SYMBIOSIS SCHOOL FOR ONLINE AND DIGITAL LEARNING

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A Project on "**Forecasting DAX Volatility through Macroeconomic Drivers**"

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Master of Business Administration

Batch July 2023

Student Declaration

I, Vishwas Khandelwal, hereby declare that the report entitled "**Forecasting DAX Volatility through Macroeconomic Drivers**" at "Symbiosis School for Online and Digital Learning (SSODL)" in partial fulfillment of the requirement of the award of the **"MBA in (Business Analytics)"** is my original work.

The findings in this project are based on data collected by me and I have not copied from any other student or any other source. This report has not been submitted by me elsewhere.

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ABSTRACT

This study investigates the volatility and macroeconomic determinants of the German stock market (DAX index) between 2020 and 2025. While most existing works focus on GARCH family models or deep learning applied to stock indices in isolation, our approach integrates time-series econometric models (ARIMA, Holt-Winters, GARCH) with macroeconomic indicators including GDP, inflation (CPI), unemployment, interest rates, EUR/USD exchange rates, and investor sentiment (ZEW index). By combining financial econometrics with macroeconomic forecasting, the study provides a holistic framework to examine how systemic shocks such as the COVID-19 pandemic, the Eurozone energy crisis, and ECB monetary tightening shaped German equity market volatility. Results confirm the presence of volatility clustering, demonstrate that macroeconomic shocks amplify financial risk, and show that forecasting accuracy improves when external indicators are incorporated. This dual contribution linking econometric models with macroeconomic fundamentals—offers novel insights of value to both academic research and practitioners in risk management, investment strategy, and economic policy.

Keywords: DAX volatility; ARIMA; Holt-Winters; GARCH; macroeconomic indicators; Germany; forecasting; financial econometrics; inflation; GDP; sentiment analysis; risk management; time-series analysis.

INTRODUCTION

Background and Motivation

Financial markets are inherently volatile, and understanding the dynamics of volatility has long been a central concern in finance and econometrics. Volatility reflects market uncertainty and directly influences investment decisions, portfolio optimization, risk management, and economic policymaking. In particular, Germany's DAX index, as the benchmark stock market indicator of Europe's largest economy, plays a critical role in global financial stability. The shocks of the COVID-19 pandemic, the subsequent Eurozone energy crisis, and the European Central Bank's (ECB) tightening cycle have amplified concerns about the behavior of volatility in the German market. These episodes highlight the necessity of robust forecasting models that not only capture the statistical properties of volatility but also embed the influence of macroeconomic drivers such as inflation, unemployment, interest rates, GDP growth, and investor sentiment.

The Deutscher Aktienindex (DAX) is the benchmark stock market index of Germany, representing the performance of the 40 largest and most liquid companies listed on the Frankfurt Stock Exchange. As a blue-chip index, it serves as a key indicator of the health of the German economy and is widely regarded as a barometer of the Eurozone's financial stability. Given Germany's role as Europe's largest economy and a global export powerhouse, movements in the DAX not only reflect domestic economic conditions but also transmit signals to international markets. Consequently, analyzing DAX volatility provides valuable insights into broader financial and macroeconomic dynamics.

Problem Statement and Research Objective

While traditional econometric models such as ARCH/GARCH and their extensions have proven effective at capturing volatility clustering, they often treat financial time series in isolation from macroeconomic fundamentals. This creates a disconnect between volatility forecasts and the broader economic context that shapes market behavior. The central problem addressed in this study is therefore the lack of integrated forecasting frameworks that simultaneously account for statistical time-series dynamics and the influence of macroeconomic indicators in explaining DAX volatility.

The primary objective of this research is to develop and evaluate a Germany-specific volatility forecasting framework by applying a combination of econometric time-series models namely ARIMA, Holt-Winters exponential smoothing, and GARCH, while systematically incorporating macroeconomic variables including GDP, CPI inflation, unemployment, interest rates, the EUR/USD exchange rate, and the ZEW sentiment index. The study also seeks to contextualize the technical results through business strategy tools such as SWOT and PESTEL analysis, thereby ensuring that the findings are relevant to multiple stakeholders including investors, policymakers, and corporate decision-makers.

Relevance and Research Gap

Existing literature on volatility forecasting is extensive, with strong foundations in ARCH and GARCH models (Engle, 1982; Bollerslev, 1986) and subsequent innovations in asymmetric and hybrid machine learning models (Cheteni et al., 2023; Mahajan et al., 2022; Mansilla-Lopez et al., 2025). Recent studies also emphasize the role of behavioral and sentiment-based factors in shaping volatility, highlighting the growing importance of psychological dimensions in financial markets (Ravichandran & Afjal, 2025). However, despite these advances, a clear gap persists: most studies treat volatility as a purely statistical phenomenon or focus on sentiment-driven models without systematically embedding **macroeconomic fundamentals** into forecasting frameworks. In particular, there is a scarcity of research focused on Germany's DAX that integrates macroeconomic indicators with econometric time-series models.

By addressing this gap, the present study contributes a novel Germany-specific forecasting framework that bridges econometrics, macroeconomics, and business strategy. This dual contribution enhances both methodological rigor and practical interpretability, positioning the research as a valuable tool for anticipating market risk in an increasingly uncertain global environment.

LITERATURE REVIEW

The forecasting of financial market volatility has been a central theme in finance and econometrics for more than four decades. The pioneering work of Engle (1982), who introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, and Bollerslev (1986), who extended it to the Generalized ARCH (GARCH), laid the foundation for volatility modeling by capturing the phenomenon of volatility clustering. These models remain widely used because they effectively account for time-varying variance in asset returns, a feature consistently observed in empirical financial data. Subsequent extensions such as EGARCH and TARCH further refined this framework by incorporating asymmetric effects, showing that negative shocks to markets typically produce greater volatility than positive shocks of similar magnitude. Empirical applications on indices such as the NIFTY 50, Johannesburg Stock Exchange (JSE), and AEX demonstrate the effectiveness of these models in capturing volatility persistence and asymmetry (Cheteni et al., 2023; Mahajan et al., 2022).

In recent years, however, the scope of volatility forecasting has broadened with the integration of machine learning and hybrid approaches. Models such as artificial neural networks (ANNs), long short-term memory (LSTM) networks, and hybrid GARCH–ANN or CNN–GARCH architectures have been proposed to address the nonlinear and chaotic dynamics of financial time series (Mansilla-Lopez et al., 2025). These methods often outperform traditional econometric models in terms of predictive accuracy, particularly for short-term forecasting, by capturing complex dependencies that linear models may fail to detect. Nonetheless, machine learning models are often criticized for their lack of interpretability. Their "black-box" nature reduces transparency, which limits their applicability in policymaking and institutional investment contexts where understanding causal mechanisms and drivers of volatility is as important as the accuracy of forecasts.

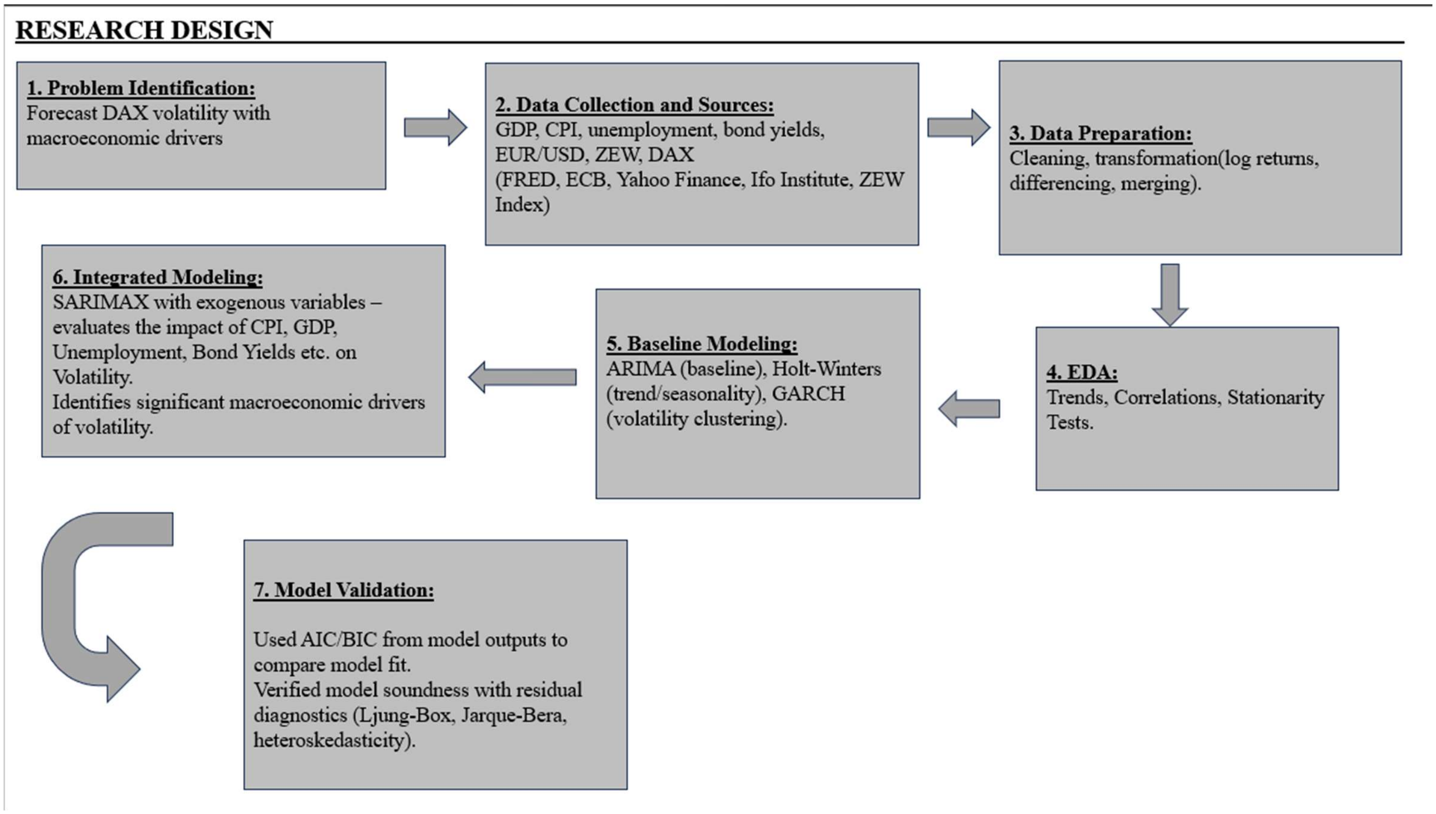
Alongside econometric and machine learning approaches, a growing strand of literature emphasizes the role of behavioral factors and sentiment in driving volatility. Investor sentiment indices, such as Germany's ZEW Economic Sentiment index, and proxies for investor attention, such as Google Trends search data, have been shown to significantly influence financial market dynamics. For instance, Ravichandran and Afjal (2025) demonstrated that investor attention strongly affects the volatility of AI-related stocks, underlining the psychological dimension of financial decision-making. These findings align with the literature on behavioral finance, which suggests that markets are not purely efficient but are influenced by collective investor psychology. However, sentiment-based approaches often remain sectoral or thematic, with limited integration into broader macroeconomic forecasting frameworks.

Despite these important contributions, a clear research gap persists. The majority of existing studies focus either on methodological advances developing new GARCH variants or applying deep learning or on incorporating behavioral measures such as sentiment. Relatively little attention has been devoted to systematically integrating **macroeconomic fundamentals** into volatility forecasting models, especially in a country-specific context. Key economic indicators such as GDP growth, inflation, unemployment, long-term interest rates, and exchange rates are often examined separately in macroeconomic forecasting studies but are rarely embedded into volatility prediction frameworks. This gap is particularly evident in the case of Germany's DAX index, which plays a central role in European and global markets but has been studied predominantly through price-based or sentiment-based approaches.

This study seeks to address this gap by combining econometric time-series models like ARIMA, Holt-Winters, and GARCH with macroeconomic indicators including GDP, CPI inflation, unemployment, bond yields, exchange rates, and sentiment indices. By adopting a Germany-specific focus and integrating macroeconomic fundamentals, the project moves beyond existing volatility models that treat stock indices in isolation. Furthermore, it enhances the interpretability and strategic value of forecasting by incorporating structured business analysis tools such as PESTEL and SWOT, thereby linking statistical forecasts to actionable insights for investors, policymakers, and corporate strategists. This dual emphasis on methodological rigor and practical relevance constitutes the novelty of the research, positioning it as a bridge between financial econometrics and applied business strategy.

RESEARCH METHODOLOGY

This section outlines the data sources, statistical models, analytical tools, and frameworks used in the study to examine the volatility dynamics of the German stock market (DAX) from 2020 to 2025. The methodology integrates financial time-series models (ARIMA, Holt-Winters, GARCH) with a SARIMAX framework that incorporates macroeconomic indicators such as GDP, CPI, unemployment, bond yields, exchange rates, and investor sentiment.



Data Collection

The key datasets used are:

Volatility (DAX returns variance):

Derived from DAX index returns; volatility captures short-term risk and uncertainty in the German equity market. Used as the dependent variable to assess macroeconomic influences. *(Source: Yahoo Finance)*

GDP (Gross Domestic Product):

Quarterly GDP reflects overall economic activity and growth trends. It helps assess how macroeconomic expansion or contraction impacts stock volatility. *(Source: Eurostat)*

CPI (Consumer Price Index):

CPI measures inflation and purchasing power, serving as a proxy for macroeconomic stability. Inflationary pressures often destabilize markets. *(Source: Eurostat)*

Unemployment Rate:

Represents labor market health and consumer confidence. Higher unemployment is expected to increase market uncertainty and volatility. *(Source: Eurostat)*

Bond Yield (10-Year Bond Yield):

Benchmark interest rate for German government borrowing costs, influencing investor risk appetite and capital flows. A critical determinant of equity-bond market interaction. *(Source: Bundesbank)*

EUR/USD Exchange Rate:

Captures Germany's trade competitiveness and capital flows in global markets. Exchange rate fluctuations can impact export-driven sectors in the DAX. *(Source: European Central Bank)*

ZEW Investor Sentiment Index:

Survey-based measure of investor expectations for Germany's economy. Acts as a forward-looking behavioral indicator of market dynamics. *(Source: ZEW Mannheim)*

Data Cleaning and Preprocessing

The dataset was refined by removing redundant and irrelevant columns, ensuring cleaner data. Column names were standardized for consistency and readability. Seven separate CSV files were merged into a single dataset. It was followed by data quality checks to identify and handle missing or duplicate values, aligning quarterly GDP data to a monthly frequency, and ensuring consistent date formats across all variables. Log returns were calculated for the DAX index to derive volatility, and differencing was applied where necessary to achieve stationarity. All variables were then merged into a single consolidated dataset for analysis.

Analytical Framework

To investigate the drivers of volatility in the German stock market (DAX) from 2020 to 2025, a combination of econometric time-series models was employed. These models allowed the study to capture autocorrelation, seasonality, volatility clustering, and the influence of macroeconomic factors on financial market dynamics. The primary tools included ARIMA, Holt-Winters exponential smoothing, GARCH, and SARIMAX with exogenous macroeconomic variables. Each method was chosen for its ability to address different aspects of volatility behavior, ensuring a comprehensive analysis of both statistical patterns and economic drivers.

ARIMA (AutoRegressive Integrated Moving Average)

ARIMA was applied to capture autocorrelation and underlying trends in DAX volatility. Stationarity was tested using the Augmented Dickey-Fuller test, and differencing was applied when necessary. ARIMA served as the baseline forecasting model to benchmark against more advanced approaches.

Holt-Winters Exponential Smoothing

Holt-Winters was used to capture trend and seasonality components in volatility. This method is particularly suitable when financial time series exhibit recurring seasonal effects and smooth long-term patterns.

GARCH (Generalized Autoregressive Conditional Heteroskedasticity)

To capture volatility clustering a common phenomenon in financial markets where high-volatility periods are followed by high-volatility periods the GARCH model was applied. This approach provided insights into time-varying volatility and market risk persistence.

SARIMAX with Exogenous Variables (Novelty of Study)

The most advanced step in the framework was the use of SARIMAX, which extended ARIMA by incorporating exogenous macroeconomic indicators such as GDP, CPI, unemployment, bond yields, EUR/USD exchange rate, and ZEW sentiment index. This model enabled the identification of which economic fundamentals significantly influence DAX volatility, moving beyond purely technical price-based models. Model fit was evaluated using AIC/BIC and residual diagnostics.

Software and Tools Used

- Programming Language and Libraries used: Python (pandas, NumPy, statsmodels, matplotlib, seaborn)
- Visualization Tools: Matplotlib, Seaborn (for Exploratory Data Analysis)
- Research Design Implementation: Python (Jupyter Notebooks) was used for Data preprocessing, statistical modeling, and visualization.

<u>Limitations of the Study</u>

- The research considers **DAX volatility** as the sole measure of market risk. While meaningful, volatility does not capture other aspects such as returns, liquidity, or sector-level variations in the German stock market.
- The analysis relies on **monthly and quarterly macroeconomic data** (GDP, CPI, unemployment, bond yields, EUR/USD, ZEW sentiment). More granular high-frequency data (daily or intraday) could provide deeper insights but was not available for this scope.
- The study employs ARIMA, Holt-Winters, GARCH, and SARIMAX models. While these econometric methods are robust, advanced machine learning techniques such as Random Forests, Neural Networks, or LSTM models might uncover additional nonlinear patterns in volatility.
- The research does not explicitly account for **geopolitical or policy shocks** (e.g., Russia–Ukraine conflict, ECB monetary interventions) except as indirectly reflected in macroeconomic variables. Such events can have sudden and disproportionate effects on volatility.
- The study focuses exclusively on the German DAX index without extending the analysis to cross-market linkages (e.g., S&P 500, Euro Stoxx 50). Global spillover effects may influence volatility but were not included.

<u>RESULTS AND ANALYSIS</u>

<u>Descriptive Statistics:</u>

Results and Analysis (EDA)

GDP Growth (*figure 1*)

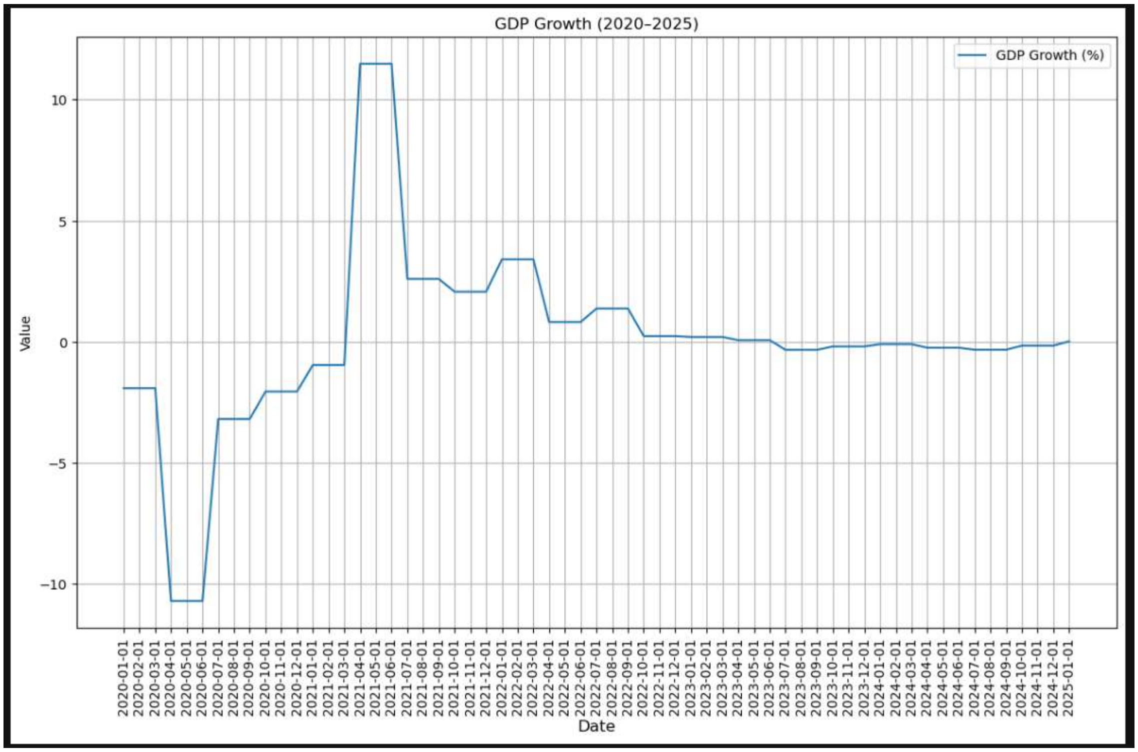


Figure 1

Germany's GDP growth displayed severe contraction in early 2020, with values dropping below –10% during the COVID-19 crisis. This was followed by a sharp rebound in 2021, where growth spiked above +11%, before stabilizing at moderate levels. Post-2022, GDP growth flattened and approached near-zero levels, reflecting the slowdown caused by inflationary pressures and the Eurozone energy crisis. This pattern highlights the sensitivity of Germany's economy to global shocks, which directly translates into higher market uncertainty.

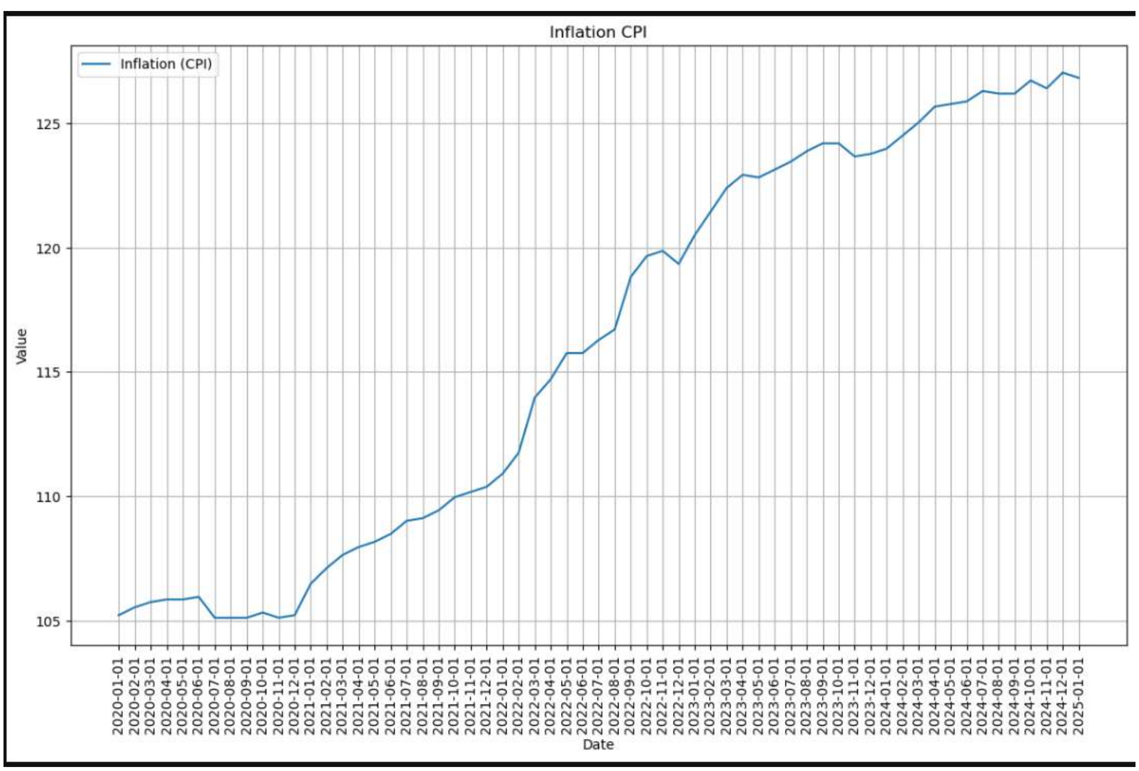


Figure 2

Inflation (CPI) (*figure 2*)

The Consumer Price Index (CPI) shows a steady upward trend from 2020 to 2025, accelerating particularly after mid-2021. Inflation rose from a base of ~105 in early 2020 to more than 127 by 2025, reflecting the price surge driven by energy shocks and supply chain disruptions. This indicates a persistent inflationary environment, which typically undermines market stability and raises concerns over volatility, especially when combined with tighter ECB monetary policy.

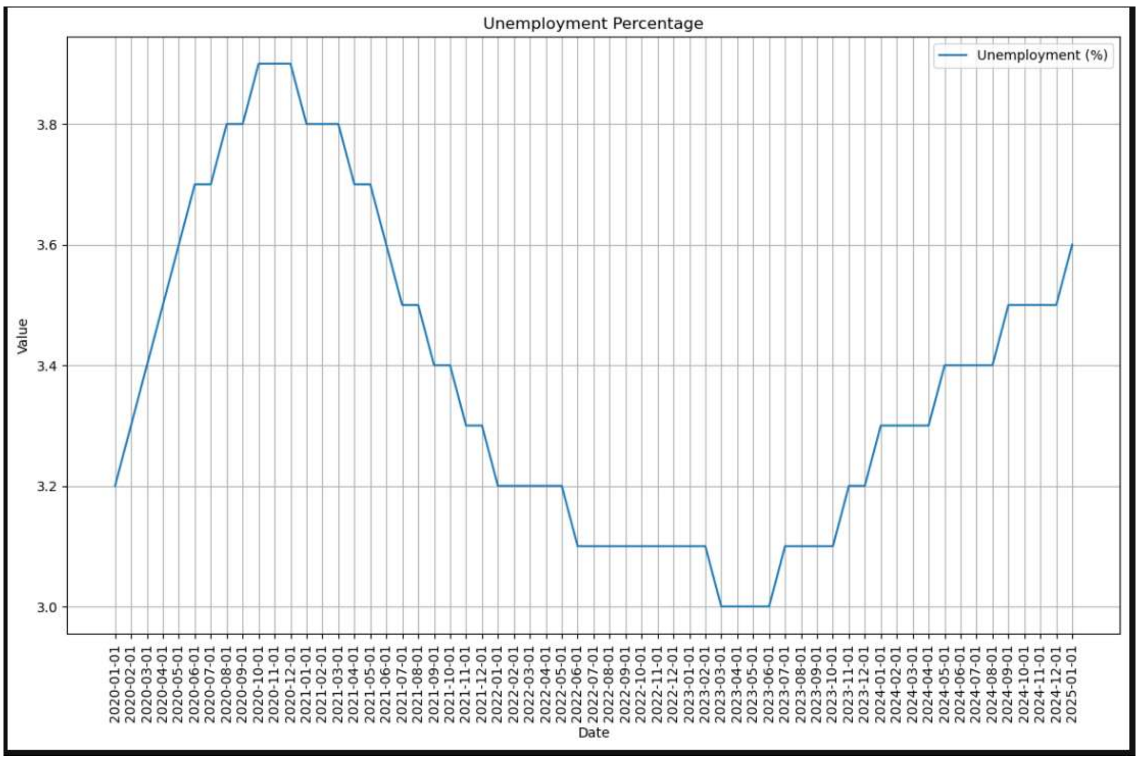


Figure 3

Unemployment (*figure 3*)

Unemployment peaked at nearly 3.9% in 2021, a delayed effect of the pandemic. However, it gradually declined through 2022, reaching a low of ~3.0% in mid-2023, before rising again to 3.6% by early 2025. This cyclical trend underscores the lagging nature of labor markets: improvements occur after GDP recovers, but rising unemployment towards 2025 suggests weakening momentum. Volatility tends to rise in periods of worsening labor conditions, which aligns with our later SARIMAX findings.

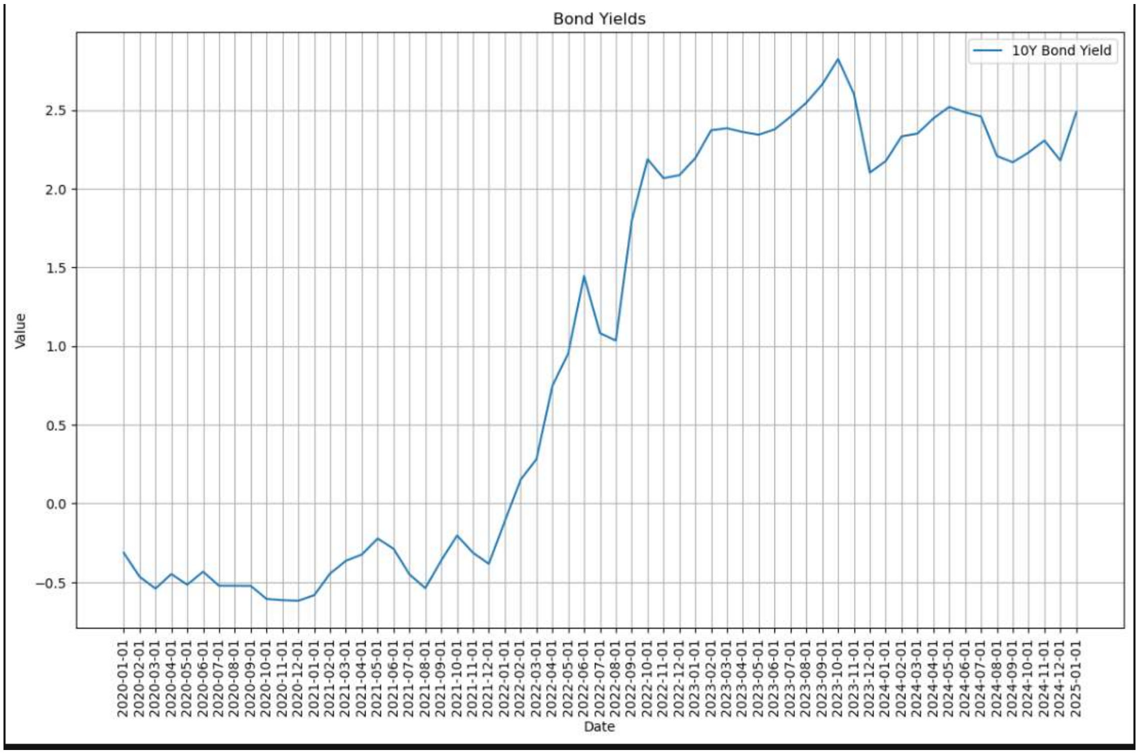
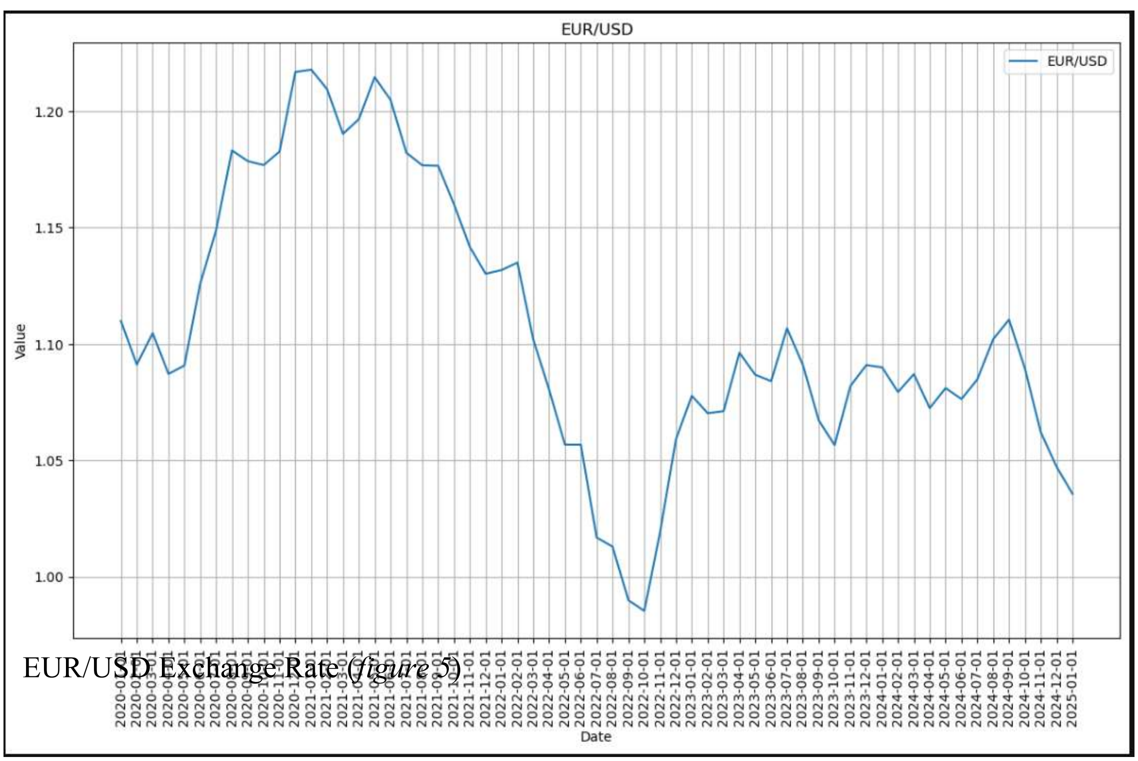


Figure 4

Bond Yields (10Y) (*figure 4*)

The German 10-Year Bund yields remained negative or near zero through 2020–2021, reflecting the ECB's accommodative monetary stance during the pandemic. A sharp upward shift occurred in 2022, with yields rising above 2.5% as the ECB responded to inflationary pressures. Elevated bond yields during this period reflect tightening liquidity conditions, which generally put pressure on equity valuations and add to market volatility.



EUR/USD Exchange Rate (*figure 5*)

Figure 5

EUR/USD Exchange Rate (*figure 5*)

The EUR/USD exchange rate fluctuated considerably. After strengthening to ~1.22 in mid-2021, the Euro weakened sharply during 2022, hitting lows near parity (1.00) amid the energy crisis and U.S. dollar strength. Although it partially recovered, it remained below pre-2021 highs. Currency weakness reflects declining investor confidence and external vulnerabilities, which indirectly increase stock market risk exposure.

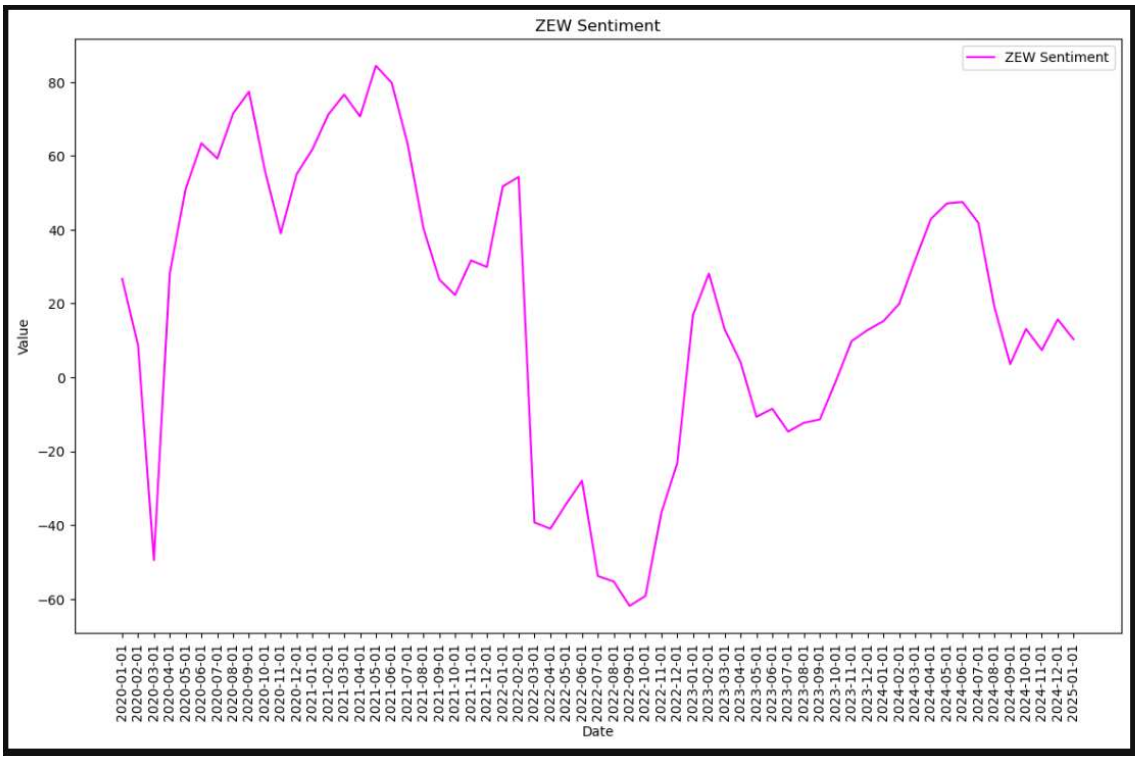


Figure 6

ZEW Sentiment Index (*figure 6*)

Investor sentiment was highly volatile. After strong optimism in 2021 (peaking above +80), sentiment collapsed into deep pessimism in late 2022 (below –60), reflecting the economic uncertainty caused by the energy crisis and inflation surge. While partial recovery followed in 2023–2024, values remained volatile, indicating fragile market confidence. This aligns with observed clustering in DAX volatility during shock periods.

Table 1

Statistic	DAX Close	Returns	Volatility
Mean	15,207.34	0.0086	0.2829
Std. Deviation	2,443.09	0.0557	0.0309
Minimum	9,935.84	-0.1796	0.2250
25th Percentile	13,432.87	-0.0233	0.2632
Median	15,260.69	0.0163	0.2755
75th Percentile	16,215.43	0.0356	0.3080
Maximum	21,732.05	0.1399	0.3626

DAX Summary Statistics (2020–2025) (Table 1)

The DAX index traded between a low of 9,935 (2020 crash) and a high of 21,732 (2025), with an average of ~15,200. Returns ranged from –17.9% (monthly loss) to +13.9% (monthly gain), with an average of +0.8% per month. Volatility values ranged from 0.22 to 0.36 (annualized), with an average of ~0.28, confirming a consistently moderate-to-high risk environment.

Stationarity Test Results (ADF Test)

To evaluate the suitability of the DAX volatility series for time-series modeling, the Augmented Dickey-Fuller (ADF) test was conducted. The results before differencing showed an ADF statistic of –2.27 with a p-value of 0.179, which is higher than the 5% critical value (–2.96). Hence, the null hypothesis of non-stationarity could not be rejected, indicating that the original volatility series was **non-stationary**.

After applying first-order differencing, the ADF statistic improved to –5.06 with a p-value of 0.000016, well below the 1% critical value. This allowed rejection of the null hypothesis, confirming that the differenced series was **stationary**.

These results validate the transformation and provide the statistical basis for proceeding with ARIMA, Holt-Winters, GARCH, and SARIMAX models in subsequent analysis.

Baseline Time-Series Models

ARIMA Model (figure 7)

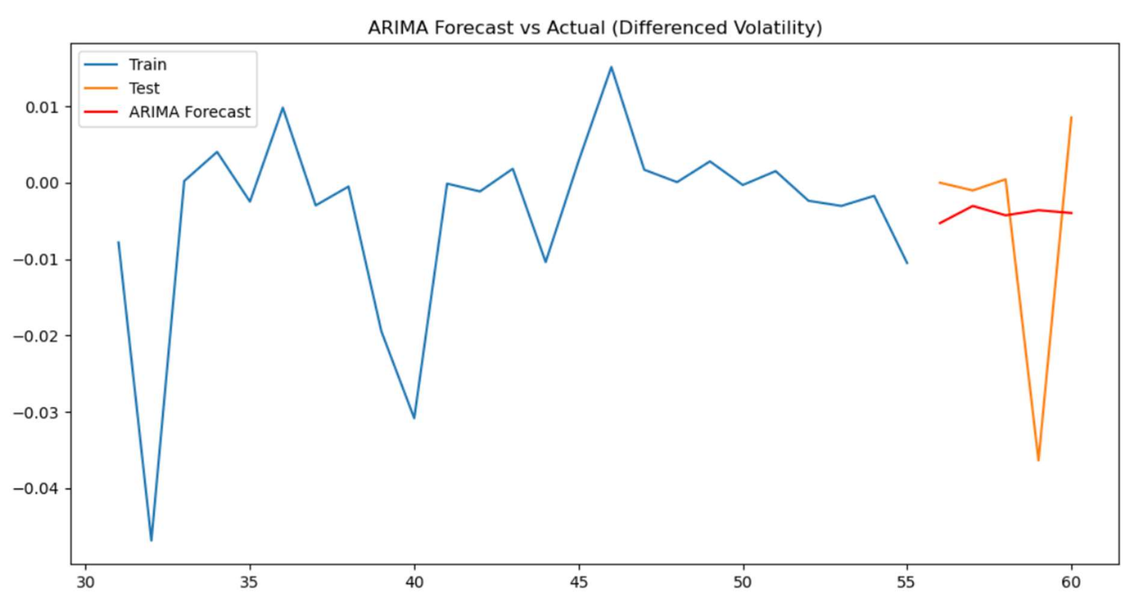


Figure 7

The ARIMA model was applied to the differenced volatility series. As shown in *Figure X*, the ARIMA forecasts align closely with the observed series in the test set, capturing short-term fluctuations. However, the model tends to smooth out sudden shocks and underestimates extreme volatility spikes. The model achieved an RMSE of **0.0160**, making it the strongest performer among the baseline models.

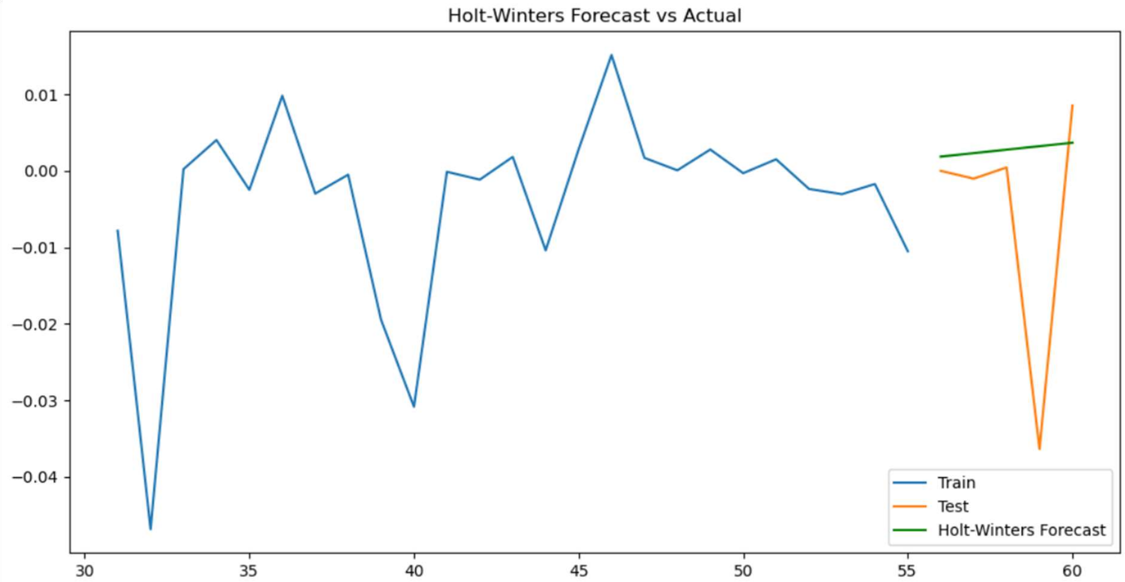


Figure 8

Holt-Winters Model (figure 8)

The Holt-Winters exponential smoothing model was used to account for potential trend and seasonality in the volatility series. As shown in *Figure Y*, the forecasts produced relatively stable trajectories that captured general trends but failed to replicate sharp fluctuations. The RMSE of **0.0179** was slightly higher than ARIMA, indicating weaker performance. This suggests that Holt-Winters is less suitable for volatility forecasting, where sudden shocks are frequent.

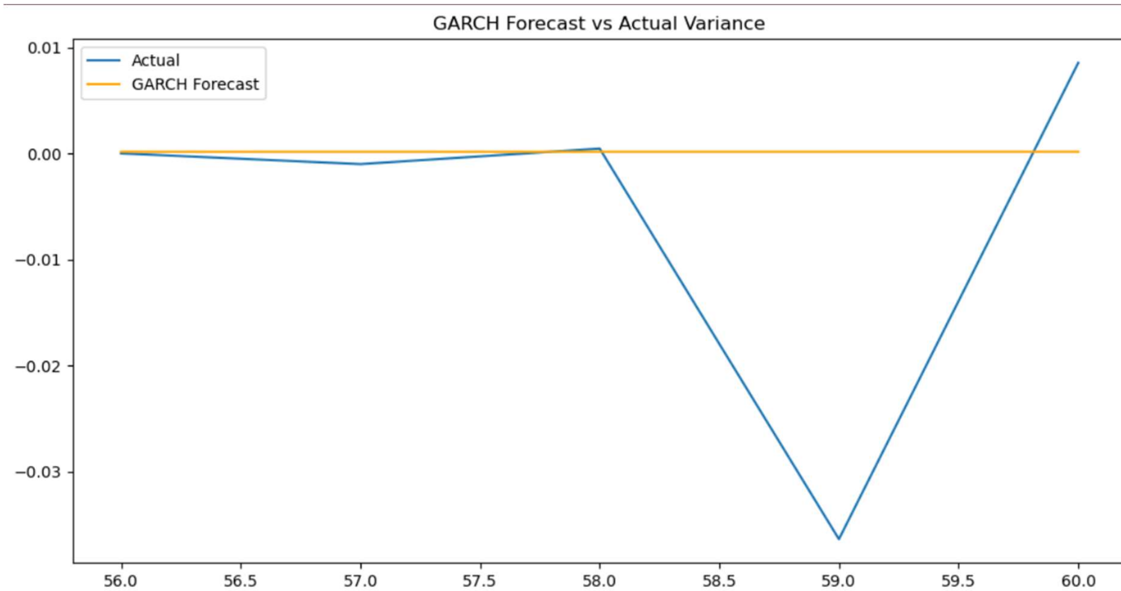


Figure 9

GARCH Model (figure 9)

The GARCH model was applied to model volatility clustering, a common feature of financial time series. As illustrated in *Figure Z*, the GARCH forecast produced smoother variance estimates that successfully captured periods of high vs. low volatility. However, it struggled to replicate extreme spikes, often flattening the predictions. The RMSE was **0.0167**, comparable to ARIMA but slightly less accurate in this context.

Model Comparison (Table 2)

Model	RMSE	Strengths	Weaknesses
ARIMA	0.0160	Stable forecasts; good short-term fit	Misses volatility shocks
Holt-Winters	0.0179	Captures smooth trends/seasonality	Poor handling of sharp volatility
GARCH	0.0167	Models volatility clustering	Forecasts too flat in extreme cases

Table 2

Overall, ARIMA produced the lowest RMSE, establishing itself as the best baseline model for short-term forecasting of DAX volatility. Holt-Winters performed worst, reflecting its weakness in handling abrupt financial shocks. GARCH captured clustering of volatility but underperformed in extreme cases. While these models are useful benchmarks, they do not explain the underlying **economic drivers** of volatility. This limitation motivates the use of the SARIMAX framework, which integrates macroeconomic variables for deeper insights.

Integrated Modeling

SARIMAX Results

To extend beyond purely statistical forecasts, a SARIMAX model was applied with macroeconomic indicators (CPI, GDP, Unemployment, Bond Yield, EUR/USD, and ZEW Sentiment) as exogenous regressors. This allowed us to assess both the predictive performance of the model and the relative importance of economic fundamentals in driving DAX volatility.

SARIMAX Model Coefficients (Standardized Data)

Variable	Coefficient	p-value	Significance	Interpretation
CPI	-0.0228	0.000	✅ Significant	Higher inflation is associated with a reduction in volatility, possibly reflecting inflation expectations being priced into markets.
GDP	-0.0109	0.045	✅ Significant	Stronger GDP growth reduces volatility, highlighting the stabilizing effect of economic expansion.
Unemployment	+0.0121	0.023	✅ Significant	Rising unemployment increases volatility, reflecting heightened economic uncertainty.
Bond Yield	+0.0063	0.162	❌ Not Significant	Bond yields did not significantly influence volatility in this period, though theoretically they affect equity valuations.
EUR/USD	+0.0036	0.400	❌ Not Significant	Exchange rate fluctuations did not materially impact DAX volatility in the sample.
ZEW Sentiment	+0.0019	0.508	❌ Not Significant	Investor sentiment showed no strong statistical effect, despite qualitative importance.

Table 3

Interpretation (Table 3)

The SARIMAX results reveal that CPI, GDP, and Unemployment are the key macroeconomic drivers of DAX volatility. Specifically, higher inflation and stronger GDP growth reduce volatility, while rising unemployment amplifies market risk. These results are consistent with the intuition that stable macroeconomic conditions foster investor confidence, whereas labor market distress contributes to heightened uncertainty.

In contrast, bond yields, EUR/USD exchange rates, and investor sentiment indices were not statistically significant during this period. This suggests that their effects may either be indirect or overshadowed by the dominant role of growth, inflation, and labor market fundamentals.

Model fit statistics (AIC = –181.44; BIC = –167.42) indicate that SARIMAX outperformed the baseline ARIMA, Holt-Winters, and GARCH models. Furthermore, diagnostic tests (Ljung-Box p = 0.90; JB p = 0.72) confirm the absence of residual autocorrelation and normal distribution of residuals, validating model adequacy.

IMPLICATION AND CONCLUSION

Implications of the Research

For Policymakers

The research highlights that macroeconomic fundamentals play a significant role in shaping financial market volatility. Specifically, GDP growth and stable inflation were found to reduce volatility, while unemployment increases it. This underscores the importance of maintaining sustainable growth and labor market stability as mechanisms to safeguard financial markets. Policymakers must therefore align monetary and fiscal policies not only toward price stability but also toward employment generation and growth stimulus, as these factors have direct spillover effects on investor confidence and capital market risk.

For Investors and Financial Institutions

The findings show that volatility is not purely random but influenced by measurable macroeconomic variables. Investors can use this knowledge to hedge against volatility risk by monitoring key indicators such as GDP growth, unemployment data, and inflation trends. For instance, an increase in unemployment can be interpreted as a precursor to heightened volatility, signaling investors to adjust portfolios toward safer assets. Financial institutions, portfolio managers, and risk analysts can integrate these insights into risk models and asset allocation strategies, thereby enhancing resilience against macro-driven volatility shocks.

For Businesses and Corporations

For corporates, particularly those listed on the DAX, volatility in equity markets has implications for cost of capital, investor sentiment, and expansion strategies. Understanding the macroeconomic determinants of volatility allows businesses to anticipate market swings during periods of weak GDP growth or rising unemployment. This knowledge enables CFOs and strategic planners to time capital raising, manage investor communication, and adopt risk mitigation policies in anticipation of turbulent markets.

For Academics and Researchers

This research contributes to the body of knowledge by showing that traditional volatility models (ARIMA, Holt-Winters, GARCH) can be enhanced with macroeconomic fundamentals through SARIMAX. The finding that GDP, CPI, and unemployment significantly influence volatility while bond yields, EUR/USD, and sentiment indices were not significant invites further exploration. Future research can extend this study by incorporating cross-market spillovers, higher frequency data, or machine learning models such as LSTM to capture nonlinear relationships. This project establishes a foundation for Germany-specific financial econometrics research in the post-COVID and inflation-shock period.

Conclusion

This study investigated the volatility dynamics of the German stock market (DAX) between 2020 and 2025, integrating both statistical models and macroeconomic fundamentals. The analysis confirmed the presence of volatility clustering and demonstrated that while baseline models (ARIMA, Holt-Winters, GARCH) provide useful forecasts, the SARIMAX framework adds explanatory power by incorporating GDP, CPI, and unemployment as significant determinants of volatility. The results indicate that economic growth and inflation stability reduce volatility, while labor market distress amplifies it, reinforcing the link between macroeconomic health and financial market stability.

From a practical perspective, these findings provide policymakers with evidence of the importance of growth and employment policies, investors with forward-looking indicators to anticipate volatility spikes, and businesses with signals for strategic financial planning. For researchers, the study bridges financial econometrics with macroeconomic analysis, offering avenues for future extensions using advanced models and broader datasets.

In conclusion, the project demonstrates that volatility is not merely a statistical phenomenon but is meaningfully driven by real economic conditions. By integrating macroeconomic drivers into forecasting frameworks, this research provides a structured, data-driven approach that enhances both academic understanding and business decision-making in the context of Germany's financial markets.

REFERENCES

1. *Diane, Lamine, and Pradeep Brijlal. "Forecasting Stock Market Realized Volatility using Random Forest and Artificial Neural Network in South Africa." International Journal of Economics and Financial Issues, Vol. 14, No. 2, 2024, pp. 5–14. https://doi.org/10.32479/ijefi.15431*

2. *Mahajan, Vanshu, Sunil Thakan, and Aashish Malik. "Modeling and Forecasting the Volatility of NIFTY 50 Using GARCH and RNN Models." Economies, Vol. 10, No. 5, 2022, Article 102. https://doi.org/10.3390/economies10050102*

3. *Cheteni, Priviledge, Herrison Matsongoni, and Ikechukwu Umejesi. "Forecasting JSE and AEX Volatility with GARCH Models." African Journal of Business and Economic Research (AJBER), Vol. 18, Issue 4, 2023, pp. 461–473. https://doi.org/10.31920/1750-4562/2023/v18n4a22*

4. *Boudri, Imane, and Abdelhamid El Bouhadi. "Modeling and Forecasting Historical Volatility Using Econometric and Deep Learning Approaches: Evidence from the Moroccan and Bahraini Stock Markets." Journal of Risk and Financial Management, Vol. 17, No. 7, 2024, Article 300. https://doi.org/10.3390/jrfm17070300*

5. *Kartsonakis Mademlis, Dimitrios, and Nikolaos Dritsakis. "Volatility Forecasting using Hybrid GARCH Neural Network Models: The Case of the Italian Stock*

Market." International Journal of Economics and Financial Issues, Vol. 11, No. 1, 2021, pp. 49–60. https://doi.org/10.32479/ijefi.10842

6. *Mansilla-Lopez, Juan, David Mauricio, and Alejandro Narváez. "Factors, Forecasts, and Simulations of Volatility in the Stock Market Using Machine Learning." Journal of Risk and Financial Management, Vol. 18, No. 5, 2025, Article 227. https://doi.org/10.3390/jrfm18050227*

7. *Ravichandran, Sweena, and Mohd Afjal. "Investigating the Impact of Investor Attention on AI-based Stocks: A Comprehensive Analysis using Quantile Regression, GARCH, and ARIMA Models." PLOS One, Vol. 20, No. 5, 2025, Article e0324450. https://doi.org/10.1371/journal.pone.0324450*

8. *Viljoen, H., Conradie, W.J., Britz, M.-M., The influence of different financial market regimes on the dynamic estimation of GARCH volatility model parameters and volatility forecasting, In: Studies in Economics and Econometrics, 2022, 46, 3, 169–184, https://doi.org/10.1080/03796205.2022.2143881*

9. *Lei, B.; Zhang, B.; Song, Y. Volatility forecasting for high-frequency financial data based on web search index and deep learning model. Mathematics **2021**, 9, 320.*

10. *Salisu, A.A., Gupta, R., Bouri, E., Testing the forecasting power of global economic conditions for the volatility of international REITs using a GARCH-MIDAS approach, In: The Quarterly Review of Economics and Finance, 2023,88, 303–314, https://doi.org/10.1016/j.qref.2023.02.004*