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Enhancing return forecasting using LSTM with agent-based synthetic data

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ABSTRACT

Financial markets, as complex adaptive systems, are characterized by historical data limitations, inherent evolution and non-stationarity, which challenge the effectiveness of deep learning models such as Long Short-Term Memory (LSTM). We address these challenges by generating synthetic data using Agent-Based Modeling (ABM) to simulate complex market conditions through "what-if" scenarios. Our method comprises three steps: (i) pre-training the LSTM model on historical data, (ii) generating synthetic data with the ABM using "what-if" scenarios, and (iii) fine-tuning the pre-trained LSTM with ABM-generated synthetic data. The results show that ABM-generated data significantly improve model performance across various statistical and economic metrics and are robust to diverse market environments, model architectures, and data frequencies. Our primary contribution is modeling the properties of complex adaptive systems with ABM-generated data, highlighting the need for new complex scenarios to better simulate future market conditions that are distinct from historical trends. We explore the potential of ABM in generating unique synthetic data, offering a framework to address the challenges imposed by the complex adaptive system properties of financial markets, particularly, improving the discriminative ability of forecasting models such as the LSTM model.

1. Introduction

The rapid growth of artificial intelligence (AI) has popularized deep learning models, particularly Long Short-Term Memory (LSTM) networks, for financial market predictions [1,2]. However, the complexity of financial markets hinders their effectiveness [3]. These markets are complex adaptive systems (CAS) that exhibit nonlinear and evolutionary traits, resulting in high volatility and unpredictable bubbles and crashes [4]. Nonlinear micro-macro feedback loops induce non-stationarity and abrupt trend shifts in financial time series [5]. Furthermore, continuous adaptation by market participants drives market evolution, causing distributional shifts that diminish the relevance of historical patterns. Therefore, even advanced deep learning models relying solely on historical data struggle to generalize effectively, leading to rapid obsolescence.

Synthetic data have been used to enhance model adaptability and overcome these challenges in financial forecasting [6]. Synthetic data can mitigate the tension between deep models' extensive parameter estimation requirements and the risk of overfitting by expanding the training dataset. Moreover, synthetic data broadens the learning scope of the model. CAS characteristics can cause financial time-series patterns to shift significantly, and rare events can profoundly affect forecasting models. Relying solely on short-term historical windows impedes the capture of long-term trends and nonlinear dependencies. By extending the temporal scope, synthetic data offer broader temporal coverage, enabling models to better recognize evolving patterns and complex nonlinear dependencies.

However, existing methods for synthetic financial data generation, such as Generative Adversarial Networks (GANs), primarily focus on replicating the statistical distribution of historical data rather than introducing new scenarios to augment the learning scope of the models. Moreover, they fail to capture the CAS characteristics of financial markets, thereby limiting the effectiveness of LSTM models based on GAN-generated data [7]. This shortcoming raises a critical question: ***how can synthetic data be generated and integrated into LSTM models to capture the complex characteristics of financial markets and enhance the models' predictive performance?***

To address this question, we first employ an Agent-Based Model (ABM) to generate synthetic data for LSTM training. ABMs have been recognized for their effectiveness in modeling dynamic agent

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interactions in the market [8]. Unlike other fields, financial ABMs prioritize quantitative accuracy by focusing on quantitative explanations of phenomena and changes rather than offering qualitative insights. Although existing financial ABMs can replicate market crises or conduct stress tests [9], they often produce scenarios that lack strong temporal connections to current conditions, limiting their usefulness in predicting imminent anomalies. To enhance forecasting models, ABMs should mirror the statistical stylized facts commonly observed across different markets while preserving short-term dynamics [10]. Therefore, we use historical prices in the training set as fundamental values in the ABM and integrate a mixed variance approach into the agent design by combining long-term trends with short-term fluctuations [11].

Another challenge is generating synthetic data that differ from historical data while maintaining temporal dependencies. Endogeneity and feedback loops in financial market changes cause abrupt shifts frequently stemming from chartists' irrational focus on historical trends and technical indicators [8,12]. In contrast to existing methods, we simulate endogenous market continuation in the imminent future by altering agents' beliefs and behavior rules, thereby generating synthetic data that differ from historical data while maintaining temporal dependencies.

Our method uses transfer learning with synthetic data to train the LSTM forecasting model for adaptability in three steps: First, we pre-train the LSTM on historical data to identify historical patterns. Second, we generate real-time artificial market data using ABM that adjusts investors' technical beliefs, creating "what-if" scenarios. Third, we apply Parameter-Efficient Fine-Tuning (PEFT) [13] to adapt the pre-trained LSTM to complex market conditions. In particular, agents adopt mean-variance portfolio logic aligned with standard bounded-rational models, balancing expected returns and risk according to broad economic principles rather than single-dataset patterns. Emphasizing chartist behavior, we capture investors' instinctive responses to shocks that trigger chaotic market dynamics and challenge forecasting models.

The results yield three key findings. First, LSTM benefits from ABM-generated data by achieving better economic and statistical performance than both the benchmark LSTM without fine-tuning and LSTM fine-tuned with GAN-generated data. The subperiod analysis shows that the enhancement brought about by ABM-generated synthetic data can be largely attributed to the model's improved adaptability to drastic market changes. Second, generating synthetic financial data requires a balance between complexity and temporal dependencies. Overly complex data diminish its effectiveness owing to its weak correlation with current market conditions. By simulating complexity from the bottom-up rather than introducing it randomly, the ABM better maintains temporal continuity when generating distinctive synthetic data. Third, robustness tests confirm that our method works effectively across different markets and trading frequencies, and it can be extended to other deep learning models, such as Transformers.

Our contributions include a novel methodological framework that integrates ABM-generated data into financial forecasting models, enabling them to learn financial markets' CAS characteristics and achieve better performance than in previous studies. We also address the variability between synthetic and historical datasets by implementing mixed variance and adjusting agents' beliefs, thereby improving the existing ABM to generate higher-quality synthetic data that are more suitable for financial forecasting. Theoretically, we provide new insights into the forecasting literature by showing that ABM-generated data improve performance primarily because of the model's better adaptability to sharp market changes. Then, by analyzing the non-monotonic relationship between data complexity and model enhancement, we emphasize the advantages of the ABM approach in balancing the extra complexity and temporal dependencies of synthetic data, thereby enriching the theoretical foundation of ABMs in generating synthetic data for predictive augmentation.

The remainder of this article is organized as follows: Section 2 reviews the literature, Section 3 outlines the model, Section 4 presents the experimental results, and Section 5 summarizes the study and discusses avenues for future research.

2. Literature review

2.1. Financial markets as complex adaptive systems

The financial market is a complex adaptive system (CAS) comprising heterogeneous agents interacting with bounded rationality and incomplete information [4]. Nonlinear dynamics are fundamental because even small market changes can trigger disproportionately large price fluctuations, often observed as volatility clustering and fat tails [3]. These dynamics amplify instability because stable periods can abruptly give way to flash crashes or bubbles. Rapid shifts challenge forecasting models, which require comprehensive data because of their path dependence [14]. However, limited historical data and rare events hinder the ability of existing models to adapt to sudden changes [15]. Furthermore, financial markets evolve as investors respond to new information, technologies, and policies, thereby producing new market structures and features [5]. Such an evolution increases the risk of model failure because historical data may not predict future conditions [16]. Distributional shifts further complicate matters, as future data can diverge from past data, rendering static models ineffective [17]. For example, policy reforms or technological revolutions can cause machine learning models trained on historical patterns to fail [18].

Despite numerous studies highlighting the nonlinear dynamics and evolutionary nature of financial markets, few incorporate the CAS characteristics into their models. Thus, current models are inadequate for addressing these complexities [19]. Therefore, financial forecasting models struggle to adapt to evolving CAS features, thereby limiting their accuracy and adaptability.

2.2. Deep learning-based forecasting models

The remarkable abilities of deep learning models in nonlinear mapping, adjustable parameters, and extensive scalability render them highly effective for return forecasting. LSTM models, which are tailored to time-series data, exemplify the role of deep learning in financial forecasting [20]. LSTM's gating mechanism captures long-term dependencies, mitigating the vanishing gradient problem in recurrent neural networks [2]. This ability supports complex tasks such as modeling financial market dynamics and can be integrated with transfer learning to enable adaptive trading strategies [21]. Unlike attention-based Transformers that demand additional mechanisms, LSTM models are typically more compact and inherently adept at performing time-series tasks [22]. Therefore, LSTM models remain the leading choice for return prediction.

Furthermore, LSTM shares similarities with other deep-learning models, allowing our method to be applied beyond LSTM. Despite architectural differences, the transfer learning mechanism operates similarly across these models [23]. Fine-tuning modifies pre-trained model weights to fit new data characteristics [2], making insights from our LSTM research beneficial for other models.

2.3. Synthetic data

Synthetic data enhance financial forecasting models by increasing the quantity and diversity of data [24]. The quality of the synthetic data is crucial, particularly when training data are scarce. Methods for generating synthetic financial data fall into two categories: transforming real data and simulating real processes. Transformation techniques, including statistical models [25], machine learning techniques [26], and data augmentation [27], create synthetic data that resemble the original characteristics. Among these methods, GAN-based models have gained popularity owing to their ability to generate synthetic financial data, particularly with forecasting models [6].

An alternative method for generating synthetic data is ABM simulation. Considering CAS, simulation methods are better for generating financial time-series data, because simple replications of historical data fail to capture the non-stationary and evolutionary nature of financial markets [28]. In comparison, ABM adopts a bottom-up approach to model agents' interactions within markets, and nonlinear feedback mechanisms naturally emerge [29]. ABM has been widely applied in economics research to replicate and explain complex processes [9] and model CAS, such as stock markets and supply chains [30].

One advantage of ABM is its ability to maintain temporal dependencies between synthetic and historical data, which is essential for time-series forecasting [31]. However, existing financial ABM models mainly serve explanatory roles, such as simulating market crises or conducting stress tests, thus emphasizing synthetic data diversity over aligning generated events with real market conditions [32]. As a result, the generated scenarios are unsuitable for training forecasting models because synthetic data may be irrelevant to the current market.

Another potential application of ABM-generated data is to provide learning samples related to rare events that are not found in historical data. Existing financial ABMs generate diverse scenarios by modifying institutional designs or simulating specific events [33]. However, because of the unpredictability of external shocks, modeling adaptive agents' responses and changes in their complex interactions is more appropriate for predicting the impact of such events on the current market [34]. In financial markets, the interaction between chartists and fundamentalist traders drives the volatile price dynamics observed in real markets [35]. Chartists' focus on historical trends leads to complex price behaviors, causing sudden shifts that can result in sharp declines [12]. Thus, adjusting agents' beliefs and behaviors to reflect market complexities for reasonable synthetic data generation remains a challenge in ABM.

3. Proposed method

Fig. 1 illustrates a forecasting system for directional return prediction, consisting of model pre-training on historical data, synthetic data generation via ABM, and fine-tuning. The model has three key components: the Time-Series Memory Layer (TSML), Market Dynamics Awareness Layer (MDAL), and Feature Fusion Layer. The TSML and MDAL are based on LSTM to capture temporal patterns and market dynamics respectively. During pre-training, all layers remain trainable to learn general market patterns. The PEFT [13] is then performed by freezing the TSML and updating the other layers.

3.1. Forecasting procedure

3.1.1. Problem formulation

We propose a model for forecasting market return directions that aims to identify upward (1) or downward (0) price movements. Given T price observations $(1 \leq t \leq T)$, p_t is the logarithmic price. The logarithmic return r_t is then computed as $r_t = p_t - p_{t-1}$. A vector of predictor variables X_t is used to predict the binary outcome y'_{t+1} as the future stock price direction, as follows:

$$y'_{t+1} = f_\theta (X_t) \tag{1}$$

where $f_\theta(\cdot)$ is the classification method with parameters θ.

We delineate feature X_t as various features that are commonly used in the literature for return prediction [1,36], including the Rate of Change (ROC), Relative Strength Index (RSI; 14 days), Moving Average Convergence-divergence (MACD; 26 days, 12 days, signal 9 days), Simple Moving Averages (SMA; 5 days, 10 days), Bollinger Bands (2 standard deviations), and momentum changes over 1-, 3-, 5-, and 10-day periods.

3.1.2. Pre-training

We pre-train the forecasting model using historical data to identify general patterns in market returns. Historical dataset $D_h = \{X_h, Y_h\}$ comprises features $X_h = \{X_1, X_2, \ldots, X_{T-\lambda}\}$ and the upcoming return direction Y_h, where T is the number of observations and λ is the lag order. The model $M(X_h, \theta_h)$ is pre-trained with parameters $\theta_h = \left\{\theta_h^{(1)}, \theta_h^{(2)}, \theta_h^{(3)}\right\}$. The model M processes the inputs in three stages. First, the TSML takes the input features X_t and generates the hidden states $h_t^{TSML} = \mathrm{TSML}\left(X_t; \theta_h^{(1)}\right)$. Second, the MDAL processes these hidden states and produces the hidden states $h_t^{MDAL} = \mathrm{MDAL}\left(h_t^{TSML}; \theta_h^{(2)}\right)$. Third, the Fully Connected (FC) feature fusion layer transforms MDAL outputs into the predicted upcoming return direction $y'_{h,t+1} = FC\left(h_t^{MDAL}; \theta_h^{(3)}\right)$. During pre-training, all parameters θ_h are updated to

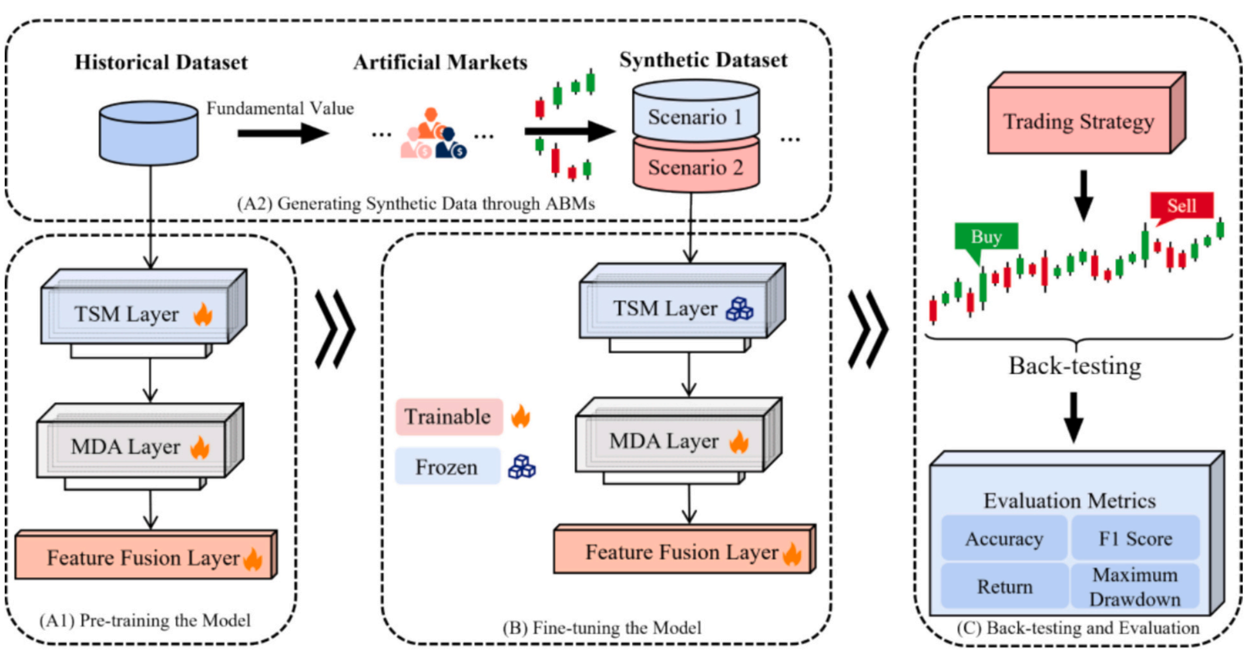

Fig. 1. An ABM-enhanced return forecasting system combining historical and synthetic data.

minimize the cross-entropy loss function, which measures the discrepancy between the predicted $y'_{h,t+1}$ and actual return direction $y_{h,t+1}$. The parameters are iteratively updated via gradient descent as $\theta'_h = \theta_h - \alpha \nabla Loss$, where α is the learning rate and $\nabla Loss$ is the gradient of the loss function.

3.2. Synthetic data generation

3.2.1. Artificial market setup

We use a continuous double-auction limit order book (LOB) to model price dynamics. Unlike quote-driven markets, the LOB captures the decentralized nature of liquidity provision [37]. Agents submit buy and sell orders that interact in real time, creating a feedback loop wherein each action reshapes the market environment. These interactions yield emergent phenomena, meaning the resulting price dynamics cannot be deduced from the rules or hyper-parameters of any individual agent [10]. Although each agent follows a standard mean-variance approach based on general economic principles [38], the aggregated effect of their actions produces unexpected patterns. For calibration, we set the moving average of the training data as the fundamental value. Instead of replicating historical data, the model generates synthetic data through interactive trading, thereby reconstructing the original patterns without transferring them directly [12]. This process introduces new information while preventing leakage. We also use mixed variance to capture time-varying fluctuations and avoid distorting stylized facts [39].

We populate this artificial market with heterogeneous agents, each with distinct investment beliefs (i.e., fundamental, chartist, and noise) [11]. Agents enter the market randomly by a Poisson process, with arrival intervals τ^i, representing both the temporal gap and investment horizon:

$$\tau^i = \frac{\tau}{1+\omega^i} \tag{2}$$

where τ represents the max investment horizon, and ω^i is the weight of chartist beliefs. In each period t, agent i can execute a market order or submit a limit order with price p_t^i and order size z_t^i, where $z_t^i > 0$ for buys and $z_t^i < 0$ for sells. Furthermore, agents observe the latest transaction price p_t, and fundamental value p_t^f (5-period moving average of historical training data). If no transaction occurs, p_t is the average of the quoted ask a_t^q and bid prices b_t^q.

Agents employ a combination of fundamental and technical rules for order submissions. Each agent forms an expectation of future logarithmic price $\mathbb{E}^i[ln(p_{t+\tau^i})\,|\mathscr{F}_t]$, as follows:

$$\mathbb{E}^i[ln(p_{t+\tau^i})\,|\mathscr{F}_t] = \left(ln(p_t^f) + \widetilde{\theta}_t\right) + \omega^i(ln(p_t) - ln(p_{t-\tau^i})) \tag{3}$$

where $\mathscr{F}_t$ contains the prices and information about the order book in the past, p_t is the latest traded price, and $p_{t-\tau^i}$ is the traded price τ^i periods ago. The potential belief error about the fundamental value follows a uniform distribution $\widetilde{\theta}_t^i \sim U\left(-\sigma_v\sqrt{\tau^i}, \sigma_v\sqrt{\tau^i}\right)$. After forming a subjective belief about the distribution of price $p_{t+\tau^i}$ at time $t+\tau^i$, and given the submission prices p_t^i, the expectation of the spot return $\widehat{r}_{t,t+\tau^i} = \mathbb{E}^i[ln(p_{t+\tau^i})\,|\mathscr{F}_t] - ln(p_t^i)$.

Risk is measured using variances, capturing the combined effect of fundamental and chartist beliefs on return variance and guiding agents' decision-making for order sizes π. The variance is the harmonic mean of fundamental and chartist variances, $\left(\sigma_{v,t}^i\right)^2$ and $\left(\sigma_{h,t}^i\right)^2$, weighted by ζ^i, balancing the contributions of different market analysis as follows:

$$\left(\sigma_t^i\right)^2 = 1 \Bigg/ \left(\frac{1-\zeta^i}{\left(\sigma_{v,t}^i\right)^2} + \frac{\zeta^i}{\left(\sigma_{h,t}^i\right)^2}\right) \tag{4}$$

where $\left(\sigma_{v,t}^i\right)^2$ is the variance of the fundamental value in the specific τ^i period, with $\left(\sigma_v^i\right)^2 = (\sigma_v)^2\tau^i$. The $\left(\sigma_{h,t}^i\right)^2$ denotes the variance of the natural logarithm of historical prices as follows:

$$\left(\sigma_{h,t}^i\right)^2 = \frac{1}{\tau^i - 1}\sum_{j=1}^{\tau^i}\left(ln\left(p_{t-j}\right) - \mu_{h,t}^i\right)^2 \tag{5}$$

where τ^i is the agent's investment horizon, p_{t-j} is the price at time $t-j$, and $\mu_{h,t}^i$ is the average of the logarithmic prices over the investment horizon τ^i. As ω^i increases, the chartist component becomes more dominant and ζ^i reaches 1. Conversely, as ω^i decreases, the fundamental component becomes more dominant and ζ^i reaches 0. The harmonic mean balances the contribution of fundamental and chartist beliefs by assigning more weight to the minor variance. Such an intentional design mitigates distortions in stylized facts when generating synthetic data. The weighting parameter $\zeta^i = \omega^i/(1+\omega^i)$ is derived from the ratio of chartist beliefs ω^i.

The agent's objective is to maximize the constant absolute risk aversion utility function of wealth, as follows:

$$\max_{\pi_t^i} \mathbb{E}_t^i\left[-exp\left(-\alpha^i W_{t+\tau^i}^i\right)\right] \tag{6}$$

where $W_{t+\tau^i}^i = W_t^i + W_t^i\pi_t^i(p_{t+\tau^i} - p_t^i)/p_t^i$ is the agent's wealth at time $t+\tau^i$ and π_t^i is the proportion of wealth invested in the risky asset. Short selling and borrowing are not allowed, and the risk-free interest rate is assumed to be zero. Assuming $W_{t+\tau^i}^i$ follows a normal distribution and the return $(p_{t+\tau^i} - p_t^i)/p_t^i \approx ln(p_{t+\tau^i}) - ln(p_t^i)$, the optimal portfolio is:

$$W_t^i\pi_t^i = \frac{\widehat{r}_{t,t+\tau^i}}{\alpha^i\left(\sigma_t^i\right)^2} \tag{7}$$

where $\left(\sigma_t^i\right)^2$ is the return variance observed by agent i, α is the reference level of risk aversion, and $\alpha^i = \alpha/(1+\omega^i)$ is the absolute risk aversion coefficient is influenced by chartist beliefs. Consequently, the order size z_t^i is expressed as follows:

$$z_t^i = \frac{W_t^i}{p_t^i}\pi_t^i - s_t^i = \frac{\widehat{r}_{t,t+\tau^i}}{p_t^i\alpha^i\left(\sigma_t^i\right)^2} - s_t^i \tag{8}$$

where s_t^i indicates the number of shares of risky assets held by agent i at time t.

The agents' decisions to buy or sell risky assets are based on the mechanism shown in Table 1. Submission price p_t^i is calculated by adjusting the agent's forecasted logarithmic price with a risk-adjusted expected return:

$$p_t^i = exp\left(\mathbb{E}^i[ln(p_{t+\tau^i})\,|\mathscr{F}_t] - \epsilon\right) \tag{9}$$

where $\mathbb{E}^i[ln(p_{t+\tau^i})\,|\mathscr{F}_t]$ is the agent's expected logarithmic price, and ϵ is a risk-adjusted expected return drawn from a uniform distribution $\epsilon \sim U\left(0, \alpha^i\left(\sigma_t^i\right)^2\right)$.

Table 1
Mechanism for buying/selling the asset by heterogeneous agents.

Price	Action	Order Type	Volume
$p_t^i < a_t^q$	*Buy*	*Limit order*	$z_t^i > 0$
$p_t^i \geq a_t^q$	*Buy*	*Market order*	$z_t^i > 0$
$p_t^i \leq b_t^q$	*Sell*	*Market order*	$z_t^i < 0$
$p_t^i > b_t^q$	*Sell*	*Limit order*	$z_t^i < 0$

Notes: p_t^i represents the price at which agent i submits an order at time t; a_t^q is the quoted ask price; b_t^q is the quoted bid price; $z_t^i > 0$ indicates a buy order.

Informed by the model predictions, two key trading scenarios emerge: opening and closing trades. Opening a trade is initiated in anticipation of price momentum, and closing a trade occurs when price momentum is expected to diminish.

3.2.2. Hyperparameter determination and simulation validation

In Table 2, the hyperparameters are set to capture the theoretical concept of how interactions among agents with regime-dependent beliefs give rise to stylized facts and complex market dynamics [11]. Stylized facts represent a key focus area in econophysics, because they capture broad market tendencies commonly observed in financial data and reflect the complex nature of financial systems [10]. By confirming that the synthetic data exhibit statistical properties similar to those of real market data, we establish the validity of the model. The internal validation is ensured by designing agents to replicate real-world trader behavior, emphasizing the ABM's ability to generate output traces that approximate reality. Table 3 shows that higher average weight of chartist beliefs amplifies volatility uncertainty, which is measured by DUVOL [40], aligning with theories of bubble formation [8]. For external validation, we confirm that synthetic data generated by the calibrated ABM (with $\omega = 0.05$) replicates key stylized facts from real-world financial markets in training dataset, such as high kurtosis and negative skewness [41], as shown in Table 3.

3.2.3. "What-if" scenarios generation

We create "what-if" scenarios by increasing the weight of agents' chartist beliefs ω to amplify chartist behavior and to trigger nonlinear expectation feedback loops, thereby increasing market instability [3]. Table 3 presents the statistical properties of ABM-generated synthetic data with the chartist beliefs weight ω between 0.05 and 2. When $\omega > 2$, the excessive weight of chartist beliefs leads to higher volatility and maximum drawdown, causing liquidity dry-ups and market failure. When $\omega < 0.05$, the synthetic data fails to capture these stylized facts. For $0.05 \le \omega \le 2$, the synthetic data matches the stylized facts of real market data. As the ω increases, the market transitions from a stable state to complex conditions, marked by higher annual volatility, larger maximum drawdowns and higher DUVOL. The optimal ω will be determined through the validation dataset and used for out-of-sample return forecasting.

To prevent information leakage, we use Dynamic Time Warping (DTW) to measure the distance between synthetic and testing data [42]. DTW is effective in analyzing time series that vary in length because the synthetic dataset corresponds to the training data, while the test data show discrepancies. In Table 3, the DTW distance between synthetic data testing data consistently exceeds that of the training dataset, and increases with a higher ω. Through the DTW distance, we confirm that the enhanced model performance stems from our approach, rather than any potential information leakage owing to the resemblances between the synthetic and testing data.

Table 2
Fixed hyperparameters for the calibrated ABM without scenarios.

Parameter	Value	Description
τ	240	*Maximum investment horizon*
α	1.00	*Risk aversion coefficient*
σ_v	[1]	*Fundamental value volatility*
p_0	[2]	*Initial asset price*
q_0	50	*Initial agent position*
N	1000	*Number of agents in the simulation*
ω	0.05	*Average weight of the agents' chartist beliefs*

Notes: [1] The fundamental value volatility σ_v is set to the standard deviation of the training data. [2] The initial asset price p_0 is set as the initial price of the training data.

3.3. Fine-tuning procedure

As shown in Fig. 2, we use PEFT to fine-tune the LSTM for complex market conditions while freezing most of the pre-trained weights, thereby preserving the knowledge acquired during pre-training [13]. The synthetic dataset $D_s = \{X_s, Y_s\}$ consists of features $X_s = \{X'_1, X'_2, \dots, X'_{T-\lambda}\}$ and the return direction Y_s, where T' is the number of observations and λ is the lag order. The model $M(X_s, \theta_s)$ is enhanced by fine-tuning the parameters $\theta_s = \left\{\theta_s^{(1)}, \theta_s^{(2)}, \theta_s^{(3)}\right\}$.

Specifically, the synthetic features X'_t are passed through the TSML to generate the hidden states $h_t^{TSML} = \mathsf{TSML}\left(X'_t; \theta_s^{(1)}\right)$, where $\theta_s^{(1)}$ are frozen parameters, which capture general patterns in the historical data. These states are then processed by the MDAL layer to generate the hidden states $h_t^{MDAL} = \mathsf{MDAL}\left(h_t^{TSML}; \theta_s^{(2)}\right)$, where $\theta_s^{(2)}$ are trainable parameters, capturing patterns overlooked in historical data. Hidden states h_t^{MDAL} are passed through the Feature Fusion Layer to forecast the return direction $y'_{s,t+1} = \mathsf{FC}\left(h_t^{MDAL}; \theta_s^{(3)}\right)$, where $\theta_s^{(3)}$ are the trainable parameters of the feature fusion layer. We apply the cross-entropy loss to evaluate model performance and define the corresponding loss function. Since $\theta_s^{(1)}$ is frozen, only $\theta_s^{(2)}$ and $\theta_s^{(3)}$ are updated via gradient descent: $\theta_s^{(l)} - \alpha \nabla Loss'^{(l)}, l = 2, 3$, where α is the learning rate, and $\nabla Loss'^{(l)}$ is the gradient with respect to the l-th layer parameters. This fine-tuning process integrates historical data knowledge with patterns from synthetic data.

4. Experiments and discussions

4.1. Experimental setting

4.1.1. Datasets

We use daily S&P 500 data from January 2008 to December 2023 for comparative analysis and validation, incorporating the impact of economic cycles by dividing the dataset based on NBER-dated cycles [43]. By covering a complete economic cycle, this partitioning overcomes two limitations. It broadens the applicability across economic states and allows the model to learn from diverse market behaviors. The first economic cycle (from January 2008 to December 2019) serves as the training set, and the second (from January 2020 to December 2023) serves as the testing set, with the validation dataset covering January 2019 to December 2019. This partitioning ensures that both the training and testing datasets span complete NBER-dated economic cycles, including expansions and recessions. After training, the validation dataset is used to determine the optimal ω for generating synthetic data with the best enhancement.

For comparison with state-of-the-art methods, we employ the widely used GAN model [26] to generate synthetic data in addition to the ABM-generated data. As expected, the GAN-generated data closely resemble the training data, with a maximum drawdown of -0.6247 and an annualized volatility of 0.1894. The DTW distance between the GAN-generated and the testing data is 23, which is similar to the DTW distance between the training and testing datasets.

4.1.2. Evaluation metrics

We evaluate models' performance through various metrics: accuracy, precision, F1 score (F1), cumulative return (CR), maximum drawdown (MDD), and Sharpe ratio (SR). Accuracy indicates the consistency of predictions, whereas precision measures the true positives among the predicted positives. The F1 score combines precision and recall to obtain a balanced view of the positive class predictions. Cumulative returns show profit generation over time, maximum drawdown assesses risk tolerance, and the Sharpe ratio evaluates excess returns relative to risk.

Table 3
Statistical properties of ABM-generated data with various chartist beliefs weight ω.

Statistical properties	Train data	Test data	Synthetic data under different ω: 0.05	0.5	1	1.5	2
Annual volatility	0.2016	0.231	0.237	0.2812	0.7059	1.0364	1.2093
Maximum drawdown	−0.5325	−0.3393	−0.5935	−0.6054	−0.872	−0.9884	−1.2594
DUVOL	0.1604	0.1974	0.1536	0.186	0.2328	0.2683	0.3110
DTW to testing data	20.1755	0.0000	27.591	34.6117	64.4413	96.8627	118.3830
Kurtosis	10.8357	12.7575	7.3336	4.2694	11.619	8.2199	7.5939
Skewness	−0.3476	−0.7833	−0.0795	−0.2817	−0.113	−0.0255	−0.0085

Notes: The training dataset comprises S&P 500 index data from January 2008 to December 2018, and the testing dataset contains data from January 2020 to December 2023.

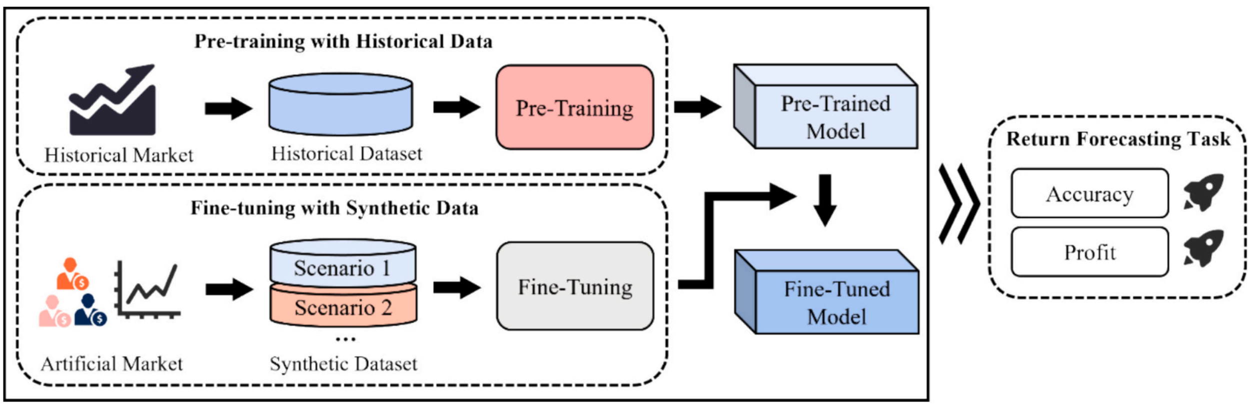

Fig. 2. Fine-tuning schematics through the ABM-generated synthetic data of the LSTM.

4.2. Model performance

According to the validation performance, we determine the optimal hyperparameter value $\omega = 1$. At this value, the ABM-generated data maintains key stylized facts while showing increased volatility and maximum drawdown, making them representative of “what-if” scenarios.

In Fig. 3, the ABM-LSTM model outperforms the other models in cumulative returns across the economic cycle, with lower volatility and reduced drawdowns. Its resilience is evident during market turbulence, where it recovers faster and maintains stable growth. In Table 4, the ABM-LSTM model outperforms other models in statistical evaluation, achieving top accuracy, precision, and F1 scores. It also delivers the highest cumulative returns, smallest maximum drawdown, and highest Sharpe ratio. Although the LSTM and GAN-LSTM models outperform the ARIMA in F1 scores and Sharpe ratio, they still fall short of the ABM-LSTM. These results highlight the advantage of “what-if” scenarios generated by agents within the market microstructure.

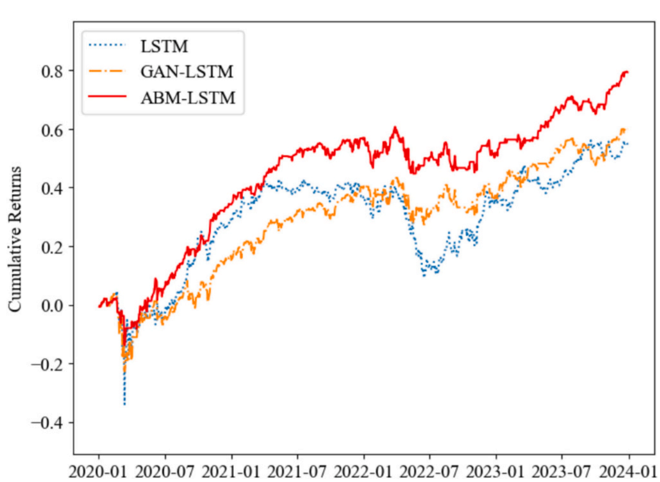

Fig. 3. Cumulative returns for different forecasting models.

Table 4
Performance metrics of various models on the S&P 500.

Model	Accuracy	Precision	F1	CR	MDD	SR
B&H	–	–	–	0.3812	−0.4144	0.4135
ARIMA	0.5159	0.5427	0.5401	0.0851	−0.3586	0.1366
LSTM	0.5388	0.5507	0.6140	0.5768	−0.2075	0.8651
GAN-LSTM	0.5427	0.5588	0.5979	0.5619	−0.1932	0.9394
ABM-LSTM	**0.5646**	**0.5639**	**0.6546**	**0.7934**	**−0.1611**	**1.2355**

Notes: “B&H" is “Buy and Hold”. “GAN-LSTM” and “ABM-LSTM” are LSTM models fine-tuned with GAN-generated data and ABM-generated data respectively.

Table 3 shows that the ABM-generated data differ from the testing data, confirming that the method, rather than information leakage, drives the improved performance of the LSTM model. Our ABM-LSTM model achieves a 6.61 % higher F1 score and a 4.79 % improvement in accuracy compared to the LSTM model, surpassing the gains of 4.17 % and 1.12 % reported previously [1].

4.3. Mechanism inspection

4.3.1. Data perspective

To investigate the mechanism behind the improved forecasting performance from a data perspective, we further examine the key stylized facts within the datasets. As shown in Fig. 4, the synthetic distribution features more frequent long-tailed returns. Notably, a clear distinction emerges between $\omega < 1$ and $\omega \geq 1$, with the latter displaying a significant increase in long-tailed returns.

Fig. 5 consists of four panels (Volatility, DUVOL, $H(t)$, and JV),

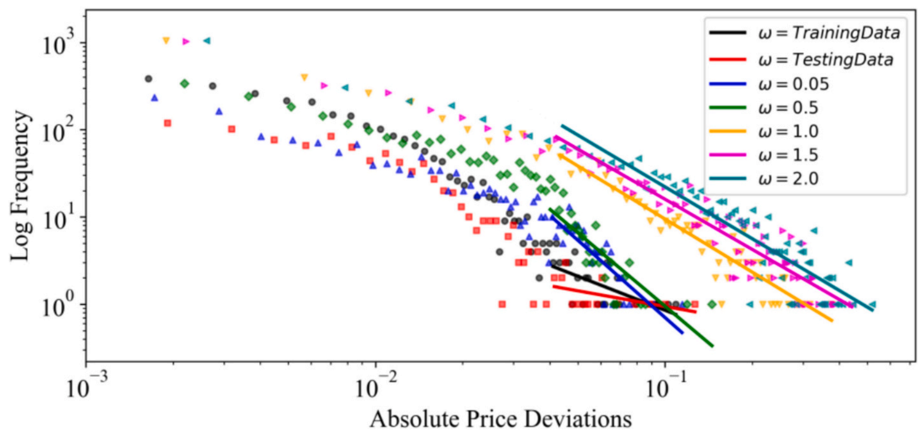

Fig. 4. The log-frequency of absolute price deviations for both real market data and synthetic data.

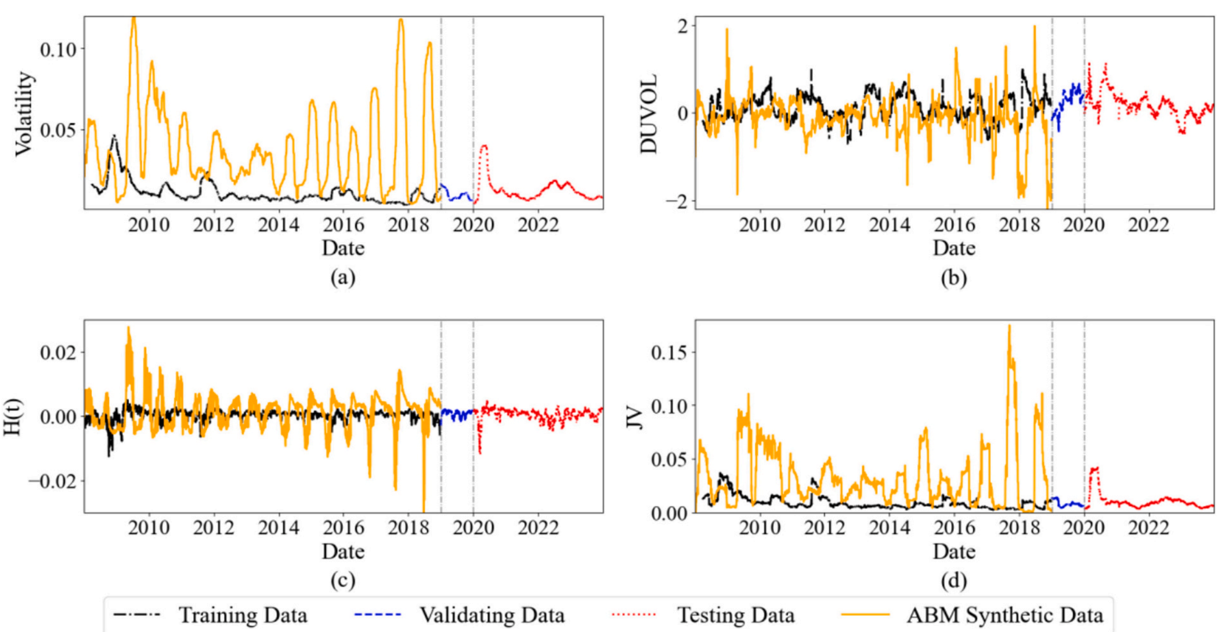

Fig. 5. Stylized facts of the training, validating, testing and ABM synthetic data ($\omega = 1$).

showing the differences in market dynamics between historical and synthetic data. Volatility captures overall fluctuations in returns, while the DUVOL measures the imbalance between downside and upside variations. $H(t)$ is a hierarchy-based momentum indicator that reflects how localized trader beliefs can escalate across market levels, potentially leading to bubbles, crashes, or regime shifts [10]. $H(t)$ aggregates short-term collective states into a single measure of speculative intensity, with higher values signaling stronger, self-reinforcing trends, and lower values indicating milder momentum. Jump risks (Jump Variation, JV) represent the difference between total realized variance (RV), and the integrated variation (IV), which measures the continuous diffusive component of variance [44]. A higher JV suggests more pronounced jumps, indicating increased jump risk.

In Fig. 5 (a), volatility remains stable in both training and testing data, with occasional spikes. In comparison, the ABM-generated synthetic data with $\omega = 1$ shows significantly higher volatility, indicating greater return fluctuations. Fig. 5 (b) shows that while real data exhibit minimal fluctuations, the synthetic data reveals sharp oscillations, indicating a greater imbalance between upward and downward price movements. Fig. 5 (c) shows the $H(t)$ indicator, with the synthetic data revealing clear momentum peaks, suggesting stronger speculative behavior than historical data. Fig. 5 (d) tracks jump risk, with synthetic data consistently showing larger jumps, reinforcing the idea that a higher ω leads to more frequent and pronounced price deviations.

These results indicate that the ABM creates more frequent patterns of bubbles, crashes, volatility and momentum, which emerge from the endogenous generation of price patterns that were previously underrepresented in the historical data. By providing more frequent and pronounced tail events than those typically observed in real data, the synthetic data fills a critical gap in tail-risk information, thereby enhancing the forecasting model's ability to handle various market conditions. The key driver of this effect is the interaction between fundamentalist and chartist behaviors through the expectations feedback mechanism. In this mechanism, agents make decisions based on predictions of endogenous variables, whose actual values are shaped by the agents' expectations [45]. This feature is inherent to Heterogeneous Agent Models (HAM) and is crucial for generating the amplified price dynamics observed in the ABM.

4.3.2. *Subperiod analysis*

To verify how ABM-generated data enhance forecasting models, we conduct a subperiod analysis using monthly DUVOL values to identify market instability in the testing dataset [40]. We select three groups based on the lowest, closest-to-median, and highest DUVOL values, with 10 months selected for each group independently, covering 30 months in total, and representing three different volatility regimes: Low, Median, and High instability.

Through comparisons with the GAN-LSTM model, we verify the mechanism underlying the enhancement. In Table 5, the ABM-LSTM and GAN-LSTM exhibit similar outperformance during low DUVOL periods. However, as DUVOL increases, the advantage of ABM-generated synthetic data grows. Although the GAN-LSTM model demonstrates a sharp performance drop during high DUVOL periods, the ABM-LSTM model remains stable, especially in drawdown control, maintaining consistency with other periods.

Unlike GAN-generated synthetic data, ABM synthetic data deviates further from a normal distribution and displays higher volatility, reflecting a more complex market environment than historical data. Therefore, ABM-generated synthetic data capture the CAS characteristics of financial markets and maintain a temporal correlation with historical data, offering the predictive model insights into likely rare market changes. The results indicate that the enhancement brought about by the ABM-generated synthetic data is largely attributable to the model's improved adaptability to drastic market changes.

4.4. Data complexity with varying chartist beliefs

We further examine the impact of data complexity, simulated through varying the level of ω. Table 6 shows that the enhancement effects of synthetic data on the LSTM model vary with different values of ω, with the optimal performance at $\omega = 1$. As ω increases from 0.05, model performance improves until peaking at $\omega = 1$, indicating that moderate complexity enhances adaptability. However, further increases in ω beyond 1 lead to performance decline owing to noise outweighing the benefits of added information.

When ω is too small (i.e., $\omega = 0.05$), the synthetic data closely resembles historical data, offering little additional information and limited enhancement. Market behaviors exhibit path dependence, meaning that past events influence market participants' actions and trends. Therefore, a moderate increase in ω generates synthetic data with fluctuations that align with the gradual changes observed in real markets, enabling the model to effectively predict future nonlinear trends. However, when ω is too large (e.g., $\omega > 1.5$), the synthetic data deviates excessively from historical data and becomes disconnected from the short-term future that the predictive model is facing, as indicated by the DTW distance in Table 3. At this point, the model not only faces the risk of overfitting to the noise during training but may also lose its adaptability to actual market data, rendering it ineffective at making accurate predictions.

The balance between increasing complexity and preserving temporal dependencies also underscores the appropriateness of using ABM as a method for generating synthetic financial data. By simulating complexity from the bottom-up rather than introducing it randomly, ABM better maintains the relevance of synthetic data to the current market conditions.

Table 6
Performance of the ABM-LSTM model under different chartist belief weights.

ω	Accuracy	Precision	F1	CR	MDD	SR
0.05	*0.5447*	*0.5576*	*0.6099*	*0.6233*	*−0.1854*	*0.9532*
0.50	*0.5517*	*0.5593*	*0.6288*	*0.6108*	*−0.1854*	*0.9321*
1.00	***0.5646***	***0.5639***	***0.6546***	***0.7934***	***−0.1611***	***1.2355***
1.50	*0.5348*	*0.5453*	*0.6220*	*0.5786*	*−0.1898*	*0.8354*
2.00	*0.5127*	*0.5266*	*0.6080*	*0.4936*	*−0.2032*	*0.8131*

4.5. Robustness

4.5.1. Performance in different markets

In Table 7, we test ABM-generated data across different markets, including the DAX (developed market) and SSE composite (emerging market) to validate the ABM-LSTM's generalization capability. The lengths of the training, validating and testing data of the DAX and SSE are kept the same as those for S&P 500. We generate synthetic data for both the DAX and SSE datasets, with $\omega = 1$ for model comparison. On the DAX index, the ABM-LSTM achieves the highest performance across most statistical metrics, emphasizing the importance of incorporating "what-if" scenarios to enhance model performance. On the SSE index, the ABM-LSTM continues to outperform other models, recording the highest values in all statistical metrics and most economic metrics.

4.5.2. Validation with attention-based models

We evaluate the robustness of the proposed method using advanced Transformer-based models [36]. The results of the Transformer-based models in Table 8 are consistent with those of the LSTM models in Table 4, confirming the robustness of our approach across model architectures. The ABM-Transformer model, which incorporates synthetic "what-if" scenarios, outperforms both the baseline and GAN-enhanced Transformer models in most statistical and economic metrics. The Transformer model shows an insignificant performance improvement over LSTM, reinforcing that LSTMs are well-suited for financial time series. Then, ABM-generated data with "what-if" scenarios enhance both models, demonstrating the generalizability of the proposed method.

4.5.3. Effectiveness in high-frequency environments

We use 1-min S&P 500 data to test the robustness of our method across time scales. The dataset is split into training (from January 2020 to Dec 2021) and testing (from January to June 2022) periods. We close the positions daily to mitigate overnight risks. The hyperparameter ω is set to 1 for comparison. Table 9 shows that the ABM-LSTM model outperforms other models in most metrics. It achieves the highest accuracy and precision, along with higher cumulative returns, lower maximum drawdown, and a higher Sharpe ratio, demonstrating its superior risk management and return performance. These results highlight the ability of ABM-LSTM to capture the evolving, nonlinear dynamics of financial markets, especially in high-frequency settings.

Table 5
Performance metrics across different DUVOL periods.

Period	Model	Accuracy	Precision	F1	CR	MDD	SR
	LSTM	*0.6046*	*0.6342*	*0.6985*	*0.0575*	*−0.0140*	*1.0633*
L	*GAN-LSTM*	*0.6157*	*0.6434*	*0.7417*	*0.0509*	*−0.0147*	*1.6330*
	ABM-LSTM	*0.6457*	*0.6673*	*0.7509*	*0.0594*	*−0.0116*	*1.7392*
	LSTM	*0.5387*	*0.5873*	*0.6273*	*0.0205*	*−0.0307*	*1.0003*
M	*GAN-LSTM*	*0.5619*	*0.5838*	*0.6593*	*0.0198*	*−0.0301*	*0.9888*
	ABM-LSTM	*0.5845*	*0.5937*	*0.7124*	*0.0235*	*−0.0225*	*1.3762*
	LSTM	*0.5072*	*0.5743*	*0.5069*	*−0.0647*	*−0.0865*	*−4.1179*
H	*GAN-LSTM*	*0.5157*	*0.5700*	*0.5782*	*−0.0309*	*−0.0581*	*−2.2975*
	ABM-LSTM	0.5586	0.5993	0.6293	−0.0192	−0.0201	−1.4854

Notes: "L", "M" and "H" represent Low, Median, and High DUVOL periods.

Table 7
Performance metrics comparison of models on the DAX index and SSE composite index.

Market	Model	Accuracy	Precision	F1	CR	MDD	SR
DAX	*B&H*	–	–	–	*0.2253*	*−0.4907*	*0.2479*
	ARIMA	*0.4907*	*0.5169*	*0.5149*	*0.1760*	*−0.3403*	*0.2980*
	LSTM	*0.5279*	*0.5411*	***0.6049***	*0.1749*	*−0.4655*	*0.2277*
	GAN-LSTM	*0.5309*	*0.5453*	*0.5971*	*0.2125*	*−0.3827*	*0.2895*
	ABM-LSTM	***0.5436***	***0.5588***	*0.5948*	***0.4568***	***−0.2345***	***0.6564***
SSE	*B&H*	–	–	–	*−0.0407*	*−0.2525*	*−0.0641*
	ARIMA	*0.5062*	*0.5102*	*0.5107*	*0.0938*	***−0.1171***	*0.2281*
	LSTM	*0.5227*	*0.5257*	*0.5347*	*0.2979*	*−0.1352*	*0.6649*
	GAN-LSTM	*0.5268*	*0.5314*	*0.5253*	*0.3143*	*−0.1730*	*0.6927*
	ABM-LSTM	***0.5423***	***0.5432***	***0.5604***	***0.3581***	*−0.1549*	***0.6948***

Table 8
Performance validation for the transformer-based models on the S&P 500.

Model	Accuracy	Precision	F1	CR	MDD	SR
B&H	–	–	–	*0.3812*	*−0.4144*	*0.4135*
ARIMA	*0.5159*	*0.5427*	*0.5401*	*0.0851*	*−0.3586*	*0.1366*
Transformer	*0.5328*	*0.5507*	*0.5892*	*0.5572*	*−0.1934*	*0.8756*
GAN-Transformer	*0.5388*	*0.5570*	*0.5887*	*0.6068*	***−0.1552***	*0.9647*
ABM-Transformer	***0.5586***	***0.5595***	***0.6509***	***0.8037***	*−0.2303*	***1.1867***

Notes: "GAN-Transformer" and "ABM-Transformer" are Transformer models fine-tuned with GAN-generated and ABM-generated data respectively, in which ω=1.

Table 9
Performance metrics of models on the S&P 500 (1-minute interval).

Model	Accuracy	Precision	F1	CR	MDD	SR
B&H	–	–	–	*−0.0725*	*−0.0907*	*−0.8392*
ARIMA	*0.4997*	*0.4997*	*0.4996*	*−0.0922*	*−0.1338*	*−1.6401*
LSTM	*0.6062*	*0.6329*	*0.5848*	*0.1823*	*−0.0392*	*2.8834*
GAN-LSTM	*0.6135*	*0.6410*	*0.5932*	*0.1975*	*−0.0565*	*2.9303*
ABM-LSTM	***0.6217***	***0.6532***	***0.6007***	***0.2231***	***−0.0303***	***3.4016***

4.6. Discussions

The improvement in our model aligns with the No Free Lunch (NFL) principle rather than pure improvement. Using ABMs to generate synthetic data for fine-tuning the LSTM model changes the original data distribution. This method's effectiveness depends on a tradeoff: altering the original data can worsen performance if historical patterns repeat, but enhancing underrepresented patterns can improve performance when testing data differs from training data. As quintessential CAS, financial markets do not merely replicate historical patterns. Instead, they continuously evolve and give rise to new dynamics, thus the gains from new knowledge outweigh the costs of lost historical patterns. Our method suits CAS like financial markets, where ABMs predict distributional shifts and advanced forecasting architectures mitigate model saturation.

Balancing effective patterns in training data with human-introduced knowledge is crucial. Heterogeneous agent models (HAMs), a subset of ABMs, illustrate how diverse agent interactions influence financial asset prices. These models explain market behaviors like price swings, bubbles, and crashes. As financial markets evolve, ABMs must adapt to new phenomena and recalibrate hyperparameters. Future research may require revisiting agent configurations in light of recent AI advancements.

5. Conclusions

We introduce a framework intended to enhance return forecasting through ABM-generated data, which incorporates "what-if" scenarios and varied market conditions to overcome historical data limitations in capturing market nonlinearities. The empirical results demonstrate ABM-enhanced LSTM outperforms benchmark and GAN-enhanced models across market conditions and forecasting setups.

This study provides important insights for future research. First, ABMs complement historical datasets by encoding stylized facts while enabling novel pattern emergence through heterogeneous agents. Second, ABM-generated data can substantially enhance model performance by exposing machine learning models to rare conditions, such as high volatility or market crashes. The primary challenge of our approach lies in the inherent complexity of ABMs. Financial ABMs contain multiple interacting components that complicate identification of the specific factors driving aggregate outcomes. Therefore, designing and interpreting ABMs demand a high level of expertise and computational resources, highlighting the need to balance model complexity and tractability.

CRediT authorship contribution statement

Lijian Wei: Funding acquisition, Conceptualization. **Sihang Chen:** Writing – original draft, Methodology. **Junqin Lin:** Writing – original draft, Funding acquisition, Data curation. **Lei Shi:** Validation, Formal analysis.

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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Data availability

Data will be made available on request.

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