The Impact of Global Stock Index Fluctuations on U.S. Inflation: An Empirical Analysis Based on ARIMA and VAR Models

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Abstract. This study investigates the influence of major global stock indices on U.S. inflation, incorporating both domestic indicators (S&P 500 and NASDAQ Composite) and international benchmarks (Hong Kong Hang Seng Index and German DAX). Using monthly data spanning over two decades, we employ Autoregressive Integrated Moving Average Models (ARIMA models) to identify time series characteristics and Vector Autoregressive Model (VAR models) to analyze dynamic interrelationships. The U.S. Dollar Exchange Rate Index is included as a control variable to account for currency effects. Results indicate that both inflation and stock index series are non-stationary but achieve stationary after first-order differencing. Empirical analysis shows that lagged returns—especially from two months prior—of all major indices exhibit a significant positive relationship with U.S. inflation, while the exchange rate exerts a more complex, lag-dependent influence. Granger causality tests suggest that certain indices, particularly the NASDAQ and DAX, contain predictive information for future U.S. inflation movements, whereas feedback from inflation to equity markets is minimal. Impulse response analysis further reveals that unexpected shocks to stock indices lead to short-term increases in inflation, peaking within five to ten months before fading. These findings underscore the important role of global equity markets in shaping U.S. inflationary trends.

Keywords: U.S. inflation, Stock indices, VAR model, Transmission mechanism.

1. Introduction

The relationship between stock market performance and inflation has long been of significant interest to economists and policymakers due to its implications for monetary policy and investment strategies. Fisher proposed that stocks serve as a natural hedge against inflation, with nominal returns rising to preserve real wealth [1]. However, empirical studies since the 1970s have consistently revealed a negative correlation between U.S. stock returns and inflation—a phenomenon known as the "inflation-stock return puzzle" [2]. This anomaly led to alternative explanations, including Fama's proxy hypothesis [3], which suggests that stock returns reflect real economic growth expectations that move inversely with inflation, and Feldstein's tax effect hypothesis [4], which argues that inflation reduces after-tax returns on capital, diminishing stock attractiveness.

Recent decades have witnessed increasing financial globalization, further complicating this relationship. The U.S. economy's deep integration into global trade and financial networks—with substantial imports from Asia and strong financial ties to Europe—means that international stock indices such as Hong Kong's Hang Seng and Germany's DAX may also affect U.S. inflation through trade channels (e.g., import prices) and financial channels (e.g., multinational corporation valuations) [5]. Despite these potential international linkages, most existing research remains domestically focused, overlooking the combined effects of global equity markets and exchange rate movements.

This study addresses three main questions: (1) How do U.S. indices (S&P 500 and NASDAQ) affect domestic inflation through wealth effects? (2) Can international indices (Hang Seng and DAX) influence U.S. inflation via trade or financial integration? (3) How does the U.S. Dollar Exchange Rate Index mediate these relationships over time? Methodologically, we employ ARIMA models to analyze U.S. inflation dynamics and VAR models to examine multivariate interactions among inflation, stock indices, and exchange rates, including Granger causality tests and impulse response analysis [6].

This paper's primary contribution is the systematic re-evaluation of classical theories using recent twenty-year data and a unified framework that incorporates both domestic and international indices. This approach provides new insights into cross-market transmission mechanisms in today's globalized financial environment.

The paper is structured as follows: Section 2 reviews relevant literature; Section 3 describes data and methodology; Section 4 presents empirical results; Section 5 discusses limitations; and Section 6 concludes with policy implications.

2. Literature Review

The relationship between stock returns and inflation has evolved from Fisher's proposition of stocks as an inflation hedge to the empirical observation of a negative correlation—termed the "inflation-stock return puzzle"—which spurred theoretical responses including Fama's proxy hypothesis and Feldstein's tax effect argument [3, 4]. Recent studies further indicate that in an increasingly integrated global economy, international stock indices and exchange rates may significantly influence domestic inflation through financial and trade linkages, yet the joint analysis of domestic and international equity markets remains underdeveloped [7].

2.1. Wealth Effect and Domestic Stock Indexes

The wealth effect represents a fundamental transmission mechanism through which stock market gains influence aggregate price levels. Rising equity values increase household financial wealth, which in turn stimulates consumer spending and amplifies aggregate demand, potentially leading to inflationary pressures [8]. This process operates through multiple channels: direct consumption from realized gains, improved household borrowing capacity, enhanced consumer confidence, and increased spending by employees participating in stock-based compensation programs.

In the U.S. context, broad market indices such as the S&P 500 and NASDAQ Composite serve as key indicators of stock market performance and household wealth dynamics. The technology-heavy NASDAQ Index exhibits particularly high sensitivity to inflation expectations and interest rate changes due to its concentration in growth stocks, making its wealth effects more pronounced than those of the more diversified S&P 500 [1]. While the primary wealth effect transmission occurs through domestic markets, global financial integration means international equity movements may also indirectly influence U.S. inflation through cross-border capital flows and trade linkages.

2.2. Indirect Impact of International Stock Indices under Globalization

Economic globalization has deepened cross-border ties, heightening the impact of worldwide economic conditions on U.S. domestic prices due to the nation's strong reliance on imports. International equity markets—including Hong Kong's Hang Seng and Germany's DAX—can also affect U.S. inflation via trade and financial linkages, reinforced by growing economic integration [8]. For instance, the Hang Seng Index serves as a gauge of Hong Kong and mainland China's economic health. Changes in China's economy often influence global commodity prices, which in turn affect U.S. import costs and consumer inflation.

Furthermore, as numerous U.S. multinational corporations generate substantial revenue from the Chinese market, fluctuations in the Hang Seng may signal changes in their profitability, subsequently affecting American household wealth and consumption. Similarly, the DAX index acts as an indicator of European economic conditions.

Strengthening economic activity in Germany can boost U.S. exports, creating upward pressure on domestic prices. Additionally, monetary policy adjustments by the European Central Bank may produce international spillover effects, indirectly influencing Federal Reserve policy and U.S. inflation [9].

This review underscores that both domestic and international equity markets affect U.S. inflation through distinct transmission mechanisms. We therefore propose the following hypotheses:

H1: U.S. domestic stock indices (S&P 500, NASDAQ) exhibit a positive relationship with U.S. inflation, primarily mediated by the wealth effect.

H2: International stock indices (e.g., DAX, Hang Seng) exert significant influence on U.S. inflation, with the direction and magnitude of effects contingent on the specific transmission channel.

3. Methodology

3.1. Data Source

All data used in this study—including the U.S. inflation rate, S&P 500 Index (GSPC), NASDAQ Composite Index (IXIC), Hang Seng Index (HSI), DAX Index (GDAXI), and the U.S. Dollar Exchange Rate Index (TWEXAFEGSMTH)—were sourced from Yahoo Finance, a widely recognized and reliable provider of financial market data. The completeness and accessibility of these data support the credibility of this empirical analysis.

To meet the stationary requirements of ARIMA and VAR modeling and avoid spurious regression, all variables were tested and transformed accordingly. The Augmented Dickey-Fuller (ADF) test was systematically applied to each time series using automated R scripts [10]. If non-stationary was detected, first-order differencing was performed until stationary was achieved.

Table 1 presents descriptive statistics for the first-differenced series, including mean, standard deviation, minimum, maximum, skewness, and kurtosis. The skewness and kurtosis values indicate deviations from normal distribution across all variables, supporting the use of robust estimation techniques in subsequent modeling.

Table 1. Descriptive statistical information

	Observation	Average	Standard deviation	Min.	Max.	Skewness	Kurtosis
US Inflation	305	0.2103	0.0174	-1.7864	1.3675	7.7095	-0.8860
GSPC	305	0.5031	0.2543	-18.5636	11.9421	1.1471	-0.6809
HSI	305	0.1202	0.3528	-25.4455	23.6049	1.4116	-0.3051
IXIC	305	0.4929	0.3604	-26.0088	15.3743	1.8054	-0.8417
GDAXI	305	0.3760	0.3337	-29.3327	19.3738	3.2211	-0.9173
TWEXAFEGSMTH	234	0.0473	0.1049	-4.1127	6.3543	0.6250	0.1933

The GSPC and IXIC exhibit the highest mean returns (0.5031 and 0.4929, respectively), surpassing the HSI and GDAXI. In contrast, U.S. Inflation (0.2103) and the TWEXAFEGSMTH (0.0473) demonstrate considerably lower average changes. Volatility, as captured by standard deviation, is most pronounced in the HSI (0.3528) and IXIC (0.3604), whereas U.S. Inflation displays the lowest variability (0.0174).

All equity indices and the exchange rate exhibit negative minima and maxima substantially distant from their means, indicating frequent extreme returns. The IXIC shows the widest range (-26.0088 to 15.3743), consistent with its high-risk profile. U.S. Inflation varies within a markedly narrower interval.

Distributional characteristics reveal positive skewness across most variables, suggesting asymmetric right tails. U.S. Inflation shows exceptionally high skewness (7.7095), followed by the GDAXI (3.2211). Kurtosis values are negative for all series except the TWEXAFEGSMTH (0.1933), indicating generally flatter distributions compared to the normal benchmark. Table 2 presents the ADF test results for the first-differenced series, confirming stationarity across all variables.

Table 2. Data after first-order differencing ADF results

	Dicky-Fuller	Lag order	p-value
US Inflation	-4.4482	6	0.01
GSPC	-5.5486	6	0.01
HSI	-5.9335	6	0.01
IXIC	-5.6154	6	0.01
TWEXAFEGSMTH	-6.037	6	0.01

As shown in Table 2, all differenced series passed the ADF test with a p-value = 0.01 (rejecting the unit root null hypothesis), ensuring no spurious regression for ARIMA/VAR modeling.

3.2. ARIMA and VAR model

The general form of an ARIMA (p, d, q) model is given in Equation (1):

$$\Delta^{d}y_{t} = c + \varphi^{1}\Delta^{d}y_{t}^{-1} + \varphi^{2}\Delta^{d}y_{t}^{-2} + \ldots + \varphi_{p}\Delta^{d}y_{t}{}^{-}{}_{p} + \varepsilon_{t} + \theta^{1}\varepsilon_{t}^{-1} + \theta^{2}\varepsilon_{t}^{-2} + \ldots + \theta_{nq}\varepsilon_{t-nq} \quad (1)$$

Where: Δ^d: d-th order differencing (to make the time series stationary); y_t: Target time series at time t; c: Constant term; $\varphi_1 \ldots \varphi_p$: Autoregressive (AR) coefficients (for lagged $\Delta^d y_t$); $\theta_1 \ldots \theta_{nq}$: Moving Average (MA) coefficients (for lagged error terms ε); ε_t: White noise error at time t; p: Order of AR component; d: Order of differencing; q: Order of MA component.

The general form of a VAR(p) model (for k variables) is given in Equation (2):

$$Y_{t} = c + A_{1}Y_{t-1} + A_{2}Y_{t-2} + \ldots + A_{p}Y_{t-p} + \varepsilon_{t} \quad (2)$$

Where: Y_t: (k×1) vector of k time series variables at time t (e.g., $[y_{1t}, y_{2t}, \ldots, y_{kt}]^T$); c: (k×1) vector of constant terms; $A_1 \ldots A_p$: (k×k) coefficient matrices (each A_i captures linear relationships between Y_t and its i-th lag Y_{t-i}); ε_t: (k×1) vector of white noise errors at time t (errors across variables may be correlated); p: Order of the VAR model (number of lagged terms).

4. Results

4.1. ARIMA Modeling Results for U.S. Inflation

The U.S. inflation series was modeled using a seasonal ARIMA (3, 0, 2) (0, 0, 1) specification with a non-zero mean. This notation indicates three autoregressive (AR) terms, two moving average (MA) terms, and one seasonal moving average term at a 12-month period, capturing both short-term dynamics and annual recurring patterns, which are shown in Table 3.

Table 3. The estimated coefficients of the ARIMA Model for U.S. Inflation

	AR1	AR2	AR3	MA1	MA2	SMA1	mean
coefficients	0.1070	0.0983	0.0826	0.0991	0.1206	-0.1100	0.2100
s.e.	0.1070	0.0983	0.0826	0.0991	0.1206	0.0613	0.0253

The mathematical expression of the model is given in Equation (3), where y_t denotes the differenced U.S. inflation rate at time t, and ϵ_t denotes the residual at time t:

$$y_t = 0.21 + 0.107y_{t-1} + 0.0983y_{t-2} + 0.0826y_{t-3} + 0.0991\epsilon_{t-1} + 0.1206\epsilon_{t-2} - 0.11\epsilon_t \quad (3)$$

The Simple Moving Average 1 (SMA1) term (-0.11) indicates that shocks from 12 months prior exert a slight reversing effect on current inflation, capturing annual seasonal patterns. Parameters AR2, AR3, and MA2 show stronger influences on short-term dynamics. The positive mean suggests a persistent upward drift in the series.

Several key statistics help assess the adequacy of this ARIMA model, which are presents in the Table 4:

Table 4. Fit Statistics of the ARIMA Model for U.S. Inflation

Residual variance (sigma^2)	0.06723
Log likelihood	-17.94
Akaike Information Criterion (AIC)	51.88
Corrected AIC (AICc)	52.36
Bayesian Information Criterion (BIC)	81.64

AIC and BIC help compare models by balancing fit and complexity; lower values mean a better trade-off. Here, AIC = 51.88 and BIC = 81.64, showing strong performance for its complexity. Model accuracy on training data is summarized via error measures in Table 5.

Table 5. The Accuracy of the ARIMA Model for U.S. Inflation

Mean Error (ME)	0.000178
Root Mean Squared Error (RMSE)	0.2563
Mean Absolute Error (MAE)	0.1795
Mean Absolute Scaled Error (MASE)	0.5646
First-lag Residual Autocorrelation (ACF1)	0.0175

Here, the ME is nearly zero, showing minimal systematic bias in the forecasts. Both RMSE and MAE are relatively low, suggesting errors are generally limited in magnitude. The first - lag residual autocorrelation (ACF1, at just 0.0175) indicates residuals are essentially uncorrelated, meaning the model has effectively captured temporal dependencies in the original data.

As shown in Figure 1, the ARIMA forecast indicates that U.S. inflation is expected to continue fluctuating near its historical mean, demonstrating low volatility and no significant directional shift in the near term.

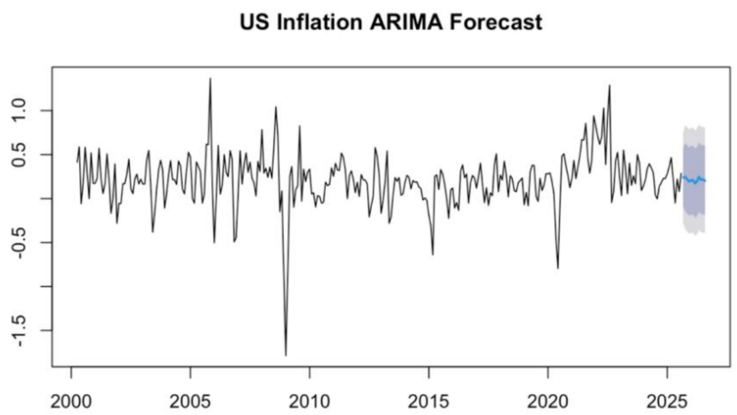

Figure 1. US Inflation ARIMA Forecast

Based on the results of the Ljung-Box test (Table 6), this study has a test statistic Q = 26.867 with 18 degrees of freedom and a p-value of 0.08153. Since this p-value is above the commonly used significance threshold of 0.05, there is insufficient evidence to reject the null hypothesis that there is no residual autocorrelation.

Table 6. Ljung-Box Test Result for Residuals

Test Statistic	Degrees of Freedom	p-value
$Q^* = 26.867$	18	0.08153

Residual diagnostics (Figure 2) further support the model's adequacy. The residual time series fluctuates randomly around zero with no discernible pattern. The autocorrelation function (ACF) plot shows nearly all correlations within confidence bounds, indicating no significant residual autocorrelation. The histogram suggests approximate normality in the residual distribution.

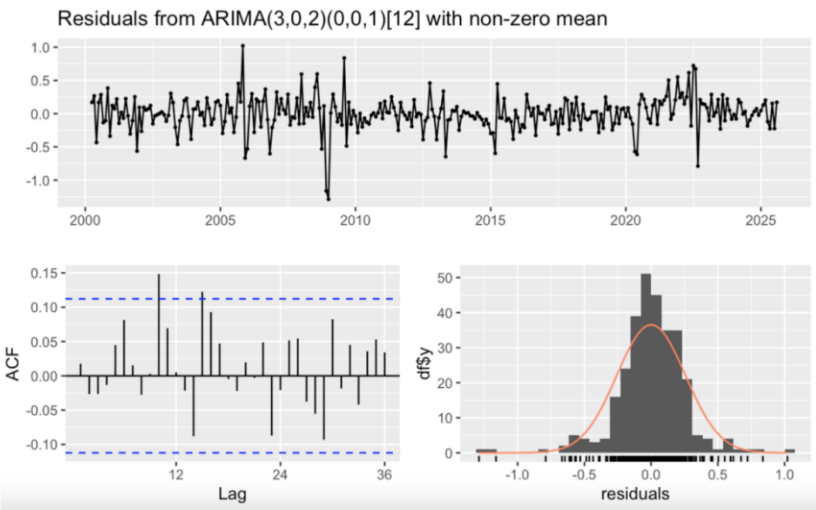

Figure 2. Residual Diagnostics Plot for the U.S. Inflation ARIMA Model

These findings, consistent with the Ljung-Box test results, indicate that the ARIMA model has effectively captured the temporal dependencies, leaving residuals resembling white noise.

4.2. Empirical Analysis Based on VAR Model

4.2.1. Stationarity Test

As non-stationary series may lead to spurious regression, the ADF test was employed to examine stationary [11]. Table 7 shows that for all variables in levels, the p-values exceed 0.05, indicating non-stationary. After first differencing, however, all p-values fall below 0.01, confirming stationary and suitability for VAR modeling.

Table 7. ADF Unit Root Test Results (After First-Order Differencing)

Variable	Dickey-Fuller Statistic	Lag Order	p-value	Stationary
U.S. Inflation	-4.4482	6	0.01	Stationary
GSPC	-5.5486	6	0.01	Stationary
HIS	-5.9335	6	0.01	Stationary
IXIC	-5.6154	6	0.01	Stationary
GDAXI	-6.0370	6	0.01	Stationary
TWEXAFEGSMTH	-6.0370	6	0.01	Stationary

4.2.2. Portmanteau test for optimal lag selection and residual autocorrelation

The Portmanteau test is commonly applied to assess whether the residuals from VAR models exhibit autocorrelation. As shown in Table 8, a non-significant p-value ($p > 0.05$) suggests that the residuals do not display significant autocorrelation. Beyond its role in diagnostic checking, the Portmanteau test can also inform the selection of the optimal lag order for VAR models. By comparing models with different lag lengths, the test helps identify the lag structure that minimizes residual autocorrelation, thereby enhancing model adequacy and reliability.

Table 8. Portmanteau Test Results

VAR Model	Lag Selection	Chi-squared	Degrees of Freedom (df)	p-value	Residual Autocorrelation
U.S. Inflation - GSPC – TWEXAFEGSMTH	4	66.00	54	0.100	None
U.S. Inflation - HSI - TWEXAFEGSMTH	3	75.71	63	0.131	None
U.S. Inflation - IXIC - TWEXAFEGSMTH	2	91.28	72	0.062	None (marginally)
U.S. Inflation - GDAXI - TWEXAFEGSMTH	2	74.70	72	0.391	None

Table 8 presents Portmanteau test results for residual autocorrelation in the estimated VAR models. For the "U.S. Inflation – GSPC" model (lag 4), the test statistic is 66.00 (df = 54, p = 0.100), indicating no residual autocorrelation. The "U.S. Inflation – HSI – TWEXAFEGSMTH" model (lag 3) yields a statistic of 75.71 (df = 63, p = 0.131), also supporting the absence of autocorrelation.

For the "U.S. Inflation – IXIC – TWEXAFEGSMTH" model (lag 2), the result is 91.28 (df = 72, p = 0.062), suggesting marginally insignificant autocorrelation. The "U.S. Inflation – GDAXI – TWEXAFEGSMTH" model (lag 2) shows clear absence of autocorrelation (χ^2 = 74.70, df = 72, p = 0.391). Overall, the results support the adequacy of the VAR specifications.

4.2.3. Model estimation

The key results for the Inflation equation (the core dependent variable) in each VAR model are reported in Table 9.

Table 9. Estimation Results of the Inflation Equation in VAR Models

Variable	U.S. Inflation - GSPC – TWEXAFEGSMTH (VAR (4))		U.S. Inflation - HSI – TWEXAFEGSMTH (VAR (3))		U.S. Inflation - IXIC – TWEXAFEGSMTH (VAR (2))		U.S. Inflation - GDAXI – TWEXAFEGSMTH (VAR (2))	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Inflation (-1)	0.6023	<0.001	0.6287	<0.001	0.6001	<0.001	0.6007	<0.001
Inflation (-2)	-0.2064	0.009	-0.1835	0.012	-0.1131	0.063	-0.1134	0.059
Inflation (-3)	0.0486	0.509	0.0615	0.152				
Inflation (-4)	0.0979	0.114						
GSPC (-1)	0.0035	0.363						
GSPC (-2)	0.0133	0.001						
GSPC (-3)	0.0013	0.751						
GSPC (-4)	0.0032	0.419						
HSI (-1)			-0.0028	0.354				
HSI (-2)			0.0080	0.008				
HSI (-3)			0.0033	0.237				
IXIC (-1)					0.0011	0.725		
IXIC (-2)					0.0077	0.018		
GDAXI (-1)							0.0015	0.649
GDAXI (-2)							0.0104	0.001
TWEXAFEGSMTH (-1)	0.0250	0.024	0.0231	0.037	0.0288	0.009	0.0298	0.007
TWEXAFEGSMTH (-2)	-0.0517	<0.001	-0.0596	<0.001	-0.0554	<0.001	-0.0525	<0.001
TWEXAFEGSMTH (-3)	0.0081	0.522	0.0131	0.345				
TWEXAFEGSMTH (-4)	-0.0153	0.209						
Constant	0.0821	<0.001	0.0961	<0.001	0.0979	<0.001	0.0982	<0.001
Residual Std. Error	0.241		0.243		0.245		0.242	
Adjusted R^2	0.414		0.403		0.390		0.403	
F – statistic (p-value)	14.5 (<0.001)		18.19 (<0.001)		25.61 (<0.001)		27.02 (<0.001)	

As shown in Table 9, U.S. inflation exhibits significant short-term persistence, with a strong positive effect at lag 1 (0.6023, p < 0.001) and a negative reversal at lag 2 (-0.2064, p = 0.009). The S&P 500 shows a significant positive effect only at the second lag (0.0133, p = 0.001), suggesting a delayed inflationary response. For the dollar index, the first lag has a positive influence (0.0250, p = 0.024), while the second lag shows a strong negative effect (-0.0517, p < 0.001), indicating a short-term boost followed by reversal.

The model achieves an R^2 of 0.445 and an adjusted R^2 of 0.414, implying that about 41% of the variation in inflation can be accounted for by the included variables and their lags. The F-statistic is 14.5 (p < 2e-16), underscoring the joint significance of the explanatory variables.

As shown in Table 9, U.S. inflation shows strong persistence at lag 1 (0.6287, p < 0.001) and mild reversion at lag 2 (-0.1835, p = 0.012). The Hang Seng Index exhibits a significant positive effect at lag 2 (0.0080, p = 0.008), suggesting delayed inflationary pressure. The U.S. dollar index shows contrasting lagged effects: positive at lag 1 (0.0231, p = 0.037) and a stronger negative impact at lag 2 (-0.0596, p < 0.001), indicating complex short-term dynamics. The model explains approximately 40% of the variance in inflation, as evidenced by an R^2 of 0.4255 and adjusted R^2 of 0.4034. The overall F-statistic is 18.19 ($p < 2.2e-16$), pointing to a strong joint significance of the repressors.

As shown in Table 9, both lags of the inflation variable are notable. The first lag (Inflation.11) displays a strong positive effect (coefficient = 0.6001, $p < 2e-16$), while the second lag (Inflation.12) shows a marginally significant negative effect (coefficient = -0.1131, $p = 0.0633$). For the NASDAQ, the second lag (IXIC.12) is positive and significant (coefficient = 0.0077, $p = 0.0183$), indicating that increases in the NASDAQ index are associated with higher inflation after a two-month delay. Regarding the U.S. dollar, both lags are significant but with opposing signs: TWEXAFEGSMTH.11 has a positive coefficient (0.0288, $p = 0.0094$), while TWEXAFEGSMTH.12 is negative (coefficient = -0.0554, $p = 2.17e-06$), which aligns with previous VAR findings. The model accounts for approximately 39% of the variance in inflation, as reflected by an R^2 of 0.4058 and an adjusted R^2 of 0.3900. The overall significance of the regression is confirmed by an F-statistic of 25.61 ($p < 2.2e-16$).

As shown in Table 9, U.S. inflation exhibits strong persistence at lag 1 (0.6007, $p < 0.001$) and a marginally negative reversion at lag 2 (-0.1134, $p = 0.059$). The GDAXI shows a significant positive effect at lag 2 (0.0104, $p = 0.001$), indicating delayed inflationary influence. The dollar index has a positive impact at lag 1 (0.0298, $p = 0.007$) and a stronger negative effect at lag 2 (-0.0525, $p < 0.001$). Model fit statistics indicate a moderate explanatory power, with R^2 at 0.4187 and adjusted R^2 at 0.4032; the joint F-statistic (27.02, $p < 2.2e-16$) underscores the overall significance of the regression, explaining roughly 40% of the variance in U.S. inflation—a notably better fit than comparable models featuring the NASDAQ.

4.2.4. Unit circle test

A VAR model is considered stable when all roots of its characteristic polynomial have a modulus less than one, meaning they lie inside the unit circle. According to the test results presented in Table 10, this condition is met, as all reported roots are indeed less than one in modulus. This verifies that the estimated models satisfy the stability requirement necessary for further dynamic analysis (see Table 10).

Table 10. Key Roots of the Characteristic Polynomial

VAR Model	Key Roots of Characteristic Polynomial	Stability
U.S.Inflation-GSPC-TWEXAFEGSMTH	0.771, 0.651, 0.557, 0.504	Stable
U.S.Inflation-HSI-TWEXAFEGSMTH	0.763, 0.628, 0.464, 0.163	Stable
U.S.Inflation-IXIC-TWEXAFEGSMTH	0.6285, 0.3994, 0.2935	Stable
U.S.Inflation-GDAXI-TWEXAFEGSMTH	0.618, 0.4154, 0.3816	Stable

4.2.5. Granger causality test

The Granger causality test is used to assess whether past values of one variable help predict changes in another variable. As shown in Table 11, the results reveal how these variables are directionally related to each other.

Results indicate that all major stock indices (GSPC, HSI, IXIC, GDAXI) Granger-cause U.S. inflation. Only the HSI exhibits bidirectional causality with inflation, reflecting particularly strong economic ties between the U.S. and Chinese markets.

Table 11. Granger Causality Test Results

VAR Model	Null Hypothesis (H_0)	F-Statistic	df1	df2	p-value	Conclusion ($\alpha = 0.05$)
U.S.Inflation-GSPC	Inflation does not Granger-cause GSPC	2.00	8	651	0.070	Fail to reject H_0
	GSPC does not Granger-cause Inflation/TWEXAFEGSMTH	2.00	8	651	0.020	Reject H_0
U.S.Inflation-HSI-TWEXAFEGSMTH	Inflation does not Granger-cause HSI/TWEXAFEGSMTH	3.00	6	663	0.006	Reject H_0
	HSI does not Granger-cause Inflation/TWEXAFEGSMTH	3.00	6	663	0.004	Reject H_0
U.S.Inflation-IXIC-TWEXAFEGSMTH	Inflation does not Granger-cause IXIC/TWEXAFEGSMTH	2.34	4	675	0.054	Fail to reject H_0 (marginally)
	IXIC does not Granger-cause Inflation/TWEXAFEGSMTH	2.73	4	675	0.028	Reject H_0
U.S.Inflation-GDAXI-TWEXAFEGSMTH	Inflation does not Granger-cause GDAXI/TWEXAFEGSMTH	1.05	4	675	0.382	Fail to reject H_0
	GDAXI does not Granger-cause Inflation/TWEXAFEGSMTH	3.47	4	675	0.008	Reject H_0

4.2.6. Impulse response analysis

Figures 3-6 present orthogonalized impulse response functions (IRFs) with 95% bootstrap confidence intervals, tracing dynamic responses over 25 months. A one-standard-deviation shock to any major stock index (GSPC, HSI, IXIC, or GDAXI) induces a short-term increase in U.S. inflation, peaking within 5–10 months (magnitude: 0.02–0.08) before fading. This supports the wealth effect channel, wherein equity gains stimulate demand and price levels.

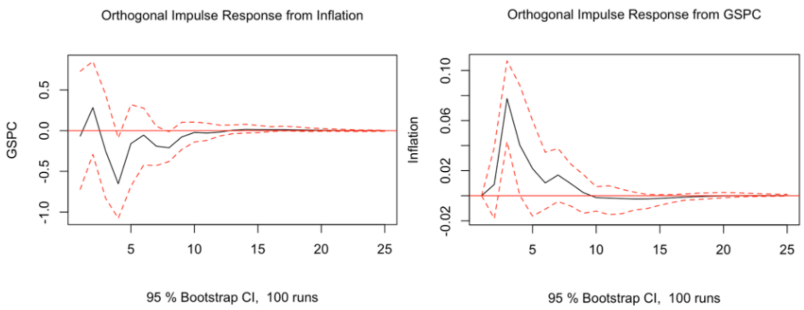

Figure 3. Orthogonal Impulse Response from Inflation and from GSPC

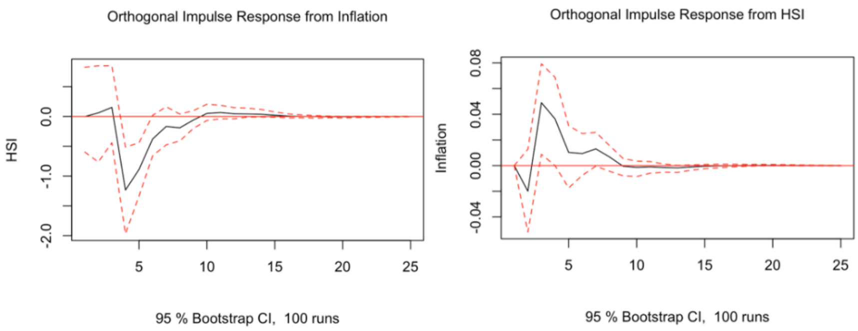

Figure 4. Orthogonal Impulse Response from Inflation and from GSPC

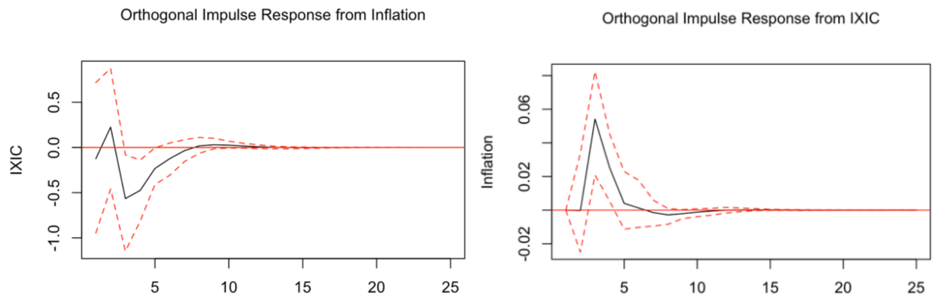

Figure 5. Orthogonal Impulse Response from Inflation and from IXIC

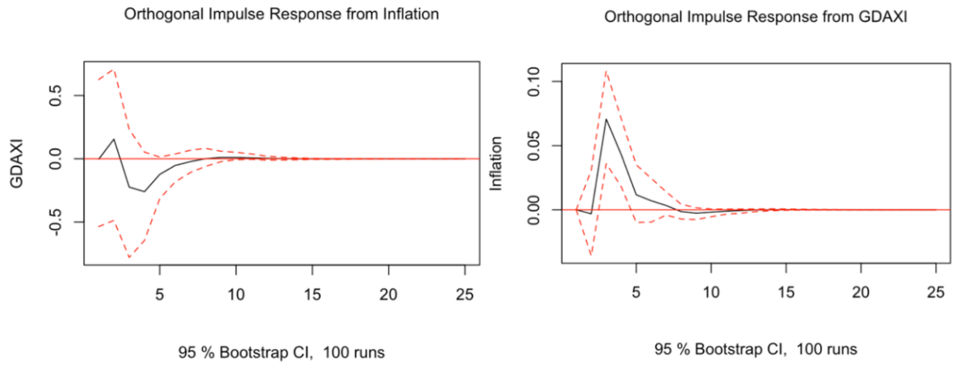

Figure 6. Orthogonal Impulse Response from Inflation and from GDAXI

Conversely, an inflation shock has limited effect on stock indices, though a slight decline (around –0.5 to –1.0 units) occurs in the GSPC and GDAXI within 3–5 months, likely reflecting anticipation of monetary tightening.

4.2.7. Future value prediction

Figures 7–10 present VAR-based forecasts of U.S. inflation from July to December 2025. Predictions align closely with actual values in the initial months (mean absolute error: 0.02–0.03), indicating strong short-term accuracy. However, forecast uncertainty increases over time, with 95% confidence intervals widening to approximately ±0.05 by the sixth month, reflecting accumulated volatility from equity and exchange rate fluctuations.

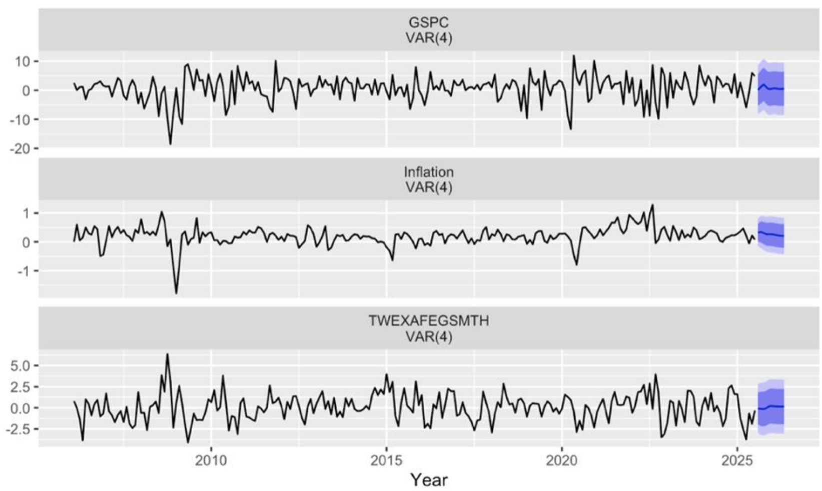

Figure 7. The VAR Forecast on GSPC, Inflation and TWEXAFEGSMTH

Figure 7 displays the time series and VAR forecasts for GSPC, inflation, and TWEXAFEGSMTH. The GSPC series shows substantial volatility, with pronounced declines around 2008 consistent with financial crises. Forecasts indicate stabilization near current levels, though with widening confidence intervals reflecting increased uncertainty. Inflation fluctuates moderately around zero, with a notable dip coinciding with the GSPC downturn. Projections remain stable near zero, but prediction intervals broaden over time. The TWEXAFEGSMTH series exhibits significant variations, particularly during

2008–2010, though recent periods show reduced volatility. Forecasts suggest values near the recent mean, with declining precision at longer horizons.

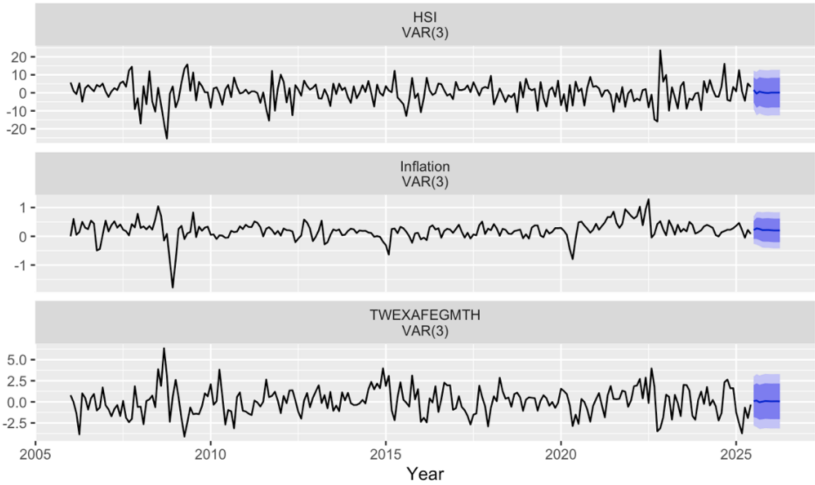

Figure 8. The VAR Forecast on HSI, Inflation and TWEXAFEGSMTH

Figure 8 presents the time series and forecasts for HSI, inflation, and the exchange rate index. HSI exhibits significant volatility, particularly during 2020 and 2023, likely reflecting financial stress or external shocks. Forecasts show widening confidence intervals, indicating growing uncertainty toward 2025. Inflation remains relatively stable overall, with sharp declines around 2009 and 2020, potentially linked to global economic disruptions. Projections suggest mild variability with expanding prediction intervals. The exchange rate index shows considerable short-term fluctuation but generally varies within a moderate range. Forecasts indicate values near recent levels, though with increasing uncertainty over time.

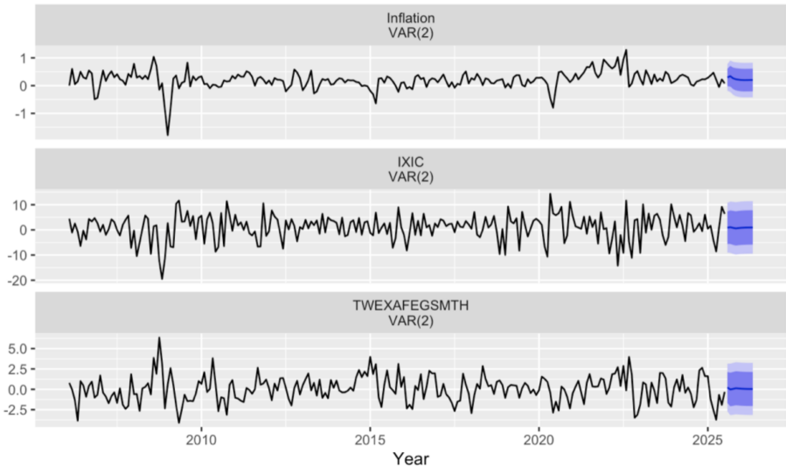

Figure 9. The VAR Forecast on IXIC, Inflation and TEWXAFEGSMTH

Figure 9 displays the time series and forecasts for inflation, IXIC, and the exchange rate index. Inflation fluctuates moderately around zero with occasional brief deflationary spikes. Forecasts remain near zero with slightly widening confidence intervals. IXIC returns show high volatility, particularly during the 2008 financial crisis. Forecasts center near zero with wide intervals, reflecting equity market uncertainty. The exchange rate index varies within a relatively narrow band, though with noticeable spikes during economic stress. Projections suggest stabilization but with persistent uncertainty.

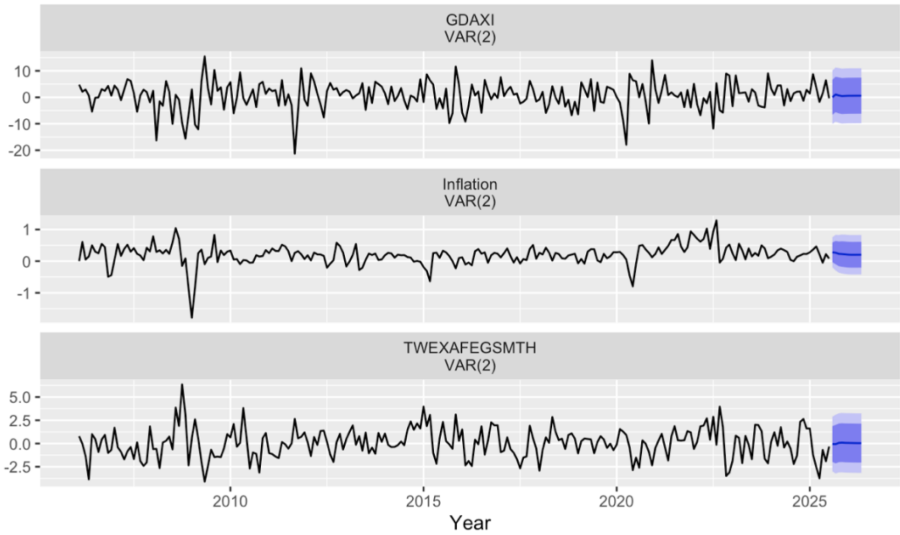

Figure 10. The VAR Forecast on GDAXI, Inflation and TEWXAFEGSMTH

Figure 10 presents the time series and forecasts for GDAXI, inflation, and the exchange rate index. GDAXI exhibits significant volatility, particularly around 2010 and 2020, though recent fluctuations have moderated. Forecasts indicate values near zero with slightly widening confidence intervals. Inflation remains relatively stable, oscillating within a narrow range around zero. Projected values show minimal deviation with comparatively narrow uncertainty bands. The exchange rate index displays moderate volatility, with periodic spikes and dips. Forecasts suggest a stable central path but increasing uncertainty over time.

5. Further Discussion

The findings of this study align with existing literature on the linkages between financial markets and inflation, while offering extended insight through a cross-market, multi-model framework. The ARIMA model effectively captures U.S. inflation dynamics, with low residual autocorrelation and stable mean-reverting forecasts, demonstrating its utility for modeling stable macroeconomic variables.

VAR analysis provides robust evidence that global equity indices—such as the S&P 500, Hang Seng, NASDAQ, and DAX—Granger-cause U.S. inflation, supporting the wealth effect channel wherein rising asset prices boost consumption and inflation with approximately a two-month lag. Notably, bidirectional causality between the Hang Seng Index and U.S. inflation underscores distinctive U.S.–China economic interconnections, often overlooked in single-market studies.

Several limitations should be acknowledged. Although Yahoo Finance is widely used, sole reliance on it may introduce bias; incorporating alternative sources such as FRED or Bloomberg could improve robustness. Key macroeconomic variables—including interest rates, commodity prices, and unemployment—are omitted, which may jointly shape stock–inflation dynamics. Monetary responses to inflation, such as rate hikes, also affect equity valuations but are not captured. Furthermore, the analysis assumes homogeneity across the sample and does not account for structural breaks during crises such as the 2008 crash or COVID-19.

Future research should integrate multi-source data and additional macroeconomic variables. Nonlinear approaches—such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) or machine learning models—could better capture volatility clustering and asymmetric effects. Segmenting the sample by economic regimes (e.g., recession vs. expansion) may further clarify time-varying market–inflation linkages.

6. Conclusion

This study used both ARIMA and VAR models to explore the relationship between U.S. inflation, major global stock indices, and the U.S. Dollar Exchange Rate Index, all based on data from Yahoo Finance. To avoid misleading results, standard procedures like Augmented Dickey-Fuller tests and first-order differencing were applied to ensure the data was stationary.

The ARIMA (3, 0, 2) (0, 0, 1) model demonstrated strong performance, with low AIC (51.88), no residual autocorrelation, and stable inflation forecasts near the historical mean. VAR analysis confirmed that all major global stock indices (S&P 500, Hang Seng, NASDAQ, DAX) Granger-cause U.S. inflation, with bidirectional causality observed for the Hang Seng Index. Impulse responses show stock shocks induce short-term inflation increases (peaking at 5–10 months), while inflation shocks mildly suppress equities, likely due to monetary policy expectations. Short-term VAR forecasts were accurate (MAE: 0.02–0.03), though uncertainty widened over longer horizons.

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