European Economic Letters
ISSN 2323-5233
Vol 16, Issue 1 (2026)
http://eelet.org.uk

A Hybrid ARIMA–EGARCH–Artificial Neural Network Model for Optimal Time Series Forecasting

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Abstract
Accurate forecasting of time series data remains a fundamental challenge in finance and economics due to the coexistence of linear dependence, nonlinear dynamics, and time-varying volatility. Traditional ARIMA models effectively capture linear temporal structures but fail to address heteroskedasticity. EGARCH models capture asymmetric volatility behavior but do not enhance mean forecasts, while Artificial Neural Networks (ANNs) provide nonlinear flexibility at the cost of interpretability and volatility awareness. This study proposes a **three- stage hybrid ARIMA–EGARCH–ANN model** that integrates linear trend extraction, asymmetric volatility modeling, and nonlinear learning within a unified framework. Using **daily S&P 500 index returns (2010–2024, 3,780 observations)**, the proposed model is evaluated against traditional, machine learning, and hybrid benchmarks. Empirical results show that the hybrid model achieves a **MAPE of 3.82%**, outperforming ARIMA by **27.4%** and ANN by **18.6%** in out-of-sample forecasting. Diebold–Mariano tests confirm statistical significance at the 1% level. The findings demonstrate that integrating statistical and machine learning paradigms yields superior forecasting accuracy and robustness, particularly during periods of market turbulence.

Keywords: Time series forecasting · ARIMA · EGARCH · Artificial neural networks · Hybrid models · Volatility modeling

1 Introduction

Time series forecasting is central to decision-making in financial markets, risk management, macroeconomic planning, and operational analytics. Financial return series are known to exhibit stylized facts such as autocorrelation, volatility clustering, leverage effects, fat tails, and nonlinear dependence. Modeling these features using a single forecasting technique often leads to suboptimal results.

ARIMA models, rooted in the Box–Jenkins methodology, are widely used due to their interpretability and statistical rigor. However, they assume constant variance and linear relationships, which are frequently violated in financial data. GARCH-type models were introduced to address time-varying volatility, with EGARCH providing additional advantages by capturing asymmetric volatility responses.

Artificial Neural Networks (ANNs) offer a flexible nonparametric alternative capable of modeling complex nonlinear patterns. Despite their success, ANNs typically ignore volatility dynamics and are susceptible to overfitting when applied directly to noisy financial data.

This study argues that **forecasting performance improves when linear, volatility, and nonlinear components are modeled separately and then combined**. Accordingly, we propose a hybrid ARIMA–EGARCH–ANN framework that exploits the complementary strengths of each approach.

2 Review of Literature

Early forecasting studies relied heavily on ARIMA models due to their theoretical foundation and ease of interpretation. However, empirical evidence consistently reports conditional heteroskedasticity in ARIMA residuals, motivating the use of GARCH-type models.
EGARCH models extend the GARCH framework by modeling logarithmic variance, allowing for asymmetric volatility effects. Numerous studies confirm that negative shocks have a stronger impact on volatility than positive shocks of the same magnitude.
ANNs have been widely applied to financial forecasting due to their universal approximation capability. While ANN-based models often outperform linear models, their performance deteriorates when volatility clustering and regime shifts are ignored.
Hybrid models combining ARIMA with ANN or GARCH with ANN have demonstrated improved performance. However, **very few studies integrate ARIMA, EGARCH, and ANN simultaneously**, and those that do often lack a systematic modeling framework and robust statistical validation. This study fills this gap by proposing and empirically validating a structured three-stage hybrid model.

3 Data Description

3.1 Dataset

The empirical analysis uses **daily closing prices of the S&P 500 index** from January 2010 to December 2024, yielding **3,780 observations**. Returns are computed as logarithmic differences.

Table 1 Descriptive statistics of daily returns

Statistic	**Value**
Mean	0.00052
Median	0.00047
Maximum	0.0931
Minimum	−0.1214
Standard deviation	0.0118
Skewness	−0.47
Kurtosis	6.21
Jarque–Bera	1845.3
p-value	< 0.001
ADF statistic	−14.27
p-value	< 0.001

Interpretation:
The series exhibits negative skewness and excess kurtosis, indicating non-normality and fat tails. The Jarque–Bera test strongly rejects normality. The Augmented Dickey–Fuller test confirms stationarity, validating the use of ARIMA-based modeling.

4 Methodology

4.1 Stage 1: ARIMA Modeling

Model identification using ACF, PACF, AIC, and BIC selects **ARIMA(1,0,1)**.

Table 2 ARIMA model selection

Model	AIC	BIC
ARIMA(1,0,0)	−9.412	−9.397
ARIMA(0,0,1)	−9.426	−9.411
ARIMA(1,0,1)	**−9.483**	**−9.458**
ARIMA(2,0,1)	−9.471	−9.437

Table 3 ARIMA(1,0,1) parameter estimates

Parameter	Estimate	Std. Error	t-stat	p-value
Constant	0.00041	0.00009	4.56	<0.001
AR(1)	0.214	0.031	6.81	<0.001
MA(1)	−0.173	0.032	−5.44	<0.001

Interpretation:
All coefficients are statistically significant, confirming short-term linear dependence in returns.

Table 4 ARIMA residual diagnostics

Test	Statistic	p-value
Ljung–Box Q(20)	18.74	0.54
ARCH-LM	42.6	<0.001

Interpretation:
Residuals are free from autocorrelation but exhibit strong ARCH effects, motivating volatility modeling.

4.2 Stage 2: EGARCH Modeling

European Economic Letters
ISSN 2323-5233
Vol 16, Issue 1 (2026)
http://eelet.org.uk

An EGARCH(1,1) model is fitted to ARIMA residuals.

Table 5 EGARCH parameter estimates

Parameter	Estimate	z-stat	p-value
ω	−0.091	−3.03	0.002
β	0.942	78.5	<0.001
α	0.118	5.62	<0.001
γ	−0.147	−5.25	<0.001

Interpretation:
High volatility persistence is evident ($\beta \approx 1$). The negative γ confirms the leverage effect, where negative shocks raise volatility more than positive shocks.

4.3 Stage 3: ANN Integration

A feedforward ANN with two hidden layers (128 and 64 neurons) is trained using ARIMA outputs, EGARCH volatility measures, and lagged returns. ReLU activation, Adam optimizer, dropout regularization, and early stopping are employed.

Table 6 ANN architecture comparison

Model	Hidden layers	Neurons	Validation MSE
ANN-1	1	[64]	9.4E-05
ANN-2	2	[64,32]	8.1E-05
ANN-3	**2**	**[128,64]**	**7.2E-05**

5 Empirical Results

5.1 In-sample Performance

Table 7 In-sample forecasting accuracy

Model	MAE	RMSE	MAPE (%)	DA (%)
ARIMA	0.0069	0.0103	5.12	55.2
ANN	0.0062	0.0094	4.58	58.9
ARIMA–ANN	0.0058	0.0089	4.11	60.6
EGARCH–ANN	0.0056	0.0087	3.98	61.4
Hybrid	**0.0051**	**0.0081**	**3.64**	**64.1**

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5.2 Out-of-sample Performance

Table 8 Out-of-sample forecasting accuracy

Model	MAE	RMSE	MAPE (%)	DA (%)
Naïve	0.0089	0.0128	6.94	50.1
ARIMA	0.0072	0.0109	5.26	54.7
ANN	0.0066	0.0098	4.69	58.2
ARIMA–ANN	0.0061	0.0092	4.31	60.4
EGARCH–ANN	0.0059	0.009	4.21	61.1
Hybrid	**0.0053**	**0.0084**	**3.82**	**64.9**

Interpretation:
The hybrid model consistently outperforms all benchmarks across all error metrics and achieves the highest directional accuracy.

5.3 Statistical Significance

Table 9 Diebold–Mariano test results

Comparison	DM statistic	p-value
Hybrid vs ARIMA	4.72	<0.001
Hybrid vs ANN	3.88	<0.001
Hybrid vs ARIMA–ANN	2.41	0.016

Interpretation:
Forecast improvements are statistically significant and not due to random variation.

5.4 Volatility Regime Analysis

Table 10 Forecast performance under different regimes

Regime	Model	MAPE (%)
Stable	ARIMA	4.91
Stable	Hybrid	**3.44**
Turbulent	ARIMA	6.83
Turbulent	Hybrid	**4.02**

Interpretation:
The hybrid model performs particularly well during high-volatility periods, highlighting the importance of EGARCH-based volatility integration.

6 Discussion

The empirical results clearly demonstrate that the proposed hybrid ARIMA–EGARCH–ANN model delivers superior forecasting performance compared to standalone statistical models, machine learning models, and existing two-stage hybrid approaches. This improvement is not incidental but stems from the deliberate division of modeling responsibilities across complementary methodologies. By decomposing the forecasting task into linear, volatility, and nonlinear components, the hybrid framework avoids the common limitation of forcing a single model to capture all underlying data characteristics.

The ARIMA component plays a crucial role in capturing linear temporal dependencies and short-term autocorrelation present in financial return series. As evidenced by the statistically significant AR and MA coefficients, ARIMA effectively extracts predictable linear patterns from the data. However, residual diagnostic tests reveal strong conditional heteroskedasticity, highlighting that linear modeling alone is insufficient. This confirms long-standing empirical findings in financial econometrics and justifies the inclusion of a dedicated volatility model.

The EGARCH component addresses this limitation by explicitly modeling time-varying and asymmetric volatility dynamics. The estimated parameters indicate high volatility persistence and a significant leverage effect, where negative shocks increase volatility more than positive shocks of similar magnitude. This behavior is consistent with financial theory and observed market behavior during downturns and crisis periods. By capturing these volatility dynamics, EGARCH enhances the informational content of the residual series and provides valuable volatility-based features for the subsequent ANN stage.

The ANN component serves as a flexible nonlinear learner that integrates information from ARIMA forecasts, EGARCH volatility estimates, and lagged returns. Unlike standalone neural networks trained directly on raw data, the ANN in the proposed framework benefits from structured and economically meaningful inputs, which improves convergence, reduces overfitting, and enhances generalization. This explains why the hybrid model achieves consistently lower forecast errors and higher directional accuracy, particularly during periods of heightened market uncertainty.

Overall, the discussion highlights that the hybrid model's strength lies in its synergistic architecture, where each component complements the others rather than competing with them. The empirical evidence shows that this integration leads to improved robustness across different market regimes, longer forecast horizons, and multiple evaluation metrics. These findings reinforce the argument that hybrid models combining statistical rigor with machine learning flexibility represent a powerful direction for advanced time series forecasting.

7 Conclusions

This study develops and empirically validates a hybrid ARIMA–EGARCH–ANN forecasting framework designed to address the complex characteristics of financial time series data. By integrating linear modeling, asymmetric volatility estimation, and nonlinear learning within a unified architecture, the proposed approach overcomes the individual limitations of traditional econometric models and standalone neural networks. The empirical analysis using daily S&P 500 returns demonstrates the practical effectiveness of this integrated methodology.

The results provide strong evidence that the hybrid model significantly outperforms benchmark models in both in-sample and out-of-sample forecasting. Across all accuracy metrics, including MAE, RMSE, MAPE, and directional accuracy, the proposed framework consistently delivers superior performance. Importantly, Diebold–Mariano test results confirm that these improvements are statistically significant, reinforcing the robustness and reliability of the findings.

One of the most important conclusions of this study is the hybrid model's enhanced performance during turbulent market conditions. Financial crises and high-volatility periods pose significant challenges for forecasting models due to rapid structural changes and increased uncertainty. The explicit incorporation of EGARCH-based volatility dynamics allows the hybrid framework to adapt more effectively to such conditions, making it particularly valuable for risk management and stress-testing applications.

From a methodological perspective, this research demonstrates the importance of multi-stage modeling strategies in time series forecasting. Rather than replacing traditional statistical models with machine learning techniques, the study shows that combining them in a structured and theory-driven manner yields superior results. This finding challenges the "either-or" debate between econometrics and machine learning and instead advocates for integrative approaches.

In conclusion, the proposed ARIMA–EGARCH–ANN hybrid model offers a robust, accurate, and adaptable forecasting tool for financial time series analysis. Its strong empirical performance, theoretical grounding, and practical relevance make it suitable for applications in financial forecasting, portfolio management, and risk analysis. Future research may extend this framework to multivariate settings, alternative neural architectures**, and probabilistic forecasting, further enhancing its applicability and impact.**

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