.0376	Yes
Nonfarm Payrolls	1.0046	0.4584	No

The test results in Table 3 indicate that, at the 5% significance level, both WTI crude oil prices and M2 money supply reject the null hypothesis of no Granger predictability for the inflation rate. This means that past values of oil prices and M2 contain statistically significant information for predicting inflation within the VAR system. However, this result should not be interpreted as evidence of structural economic causality, because Granger causality reflects predictive precedence and may be affected by omitted variables, simultaneity, monetary policy endogeneity, and unobserved inflation expectations. This finding is broadly consistent with the existing literature. As a fundamental energy source and key industrial input, crude oil prices may be associated with inflationary pressure through energy costs and production costs [16]. The predictive power of M2 also suggests that monetary aggregates contain useful information for short-run inflation monitoring.

Meanwhile, nonfarm payrolls do not show significant Granger predictive power for the inflation rate. This finding seems to contradict the classical Phillips curve theory, but in fact reflects important evolutions in the academic understanding of the inflation-unemployment relationship over the past two decades. A large number of empirical studies point out that the slope of the US Phillips curve has flattened significantly since the 1990s, and the transmission from unemployment changes to inflation has greatly weakened. Some scholars further argue that the Phillips curve should be specified with wage inflation rather than price inflation as the core variable, and that nonfarm payrolls lack sufficient micro foundations to predict the CPI. Moreover, during the 2021-2023 period, although the US unemployment rate fell to historic lows, the inflation rate did not decline correspondingly but instead accelerated—this anomaly has once again challenged the empirical validity of the traditional Phillips curve. Therefore, the fact that nonfarm payrolls do not show significant Granger predictive power for the inflation rate is consistent with the widespread observation in recent literature of a flattening or even "breakdown" of the Phillips curve.

In addition, the test results also show significant reverse Granger predictability from inflation to M2 money supply. This bidirectional relationship is consistent with findings in some studies that inflation and money supply interact with each other. In contrast, the Granger predictive relationship from the inflation rate to WTI oil prices is not significant, i.e., the inflation level is not an effective predictor of crude oil price movements. This may suggest that crude oil price movements are more closely associated with global supply-demand conditions and geopolitical factors than with domestic price levels. The reverse Granger predictive relationship from inflation to nonfarm payrolls is also not significant, which is broadly consistent with the view that labor-market indicators are usually examined as predictors of inflation rather than the reverse.

3.3. Garch Modelling

In the residual diagnostics of the VAR model, the McLeod-Li test indicated that the residual series of the inflation rate, WTI oil price, and M2 exhibit significant conditional heteroskedasticity. To address this issue, this study fits GARCH-type models to the VAR residual series. The lag order is selected by considering information criteria, residual diagnostic performance, and the ability to remove remaining ARCH effects. Although lower-order GARCH specifications are more parsimonious, the GARCH(7,8) specification provides a better empirical representation of volatility persistence in the residual series [16]. Therefore, GARCH(7,8) is retained as the benchmark volatility specification in the main analysis. However, because a high-order GARCH model may involve overparameterization, the results are interpreted with caution and are not presented as evidence of a distinct structural volatility mechanism. After model estimation, the standardized residuals (i.e., $\hat{\varepsilon}_t/\hat{\sigma}_t$) are extracted and subjected to multidimensional tests of independence; the results are presented in Table 3.

Table 4 reports the diagnostic results for the standardized residuals of each variable. The p-values of the Ljung-Box Q test (0.9759 for inflation, 1 for WTI oil, 0.9439 for M2, and 0.9974 for nonfarm payrolls) are all well above 0.05, indicating that the standardized residuals exhibit no significant autocorrelation. The p-values of the McLeod-Li Q test (0.9574 for inflation, 0.7252 for WTI oil, 1 for M2, and 1 for nonfarm payrolls) are also all greater than 0.05, suggesting that the conditional heteroskedasticity has been effectively eliminated. Furthermore, the p-values of the Turning points T, Diff signs S, and Rank P tests are all above 0.05 (the largest being 0.9753, with the Rank P for nonfarm payrolls at 0.8106, etc.), and no systematic structural deviations are found in the standardized residuals [4]. In summary, after being processed by the GARCH(7,8) model, the standardized residuals of all variables satisfy the i.i.d. (independent and identically distributed) assumption, providing a reliable error structure foundation for the subsequent impulse response analysis and forecasting. Future work may further compare the benchmark GARCH(7,8) specification with alternative volatility models such as GARCH(1,1), EGARCH, and TGARCH to assess the sensitivity of the results.

Table 4. Diagnostic Tests on Standardized Residuals from the Garch(7,8) Model.

	Inflation Rate	WTI oil price	M2 Money Supply	Nonfarm Payrolls
Ljung-Box Q	0.9759	1	0.9439	0.9974
Mcleod-Li Q	0.9574	0.7252	1	1
Turning points T	0.289	0.0594	0.289	0.1256
Diff signs S	0.4927	0.1227	0.7316	0.3035
Rank P	0.2127	0.3757	0.4682	0.8106

3.4. Impulse Response Analysis

Based on the Granger causality test results and the recursive identification scheme described in Section 2.1, this section reports orthogonalized impulse response functions [16]. A one-standard-deviation positive shock is applied to crude oil prices, M2 money supply, and nonfarm payrolls, respectively, to examine the dynamic response path of inflation. The baseline ordering is WTI crude oil prices, M2 money supply, nonfarm payroll employment, and inflation rate. Because orthogonalized impulse responses may be sensitive to variable ordering, the results are interpreted as conditional dynamic response patterns rather than structural causal effects.

3.4.1. Crude Oil Price Shock

A crude oil price shock produces a positive-then-negative, short-lived significant response in inflation. Inflation rises by 0.11 at period 0, peaks at 0.13 in period 1, and then declines rapidly. It remains positive but at half the magnitude in periods 2-3. The positive effect disappears after period 4. A significant negative response (-0.028) occurs in period 14, after which it converges to zero. The inflationary impact of an oil price shock is concentrated within 1-2 periods, with no sustained long-term effect (see Figure 2).

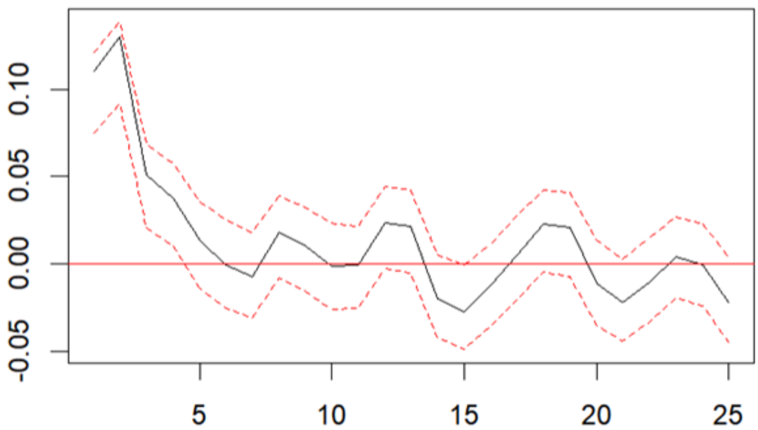

Figure 2. The Impulse Response of Inflation Rate to Oil Price Shocks

3.4.2. M2 Money Supply Shock

An M2 shock has a predominantly positive and repeatedly significant effect on inflation. The first significant positive response (0.035) appears in period 3, followed by significant positive peaks in periods 14 (0.029), 18 (0.035), and 23 (0.028), showing a multi-peak, long-lasting pattern. The response approaches zero by period 36. Monetary expansion transmits to inflation with a lag and in a recurrent pattern (see Figure 3).

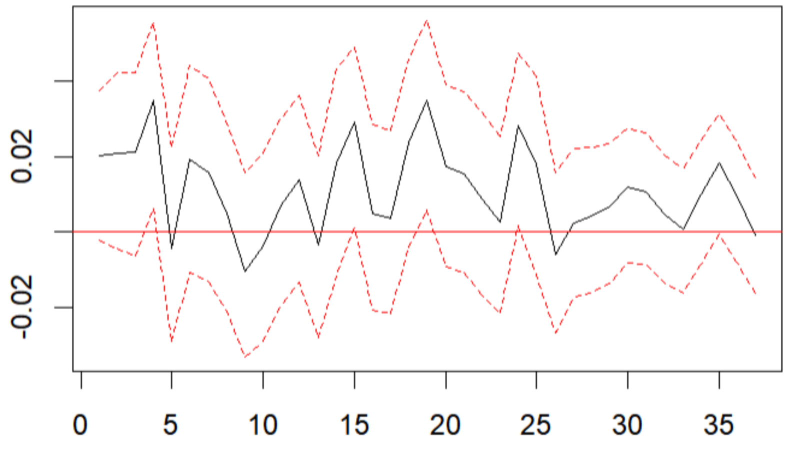

Figure 3. The Impulse Response of Inflation Rate to M2 Money Supply Shocks

3.4.3. Nonfarm Payrolls Shock

Although nonfarm payrolls are not a Granger cause of inflation, the impulse response shows two significant positive peaks at periods 5 and 24 (0.032 and 0.036, respectively). For all other periods, the confidence intervals contain zero [14]. Overall, employment shocks have no systematic impact on inflation, consistent with the Granger causality result (see Figure 4).

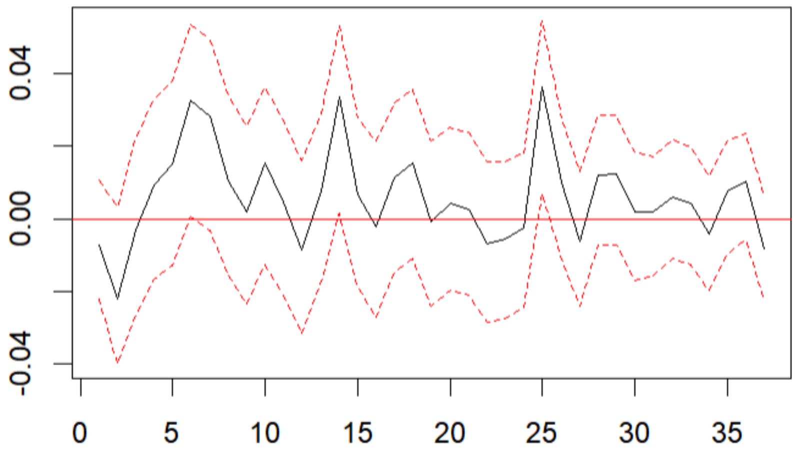

Figure 4. The Impulse Response of Inflation Rate to Nonfarm Payrolls Shocks

In summary, crude oil prices affect inflation quickly but briefly; M2 money supply has a slow but persistent effect; nonfarm payrolls have essentially no effect. The impulse response results are consistent with the Granger causality tests.

3.5. Forecast and Uncertainty Analysis

Based on the estimated VAR-GARCH model, this paper conducts dynamic forecasts of the U.S. inflation rate for the next 24 months, from January 2026 to December 2027, and constructs a 95% confidence interval. The interval estimates are presented in Figure 5. The forecast results indicate that the point estimates of the inflation rate over the forecast horizon generally fluctuate within the range of 0.11–0.32, showing a moderate overall trend. The width of the confidence interval reflects the uncertainty associated with future inflation dynamics under the historical relationships captured by the model. It should be noted that this forecasting exercise is intended to illustrate the model-implied inflation path and uncertainty range, rather than to provide a formal forecast competition against alternative models. Therefore, the results should not be interpreted as evidence that the VAR-GARCH model outperforms ARIMA, random walk, standard VAR, or other forecasting approaches.

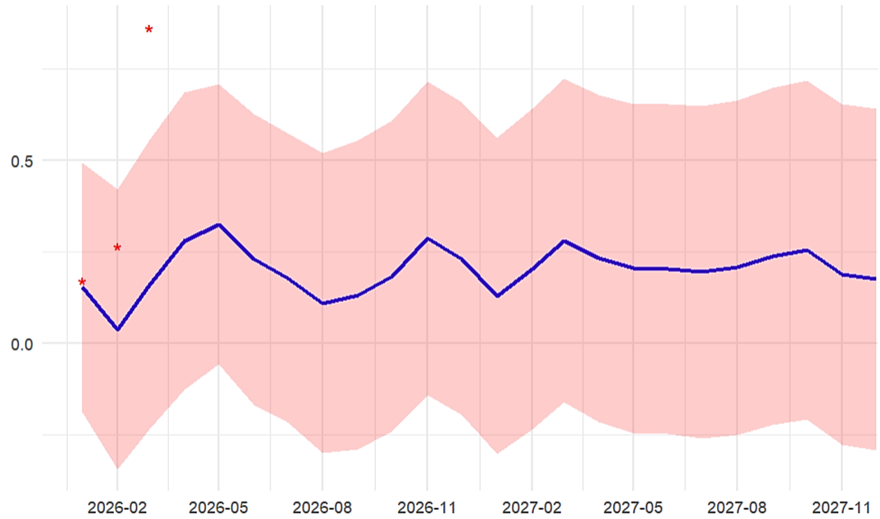

Figure 5. 24-Month Dynamic Forecast of Inflation Rate with 95% Confidence Interval

Since the forecast horizon lies outside the estimation sample, the results should be interpreted as model-based projections rather than as ex-post validation against realized future observations. The VAR-GARCH model generates forecasts based on historical dynamic relationships among inflation, crude oil prices, money supply, and nonfarm payrolls. Therefore, unexpected geopolitical events, sudden energy supply disruptions, abrupt policy changes, or other structural shocks outside the information set of the model may lead realized inflation to deviate from the forecast interval.

This limitation does not necessarily imply that the model fails under normal economic conditions. Rather, it suggests that statistical forecasting models based on historical patterns are better suited for capturing regular dynamic relationships than for anticipating sudden exogenous shocks. Therefore, when applying the VAR-GARCH framework to inflation forecasting, model-based projections should be supplemented with scenario analysis, structural judgment, and formal benchmark comparisons in future research, especially under periods of heightened geopolitical or macroeconomic uncertainty.

4. Discussion

The findings of this paper should be interpreted as an empirical extension of existing inflation studies rather than as evidence of a new structural mechanism. By placing oil prices, money supply, and nonfarm payroll employment in the same VAR-GARCH framework, the analysis compares their relative predictive content for U.S. inflation within a parsimonious four-variable system and examines whether residual volatility can be captured through conditional heteroskedasticity modelling [4].

First, regarding the Granger predictive relationship between oil prices, money supply, and inflation, this paper finds that both WTI crude oil prices and M2 money supply show significant Granger predictive power for the inflation rate. This finding is consistent with studies showing that monetary aggregates exhibit Granger predictive ability in relation to real oil prices. However, Granger causality indicates predictive precedence rather than structural economic causality. Therefore, these results should not be interpreted as proving that oil prices or M2 mechanically cause inflation. They may still be affected by omitted macroeconomic variables, simultaneity, monetary policy endogeneity, and unobserved inflation expectations. This paper also finds reverse Granger predictability between inflation and M2, while the predictive relationship from inflation to oil prices is not significant. This difference may be related to sample periods, lag-order selections, and model specifications. Overall, oil prices and money supply provide useful predictive information for inflation monitoring, but not sufficient evidence for strong causal or policy conclusions.

Second, regarding nonfarm payrolls and inflation, this paper finds that nonfarm payrolls do not show significant Granger predictive power for the inflation rate, which differs from the classical Phillips curve prediction. However, this is broadly consistent with recent evidence that the Phillips curve has flattened or weakened. Existing studies show that the slope of the U.S. Phillips curve has become much flatter since the 1990s and that the transmission from labor-market conditions to price inflation has weakened. Thus, nonfarm payrolls provide limited predictive information for inflation within the current VAR system. This does not mean that labor-market conditions are irrelevant to inflation, because wage growth, unemployment, inflation expectations, and other labor-market indicators are not fully included in the model.

Third, regarding the forecasting performance of the VAR-GARCH model, this paper uses the VAR-GARCH framework to generate 24-month dynamic projections of the inflation rate. The results show relatively stable projected inflation paths and reasonable confidence intervals under the historical relationships captured by the sample. However, this exercise is a model-based projection rather than a formal forecast competition. Since no benchmark comparison with ARIMA, random walk, standard VAR, or machine-learning models is provided, the results should not be interpreted as evidence of superior predictive performance. The use of GARCH-type conditional heteroskedasticity is broadly consistent with studies showing that volatility modelling can improve the characterization of inflation uncertainty in multivariate time-series settings. Since the VAR-GARCH model is estimated from historical relationships, it may not fully capture unexpected geopolitical events, energy supply disruptions, sudden policy changes, or other structural shocks outside the model's information set. Therefore, the forecasting results should be supplemented with scenario analysis, structural judgment, and formal benchmark comparisons in future research.

On the basis of the foregoing discussion, the policy implications of this paper should be interpreted as suggestive rather than prescriptive [4]. First, oil prices and money supply may provide useful supplementary information for inflation monitoring, but they should not replace a broader macroeconomic assessment. Second, the weak Granger predictive power of nonfarm payrolls suggests caution when relying solely on employment indicators, but it does not imply that labor-market conditions should receive less attention in monetary policy. Third, statistical forecasting models should be complemented with scenario analysis and structural judgment, especially under geopolitical risks, energy supply disruptions, or major policy changes. Thus, the findings should be viewed as empirical evidence for inflation monitoring rather than direct policy prescriptions.

5. Conclusion

This paper uses a VAR-GARCH model to examine the dynamic relationship between WTI crude oil prices, M2 money supply, nonfarm payrolls, and the inflation rate in the U.S. from January 1990 to December 2025. After stationarizing the series, this paper determines the appropriate lag order and performs Granger causality tests, impulse response analysis, and out-of-sample forecasts. The findings indicate that oil prices and M2 money supply show significant Granger predictive power for inflation, whereas nonfarm payrolls do not show comparable predictive power. These results should be interpreted as predictive relationships rather than structural causal effects. The standardized residuals fulfill the i.i.d. assumption after modeling the conditional heteroskedasticity of VAR residuals using a GARCH(7,8) specification, although its relatively high order requires cautious interpretation because of possible overparameterization. The 24-month-ahead forecasting exercise suggests that the model can generate internally consistent inflation projections under historical dynamic relationships. However, these projections should not be interpreted as unconditional predictions, because geopolitical shocks, supply disruptions, or structural breaks may lead to substantial deviations from model-based forecasts.

Several limitations should be recognized. First, this study uses a linear VAR specification, which may not fully capture nonlinearities and structural breaks, especially during the 2008 global financial crisis, the COVID-19 pandemic, and the post-pandemic inflation episode. Therefore, the estimated relationships should be interpreted as average full-sample predictive patterns rather than stable structural mechanisms. Future studies may use structural break tests, rolling-window estimation, Markov-switching VAR, or time-varying parameter VAR models to examine regime-dependent inflation dynamics. Second, the GARCH(7,8) model is parameter intensive, although it helps eliminate conditional heteroskedasticity. Future research should compare it with more parsimonious volatility specifications, such as GARCH(1,1), EGARCH, and TGARCH models. Third, the study is based on a parsimonious four-variable system using aggregate U.S. data. Although oil prices, M2 money supply, and nonfarm payrolls represent energy, monetary, and labor-market channels, the model omits other relevant determinants, such as the Federal Funds Rate, unemployment rate, wage growth, inflation expectations, exchange rates, fiscal policy shocks, and core inflation indicators. Thus, the results are conditional on the selected variables rather than a complete explanation of U.S. inflation dynamics. Cross-country or regional heterogeneity is also not examined. Finally, the forecasting exercise does not include formal benchmark comparisons or tests. Future studies should incorporate forecast competitions, structural break analysis, event-based scenarios, and additional macroeconomic variables to further assess predictive robustness.

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