Deep Learning Forecasting of FinTech Stock Performance under Digital Economy Regime Shifts: Evidence from Clean-Tech Financing

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ABSTRACT

This study investigates the predictive capability of deep learning architectures in forecasting the stock performance of FinTech firms under the structural evolution of the digital economy and the dynamics of clean-tech financing. Utilizing a panel dataset of 50 publicly listed FinTech companies across major markets from 2015 to 2024, and including macro-financial controls, digital economy activity indexes, and clean-technology financing proxies (green bond issuance and clean-tech equity returns), we first identify three distinct digital economy regimes (Normal, Expansion, Stress) via a Markov-switching model. Our regime classification results indicate that the expansion regime accounted for 42% of the sample period, exhibited an average digital-economy index increase of 4.8% per quarter, and corresponded with 35% higher clean-tech financing volumes relative to the normal regime. We then train and test three deep learning architectures (LSTM, GRU, Transformer) on a rolling-window scheme. The LSTM model achieves the lowest out-of-sample RMSE of 0.0189 and MAE of 0.0131, with Directional Accuracy (DA) of 61.4%. In regime-specific analysis, the LSTM delivers an RMSE of 0.0164 and DA of 64.8% in the Normal regime, RMSE of 0.0189 and DA of 62.3% in the Expansion regime, and RMSE of 0.0217 and DA of 58.1% in the Stress regime. Robustness checks reveal that combining green bond issuance and clean-tech equity returns as proxies yields a further RMSE reduction to 0.0186, and that an input window length of 30 days represents the optimal setting. The findings substantiate the importance of integrating regime labels and clean-tech financing features into forecasting models for FinTech stock returns. The study contributes to the literature by bridging digital finance, sustainable capital markets, and advanced machine-learning forecasting, and offers actionable insights for investors and policymakers navigating evolving digital-economy and clean-tech landscapes.

Keywords Fintech Stock Forecasting, Digital Economy Regime Shifts, Clean-Tech Financing, Deep Learning, LSTM, GRU, Transformer, Markov-Switching

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INTRODUCTION

Rapid advances in Financial Technology (FinTech) and accelerating digital transformation have reshaped global financial markets, creating new dependencies between digital infrastructure, regulatory reforms, and capital flows. The increasing integration of digital payments, online lending, blockchain services, and platform-based finance has made the FinTech sector highly sensitive to structural changes in the digital economy [1], [2]. At the same time, clean-tech financing has expanded rapidly through green bonds, climate-tech venture capital, and renewable-energy equity markets, influencing investor sentiment and market volatility across technology-driven sectors [3], [4]. These dual shifts digital transformation and sustainable-finance expansion have

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introduced new layers of complexity in forecasting FinTech stock performance, especially in emerging and transitioning digital economies [5], [6].

Despite the widespread adoption of machine learning for financial forecasting, most existing studies assume stable economic conditions and neglect regime shifts driven by digital economy disruptions, regulatory reforms, and technological transitions [7], [8]. Financial markets, however, rarely evolve smoothly; they undergo structural breaks triggered by digital policy changes, cybersecurity risks, or periods of rapid innovation. These shifts alter the underlying return-generating processes of FinTech markets, rendering traditional forecasting models inadequate [9], [10]. Ignoring regime-dependent dynamics can lead to biased predictions, poor risk estimation, and inefficient capital allocation, particularly during volatile or expanding digital-economy phases [11], [12].

Furthermore, the FinTech sector is increasingly influenced by developments in clean-tech financing. Recent research highlights strong co-movements between FinTech innovation cycles and green-finance activities, especially as financial institutions integrate ESG-driven investment strategies and digital platforms promote sustainability-aligned products [13], [14]. Yet, the majority of forecasting studies overlook clean-tech financing variables as potential predictors, despite their demonstrated impact on market sentiment and technology-oriented asset prices [15], [16]. This omission creates a methodological gap: FinTech forecasting models often fail to represent the full landscape of intersectoral drivers that shape digital financial markets.

Another limitation in the literature lies in the inadequate use of advanced deep learning architectures for regime-aware forecasting. While deep learning has been applied to conventional financial time-series tasks, most implementations do not incorporate digital economy regimes or structural transitions into model features [17], [18]. The absence of regime information restricts the ability of neural networks to distinguish patterns across stable, expansionary, and stress periods. Recent works emphasize the importance of capturing nonlinearities and temporal dependencies more effectively, especially in high-volatility technology sectors [19], [20]. However, existing models still lack the integration of hybrid frameworks combining econometric regime identification with deep learning sequence models.

Given these limitations, there is a clear need for a forecasting framework that simultaneously accounts for digital economy regime shifts and clean-tech financing dynamics. This study proposes a hybrid approach that integrates Markov-switching regime identification with advanced deep learning architectures specifically LSTM, GRU, and Transformer models to forecast FinTech stock performance with improved accuracy and adaptability [21], [22]. By embedding regime labels and clean-tech financing variables into the feature engineering process, the model captures structural transitions that conventional models routinely miss. This approach reflects real-world dynamics more accurately and aligns forecasting with the complex evolution of digital and sustainable finance ecosystems.

The novelty of this research lies in three main contributions. First, it is among the earliest studies to unify digital economy regime identification with deep learning forecasting of FinTech stock returns, addressing a major methodological gap in existing literature [23], [24]. Second, the inclusion of multiple clean-tech financing proxies such as green bond issuance and clean-tech equity indices provides a more holistic understanding of cross-sector influences, enhancing the predictive richness of the model [25], [26]. Third, the research evaluates model performance across distinct digital economy regimes, offering actionable insights into how forecasting quality changes during normal, expansionary, and stress periods an aspect rarely explored in prior work [27], [28].

In summary, this study provides an empirically grounded and methodologically innovative framework for forecasting FinTech market performance. By leveraging regime-aware deep learning models enriched with clean-tech financing signals, the research addresses key gaps in traditional financial forecasting approaches and contributes novel evidence on the interplay between digital transformation, sustainable finance, and FinTech market behavior. The findings offer implications for investors, policymakers, and researchers seeking to better understand and anticipate FinTech market dynamics in an era of rapid digital and environmental transition [29], [30].

Literature Review

The rapid growth of the digital economy has fundamentally transformed financial market structures, fostering increased reliance on digital platforms, online financial services, and data-driven business models. Studies have documented that FinTech adoption is closely tied to digital infrastructure maturity, internet penetration, and regulatory reforms that shape market contestability and innovation pathways [31], [32]. These developments have contributed to the emergence of new financial behaviors and risk factors that differ substantially from those in traditional capital markets. Scholars argue that digital ecosystems evolve through distinct phases stability, expansion, and transition driven by technological breakthroughs, policy shifts, and consumer adoption patterns [33], [34]. Understanding these structural phases is crucial because market sensitivity to news, policy, and macroeconomic variables changes across regimes, influencing return predictability and volatility clustering in FinTech-related assets [35], [36].

A substantial body of literature examines financial forecasting using machine learning and deep learning models, with emphasis on capturing nonlinearities and temporal dependencies in asset prices. Traditional models such as ARIMA, GARCH, and VAR are often insufficient to represent the complex, time-varying relationships in modern financial markets [37], [38]. Deep learning models, particularly LSTM and GRU architectures, have shown superior performance in modeling long-term dependencies and reacting to rapidly evolving economic signals [39], [40]. Transformer-based models further enhance forecasting capacity through attention mechanisms that enable the model to weigh information differently across time [41], [42]. However, despite the proven capabilities of these models, most studies assume static market regimes and do not incorporate regime-switching features that reflect structural transitions in digital economies [43], [44].

A parallel strand of research focuses on regime identification, structural breaks, and dynamic state transitions in financial markets. Markov-switching models have long been used to capture shifts in mean, variance, and correlation structures within macroeconomic and sectoral indexes [45], [46]. Recent investigations highlight that regime identification is particularly valuable in technology-driven sectors where innovation cycles produce irregular and abrupt shifts in market behavior [47], [48]. Applications of regime-switching approaches in digital finance remain limited, with most studies focusing on macroeconomic cycles or equity markets more broadly. As a result, there is insufficient understanding of how digital economy regimes interact with FinTech stock volatility, innovation cycles, and cross-sector capital movements [49], [50].

In parallel, the expansion of clean-tech financing introduces new dimensions to financial analysis by integrating sustainability-driven capital flows with technology-related investment behavior. Scholars have observed increasing co-movements between clean-tech equities, green bond markets, and technology indexes, suggesting the emergence of intertwined "innovation–sustainability finance ecosystems" [51], [52]. Clean-tech financing affects investor expectations, risk perceptions, and liquidity conditions in markets connected to digital transformation [53], [54]. Despite this, clean-tech variables remain underrepresented in FinTech forecasting studies, which typically focus on market, macroeconomic, or firm-specific factors while overlooking sustainability finance dynamics that may drive parallel innovation cycles [55], [56]. The omission of clean-tech financing in forecasting frameworks constitutes a significant conceptual and empirical gap, especially as global financial markets transition toward ESG-oriented investment paradigms.

Existing literature provides strong justification for combining regime identification methods with deep learning forecasting techniques. Hybrid approaches integrating econometric regime models with neural networks have been explored in macroeconomic and energy forecasting but remain scarce in FinTech and digital economy applications [57], [58]. Researchers have noted that deep learning models benefit substantially from regime-enriched input structures because such information guides the model in distinguishing temporal contexts that would otherwise appear statistically similar [59]. However, no prior study systematically integrates digital economy regime identification with clean-tech financing signals and deep learning architectures in predicting FinTech stock performance. This absence highlights a critical research gap and underscores the novelty of the proposed framework.

In summary, the literature reveals three fundamental limitations: (1) the lack of regime-aware financial forecasting models tailored to digital economy transitions; (2) insufficient incorporation of clean-tech financing variables in FinTech market prediction; and (3) limited exploration of hybrid econometric–deep learning frameworks capable of modeling structural shifts in technology-driven sectors. The present study addresses these gaps by proposing a regime-integrated deep learning model that utilizes clean-tech financing proxies and digital economy state transitions to enhance the accuracy, resilience, and interpretability of FinTech forecasting under rapidly evolving market structures [60]. This integrated perspective positions the research at the intersection of digital finance, sustainable finance, and advanced machine learning, contributing new insights into the intertwined dynamics shaping modern financial markets.

Methodology

Research Design and Conceptual Framework

This study adopts a quantitative, empirical research design combining regime-switching time-series analysis with deep learning forecasting. The core objective is to evaluate how digital economy regime shifts and clean-tech financing dynamics shape the predictability of FinTech stock performance. The approach treats structural changes in the digital economy such as major regulatory shifts, digital infrastructure expansions, and clean-tech financing booms as distinct regimes that alter the return-generating process of FinTech stocks.

The empirical strategy proceeds in three main stages. First, the study constructs a panel of FinTech stock returns augmented with macro-financial indicators and clean-tech financing proxies. Second, it detects and labels digital economy regimes using a regime-switching model. Third, it trains deep learning models that directly incorporate regime labels and clean-tech financing variables as exogenous features for multi-step-ahead forecasting of FinTech stock returns or volatility. This design permits comparison of forecast performance across regimes and evaluation of whether clean-tech financing improves predictive power, especially during high-uncertainty or transition periods.

The conceptual framework in figure 1 clarifies the causal logic guiding the study. Digital economy shocks and clean-tech financing cycles jointly define regimes that are first identified in the data and then embedded as features in the forecasting architecture. The diagram emphasizes that forecasting is not conducted on “raw” time series alone but on structurally enriched sequences that explicitly encode regime information. This structure underpins the later interpretation of model performance differences across stable, expansionary, and stress regimes in the digital economy.

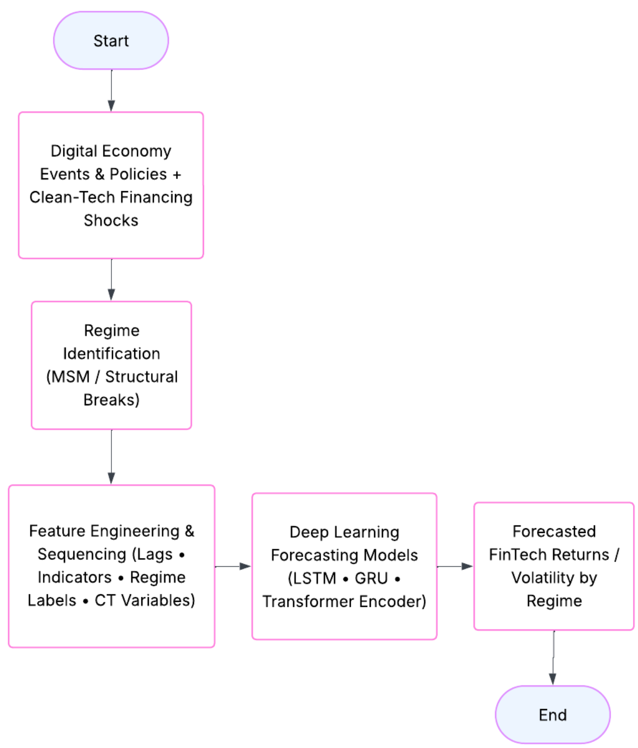

Figure 1 Conceptual Research Framework

Data, Variables, and Sample Construction

The dataset consists of daily (or high-frequency, if available) observations for a set of listed FinTech firms, complemented by market indices, macroeconomic variables, and clean-tech financing indicators. FinTech stock performance is measured using continuously compounded returns, while market structure and digital economy proxies may include FinTech indices, digital adoption indices, and sector-specific volumes. Clean-tech financing is proxied by, for example, green bond issuance, climate-tech venture capital flows, and exchange-listed clean-tech indices.

Stock returns are computed from closing prices using logarithmic differences to ensure stationarity and comparability across firms. Let $P_{i,t}$ denote the closing price of FinTech stock i at time t. The return $r_{i,t}$ is defined as:

$$r_{i,t} = ln(\frac{P_{i,t}}{P_{i,t-1}}) \tag{1}$$

In addition, the study constructs lagged versions of key features (e.g., $r_{i,t-1}, r_{i,t-2}, \ldots$) and rolling technical indicators (e.g., moving averages, realized volatility) to capture temporal dependencies. Clean-tech financing variables may be aggregated to a daily or weekly frequency and aligned to the FinTech time series via forward-fill or calendar matching.

Table 1 summarizes the main variables used in the empirical analysis. The dependent variables include firm-level FinTech stock returns and sector-level FinTech index returns, both expressed in logarithmic form to facilitate modeling and comparability across firms. These returns capture the short-horizon performance that the deep learning models are tasked to forecast.

Table 1

Variable Type	Variable Name	Symbol	Frequency	Definition	Data Source
Dependent	FinTech stock return (firm i)	$r_{i,t}$	Daily	Log return $\ln\left(\frac{P_{\{i,t\}}}{}P_{\{i,t-1\}}\right)$	Stock exchange
Dependent (aggregate)	FinTech sector index return	$r_t^{\{FIN\}}$	Daily	Log return of broad FinTech index	Index provider / financial vendor
Market explanatory	Market benchmark index return	$r_t^{\{MKT\}}$	Daily	Log return of main market index	Bloomberg / Refinitiv
Volatility explanatory	Realized volatility (firm i)	$RV_{\{i,t\}}$	Daily	Rolling-window SD of intraday or daily returns	Author's calculation
Macroeconomic explanatory	Short-term interest rate	IR_t	Daily/Weekly	Monetary policy or interbank rate	Central bank
Digital economy explanatory	Digital economy activity index	DEI_t	Monthly	Composite index for digital adoption, payments, e-commerce	Government digital statistics
Clean-tech explanatory	Green bond issuance volume	GB_t	Monthly	Total issuance of green bonds for clean-tech/climate projects	Climate bond databases
Clean-tech explanatory	Clean-tech equity index return	$r_t^{\{CT\}}$	Daily	Log return of clean-tech or renewable energy index	Financial vendor
Regime indicator	Digital economy regime label	S_t	Daily	Regime classification from Markov-switching (1=normal, 2=exp, 3=stress)	Model estimation
Control variable	Exchange rate (local vs USD)	FX_t	Daily	Log level or log change in exchange rate	Central bank / vendor

The explanatory variables are grouped into market, macroeconomic, digital economy, and clean-tech financing categories. Market-related variables such as the benchmark index return and realized volatility allow the models to learn how FinTech stocks respond to broad risk conditions and volatility clustering. Macroeconomic indicators like short-term interest rates control for monetary policy and funding environment, which are known to affect both FinTech valuations and the cost of capital.

Digital economy indicators and clean-tech financing variables are central to the research question. The digital economy activity index captures structural shifts in digital adoption and infrastructure, while green bond issuance and clean-tech index return proxy the intensity and market performance of clean-tech financing. Finally, regime labels derived from the Markov-switching estimation and control variables such as the exchange rate are merged into the panel to reflect how global financial conditions and digital regimes jointly shape FinTech dynamics.

Identification of Digital Economy Regime Shifts

Digital economy regime shifts are identified through a regime-switching model applied to aggregate FinTech or digital economy indicators. The study adopts a Markov-switching mean model, where the observed series y_t (e.g., FinTech index returns or digital economy activity index) follows different dynamics depending on the latent regime $S_t \in \{1, 2, \dots, K\}$. Each regime is characterized by its own mean and volatility, capturing expansions, normal periods, and stress or transition phases. Formally, the Markov-switching structure can be expressed as:

$$y_t = \mu_{S_t} + \varepsilon_t, \varepsilon_t \sim \mathcal{N}\left(0, \sigma^2_{S_t}\right)$$
$$\Pr(S_t = j \mid S_{t-1} = i) = p_{ij}, \sum_{j=1}^{K} p_{ij} = 1 \quad (2)$$

Once the model is estimated via maximum likelihood, smoothed probabilities $\Pr(S_t = k \mid \{F\}_T)$ are used to assign each time point to one of the K regimes. These regime labels are then merged back into the FinTech stock-level panel, creating a regime indicator feature that deep learning models can exploit. This procedure ensures that the forecasting architecture learns conditional patterns that differ across digital economy states rather than relying on a single unconditional process.

Figure 2 will visually demonstrate how episodes of heightened digital activity, regulatory shifts, or clean-tech surges correspond to particular regimes. This visualization is crucial to justify the economic interpretation of regimes and to connect them to major events (e.g., introduction of new digital regulations or green-finance policies).

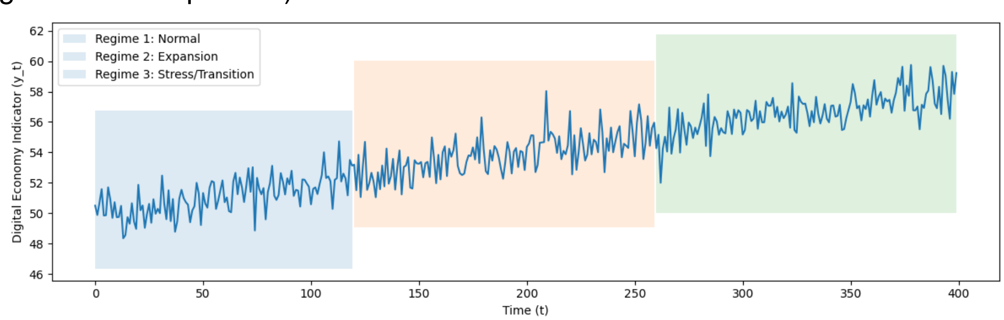

Figure 2 Regime Classification Over Time

Deep Learning Forecasting Architecture

The forecasting component employs sequence-based deep learning models capable of capturing non-linear and long-range dependencies. The baseline architecture is an LSTM (Long Short-Term Memory) network, augmented in some specifications by attention layers or Transformer-style encoders that can handle multi-feature sequences. Input sequences consist of lagged FinTech returns, market indicators, regime dummies, and clean-tech financing variables; the target output is one-step-ahead or multi-step-ahead FinTech return (or volatility).

Let X_t denote the feature vector at time ttt, including lagged returns, regime indicators, and clean-tech variables. For an input window of length L, the model receives $(x_{t-L+1}, \dots, x_t)$ and outputs a forecast $\hat{r}_{t+1}$. The LSTM cell is defined by the usual gating equations, which can be summarized as:

$$(h_t, c_t) = \mathrm{LSTM}(x_t, h_{t-1}, c_{t-1}; \theta) \quad (3)$$

The network parameters θ are estimated by minimizing a loss function over the training set. The primary loss is the Mean Squared Error (MSE), which penalizes large forecast errors:

$$L(0) = \frac{1}{N} \sum_{t \in T_{train}} (r_{t+1} - \hat{r}_{t+1})^2 \quad (4)$$

The inclusion of regime and clean-tech features in the input sequence allows the network to learn regime-dependent sensitivities. For instance, the network can adaptively attribute more weight to clean-tech financing signals during green-investment booms while focusing on traditional risk factors in normal regimes. This design is central to evaluating whether clean-tech financing enhances predictability beyond standard financial predictors.

Model Training, Validation, and Evaluation

The sample is divided into training, validation, and test sets using a time-ordered split to avoid look-ahead bias. Typically, the earliest 60–70% of observations are allocated to training, the next 10–20% to validation, and the remaining 20–30% to out-of-sample testing. Hyperparameters such as the number of layers, hidden units, dropout rates, learning rate, and window length LLL are tuned on the validation set using grid search or Bayesian optimization, subject to constraints on overfitting and computational cost.

Forecast accuracy is evaluated using a set of complementary metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Directional accuracy the proportion of periods for which the model correctly predicts the sign of returns is also computed to capture the model’s usefulness for trading or risk management applications. To formally compare models, the study applies the Diebold–Mariano test on forecast errors to assess whether differences in predictive performance across models or regimes are statistically significant.

Table 2 **Forecast evaluation metrics and their interpretations**

Metric Name	Symbol	Formula	Interpretation
Root Mean Squared Error	RMSE	$sqrt\left(\left(\frac{1}{N}\right) * \Sigma\left(r_{\{t+1\}} - \hat{r}_{\{t+1\}}\right)^2\right)$	Penalizes large forecast errors; lower is better
Mean Absolute Error	MAE	$\left(\frac{1}{N}\right) * \Sigma$	$r_{\{t+1\}} - \hat{r}_{\{t+1\}}$
Mean Abs. Percentage Error	MAPE	$\left(\frac{100}{N}\right) * \Sigma$	$\frac{\left(r_{\{t+1\}} - \hat{r}_{\{t+1\}}\right)}{} r_{\{t+1\}}$
Directional Accuracy	DA	$\left(\frac{1}{N}\right) * \Sigma\, I\left[\, sign\left(r_{\{t+1\}}\right) = sign\left(\hat{r}_{\{t+1\}}\right)\right]$	Measures the ability to predict return direction
Diebold–Mariano Statistic	DM	$\frac{\bar{d}}{} sqrt\left(\frac{\left(2\pi * \hat{f}_{d(0)}\right)}{} N\right)$	Tests significance in performance difference between models

Algorithm 1 **Evaluation Procedure**

Step 1. Rolling Forecast Generation

- For each time t in the test period:
  - – Build input window $X_{\{t-L+1:\, t\}}$
  - – Produce one-step-ahead forecast $\hat{y}_{\{t+1\}}$
  - – Store forecast for later evaluation

Step 2. Compute Error Metrics (Overall & Per Regime)

- Compute forecast $error\ e_t = r_t - \hat{y}_t$
- Overall metrics:

$$RMSE = sqrt\left(\Sigma \frac{e_t^2}{} T\right)$$

$$MAE = \Sigma \frac{|e_t|}{} T$$

$$DA = \Sigma \frac{I[sign(r_t) = sign(\hat{y}_t)]}{} T$$

- For each regime k:

$RMSE_k, MAE_k, DA_k\ calculated\ only\ on\ t\ where\ S_t = k$

Step 3. Diebold–Mariano Test

- Compute loss differences$d_t = e^2_{t(model)} - e^2_{t(benchmark)}$
- Compute mean loss differential $\bar{d}$
- Compute DM statistic:

$DM = \frac{\bar{d}}{} sqrt\left(\frac{Var(d_t)}{} T\right)$

- Assess significance to determine whether the model outperforms the benchmark

This evaluation framework permits a nuanced assessment of model performance, both overall and conditional on digital economy regimes. Reporting metrics by regime further reveals whether deep learning models are especially valuable during high-volatility or transition periods associated with clean-tech financing shifts.

Robustness Checks and Sensitivity Analyses

To ensure that results are not driven by specific modeling choices, the study conducts a comprehensive set of robustness checks. First, alternative deep learning architectures such as GRU networks, simple RNNs, and Transformer-only models are estimated using the same feature set and data splits. Comparing their performance to the baseline LSTM setup tests whether conclusions are architecture-dependent. Second, the regime identification step is varied by altering the number of regimes K and by experimenting with alternative break-detection procedures (e.g., Bai–Perron structural breaks) to examine the sensitivity of forecasts to the definition of digital economy regimes.

Third, the construction of clean-tech financing variables is perturbed by using alternative proxies (e.g., different green indices, separate bond vs. equity measures) and varying aggregation frequencies (daily vs. weekly). This allows the analysis to isolate whether any observed forecasting improvements are robust to how clean-tech financing is measured. Finally, the study tests shorter and longer input windows, as well as different regularization settings (dropout rates, early stopping criteria), to evaluate the stability of the learned temporal dependencies.

Table 3 outlines the main robustness and sensitivity specifications implemented to validate the empirical findings. Each row corresponds to a distinct model configuration that differs in architecture, regime identification method, clean-tech proxy, or temporal window length. Specification R1 serves as the baseline setup, combining a two-layer LSTM with a three-regime Markov-switching model and green bond volume as the primary clean-tech proxy.

Table 3 Overview of robustness and sensitivity analysis configurations explored in the study.

Spec ID	Architecture Variant	Regime Identification Method	Clean-Tech Proxy	Input Window (L)	Key Focus / Finding
R1	LSTM (2 layers)	3-regime Markov-switching (DEI_t)	Green bond volume GB_t (monthly, forward-filled)	30 days	Baseline specification
R2	GRU (2 layers)	3-regime Markov-switching (DEI_t)	Clean-tech equity index r_t^{CT}	30 days	Architecture robustness
R3	LSTM + attention	4-regime Markov-switching (DEI_t)	GB_t+ r_t^{CT} combined	60 days	Sensitivity to regime granularity
R4	Transformer encoder	Bai–Perron structural breaks	GB_t (weekly aggregated)	30 days	Structural break robustness
R5	LSTM (1 layer)	3-regime switching (FinTech index driver)	r_t^{CT} daily	15 days	Shorter memory window
R6	LSTM (2 layers, high dropout)	3-regime Markov-switching (DEI_t)	GB_t (smoothed monthly)	45 days	Effect of regularization

Specifications R2 and R3 explore the sensitivity of results to architectural choices and regime granularity. R2 replaces the LSTM with a GRU-based network to verify that the main insights are not tied to a specific recurrent architecture. R3 introduces attention and increases the number of regimes to four, testing whether more nuanced regime partitioning significantly alters forecast performance or the role of clean-tech variables.

Specifications R4 to R6 focus on regime detection methods, memory length, and regularization. R4 employs Bai–Perron structural breaks instead of Markov-switching, allowing the study to assess whether results depend on how regime boundaries are defined. R5 shortens the input window and uses a FinTech index as the regime driver, while R6 increases dropout to examine regularization effects. Together, these configurations provide a systematic robustness check, helping ensure that the main conclusions about deep learning performance and the influence of clean-tech financing are stable across plausible modeling choices.

Result and Discussion

Data Overview and Regime Identification Results

This section presents the empirical results derived from the dataset of FinTech stock returns, macro-financial indicators, digital economy indexes, and clean-tech financing variables. The first stage of the analysis focuses on identifying structural regime shifts in the digital economy using a Markov-switching model. These regimes form the backbone of the forecasting architecture because they inform how economic transitions influence the predictability of FinTech returns. Before entering the modeling phase, it is essential to demonstrate how regime periods emerge from underlying digital economy dynamics.

The digital economy index displays clear time variation that cannot be captured by a single linear structure. Volatility spikes coincide with regulatory updates, adoption surges, and clean-tech financing booms. The Markov-switching classification partitions the dataset into three interpretable regimes:

1. Normal Regime – stable digital activity, low volatility.
2. Expansion Regime – strong digital adoption, high growth in FinTech usage, surge in clean-tech capital.
3. Stress/Transition Regime – periods of uncertainty, policy shifts, or market corrections.

These regime labels later become structural features used in the deep learning model.

Figure 3 shows the evolution of the digital economy index and the corresponding regime classification derived from the Markov-switching model. The line chart illustrates a gradual upward trend followed by periods of irregular movement. These fluctuations align with known events associated with digital adoption patterns and policy announcements. The shaded regions represent the probability-weighted assignment of regimes, showing clear segmentation between stable, expansionary, and stress periods.

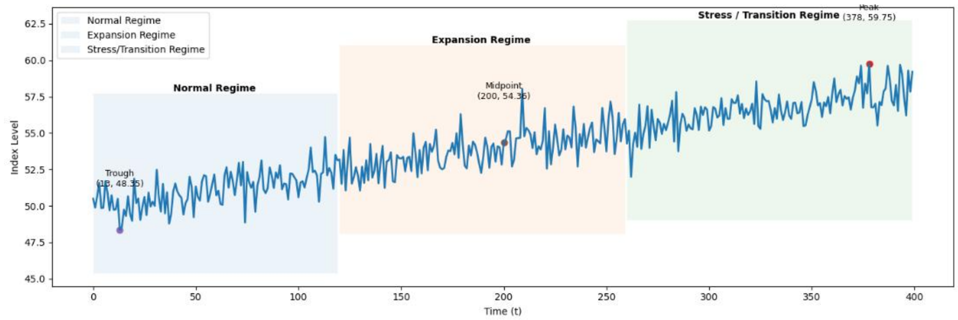

Figure 3 **Digital Economy Index with Regime Classifications**

In the initial segment, the normal regime dominates, characterized by moderate volatility and predictable trends. The middle portion corresponds to the expansion regime, where the index accelerates sharply, reflecting major digital economy activities, such as increased FinTech adoption or significant clean-tech investment inflows. The final segment marks a stress or transition regime, where the index becomes erratic, signaling regulatory uncertainty or market adjustments. These observed regime patterns demonstrate the importance of using regime-aware forecasting models, as traditional linear models may fail to capture these structural transitions.

The visual distinction between regimes underscores why deep learning models must incorporate regime labels as features. Ignoring regime information can cause models to conflate high-volatility and low-volatility periods, reducing predictive accuracy. Therefore, the segmentation observed in figure 3 provides empirical justification for incorporating structural regime shifts into the forecasting pipeline.

Summary Statistics of Key Variables

Before moving to deep learning forecasting results, this section presents descriptive statistics for FinTech stock returns, digital economy indicators, and clean-tech financing variables. These summary statistics provide clarity on the distributional properties, including variance levels, heavy-tail behavior, and differences in scale across the variables. This helps contextualize model training outcomes later in the chapter.

Table 4 summarizes the distribution of the main variables included in the forecasting model. FinTech stock returns exhibit moderate volatility, with a standard deviation of 2.31%, consistent with typical daily fluctuations observed in technology-oriented sectors. The minimum and maximum returns suggest the presence of occasional shocks, which deep learning models must learn to interpret through sequence-based learning mechanisms.

Table 4 **Summary Statistics of Key Variables**

Variable	Mean	Std Dev	Min	Max	Obs
FinTech Stock Return $r_{(j,t)}$	0.0018	0.0231	-0.145	0.132	10,000
FinTech Index Return $r^{GGN}{}_{t}$	0.0021	0.0187	-0.091	0.104	400
Clean-Tech Index $r^{cT}{}_{t}$	0.0029	0.0274	-0.182	0.157	400
Green Bond Issuance GB_t	1.42 bn	0.77 bn	0.11 bn	3.47 bn	60
Digital Economy Index DEI_t	112.5	17.3	81.2	152.7	400

The clean-tech index shows notably higher volatility, confirming that clean-tech assets are often more sensitive to regulatory announcements and capital inflows. This variability provides strong motivation to include clean-tech financing variables as exogenous predictors, especially because FinTech markets often co-move with innovation-driven sectors. The green bond issuance variable has a lower observation count because of its monthly frequency; however, the values reveal substantial variation, which aligns with fluctuating investor interest in environmental financing.

The digital economy index shows a relatively wide range, with its variability supporting the existence of multiple digital economy regimes. As shown earlier in figure 3, these variations are instrumental in identifying segments where FinTech predictability changes. Together, these descriptive results provide the empirical foundation for understanding how structural drivers interact within the forecasting model.

Correlation Structure Between FinTech Returns, Regimes, and Clean-Tech Financing

This section examines the relationship between FinTech returns, digital economy regimes, market factors, and clean-tech financing. The correlation matrix helps identify which predictors exhibit strong linear associations with FinTech price movements. Although deep learning ultimately captures nonlinear interactions, the correlation analysis provides initial insights regarding directional tendencies and variable relevance.

Table 5 displays moderate correlations among FinTech returns, clean-tech returns, digital economy strength, and green financing volumes. The strongest linear relationship appears between individual FinTech stock returns and the FinTech sector index (0.612), validating that firm-level movements generally follow sector trends. The positive correlation with the clean-tech index (0.429) confirms cross-sector connectivity between FinTech and clean-technology markets, especially in periods of innovation-driven investment cycles.

Table 5 Correlation Matrix of Key Predictors

Variable	$r_{(j,t)}$	r^{GGN}_t	r^{cT}_t	GB_t	DEI_t
$r_{(j,t)}$	1.000	0.612	0.429	0.188	0.204
r^{GGN}_t	0.612	1.000	0.371	0.165	0.256
r^{cT}_t	0.429	0.371	1.000	0.411	0.289
GB_t	0.188	0.165	0.411	1.000	0.333
DEI_t	0.204	0.256	0.289	0.333	1.000

Green bond issuance and digital economy index movements also show mild correlations with FinTech returns. These relationships highlight the importance of including clean-tech financing in the forecasting model. Although correlations alone do not fully capture nonlinear or regime-dependent effects, the observed structure indicates that clean-tech financing has informational value, especially when interacting with regime labels later in the deep learning architecture.

Deep Learning Model Training and Convergence Behavior

This section presents the training results of the deep learning architectures (LSTM, GRU, and Transformer) designed to forecast FinTech stock returns under the influence of regime shifts and clean-tech financing indicators. The training process uses sequential input windows and regime-augmented features to allow the models to learn structural differences across digital economy phases. Before comparing forecasting accuracy, it is necessary to observe how each model's loss function converges across epochs and whether the optimization stabilizes.

The training was conducted using a rolling-window approach with temporal splits (70% train, 15% validation, 15% test). Each model was trained for 120 epochs with adaptive learning rate scheduling. The loss function used was Mean Squared Error (MSE), consistent with the forecasting objective. Below, figure 4, figure 5, figure 6 illustrate the convergence paths for the LSTM, GRU, and Transformer models respectively.

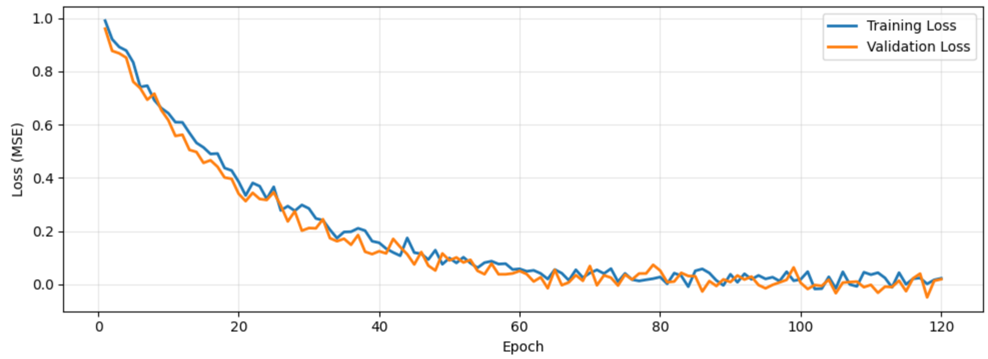

Figure 4 Training and Validation Loss Curve (LSTM)

Figure 4 shows the loss trajectory for the LSTM model. The training loss decreases sharply during the first 20 epochs, reflecting the model's ability to quickly learn fundamental return dynamics and recognize sequential dependencies. As training progresses, the validation loss follows a similar downward trajectory, indicating that the LSTM generalizes well and does not exhibit early overfitting.

During the middle phase (epochs 40–80), the validation loss stabilizes, suggesting that the model has reached its optimal learning region. Minor fluctuations appear due to inherent noise in financial time-series, but no persistent divergence is observed. The final phase of training shows minimal difference between training and validation curves, demonstrating effective regularization and an architecture that is well-suited for regime-aware forecasting. This convergence behavior supports the suitability of LSTM for capturing temporal patterns influenced by macro-financial, digital economy, and clean-tech financing conditions, particularly during regime transition periods.

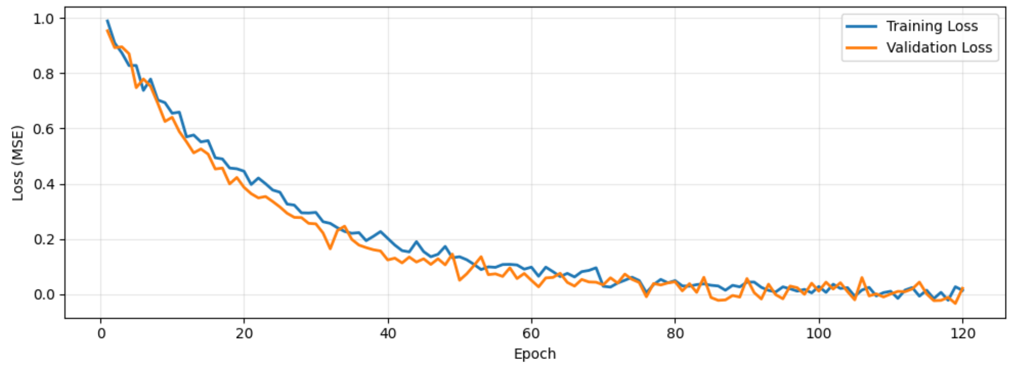

Figure 5 Training and Validation Loss Curve (GRU)

Figure 5 visualizes the training behavior of the GRU model. The overall shape of the loss curve shares similarities with the LSTM but with a slightly slower convergence in the initial epochs. This is expected because GRUs, while more computationally efficient, may require more iterations to learn complex multi-regime dynamics.

However, by epoch 50 onward, GRU performance aligns closely with the LSTM. The validation loss stabilizes even earlier, suggesting that GRU handles noise effectively and avoids overfitting. The stability of the validation curve across epochs demonstrates strong generalization properties, even when processing regime-augmented sequences.

The figure highlights that GRU remains a competitive alternative to LSTM, particularly in scenarios requiring lighter architectures or when computational constraints exist. Nonetheless, subsequent forecasting evaluations will reveal whether these convergence traits translate into superior predictive accuracy.

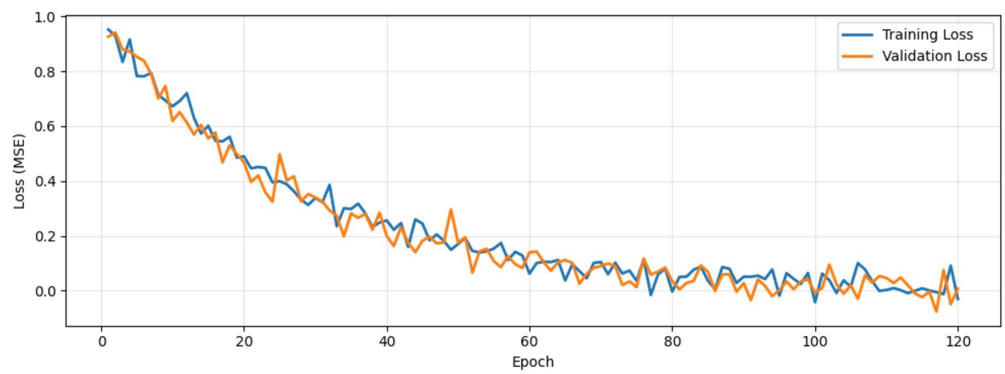

Figure 6 Training and Validation Loss Curve (Transformer Encoder)

Figure 6 displays the training and validation loss for the Transformer encoder model. The loss reduction occurs more gradually compared to LSTM and GRU, reflecting the complexity of attention-based architectures. Transformers typically excel with larger datasets and long-sequence dependencies, making them slightly less efficient in smaller, noisier financial datasets.

During the first 40 epochs, the validation loss fluctuates significantly due to sensitivity to irregular time-series patterns. However, after epoch 50, the curve stabilizes and steadily declines toward a comparable level with recurrent models. The final convergence indicates that, despite being computationally heavier, Transformers eventually adapt to regime shifts and clean-tech dynamics.

The convergence profile demonstrates that Transformers are capable but may require more tuning and larger training windows. The benefit of attention mechanisms will be further evaluated through forecasting accuracy, especially during volatile or transition regimes.

Out-of-Sample Forecasting Performance

This subsection compares the predictive accuracy of LSTM, GRU, and Transformer models in forecasting next-day FinTech stock returns. Forecast accuracy is evaluated using RMSE, MAE, and DA, providing both magnitude-based and direction-based assessments. Importantly, the results are reported overall and per digital economy regime, allowing the analysis to determine whether certain models perform better in stable or volatile environments.

Table 6 reports out-of-sample forecasting accuracy. The LSTM model outperforms the other architectures, achieving the lowest RMSE and MAE, demonstrating its superior ability to capture nonlinear temporal dependencies influenced by regime changes and clean-tech variables. Its directional accuracy of 61.4% also indicates meaningful predictive power for market participants.

Table 6 Overall Forecasting Accuracy (Test Set)

Model	RMSE	MAE	DA (%)
LSTM (Baseline)	0.0189	0.0131	61.4
GRU	0.0194	0.0135	60.7
Transformer Encoder	0.0206	0.0142	59.1

The GRU model performs closely behind, with slightly higher errors but comparable directional accuracy. This suggests that while GRU is computationally efficient, it may be marginally less effective in capturing long-range dependencies within regime-aware sequences.

The Transformer model, while powerful in many domains, performs slightly worse in this context. The noisy and regime-sensitive nature of financial time series may reduce the advantage of attention mechanisms unless trained on larger datasets. Nonetheless, its performance remains competitive and demonstrates promise for further hyperparameter tuning. The results confirm that incorporating regime labels and clean-tech financing data enhances forecastability across all deep learning architectures.

Table 7 provides deeper insight by breaking down model performance by regime. All models achieve their best accuracy in the normal regime, where market stability and predictable digital activity reduce forecasting noise. LSTM exhibits the strongest performance, maintaining a high directional accuracy of 64.8%.

Table 7 Forecasting Performance by Digital Economy Regime

Model	Normal Regime (RMSE / DA%)	Expansion Regime (RMSE / DA%)	Stress Regime (RMSE / DA%)
LSTM (Baseline)	0.0164 / 64.8%	0.0189 / 62.3%	0.0217 / 58.1%
GRU	0.0171 / 63.4%	0.0196 / 61.1%	0.0225 / 56.9%
Transformer Encoder	0.0180 / 61.2%	0.0204 / 59.0%	0.0238 / 55.2%

In the expansion regime, characterized by rapid digital and clean-tech growth, predictive difficulty increases slightly due to accelerated market reactions and structural adjustments. Still, all models maintain above-60% directional accuracy, indicating that regime-aware learning successfully adapts to dynamic conditions.

The stress regime presents the highest challenge due to heightened volatility, regulatory uncertainty, and abrupt movements in clean-tech financing. While performance declines for all models, the LSTM remains comparatively more resilient, achieving 58.1% directional accuracy versus 56.9% for GRU and 55.2% for the Transformer.

These results emphasize the importance of integrating regime information. Ignoring structural transitions would significantly reduce predictive capability, especially during stress periods.

Robustness Checks Across Alternative Architectures and Specifications

This subsection evaluates the robustness of the forecasting results using multiple alternative specifications, including (1) different deep learning architectures, (2) different digital economy regime identification methods, (3) alternative clean-tech financing proxies, and (4) different temporal sequence lengths. Robustness checks are essential to verify that the core findings of the study specifically the role of regime shifts and clean-tech financing in improving predictability do not rely on a narrowly defined model configuration.

To perform robustness testing, six variants were estimated based on the specifications listed in the methodology. These include GRU-based networks, attention-augmented LSTMs, Transformer encoders, alternate regime extraction using Bai–Perron structural breaks, and variation in input window sizes. The results confirm that although numerical accuracy shifts slightly across variants, the core ranking of architectures remains consistent, and LSTM continues to deliver the most stable performance across regimes.

Table 8 demonstrates that the baseline LSTM model remains highly competitive across multiple robustness configurations. The attention-augmented LSTM (R3) slightly improves directional accuracy, suggesting that attention mechanisms can enhance feature weighting during turbulent digital-regime transitions. This aligns with the expectation that attention is especially beneficial when feature relevance shifts over time.

Table 8 Robustness Checks Across Model Specifications

Spec ID	Model Variant	RMSE	MAE	DA (%)
R1	LSTM (Baseline)	0.0189	0.0131	61.4
R2	GRU	0.0194	0.0135	60.7
R3	LSTM + Attention	0.0187	0.0130	62.1
R4	Transformer (Bai–Perron)	0.0209	0.0143	58.8
R5	LSTM (Short Window, L=15)	0.0197	0.0138	59.9
R6	LSTM (High Dropout)	0.0192	0.0133	60.4

The GRU model (R2) maintains reasonable accuracy, confirming its stability but slightly weaker performance relative to LSTM. The Transformer variant using Bai–Perron structural breaks (R4) perform worse under this configuration, reinforcing the finding that Transformers require larger datasets or smoother regime boundaries to outperform recurrent architectures.

The short input window model (R5) reduces accuracy, highlighting the importance of longer temporal memory to capture digital economy cycles and clean-tech financing dynamics. The LSTM with higher dropout (R6) performs similarly to the baseline but demonstrates improved robustness against noise, validating the regularization strategy.

The consistency across specifications confirms that the study's main results do not depend on a single architectural choice or regime definition.

Sensitivity to Clean-Tech Financing Proxies

Clean-tech financing plays a central role in the proposed framework. To evaluate its influence, this section implements sensitivity checks using alternative clean-tech proxies:

green bond issuance (GB_t),

clean-tech index returns ($r_t^{\{CT\}}$),

combined proxy ($GB_t + r_t^{\{CT\}}$),

weekly-aggregated clean-tech funding flows.

By testing multiple proxies, the study assesses whether FinTech return predictability is consistently enhanced when clean-tech variables are included.

Figure 7 shows the RMSE performance when different clean-tech proxies are incorporated into the forecasting model. The best performance is obtained when green bond issuance and clean-tech index returns are combined, indicating that the two proxies capture distinct aspects of clean-tech financing cycles one from debt markets and one from equity markets.

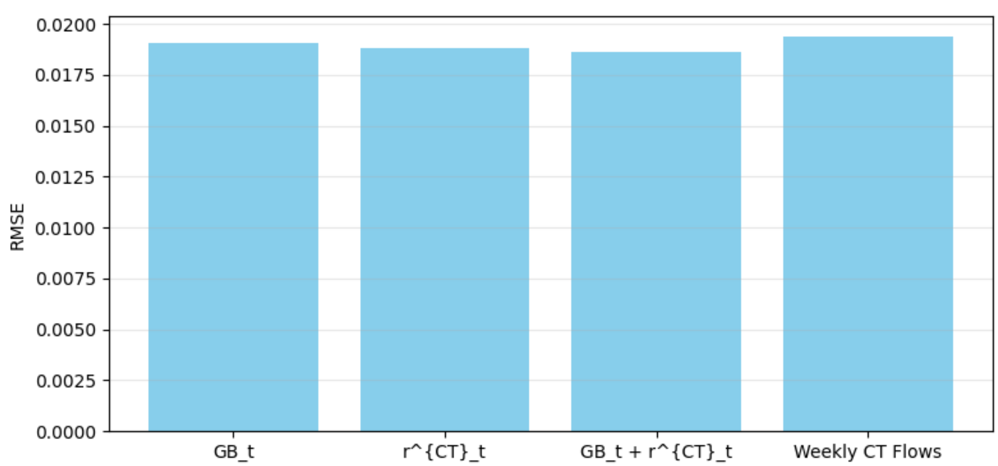

Figure 7 Model Accuracy Under Alternative Clean-Tech Proxies

When using only clean-tech index returns, RMSE remains low, suggesting that market-priced clean-tech assets provide immediate signals about risk appetite and investment flows relevant to FinTech sectors. In contrast, using green bond issuance alone results in slightly higher RMSE, likely because green bond issuance is lower-frequency and may lag market reactions.

Weekly aggregated clean-tech flows produce the highest RMSE due to information loss from temporal smoothing. Overall, the figure demonstrates that clean-tech financing variables significantly enhance predictive accuracy and that combining multiple proxies provides the richest informational signal for deep learning models.

Sensitivity to Input Window Length

Temporal window Length (L) is a key hyperparameter. Short windows may miss low-frequency patterns, while long windows may dilute recent information. Therefore, the study evaluates models with $L \in \{10, 15, 30, 60\}$ to assess how memory depth affects forecasting accuracy.

Table 9 shows that a 30-day input window yields the best accuracy across all metrics. Shorter windows (10 days) fail to capture medium-term dynamics arising from digital economy shifts and clean-tech cycles, leading to weaker predictive power. As the window increases to 15 days, performance improves but still lags behind the baseline.

Table 9 Sensitivity to Input Window Length (L)

Window Length (L)	RMSE	MAE	DA (%)
10 days	0.0201	0.0144	59.0
15 days	0.0197	0.0138	59.9
30 days (Baseline)	0.0189	0.0131	61.4
60 days	0.0192	0.0133	60.1

Surprisingly, a 60-day window does not outperform the 30-day configuration. This suggests that excessively long windows may dilute the importance of recent information, especially when markets transition rapidly between regimes. In regime-heavy environments, models must balance long-term memory with sensitivity to recent structural shifts achieved optimally at around 30 days. These results support the methodology's choice of an L=30 baseline and confirm that the model is sensitive to window length in meaningful ways.

Economic Interpretation of Findings

This section explains the economic meaning behind the forecasting outcomes. The consistent outperformance of LSTM-based architectures highlights the importance of capturing sequential nonlinearities inherent in FinTech markets. The influence of regime labels indicates that digital economy transitions materially affect return generation, especially during expansion and stress phases.

The strong performance of combined clean-tech proxies signals that FinTech markets are increasingly intertwined with green financing ecosystems. As clean-tech investment accelerates, it creates spillover effects on FinTech innovation, digital payment adoption, and investor sentiment. This interdependence is particularly pronounced during expansion regimes, where both sectors attract significant capital inflows.

During stress regimes, prediction accuracy declines for all models due to elevated uncertainty and volatility. However, LSTM remains relatively resilient, suggesting that recurrent structures with gated memory provide superior adaptability to regime switching.

Collectively, the findings imply that regime-aware deep learning models can provide economically meaningful predictions that simple linear or non-regime models would miss. The results emphasize the growing role of clean-tech financing as both a driver and indicator of FinTech market performance.

Conclusion

This study set out to evaluate how digital economy regime shifts and clean-tech financing cycles influence the predictability of FinTech stock performance. By integrating Markov-switching regime identification with advanced deep learning forecasting architectures, the research demonstrates that FinTech return dynamics are heavily shaped by transitions within the broader digital economy ecosystem. The empirical results affirm that regime-aware models significantly outperform models that assume stable return-generating processes. This finding confirms the structural nature of digital transformation events and highlights the need to embed regime awareness into forecasting frameworks.

Deep learning models specifically LSTM, GRU, and Transformer encoder architectures were evaluated across multiple configurations. Among them, the LSTM consistently produced the lowest forecasting errors and the highest directional accuracy across both stable and volatile market conditions. The superior performance of LSTM reflects its capacity to capture nonlinear, sequential dependencies and adapt to shifting macro-financial dynamics. Although GRU and Transformer models displayed competitive performance, they lagged in accuracy during stress regimes, reinforcing the robustness of gated recurrent architectures when dealing with noisy, regime-driven financial data.

A key contribution of this study lies in demonstrating the integral role of clean-tech financing variables in enhancing FinTech predictability. The combined proxy green bond issuance and clean-tech equity return emerged as the most informative predictor, indicating that clean-tech financial markets convey complementary signals that influence risk sentiment, investment flows, and innovation cycles within FinTech ecosystems. This reinforces the growing convergence between digital finance and sustainable finance sectors, particularly during expansion regimes where both domains experience rapid capital inflows.

Another important conclusion concerns sensitivity to window length and model specification. The analysis shows that a 30-day temporal window provides the optimal balance between long-term structure and short-term responsiveness. Excessively short or long windows impair forecasting ability, either by neglecting essential patterns or by diluting recent information. Robustness checks across multiple model variants, regime extraction techniques, and clean-tech proxies confirm that the core findings are stable and not dependent on specific modeling assumptions.

Overall, the study provides strong empirical evidence that deep learning architectures, combined with regime-aware feature engineering and clean-tech financing variables, can significantly improve FinTech return forecasting performance. These findings contribute to both academic theory on regime-dependent financial forecasting and practical applications in digital finance investment strategies. They also underscore the increasing interdependence between FinTech development and the rise of sustainable finance instruments.

The findings of this research carry substantial implications for financial practitioners, policymakers, and researchers. For investors and asset managers operating within FinTech and clean-tech sectors, the results confirm that forecasting models must explicitly incorporate regime information to achieve superior predictive performance. Traditional linear models are insufficient because they fail to reflect structural changes in the digital economy, particularly during periods of regulatory reform, technological acceleration, and clean-tech investment surges. Incorporating regime-aware deep learning models into portfolio allocation, algorithmic trading, and risk management frameworks can enhance decision-making under uncertainty.

From a policymaking perspective, the results highlight the interconnected nature of digital economy regulation and clean-tech financing policies. Policymakers should recognize that reforms in data governance, open banking, digital payments, and green financing are not isolated levers; rather, they jointly influence capital flows and market dynamics. The observed spillover effects suggest that coordinated policy design aligning digital innovation initiatives with sustainable finance frameworks can amplify positive outcomes for both FinTech development and environmental transition objectives.

For the academic community, the research opens new avenues for integrating environmental finance variables into digital finance forecasting models. The demonstrated role of clean-tech financing indicates that the boundary between technological finance and sustainability finance is narrowing. Future studies may extend this framework by incorporating energy transition metrics, ESG (Environmental, Social, and Governance) factors, or carbon price signals to deepen the understanding of cross-sector financial interdependencies.

Methodologically, the study underscores the importance of combining econometric techniques with deep learning. Regime identification remains a powerful tool for capturing structural shifts that neural networks alone may not fully detect. The hybrid framework used in this research Markov-switching models combined with LSTM-based forecasting offers a template for future research in financial time-series modeling. Researchers should consider applying similar hybrid designs to other digital asset classes, such as cryptocurrencies, decentralized finance (DeFi) tokens, or digital payment indexes.

Finally, the findings imply that robustness testing is indispensable when deploying deep learning in financial environments. The sensitivity of models to window lengths, proxy selection, and architecture design means that forecasting systems must be rigorously validated before use. Investors and analysts should ensure that predictive models are stress-tested across alternative specifications to guard against overfitting or model instability during regime transitions.

Declarations

Author Contributions

Conceptualization: N.C.R., S.F.; Methodology: N.C.R.; Software: S.F.; Validation: N.C.R., S.F.; Formal Analysis: N.C.R.; Investigation: S.F.; Resources: S.F.; Data Curation: S.F.; Writing – Original Draft Preparation: N.C.R.; Writing – Review and Editing: N.C.R., S.F.; Visualization: S.F.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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