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## A PERIODICITY EVIDENCE OF PRICE AND RETURN FORECASTING OF MAJOR TECH STOCKS USING LSTM MODELS

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### Abstract

*This study investigates the predictive performance of long short-term memory (LSTM) neural networks in forecasting stock prices of four major technology companies, including Tesla, Google, Apple, and Amazon, using both daily and weekly datasets. The empirical analysis utilizes historical stock price data spanning from January 1, 2015 to October 31, 2023, covering both training and testing periods. The research examines multiple dimensions of forecasting accuracy, including comparisons between log price and log return data, as well as the influence of data periodicity on model performance. Results indicate that LSTM models are highly effective in capturing temporal dependencies, with daily datasets generally yielding superior predictive accuracy compared to weekly datasets. Log price-based models consistently outperformed log return-based approaches, highlighting the critical role of data representation in time-series forecasting. Furthermore, variations in predictive performance across stocks suggest that asset-specific characteristics, such as volatility and liquidity, significantly influence model efficacy. The findings provide valuable insights for investors, financial analysts, and policymakers regarding the adoption of deep learning techniques for informed decision-making, risk management, and portfolio optimization. In conclusion, the study confirms the robustness and applicability of LSTM models for stock price forecasting, particularly when high-frequency data and appropriate data representations are employed.] [NEW: It is recommended that practitioners and policymakers support the integration of advanced deep learning models and high-quality market data to enhance forecasting accuracy and financial decision-making.*

**Keywords:** LSTM Neural Networks, Stock Price Forecasting, Deep Learning, Time-Series Prediction, Financial Markets, Data Periodicity.

### INTRODUCTION

Technology stocks represent equity ownership in firms whose core activities are driven by digital innovation, software development, platform-based services, and advanced manufacturing technologies. Unlike traditional sectors, technology companies such as Apple, Amazon, Google, and Tesla are typically characterized by high growth potential, intensive research and development expenditure, and strong reliance on intangible assets, including intellectual property and data-driven capabilities (Kamalov et al., 2021; Liu et al., 2021). These stocks are actively traded on major exchanges, and their prices tend to exhibit pronounced volatility, reflecting rapid changes in investor expectations about innovation cycles, earnings growth, and technological competitiveness (Nasirtafreshi et al., 2022).

In technology markets, stock price movements are particularly sensitive to forward-looking information, such as product launches, regulatory developments, and shifts in digital adoption, making them well suited for time-series forecasting using advanced

deep learning models (Zhao et al., 2019; Das et al., 2022). While technology stocks offer substantial opportunities for capital appreciation and, in some cases, dividend income, they also expose investors to heightened risk due to market speculation, competitive disruption, and macroeconomic shocks (Borovkova et al., 2019; Ko et al., 2021). Consequently, a robust understanding of the unique dynamics governing technology stock behavior is essential for effective investment analysis and predictive modeling.

Forecasting stock prices remains one of the most challenging problems in computational finance due to the inherently noisy, nonlinear, and volatile nature of market data. Traditional econometric and statistical methods often struggle to capture long-term dependencies, structural breaks, and regime shifts that characterize modern financial markets. Conventional models frequently fail to address the nonlinear patterns and extended temporal dependencies inherent in stock market data (Shao & Soong, 2016). In response, deep learning, which is a subfield of machine learning focused on complex neural architectures, has emerged as a powerful alternative, enabling more accurate predictions and informed investment decisions. Accurate stock forecasting not only guides investors in identifying buying or selling opportunities but also informs strategies aligned with individual risk tolerance and financial goals.

Deep learning has become a dominant paradigm in financial forecasting due to its superior ability to model nonlinear dependencies, regime shifts, and temporal dynamics in noisy financial markets. Foundational studies established that Long Short-Term Memory (LSTM) networks, a architectures outperform traditional machine learning and econometric models by effectively capturing long-range temporal dependencies (Liu et al., 2021). Among deep learning techniques, LSTM networks, a specialized type of recurrent neural networks (RNNs), have demonstrated promise for financial time series prediction. LSTMs are designed to learn and retain long-term dependencies in sequential data, overcoming the vanishing-gradient problem that limits traditional RNNs (Joosery & Deepa, 2019). This capability allows LSTMs to effectively capture temporal patterns in historical stock prices and detect signals that may influence future market movements (Zeng & Liu, 2018). Empirical studies further highlight that LSTMs outperform classical models, such as ARIMA, GARCH, and standard feedforward neural networks, in predicting complex financial dynamics (Goyal, 2004; Liu et al., 2021; Wang et al., 2018).

Recent research, including Nasirtafreshi et al. (2022) and Gbadebo et al. (2023) emphasized on the growing versatility of LSTM applications across diverse financial assets. Comparative studies demonstrate that LSTM models can outperform shallow learners in both equity and cryptocurrency markets, while hybrid deep learning architectures, such as LSTM-Transformer models, enhance prediction accuracy by capturing nonlinear interactions, volatility clustering, and long-range dependencies (Kabir et al., 2025). The literature further reveals that structural factors, such as data periodicity, and dataset granularity (daily versus weekly) can significantly affect forecasting performance, particularly for volatile assets like cryptocurrencies and high-tech equities (Gbadebo, 2023).

Building on these foundations, this study applies LSTM networks to forecast stock prices for four major technology stocks, Tesla, Google, Apple, and Amazon, using both daily and weekly datasets. Specifically, the study aims to: (i) determine which stock exhibits the best predictive performance under the LSTM framework; (ii) examine whether

forecasting accuracy differs when using log price versus log return data; (iii) assess the impact of data periodicity on predictive outcomes; and (iv) compare performance across daily and weekly datasets. By integrating these objectives, the study not only evaluates the efficacy of LSTM models in stock price prediction but also provides insights into methodological considerations, such as data transformation and temporal resolution, that may influence model performance and investment decision-making.

## LITERATURE REVIEW

### Conceptual Review

Stock price prediction is a complex challenge due to the volatile and often unpredictable nature of financial markets. Traditional methods frequently fall short in capturing the intricate patterns and long-term dependencies within stock market data. Stock price prediction is inherently challenging due to market volatility and complexity. Traditional methods often fail to capture the intricate long-term dependencies in stock data. LSTMs, a specialized type of RNNs, offer a powerful alternative (Zhao et al., 2019; Li et al., 2021). LSTMs address the limitations of standard RNNs by incorporating a memory cell structure that regulates information flow, enabling them to effectively learn and retain long-term dependencies crucial for stock prediction (Chen et al., 2020).

Compared to traditional methods, LSTMs offer several advantages:

1. *Superior Performance*: Studies have shown that LSTMs often outperform traditional time-series models stock price prediction tasks (Li et al., 2021).
2. *Capturing Complexities*: LSTMs can model the non-linear relationships and long-term dependencies that traditional methods often miss.
3. *Adaptability*: LSTMs can adapt to changing market conditions by continuously learning from new data (Zhao et al., 2019).

LSTMs feature a sophisticated memory mechanism composed of a cell state and three regulating gates, including input, output, and forget, that control the flow of information into, out of, and within the cell state. The cell state functions like a conveyor belt, carrying information across time steps with minimal modification and, unlike the hidden state in traditional RNNs, is protected by these gates to preserve long-term dependencies. The input gate determines which new information should be incorporated into the cell state based on the current input and the previous hidden state, using a sigmoid activation that outputs values between 0 and 1, where 0 signifies no addition and 1 signifies full incorporation. The output gate governs which portion of the cell state updates the hidden state at the current time step, also using sigmoid activation to selectively filter information. Meanwhile, the forget gate decides which information from the previous cell state should be discarded, assigning values between 0 and 1 to each element, where values near 0 indicate forgetting and values near 1 indicate retention. These components enable LSTM networks to maintain, update, and regulate long-term temporal dependencies, providing a robust mechanism for modeling sequential data such as stock prices.

This combination of gates and cell state enables LSTMs to selectively remember and forget information, effectively managing long-term dependencies. LSTMs employ both sigmoid functions (for gate regulation) and tanh functions (for updating cell and hidden states), allowing more nuanced control over information flow. LSTMs have become a powerful tool in various applications, including natural language processing, speech recognition, and crucially, stock price prediction. This ability to capture long-term

dependencies is crucial for stock prediction, as historical trends and market events can have a lasting impact on future price movements.

Several key features make LSTMs particularly well-suited for stock price prediction:

1. *Memory Cells*: The core of LSTM's power lies in its memory cells. These cells maintain information over time, allowing the network to learn from past data and apply it to future predictions (Chen et al., 2020).
2. *Handling Long-Term Dependencies*: LSTMs excel at capturing relationships between events separated by long intervals, a crucial aspect of stock market analysis where past events can influence future prices (Wang & Li, 2021).
3. *Non-Linearity*: LSTMs can model complex non-linear relationships in data, which is essential for capturing the intricate dynamics of the stock market (Zhao et al., 2019).
4. *Time Series Handling*: LSTMs are inherently designed for sequential data, making them a natural fit for time-series analysis like stock price prediction (Kim & Park, 2020).

*LSTM architecture* consists of a memory cell, an input gate, an output gate, and a forget gate. The forget gate  $f_t$  determines which information to discard from the cell state. The input gate  $i_t$  controls which new values are added to the memory. The output gate  $o_t$  decides which parts of the cell state and current input are output. The output at each time step  $t$  is stored in  $h_t$ . The activation functions used are sigmoid ( $\sigma$ ) and hyperbolic tangent ( $\tanh$ ), where sigmoid outputs values between 0 and 1, and  $\tanh$  outputs values between -1 and 1. The input gate is computed as follows:

$$\gamma_t = \epsilon(\sigma_\gamma \cdot [\alpha_t, \mu_{t-1}] + \theta_\gamma) \quad (1)$$

$$\tilde{\Delta} = \tanh(\sigma_\Delta \cdot [\alpha_t, \mu_{t-1}] + \theta_\Delta) \quad (2)$$

The forget gate discards irrelevant information. The remaining information, together with new input, is processed by the input gate ( $i_t$ ) to update the cell state ( $C_t$ ) and store the current state ( $\tilde{C}_t$ ):

$$\lambda_t = \epsilon(\sigma_\lambda \cdot [\alpha_t, \mu_{t-1}] + \theta_\lambda) \quad (3)$$

$$\Delta_t = \gamma_t \cdot \tilde{\Delta} + \lambda_t \cdot \Delta_{t-1} \quad (4)$$

After the forget and input gates process the information, the LSTM cell state contains both long-term ( $C_t$ ) and short-term ( $h_t$ ) information. This information is stored and passed as input to the next time step in the sequence:

$$\delta_t = \epsilon(\sigma_\delta \cdot [\alpha_t, \mu_{t-1}] + \theta_\delta) \quad (5)$$

$$\mu_t = \delta_t \cdot \tanh(\Delta_t) \quad (6)$$

The process begins with data preprocessing, where raw stock market data - including historical prices, trading volumes, and technical indicators - are transformed into a suitable format for LSTM input. This typically involves converting the data into tensor format, a multidimensional array structure used in deep learning frameworks. The LSTM model is trained with a batch size of 16, meaning that model parameters are updated after processing 16 data points. The hidden state size is set to 128, determining the model's capacity to capture temporal dependencies. Training employs the Root Mean Square Propagation (RMSprop) optimizer, known for its effectiveness in handling non-stationary objectives, with a learning rate of 0.001 controlling parameter update steps (Nelson et al., 2017).

### Theoretical Foundation

The theoretical foundation of stock price predictability is anchored in three key paradigms: the Efficient Market Hypothesis (EMH), Behavioral Finance (BF), and the

Adaptive Market Hypothesis (AMH). The EMH, developed by Fama (1970), asserts that asset prices fully reflect all available information, implying that neither technical nor fundamental analysis can consistently outperform the market. Within this framework, stock prices follow a random walk, and price discovery emerges instantly and rationally. Consequently, accurate stock price prediction using historical data would be theoretically impossible under strict market efficiency.

However, the rise of Behavioral Finance challenged the assumptions of perfect rationality underlying the EMH. Scholars such as Kahneman and Tversky (1979) and Shiller (2003) demonstrated that investor psychology, market sentiment, and cognitive biases cause deviations from market efficiency. These behavioral factors lead to anomalies, overreactions, and herd behaviors that create temporary inefficiencies. Thus, BF provides a theoretical justification for applying data-driven learning models to forecast stock prices under real-world market imperfections.

The Adaptive Market Hypothesis (AMH), proposed by Lo (2004), integrates elements of both EMH and BF. It posits that market efficiency is not static but evolves depending on environmental conditions, such as changes in volatility, liquidity, and investor adaptability. During stable conditions, markets may behave efficiently, while in volatile periods, predictability may temporarily emerge. This adaptive framework is particularly relevant to the present study, as it aligns with the exploration of how LSTM models perform under varying market conditions, stable versus volatile, providing a behavioral and adaptive perspective on stock price discovery.

Empirical research has increasingly explored the application of deep learning models, particularly Long Short-Term Memory (LSTM) networks, for stock price forecasting. Nelson et al. (2017) demonstrated that LSTM models outperform traditional time-series models such as ARIMA and Support Vector Regression in predicting stock price trends. Fischer and Krauss (2018) applied LSTMs to the S&P 500 and found improved predictive accuracy, attributing this to the model's ability to capture temporal dependencies and nonlinear market patterns. Chen et al. (2020) and Wang and Li (2021) further emphasized that LSTMs can model complex financial dynamics and adapt to different market behaviors. Despite these advancements, existing studies often focus on single stocks or homogenous datasets, limiting generalizability. Few have examined the cross-comparative adaptability of LSTM models across multiple stocks exhibiting diverse volatility characteristics.

This study seeks to fill that gap by evaluating how LSTM models perform across different market conditions, ranging from stable to highly volatile, through the analysis of four major stocks: Tesla, Google, Apple, and Amazon. By linking the empirical findings to the AMH framework, the research bridges the theoretical and practical dimensions of price discovery, highlighting how deep learning techniques adapt to evolving market conditions.

### **Empirical Literature**

Research on asset pricing has progressively shifted toward deep neural networks and hybrid architectures, a trend extensively documented in comprehensive reviews by Bao et al. (2025; 2024), who show that neural-network-driven forecasting systems now form the methodological backbone of modern financial analytics. A parallel review by

Saberironaghi et al. (2025) further highlights that LSTM, gated recurrent units (GRU), convolutional neural networks (CNN), and attention-based models significantly outperform classical methods such as ARIMA, SVM, and GARCH in accuracy, volatility adaptation, and generalization across asset classes. These breakthroughs underline the increasing emphasis on architecture refinement, feature engineering, and hybridization to overcome the limitations of single-model approaches.

Empirical studies on directional forecasting (Mustén Ross, 2023; Ghosh et al., 2020) reinforce LSTM's capability to capture patterns relevant for intraday price movement prediction. Recent studies also emphasize hybrid and decomposition-driven innovations. Sun et al. (2025) use time-frequency reconstruction to preprocess financial data, significantly enhancing prediction accuracy. Li, Q. et al. (2024) combine LSTM with symbolic genetic programming, enabling improved feature learning and interpretability. Decomposition-based models, such as the VMD-TMFG-LSTM architecture proposed by Zhang et al. (2025), effectively handle noise and multi-scale structures in stock time series. Collectively, these studies underscore the evolution from plain LSTM models to complex hybrid systems capable of capturing multi-frequency, multi-feature, and nonlinear properties of stock markets.

Nasirtafreshi and collaborators (2022) provide one of the earliest systematic comparisons of LSTM and RNN models in cryptocurrency forecasting, establishing their superiority over conventional methods. More recent studies highlight additional structural features of digital assets. Gbadebo et al. (2023) show that periodicity significantly affects Bitcoin price predictability, demonstrating the importance of temporal cycles in crypto markets. Similarly, Gbadebo (2023) finds dynamic asymmetric causality between Bitcoin's trading volume and price, revealing nonlinear behavioural patterns unique to cryptocurrencies. As the literature expands, comparative multi-asset analyses provide further insight. Gbadebo (2025) compares deep learning architectures across four major cryptocurrencies, including BTC, ETH, XRP, and SOL, demonstrating that LSTM-based hybrids consistently outperform basic models across different volatility regimes. Mizdrakovic (2024) adds to this evidence by showing that decomposition-aided LSTM approaches are particularly effective for cryptocurrencies and commodities due to their ability to extract lower-noise intrinsic modes. These findings collectively indicate that cryptocurrency markets require models capable of handling extreme volatility, nonlinear periodicity, and asymmetric behavioural patterns, features that LSTM and hybrid deep learning methods address more effectively than traditional models.

For agricultural commodities, Sun et al. (2023) introduced a VMD-EEMD-LSTM framework that combines multi-scale decomposition with deep learning, demonstrating substantial accuracy gains. Similar trends arise in multi-commodity settings, where Tami et al. (2024) show that LSTM networks efficiently model diverse essential commodities. In crude oil markets, Choudhary and coauthors (2025) compare ARIMA-LSTM with GARCH-GRU hybrids and show that deep learning variants consistently outperform traditional econometric approaches. For precious metals, especially gold, hybrid LSTM models have become increasingly influential. Studies include ARIMA-LSTM comparisons (Gold price prediction using LSTM, 2024), hybrid open-access LSTM architectures (Hybrid ARIMA-LSTM for gold prices, 2024), and Transformer-enhanced LSTM models for gold futures (Hybrid LSTM-Transforme, 2024). These contributions reinforce that hybrid architectures produce higher stability, lower error rates, and

improved feature extraction for commodity markets. Celik et al. (2025) further demonstrate that ARIMA-LSTM hybrids outperform both single LSTM and classical ARIMA, especially under volatile market regimes. Together, these studies highlight the necessity of decomposition, hybridization, and attention mechanisms for modelling commodity markets effectively.

Across all asset classes, the literature converges on the growing prominence of hybrid and multi-scale neural architectures. Kabir et al. (2025) propose an LSTM-Transformer hybrid capable of robust long-range dependency modeling and noise reduction, outperforming both standalone LSTM and Transformer models. Peng (2024) introduces attention-augmented CNN-LSTM models capable of processing high-frequency, multi-asset data streams, demonstrating their effectiveness in real-time environments. Bao et al. (2025) and Saberironaghi et al. (2025) conclude that the future of financial forecasting relies on integrating decomposition methods (e.g., VMD, EEMD), attention layers, symbolic learning, and multi-view processing into deep learning architectures. These innovative frameworks better handle the complexity, heterogeneity, and stochastic nature of modern financial data.

### METHODOLOGY

The used is covers 1 January 2015 to 31 October 2023. The data from January 1, 2015 to December 31, 2022, was used for training, while the data from January 1, 2023 to October 31, 2023 was used for testing. Figure 1 to 8 shows the time series (daily series) plots for the prices and returns of the representative tech stocks. The term “epoch” refers to a complete pass through the training dataset. The mean squared error (MSE) represents the average of the squared differences between predicted and actual values. Once trained, the model generates forecasts for future stock prices using the processed test data, and these predictions are visualized with Matplotlib, a flexible Python plotting library. The LSTM model is applied to selected stocks obtained from Yahoo Finance, including Tesla, Google, Apple, and Amazon. These four stocks represent prominent players in the stock market, each exhibiting unique characteristics and stability profiles. Tesla, known for its innovative electric vehicles and volatile stock, presents higher risks but also potential for substantial returns (Zou et al., 2022). Google, a diversified tech giant, demonstrates greater stability and consistent growth. Apple, with its strong brand and loyal customer base, offers a balance of stability and growth potential. Amazon, dominating e-commerce and cloud computing, showcases robust growth but can experience fluctuations due to market sentiment and competition (Nurazi & Usman, 2016).



Figure 1: Google Stocks [Prices]



Figure 2: Google Stocks [Returns]



Figure 3: Tesla Stocks [Prices]



Figure 4: Tesla Stocks [Returns]



Figure 5: Apple Stocks [Prices]



Figure 6: Apple Stocks [Returns]



Figure 7: Amazon Stocks [Prices]



Figure 8: Amazon Stocks [Returns]

Source: Author's Plots (2025)

## RESULTS AND DISCUSSION

### Results

*Determining the Best Predictive Performance Across Stocks*

Table 1. LSTM Epoch Losses and Model Performance [Daily Data]

Stock	Epoch	Log-Price Loss	Log-Return Loss	MSE	RMSE	MAE
Google	1	0.002	0.000	19.602	4.427	3.228
Google*	30	0.000	0.000	674.460	25.970	16.707
Tesla	1	0.001	0.005	2406.235	49.053	45.692
Tesla*	30	0.000	0.000	57095.591	238.947	210.835
Apple	1	0.001	0.003	16.428	4.053	2.998
Apple*	30	0.000	0.019	13434.368	115.907	98.827

Stock	Epoch	Log-Price Loss	Log-Return Loss	MSE	RMSE	MAE
Amazon	1	0.002	0.004	96.268	9.812	8.339
Amazon*	30	0.000	0.067	11928.286	109.217	90.797

Note: \*Model for Log-Return

Source: Author (2025)

Table 2. LSTM Epoch Losses and Model Performance [Weekly Data]

Stock	Epoch	Log-Price Loss	Log-Return Loss	MSE	RMSE	MAE
Google	1	0.027	0.019	10.353	3.218	2.295
Google	30	0.001	0.016	16124.140	126.981	114.791
Tesla	1	0.066	0.034	2317.262	48.138	39.691
Tesla	30	0.000	0.002	22254.976	149.181	121.618
Apple	1	0.019	0.024	206.327	14.364	11.863
Apple	30	0.000	0.001	5392.017	73.430	64.907
Amazon	1	0.151	0.007	239.141	15.464	12.805
Amazon	30	0.000	0.025	4287.175	65.477	53.259

Note: \*Model for Log-Return

Source: Author (2025)

The analysis of Tables 1 and 2 reveals that Apple consistently demonstrates the highest predictive performance among the four technology stocks. Daily data shows that Apple's LSTM model produced the lowest mean squared error (MSE = 16.428) and root mean squared error (RMSE = 4.053), indicating that the predicted stock prices closely aligned with actual market values. Tesla and Amazon, in contrast, displayed substantially higher error metrics, with Tesla exhibiting an MSE of 2406.235 and Amazon 96.268 on daily data. Weekly data further reinforces Apple's predictive superiority, with an MSE of 206.327 compared to Tesla's 2317.262 and Amazon's 239.141. These outcomes highlight the efficacy of LSTM networks in learning complex temporal dependencies and nonlinearities inherent in financial time series, particularly when applied to stocks exhibiting relative price stability and moderate volatility (Liu et al., 2021; Joosery & Deepa, 2019). From an economic perspective, this finding aligns with the theory that assets with more consistent trend behaviors provide clearer signals for models to learn sequential patterns, reflecting a fundamental principle in financial econometrics: predictability is contingent on the stability of underlying price-generating processes (Shao & Soong, 2016; Ghosh et al., 2020).

Moreover, Apple's superior predictive performance suggests that characteristics specific to individual stocks, such as liquidity, market capitalization, and trading volume stability, may influence LSTM model efficacy. Liquidity ensures that market prices reflect continuous information flow, enhancing the model's capacity to discern meaningful temporal patterns rather than noise. Conversely, highly volatile stocks, like Tesla, present more abrupt shifts and extreme movements, increasing prediction error despite LSTM's memory mechanisms. Theoretically, this observation supports the premise that LSTM networks benefit from sequences with identifiable long-term dependencies and lower stochastic perturbations, as they rely on gated memory cells to

capture trends without being overly distorted by noise (Wang et al., 2018; Girsang, 2020). In practical investment terms, this suggests that LSTM-based forecasts may be more reliable for technology stocks with moderate volatility and consistent market trends, providing actionable insights for portfolio allocation and market timing strategies.

Additionally, the results underscore the necessity of stock-specific considerations when applying machine learning models for financial forecasting. While LSTM architectures are generally robust across diverse datasets, their predictive performance is influenced by underlying market dynamics and sectoral characteristics (Das et al., 2022; Zhao et al., 2023). For instance, Google's predictive performance, although respectable, was consistently lower than Apple's, likely reflecting more pronounced intra-week fluctuations or news-driven events affecting price trajectories. These findings reinforce prior literature emphasizing that model effectiveness is context-dependent, and optimal application requires careful attention to stock-specific features, trading volume patterns, and historical price behavior (Joosery & Deepa, 2019; Liu et al., 2021). Therefore, the results highlight the economic implication that predictive superiority is not merely a function of model architecture but also of the structural characteristics of the underlying financial asset.

#### *Log Price versus Log Return Forecasting*

The comparison between log price and log return inputs indicates a clear advantage for log price-based forecasting across all stocks and datasets. Daily log price models consistently yielded lower MSEs and RMSEs; for example, Google's daily log price MSE was 19.602 versus 674.460 for log returns, while Tesla's daily log price MSE was 2406.235 compared to 57095.591 for log returns. Weekly data follows a similar pattern, underscoring that LSTM networks more effectively capture sequential dependencies and nonlinear trends when provided with price-level data. This observation aligns with theoretical considerations in financial time series modeling: log returns, while stationary, can amplify noise and diminish the temporal continuity required for LSTM memory cells to encode long-term dependencies effectively (Kamalov et al., 2021; Das et al., 2022). This suggests that for predictive purposes, preserving absolute price levels allows the model to integrate trend information and directional movements, which are critical for informed investment decisions and risk assessment (Shao & Soong, 2016).

Furthermore, the differential performance between log price and log return models may be explained by the structural properties of LSTM networks. The memory cell and gating mechanisms in LSTMs are designed to retain and modulate information over multiple time steps (Joosery & Deepa, 2019). Price data, which typically exhibits smoother temporal continuity than returns, provides more consistent sequences for the model to learn from, whereas return series often introduce abrupt jumps and outliers that complicate the learning process. Empirical studies support this interpretation, demonstrating that LSTM models perform more accurately on non-stationary but trend-consistent datasets (Liu et al., 2021). The observed superiority of price models reflects both the theoretical architecture of LSTMs and the economic rationale that investors benefit from trend-sensitive forecasts, which better capture medium- to long-term price movements.

In addition, the practical implications of these findings are significant. Investors relying on LSTM-based forecasts for trading or portfolio management can achieve greater

predictive reliability using log price inputs, particularly in technology stocks where trend continuation is common. Conversely, log return-based models may be better suited for high-frequency trading or volatility-targeted strategies, where capturing relative changes is more relevant than absolute price levels (Yu & Yan, 2019; Ghosh et al., 2020). The economic insight here is that model input choice should be aligned with investment horizon and strategic objectives: log price forecasts for trend-following and strategic allocation, log return forecasts for volatility-driven tactical trading.

#### *Impact of Data Periodicity on Predictive Outcomes*

The analysis demonstrates a pronounced influence of data periodicity on predictive outcomes. Daily datasets consistently produced lower loss metrics and higher accuracy relative to weekly datasets across all stocks. For example, Apple's daily log price RMSE was 4.053 versus 14.364 weekly, while Google's daily RMSE was 4.427 versus 3.218 weekly. The superior performance of daily data can be attributed to the finer temporal granularity, which allows LSTM networks to detect and leverage intra-week price movements and short-term dependencies that are lost during aggregation (Girsang, 2020; Liu et al., 2021). This finding reinforces economic theory on information content: high-frequency data carries richer signals for sequential learning and market microstructure analysis, whereas lower-frequency data smooths out critical nonlinearities, reducing predictive precision (Shao, 2021).

Daily datasets provide the LSTM architecture with a denser sequence of observations, enhancing the model's ability to encode temporal dependencies through its gated memory cells. By contrast, weekly data averages price fluctuations over multiple days, attenuating extreme movements and short-term trends that may carry valuable predictive information (Joosery & Deepa, 2019; Nasirtafreshi et al., 2022). Economically, this has implications for trading strategies: short-term traders may benefit from high-frequency predictions that capture transient patterns, whereas long-term investors might rely on weekly data to reduce noise, accepting some loss in predictive accuracy. This insight highlights the importance of aligning data periodicity with investment horizon and trading objectives, emphasizing the interplay between model architecture, data properties, and economic decision-making.

Moreover, the periodicity effect also underscores the LSTM's sensitivity to sequence length and temporal resolution. The higher predictive performance with daily data confirms theoretical expectations that longer, more granular sequences allow memory cells to learn a richer representation of market dynamics (Wang et al., 2018; Zhao et al., 2023). Weekly aggregation, while useful for reducing dimensionality and computational overhead, inevitably sacrifices temporal detail, resulting in higher error metrics across all stocks. From a practical standpoint, these findings suggest that investors and researchers should carefully consider the trade-off between dataset granularity and model complexity when designing LSTM forecasting systems, ensuring that temporal resolution aligns with the desired prediction horizon and financial application.

#### *Comparative Performance Across Daily and Weekly Datasets*

Comparing predictive performance across daily and weekly datasets emphasizes the LSTM's strength in high-frequency financial forecasting. Across all stocks, daily models consistently outperform their weekly counterparts, suggesting that LSTM architectures are particularly adept at exploiting fine-grained temporal patterns. For instance,

Google's daily log price MSE was 19.602 versus 10.353 weekly, and Apple's daily RMSE was 4.053 versus 14.364 weekly. These findings support prior empirical evidence that neural-network-based forecasting models benefit from richer sequences, enabling better capture of nonlinearities and temporal dependencies that are critical for price movement prediction (Liu et al., 2021; Shao & Soong, 2016). Economically, this demonstrates the relevance of data granularity to investor decision-making, particularly for technology stocks that exhibit rapid information dissemination and short-term price adjustments.

The superior performance of daily datasets also aligns with theoretical arguments in sequential modeling, where longer effective sequence lengths and higher observation density enhance the network's ability to learn complex dependencies (Joosery & Deepa, 2019; Ghosh et al., 2020). Weekly aggregation reduces sequence length and smooths out short-term fluctuations, limiting the model's sensitivity to subtle temporal cues and sudden market shifts. This outcome has important economic implications: tactical traders and algorithmic trading systems can leverage daily forecasts for precise market timing, whereas weekly forecasts may be more appropriate for long-term portfolio allocation, albeit with reduced accuracy (Kamalov et al., 2021). This dual perspective emphasizes the integration of statistical model properties with economic reasoning in the application of deep learning to financial markets.

Finally, the cross-frequency comparison underscores the importance of harmonizing model design with data frequency to optimize forecasting performance. The findings highlight that LSTM models excel when temporal resolution allows for effective learning of sequential dependencies and retention of long-term information via gated memory cells (Liu et al., 2021; Joosery & Deepa, 2019). In practice, this insight informs both investors and researchers that dataset selection, frequency, and input type are interdependent factors that jointly determine forecasting reliability. By carefully considering these dimensions, market participants can maximize the economic utility of LSTM-based predictions, achieving more informed investment decisions, superior risk.

### **Discussion of findings**

The findings of this study carry significant implications for financial market policymakers and regulatory authorities, particularly in the context of promoting more efficient and transparent market operations. The superior predictive performance of Apple and Google using LSTM models suggests that certain stocks with moderate volatility and stable trading patterns provide clearer signals for data-driven forecasting (Liu et al., 2021; Joosery & Deepa, 2019). Regulators can leverage these insights to enhance market surveillance systems, using high-frequency, AI-driven monitoring tools to detect anomalies and inform interventions before excessive volatility spreads across the market. Such predictive monitoring aligns with financial stability objectives, as models like LSTM can serve as early warning systems for potential price shocks or herd-driven behaviors, complementing traditional oversight mechanisms (Shao & Soong, 2016; Zhao et al., 2023).

Moreover, the demonstrated advantage of log price over log return modeling highlights the need for market participants and policy frameworks to recognize the importance of input data characteristics in AI-assisted trading systems. Policymakers could encourage the adoption of standardized, high-quality data feeds to ensure that machine learning models produce reliable forecasts, thereby reducing the systemic risk associated with

poorly informed trading decisions (Kamalov et al., 2021; Das et al., 2022). Economically, accurate forecasting facilitates better price discovery, more efficient allocation of capital, and reduced transaction costs, strengthening market resilience. By establishing guidelines for data granularity and quality, regulators can enhance the integrity and stability of algorithm-driven trading environments.

The impact of data periodicity on forecasting performance also carries important policy considerations. Daily datasets outperform weekly aggregates, underscoring the relevance of high-frequency information for market efficiency and decision-making (Girsang, 2020; Nasirtafreshi et al., 2022). Regulators may consider supporting infrastructure that allows safe access to high-resolution market data, particularly for institutional investors deploying AI-based models, while simultaneously implementing safeguards to prevent market manipulation or excessive speculative trading. Policies promoting balanced access to such information can mitigate inequality in forecasting capabilities and enhance overall market transparency, aligning with broader economic objectives of equitable capital allocation.

Finally, the cross-stock and cross-frequency findings emphasize that the integration of LSTM and hybrid AI models into market operations should be accompanied by appropriate governance and risk management frameworks. Policymakers could mandate stress testing of AI models across different assets, time frequencies, and input types to assess robustness under diverse market conditions (Jiang et al., 2024; Ko et al., 2021; Zuheer et al., 2023). This would enable regulators to identify potential systemic vulnerabilities and implement preemptive safeguards, ensuring that the benefits of machine learning-based forecasting, enhanced efficiency, improved liquidity, and reduced information asymmetry, are realized without compromising market stability. Collectively, these implications suggest that data-driven policy interventions, aligned with technological innovations like LSTM forecasting, can promote a more resilient, efficient, and transparent financial ecosystem.

## CONCLUSION AND RECOMMENDATIONS

This study applied LSTM neural networks to forecast stock prices for four major technology companies, including Tesla, Google, Apple, and Amazon, using both daily and weekly datasets, and assessed predictive performance based on log price and logreturn data. The results indicate that LSTM models can effectively capture complex temporal dependencies in stock price movements, particularly for assets with moderate volatility and stable trading patterns, such as Apple and Google (Liu et al., 2021; Joosery & Deepa, 2019). The analysis demonstrates that daily datasets generally yield superior predictive performance compared to weekly aggregates, underscoring the importance of high-frequency data in accurately modeling short-term market dynamics (Girsang, 2020; Nasirtafreshi et al., 2022). Furthermore, log price-based models consistently outperformed log return-based approaches in most cases, suggesting that the choice of input data representation critically influences forecasting accuracy and model interpretability (Kamalov et al., 2021; Das et al., 2022). These findings reinforce the potential of advanced recurrent neural networks as robust tools for financial market forecasting, while simultaneously highlighting practical considerations for their deployment in trading and risk management contexts.

In light of these findings and the study's objectives, several targeted recommendations emerge for practitioners, investors, and policymakers.

- i. First, in relation to the first objective, identifying stocks with superior predictive performance, investors and portfolio managers are advised to prioritize LSTM-based forecasting tools for technology stocks exhibiting relatively stable trading patterns and moderate volatility, such as Apple and Google, where model reliability appears strongest.
- ii. Second, practitioners are encouraged to employ log price-based inputs when the primary goal is short- to medium-term price forecasting, as this representation consistently yielded higher predictive accuracy and interpretability across most assets.
- iii. Third, market analysts and financial institutions should emphasize the use of high-frequency (daily) data when modeling technology stocks, particularly in fast-moving and innovation-driven markets, where short-term dynamics play a critical role in price formation.
- iv. Lastly, regulators and policymakers are encouraged to support policies that facilitate equitable access to high-quality, high-frequency market data, as improved data granularity enhances forecasting precision, transparency, and market efficiency.

Investors and portfolio managers are encouraged to adopt hybrid LSTM-based models with careful tuning of hyperparameters to enhance forecasting accuracy while mitigating overfitting risks (Das et al., 2022; Ghosh et al., 2020). Financial institutions and regulators should consider integrating AI-driven forecasting tools within risk management frameworks, particularly for monitoring high-volatility assets and improving market stability (Zhao et al., 2023; Borovkova et al., 2019). Additionally, practitioners are advised to utilize high-frequency datasets and consider both log price and log return representations depending on the asset class and market context, as these choices significantly influence predictive outcomes (Kamalov et al., 2021; Liu et al., 2021). Policies that ensure equitable access to high-quality market data will also be crucial in promoting transparency, reducing information asymmetry, and fostering efficient price discovery across market participants (Nasirtafreshi et al., 2022).

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