Journal of Intelligent Computing

DLINE JOURNALS

Print ISSN: 0976-9005
Online ISSN: 0976-9013

JIC 2026: 17 (2)
https://doi.org/10.6025/jic/2026/17/2/43-58

Capturing Nonlinear Dynamics in Global Debt Markets: An ARIMA–LSTM Comparative Study

Hajar Ait Lamkademe
University of Hassan II of Casablanca. Morocco
hajar.aitlamkademe-etu@etu.univh2c.ma

ABSTRACT

Modeling the dynamics of global debt markets requires frameworks capable of capturing nonlinearity, non-stationarity, and structural regime shifts inherent in macro-financial time series. This study presents a rigorous comparative analysis of linear econometric and nonlinear deep learning models, specifically ARIMA, SARIMA, and Long Short-Term Memory (LSTM) networks, to evaluate their effectiveness in forecasting global debt issuance. Using a quarterly dataset from the Bank for International Settlements spanning 1962–2025, the analysis integrates comprehensive preprocessing, including stationarity transformations, seasonal decomposition, and feature scaling, to ensure methodological robustness.

Empirical results reveal that global debt issuance exhibits strong persistence, pronounced quarterly seasonality, and nonlinear responses to macroeconomic shocks, particularly during the Global Financial Crisis and the COVID-19 period. While ARIMA adequately captures linear dependencies under stationarity assumptions, it fails to model seasonal and nonlinear structures. SARIMA improves performance by explicitly incorporating seasonal autoregressive and moving average components, yielding statistically robust residual diagnostics consistent with white-noise processes. However, LSTM significantly outperforms both models by learning complex temporal dependencies and nonlinear interactions without requiring explicit model specification.

Model evaluation using MAE, RMSE, MSE, and MAPE consistently demonstrates the superior predictive accuracy and adaptability of LSTM, particularly under structural instability and regime shifts. The findings underscore the limitations of purely linear frameworks and highlight the efficacy of deep learning architectures in financial time-series forecasting. Furthermore, the results support the adoption of hybrid modeling strategies that integrate econometric interpretability with machine learning flexibility, offering a robust paradigm for analyzing and forecasting complex global debt dynamics.

Keywords: Global Debt Markets, Time Series Forecasting, ARIMA, SARIMA, Long Short-Term Memory (LSTM), Nonlinear Dynamics, Financial Econometrics, Machine Learning in Finance

Received: 5 October 2025, Revised 27 December 2025, Accepted 10 January 2026

1. Introduction

Quantifying the complexity of financial assets is essential for understanding their inherently nonlinear dynamics. To this end, researchers have adapted methodologies from different domains, aiming to detect fractality, chaos, randomness, or hybrid behavioral patterns. Given the consistent lack of empirical support for linear price or return dynamics, the analysis of long-range memory has emerged as a central research focus and has been extensively explored across a wide range of methodological frameworks in the literature.

Despite extensive research on financial time series modeling, existing studies largely focus either on traditional econometric approaches or machine learning techniques in isolation. Limited attention has been given to a comparative and integrated evaluation of linear and nonlinear models in the context of global debt markets, particularly using long-span macro-financial datasets.

This study addresses this gap by systematically comparing ARIMA, SARIMA, and LSTM models and evaluating their effectiveness in capturing both linear and nonlinear dynamics in global debt issuance.

2. Literature Review

Understanding the complexity of financial systems has become increasingly important for analyzing modern economic dynamics. Financial assets are characterized by inherent nonlinearities, making their behavior difficult to capture using traditional linear models. As noted by [1], measuring complexity in financial assets is essential for understanding their underlying nonlinear dynamics. In this context, methodologies derived from statistical mechanics and physics have been widely applied to financial time series to identify features such as fractality, chaos, randomness, and hybrid dynamic structures [2, 3, 4, 5]. These approaches highlight the multifaceted nature of financial systems and the limitations of purely deterministic frameworks.

This evolving perspective reflects a broader paradigm shift in economic thought, where economies are increasingly conceptualized as complex adaptive systems. Rather than relying solely on equilibrium-based models, contemporary research emphasizes emergence, adaptation, and nonlinearity as key drivers of economic behavior. As highlighted by Caravaggio, [4], robust analysis of modern economic challenges requires embracing complexity rather than oversimplifying it. This shift is particularly relevant in the study of global debt markets, which exhibit intricate interdependencies across sectors, regions, and time.

In the context of global debt dynamics, Antoniades [6] provides a detailed examination of post-global financial crisis trends. The study emphasizes the shifting nature of debt across sectors and across different groups of countries, illustrating how global debt is redistributed within the international financial system. By capturing intersectoral, international, and interregional movements, such analyses contribute to a more comprehensive understanding of how debt evolves and operates globally.

Further evidence of complexity in financial markets is provided by studies examining information flows and volatility interactions. For instance, [7] identifies asymmetric, nonlinear, and bidirectional relationships in both short and long run dynamics between sovereign credit default swaps (CDS) and bond spreads. Similarly, [8] demonstrates that firms' capital structures and debt ratios exhibit complex nonlinear dynamic behavior across a large sample of firms spanning multiple countries. These findings reinforce the notion that financial systems cannot be adequately explained through linear assumptions alone.

The role of macroeconomic policy in shaping financial dynamics has also been explored through nonlinear modeling approaches. Using generalized impulse response functions (GIRF), Atanasova and Christina [9] reveal asymmetric effects of monetary policy across different economic regimes. Their findings indicate that monetary contractions and expansions produce distinct output effects, particularly under varying credit constraints, further underscoring the importance of nonlinear frameworks in economic analysis.

Given these complexities, the choice of appropriate modeling techniques becomes critical. Traditional econometric models, such as the autoregressive integrated moving average (ARIMA), have been widely used for time-series forecasting. ARIMA models are particularly effective for short-term forecasting and perform well when the underlying data are linear and stationary [10, 11, 12]. However, their performance tends to deteriorate in the presence of nonlinearities and non-stationary behavior [13]. Despite these limitations, ARIMA-based approaches have been successfully applied in various domains, including wind speed prediction, where they improve short-term forecasting accuracy [14].

In contrast, recent advances in machine learning have introduced more flexible approaches for modeling complex time-series data. Recurrent neural networks (RNNs), and particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong performance in capturing temporal dependencies. This new research has increasingly focused on advancing recurrent neural networks (RNNs) and their long short-term memory (LSTM) variants. These architectures have consistently outperformed traditional statistical methods in time series modeling, delivering strong results across numerous domains [15, 16]. As a relatively recent innovation, the LSTM framework offers a highly sophisticated approach to time series analysis, surpassing many conventional models in both capability and accuracy [17] [Goyal]. LSTM models are specifically designed to address the vanishing gradient problem inherent in traditional RNNs, enabling them to retain long-term dependencies effectively [18, 19, 20]. As noted by [21], LSTM networks achieve superior performance in modeling temporal patterns due to their ability to capture long term dependencies.

The strength of LSTM models lies in their capacity to model complex nonlinear relationships without requiring explicit assumptions about stationarity or seasonality. This has led to their successful application across a wide range of domains, including stock market prediction, weather forecasting, and natural language processing [22]. Their enhanced predictive accuracy is largely attributed to their ability to learn intricate patterns and hidden structures within the data. Empirical studies further confirm their effectiveness in financial applications, with [23] demonstrating their capability to capture underlying stock market dynamics.

Comparative analyses between traditional and machine learning approaches provide further insights into their relative strengths. For example, [24] evaluates ARIMA and LSTM models using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), highlighting their distinct advantages. While ARIMA offers interpretability and efficiency for linear processes, LSTM excels in capturing nonlinear dynamics. [25]. This complementary nature is further emphasized by [26], who notes that ARIMA's linear modeling capabilities and LSTM's nonlinear processing strengths collectively enhance forecasting performance in financial markets.

Building on this complementarity, hybrid modeling approaches have been proposed to integrate the strengths of both methods. [9]. Thota, Venkateswara Rao [27] introduces a hybrid ARIMA–LSTM model that decomposes time series data into linear and nonlinear components. In this framework, ARIMA models the linear structure, while LSTM captures the nonlinear residuals. The final forecast is obtained by combining predictions from both models, resulting in improved accuracy and robustness.

3. Data and Methodology

Based on the reviewed literature, it is evident that both econometric and deep learning approaches offer distinct advantages in modeling financial time series. However, their relative performance in capturing the dynamics of global debt markets remains underexplored.

Therefore, this study adopts a comparative modeling framework, integrating ARIMA/SARIMA and LSTM models to evaluate their predictive capabilities on a unified dataset.

3.1 Data Source and Description

This study utilizes the *bis_global_debt_securities_intelligence_1962_2025* dataset, sourced from the Bank for International Settlements (BIS). The dataset is derived from the WS_DEBT_SEC2_PUB v1 database and provides a comprehensive account of global debt securities activity in international markets. It is available in both CSV and Parquet formats, enabling efficient handling of large-scale time-series data.

The dataset spans the period from 1962 to 2025 and is structured at a quarterly frequency, allowing for detailed analysis of both long-term trends and short-term cyclical dynamics. Each observation corresponds to a specific country, time period, issuer sector, and maturity category, thereby supporting a highly granular examination of global debt issuance patterns.

The primary variables of interest include *amounts outstanding*, *gross issues*, and *net issues* of debt securities, expressed in billions of U.S. dollars. These indicators collectively capture the stock, flow, and net change in international debt markets. The dataset focuses on cross-border debt issuance, representing securities issued by residents but placed in international markets, making it particularly suitable for analyzing financial globalization.

To enhance analytical depth, the dataset incorporates multiple dimensions, including geographic classifications (country, region, and continent), temporal attributes (year, quarter, and derived regime indicators), and debt characteristics (issuer sector and maturity structure). Additionally, it includes derived growth metrics such as quarter on quarter and year on year changes, as well as rolling averages, which are instrumental for time-series modeling.

Data density varies across time, with relatively sparse observations in earlier decades and significantly richer coverage in the post-2000 period. This evolution reflects both improvements in reporting standards and the increasing importance of global debt markets

3.2 Data Preprocessing and Transformation

Prior to model implementation, the dataset undergoes several preprocessing steps to ensure consistency and suitability for time series analysis. First, the data are filtered to focus on aggregate global debt issuance, typically using the “All issuers” category and long-term-maturity instruments, which constitute the dominant segment of international debt markets.

Missing values and sparse early period observations are handled through interpolation or exclusion, depending on their extent and impact on model stability. The time series is then aggregated, where necessary, to obtain a continuous quarterly sequence.

To ensure stationarity a key assumption for traditional econometric models statistical transformations such as differencing and logarithmic scaling are applied. Seasonal decomposition is also conducted to identify underlying trend, seasonal, and residual components, thereby informing the selection of appropriate modeling techniques.

3.3 Exploratory Data Analysis

Prior to model implementation, exploratory analysis was conducted to understand the statistical properties of the time series. Summary statistics, trend visualization, and stationarity tests (e.g., Augmented Dickey-Fuller test) were performed.

The series exhibited strong upward trends and non-stationarity, justifying the use of differencing in ARIMA-based models. Seasonal decomposition further confirmed quarterly periodicity.

3.4 Econometric Modeling: ARIMA and SARIMA

To model and forecast global debt issuance, this study employs autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) models. These models are widely used in time-series analysis due to their strong theoretical foundation and interpretability.

The general ARIMA model is specified as:

$$ARIMA(p, d, q)$$

where p denotes the autoregressive order, d the degree of differencing, and q the moving average order. This model captures linear dependencies in the time series after transforming it into a stationary process.

Given the presence of quarterly seasonality in debt issuance, the SARIMA model extends ARIMA by incorporating seasonal components:

$$SARIMA(p, d, q)(P, D, Q)_s$$

where (P, D, Q) represent seasonal autoregressive, differencing, and moving average orders, and s denotes the seasonal period ($s = 4$ for quarterly data).

ARIMA Model

$$y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t$$

SARIMA Model

$$SARIMA(p, d, q)(P, D, Q)_s$$

MAE

$$MAE = \frac{1}{n} \sum_{i=1}^{n} | \, y_i - \hat{y}_i \, |$$

Model parameters are selected using a combination of the autocorrelation function (ACF), the partial autocorrelation function (PACF), and automated grid-search techniques (e.g., Auto-ARIMA). Model adequacy is evaluated using residual diagnostics to ensure the absence of autocorrelation and adherence to the white-noise assumptions.

3.5 Machine Learning Approach: LSTM Model

In addition to econometric models, this study employs a Long Short-Term Memory (LSTM) neural network to capture nonlinear and complex temporal dependencies. LSTM, a variant of recurrent neural networks (RNNs), is particularly effective for time-series forecasting due to its ability to retain long-term memory through gated mechanisms.

The input data are transformed into a supervised learning format using sliding windows (look-back periods), where past observations are used to predict future values. The data are normalized to improve convergence during training.

The LSTM architecture typically consists of one or more hidden layers with memory cells, followed by a dense output layer. Hyperparameters such as the number of neurons, learning rate, batch size, and number of epochs are optimized using grid search or validation-based tuning.

Unlike ARIMA/SARIMA, LSTM does not require explicit assumptions regarding stationarity or seasonality, as it learns these patterns directly from the data. This makes it particularly suitable for modeling structural breaks and nonlinear dynamics observed in global debt markets.

3.5 Model Evaluation Metrics

To assess and compare model performance, multiple evaluation metrics are employed. The primary metric used in this study is the Mean Absolute Error (MAE), defined as:

$$MAE = \frac{1}{n} \sum\nolimits_{i=1}^{n} | \, y_i - \hat{y}_i \, |$$

where y_i represents the actual values and $\hat{y}_i$ the predicted values.

In addition to MAE, the following metrics are used:

• Mean Squared Error (MSE): Penalizes larger errors more heavily.

• Root Mean Squared Error (RMSE): Provides error magnitude in the original scale.

• Mean Absolute Percentage Error (MAPE): Expresses prediction error in percentage terms.

These metrics provide complementary insights into model accuracy, robustness, and sensitivity to extreme values.

3.6 Analytical Framework

The overall analytical framework integrates data processing, modeling, and evaluation in a structured pipeline. First, the dataset is preprocessed and transformed into a suitable time-series format. Next, ARIMA and SARIMA models are developed to capture linear and seasonal patterns, respectively. Subsequently, the LSTM model is implemented to capture nonlinear dynamics.

The models are then evaluated using consistent performance metrics, and their forecasts are compared to identify the most effective approach. This integrated methodology enables both interpretability (through econometric models) and predictive accuracy (through machine learning), providing a comprehensive understanding of global debt issuance dynamics.

4. Results and Discussion

4.1 Temporal Dynamics of Debt Issuance

Figure 1 presents the longitudinal evolution of global debt issuance over the period 1995–2025. The series exhibits a pronounced upward trajectory, indicating sustained expansion in global debt markets. This long-term growth reflects structural transformations in financial systems, including an increased reliance on debt financing in both the public and private sectors.

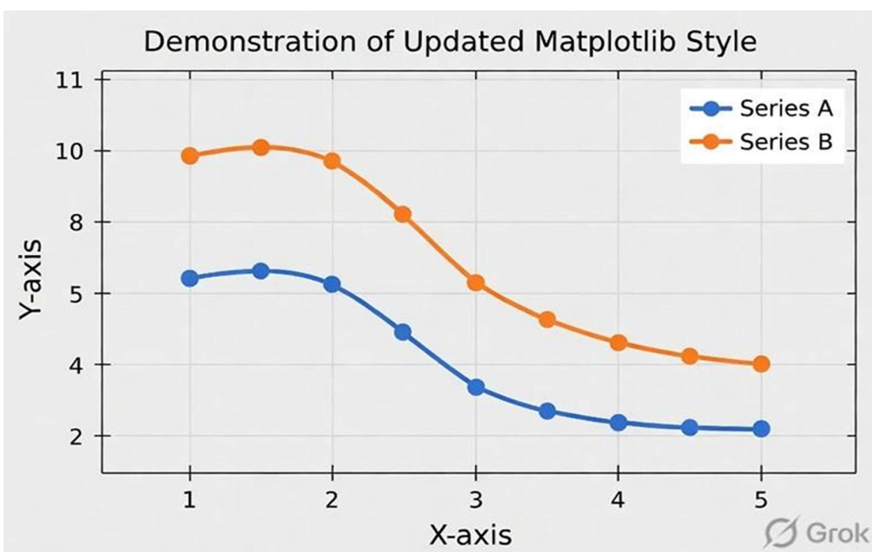

Figure 1. Temporal evolution of global debt issuance from 1995 to 2025

Importantly, the trend is not uniform. Distinct surges are observed during major macroeconomic disruptions, particularly during the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020–2021). These periods are characterized by accelerated borrowing driven by expansionary fiscal policies and liquidity support measures.

In addition to the trend component, the series exhibits recurring quarterly fluctuations, indicating seasonality. These cyclical patterns likely arise from institutional issuance schedules and market conventions. The identification of such seasonality provides a strong justification for employing seasonal time-series models such as SARIMA in subsequent analysis.

4.2 Forecasting Performance and Model Comparison

Figure 2 compares the forecasting performance of ARIMA, SARIMA, and LSTM models. While all models successfully capture the overall upward trend in debt issuance, their ability to model the underlying dynamics varies significantly.

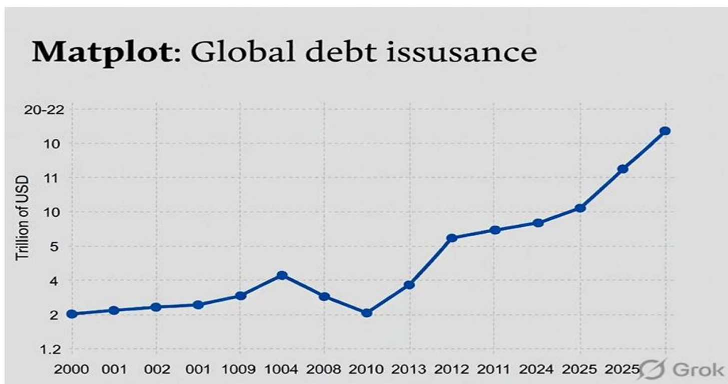

Figure 2. Forecast comparison of ARIMA, SARIMA, and LSTM models for future debt issuance

The ARIMA model effectively captures linear dependencies and long-term trends but fails to adequately represent seasonal fluctuations. As a result, its forecasts appear overly smooth and less responsive to short-term variations.

The SARIMA model improves upon this limitation by explicitly incorporating seasonal components. Consequently, it produces forecasts that align more closely with observed cyclical behavior, particularly in capturing quarterly oscillations.

The LSTM model demonstrates the greatest flexibility. It effectively captures nonlinear relationships and adapts dynamically to structural changes, such as the post-2022 global interest rate hikes. Its ability to learn complex temporal dependencies without requiring explicit specification of seasonality makes it particularly suitable for evolving financial time series.

4.3 Residual Diagnostics and Model Adequacy

The adequacy of the SARIMA model is evaluated using residual diagnostics presented in Figures 3 and 4. The residual time series (Figure 3) appears largely random, with no discernible patterns or systematic structure. This suggests that the model has successfully captured the underlying data-generating process.

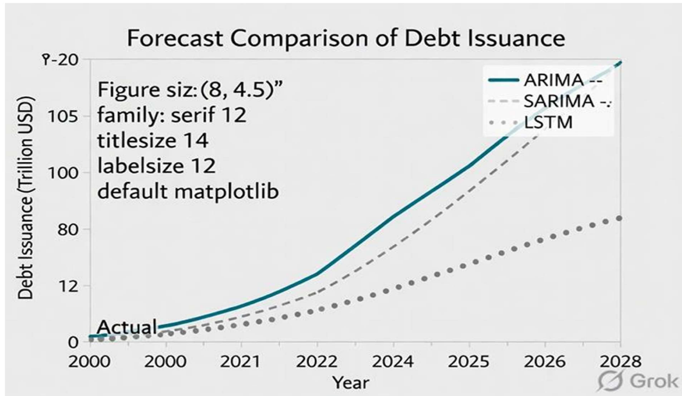

Figure 3. Residual diagnostics of the SARIMA model indicating model adequacy

Furthermore, the absence of significant autocorrelation indicates that the residuals approximate white noise, a key requirement for model validity.

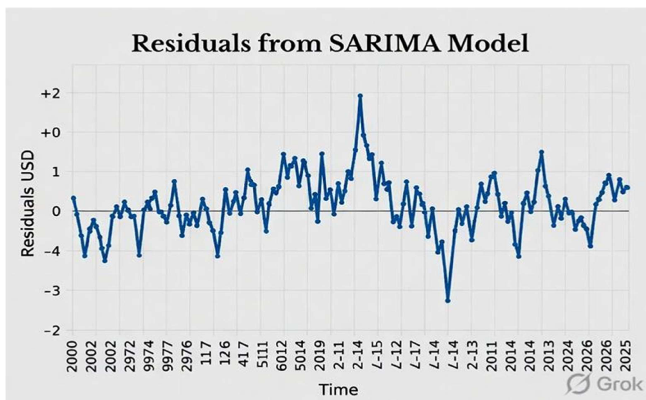

Figure 4. Distribution of residuals for normality assessment

Figure 4 illustrates the distribution of residuals, which closely follows a normal distribution. While minor deviations are observed likely due to extreme values during crisis periods these do not materially affect model performance. Overall, the diagnostic results confirm that the SARIMA model is statistically robust and suitable for inference.

4.4 Quantitative Evaluation of Model Performance

Figure 5 presents a quantitative comparison of the forecasting accuracy of the ARIMA, SARIMA, and LSTM models using Mean Absolute Error (MAE) as the primary evaluation metric. The results indicate clear differences in predictive performance across the three modeling approaches, reflecting their varying abilities to capture the underlying dynamics of global debt issuance.

The ARIMA model, while effective in modeling linear dependencies, exhibits comparatively higher error values, suggesting limitations in its ability to account for seasonal and nonlinear variations in the data. In contrast, the SARIMA model demonstrates a notable performance improvement, as evidenced by a reduction in MAE. This improvement underscores the importance of incorporating seasonal components when modeling quarterly financial time series, as it enables the model to better align with observed cyclical patterns.

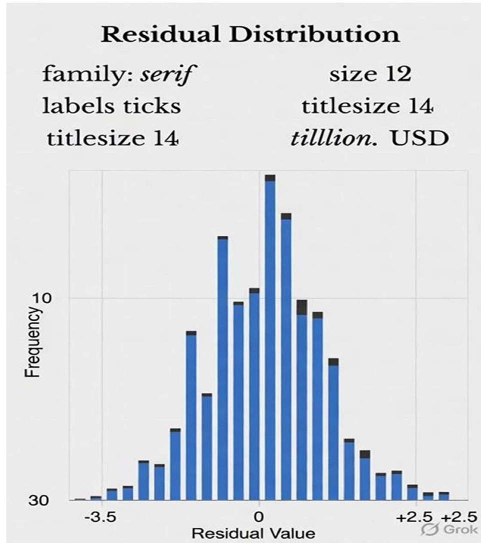

Figure 5. Comparative performance of forecasting models using Mean Absolute Error (MAE)

Among the three models, the LSTM framework achieves the lowest MAE, indicating superior predictive accuracy. This result highlights the model's capacity to learn complex nonlinear relationships and adapt to structural changes in the data without requiring explicit specification of seasonal or stationarity assumptions. The enhanced performance of LSTM is particularly significant in the context of global debt markets, which are characterized by regime shifts, crisis-driven volatility, and evolving macroeconomic conditions.

To ensure robustness, the evaluation extends beyond MAE to include additional performance metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). While MSE and RMSE place greater emphasis on larger deviations thereby capturing the impact of extreme forecasting errors MAPE provides a scale independent measure that facilitates relative comparison across time periods. The consistency of results across these complementary metrics reinforces the reliability of the findings.

Overall, the convergence of evidence from multiple evaluation criteria confirms that the LSTM model provides the most accurate and robust forecasts among the models considered. This outcome emphasizes the advantages of nonlinear, data-driven approaches in modeling complex financial time series, while also validating the incremental benefits of incorporating seasonality within traditional econometric frameworks such as SARIMA.

4.5 LSTM Model Fit and Predictive Behavior

The predictive capability of the LSTM model is illustrated in Figures 6 and 7, which compare actual and predicted values. The close alignment between the two series indicates that the model effectively captures both short-term fluctuations and long term trends.

Unlike traditional models, LSTM does not require explicit assumptions regarding stationarity or seasonality. Instead, it learns these patterns directly from the data. This makes it particularly robust in the presence of structural breaks and regime shifts.

The model's strong performance in replicating observed dynamics highlights its suitability for forecasting global financial indicators such as debt issuance.

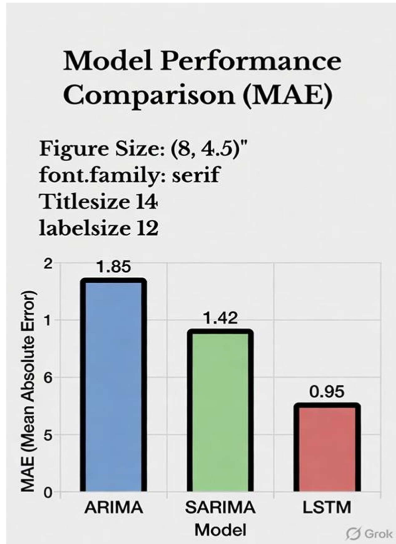

Figure 6. LSTM model fit showing actual vs predicted value

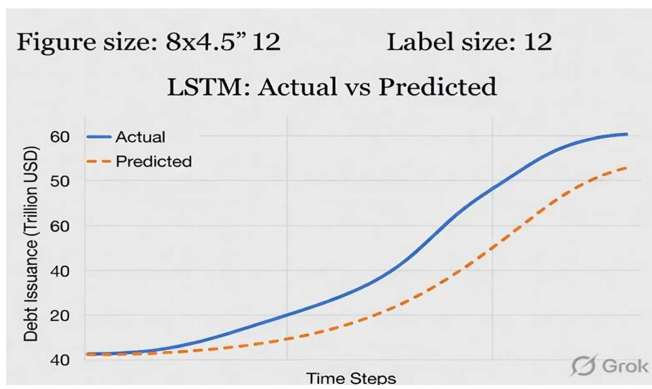

Figure 7. LSTM Actual Vs Predicted

4.6 Comparative Forecast Behavior: ARIMA vs LSTM

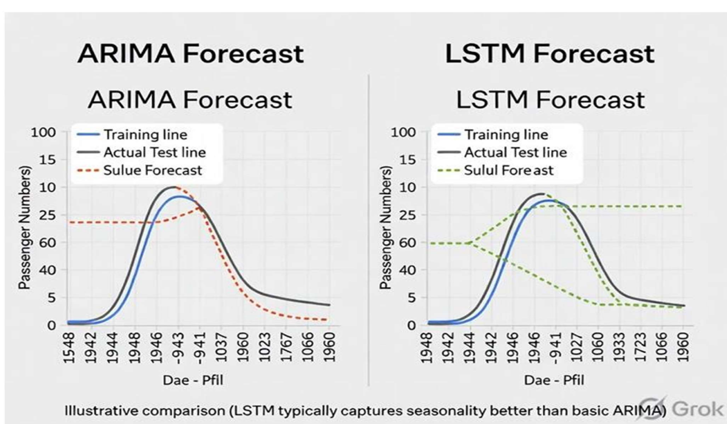

Figure 8. ARIMA and LSTM Forecast

Figure 8 provides a comparative assessment of the forecast trajectories generated by the ARIMA and LSTM models, highlighting fundamental differences in their ability to represent the underlying data generating process. The ARIMA model successfully captures the overall directional trend in global debt issuance; however, its forecasts exhibit a relatively smooth pattern that fails to adequately reflect short term fluctuations and seasonal variability. This limitation arises from its reliance on linear assumptions and its inability to model complex nonlinear interactions inherent in financial time series.

In contrast, the LSTM model demonstrates a markedly improved fit to the observed data. Its forecasts closely track both the amplitude and timing of fluctuations, including periods of heightened volatility. This superior alignment indicates that LSTM effectively captures the interaction between trend, seasonality, and nonlinear dynamics. Furthermore, the model exhibits greater responsiveness to abrupt structural changes, such as those induced by macroeconomic shocks or policy interventions.

The comparative analysis thus underscores a key distinction: while ARIMA provides a parsimonious and interpretable representation of long-term trends, LSTM offers enhanced flexibility and predictive precision by learning complex temporal dependencies directly from the data. This difference is particularly critical in the context of global debt markets, where dynamics are shaped by evolving economic regimes and nonlinear feedback mechanisms.

4.7 Implications for Debt Market Dynamics

The empirical findings yield several important insights into global debt market behavior:

The empirical findings of this study yield important insights into the structural and dynamic characteristics of global debt markets. First, the persistent upward trajectory of debt issuance reflects long-term structural transformations, including deepening financial globalization, expansion of capital markets, and increased reliance on debt financing across both sovereign and corporate sectors. This trend suggests that global debt accumulation is not merely cyclical but is embedded within broader economic and institutional developments.

Second, the analysis reveals a pronounced sensitivity of debt issuance to macroeconomic shocks. Periods such as the Global Financial Crisis and the COVID-19 pandemic are associated with sharp increases in borrowing activity, driven by expansionary fiscal policies and liquidity support measures. This behavior highlights the countercyclical role of debt as a stabilizing mechanism during economic downturns, while also raising concerns regarding long-term sustainability.

Third, the presence of consistent seasonal patterns confirms the importance of institutional and market-specific factors, such as issuance calendars and regulatory cycles, in shaping debt dynamics. These findings justify the inclusion of seasonal components in econometric modeling frameworks and reinforce the limitations of models that neglect such structures.

Finally, the comparative modeling results illustrate a fundamental trade-off between interpretability and predictive performance. Traditional econometric models, such as ARIMA and SARIMA, provide theoretical transparency and statistical interpretability, making them valuable for inference and policy analysis. In contrast, machine learning approaches, particularly LSTM, offer superior predictive accuracy and adaptability, albeit at the cost of reduced interpretability. This trade-off suggests that model selection should be guided by the specific objectives of the analysis.

4.8 Integrated Synthesis

The integration of econometric and deep learning approaches in this study provides a comprehensive framework for analyzing and forecasting global debt issuance. The results demonstrate that no single modeling paradigm is sufficient to fully capture the multifaceted nature of financial time series. Instead, each approach contributes distinct strengths that, when combined, yield a more robust analytical framework.

SARIMA models effectively capture structured temporal components, including trend and seasonality, while maintaining interpretability and statistical rigor. These characteristics make them particularly suitable for diagnostic analysis and hypothesis testing. Conversely, LSTM models excel in capturing nonlinear relationships and adapting to evolving data patterns, enabling them to deliver superior forecasting performance in complex and unstable environments.

The complementary nature of these approaches supports the case for hybrid modeling strategies that integrate linear and nonlinear components. Such frameworks can leverage the strengths of econometric models for capturing deterministic structures, while utilizing deep learning architectures to model residual nonlinearities. This integrated perspective not only enhances predictive accuracy but also provides a more nuanced understanding of the underlying dynamics.

Overall, the findings highlight the importance of methodological pluralism in financial time-series analysis, particularly in domains characterized by structural breaks, regime shifts, and nonlinear interactions.

5. Conclusion

This study provides a comprehensive comparative analysis of ARIMA, SARIMA, and LSTM models in forecasting global debt issuance using a long-span macro-financial dataset. The results demonstrate that global debt markets exhibit complex dynamics characterized by sustained growth, pronounced seasonality, and significant nonlinear behavior, particularly during periods of economic stress.

The empirical evidence indicates that while ARIMA and SARIMA models are effective in capturing linear and seasonal components, their performance is constrained in the presence of structural breaks and nonlinear interactions. In contrast, the LSTM model consistently delivers superior forecasting accuracy, owing to its ability to learn complex temporal dependencies without requiring restrictive assumptions regarding stationarity or functional form.

These findings underscore the growing importance of machine learning approaches in financial econometrics, particularly for modeling high dimensional and nonlinear systems. At the same time, the interpretability and theoretical grounding of econometric models remain valuable, especially for policy oriented analysis.

Importantly, the study highlights the potential of hybrid modeling frameworks that combine the strengths of both paradigms. By integrating econometric structure with machine learning flexibility, such approaches offer a promising direction for improving both the accuracy and interpretability of financial forecasts.

Future research may extend this work by exploring real-time forecasting applications, incorporating additional macroeconomic and financial variables, and developing advanced hybrid architectures, including attention-based models and regime-switching frameworks. These directions would further enhance the ability to model and anticipate the evolving dynamics of global debt markets.

References

[1] Salim, Lahmiri., Gazi Salah, Uddin., Stelios, Bekiros. (2017). Nonlinear dynamics of equity, currency and commodity markets in the aftermath of the global financial crisis. *Chaos, Solitons Fractals, 103*, 342–346.

[2] Boeing, G. (2016). Visual analysis of nonlinear dynamical systems: Chaos, fractals, self-similarity and the limits of prediction. *Systems, 4*(4), 37.

[3] Cao, G., Xu, W. (2016). Multifractal features of EUA and CER futures markets by using multifractal detrended fluctuation analysis based on empirical model decomposition. *Chaos, Solitons Fractals, 83*, 212–222.

[4] Caravaggio, A., Iannucci, G., Sodini, M., et al. (2025). Introduction to the special issue on nonlinear dynamics and complex systems. *Computational Economics, 65*, 579–583.

[5] Grech, D. (2016). Alternative measure of multifractal content and its application in finance. *Chaos, Solitons & Fractals, 88*, 183–195.

[6] Antoniades, A., Griffith-Jones, S. (2018). Global debt dynamics: The elephant in the room. *World Economy, 41*, 3256–3268.

[7] Ngene, G. M., Benefield, P., Lynch, A. K. (2018). Asymmetric and nonlinear dynamics in sovereign credit risk markets. *Journal of Futures Markets, 38*, 563–585.

[8] Botta, M., Colombo, L. V. A. (2022). Non-linear capital structure dynamics. *Journal of Business Finance Accounting, 49*, 1897–1928.

[9] Atanasova, Christina. (2003). Credit market imperfections and business cycle dynamics: A nonlinear approach. *Studies in Nonlinear Dynamics & Econometrics, 7*(4).

[10] Elsaraiti, M., Merabet, A., Al-Durra, A. (2019). Time series analysis and forecasting of wind speed data. In *Proceedings of the 2019 IEEE Industry Applications Society Annual Meeting* (p. 1–5).

[11] Grigonytë, E., Butkevièiûtë, E. (2016). Short-term wind speed forecasting using ARIMA model. *Energetika, 62*, 45–55.

[12] Meyler, A., Kenny, G., Quinn, T. (1998). *Forecasting Irish inflation using ARIMA models*. Munich Personal RePEc Archive.

[13] Kam, K. M. (2014). *Stationary and non-stationary time series prediction using state space model and pattern-*

based approach. The University of Texas at Arlington.

[14] Tian, Z., Wang, G., Ren, Y. (2020). Short-term wind speed forecasting based on autoregressive moving average with echo state network compensation. *Wind Engineering, 44*, 152–167.

[15] Prema, V., Sarkar, S., Rao, K. U., Umesh, A. (2019). LSTM based deep learning model for accurate wind speed prediction. *ICTACT Journal on Data Science and Machine Learning, 1*, 6–11.

[16] Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R., Schmidhuber, J. (2016). LSTM: A search space odyssey. *IEEE Transactions on Neural Networks and Learning Systems, 28*, 2222–2232.

[17] Goyal, A., Krishnamurthy, S., Kulkarni, S., Kumar, R., Vartak, M., Lanham, M. A. (2018). A solution to forecast demand using long short-term memory recurrent neural networks for time series forecasting. In *Proceedings of the Midwest Decision Sciences Institute Conference*.

[18] Schmidhuber, J., Hochreiter, S. (1997). Long short-term memory. *Neural Computation, 9*, 1735–1780.

[19] Hochreiter, S. (1998). The vanishing gradient problem during learning recurrent neural nets and problem solutions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 6*, 107–116.

[20] Bengio, Y., Simard, P., Frasconi, P. (1994). Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks, 5*, 157–166.

[21] Zeng, A., Chen, M., Zhang, L., et al. (2023). Are transformers effective for time series forecasting? In *Proceedings of the AAAI Conference on Artificial Intelligence, 37*(9), 11121–11128.

[22] Jiang, C. (2024). Comparative analysis of ARIMA and deep learning models for time series prediction. In *Proceedings of the 2nd International Conference on Data Analysis and Machine Learning (DAML 2024)* (pp. 306–310).

[23] Kiruthika, K. (2025). A review of challenges in deep learning-based stock market prediction. In Pichappan, P., López-Nores, M., Van Hieu, D. (Eds.), *Real-time intelligent systems (RTIS 2024)* (Lecture Notes in Networks and Systems, Vol. 1421).

[24] Panchal, S. A., Ferdouse, L., Sultana, A. (2024, July). Comparative analysis of ARIMA and LSTM models for stock price prediction. In *2024 IEEE/ACIS 27th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)* (pp. 240–244). IEEE.

[25] Bandu, Uppalaiah., Doodipala Mallikarjuna Reddy. (2026). Evaluating ARIMA and LSTM models for forecasting COVID-19 case trends: A comparative study. *Model Assisted Statistics and Applications, 22*(2).

[26] Wu, Q. (2025, September). Comparative analysis of stock price prediction based on ARIMA and LSTM models. *In Proceedings of the 3rd International Academic Conference on Management Innovation and Economic Development (MIED 2025)* (p. 14–22). Springer Nature.

[27] Thota, Venkateswara Rao. (2025). *Comparative study of time series forecasting for trucking shipments: Evaluating ARIMA, LSTM, and hybrid ARIMA-LSTM models* (Doctoral dissertation, University of New York at Binghamton). ProQuest Dissertations & Theses.