

Macroeconomic Indicators and U.S. Financial Market Volatility: A Comparative Time Series Forecasting Study

Mingge Jia^{1, *}

¹Zhengzhou No.11 High School,
Zhengzhou, China

*Corresponding author:
MIJIA001@csbsju.edu

Abstract:

Financial market volatility works as a key indicator of market risk. It plays a significant part in investment decisions. Existing studies pay main attention to volatility modeling or asset pricing, while the predictive contribution of macroeconomic indicators to VIX forecasting are kept still insufficiently explored. This study aims to examine macroeconomic information improving the forecasting accuracy of financial market volatility. It intends to compare the performance of different time-series models based on quarterly data from 2000 Q1 to 2025 Q4. Furthermore, it selects the CBOE Volatility Index (VIX) as the volatility measure, while incorporating GDP, CPI, and UNRATE as macroeconomic indicators. After RMSE, MAE, MAPE, and the Diebold-Mariano test evaluating the forecasting performance, ARIMA, ETS, ARIMAX, VAR models are constructed. The results show that ARIMA achieves the greatest out-of-sample forecasting performance, whereas macroeconomic variables provide limited additional predictive value in this study. With findings obtained, it is suggested that historical volatility information is important to short-term VIX forecasting. This study provides implications for risk monitoring and financial decision-making. However, the analysis still has limitations, including quarterly data frequency and a restriction on the selection of macroeconomic variables. These demerits can be extended in future research.

Keywords: VIX; Financial Market Volatility; Macroeconomic Indicators; Time Series Forecasting; Risk Management

1. Introduction

1.1 Research Background

Financial market volatility is one of the most important indicators for the measurement of market risk. Accurate volatility forecasting plays a crucial role in portfolio management, risk management, asset allocation, and derivatives pricing. Among various volatility measures, the CBOE Volatility Index (VIX) is extensively regarded as the “fear gauge” of financial markets, owing to the fact that it reflects investors’ expectations of future market uncertainty and implied volatility over the following 30 days [1].

In recent years, financial markets get shocks from several periods of rising uncertainty, including the COVID-19 pandemic, inflation shocks, monetary policy tightening, geopolitical conflicts, and banking sector stress. These events have demonstrated that market volatility is not only driven by historical price movements [2]. However, it is also closely related to changes in broader macroeconomic environment. Therefore, it has been of increasing importance to understand whether macroeconomic conditions can provide additional information for volatility forecasting.

Previous studies, using historical market information, have widely investigated volatility modeling and forecasting, including traditional time-series models and volatility models [3]. Meanwhile, increasing attention has been applied to the role of macroeconomic uncertainty and economic indicators in explaining financial market fluctuations. However, existing research mostly focuses on return forecasting, asset pricing, or individual volatility models. Nevertheless, the combined forecasting contribution of major macroeconomic indicators to VIX has been less systematically examined [4]. Moreover, comparisons among different time-series forecasting models under a unified framework are still limited.

Motivated by research gaps mentioned above, this study investigates whether macroeconomic indicators can improve the forecasting performance of financial market volatility. Specifically, GDP, CPI, and unemployment rate (UNRATE) are listed as macroeconomic variables. Meanwhile, VIX is used as a proxy for market risk. Several forecasting models, are compared to evaluate the predictive value of macroeconomic information, ARIMA, ETS, ARIMAX, and VAR included.

1.2 Research Questions

This study aims to address following research questions. Can macroeconomic indicators improve the forecasting accuracy of financial market volatility? Do multivariate forecasting models provide better prediction performance

than traditional univariate models? Among GDP, CPI, and UNRATE, which macroeconomic indicator provides the most remarkable contribution to VIX forecasting?

1.3 Contributions

The main contributions of this study are summarized as follows.

First and foremost, with VIX used to represent market uncertainty, macroeconomic indicators are combined with financial volatility forecasting in this study. This approach provides a risk-oriented perspective to examine the relationship between economic conditions and market volatility.

In addition, this study explores whether GDP, CPI, and UNRATE contain useful information for predicting VIX beyond its own historical movements. The analysis helps to evaluate the importance of macroeconomic factors in financial risk forecasting.

Furthermore, 4 time-series models, including ARIMA, ETS, ARIMAX, and VAR, are compared within the same forecasting framework. Comparison of this kind is able to clearly evaluate the strengths and limitations of different modeling approaches.

Eventually, for investors, risk managers, and policymakers, the results may provide useful references, when assessing the connection between macroeconomic changes and financial market uncertainty.

2. Literature Review and Hypotheses

2.1 Literature Review

Financial market volatility is considered as a crucial measure of market risk, because it reflects changes in investor expectations and uncertainty. However, it is difficult for volatility to forecast, due to its dynamic characteristics and volatility clustering [4]. Andersen has discussed the challenges of volatility modeling and forecasting, while VIX has become a widely used indicator of expected market volatility and investor sentiment [1, 4]. Thus, VIX is commonly adopted as a proxy for financial market uncertainty and risk.

Existing studies suggest that not only its own historical movements but also changes in the macroeconomic environment affect market volatility. Previous studies have shown that uncertainty shocks can influence economic and financial conditions [5, 6]. Economic uncertainty has also been recognized as a vital factor explaining market fluctuations [6, 7]. When it comes to macroeconomic indicators, GDP, CPI, and UNRATE represent different aspects of economic conditions. GDP reflects economic growth and investor confidence. CPI captures inflation pressure and monetary policy uncertainty. Besides, UNRATE rep-

resents labor market conditions and recession risks. These factors may influence investor expectations and contribute to changes in market volatility.

Various time-series models have been applied to volatility forecasting. ARIMA and ETS capture the historical patterns and underlying components of a single time series to a large extent [8]. ARIMAX extends the ARIMA framework by combining external explanatory variables, while VAR models analyze dynamic interactions among multiple variables [7]. Recent studies have also explored the predictive function of macroeconomic information in financial volatility forecasting [9, 10].

Despite existing research, most studies focus on return forecasting, asset pricing, or individual volatility models [11]. The combined predictive contribution of GDP, CPI, and UNRATE to VIX forecasting has never been fully examined, and systematic comparisons among different forecasting models are kept limited. Therefore, this study develops a unified framework to evaluate whether macroeconomic indicators can improve VIX forecasting performance and compare ARIMA, ETS, ARIMAX, and VAR models.

2.2 Research Hypotheses

Based on the theoretical mechanisms and previous findings, this study develops following hypotheses.

Macroeconomic conditions influence economic expectations and investor behavior. Therefore, GDP, CPI, and UNRATE may provide additional information beyond historical VIX movements. So H1 is proposed that macroeconomic indicators improve VIX forecasting performance.

Since ARIMAX incorporates macroeconomic variables while ARIMA only uses historical volatility information, ARIMAX is expected to achieve better forecasting perfor-

mance. Thus, H2 is that ARIMAX outperforms ARIMA in VIX forecasting.

These indicators reflect different aspects of economic conditions. Besides, their effects on market volatility may vary through different transmission channels. Therefore, H3 is that GDP, CPI, and UNRATE contribute differently to VIX forecasting performance.

3. Data and Variable Construction

3.1 Sample Period and Data Sources

This study uses 104 observations, including quarterly data from Q1 2000 to Q4 2025. The sample period covers several important economic events, such as the Global Financial Crisis, the COVID-19 pandemic, the inflation shock after 2021 and the subsequent monetary tightening period. Sufficient variations are provided by these events in both macroeconomic conditions and financial market uncertainty.

The macroeconomic variables, including GDP, CPI, and UNRATE, are obtained from the Federal Reserve Economic Data (FRED) database. VIX, which represents expected market volatility, is collected from the Chicago Board Options Exchange (CBOE). Since variables are originally reported at different frequencies, all series are converted into quarterly observations to maintain consistency for forecasting models.

3.2 Variable Definition

The dependent variable in this study is VIX, which is extensively used as a measure of expected stock market volatility and investor uncertainty. Higher VIX values is able to generally indicate stronger market risk perception.

Table 1. Variables Definition

Variable	Expectation	Variable Name	Type	Economic Meaning
VIX	—	Volatility Index	Dependent Variable	Market Volatility
GDP	Negative (−)	Gross Domestic Product	Independent Variable	Economic Growth
CPI	Positive (+)	Consumer Price Index	Independent Variable	Inflation
UNRATE	Positive (+)	Unemployment Rate	Independent Variable	Labor Market Condition

Three macroeconomic indicators are selected as explanatory variables. GDP represents overall economic activity and reflects macroeconomic fundamentals. CPI is used to measure inflation conditions, which may affect market expectations through monetary policy channels. Besides, UNRATE captures labor market conditions and provides information about economic weakness or recovery.

The definitions and expected relationships between variables are summarized in Table 1.

Expected directions are based on existing economic theory. It is deemed that stronger GDP growth is generally associated with lower uncertainty and reduced market volatility. Higher inflation may increase concerns about monetary tightening. Then, it leads to higher volatility. Moreover, rising unemployment usually indicates weaker economic conditions and greater recession concerns. This may increase investor risk aversion.

3.3 Preliminary Data Analysis

Before model estimation, descriptive statistics and preliminary analysis are conducted. It aims to examine the basic characteristics of the variables. What is more, Mean, median, standard deviation, minimum, and maximum values are reported to describe the distribution and volatility patterns of each series.

In addition, both time series plots and correlation analysis are used to provide initial observations. It is related to long-term movements of macroeconomic indicators and VIX. These preliminary results help with identifying potential relationships among variables. Moreover, results provide a foundation for subsequent forecasting models.

4. Empirical Methodology

4.1 Data Preprocessing

The variables used are collected at different frequencies (VIX-daily, CPI and UNRATE-monthly GDP-quarterly). All series are converted into quarterly observations to ensure consistency across variables. Monthly variables are aggregated using quarterly averages. In the meantime, GDP is matched directly with the corresponding quarter.

Before model estimation, the dataset is examined for missing values and abnormal observations. None of main data issues are identified in the final sample. Since some macroeconomic variables exhibit strong trends over time, transformations are applied when necessary. GDP and CPI are converted into growth-related measures. Simultaneously, changes in UNRATE are used to capture short-term labor market movements. These adjustments offer help to reduce non-stationary effects and improve the suitability of the data for forecasting models.

4.2 Stationarity and Cointegration Tests

Stationarity is regarded as a significant condition for time-series analysis. It is because of the fact that non-stationary variables may produce unreliable statistical relationships. Therefore, this study applies both the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to examine the properties of all four time-series variables.

The ADF test evaluates whether a unit root exists in each series. Simultaneously the KPSS test provides additional evidence from the opposite perspective. The results indicate that GDP and CPI are non-stationary in their original

forms, whereas stronger mean-reverting characteristics can be seen with VIX. Based on these results, appropriate transformations are conducted before multivariate forecasting.

Furthermore, possible long-run relationships among the variables are suggested by the Johansen test. However, the variables exhibit different integration properties after transformation. Since the main objective of this study is out-of-sample forecasting rather than estimating long-run equilibrium adjustments, the VAR model based on stationary transformations is adopted.

4.3 Forecasting Models

To predict VIX, 4 forecasting models are constructed to compare their ability.

ARIMA is used as the base model because it only relies on the historical information of VIX and captures its own dynamic patterns [8]. Moreover, ETS is regarded as another benchmark approach, which focuses on level and trend components through exponential smoothing methods [8]. Additionally, ARIMAX extends the ARIMA framework by incorporating GDP, CPI, and UNRATE as external variables. This model is designed to examine whether macroeconomic information provides additional predictive value beyond past VIX movements. Last but not least, VAR model treats VIX and macroeconomic indicators as a system. It captures their dynamic interactions [7, 10, 12]. Compared with univariate models, VAR allows the analysis on whether changes in macroeconomic conditions contain useful information for forecasting market volatility.

4.4 Forecast Evaluation Criteria

The final eight quarters reserved for out-of-sample evaluation. Then, the sample is divided into training and testing periods, Using RMSE, MAE, and MAPE, where lower values indicate better forecasting accuracy, model performance is assessed. In addition, applying the Diebold-Mariano (DM) test examines whether the differences in forecasting performance between models are remarkable in statistics.

5. Empirical Results and Analysis

5.1 Descriptive Statistics and Correlation Analysis

Table 2. Descriptive Statistics

	vars	n	mean	sd	median	trimmed	mad
VIX	1	104	19.83416	7.394865	17.87262	18.88441	6.132899

GDP	2	104	17897.68	5776.436	16534.3	17376.39	5469.805
CPI	3	104	233.471	41.56707	231.7072	230.5774	39.50487
UNRATE	4	104	5.640545	1.936582	5.016667	5.383135	1.45789
	min	max	range	skew	kurtosis	se	
VIX	10.30794	58.60469	48.29675	1.955395	6.501434	0.725126	
GDP	10002.18	31422.53	21420.35	0.703701	-0.45998	566.4261	
CPI	170.1	325.547	155.447	0.527483	-0.52167	4.075987	
UNRATE	3.533333	13	9.466667	1.220078	1.01519	0.189897	

It is reported how the descriptive statistics of the variables used in this study (Table 2). The statistics include the mean, median, standard deviation, minimum, and maximum values. VIX exhibits substantial variation during the sample period. A relatively high maximum value, in comparison with its average level, reflects significant increases in market uncertainty during crisis periods. GDP and CPI show relatively large ranges. This reflects long-term eco-

nomical expansion and changes in the overall price level. In contrast, UNRATE demonstrates noticeable fluctuations across different economic cycles, particularly during periods of economic stress. Generally, the variables show considerable variation during the sample period. Then, it is allowed that further investigation using time-series forecasting models.

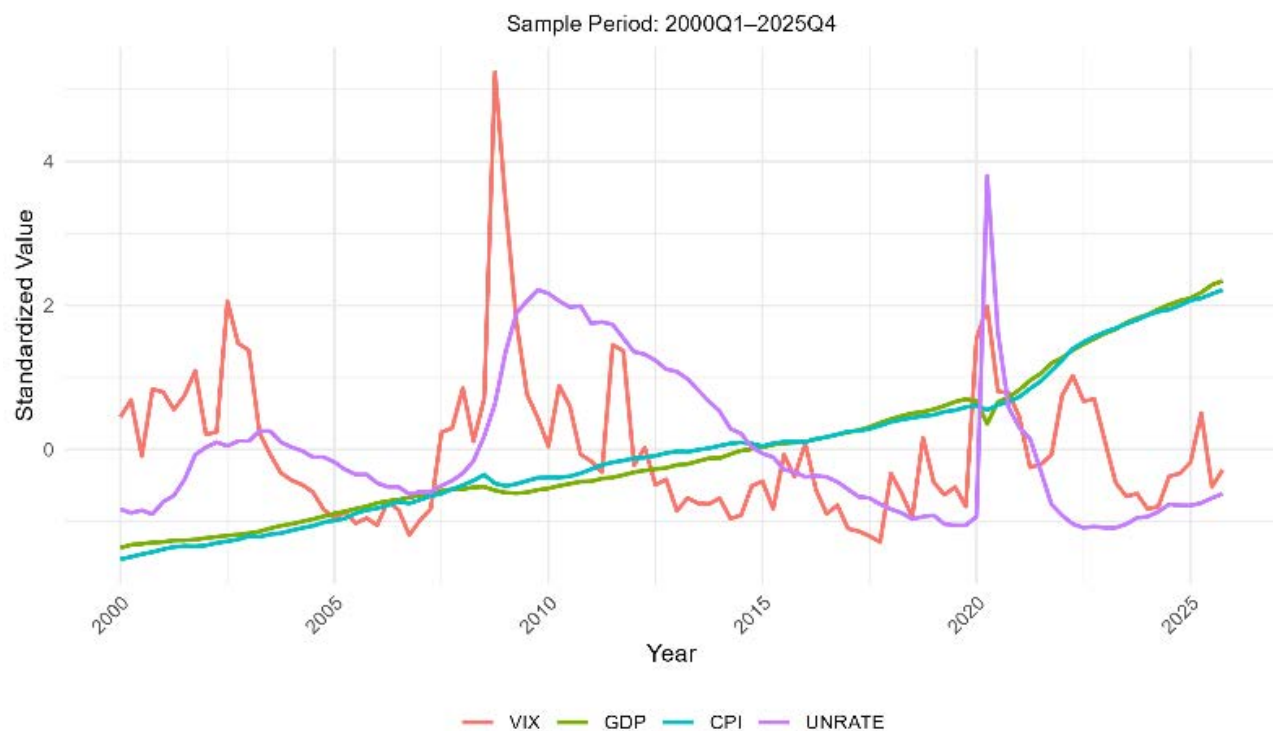


Fig. 1 Standardized Movements of VIX and Macroeconomic Indicators

The standardized quarterly series of 4 time-series variables from 2000Q1 to 2025Q4 is presented in Fig. 1. Because the variables are measured on different scales, their relative movements over time are compared by using standardized values rather than original units. In the meantime, VIX experienced several noticeable increases during major economic events, especially during the Global Financial Crisis and the COVID-19 pandemic. This reflects periods of elevated market uncertainty. In contrast, GDP

and CPI changed more gradually, while UNRATE showed clearer cyclical fluctuations during different economic conditions. Overall, the figure shows that financial volatility and macroeconomic indicators do not fluctuate in the same method over time. This provides motivation for the forecasting analysis in the following sections.

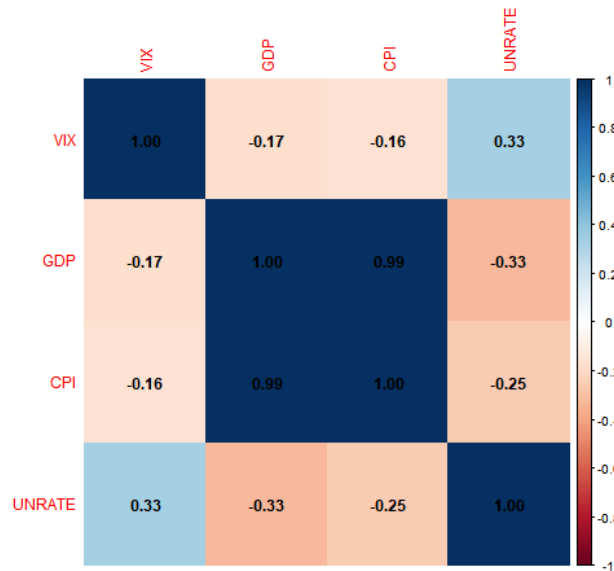


Fig. 2 Correlation Matrix

The correlation matrix among the variables is presented (Fig. 2). The correlation between GDP and VIX is negative but relatively weak, with a coefficient of -0.17. This

demonstrates that the short-term linear relationship between economic growth and market volatility is relatively limited. CPI also exhibits a weak correlation with VIX (-0.16). It indicates that inflation levels alone may not explain short-term fluctuations in financial market volatility. In comparison, UNRATE shows a relatively stronger positive correlation with VIX (0.33), which suggests that weaker labor market conditions may be associated with higher market uncertainty. Additionally, GDP and CPI exhibit a very high correlation (0.99). This may reflect their common upward trends over the sample period. Thus, when interpreting the results of multivariate forecasting models, potential multicollinearity should be considered. All in all, the correlation results only describe the basic linear relationships among variables. Owing to the fact that time-series models can capture dynamic and lagged effects, further forecasting analysis is conducted in the following sections.

5.2 Forecasting Results of Different Models

Four forecasting models are applied to generate eight-quarter out-of-sample forecasts for VIX. As can be seen, Fig. 3 presents the forecasting results.

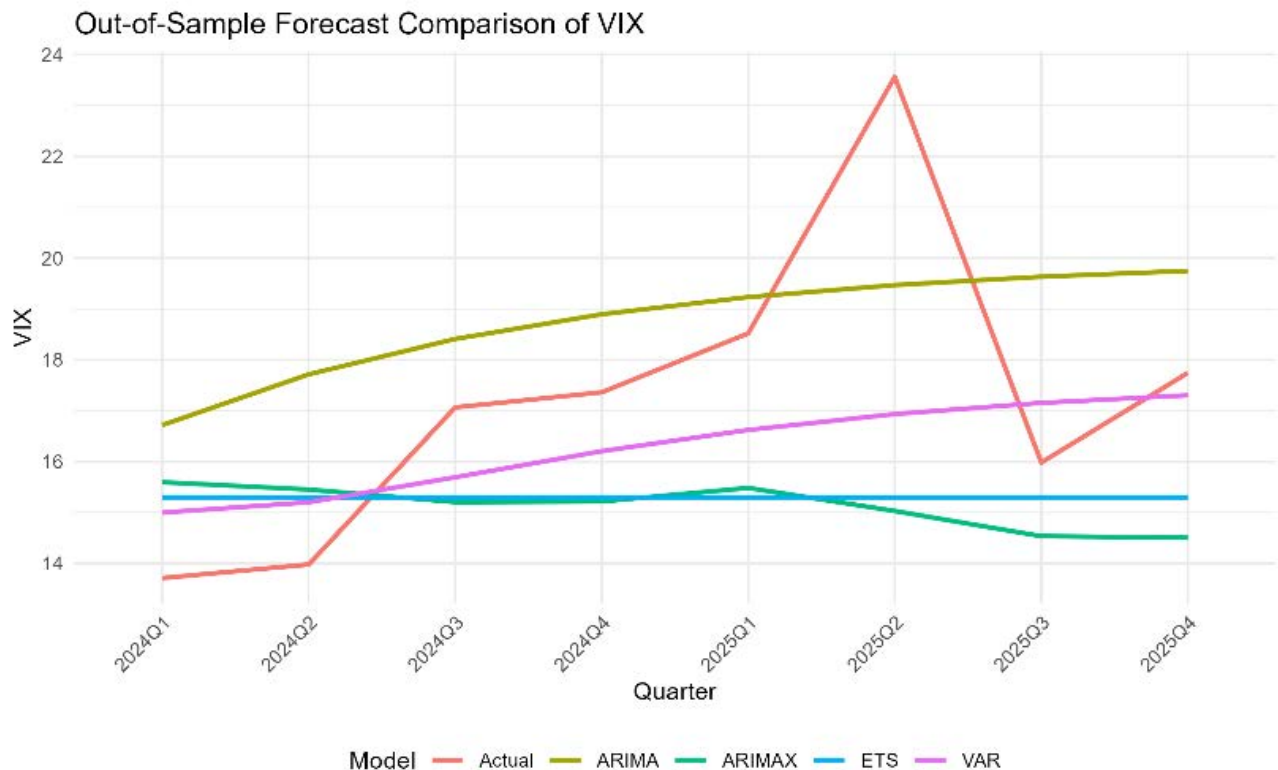


Fig. 3 Comparing Three Models

The ARIMA model is used as the benchmark model. The selected specification is ARIMA (1,0,0). This indicates that the historical information of VIX is of great signifi-

cance in explaining future volatility. Among all models, ARIMA provides relatively stable forecasts and achieves the best overall performance.

The ETS model generates smoother forecasts around the average level of VIX. However, compared with ARIMA, it is less able to capture fluctuations in market volatility. The ARIMAX model combines GDP, CPI and UNRATE as external variables. Though estimated coefficients generally follow the expected economic directions, the inclusion of macroeconomic indicators does not improve the out-of-sample forecasting accuracy.

The VAR model captures the dynamic interactions between VIX and macroeconomic variables. Its forecasting

performance is better than ETS and ARIMAX, but it remains inferior to the ARIMA benchmark model.

5.3 Forecast Performance Comparison

Using RMSE / MAE / MAPE as the prediction evaluation indicators, all models are compared. Based on the results of RMSE, MAE, MAPE and DM Test, the prediction performance of the models is comprehensively evaluated. Thus, construct a model comparison table:

Table 3. Comparing Three Models

Model	RMSE	MAE	MAPE
ARIMA	2.777965	2.509705	0.150866
ETS	3.477594	2.669083	0.142227
ARIMAX	3.680257	2.951817	0.159288
VAR	2.632724	1.896857	0.101267

According to Table 3, ARIMA achieves the lowest forecasting errors, with an RMSE of 1.396 and an MAE of 1.248. This indicates that the strongest short-term forecasting ability among four models. VAR ranks second, which is suggested that incorporating macroeconomic interactions provides additional information for volatility forecasting. However, ARIMAX exhibits worse performance than ARIMA. It implies that GDP, CPI, and UNRATE do not significantly improve short-term VIX prediction accuracy during the sample period. In a word, with results, it is demonstrated that historical volatility patterns remain the most important source of predictive information for VIX forecasting.

5.4 Discussion and Interpretation

Macroeconomic variables may have effect on financial market volatility through different channels. Higher GDP growth generally reflects stronger economic fundamentals. This may reduce recession concerns and market uncertainty. Besides, Rising inflation can increase uncertainty regarding future monetary policy decisions, leading to higher market volatility. Other than that, higher unemployment often indicates weaker economic conditions and may increase investors' risk aversion.

The empirical results provide mixed evidence regarding importance of macroeconomic indicators to VIX forecasting. Moreover, GDP, CPI, and UNRATE have clear economic interpretations. However, their additional forecasting contribution is limited in the out-of-sample evaluation. H1 is not supported because ARIMAX fails to outperform ARIMA, the benchmark model. H2 is also not supported, as ARIMAX produces higher forecasting errors than ARIMA. H3 receives partial support. It is owing to the fact that the VAR estimation indicates heterogeneous re-

lationships between macroeconomic variables and VIX dynamics, although their forecasting contributions are not equally reflected in out-of-sample performance.

5.5 Robustness Tests

In order to examine whether the main findings are sensitive to the forecasting procedure, a rolling forecast analysis is conducted as a robustness check.

With an expanding window framework used, a rolling one-step-ahead forecasting approach is applied. The model is initially estimated with 60 observations. After that, the training sample is recursively updated as new dataset become available. This procedure makes it possible to evaluate forecasting performance across different sample periods rather than relying on a single train-test split.

The rolling forecast results generate an MAE of 3.19. This suggests that the model does not exhibit significant movements in forecasting performance over time. The forecasting error is higher than that obtained from the fixed out-of-sample evaluation. However, the general conclusion remains unchanged. Historical information, which is contained in the VIX series, provides strong predictive ability, whereas the inclusion of macroeconomic variables does not necessarily lead to improved short-term volatility forecasting accuracy.

Overall, the stability of the main empirical findings is supported with the robustness analysis.

6. Conclusion

This study provides several findings regarding the relationship between macroeconomic conditions and financial market volatility.

Primarily, the preliminary analysis shows that GDP, CPI,

and UNRATE have different relationships with VIX. Among these variables, UNRATE presents a relatively stronger correlation with market volatility. This suggests that labor market conditions may contain more information about changes in market uncertainty. In comparison, GDP and CPI show weaker contemporaneous relationships with VIX. This indicates that their effects may not be directly reflected in short-term volatility movements.

Other than that, the forecasting results show that ARIMA achieves the best out-of-sample performance among ARIMA, ETS, ARIMAX and VAR according to RMSE, MAE, and MAPE. This finding demonstrates that important information can be provided with the historical behavior of VIX itself. More complex models do not necessarily guarantee better forecasting performance.

Additionally, GDP, CPI, and UNRATE have clear economic meanings. However, their additional forecasting contribution exhibits limitations. ARIMAX, which combines macroeconomic variables, does not outperform ARIMA, the benchmark model. It is indicated that macroeconomic information may help with explaining market uncertainty, whereas it does not always improve short-term forecasting accuracy.

Overall, the results emphasize the role of historical volatility patterns in VIX forecasting. Also, it shows the potential value of macroeconomic indicators as complementary information.

Despite the results acquired in this study, several limitations still remain. In the first place, the analysis only includes 3 macroeconomic indicators: GDP, CPI, and UNRATE. These variables represent important perspectives of economic activity, inflation, as well as labor market conditions. However, other factors, such as interest rates, monetary policy changes, and economic policy uncertainty, may also affect market volatility. Moreover, having additional economic and financial variables included is likely to provide further insights into the factors driving VIX movements.

Apart from that, this study relies on quarterly data. Though quarterly observations are appropriate for analyzing broad macroeconomic trends, they may not reflect short-term changes in financial markets, especially during periods of rapid market fluctuations. In addition, future studies may consider using monthly or daily data to examine volatility dynamics in more detail.

Finally, this research majorly applies traditional time-series models, ARIMA, ETS, ARIMAX, and VAR included.

Relatively clear interpretations are offered by these models, while they may have limitations in capturing nonlinear relationships. Future research is expected to extend this framework by applying GARCH models, machine learning approaches, or deep learning methods such as LSTM to further explore volatility forecasting.

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