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Hybrid ARMA-GARCH-Neural Networks for intraday strategy exploration in high-frequency trading

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ABSTRACT

The frequency of armed conflicts increased during the last 20 years. The problems of the emergence of military disputes, not only concern social parameters, but also economic and financial dimensions. This study examines the potential impact of global geopolitical events on the stock market prices of the Dow Jones U.S. Aerospace & Defense Index and Foreign Exchange (FOREX) markets movements. We analyse whether defence stocks and exchange rate perform similarly during military incidents or geopolitical crises. We built an Autoregressive Moving Average Model with a Generalized Autoregressive Conditional Heteroskedasticity process (ARMA-GARCH) with the machine learning methods of Neural Networks, Deep Recurrent Convolutional Neural Networks, Deep Neural Decision Trees, Quantum Neural Networks, and Quantum Recurrent Neural Networks, aimed at detecting intraday patterns for forecasting defence stock market and FOREX markets disturbances in a market microstructure framework. The empirical results provide preliminary findings on the foreseeability of market disturbances and small differences are observed before and during geopolitical events. Additionally, we confirm the effectiveness of the hybrid model ARMA-GARCH with the machine learning approaches, being ARMA-GARCH-Quantum Recurrent Neural Network the technique that achieves the best accuracy results. Our work has a large potential impact on investment market agents and portfolio managers, as shocks from geopolitical events could provide a new methodology to support the decision-making process for trading in High-Frequency Trading.

1. Introduction

Financial markets have been recognized in the literature as strongly reacting to a range of geopolitical news/events, such as terrorist acts, military attacks, wars, or diplomatic conflicts all over the world. Geopolitical risks influence economic cycles and financial markets, and as a result, central bankers and corporate investors frequently mention geopolitical risks as a determinant of investment decisions [2]. For instance, following the September 11 attacks, the October 2001 Federal Open Market Committee meeting reported that "the events of September 11 produced a marked increase in uncertainty that depressed investment by fostering an increasingly widespread wait-and-see attitude" [2]. Remarking that geopolitical shocks and, especially, terrorist events are mostly unforeseen, Balcilar et al. [5] highlight the relevance of a strong financial sector able to contribute to restoring stability to the market and an open economy for local investors to spread country-specific risks in their investment portfolios. Furthermore, these authors have shown that the impact of geopolitical risk differs according to the geopolitically sensitive sectors. For example, tourism and its associated areas may be affected greatly when geopolitical risk increases. In contrast, defense sectors can profit from an upsurge in geopolitical risk.

The volatile environment induced by geopolitical risks leads investors to hope for higher dividends from the defense industry. Events in geopolitics often provide a learning mechanism for investors and risk managers, who re-evaluate the risk component of their portfolios investors try to mitigate the impact on their portfolio by diversifying into industries that are already stable and strong, and their activities are geared towards providing a sense of stability and security [3]. Besides, there are expectations of increased demand for military equipment offerings toward customers who are considered targets of geopolitical

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risks and events or who plan to take military action against such risks. Apergis et al. [4] examine the effect of geopolitical risks on the equity returns and volatility of defense firms, based on a geopolitical risk index. This index is a wide measurement of global uncertainty, including not only terrorist attacks, but other types of geopolitical pressures such as war risks, military threats, and tensions in the Middle East. It is therefore important to analyze the evolution of the share prices of defense companies before and after armed conflicts, as these companies play a unique role in providing national governments with the latest generation of equipment and services necessary for national security as well as for conducting their military operations in the face of war or terrorist acts.

On another note, given the importance of efficiency, liquidity, and volatility in defence securities markets, it is essential to identify why and how prices in this market change. The study of financial markets and their functioning is the focus of market microstructure, which is mainly concerned with price formation mechanisms, trading behavior, spreads, and transaction costs [36]. An important aspect of market microstructure is liquidity. Failure to consider the liquidity dimension in the modelling of financial questions could have serious consequences, for instance, mispricing and underestimation of risk. Liquidity plays an essential role in the price-formation process of defence markets [34]. Market microstructure theory proposes that markets with greater volume are less volatile and that an inverse relationship can be observed between liquidity and volatility, suggesting that higher volatility may induce a decrease in the liquidity of a stock market and vice versa [36]. Liquidity measures are used by many academic researchers and professionals to estimate intraday market liquidity to predict market structure. In addition, financial market yields and their volatility (frequently linked to uncertainty) remain the most relevant signals for professionals in making capital budgeting and investment portfolio management decisions, since they provide a direct indicator of financial health of a corporation. The use of high-frequency intraday data provides real-time updates on the economy and crucial information in uncertain market environments [34].

Several authors have applied Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques in the estimation and prediction of volatility in financial markets. Yapeng, Hui and Wenbiao [44] conclude that GARCH-type models can describe the behavior of volatility, but they consider volatility as a function of deterministic historical information, which means that they cannot be fitted flexibly to financial time series. Shakeel and Srivastava [34] analyse the intraday market liquidity and volume concentration of the S&P CNX NIFTY futures index using high-frequency financial time series data. Specifically, they analyse tightness, market depth, resilience and trading time using different indicators. They conclude that the intraday market tightness and the time dimension follow a GARCH and Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model, while the depth and resilience dimensions follow an Autoregressive Conditional Heteroskedasticity (ARCH) and GARCH model. Apergis and Apergis [3] investigate the effect of the 11/13 terrorist attacks in Paris on the equity returns and volatility of the main participants in the global defence industry. They apply the GARCH model to measure the impact of the terrorist episode on both average and volatility of returns, together with day-to-day data for 22 global defence firms. Their results revealed the significant positive impact of these attacks on both yields and volatility.

Moreover, related literature has examined the impact of geopolitical news or events, such as terrorist attacks, on the predictability of yield movements and volatility in financial markets. They conclude that geopolitical risks, such as domestic terrorist attacks, as well as attacks on major financial markets, are likely to influence domestic equity returns and volatility [4,5]. Apergis et al. [4] employ the k-order non-parametric causality test of Nishiyama et al. [32] on a sample of twenty-four large firms in the global defence industry at a monthly frequency over the period 1985:1 to 2016:06. They use squared returns to capture volatility with daily data on the equity prices of defence firms. Their results conclude that while lacking evidence of the predictability of returns of the shares of these defence companies derived from the measure of geopolitical risk, they find that the index predicts the achieved volatility of 50% of the firms. These authors propose, for future research, to analyse whether the results remain consistent over a period outside the sample, as in-sample forecasting predictability may not ensure predictive gains.

In the last few years, the development of data-driven Machine Learning (ML) techniques has greatly improved the modelling of financial market dynamics. ML is gaining popularity in Finance field due to the complex decision-making and high risks [36]. According to Goldblum et al. [16], ML is playing an important and growing role in financial business applications as this method develops algorithms that can be used to train complex data and predict output. Using ML techniques in their portfolio optimisation algorithms, Ban, El Karoui and Lim [6] achieved better performance in dealing with average variance and value-at-risk mean-conditional problems. Several authors have focused on investigating the use of neural networks (NNs) for financial applications based on their power to handle linear as well as nonlinear tasks by not depending on strong suppositions [38]. A number of them have been based on prediction problems, namely index prediction [10], and exchange rate prediction [24].

Cheng et al. [12] propose a new approach using a graph neural network that combines multiple modalities for forecasting financial time series. Their method addresses the main challenge of predicting prices in the financial industry by capturing the lead-lag effects using informative data sources. They achieve this through the use of inner-modality graph attention and inter-modality source attention mechanisms. They extend the graph attention model to handle scenarios involving multiple modalities and enhance financial forecasting by incorporating learning from alternative data. Ang and Lim [1], on the other hand, introduce a model that captures both global and local multimodal information for forecasting tasks related to investment and risk management. They present the Guided Attention Multimodal Multitask Network (GAME) model, which performs strongly on three forecasting tasks and two real-world applications. Their results demonstrate the value of guided attention learning in capturing both global and local multimodal information. They conclude that GAME can support better investment and risk management decisions and offer benefits across various real-world applications. Masini, Medeiros, and Mendes [29] provide a survey of the latest advancements in supervised machine learning (ML) and high-dimensional models for time-series forecasting. They consider both linear and nonlinear alternatives. Their conclusion highlights the usefulness of nonlinear ML models when combined with large datasets for economic forecasting. They also suggest a potential future research direction, which involves evaluating ML techniques in highly unstable environments with frequent structural breaks. Emmanoulopoulos and Dimoska [13] compare the predictive power of quantum neural networks (QNNs), represented as parametrized quantum circuits (PQCs), with bidirectional long short-term memory (BiLSTM) neural networks for forecasting time series signals using simulated quantum forward propagation. Their findings reveal that for time series signals comprising small amplitude noise variations, PQCs, equipped with only a few parameters, perform similarly to classical BiLSTM networks, which have thousands of parameters, and surpass them for signals with higher amplitude noise variations. Consequently, QNNs can be effectively employed to model time series while simultaneously boasting the significant advantage of being trained considerably faster than a classical ML model on a quantum computer. Kumar et al. [25] put forward two metrics, specifically mean weighted square error (MWSE) and mean weighted square ratio (MWSR), for dependable performance evaluation of cryptocurrency time series forecasting. Their findings have indicated that ARIMA and LSTNet are well-suited for medium-term forecasting, whereas Prophet is beneficial for long-term forecasting.

Other authors have developed hybrid models. Tseng, Yu and Tzeng [42] employed the forecast results produced by Autoregressive

Integrated Moving Average (ARIMA) and residuals as NN inputs to forecast two seasonal time series of the total value of the output of Taiwan's machinery industry. The results showed that the hybrid model outperformed ARIMA and NN. Khashei and Bijari [24] suggested hybrid approaches employing ARIMA residuals and original data as inputs to NNs. Their techniques improved ARIMA in forecasting weekly GBP/USD exchange rates. Charef [11] focuses on merging modeling techniques, specifically the GARCH model and ANN model, to predict financial series, particularly the exchange rate series in Tunisia. The findings indicate that the hybrid model (GARCH-NN) outperforms and is more efficient than the individual models, yielding better results. Thus, it can serve as an alternative to the standard linear autoregressive model. Secondly, the combination of ARMA, GARCH, and NN methods enables the incorporation of various types of information and data sources, leading to more accurate and robust forecasts. Sun, Dong, and Shan [39] propose the ARIMA-GARCH-MLP model to predict the fluctuations of A-share stocks in 2021. They compare the predictions of the Shanghai Composite Index using ARIMA, GARCH, MLP, ARIMA-GARCH, MLP-ARIMA, and ARIMA-GARCH-MLP models at different time intervals. The results demonstrate that the ARIMA-GARCH-MLP algorithm outperforms the other six algorithms, as evidenced by comparisons of control groups, R-Squared values, and Mean Absolute Error. This study verifies that the constructed weighted model improves the accuracy of stock predictions compared to using ARIMA, GARCH, and MLP algorithms independently. The authors conclude that constructing various index prediction algorithms through weighted prediction models, combined with deep learning algorithms, will be a focus of future research. He et al. [21] put forward a novel financial time series forecasting model, which combines the ARMA model with the convolutional neural network-long short-term memory (CNN-LSTM) model. The CNN-LSTM model is introduced to handle the spatiotemporal data feature, while the ARMA model is used to address the autocorrelation data feature. Empirical findings using financial time series data demonstrate that the proposed deep learning ensemble-based financial time series forecasting model attained superior performance concerning forecasting accuracy and robustness when compared to the benchmark individual models.

In this paper, we analyse the evolution of market microstructure with defence stock markets before and after armed conflicts. The aim is to predict shocks in intraday patterns with neural networks, specifically, we develop a model of Autoregression Analysis and Moving Average-Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) with different machine learning approaches Neural Network (ARMA-GARCH-NN), Deep Recurrent Convolutional Neural Network (ARMA-GARCH-DRCNN), Deep Neural Decision Trees (ARMA-GARCH-DNDT), Quantum Neural Network (ARMA-GARCH-QNN) and Quantum Recurrent Neural Network (ARMA-GARCH-QRNN). The database collects daily observations from 4 January to 19 December 2022 from the Dow Jones U.S. Aerospace & Defense Index, and we have considered the following international conflicts that have occurred in this period: The Afghanistan conflict (Oct 7, 2001 – Aug 30, 2021), Syrian Civil War (March 15, 2011-Present), The Libyan Revolution (15 February – 23 October 2011), Yemeni Civil War (September 16, 2014-Present), Ukraine-Russia War (February 24, 2022-Present). This analysis is much more complicated to capture with econometric methods. So our study fills the gap in the literature by applying ML methods in finance to formulate and examine research questions that can be addressed by innovative computational methods, as traditional financial price-setting models exhibit imprecise prediction accuracy on real-world data owing to their restricted ability to represent complicated market movements. ML methods can uncover more valuable information, such as predicting occurrences, pricing assets, and forecasting returns [18].

Forecasting multivariate time series is a significant machine learning challenge spanning various domains. Deep neural networks have garnered growing attention in the analysis of time series data and have also been explored for time series prediction. Lai et al. [26] established that multivariate time series data are prevalent in our daily lives, encompassing areas such as stock market prices, traffic flow on roads, outputs of solar power plants, and temperatures in different cities, among others. They proposed an innovative deep learning framework for multivariate time series forecasting, which enhanced the best-known outcomes in time series prediction using several benchmark datasets. Therefore, in our study research, we also include time series of exchange rates to test and analyze the application of our developed methodology in this context, specifically focusing on the pound sterling and the Chinese renminbi currencies, from 1990 to 2016.

We make at least three further contributions to the literature. First, we analyse defence equity markets with high-frequency intraday patterns as high-frequency intraday financial data contain refined information about the local second moment of returns. In this way, one can locate the volatility estimation and focus only on the returns inside a small window to approximate the local second moment. Second, we apply neural networks methodology since most of the previous studies employ statistical and econometric methods. ML techniques are attractive to the financial sector because of their ability to effectively discover patterns, correlations, and anomalies in large and complex data sets. ML techniques enhance the capabilities of financiers by eliminating 'momentary irrationality' and can adapt to change as they enter a system. This aspect in particular is vital for the investment and finance environment, constantly changing and in continuous movement [14]. Although artificial neural networks possess specific strengths that enable them to handle a considerable number of encountered problems, they still encounter logical limitations in certain models, hindering their standalone application in some cases or the enhancement of their results. Consequently, certain combinations are proposed to advance research and discover methods that can overcome the weaknesses and challenges associated with each approach, such as Lin, Koprinska and Rana [27]. Thus, we refer to the fusion of two approaches, specifically the GARCH-ANN combination in our case, which allows us to leverage the respective strengths of both methods.

So, our third contribution is the combination of deep learning and statistical models. The advantage of the combination of these methods in our study is that we can address the issue of non-stationarity in the data. Financial time series often exhibit non-stationary behavior, characterized by changing means and volatilities over time. The ARMA and GARCH models can handle such non-stationarity to some extent. Thus, the combination of ARMA, GARCH, and NN in our proposed method offers an advantage, especially the strengths of both techniques, and that the combined model is an effective way to better the prediction quality whatever be the studied series. Consequently, by combining these two techniques, we harness the strengths of both models: the deterministic and theoretical aspects of the GARCH model, and the empirical nature of the ANN model. Our approach offers several advantages. Firstly, it benefits from the speed of empirical modeling, which contrasts with the complex and time-consuming calculations involved in deterministic equations. Secondly, the conceptual and theoretical model aspect remains a static model. Hence, the neuronal network's capability to adopt a holistic perspective can serve as data preprocessing, retaining only the most relevant and impactful information. On the other hand, the GARCH model's capacity for information structuring facilitates refined predictions [11].

The rest of the paper is organized as follows. In Section 2, the methodology is described. Section 3 details the sample and data involved in the research. Section 4 points out the results and findings obtained. By last, Section 5 finishes explaining the conclusions reached.

2. Methodology

We apply the machine learning ARMA-GARCH-NN, ARMA-GARCH-DRCNN, ARMA-GARCH-DNDT, ARMA-GARCH-QNN, and ARMA-GARCH-QRNN techniques and these methods contain three main elements: estimation of market shocks, extraction and selection of characteristics, and optimisation of the model. Firstly, we adjust an ARMA-GARCH model using high-frequency equity yields and derive the market disturbances. Next, we apply a process of feature extraction and selection to determine which variables are considered more relevant for forecasting market disturbances. Lastly, artificial neural networks and joint learning techniques to predict future market shocks are incorporated into our process.

The combination of ARMA, GARCH, and NN approaches is recommended to advance research and address the weaknesses and challenges associated with each approach, as this combination can capture both linear and nonlinear dynamics. Notably, authors like Charef [11], He et al. [21], Sun, Dong, and Shan [39], mentioned in the previous section, have concluded that the fusion of ARMA, GARCH, and NN methods leads to more robust results. The literature and empirical studies highlight the advantage of hybrid models in providing a robust modeling framework by leveraging the strengths of different techniques. Prediction methods based on hybrid models outperform traditional models, including neural networks and econometric models. Sun et al. [40] further demonstrate that the hybrid model (GARCH-NN) not only outperforms but also proves to be more efficient than the individual models. In conclusion, the hybrid model emerges as the most efficient and effective overall for financial time series forecasting.

We have created an additional document to complement our manuscript, "Supplementary File. Within this supplementary file, we have included details regarding the input variables, the network structure and hyperparameters, and the codes for each methodology used.

2.1. ARMA-GARCH model

2.1.1. Estimation of market shock

We compute market distortions relying on the classical ARMA-GARCH model, confirmed to be effective in many research studies of financial prices [37]. Since r_t is the market return in period t, the general ARMA(p, q)-GARCH(m, s) model takes the following form:

$$r_t = c + \sum_{i=1}^{p} \varphi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

$$\varepsilon_t = \sigma_t z_t, z_t \sim N(0,1) \tag{2}$$

$$\sigma_t^2 = \omega + \sum_{k=1}^{m} \alpha_k \varepsilon_{t-k}^2 + \sum_{l=1}^{s} \beta_l \sigma_{t-l}^2 \tag{3}$$

in which Eq. (1) details the ARMA element, and Eqs. (2) and (3) describe the GARCH element; $r_{t-i}, \ldots, r_{t-p}$ are autoregressive terms representing the historical market returns over the last p periods; $\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ reflect the moving mean terms measuring the lagged q errors; φ_i, θ_j, α_k, and β_l refer to coefficients of the model; c and ω relate to the constant terms.

The property of autocorrelation of ε_t, captured by the clustering characteristics of volatility in stock returns, is embodied by the GARCH element. In other words, ε_t stands for a product of $\sigma_t$and z_t (see Eq. (2)), and z_t also referred to as the innovation term of the ARMA-GARCH model. Observe that the lag orders (i.e. p, q, s, and m) could be fixed by the goodness-of-fit of the model, whereas they are usually assigned to be one. The ARMA(1,1)-GARCH(1,1) model has been deployed for studies of high-frequency financial data [23]. Hence, the ARMA-GARCH-based market shock can be estimated by the following:

$$z_t = \frac{r_t - (\widehat{c} + \widehat{\varphi_1} t_{t-1} + \widehat{\theta}_1 \varepsilon_{t-1})}{\sqrt{\widehat{\omega}} + \widehat{\alpha_1}\epsilon_{t-1}^2 + \widehat{\beta_1}\sigma_{t-1}^2} \tag{4}$$

2.1.2. Feature selection

This component of the methodological process concerns the assembly of a sample of explicative variables to be used as input to the forecasting models. We first build a pool of candidate characteristics that includes historical time series elements of the ARMA-GARCH model and information on market microstructure, including technical indicators, and high-frequency volatility measures, to obtain features from the historical information.

We choose the optimal feature subset based on the mutual information of Shannon [35], a machine learning principle. The mutual information between two variables, X and Y, can be defined as:

$$I(X,Y) = \frac{1}{N}\sum_{i=1}^{N} ln \frac{P_{X,Y}(X_i,\ Y_i)}{P_X(X_i)P_Y(Y_i)} \tag{5}$$

being $P_X(X_i)$, $P_Y(Y_i)$, and $P_{X,Y}(X_i,\ Y_i)$ the marginal and joint density functions derived from the sample data. Observe this form of mutual information is nonparametric and requires no assumptions that are simplifying, for example, the Gaussian distribution. Mutual information means, intuitively, the mean reduction in surprise between information sources (for instance, a feature X and the target z), so that high mutual information indicates precise forecasts. Furthermore, we calculate the redundancy from a set of selected features like:

$$RD(S) = \frac{1}{|S|^2}\sum_{X_i,X_j\in S} I(X_i,X_j) \tag{6}$$

being S the feature set. Based on mutual information and redundancy, we build a method of two-step feature selection that involves a screening process followed by the principal selection procedure.

The first step is pre-selection noise filtering. Considering that our process seeks to deal with a great number of candidate features, the main objective of the pre-selection stage consists of efficiently discarding features with a reduced significance for the market shock. To this end, we perform a time series of white noise u_t and calculate its importance for the purpose. If a characteristic proves in comparison to white noise to be weaker for the target, we determine that it holds poor information and should be discarded. To improve the comparison robustness, we perform random u_t generation several times and rely on the mean mutual information between ut and the market shock z_t. This pre-selection algorithm removes irrelevant candidates and decreases the computing cost for the second round of feature selection.

The second step is the feature selection. Battiti [7] stated the problem of feature selection to be the procedure of identifying the best and most outstanding characteristics from a set of features. In this paper, we implement two known extensions of Battiti's [7] research, regarding relevance and redundancy differently. Firstly, we adopt the Forward Selection Minimal-Redundancy-Maximal-Relevance (FSMRMR) criterion of Meyer et al. [30], which employs the mean bivariate mutual information employed as a proxy in the feature selection process. X_{input} is the set of selected variables, the FSMRMR continues to update X_{input} replacing the next variable that optimizes the trade-off between mutual information and redundancy. Secondly, we also apply a different strategy, Conditional Mutual Information Maximisation (CMIM) [15], giving redundancy greater weight to be addressed to study the significance of both relevance and redundancy for our forecasting issue. Minimal-Redundancy-Maximal-Relevance (MRMR), since it maintains a balance between high relevance and low redundancy simultaneously during the feature selection process, may perform better if applied to our problem.

2.1.3. Ensemble neural networks

Given the market disturbances z and the outstanding characteristics Ω, we optimize the prediction function g(.) to approximate the following equation:

$$z_t \sim g(r,\varepsilon,\sigma,\Omega|t-1) \tag{7}$$

The principle driving the modeling of the g(.) function is to equilibrate between under-fitting and over-fitting, in which an under-fitting function is not optimal in terms of prediction accuracy, and an over-fitting function is not effective in predicting out-of-sample events, like market shocks in the future. NNs become capable of approaching complicated data dependencies, whereas a challenge is to avoid overfitting. For this purpose, we perform ensemble NNs for our forecasting work.

In particular, for each mobile window, we split the historical data into the training set and the validation set. So, V NN models are then trained following the bootstrapping method, and only the models with selectable performance (say the best v% of models) in the validation set are selected for posterior estimation. Owing to the temporal sensitivity of our time series problem, we employ a new cross-validation approach, the nearest K cross-validation (NK-CV), to evaluate the output of each NN model. Assume that the sample size of each moving window is N. For time t, the samples from (t - kN + 1) to t become the validation set. Unlike cross-validation, NK-CV chooses the last kN samples to approve the model output rather than choosing samples at random. The reason for this is that our focus is on time series prediction, and our model is constantly adjusted to reflect the latest characteristics of the market.

With the highest v% models in each moving window, our model returns several predictions of innovation and its direction at time $t+1$. We then employ a joint voting technique to ultimately reach the forecasting outcomes. We regard every sub-model as an expert in a decision committee. Depending on the expected innovation value, members vote for the direction of innovation. In the end, the direction receiving the largest amount of votes becomes the final prediction.

To enhance forecasting performance additionally, we implement a threshold approach for the system to decide when to forecast. The main concept is to activate the forecasting procedure if strong signals of innovation happen. Specifically, our method will make forecasting only when the following requirement is met.

$$\frac{|positiveSign - V/2|}{V/2} > threshold \tag{8}$$

being *positiveSign* the number of positive votes generated by the V NN models.

2.2. Theoretical analysis

We consider two propositions. The first proposition is premized on the fact that the market return is composed of a linear component and a non-linear component, the market crash calculated by ARMA-GARCH is expected to be non-linear. So, we assume that the yield of the market is expressed as:

$$r_t = \mathscr{L}_t + \mathscr{N}_t \tag{9}$$

where $\mathscr{L}_t$ stands for the linear component and $\mathscr{N}_t$ for the non-linear component. As ARMA-GARCH only catches the linear features in r_t and its volatility σ_t, there should be an estimated bias. Furthermore, by disaggregating $\mathscr{N}_t$ into the ARMA- and GARCH-related components, the real value of r_t may be reported below.

$$r_t = (\widehat{c} + c_{bias}) + \sum_{i=1}^{p}(\widehat{\varphi}_i + \varphi_{bias,i})r_{t-1} + \varepsilon'_t + \sum_{j=1}^{q}(\widehat{\theta}_i + \theta_{bias,j})\varepsilon'_{t-j} \tag{10a}$$

$$\varepsilon'_t = \sigma'_t z'_t \textbf{being } z'_t = z_t^{\mathscr{L}} + \mathscr{N}_t^{arma}, z_t^{\mathscr{L}} \sim N(0,1) \tag{10b}$$

$$\sigma_t^{\prime 2} = (\widehat{\omega} + \omega_{\text{bias}}) + \sum_{m}^{k=1}(\widehat{\alpha}_k + \alpha_{\text{bias},k})\varepsilon_{t-k}^{\prime 2} + \sum_{s}^{l=1}(\widehat{\beta}_l + \beta_{bias,l})\sigma_{t-l}^{\prime 2} + \mathscr{N}_t^{\text{garch}} \tag{10c}$$

being c_{bias}, $\varphi_{bias,i}$, $\theta_{bias,j}$, ω_{bias}, $\alpha_{bias,k}$, and $\beta_{bias,l}$ estimated biases of ARMA-GARCH estimators $\widehat{c}$, $\widehat{\varphi}_i$, $\widehat{\theta}_i$, $\widehat{\omega}$, $\widehat{\alpha_k}$, $\widehat{\beta}_l$ if we add a non-linear component to the data; $\mathscr{N}_t^{arma}$ represents the non-linear auto-dependency of σ_t.

Ordering the previous equations, we obtain an enlarged form of ARMA-GARCH:

$$r_t = \widehat{r}_t + \mathscr{N}_t^{arma} + \widehat{r}_{bias,\ t} \tag{11a}$$

$$\varepsilon'_t = \sigma'_t z'_t \textbf{being } z'_t = z_t^{\mathscr{L}} + \mathscr{N}_t^{arma} z_t^{\mathscr{L}} \sim N(0,1) \tag{11b}$$

$$\sigma_t^2 = \widehat{\sigma}_t^2 + \mathscr{N}_t^{garch} - \widehat{\sigma}_{bias,\ t}^2 \tag{11c}$$

being $\widehat{r}_t$ the estimation by ARMA, and $\widehat{\sigma}$ the estimation by GARCH; $\widehat{r}_{bias,\ t} = c_{bias} + \sum_{i=1}^{p}\varphi_{bias,i}r_{t-1} + \sum_{j=1}^{q}\theta_{bias,j}\varepsilon_{t-j}$ symbols the estimation bias of ARMA, and $\widehat{\sigma}_{bias,\ t}^2 = \omega_{bias} + \sum_{k=1}^{s}\alpha_{bias,k}\varepsilon_{t-k}^2 + \sum_{l=1}^{m}\beta_{bias,l}\sigma_{t-l}^2$ embodies the estimation bias of GARCH

The impact of the market shock may be assessed as:

$$z_t = \frac{\mathscr{N}_t^{arma} - \widehat{r}_{bias,\ t}}{\sqrt{\sigma_t^2 + \mathscr{N}_t^{garch} - \widehat{\sigma}_{bias,\ t}^2}} \tag{12}$$

This suggests that the non-linear self-dependence of ARMA and GARCH is expected to prevail in the estimated market shock.

In theory, the ARMA-GARCH model only catches the linear characteristics of momentum in time series data, but market turmoil is a complicated phenomenon impacted by many variables, for example, macro- and micro-level economic factors as well as the perceptions and behaviors of investors. Therefore, inspired by current developments in research on artificial neural networks and machine learning, the problem of forecasting market disturbances is tackled by adopting a data-driven framework.

The second proposition is based on the assumption that it is possible to make one-step forecasting of the direction of the market disturbance derived by the ARMA-GARCH model based on historical price information, if there are non-linear patterns in the original price data, for a series of market disturbances.

Non-linear constituents of the initial price data may not be characterized by ARMA-GARCH methods, hence non-linear patterns, if present, will persist in the expected market shocks. These standards could be caught by suitable non-linear models. Hence, one-step forecasting of the direction of market shocks becomes achievable. Because of the precision rate achieved for the forecasting of market shocks ($\mathscr{R}$), the hypotheses that are under test are

H_0 : $\mathscr{R} \leq 0.5$ (unpredictable market shock)
H_a : $\mathscr{R} > 0.5$ (predictable market shock)

We explore the value of historical information to uncover the missing patterns hidden behind the ARMA-GARCH model by analyzing the hypotheses. Many non-linear regression-based models have been suggested to manage non-linear time series patterns, but the problem with these models remains that all of them are derived from a few specific formats (e.g. aXb). Given the complexity of market dynamics, market shocks need not necessarily consistently adopt these formats.

2.3. ARMA-GARCH-Deep Recurrent Convolutional Neural Network (ARMA-GARCH-DRCNN)

Following the previous development of ARMA-GARCH, RNNs have been deployed in many fields in time series forecasting with success owing to their enormous predictive power. The standard RNN framework is structured by the output, which depends on its past estimations [43]. An input sequence vector x, the hidden states of a recurrent layer s, and the output of a unique hidden layer y can be obtained from formulas (13) and (14).

$$s_t = \sigma(W_{xs}x_t + W_{ss}s_{t-1} + b_s) \tag{13}$$

$$y_t = o(W_{so}s_t + b_y) \tag{14}$$

being W_{xs}, W_{ss}, and W_{so} the weights from the input layer x to the hidden layer s, the hidden layer to itself, and the hidden layer to its output layer, respectively. b_y represent the biases of the hidden layer and output layer.

Formula (15) points out σ and o as a symbol of the activation functions.

$$STFT\{z(t)\}(\tau,\omega)=\int_{-\infty}^{+\infty} z(t)\omega(t-\tau)e^{-j\omega t}dt) \tag{15}$$

where $z(t)$ denotes the vibration signals, $\omega(t)$ symbols represent the implementation of the ARMA-GARCH in Eq. (4). $T(\tau,\ \omega)$ represents a complex function defining the vibration signals over time and frequency. To compute the hidden layers with the convolutional operation formulas (16) and (17) are used.

$$S_t=\sigma(W_{TS}*\ T_t+W_{SS}*\ S_{t-1}+B_s) \tag{16}$$

$$Y_t=o(W_{YS}*\ S_t+B_y) \tag{17}$$

being W the convolution kernels.

To establish a deep architecture, the recurrent convolutional neural network (RCNN) can be stacked and form the DRCNN. In this combination case, the last part of the model is a supervised learning layer, set by formula (18).

$$\widehat{r}=\sigma(W_h*h+b_h) \tag{18}$$

being W_h the weight and b_h the bias, respectively. The error of predicted and actual observations in the prediction training data may be estimated and fed back into model training [28]. Stochastic gradient descent is implemented to optimize parameter learning. Assuming that the real data at time t is r, the loss function is given in the formula (19).

$$L(r,\ \widehat{r})=\frac{1}{2}r-\widehat{r}_2^2 \tag{19}$$

2.4. ARMA-GARCH-Deep Neural Decision Trees (ARMA-GARCH-DNDT)

DNDTs are Decision Tree (DT) models run by deep-learning neural networks. All parameters are optimized with stochastic gradient descent (SGD) instead of a complex greedy partitioning process; this enables large-scale processing with mini-batch-based learning and can be linked to any larger neural network (NN) model for end-to-end learning with backpropagation. In addition, conventional DTs learn by greedy, recursive feature partitioning [33]. This may have benefits for the selection of functions; however, this greedy search may transform inefficiently. The algorithm starts by executing a soft binning function to evaluate the error rate for every node, enabling it to make decisions divided into DNDTs. Generally, the input of a binning function is a real scalar x building an index of the containers to which x belongs. Supposing x is a continuous variable, group it into $n+1$ intervals. This requires n cut-off points which are trainable variables in this context. The cut-off points are denoted as $(\beta_1, \beta_2,\ldots, \beta_n)$ and are strictly ascending such that $\beta_1<\ \beta_2<\ \ldots\ <\ \beta_n$.

The activation function of the DNDT algorithm is based on the NN described in Formula (20).

$$\pi=fw,\omega(t),b,\tau(x)=softmax((wx\omega+b)\,/\,\tau) \tag{20}$$

being w a constant with value $w=[1,\ 2,\ \ldots,\ n+1]$, $\tau>0$ denotes a temperature factor, and b is illustrated in Eq. (21).

$$b=[0,-\beta_1,\ -\beta_1,-\ \beta_2\ldots,\ -\beta_1-\ \beta_2-\ldots-\ \beta_{n]} \tag{21}$$

The NN defined in Eq. (29) gives a coding of the binning function x. Additionally, if τ tends to 0 (often the most common case), the vector sampling is implemented using the Straight-Through (ST) Gumbel–Softmax method [22].

According to the binning function indicated before, the key idea is to create the DT applying the Kronecker product. Assuming we have an input instance $x\in\ R^D$ with D characteristics. Associating each characteristic x_d with its NN $f_d(x_d)$, we can determine all the final nodes of the DT as Eq. (22).

$$z=f_1(x_1)\ \otimes\ f_2\ (x_2)\otimes\ \ldots\ \ \otimes f_D(x_D) \tag{22}$$

where z represents a vector that specifies the index of the leaf node reached by instance x. The number of cut points per feature is the complexity parameter of the model and is not limited. For example, they are smaller than the minimum x_d or greater than the maximum x_d.

2.5. ARMA-GARCH-Quantum Neural Network (ARMA-GARCH-QNN)

The combination of CNNs and quantum computing could provide a computational technique with a high forecasting power [43]. In quantum computing, a qubit is the smallest unit of information, which is a probabilistic representation. A qubit can be in either "1″ or "0″ or any superposition of the two [17]. The qubit state is described in Eq. (23):

$$|\psi=\alpha|o+\beta|1 \tag{23}$$

being α and β the numbers that denote the amplitude of the corresponding states such that $|\alpha|^2+|\beta|^2=1.$ It is determined as a pair of numbers. $\begin{bmatrix}\alpha\\ \beta\end{bmatrix}$ The angleθ represents the specification of geometrical aspects, defined as such that: $\cos(\theta)\ =\ |\alpha|\ and\sin(\theta)\ =\ |\beta|$. Quantum gates could be implemented to fit probabilities based on weight enhancement [45]. A rotation gate example is proposed in formula (24):

$$U(\Delta\theta)=\begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta\\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix} \tag{24}$$

A qubit state becomes upgradable via the application of the quantum gate described above. The application of the spin gate on a qubit is given below:

$$\begin{bmatrix}\alpha'\\ \beta'\end{bmatrix}=\begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta\\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}\begin{bmatrix}\alpha\\ \beta\end{bmatrix} \tag{25}$$

The process initiates with a quantum hidden neuron from the state $|o$, which prepares the superposition as specified in Formula (26).

$$\sqrt{p}\Big|O+\sqrt{1}-p|1\ \ with\ O\le|p|\le 1 \tag{26}$$

where p expresses the random probability of starting the system in the state $|O$. The classical neurons are inducted by random number generation [45]. The output from the quantum neuron is determined as follows in Eq. (27).

$$v_j=f\left(\sum_{i=1}^{n}w_{ji}\ *\ x_i*\omega(t)\right) \tag{27}$$

being f a problem-dependent sigmoid or Gaussian function and $\omega(t)$ is the signals of the ARMA-GARCH equation. The output from the network is described in the next formula:

$$y_k=f\left(\sum_{j=1}^{l}w_{jk}\ *\ v_j\right) \tag{28}$$

The desired output is the o_k and the upgrading of output layer weight is given in Formulas (29) and (30):

$$E_k^2=\frac{1}{2}\ |y_k-o_k|^2 \tag{29}$$

$$\Delta w_{jk}=\eta e_k f' v_j \tag{30}$$

2.6. Quantum Recurrent Neural Network (ARMA-GARCH-QRNN)

A quantum system on n qubits exists in the n-fold Hilbert space of tensor product $\mathscr{H}=(\mathbb{C}^2)^{\otimes d}$ with resulting dimension 2^d . A quantum state represents a unit vector $\psi \in \mathscr{H}$, commonly described in quantum computing in bra-ket notation $|\psi \in \mathscr{H}$ |; its conjugate transpose with $\psi| = |\psi^{\dagger}$; then the inner product $\psi|\psi = \psi_2^2$ means the square of the 2-norm of ψ. $[\psi\psi]$ then denominates the outer product, yielding a tensor of rank 2. The computational ground conditions correspond to $|0 = (1, 0)$, $|1 = (0, 1)$, and compound ground states are for example set by $|01 = |0 \otimes |1 = (0, 1, 0, 0)$.

Thus a quantum gate becomes a unitary operation $\mathbb{U}$ on $\mathscr{H}$; where the operation nontrivially operates on a subset $\mathbb{S} \subseteq [n]$ of qubits, then $\mathbb{U}\epsilon\mathbb{S}\mathbb{U}(2^{|\mathbb{S}|})$; to operate on $\mathscr{H}$ we expand $\mathbb{U}$ to operate as identity on the remainder of the space, i.e. $\mathbb{U}_{\mathbb{S}} \otimes 1_{[n]\setminus\mathbb{S}}$. This extension is usually ignored, and indicates if the gate operates in a quantum circuit: the first gate R(θ) represents a unitary of a qubit that operates on the second qubit from below, and which depends on the parameter θ. The dotted line extending from the gate designates a "controlled" operation, if the control, for example, acts only on a single qubit denominates the single block-diagonal unitary map $|00| \otimes 1 + |11| \otimes \mathbb{R}(\theta) = 1 \oplus \mathbb{R}(\theta)$it stands for "if the control qubit is in state $|1$ apply $\mathbb{R}(\theta)$". The gate sequences are computed as matrix products, and the circuits.

The projective measures of a single qubit are provided by a hermitian 2×2 matrix P, such as $\mathrm{M}|11| = \mathrm{diag}(0, 1)$; the complementary outcome is then $M^{\perp} = 1 - M$. They are measured by metres in the circuit. Considering a quantum state $|\psi$, the post-measurement state is $M|\psi\ /p\ /\mathrm{p}$ with probability $p = M|\psi_2$. This is also the post-selection likelihood to ensure a measured result M; this likelihood may be extended close to 1 using $\sim \sqrt{1/p}$ rounds of amplitude amplification [19].

The quantum recurrent neural networks within this proposal are all runnable on classical hardware in which the "hidden state" on n qubits is expressed by an array of size $2^{\,n}$, and the set of parameters is provided by the collection of all parameterized quantum gates in the process, leading to matrices with parameterized inputs. To run a QRNN conventionally, we employ a series of matrix-vector multiplications for the gates, and matrix-vector multiplications with subsequent renormalisation of the status for norm 1 for the measure and post-select transactions. Running on quantum hardware, matrix multiplications are "free", and the hidden state in n qubits, which classically requires exponential memory, may be contained in $\sim$ n qubits only.

Quantum VQE circuits are very compact, meaning that they alternate single-qubit parameterized gates with entangled gates, such as controlled-no transactions. Hence, this offers the advantage of packing a large number of parameters in a rather dense circuit. Moreover, although these circuits are known to form a universal family, their high entanglement gate density, as well as the missing correlation between the parameters, results in very over-parameterized models which are difficult to train in sorting tasks for inputs of more than a few bits [8].

We build a highly structured parameterized quantum circuit in which a few parameters are reused again and again. It is mainly based on a new type of quantum neuron that spins its target lane following a non-linear activation function attached to the polynomials of its inputs. The cell consists of a composite of an input stage that, at every step, puts the actual input into the state of the cell. Multiple work steps follow which calculate the input and the cell state, plus a concluding output step that generates a density of probability on possible forecasts. The application of these QRNN cells in an iterative fashion over the input sequence in a recurrent model is very similar to traditional RNNs.

In training, we implement quantum amplitude amplification [20]. on the output vias, to make sure we measure the right token of the training data at all steps. Although the measures are usually non-unitary operations, using the amplitude amplification step ensures that the measures while training remains as close to unitary as we want them to be.

The power of classical neural networks arises from the implementation of non-linear activation factors to the related converse transformations in the layers of the network. Instead, because of the nature of quantum mechanics, any quantum circuit would inevitably be a linear operation.

Nevertheless, nonlinear behavior does not happen anywhere in quantum mechanics: a simple example is a single-qubit gate R(θ)= exp (iYθ) for the Pauli matrix Y [31], acting as a:

$$R(\theta) = \exp\left(i\theta\begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}\right) = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \tag{31}$$

namely like a rotation within the two-dimensional space covered by the computational basis vectors of a single qubit, $\{|0, |1\}$. Meanwhile, the rotation matrix itself remains linear, we observe that the state amplitudes — $\cos\theta$ and $\sin\theta$—depend non-linearly on the angle θ. Lifting the rotation to a checked operation cR(i, θ_i) conditional on the i^{th} qubit of a state $|x$ for $x \in \{0, 1\}^n$, we obtain the next map:

$$R(\theta_0)cR(1, \theta_1\ )\ldots cR(n, \theta_n\ )|x|0 = |x(cos(\eta)|0 + sin(\eta)|1)$$

for

$$\eta = \theta_0 + \sum_{i=1}^{n} \theta_i x_i \tag{32}$$

Hence, this corresponds to a rotation by an infinite transformation of the basis vector $|x$with $x = \{x_{1,\ldots,}x_n\} \in \{0, 1\}^n$, by a parameter vector $\theta = (\theta_0, \theta_1, \ldots, \theta_n\ )$. The process is linearly expanded to the base and target state superpositions, and owing to the form of R(θ) all changes in amplitude just introduced are true-valued.

This transformation of the cosine of the amplitudes through a checked transaction is already non-linear; however, a sine function is not especially sharp, lacking also a sufficient "flat" region where the activation stays constant, as is the case of a linear rectified unit. Cao, Guerreschi and Aspuru-Guzik [9] suggested an approach to implement a linear map into a set of qubits that produces amplitudes that exhibit these steeper slopes and plateaus, in a manner very similar to a sigmoidal activation function. The activation has a parameter of order ord ≥ 1 governing the tilt, the circuit resulting in the activation amplitude. This quantum neuron in pure states is rotated by an angle $f(\theta) = \arctan(tan(\theta)^{2ord})$, where ord ≥ 1 is the order of the neuron. Assuming an affine transformation η for the input bitstring x_i as shown in formula (33), this rotation is translated into the amplitudes.

$$cos(f(\eta)) = \frac{1}{\sqrt{1 + tan(\eta)^{2x2^{ord}}}} \text{ and } sin(f(\eta)) = \frac{tan(\eta)^{2^{ord}}}{\sqrt{1 + tan(\eta)^{2x2^{ord}}}} \tag{33}$$

which arises by standardising the transform $|0 \mapsto \longrightarrow cos(\theta)^{2^{ord}}\left|0 + sin(\theta)^{2^{ord}}\right|1$ as can be seen clearly. For ord = 1, the circuit is shown on the left; for ord = 2 on the right. Superior orders are recursively buildable.

A so-called repetition-to-success (RUS) circuit is this quantum neuron, indicating that the measured ring signals if the circuit has been performed correctly. If the result is zero, the neuron has been committed. A correction circuit returns the state to its original configuration when the result is one. Beginning with a pure state (e.g. $|x$ for $x \in \{0, 1\}^2$ and recurring every time a 1 is measured, an arbitrarily high probability of success is reached.

For control in superposition, such as a state $|x + |y\ /\sqrt{2}$, this does not work for $x \neq y$ two bit-strings of length n. The amplitudes within the overlap, in this case, will rely on the success story. A technique called fixed-point oblique amplitude amplification [41], essentially post-selects in the measurement of result 0 while preserving the unitarity of the operation with arbitrary precision. There is the additional cost of multiple rounds of these quantum circuits, whose number will depend on the chance of a zero being measured in the first place. This depends obviously on the parameters of the neuron, θ, and the input state is given. We stress that by selecting sufficiently large individual post-selection probabilities, there is no exponential reduction in the overall probability of success across the number of quantum neurons employed.

We extend this quantum neuron in this paper with an increase in the number of check terms. More precisely, η as provided in formula (32) is an affine transform of the boolean vector $x = \{x_{1,...,}x_n\}$ for $x_i \in \{0, 1\}$. When we introduce multi-control gates - having their own parameterized rotation, where we can include the signals of ARMA-GARCH equation, labelled by a multi-index θ_I that varies depending on the qubits $i \in I$ on which the gate conditions - we get the option of incorporating higher-degree polynomials, i.e.

$$\eta' = \theta_0 + \sum_{i=1}^{n} \theta_i x_i \omega(t) + \sum_{i=1}^{n} \sum_{j=1}^{n} \theta_{ij} x_i x_j \omega(t) + \ldots = \sum_{\substack{I \subseteq [n] \\ |I| \leq d}} \theta_I \prod_{i \in I} x_i \omega(t) \tag{34}$$

being d the degree of the neuron; for $d = 2$ and $n = 4$ an example of a checked rotation that increase to this higher-order transformation η' on the bit string x_i. So, higher degree boolean logic operations could be directly encrypted inside a unique conditional rotation: an AND operation between two bits x_1 and x_2 is simply $x_1 x_2$.

The identified quantum neuron becomes the central component in building our quantum recurrent neural network cell. As for conventional RNNs and LSTMs, we provide such a cell to be applied successively to the input submitted to the network. In particular, the cell consists of input and output lanes that are restored following each step, plus a cell-internal state that is transmitted into the next iteration of the network.

To implement the constructed QRNN cell, we require an iterative application of the QRNN cell to a sequence of input words $in_{1,}$ $in_{2,}$ …, in_L .

The outgoing lanes out_i label a discrete distribution measuring p_i over the class labels (we could read the state vector weights if a simulation is run on a classical computer, or through replicated measurements on quantum hardware). The distribution could be entered into an assigned loss function, like cross-entropy or CTC loss.

3. Sample and data

The database collects daily observations from 4 January 2000 to 19 December 2022, from the Dow Jones U.S. Aerospace & Defense Index, extracted from Thomson Reuters Eikon. Within this period there have been the following international conflicts: The Afghanistan conflict (Oct 7, 2001 – Aug 30, 2021), the Syrian Civil War (March 15, 2011-Present), The Libyan Revolution (15 February – 23 October 2011), Yemeni Civil War (September 16, 2014-Present), Ukraine-Russia War (February 24, 2022-Present).

Besides, we have examined the methodologies using time series data related to exchange rates, specifically focusing on the British pound sterling and the Chinese renminbi currencies. The rationale behind selecting these two currencies lies in their distinctiveness: one hails from a developed nation, while the other originates from an emerging economy. Additionally, this choice was made to avoid excessive length in our article. The dataset covers the timeframe spanning 1990 to 2016. The data has been sourced from the GitHub repository accessible through the following link: https://github.com/laiguokun/multivariate-time-series-data.

Regarding the input variables, in the supplementary file, we have included details about the input variables, the network structure and hyperparameters. We perform a pre-test based on randomly assigned samples to establish the optimal number of these variables. We execute a one-step ahead prediction for 100 moving windows using the samples selected randomly, but not used in the main training and testing process of the model. In the defense stock market case, Table 1 shows the dynamics of the root mean square error (RMSE) related to the training and testing results based on the selections of 10, 20, 30, and 40 variables. Figs. 1–5 show the average RMSE for each technique with different numbers of inputs. These figures are in another supplementary file that we have created.

Table 1
Average RMSEs for training and test sets with the different methods for defense stock market.

Features	Training	Testing
ARMA-GARCH-NN		
10	0.5946	0.6176
20	0.2591	0.5616
30	0.4559	0.4952
40	0.3619	0.4577
ARMA-GARCH-DCRNN		
10	0.4380	0.4615
20	0.4746	0.5525
30	0.4206	0.4221
40	0.3237	0.3730
ARMA-GARCH-DNDT		
10	0.4024	0.4255
20	0.4202	0.2985
30	0.2700	0.3722
40	0.2761	0.3051
ARMA-GARCH-QNN		
10	0.3826	0.4050
20	0.3052	0.3066
30	0.3074	0.3938
40	0.3662	0.4439
ARMA-GARCH-QRNN		
10	0.2765	0.2993
20	0.2567	0.2817
30	0.1891	0.2672
40	0.1565	0.2481

Although the goodness of fit in the training set improves as the number of inputs grows, it can lead to overfitting. We obtain a reversal of performance when increasing the number from 20 to 30 entries based on the results of the test set. In addition, we perform similar CMIM-based tests also leading to coherent results. Hence, we define 20 as the number of input variables. The best average RMSE in the testing set with 20 features is in the DNDT technique (0.29853191) followed by the QNN method (0.30660715) and in third place the QRNN approach (0.36228718).

In the exchange rate case, Table 2 presents the variations in the RMSE concerning both the training and testing outcomes for exchange rates, contingent upon the choices of 10, 20, 30, and 40 variables. The

Table 2
Average RMSEs for training and test sets for exchange rate with the different methods.

British Pound			**Chinese Renmimbi**		
Features	Training	Testing	Feature	Training	Testing
ARMA-GARCH-NN			ARMA-GARCH-NN		
10	0.6207	0.6388	10	0.6473	0.6662
20	0.4273	0.5809	20	0.4821	0.6058
30	0.4759	0.5122	30	0.4963	0.5342
40	0.3778	**0.4734**	40	0.3940	**0.4937**
ARMA-GARCH-DCRNN			ARMA-GARCH-DCRNN		
10	0.4572	0.4815	10	0.48662	0.51251
20	0.4568	0.5113	20	0.48614	0.54412
30	0.4391	0.4447	30	0.46729	0.47324
40	0.3379	**0.3858**	40	0.35963	**0.41063**
ARMA-GARCH-DNDT			ARMA-GARCH-DNDT		
10	0.4201	0.4401	10	0.4471	0.4684
20	0.4386	**0.3088**	20	0.4668	**0.3286**
30	0.2819	0.3850	30	0.3000	0.4098
40	0.2882	0.3156	40	0.3067	0.3359
ARMA-GARCH-QNN			ARMA-GARCH-QNN		
10	0.3677	0.3732	10	0.3902	0.3982
20	0.3234	0.3422	20	0.3442	0.3654
30	0.2946	0.3637	30	0.3135	0.3870
40	0.2895	**0.3222**	40	0.3081	**0.3429**
ARMA-GARCH-QRNN			ARMA-GARCH-QRNN		
10	0.2642	0.2764	10	0.2911	0.3036
20	0.2712	0.3151	20	0.2988	0.3462
30	0.1813	0.2467	30	0.1991	0.2711
40	0.1237	**0.1801**	40	0.1359	**0.1979**

average RMSE of several techniques, each with different input quantities, are shown in the Figs. 6–10 (supplementary file) for British pound, and Figs. 11–15 (supplementary file) for Chinese rebnmimbi.

Drawing upon the outcomes derived from the test suite, the inclusion of 40 inputs generally yields the most favorable results for both currencies. As a consequence, we establish the count of 40 as the designated number of inputs. Notably, when considering the British pound scenario, the optimal average RMSE within the test dataset is achieved using the ARMA-GARCH-QRNN technique (0.1801), closely pursued by the ARMA-GARCH-DNDT approach (0.3088). Similarly, for the Chinese renminbi case, the methods delivering the smallest errors align with those of the British pound, attaining results of 0.1979 and 0.3286 respectively.

4. Results

Using the MRMR and CMIM feature selection algorithms with random cross-validation and k-nearest cross-validation (denoted Rand-CV and NK-CV, respectively), we investigate the prediction performance of our methods. MRMR is an algorithm that selects a subset of characteristics that have the highest correlation with the class (output) and the lowest correlation with each other. CMIM does not select a feature similar to those already chosen since it provides no further information about the class to be forecasted. Therefore, this criterion guarantees a good balance between independence and discrimination. The prediction output is evaluated in terms of the accuracy index for each method (see Table 3) and root mean square error (RMSE, see Table 4) for the defense market.

Table 3
Comparison of performances in market shock direction prediction for defense stock market.

	MRMR		CMIM	
ARMA-GARCH-NN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.473	0.519	0.512	**0.562**
	0.116	0.041	0.037	**0.000**
Downward	0.494	0.508	0.535	**0.550**
	0.028	0.003	0.013	**0.009**
ARMA-GARCH-DCRNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.441	0.492	0.498	**0.517**
	0.071	0.018	0.024	**0.019**
Downward	0.487	0.490	**0.521**	0.513
	0.006	0.034	**0.018**	0.024
ARMA-GARCH-DNDT				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.466	0.519	**0.532**	0.527
	0.074	0.064	**0.028**	0.004
Downward	0.506	0.525	0.527	**0.533**
	0.008	0.007	0.021	**0.007**
ARMA-GARCH-QNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.475	0.535	**0.565**	0.546
	0.093	0.071	**0.042**	0.049
Downward	0.547	0.534	**0.550**	0.540
	0.014	0.031	**0.026**	0.005
ARMA-GARCH-QRNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.450	0.513	**0.524**	0.510
	0.054	0.070	**0.019**	0.048
Downward	0.509	0.502	**0.538**	0.537
	0.022	0.022	**0.018**	0.026

Table 4
Comparison of forecasting performances based on root mean squared error (RMSE) for defense stock market.

	MRMR		CMIM	
ARMA-GARCH-NN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.834	0.821	0.804	**0.785**
Downward	0.871	0.869	0.849	**0.828**
ARMA-GARCH-DCRNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.760	0.734	0.731	**0.694**
Downward	0.672	0.654	0.619	**0.583**
ARMA-GARCH-DNDT				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.566	0.526	0.484	**0.473**
Downward	0.542	0.497	0.494	**0.454**
ARMA-GARCH-QNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.355	0.338	0.303	**0.259**
Downward	0.470	0.466	0.455	**0.440**
ARMA-GARCH-QRNN				
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.350	0.327	0.286	**0.246**
Downward	0.394	0.384	0.347	**0.339**

We can observe that the CMIM can lead to significantly better performance in predicting the direction of the market shock in all techniques when applied in conjunction with the NK-CV method in the DNDT, QRNN, and QNNN techniques, and in the case of the NN and DCRNNN approaches when applied in conjunction with the Rand-CV method. Furthermore, the application of NK-CV leads to better results than the use of Rand-CV also for MRMR. Finally, in all methods, the RMSE results serve as evidence supporting that CMIM is superior to MRMR.

In the exchange rate case, the prediction output is also evaluated in terms of the accuracy index for each method and for each currency (see Table 5) and root mean square error (RMSE, see Table 6).

When considering both the British pound and the Chinese renminbi, a discernible trend emerges: the integration of CMIM with the Rand-CV method consistently yields notably enhanced performance across all techniques in predicting market shock direction. Additionally, in the context of both currencies, the utilization of Rand-CV outperforms NK-CV in the context of MRMR. Lastly, this pattern holds true across all methods and both currencies, as the RMSE results substantiate the superiority of CMIM over MRMR.

We study the efficacy of the thresholded ensemble voting technique that we design to further improve the prediction performance. By using the CMIM -NK-CV model, accuracy rates can be improved by implying threshold adjustment in both bottom-up and top-down samples. Table 7 illustrates for the defense stock market that for all methods the performance improves systematically when the threshold is involved in the prediction process. For the uptrend, the accuracy rate increases by an average of all techniques up to 55.72%; for the downtrend, the accuracy rate achieves an average of 55.34%. These two results are both considerably higher than 50%, indicating accurate predictions of market disturbances. The results are consistent with our second proposition in the theoretical analysis section supporting the presence of patterns of market disruptions, that can be derived from historical price information.

Compared to other previous research, Apergis [4] analyse the role of geopolitical risks in predicting movements in the stock returns and

Table 5
Comparison of performances in market shock direction prediction for exchange rate.

British Pound					Chinese Renminbi				
ARMA-GARCH-NN					ARMA-GARCH-NN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.473	0.519	0.512	**0.562**	Upward	0.458	0.502	0.496	**0.544**
	0.087	0.053	0.049	0.002		0.084	0.051	0.047	0.002
Downward	0.481	0.497	0.526	**0.538**	Downward	0.466	0.481	0.509	**0.521**
	0.023	0.001	0.008	0.003		0.022	0.001	0.008	0.003
ARMA-GARCH-DCRNN					ARMA-GARCH-DCRNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.446	0.480	0.489	**0.519**	Upward	0.442	0.487	0.451	**0.508**
	0.045	0.032	0.034	0.023		0.045	0.008	0.026	0.035
Downward	0.442	0.457	0.513	**0.536**	Downward	0.451	0.476	**0.501**	0.480
	0.018	0.032	0.034	0.011		0.007	0.027	0.021	0.023
ARMA-GARCH-DNDT					ARMA-GARCH-DNDT				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.478	0.514	0.518	**0.558**	Upward	0.466	0.525	0.477	**0.518**
	0.045	0.069	0.058	0.021		0.066	0.017	0.044	0.032
Downward	0.451	0.489	**0.546**	0.545	Downward	0.452	0.488	**0.508**	0.494
	0.017	0.030	0.003	0.004		0.006	0.009	0.003	0.007
ARMA-GARCH-QNN					ARMA-GARCH-QNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.490	0.526	0.530	**0.578**	Upward	0.504	0.532	0.522	**0.558**
	0.075	0.081	0.084	0.041		0.069	0.031	0.080	0.000
Downward	0.462	0.531	0.591	**0.549**	Downward	0.468	0.531	**0.531**	0.528
	0.016	0.011	0.030	0.001		0.040	0.022	0.034	0.011
ARMA-GARCH-QRNN					ARMA-GARCH-QRNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.479	0.510	0.528	**0.561**	Upward	0.466	0.487	0.498	**0.552**
	0.061	0.057	0.058	0.009		0.057	0.014	0.079	0.044
Downward	0.445	0.516	**0.562**	0.505	Downward	0.450	0.511	0.495	**0.526**
	0.055	0.043	0.012	0.030		0.018	0.015	0.016	0.018

Table 6
Comparison of forecasting performances based on root mean squared error (RMSE) for exchange rate.

British Pound					Chinese Renminbi				
ARMA-GARCH-NN					ARMA-GARCH-NN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.724	0.713	0.702	**0.665**	Upward	0.693	0.683	0.674	**0.636**
Downward	0.865	0.848	0.817	**0.812**	Downward	0.828	0.827	0.815	**0.770**
ARMA-GARCH-DCRNN					ARMA-GARCH-DCRNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.678	0.651	0.616	**0.583**	Upward	0.460	0.438	0.438	**0.433**
Downward	0.791	0.758	0.753	**0.711**	Downward	0.681	0.644	0.628	**0.606**
ARMA-GARCH-DNDT					ARMA-GARCH-DNDT				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.552	0.533	0.489	**0.486**	Upward	0.419	0.379	0.372	**0.353**
Downward	0.774	0.746	0.706	**0.671**	Downward	0.636	0.604	0.575	**0.570**
ARMA-GARCH-QNN					ARMA-GARCH-QNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.521	0.499	0.495	**0.472**	Upward	0.405	0.389	0.347	**0.317**
Downward	0.585	0.583	0.560	**0.558**	Downward	0.469	0.449	0.448	**0.431**
ARMA-GARCH-QRNN					ARMA-GARCH-QRNN				
	MRMR		CMIM			MRMR		CMIM	
Trend	NK-CV	Rand-CV	NK-CV	Rand-CV	Trend	NK-CV	Rand-CV	NK-CV	Rand-CV
Upward	0.375	0.359	0.342	**0.298**	Upward	0.369	0.338	0.302	**0.294**
Downward	0.360	0.323	0.313	**0.312**	Downward	0.313	0.267	0.258	**0.222**

Table 7
Enhanced performance with ensemble vote (NK-CV) by accuracy rate for defense stock market.

ARMA-GARCH-NN Trend	With threshold	Without threshold
Upward	**0.563**	0.562
	0.038	0.000
Downward	**0.565**	0.550
	0.031	0.009
ARMA-GARCH-DCRNN Trend	With threshold	Without threshold
Upward	**0.531**	0.517
	0.014	0.019
Downward	**0.521**	0.513
	0.018	0.024
ARMA-GARCH-DNDT Trend	With threshold	Without threshold
Upward	**0.572**	0.527
	0.006	0.004
Downward	**0.567**	0.533
	0.038	0.007
ARMA-GARCH-QNN Trend	With threshold	Without threshold
Upward	**0.583**	0.546
	0.057	0.049
Downward	**0.575**	0.540
	0.016	0.005
ARMA-GARCH-QRNN Trend	With threshold	Without threshold
Upward	**0.537**	0.510
	0.087	0.048
Downward	**0.539**	0.537
	0.015	0.026

volatility of twenty-four firms in the defence industry. They use the k-th order non-parametric causality test of Nishiyama et al. [32] and find that the index predicts realized volatility in 50 percent of the firms. Their results indicate although global geopolitical events over some time are less likely to predict returns, the effect is more focused on modifying the future risk profile of defence firms. Apergis and Apergis [3] investigate the impact of the Paris terrorist attacks both on stock market returns and the volatility of major firms in the global defence industry. They use the General Autoregressive Conditional Heteroscedasticity (GARCH) methodology. Their results strongly suggest that this terrorist event impacts positively the returns and volatility of these stocks. Sun et al. [40] develop a machine learning approach through ARMA-GARCH-NN to analyse the intra-day patterns for stock market shocks forecasting and confirm the predictability of this model. Their results conclude that for their upward trend, the accuracy rate is enhanced to 54.3%, and for the downtrend, the accuracy rate reaches 52.59%. Concerning the latter research, we can therefore conclude that our model improves the accuracy ratio for both the uptrend and the downtrend. Furthermore, we analyse and compare the model with various computational methodologies.

In the exchange rate case, Table 8 illustrates a consistent pattern across all methods wherein performance systematically improves upon the incorporation of thresholds into the prediction process. In the context of the British pound, during uptrends, the accuracy rate experiences an average enhancement across all techniques, reaching 59.14%; conversely, for downtrends, the accuracy rate averages at 55.90%. Similarly, for the Chinese renminbi, uptrends witness an average accuracy rate augmentation across all techniques, reaching 55.34%, while downtrends achieve an average accuracy rate of 53.54%. These outcomes significantly surpass the 50% mark, underscoring precise predictions of market disruptions.

For the defense stock market, we re-run the same tests for robustness

Table 8
Enhanced performance with ensemble vote (NK-CV) by accuracy rate for exchange rate.

British Pound ARMA-GARCH-NN Trend	With threshold	Without threshold	Chinese Renmimbi ARMA-GARCH-NN Trend	With threshold	Without threshold
Upward	**0.591**	0.562	Upward	**0.550**	0.544
	0.047	0.002		0.035	0.002
Downward	**0.566**	0.538	Downward	**0.531**	0.521
	0.004	0.003		0.032	0.003
ARMA-GARCH-DCRNN Trend	With threshold	Without threshold	ARMA-GARCH-DCRNN Trend	With threshold	Without threshold
Upward	**0.564**	0.519	Upward	**0.512**	0.508
	0.017	0.023		0.027	0.035
Downward	**0.547**	0.536	Downward	**0.524**	0.480
	0.030	0.011		0.022	0.023
ARMA-GARCH-DNDT Trend	With threshold	Without threshold	ARMA-GARCH-DNDT Trend	With threshold	Without threshold
Upward	**0.597**	0.558	Upward	**0.543**	0.518
	0.027	0.021		0.022	0.032
Downward	**0.566**	0.545	Downward	**0.503**	0.494
	0.009	0.004		0.024	0.007
ARMA-GARCH-QNN Trend	With threshold	Without threshold	ARMA-GARCH-QNN Trend	With threshold	Without threshold
Upward	**0.607**	0.578	Upward	**0.585**	0.558
	0.085	0.041		0.025	0.000
Downward	**0.585**	0.549	Downward	**0.565**	0.528
	0.037	0.001		0.043	0.011
ARMA-GARCH-QRNN Trend	With threshold	Without threshold	ARMA-GARCH-QRNN Trend	With threshold	Without threshold
Upward	**0.598**	0.561	Upward	**0.577**	0.552
	0.052	0.009		0.007	0.044
Downward	**0.531**	0.505	Downward	**0.554**	0.526
	0.014	0.030		0.026	0.018

using a randomly defined sample covering periods from 4 January 2000 to 19 December 2022. Fig. 16 (supplementary file) shows the results according to the MRMR-NK-CV model with and without a threshold. We conclude that the results are coherent as we obtain high accuracy rates in every method. In addition, we compare the average accuracy rate of each technique (see Table 9), with ARMA-GARCH-QRNN being the technique that achieves the best accuracy results (93.59%) followed by ARMA-GARCH-QNNN (88.86%) and third place ARMA-GARCH-DNDT (84.51%). So, we support the effectiveness of our model in predicting market shocks.

Figs. 17 and 18 (supplementary file) illustrate the outcomes derived from the MRMR-NK-CV model, presenting results both with and without the integration of a threshold, for the British pound and the Chinese Renminbi respectively. Our analysis leads to a coherent conclusion, with consistently high accuracy rates observed across all methods. Furthermore, a comparative examination of the average accuracy rates for each technique in both currencies is detailed in Table 10. Evidently, the

Table 9
Average Performance comparison based on a long-period sample for defense stock market.

	Average (%)
ARMA-GARCH-NN	67.72
ARMA-GARCH-DCRNN	82.08
ARMA-GARCH-DNDT	84.51
ARMA-GARCH-QNN	88.86
ARMA-GARCH-QRNN	93.59

Table 10
Average performance comparison based on a long-period sample for exchange rate.

	British Pound Average (%)	Chinese Renminbi
ARMA-GARCH-NN	68.67	64.31
ARMA-GARCH-DCRNN	83.19	77.95
ARMA-GARCH-DNDT	85.66	81.41
ARMA-GARCH-QNN	90.34	84.92
ARMA-GARCH-QRNN	**93.81**	**87.74**

ARMA-GARCH-QRNN technique emerges as the standout performer, achieving impressive accuracy results of 93.81% for the British Pound and 87.74% for the Chinese Renminbi. Following closely, the ARMA-GARCH-QNNN approach secures the second-best position with an accuracy rate of 90.34% for the British Pound and 84.92% for the Chinese Renminbi. These findings collectively bolster the credibility and efficacy of our model in accurately predicting market shocks.

In addition, we test our hybrid model to explore ways in which an optimal predictive approach to market disturbances could be employed in the development of trading strategies. We propose a trading strategy as a new trading signal besides the prediction based on ARMA (1,1)-GARCH(1,1). The trading strategy is challenged on a randomly selected sample of data of S&P500 5-min prices. Fig. 19 (supplementary file) shows the comparison of the final cumulative return based on the trading strategy with the signals of each method with different thresholds. Our sample comprises 1000 5-minute time points, therefore the reported returns reflect the returns of approximately 14 trading days. The minimum return obtained is 1.7% in the ARMA-GARCH-NN method, followed by ARMA-GARCH-DCRNN (2.1%) and the maximum return reaches 3.6% in the ARMA-GARCH-QNN approach, having a close percentage of both ARMA-GARCH-QRNN and ARMA-GARCH-DNDT (3.4%). As can be observed, ARMA-GARCH-QNN and ARMA-GARCH-QRNN techniques significantly improve on the other methods concerning the cumulative return achieved. Additionally, in Fig. 20 (supplementary file), we display the cumulative performances over time by setting a threshold = 0.00025. Again, we show that ARMA-GARCH-QNN and ARMA-GARCH-QRNN also consistently exceed the other techniques, having a maximum return of 2.2% and 2.3% respectively.

Detailed comparisons of the cumulative returns stemming from the trading strategy against the signals generated by each method at various thresholds are presented in Figs. 21 and 22 (supplementary file) for the British pound and Chinese Renminbi, respectively. Moreover, Figs. 23 and 24 (supplementary file) showcase the cumulative performance trends over time, with a threshold value set at 0.00025, for both the British pound and the Chinese Renminbi.

5. Conclusions

This study has developed a model that analyse the evolution of market microstructure with defence stock markets before and after armed conflicts. The aim is to predict shocks in intraday patterns with a machine learning approach, called ARMA-GARCH-NN, ARMA-GARCH-DRCNN, ARMA-GARCH-DNDT, ARMA-GARCH-QNN, and ARMA-GARCH-QRNN. The sample under study has been daily observations from the Dow Jones U.S. Aerospace & Defense Index in the period from 4 January to 19 December 2022, and we have considered the following international conflicts that have occurred in this period: The Afghanistan conflict (Oct 7, 2001 – Aug 30, 2021), Syrian Civil War (March 15, 2011-Present), The Libyan Revolution (15 February – 23 October 2011), Yemeni Civil War (September 16, 2014-Present), Ukraine-Russia War (February 24, 2022-Present). Besides, we have analyzed the methodologies utilizing time series data concerning exchange rates, with a specific emphasis on the currencies of the British Pound and the Chinese Renminbi. Our results indicate that our methods of ARMA-GARCH market shocks at the intraday level are predictable.

Our results show that CMIM feature selection significantly performs much better in forecasting the direction of the market disturbance across all approaches if applied together with the NK-CV method in the DNDT, QRNN, and QNN techniques, and for NN and DCRNN techniques if used in combination with the Rand-CV method. Finally, in all methods, the RMSE results serve as evidence supporting that CMIM is superior to MRMR. Furthermore, RMSE results for all methods provide evidence to confirm that CMIM appears to be stronger than MRMR. In addition, the predictions of equity market shocks analysed have the potential to act as new trading signals to assist the financial investment decision-making process. Moreover, our computational methodologies achieve good accuracy results despite having included breakpoints within the base according to the Chow test performed.

In contrast to previous research, our model improves accuracy rates by involving threshold adjustment in both upstream and downstream samples. In addition, we apply the neural network methodology in several techniques and compare them, with ARMA-GARCH-QRNN being the technique that achieves the best accuracy results.

Our study can serve as a resource for practitioners, as a point of reference for evaluating high-frequency trading arguments, forecasting market crashes, and estimating liquidity for researchers. Our results are also of great importance for market participants the same as for investment portfolio managers as expected market disturbances could provide new commercial signs supporting the decision-making procedure for financial investments. Furthermore, the results reported in this work could provide a better understanding of defence stock market and FOREX markets dynamics and volatility in various geopolitical events. Moreover, they may have relevance for both commodity analysts and macro-financial economists and forecasters.

In summary, this research provides an essential contribution to the field of finance as our work could be a useful contribution to the financial industry as well as to academic research to further explore the microstructure of the defence stock market and price formation through a bottom-up perspective.

This study acknowledges limitations for potential future research. Firstly, Quantum Neural Networks' effectiveness may rely on ample quantum resources for extensive data. As quantum hardware advances, investigating their performance on larger financial datasets becomes relevant. Secondly, Deep Neural Networks and quantum circuits demand significant computation and training time. Balancing model complexity and training duration warrants exploration. Economically, events like policy changes, trade agreements, and macro shifts impact financial markets. Future research could include more macro factors to anticipate such occurrences. Financial markets can experience abrupt shifts, challenging ARMA-GARCH models. Quantum Neural Networks might require adaptations for effective handling.

In addition, further research should address the application of these techniques and trading strategies in other financial markets that have been affected by unique and large shocks, such as the effect of this same period studied where there have been armed conflicts or COVID-19 in the different commodity markets. With this, it will be possible to analyze the possible generalization of these methods for any financial market, as well as a greater specification of the trading strategies according to the nature of the volatility of the specific financial market studied.

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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.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.patcog.2023.110139.

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