공학석사학위논문

Enhancing non-linear asset volatility forecasting models with investor sentiment and explainable AI

투자자 심리와 설명 가능 인공지능 기법을 적용한 비선형 자산 변동성 예측 모델 개선

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이 논문을 공학석사 학위논문으로 제출함

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Abstract

Enhancing non-linear asset volatility forecasting models with investor sentiment and explainable AI

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This study investigates the enhancement of non-linear asset volatility forecasting models by incorporating exogenous variables, including investor sentiment, and using explainable AI with SHAP analysis. Comparing non-linear neural network models to the traditional HAR model, we demonstrate superior forecasting performance. Our findings underscore the significance of economic variables and the role of investor sentiment and attention in non-linear volatility prediction, as revealed by SHAP analysis. Specifically, we discover that exogenous variables take precedence as the primary drivers in the realized volatility forecast, surpassing the influence of return and historical volatilities.

Keywords: Volatility Forecasting, Explainable AI, Investor Sentiment, SHAP, Industrial Engineering

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

This chapter provides a concise overview of the research's context, describes the problem, explains the research motivation and contribution with objectives, and highlights its significance.

1.1 Understanding Asset Volatility and its Significance for Investors

In the ever-changing landscape of financial markets, asset volatility plays a pivotal role in shaping investment decisions and strategies. Volatility, defined as the degree of price fluctuations or variability exhibited by an asset over a given period, captures the inherent uncertainties and risks embedded within financial markets, reflecting the speed and magnitude of price movements [45]. This concept is closely related to the Efficient Market Hypothesis (EMH) [21], which posits that financial markets incorporate all available information and promptly adjust asset prices to reflect their intrinsic values. In line with the EMH, asset volatility represents the collective market consensus on the uncertainties and potential risks associated with an asset.

For investors, while returns are the primary concern, volatility holds equal importance. Investors seek to optimize their returns while managing risk, recognizing that higher volatility can imply greater potential for both profits and losses [39]. When formulating their investment strategies, prudent investors consider both the return potential and the volatility characteristics of an asset. They aim to strike a balance between maximizing returns and mitigating the risks associated with price fluctuations. High volatility implies greater potential for both profits and losses, making it a vital consideration for investors seeking to optimize returns, protect capital, and make informed investment choices. By carefully assessing the relationship between returns and volatility, investors can tailor their investment approaches to align with their risk tolerance, investment goals, and time horizons.

1.2 Problem Description: Asset Volatility Forecasting

The forecasting of asset volatility has been a topic of extensive research over the years, driven by the increasing demand for accurate and dependable models capable of capturing and predicting the dynamics of volatility. However, the inherent nature of volatility presents a formidable obstacle to overcome. Volatility represents a latent and unobservable movement within an asset, rendering its prediction a complex task [45]. This intangible characteristic of volatility, though elusive, holds immense significance within financial markets, exerting a profound influence on investment decisions, risk management strategies, and portfolio optimization techniques. Thus, there is a pressing need to develop suitable models and methodologies that can effectively capture and forecast asset volatility, enabling investors and market participants to make informed decisions and navigate the complexities of the financial landscape.

Forecasting asset volatility is a complex task due to its dynamic and multifaceted characteristics. Volatility manifests itself in a variety of ways, including time-varying patterns [51], non-linear relationships [22], and sporadic spikes or clusters [50], all of which contribute to the difficulty of achieving accurate predictions. Furthermore, the drivers of volatility can differ across assets and market conditions, introducing additional intricacies to the forecasting process. In response to these challenges, researchers have pursued diverse approaches aimed at overcoming them. These approaches involve exploring the incorporation of exogenous variables and the utilization of advanced modeling techniques. By considering external factors and employing sophisticated methodologies, researchers strive to enhance the accuracy and reliability of asset volatility forecasts.

One approach involves incorporating exogenous variables into volatility forecasting models. Researchers have investigated variables such as investor sentiment and macroeconomic indicators, aiming to capture the impact of these factors on volatility dynamics. For example, the advent of social media platforms has facilitated the widespread sharing of investors' thoughts and opinions. Platforms like Twitter, StockTwits, and Reddit allow investors to freely express their views on the recent price movements of assets within their portfolios. As reported by several studies, it is widely acknowledged that investor sentiment, as expressed through these platforms, can significantly influence price movements [3, 8, 34, 48]. By integrating exogenous variables, researchers seek to enhance forecasting accuracy and capture the effects of external factors on asset volatility.

Another promising avenue of research involves the application of advanced modeling techniques. Traditional econometric models, such as generalized autoregressive conditional heteroskedasticity (GARCH) models [11], have been widely used in volatility forecasting. However, in recent years, more complex models, including machine learning and deep learning approaches, have gained popularity. In particular, neural network architectures have shown considerable potential in capturing volatility dynamics and have exhibited superior performance compared to traditional methods in certain cases [47, 52, 53]. This shift towards more sophisticated modeling techniques reflects the desire to leverage the strengths of advanced algorithms and computational capabilities to enhance the accuracy and robustness of asset volatility forecasts.

1.3 Research Motivation and Contribution

Despite the progress made in incorporating exogenous variables and utilizing complex modeling techniques, a significant limitation of many sophisticated volatility forecasting models is their lack of interpretability. In the field of finance, the ability to understand and interpret model results is crucial for establishing trust and ensuring the reliability of future applications. Even if a model demonstrates superior forecasting performance, the absence of sufficient explanations for its predictions can hinder investors' understanding of volatility dynamics and raise doubts about relying on the model's forecasts. Thus, there exists an imperative need to develop enhanced models that not only enhance forecasting accuracy but also offer interpretability, effectively bridging the gap between advanced methodologies and practical usability within the financial industry.

To address this limitation, this research aims to incorporate interpretability into the analysis of non-linear volatility forecasting models. By employing an explainable AI model, this study seeks to unravel the opaque nature of these complex models and attain a deeper understanding of the underlying drivers of volatility. Furthermore, the research endeavors to examine whether these non-linear models appropriately account for the influence of exogenous variables, such as investor sentiment, investor attention, and macroeconomic indicators, on volatility dynamics. By shedding light on the impact of these exogenous variables, the goal is to not only enhance the forecasting accuracy of non-linear models but also facilitate a more comprehensive comprehension of the intricate dynamics that drive volatility.

Through the integration of interpretability and the analysis of exogenous variables, this research contributes to the advancement of non-linear asset volatility forecasting, providing valuable insights for both researchers and practitioners in the financial domain. The contributions of this research can be summarized as follows:

- Integration of interpretability into non-linear asset volatility forecasting models, allowing for a deeper understanding of model predictions and enhancing transparency in the decision-making process.

- Novel construction of a dataset specifically tailored for the research, enabling a comprehensive comparative analysis of predictive performance among different types of models.

- Examination of the impact and appropriate incorporation of exogenous variables, such as investor sentiment, investor attention, and macroeconomic indicators, in capturing the dynamics of asset volatility.

- Employing an explainable AI framework to unveil the intricacies of complex forecasting models, fostering a deeper understanding of the underlying drivers of volatility.

Overall, this research contributes to the development of more reliable, transparent, and accurate non-linear asset volatility forecasting models, fostering advancements in the field and offering valuable guidance for decision-makers in the financial domain. By bridging the gap between advanced modeling techniques and practical usability, this research empowers stakeholders with enhanced insights into volatility dynamics, enabling more effective risk management and informed investment strategies. This contribution directly benefits retail investors by providing them with valuable tools to navigate the complex world of finance, make well-informed decisions, and ultimately improve their financial outcomes.

1.4 Organization of the Thesis

The thesis is organized into five chapters. Chapter 1 serves as the introduction, while Chapter 2 provides a comprehensive review of relevant literature on asset volatility forecasting and explainable AI. Chapter 3 presents the methodology and data employed in this study, followed by the discussion of empirical findings in Chapter 4. Finally, Chapter 5 concludes the thesis and offers potential avenues for future research.

Chapter 2

Literature Review

This chapter provides a comprehensive review of the literature on volatility forecasting models, including the definition of volatility and various modeling methods. It explores both traditional econometric approaches and emerging techniques like machine learning and deep learning-based models. Additionally, the chapter explores the concept of explainable AI and demonstrates how this method enhances transparency and interpretability.

2.1 Definition of Volatility

The concept of volatility, characterized by the degree of price fluctuations or variability observed in an asset, is inherently intangible. Unlike other measurable financial metrics like returns or market capitalization, volatility represents a dynamic and elusive characteristic of an asset. As a result, there exist multiple definitions and interpretations of volatility, enabling researchers and practitioners to adopt the definition that best suits their specific requirements. This flexibility empowers them to delve into the essence and implications of volatility within their respective domains, facilitating a comprehensive understanding of its significance.

Standard Deviation of Returns A widely adopted definition of volatility is based on the concept of standard deviation [45]. The standard deviation-based definition calculates volatility as the standard deviation of asset returns over a specific period. The formula used for this calculation is:

$$\hat{\sigma}^2 = \frac{1}{N-1} \sum_{t=1}^{N} \left(R_t - \overline{R}\right)^2 \tag{2.1}$$

In the equation, $\hat{\sigma}^2$ represents the estimated volatility, N denotes the number of observations, R_t is the return at time t, and $\overline{R}$ signifies the mean return within the given time period. Log returns, which are calculated using the formula $R_t = \log\left(\frac{P_t}{P_{t-1}}\right)$, where P_t denotes the price at time t, are commonly utilized in this context. By quantifying the dispersion of returns around the mean, the standard deviation provides a numerical measure of the asset's price fluctuations. This definition allows for the application of various statistical tests when the underlying distribution of the return series follows a Gaussian distribution [24]. It is worth noting that this definition is commonly employed by computing returns based on the closing price of an asset, effectively capturing the dynamics reflected in the closing prices. However, it is important to acknowledge a potential limitation of this approach, as it primarily captures the dynamics reflected in the closing prices and may not fully account for intraday or interday price movements.

Realized Volatility (RV) An alternative approach to measuring volatility is realized volatility (RV), which leverages high-frequency intraday data to capture the actual price fluctuations experienced by an asset. Unlike traditional methods, which rely on aggregated daily or periodic data, RV takes into account the observed price changes within shorter time intervals [1]. By doing so, it provides a more granular and dynamic measure of volatility. The estimation of RV typically involves summing the squared intraday returns over a specific time period, such as minutes or hours. This approach allows for the inclusion of intraday price dynamics, capturing the volatility that arises within shorter time intervals. The formula for computing realized volatility at time T is given by:

$$RV_T = \sum_{t=1}^{N} R_t^2 \tag{2.2}$$

where R_t represents the return at time t, and N denotes the total number of intraday returns considered within the specific time period under analysis. The choice of N depends on the research or analysis objectives, as well as the availability and granularity of the intraday data.

This approach has gained significant attention in research, with studies highlighting its ability to capture microstructure effects and sudden price movements that may not be fully reflected in traditional volatility measurements [2, 6]. Furthermore, realized volatility has implications for risk management and pricing of financial instruments. Its ability to capture finer-grained price movements can enhance risk models and improve the accuracy of value-at-risk (VaR) estimates [25, 35]. Incorporating realized volatility in option pricing models can also lead to more precise valuation of derivative instruments, as it accounts for the true volatility experienced by the underlying asset [5]. By considering the actual price fluctuations, option prices can be more accurately determined, aiding investors and traders in making informed decisions.

Implied Volatility (IV) Implied volatility is another important measure of volatility that is widely used in financial markets. Unlike historical or realized volatility, which rely on past price data, implied volatility derives its value from the prices of financial derivative instruments, particularly options. It represents the volatility level implied by the market's pricing of options contracts. Through reverse-engineering option pricing models, such as the classical Black & Scholes formula [10], implied volatility is calculated, establishing the volatility parameter that equates the observed market price of an option with its theoretical value.

The key assumption behind implied volatility is that option prices in the market are determined by the collective wisdom and expectations of market participants, adhering to the principles of the efficient market hypothesis. As a result, implied volatility can be considered a reliable forecast of future volatility. However, empirical studies have critically examined the effectiveness of implied volatility, raising questions about its ability to consistently provide accurate forecasts in practice [14, 40]. Several factors contribute to these challenges, including the presence of market frictions, model misspecification, and the impact of outliers. The assumptions embedded in option pricing models, such as constant volatility and efficient markets, may not always hold in real-world scenarios, leading to potential deviations between implied volatility and actual future volatility.

2.2 Traditional Econometric Volatility Forecasting Models

Over the years, econometric volatility forecasting models have played a pivotal role in the field of financial analysis. These models, rooted in statistical techniques and econometric methodologies, have provided valuable insights into the dynamics of volatility by leveraging historical price data and incorporating relevant variables.

Autoregressive Conditional Heteroskedasticity (ARCH) Models The Autoregressive Conditional Heteroskedasticity (ARCH) models, along with their subsequent Generalized Autoregressive Conditional Heteroskedasticity (GARCH) extensions, have emerged as prominent tools for volatility forecasting [11, 20]. ARCH models capture the persistence and clustering of volatility by incorporating past squared returns as a determinant of conditional variance. This recognition of the relationship between past volatility and current volatility allows for a more accurate estimation of future volatility patterns. Building upon the ARCH framework, GARCH models enhance volatility forecasting by introducing lagged conditional variances, effectively capturing additional volatility dynamics and further improving forecast accuracy.

The advancement continues with GARCH-M models, which integrate exogenous variables, such as macroeconomic indicators or investor sentiment, into the volatility modeling process [19, 26]. These models acknowledge that volatility can be influenced by various factors beyond historical price data alone. By considering both past returns, lagged variances, and the influence of external factors, GARCH-M models aim to enhance the accuracy of volatility forecasts and provide a more comprehensive understanding of the drivers behind volatility fluctuations. This incorporation of exogenous variables offers a more nuanced and holistic approach to volatility forecasting, enabling researchers and practitioners to gain deeper insights into the underlying factors shaping market volatility.

Heterogeneous Autoregressive (HAR) Model The Heterogeneous Autoregressive (HAR) model is a popular econometric volatility forecasting model that incorporates multiple lagged realized volatilities [16]. Unlike traditional models that rely solely on past squared returns, the HAR model incorporates information from different time scales by considering the lagged volatilities calculated using high-frequency intraday data. By including volatilities from various time scales, such as daily, weekly, and monthly, the HAR model provides a more comprehensive and accurate representation of volatility dynamics.

One specific formulation of the HAR model, similar to the approach used in a relevant study [4], can be represented by Equation 2.3:

$$\log RV_{t+1}^{(d)} = c + \beta^{(d)} \log RV_t^{(d)} + \beta^{(w)} \log RV_t^{(w)} + \beta^{(m)} \log RV_t^{(m)} + \epsilon_{t+1} \tag{2.3}$$

In this formulation, $\log RV_t^{(w)}$ and $\log RV_t^{(m)} = \frac{1}{22} \sum_{i=1}^{22} \log RV_{t-i+1}^{(d)}$ are the weekly and monthly averages of daily log realized volatilities, respectively. The coefficients $\beta^{(d)}$, $\beta^{(w)}$, and $\beta^{(m)}$ capture the impact of lagged volatilities from different time scales on the future volatility. The constant term c represents the intercept, and ϵ_{t+1} denotes the noise term.

The simplicity of the HAR model formulation, coupled with its robust performance, highlights its practical significance in capturing and forecasting volatility patterns in financial markets. By incorporating volatilities from multiple time scales, the HAR model is able to capture both short-term and long-term volatility dynamics, providing a more comprehensive understanding of volatility behavior.

Stochastic Volatility Models Stochastic volatility models are a class of econometric models that capture time-varying behaviors in volatility by assuming it follows a stochastic process. Compared to traditional models with constant volatility assumptions, stochastic volatility models offer a more flexible framework to capture the complex dynamics of volatility in financial markets. These models can effectively capture important characteristics such as volatility clustering, leverage effects, and regime shifts.

One prominent example of a stochastic volatility model is the Heston model [29]. In the Heston model, volatility follows a mean-reverting square-root diffusion process, while the asset price follows a geometric Brownian motion. A notable feature of the Heston model is its ability to capture the volatility smile phenomenon observed in options pricing. The volatility smile represents the implied volatility as a function of the strike price, indicating that options with different strike prices but the same maturity can have different implied volatilities. By incorporating stochastic volatility, models like the Heston model provide a more realistic representation of option pricing. However, it's important to note that stochastic volatility models can be computationally intensive, may require advanced estimation techniques, and interpreting these models can also be challenging due to their complexity.

2.3 Machine Learning and Deep Learning Approaches in Volatility Forecasting

AI approaches, known as machine learning and deep learning techniques, have emerged as potent instruments for predicting volatility by harnessing their capacity to capture intricate patterns and relationships within financial data.

Machine Learning Approaches Unlike traditional econometric models that rely on specific parametric forms and distributional assumptions, machine learning models offer greater flexibility and the capacity to model complex, non-linear dependencies. Methods such as support vector machines (SVM) [23] and random forests [37] have demonstrated their effectiveness in capturing intricate patterns and enhancing volatility forecasts in certain scenarios. These approaches have showcased their ability to handle diverse datasets and exploit the underlying information contained in financial time series, contributing to more accurate and data-driven volatility predictions.

Artificial Neural Networks (ANNs) In addition to traditional machine learning methods, recent advancements in deep learning technologies have introduced neural network structures into volatility forecasting. Artificial Neural Networks (ANN) are widely used in various studies, showcasing their effectiveness in capturing complex patterns and improving volatility forecasts [18, 41, 46]. Inspired by the human brain, ANNs consist of interconnected nodes or neurons organized into layers. The input layer receives the data, and the output layer generates the desired forecast. Hidden layers, positioned between the input and output layers, process and transform the information. Neurons apply mathematical operations to the weighted sum of their inputs, which are then passed through activation functions, introducing non-linearities into the model.

The most popular type of ANN used in volatility forecasting is the feedforward neural network. This network structure allows information to flow in one direction, from the input layer through the hidden layers to the output layer. By employing fully connected feedforward networks with multiple hidden layers, the dynamics of volatility can be captured. Figure 2.1 illustrates an example of an ANN architecture with two hidden layers, where the input consists of j historical realized volatilities. To train an ANN for volatility forecasting, historical price data and other relevant variables are utilized as input. The network iteratively adjusts the weights and biases of its neurons using optimization algorithms like backpropagation. The objective is to minimize the difference between predicted and actual volatility values. Once trained, the ANN can be employed to make forecasts on new, unseen data. Moreover, ANNs can be combined with other models, such as GARCH and HAR, in hybrid approaches, taking advantage of their flexible structure and improving modeling accuracy [7, 17].

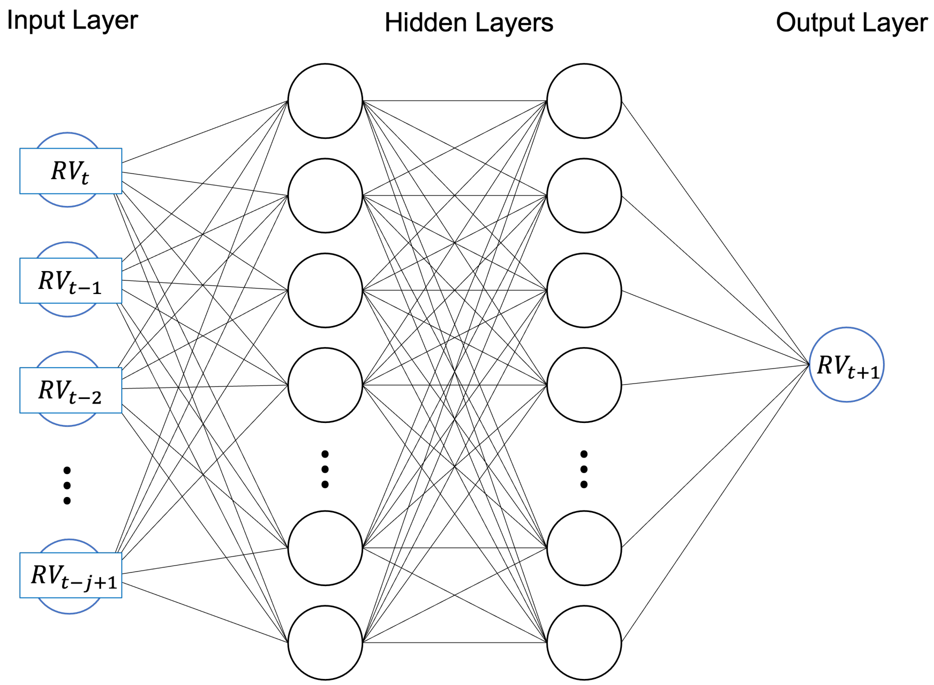


Figure 2.1: Neural Network architecture for Realized Volatility

ANNs offer several advantages in volatility forecasting. They excel in capturing complex patterns and non-linear relationships, enabling more accurate and flexible volatility predictions. Furthermore, ANNs demonstrate proficiency in handling large and high-dimensional datasets, making them well-suited for analyzing vast amounts of financial information. However, it is crucial to consider certain factors when working with ANNs. Selecting and tuning model architectures, activation functions, and optimization algorithms require careful attention. Overfitting is a potential concern if the model is not adequately regularized, resulting in overly optimistic performance on training data but poor generalization to new data. Additionally, the black-box nature of ANNs can make it challenging to interpret the underlying relationships between inputs and outputs.

Recurrent Neural Networks (RNNs) The development of Recurrent Neural Networks (RNNs) was motivated by the need to capture temporal dependencies and sequential information in data, which is particularly relevant in volatility forecasting. Unlike feedforward neural networks, RNNs have the ability to retain information from previous time steps and use it to influence the predictions at the current time step. This characteristic allows RNNs to handle variable-length sequences and resolve the limitation of feedforward networks in capturing long-term dependencies.

The structure of an RNN involves recurrent connections, where the output of a neuron at a certain time step is fed back as an input to the same neuron at the next time step. This feedback loop enables RNNs to maintain an internal memory that captures the historical context of the sequence being processed. By leveraging the temporal dependencies within the data, RNNs can capture the patterns and relationships that are crucial for accurate volatility predictions. However, traditional RNNs suffer from the vanishing gradient problem, which hinders their ability to capture long-term dependencies.

To overcome the vanishing gradient problem, advanced variants of RNNs, such as Long Short-Term Memory (LSTM) [30] and Gated Recurrent Unit (GRU) [15], have been introduced. LSTM networks incorporate memory cells and three gating mechanisms (input gate, forget gate, and output gate) to control the flow of information within the network. These gates allow LSTMs to selectively retain or forget information over long sequences, enabling them to capture long-term dependencies effectively. Similarly, GRU networks employ gating mechanisms to control the flow of information, but with a simpler structure compared to LSTMs.

Several studies have demonstrated the effectiveness of LSTM networks in volatility forecasting. For example, it has been shown that RNNs, particularly LSTMs, outperform traditional econometric methods in predicting the realized volatility of the S&P 500 index [12]. In the context of individual stocks, LSTM-based models have been found to achieve superior performance compared to traditional machine learning and econometric models for some stocks [33].

2.4 Explainable AI

The growing adoption of machine learning and deep learning algorithms has led to impressive performance across various domains. However, the inherent complexity of these models often results in a lack of transparency, making it challenging to understand the reasoning behind their predictions or decisions. This limitation has spurred the development of eXplainable AI (XAI), a field dedicated to creating interpretable models and providing meaningful explanations for their outputs.

One approach within explainable AI is feature importance analysis, which aims to quantify the contribution of each input feature to the model's predictions. By understanding the importance and impact of different features on the model's output, stakeholders can gain insights into the decision-making process of AI models and enhance trust and interpretability. Several techniques have been developed for feature importance analysis, including SHAP (SHapley Additive exPlanations) [36] and LIME (Local Interpretable Model-Agnostic Explanations) [49].

In the field of finance, SHAP has gained prominence as a robust tool for interpreting and explaining models. It draws inspiration from cooperative game theory, specifically leveraging the concept of Shapley values. Shapley values quantify the marginal contribution of each feature when considering all possible feature subsets. By computing Shapley values for each feature, SHAP provides a unified framework for quantifying the impact of features on a model's predictions. This enables researchers and practitioners in finance to gain a deeper understanding of the underlying drivers behind predictions and enhances the interpretability of complex models. Several studies have demonstrated the effectiveness of SHAP in interpreting time series models [28, 31].

The computation of SHAP values involves evaluating the prediction function for different subsets of features. Mathematically, the SHAP value for a specific feature i can be expressed as follows:

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (v(S \cup \{i\}) - v(S)) \tag{2.4}$$

In this equation, i represents the feature for which we are calculating the Shapley value, N represents the set of all features, v represents the prediction function, and S represents a subset of features excluding the feature i. The SHAP value $\phi_i(v)$ represents the marginal contribution of feature i in the cooperative game theory context. Calculating SHAP values for each feature allows us to ascertain the relative significance of features, unveiling their individual contributions to the model's predictions.

Chapter 3

Methodology and Data

This chapter presents an overview of the modeling method and data employed in this study. It is followed by a discussion of the experimental settings and an explanation of how an explainable AI technique is utilized.

3.1 Models

The modeling approach adopted in this study builds upon the concept of the HAR model with exogenous variables introduced in a previous study [4]. The HAR model used in this paper is represented by Equation 3.1:

$$\log RV_{t+1}^{(d)} = c + \big(\log RV_t\big)'\beta_{(RV)} + M_t'\gamma_{(eco)} + Z_t'\theta_{(sent)} + \epsilon_{t+1} \tag{3.1}$$

In this equation, the term log RV_t refers to a 3-dimensional column-vector consisting of the daily log realized volatilities, as well as the weekly and monthly average daily log realized volatilities. The vector M_t represents a q-dimensional column-vector containing economic and financial variables, while Z_t represents a p-dimensional column-vector containing sentiment and attention variables. The coefficients $\beta_{(RV)}$, $\gamma_{(eco)}$, and $\theta_{(sent)}$ capture the respective impacts of lagged volatilities, economic variables, and sentiment variables on the future volatility. The constant term c represents the intercept, and ϵ_{t+1} denotes the error term in the model.

In contrast to utilizing the HAR factors in the previous model, this study employs an Artificial Neural Network (ANN) with a similar approach. Based on a comprehensive analysis of relevant literature, the decision to employ an ANN model in this study was driven by its extensive adoption within the research community, as evidenced by the greater number of studies utilizing ANN compared to Recurrent Neural Networks (RNN) in the field [24]. The ANN model incorporates lagged realized volatilities from time t to time $t-j+1$ as one input, capturing the historical volatility dynamics using j past values. Additionally, all models in this study include the daily log return at time t as an input to measure its impact on future volatility. Exogenous variables for time t are also included as inputs to capture the influence of external factors on volatility. By combining these inputs, the ANN model aims to predict the realized volatility at time $t+1$, providing a comprehensive framework for volatility forecasting. The models are trained using the Mean Squared Error (MSE) loss function, a common objective function for regression tasks, and optimized using the Adam optimizer.

The determination of the optimal architecture for the neural network models follows a systematic approach. The number of nodes in each hidden layer is carefully selected by evaluating the test loss. Different configurations with 16, 32, and 64 nodes for each hidden layer are considered, while maintaining a consistent two hidden layer structure. The models are trained and their performance is assessed using the test MSE as the evaluation metric. The model with the lowest test MSE among the considered configurations is chosen as the best model. This meticulous process ensures that the neural network models are fine-tuned to maximize their predictive accuracy for volatility forecasting.

To evaluate the significance of incorporating exogenous variables, the study conducts a comparative analysis between the baseline ANN model, which solely relies on daily log return and historical realized volatility values, and the extended models that include additional exogenous variables. For the analysis of different exogenous features, various model variations are explored. The model list includes:

- Models incorporating investor sentiment and attention variables along with log return and historical realized volatility
- Models incorporating macroeconomic variables along with log return and historical realized volatility
- Models incorporating both investor sentiment and attention variables, as well as macroeconomic variables, along with log return and historical realized volatility
- Models incorporating investor sentiment and attention variables, macroeconomic variables, and sentiment and attention variables related to macroeconomic variables along with log return and historical realized volatility

3.2 Data

In this study, the asset universe consisted of the top five stocks, ranked by market capitalization, within each Global Industry Classification Standard (GICS) sector as of March 1, 2023. The specific stocks included in the analysis are presented in Table 3.1. Hourly price data was collected for these stocks from March 2021 to February 2023. Realized volatility was calculated using the hourly log returns, as it provides

Code	Sector	1st	2nd	3rd	4th	5th
10	Energy	XOM	CVX	COP	SLB	EOG
15	Materials	APD	FCX	SHW	ECL	CTVA
20	Industrials	UPS	RTX	HON	CAT	UNP
25	Consumer Discretionary	AMZN	TSLA	HD	MCD	NKE
30	Consumer Staples	WMT	PG	KO	PEP	COST
35	Health Care	UNH	JNJ	LLY	ABBV	MRK
40	Financials	BRK-B	JPM	BAC	WFC	MS
45	Information Technology	AAPL	MSFT	NVDA	V	MA
50	Communication Services	GOOG	META	DIS	TMUS	VZ
55	Utilities	NEE	DUK	SO	SRE	D
60	Real Estate	PLD	AMT	EQIX	CCI	PSA

Table 3.1: Sector-wise Composition of Included Assets

a measure of the volatility experienced within each trading day. Specifically, daily realized volatility of an asset was defined as the sum of squared hourly log returns for each trading day. By summing the squared hourly log returns, a comprehensive representation of the overall volatility within a given day was obtained. Furthermore, alongside the hourly data, daily closing prices were collected to explore the impact of daily returns on asset volatility.

Investor sentiment data was collected from StockTwits[1], a prominent social media platform utilized for gauging and analyzing investor sentiment in financial research studies [27, 32, 42]. StockTwits allows users to express their opinions about assets using Bullish or Bearish tags, accompanied by twit messages. Leveraging the platform's *cashtag* feature, which represents symbols for each asset (e.g., *$AAPL*), users were able to associate their opinions with specific stocks. Sentiment data was collected for all 55 stocks in the asset universe. Twit messages that contained the indicated sentiment labels were systematically gathered over the same data period

[1]stocktwits.com

as the price data, ensuring a comprehensive alignment between investor sentiment and price dynamics.

In addition to investor sentiment, the study also collected data on investor attention. Investor attention was measured using Google Trends[2], which provides insights into the number of queries searched by users on Google over a specific period. To analyze investor attention, the daily changes in Google Trends data were assessed for both the company name and ticker symbols of the 55 stocks in the asset universe. However, it is worth noting that Google Trends provides data in the form of relative search interest and does not directly provide daily change values. To address this limitation, a rolling window-based approach was employed. This involved searching Google Trends for the past three months and overlapping one month with the previous search period. By comparing values from the extended and overlapping periods, a continuous and comprehensive dataset for investor attention was generated.

In addition to collecting investor sentiment and attention data, this study also incorporated macro variables, or economic variables, to comprehensively capture the broader market and economic conditions, given their recognized influence on volatility [4, 43, 44]. The selected macro variables included the VIX closing price, obtained from WRDS - CBOE Indexes, which serves as a well-established measure of market volatility. The Fama-French three-factor model factors, comprising market excess return, size factor, and value factor, were sourced from the official Fama French website[3] to account for systematic risk factors. Additionally, economic indicators such as U.S. Treasury yields (5-year, 10-year, 30-year bonds, and 13-week Treasury bill yield), Consumer Price Index (CPI) data from the Federal Reserve

[2]trends.google.com

[3]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Bank of St. Louis[4], and short-term interest rates from the OECD[5] were included to provide insights into monetary policy, inflationary pressures, and overall economic conditions.

Finally, the sentiment and attention surrounding macro variables were investigated. Sentiment data was collected for widely followed market indices, including *$SPY*, *$QQQ*, and *$DJIA*, providing insights into the overall sentiment towards the broader market, using the same data collection method as described previously. Moreover, attention data was gathered for key terms including "stocks," "financial markets," "stock market," "interest rate," "S&P," "Dow Jones," "Wall Street," and "stock price." By analyzing the sentiment and attention surrounding these macro variables, this study aimed to gain insights into the broader market sentiment and attention dynamics, which may play a significant role in shaping asset volatility and overall market trends.

3.3 Experimental Settings

To ensure a comprehensive analysis and accurate volatility forecasting, specific experimental settings were implemented. This section highlights the key elements of the experimental setup used in this study.

Firstly, the volatility forecasting models were trained individually for each company using their respective training data. This company-specific approach allowed the models to capture the unique characteristics and dynamics of each company's volatility patterns. By tailoring the models to the specific data of each company, more accurate and reliable volatility forecasts could be obtained.

[4]https://fred.stlouisfed.org/series/CPIAUCSL

[5]https://data.oecd.org/interest/short-term-interest-rates.htm

In order to capture the weekly effect, a lag of 5 was utilized for the inclusion of lagged realized volatilities. This means that the models incorporated the realized volatilities from time t to $t-j+1$, where j represents the lag value of 5. By considering the historical volatility dynamics over the course of a week, the models were able to identify and incorporate weekly patterns or dependencies in the volatility data. This approach enhanced the accuracy of the forecasting models by accounting for the temporal dynamics at a weekly level.

Incorporating sentiment as a feature involved calculating a sentiment ratio (sentiment score). The sentiment ratio was derived by dividing the number of bullish tweets by the sum of the number of bullish and bearish tweets. This aggregation provided an overall sentiment measure that reflected the sentiment among investors. By including this sentiment feature in the volatility forecasting models, the influence of investor sentiment on volatility dynamics could be captured and analyzed.

To ensure consistency in the data analysis, all data points were transformed into a daily basis. This was particularly important for variables that were originally reported at a different frequency. For example, economic indicators such as Consumer Price Index (CPI) and interest rates are typically released on a monthly basis. To incorporate these variables into the daily-based volatility forecasting models, interpolation techniques were employed to fill in the missing values and ensure that the data remained consistent at a daily frequency. This data transformation allowed for a more coherent analysis of the volatility dynamics and improved the accuracy of the models.

By implementing these experimental settings, the aim was to enhance the reliability and effectiveness of the volatility forecasting models. The company-specific training, utilization of sentiment scores, and handling of missing data enabled a more comprehensive and accurate analysis of volatility dynamics. These settings contributed to a deeper understanding of the underlying factors driving volatility, leading to more informed decision-making processes.

3.4 Interpreting Volatility Forecasting Models with SHAP

In order to gain insights into the predictions made by the volatility forecasting models developed in accordance with the methodology outlined in Sections 3.2 and 3.3, an explainable AI approach, specifically SHAP, is employed for interpretability in this study. SHAP values are calculated for each model variation to provide insights into their predictions. Given that the volatility forecasting models are based on neural network architectures, DeepSHAP is employed to estimate the SHAP values. DeepSHAP combines the concepts of DeepLIFT and SHAP values, offering a comprehensive framework for attributing the model's predictions to the input features [36]. This enables a fine-grained analysis of the relative contributions of each feature to the volatility predictions. For a more comprehensive understanding of DeepSHAP, refer to the original paper [36].

To present the SHAP values in a concise manner, the absolute SHAP values for each feature are aggregated. Following the approach of [9], the sum of the absolute SHAP values provides a measure of the overall impact of each feature on the volatility predictions. This aggregation facilitates the identification of key drivers of volatility and enhances our understanding of their contributions. By focusing on the significant drivers of volatility, this approach assists in decision-making processes and provides deeper insights into the underlying dynamics.

Chapter 4

Empirical Findings

This chapter presents the empirical findings of the volatility forecasting models discussed in previous chapters, focusing on their forecasting performance and the importance of features at the variable category level. The analysis provides insights into the effectiveness and reliability of the models by examining their forecasting performance and feature importance.

4.1 Forecasting Results: Model Performance Comparison

This section presents the forecasting results of the volatility models, focusing on the MSE loss metric. The performance of each model type is evaluated by comparing the MSE loss for each company's data. The objective is to determine the impact of including exogenous variables on the forecasting performance and establish the superiority of the ANN model over the HAR model. The HAR models implemented in this study follow the methodology outlined in [4]. For convenience, shorter model names are proposed to refer to the various models used in the analysis:

(a) **HAR**: Baseline HAR model (implemented using GLS to address multicollinearity)

(b) **ANN**: Baseline ANN model

(c) **HAR-S**: HAR model with investor sentiment and attention variables

(d) **ANN-S**: ANN model with investor sentiment and attention variables

(e) **HAR-E**: HAR model with macroeconomic variables

(f) **ANN-E**: ANN model with macroeconomic variables

(g) **HAR-SE**: HAR model with investor sentiment, attention variables, and macroeconomic variables

(h) **ANN-SE**: ANN model with investor sentiment, attention variables, and macroeconomic variables

(i) **HAR-T**: HAR model with investor sentiment, attention variables, macroeconomic variables, and sentiment and attention variables related to macroeconomic variables

(j) **ANN-T**: ANN model with investor sentiment, attention variables, macroeconomic variables, and sentiment and attention variables related to macroeconomic variables

These shorter model names aid in the discussion and analysis of the results, facilitating the comparison and interpretation of the forecasting performance across the different models.

To gain a comprehensive understanding of the model performance on the test set, Tables 4.1 and 4.2 present the MSE values for each volatility forecasting model across different companies. Table 4.1 focuses on the HAR models, while Table 4.2 focuses on the ANN models.

Sector	Company	Model Type					Sector	Company	Model Type				
		HAR	HAR-S	HAR-E	HAR-SE	HAR-T			HAR	HAR-S	HAR-E	HAR-SE	HAR-T
Energy	XOM	0.004079	0.008758	0.006868	0.006458	0.006884	Financials	BRK-B	0.024689	0.025539	0.025967	0.026804	0.034901
	CVX	0.002518	0.004516	0.0099	0.006651	0.005954		JPM	0.007248	0.00712	0.008053	0.008428	0.008097
	COP	0.009773	0.009823	0.009559	0.011969	0.015096		BAC	0.013833	0.014682	0.018013	0.017322	0.016423
	SLB	0.00965	0.010221	0.009466	0.009786	0.010646		WFC	0.00446	0.005594	0.00891	0.00937	0.00814
	EOG	0.006276	0.005856	0.00731	0.006717	0.007601		MS	0.015465	0.015842	0.015649	0.015343	0.015863
Materials	APD	0.015954	0.017355	0.01762	0.018986	0.018015	Information Technology	AAPL	0.02341	0.020918	0.026067	0.023317	0.024815
	FCX	0.015141	0.015617	0.018487	0.018935	0.024302		MSFT	0.020914	0.018809	0.022822	0.020391	0.020718
	SHW	0.004138	0.003097	0.005735	0.00551	0.003918		NVDA	0.013683	0.013008	0.016053	0.01532	0.013218
	ECL	0.017346	0.019403	0.018938	0.021159	0.021363		V	0.006157	0.006026	0.017623	0.025669	0.021655
	CTVA	0.002911	0.003059	0.004938	0.003644	0.005023		MA	0.014026	0.014997	0.070159	0.073543	0.077572
Industrials	UPS	0.000544	0.000716	0.001176	0.002303	0.001609	Communication Services	GOOG	0.026813	0.024616	0.035072	0.028079	0.028862
	RTX	0.002396	0.002471	0.004259	0.004415	0.005963		META	0.010164	0.00446	0.011071	0.004802	0.005002
	HON	0.003453	0.004196	0.003884	0.003793	0.003767		DIS	0.011373	0.010117	0.012154	0.011089	0.011391
	CAT	0.011999	0.012194	0.013576	0.01344	0.012881		TMUS	0.003153	0.002578	0.004421	0.004602	0.005617
	UNP	0.011076	0.011233	0.010754	0.010662	0.011054		VZ	0.007688	0.007854	0.007787	0.008105	0.00869
Consumer Discretionary	AMZN	0.009804	0.005921	0.016607	0.006304	0.005765	Utilities	NEE	0.011757	0.011718	0.011707	0.011632	0.011822
	TSLA	0.02505	0.022107	0.02777	0.024975	0.027063		DUK	0.021108	0.021943	0.026931	0.029516	0.029151
	HD	0.012551	0.012431	0.01565	0.016393	0.014774		SO	0.011327	0.017883	0.019998	0.022283	0.02263
	MCD	0.01829	0.029565	0.03139	0.042892	0.03289		SRE	0.029999	0.046209	0.043222	0.039573	0.043622
	NKE	0.00775	0.005834	0.007568	0.005136	0.005427		D	0.013154	0.013069	0.012905	0.012768	0.012504
Consumer Staples	WMT	0.003418	0.003619	0.005001	0.004323	0.003915	Real Estate	PLD	0.005812	0.005963	0.006316	0.006129	0.011421
	PG	0.001965	0.002065	0.008483	0.007681	0.006131		AMT	0.013153	0.013302	0.012913	0.013	0.013709
	KO	0.00459	0.004906	0.008403	0.007813	0.005462		EQIX	0.014214	0.015908	0.022125	0.026096	0.029562
	PEP	0.014802	0.014713	0.01766	0.019671	0.014495		CCI	0.015657	0.016967	0.015706	0.01906	0.016084
	COST	0.003496	0.00342	0.00521	0.008203	0.00986		PSA	0.013443	0.014332	0.014332	0.014644	0.014429
Health Care	UNH	0.018107	0.018058	0.028905	0.029604	0.027738							
	JNJ	0.012623	0.012719	0.013526	0.013686	0.012367							
	LLY	0.002588	0.002979	0.002733	0.002939	0.003994							
	ABBV	0.001578	0.001625	0.001749	0.002037	0.002107							
	MRK	0.000537	0.000558	0.000976	0.000937	0.001219							

Table 4.1: Mean Squared Error (MSE) Comparison of Volatility Forecasting Models - HAR Models

Sector	Company	Model Type					Sector	Company	Model Type				
		ANN	ANN-S	ANN-E	ANN-SE	ANN-T			ANN	ANN-S	ANN-E	ANN-SE	ANN-T
Energy	XOM	0.003947	0.00466	0.003467	0.003674	0.003648	Financials	BRK-B	0.023023	0.023925	0.023243	0.023743	0.023719
	CVX	0.002581	0.002734	0.002763	0.003059	0.002298		JPM	0.007885	0.008103	0.007266	0.007113	0.006514
	COP	0.009729	0.009596	0.011509	0.009668	0.00891		BAC	0.013431	0.013808	0.012903	0.01277	0.012906
	SLB	0.009531	0.009439	0.012371	0.011896	0.0095		WFC	0.004881	0.004322	0.003521	0.003419	0.00332
	EOG	0.00603	0.005768	0.006226	0.005466	0.005604		MS	0.014941	0.01551	0.014597	0.014578	0.01496
Materials	APD	0.015815	0.016796	0.015715	0.016852	0.016341	Information Technology	AAPL	0.021367	0.01964	0.021629	0.01901	0.019081
	FCX	0.015062	0.014824	0.01466	0.015345	0.014765		MSFT	0.019805	0.019098	0.019535	0.018569	0.018328
	SHW	0.003914	0.002696	0.003871	0.002616	0.002577		NVDA	0.012804	0.012695	0.012718	0.012127	0.012419
	ECL	0.016263	0.018611	0.016051	0.018386	0.01853		V	0.005868	0.005823	0.005962	0.006046	0.005783
	CTVA	0.002866	0.00301	0.002821	0.002606	0.002379		MA	0.014067	0.014054	0.013553	0.013744	0.013784
Industrials	UPS	0.000529	0.000528	0.000525	0.000524	0.000541	Communication Services	GOOG	0.02581	0.023657	0.024854	0.023977	0.023516
	RTX	0.002501	0.002329	0.002292	0.002121	0.00205		META	0.009784	0.00822	0.009711	0.007912	0.007396
	HON	0.003371	0.003327	0.003315	0.003377	0.003351		DIS	0.010799	0.010288	0.010837	0.010332	0.01051
	CAT	0.011533	0.011537	0.011677	0.011411	0.011237		TMUS	0.003059	0.002878	0.003015	0.002819	0.002844
	UNP	0.010342	0.010524	0.010182	0.010487	0.010549		VZ	0.007556	0.007623	0.007259	0.007065	0.007156
Consumer Discretionary	AMZN	0.009181	0.00561	0.009246	0.005762	0.006304	Utilities	NEE	0.010582	0.010648	0.0105	0.010468	0.010511
	TSLA	0.023575	0.022308	0.024015	0.02236	0.02273		DUK	0.022901	0.023534	0.022919	0.02316	0.022676
	HD	0.011762	0.011573	0.011685	0.011494	0.01157		SO	0.017699	0.019961	0.017669	0.019723	0.020027
	MCD	0.017267	0.017239	0.016636	0.016138	0.016222		SRE	0.030363	0.035411	0.028265	0.033382	0.033844
	NKE	0.007496	0.004969	0.00763	0.004865	0.005254		D	0.012317	0.011974	0.012329	0.012851	0.012975
Consumer Staples	WMT	0.003243	0.003254	0.003335	0.002928	0.003115	Real Estate	PLD	0.005542	0.005661	0.005241	0.00538	0.005339
	PG	0.001962	0.001948	0.001839	0.001802	0.0018		AMT	0.012578	0.012101	0.012059	0.012252	0.012355
	KO	0.004576	0.004801	0.004073	0.004084	0.004232		EQIX	0.014317	0.015306	0.014007	0.015432	0.014942
	PEP	0.014654	0.014559	0.01409	0.013671	0.013519		CCI	0.014828	0.015935	0.014701	0.015585	0.015064
	COST	0.003349	0.003305	0.003405	0.003363	0.003336		PSA	0.012559	0.013941	0.012425	0.013464	0.0133
Health Care	UNH	0.017244	0.017762	0.017288	0.016891	0.016277							
	JNJ	0.012227	0.012157	0.01206	0.011964	0.011676							
	LLY	0.002436	0.002422	0.002993	0.002902	0.002408							
	ABBV	0.001545	0.001521	0.001541	0.001539	0.001539							
	MRK	0.000731	0.000717	0.000716	0.000704	0.000715							

Table 4.2: Mean Squared Error (MSE) Comparison of Volatility Forecasting Models - ANN Models

The MSE values serve as indicators of forecasting accuracy, with lower values representing better performance and higher values indicating greater deviations from observed volatility. Among the 55 companies analyzed, the baseline ANN model, incorporating a lag of 5 for historical realized volatility, exhibited lower MSE values compared to the HAR model in 45 companies. It is noteworthy that while the HAR model captures volatility dynamics even with monthly history, the ANN model with a shorter lag period of 5 demonstrated superior forecasting performance.

Moreover, when comparing models with identical data but different architectural approaches, such as ANN-S versus HAR-S, the ANN models consistently displayed competitive performance relative to the HAR models. This observation held true across various model configurations mentioned earlier. For instance, when comparing ANN-SE and HAR-SE, the ANN-SE model exhibited lower MSE values in all companies except for 3. Overall, the MSE values generally indicated the ANN models' enhanced ability to capture volatility dynamics compared to the HAR models.

Next, we conduct a comparison within the ANN-based models to assess their overall performance and determine if there are significant differences. This analysis involves a ranking evaluation followed by the application of the Mann Whitney U Test [38], a non-parametric statistical test used to compare two independent groups and identify significant differences between them. The ranking evaluation assigns ranks to each model based on their MSE loss for each company dataset, with lower ranks indicating better performance. To examine the relative performance of the ANN-based models and identify any significant differences in their forecasting accuracy, we employ the Mann Whitney U Test comparing the ranks assigned to the models in the first column with the ranks assigned to the models in the first row of

	ANN	ANN-S	ANN-E	ANN-SE	ANN-T
ANN		1650.0	1916.0**	2240.5***	2387.0***
ANN-S			1770.0	2070.0***	2212.0***
ANN-E				1774.5	1915.0***
ANN-SE					1653.5
ANN-T					

Table 4.3: ANN-Based Models: Mann Whitney U Test Results

Table 4.3. The alternative hypothesis for the test states that the model in the first column has a greater MSE rank than the model in the first row.

The results of the Mann Whitney U Test, including the p-values, are summarized in Table 4.3. Asterisks in the table indicate the significance level of the p-values, where *** indicates a p-value lower than 0.001, ** indicates a p-value lower than 0.01, and * indicates a p-value lower than 0.05. Therefore, the cell values in Table 4.3 with significant p-values indicate that the model corresponding to the row index has a greater MSE rank compared to the model corresponding to the column index. These significant differences highlight variations in the forecasting accuracy among the ANN-based models and provide insights into their relative performance.

The results show that the ANN model consistently demonstrates worse performance compared to the ANN-E, ANN-SE, and ANN-T models, with the exception of the ANN-S model. These findings suggest that incorporating additional variables in the ANN architecture contributes to improved forecasting accuracy. However, when comparing the ANN-S model to the other models, the difference is not significant, implying that including sentiment and attention variables alone may not significantly enhance the model's performance. These findings suggest the importance of carefully selecting and incorporating these exogenous variables to capture the intricate dynamics of asset volatility.

Furthermore, the ANN-S model demonstrates poorer performance compared to both the ANN-SE and ANN-T models. This implies that incorporating investor sentiment and attention variables alone leads to inferior forecasting accuracy compared to including sentiment and attention variables associated with macroeconomic factors. The result also suggests that the inclusion of macroeconomic variables in conjunction with sentiment and attention variables leads to improved forecasting accuracy. These results highlight the importance of considering the impact of macroeconomic factors in volatility forecasting.

Interestingly, the ANN-E model also performs worse than the ANN-T model. This suggests that while the inclusion of macroeconomic variables contributes to improved forecasting accuracy, the specific inclusion of sentiment and attention variables related to macroeconomic factors with the sentiment and attention variables of the stock itself enhances the performance further. These results indicate that the joint consideration of macroeconomic indicators and sentiment/attention variables related to macroeconomic factors yields better forecasting accuracy.

To summarize, the diverse performance of ANN-based models emphasizes the crucial role of variable selection in volatility forecasting. The results reveal that incorporating economic variables enhances model performance, while relying solely on sentiment variables does not yield statistical superiority. However, the combination of economic and sentiment variables leads to improved forecasting accuracy, highlighting their complementary nature in capturing volatility dynamics. These findings underscore the significance of thoughtful variable selection in enhancing the performance and reliability of volatility models.

4.2 Feature Importance Analysis

This section aims to explore the results of the feature importance analysis using SHAP, with a specific focus on the utilization of DeepSHAP across different ANN-based models. While SHAP provides a valuable means of quantifying the individual impact of each feature, there are inherent challenges associated with variables that may exhibit high levels of correlation. The presence of correlations among features can complicate the assignment of precise importance values to individual features, as their effects become entangled or shared. As a result, interpreting the individual effects accurately can be difficult. It is essential to approach the interpretation of DeepSHAP results with caution, recognizing that the explanations it provides are approximations rather than absolute ground truth.

To ensure a robust and trustworthy interpretation, this analysis adopts a strategic approach that prioritizes the identification of patterns and trends at the variable-category level, rather than focusing solely on detailed explanations at the individual feature level. This choice is motivated by the recognition that analyzing individual features in isolation may lead to potentially misleading or exaggerated conclusions. By grouping features into variable categories, such as investor sentiment and attention variables, macroeconomic variables, or sentiment and attention variables related to macroeconomic factors, the analysis can uncover broader themes and patterns within each category. This comprehensive understanding of feature importance helps mitigate the potential distortions introduced by highly correlated features.

Table 4.4 presents the results of the feature importance analysis using DeepSHAP for each company dataset and model type. The table showcases the top-ranked features that have been identified as the most important variables contributing to the predictions made by each model [1]It is important to note that the analysis focuses on the top features rather than providing an exhaustive list of all feature contributions. This deliberate choice is driven by the inherent challenge of assigning precise importance values to each feature, especially in the presence of strong correlations among them. By prioritizing the top features, the analysis aims to provide a more manageable approach to understanding the key drivers of the models. While other factors may also contribute to the predictions, the emphasis on the top features allows for a more meaningful and interpretable analysis, capturing the most influential variables without getting overwhelmed by the complexity of correlated effects. By analyzing the top features at a variable-category level, the analysis strikes a balance between granularity and comprehensibility, offering valuable insights into the main drivers while managing the complexity of individual feature-level interpretations.

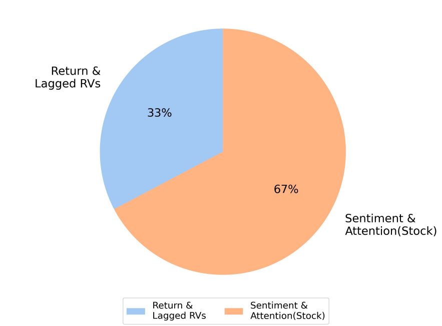
While the primary focus of the analysis is on interpreting feature importance at the variable category level, it is noteworthy that one feature consistently demonstrates significant importance across multiple companies and models: the VIX (CBOE Volatility Index). Commonly known as the "fear gauge," the VIX serves as a widely recognized measure of market volatility and investor sentiment. Despite the analysis's emphasis on variable category analysis, the consistent and significant importance of the VIX stands out, warranting special attention. Its recurring high rankings in the feature importance analysis underscore its robust impact on volatility forecasting, suggesting a strong likelihood that individual stock's volatility is influenced by market volatility. This finding aligns with previous studies that have emphasized the relevance of the VIX as a predictive factor [4, 13].

[1]The table presents the variables in an abbreviated form for brevity

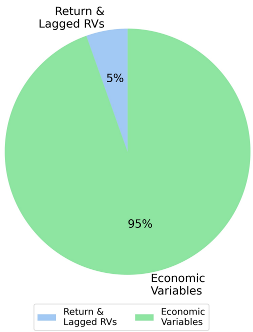
Sector	Company	Model Type				
		ANN	ANN-S	ANN-E	ANN-SE	ANN-T
Energy	XOM	rv_lag_4	sent_ratio_stock	vix	vix	Mkt-RF
	CVX	daily_log_ret	sent_ratio_stock	vix	sent_ratio_stock	sent_ratio_stock
	COP	daily_log_ret	sent_ratio_stock	vix	vix	vix
	SLB	realized_vol	attention_ticker	vix	treasury_yield_10yrs	attention_dow_jones
	EOG	rv_lag_4	attention_name	vix	vix	vix
Materials	APD	rv_lag_4	attention_ticker	vix	vix	sent_ratio_stock
	FCX	rv_lag_4	attention_name	daily_log_ret	vix	vix
	SHW	rv_lag_3	daily_log_ret	Mkt-RF	attention_name	vix
	ECL	realized_vol	sent_ratio_stock	vix	sent_ratio_stock	cpi
	CTVA	rv_lag_4	num_twit_stock	vix	num_twit_stock	num_twit_stock
Industrials	UPS	daily_log_ret	sent_ratio_stock	vix	sent_ratio_stock	sent_ratio_stock
	RTX	daily_log_ret	daily_log_ret	vix	vix	attention_dow_jones
	HON	daily_log_ret	daily_log_ret	SMB	vix	vix
	CAT	rv_lag_3	sent_ratio_stock	vix	vix	vix
	UNP	realized_vol	daily_log_ret	Mkt-RF	vix	sent_ratio_stock
Consumer Discretionary	AMZN	rv_lag_2	attention_ticker	HML	attention_ticker	attention_ticker
	TSLA	rv_lag_1	sent_ratio_stock	vix	attention_ticker	num_twit_stock
	HD	daily_log_ret	attention_name	vix	vix	sent_ratio_stock
	MCD	rv_lag_3	sent_ratio_stock	vix	vix	vix
	NKE	rv_lag_3	num_twit_stock	vix	num_twit_stock	num_twit_stock
Consumer Staples	WMT	daily_log_ret	sent_ratio_stock	HML	sent_ratio_stock	sent_ratio_stock
	PG	realized_vol	attention_ticker	vix	vix	vix
	KO	realized_vol	attention_ticker	vix	sent_ratio_stock	vix
	PEP	rv_lag_1	daily_log_ret	Mkt-RF	vix	vix
	COST	daily_log_ret	sent_ratio_stock	HML	sent_ratio_stock	attention_financial_markets
Health Care	UNH	rv_lag_4	attention_name	vix	attention_name	vix
	JNJ	daily_log_ret	daily_log_ret	vix	cpi	vix
	LLY	rv_lag_4	sent_ratio_stock	RF	cpi	num_twit_qqq
	ABBV	daily_log_ret	sent_ratio_stock	daily_log_ret	treasury_yield_30yrs	sent_ratio_stock
	MRK	realized_vol	sent_ratio_stock	vix	sent_ratio_stock	vix

Sector	Company	Model Type				
		ANN	ANN-S	ANN-E	ANN-SE	ANN-T
Financials	BRK-B	realized_vol	rv_lag_1	vix	vix	realized_vol
	JPM	rv_lag_1	realized_vol	vix	vix	vix
	BAC	realized_vol	realized_vol	vix	vix	vix
	WFC	daily_log_ret	daily_log_ret	vix	vix	vix
	MS	daily_log_ret	sent_ratio_stock	vix	vix	vix
Information Technology	AAPL	realized_vol	rv_lag_2	vix	vix	vix
	MSFT	rv_lag_2	attention_ticker	Mkt-RF	vix	vix
	NVDA	realized_vol	sent_ratio_stock	RF	sent_ratio_stock	vix
	V	daily_log_ret	sent_ratio_stock	vix	vix	vix
	MA	realized_vol	realized_vol	vix	vix	vix
Communication Services	GOOG	daily_log_ret	num_twit_stock	vix	num_twit_stock	num_twit_stock
	META	rv_lag_3	num_twit_stock	Mkt-RF	num_twit_stock	num_twit_stock
	DIS	daily_log_ret	num_twit_stock	vix	num_twit_stock	num_twit_stock
	TMUS	rv_lag_4	sent_ratio_stock	vix	vix	vix
	VZ	daily_log_ret	daily_log_ret	daily_log_ret	vix	daily_log_ret
Utilities	NEE	rv_lag_4	num_twit_stock	vix	vix	sent_ratio_stock
	DUK	rv_lag_2	rv_lag_2	vix	vix	vix
	SO	rv_lag_2	rv_lag_2	vix	vix	vix
	SRE	realized_vol	daily_log_ret	vix	attention_ticker	attention_ticker
	D	rv_lag_3	daily_log_ret	vix	sent_ratio_stock	sent_ratio_stock
Real Estate	PLD	rv_lag_3	rv_lag_2	vix	vix	vix
	AMT	daily_log_ret	attention_name	SMB	vix	sent_ratio_stock
	EQIX	daily_log_ret	num_twit_stock	vix	RF	num_twit_stock
	CCI	daily_log_ret	sent_ratio_stock	vix	vix	vix
	PSA	rv_lag_3	sent_ratio_stock	vix	vix	sent_ratio_stock

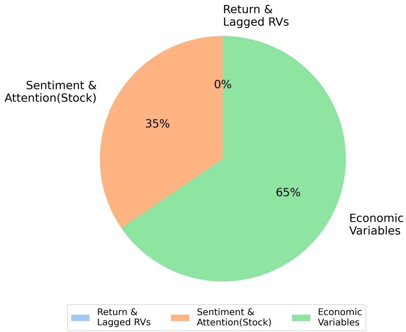
Table 4.4: Top-Ranked Features Identified by DeepSHAP for ANN-based Volatility Forecasting Models



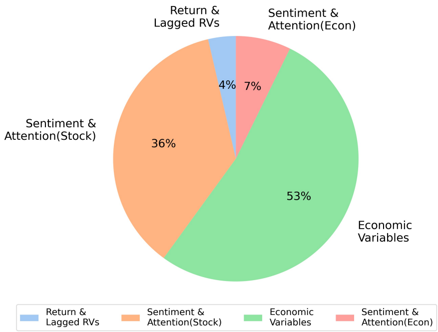
(a) Model type: ANN-S



(b) Model type: ANN-E



(c) Model type: ANN-SE



(d) Model type: ANN-T

Figure 4.1: Most Important Feature Categories for Different Model Types

Figure 4.1 displays four pie charts, each representing the most important feature categories for a specific model type analyzed in this study. The four model types examined are ANN-S, ANN-E, ANN-SE, and ANN-T, which incorporate various exogenous variables. The baseline ANN model, without any exogenous variables, is excluded from the pie charts. These pie charts were generated by counting the occurrences where each category type was identified as the most important feature in the volatility forecasting models.

The analysis of the ANN-S model reveals an intriguing pattern, as shown in Figure 4.1a. The pie chart demonstrates that sentiment and investor attention-related variables are selected as the most important features in approximately 67% of the cases, while the remaining cases prioritize return-volatility values. This observation suggests the possibility of market sentiment and investor attention playing a role in volatility forecasting within the ANN-S model. By according significant importance to these variables, the model hints at the potential benefits of incorporating psychological factors and market perception in improving the accuracy of volatility predictions. This finding raises the need for further investigation into the influence of sentiment and attention on volatility dynamics. If confirmed, it may underscore the importance of capturing the market's emotional response and investor behavior driven by attention to achieve more precise volatility forecasts.

Shifting our attention to the ANN-E model, Figure 4.1b provides compelling evidence of the dominance of economic variables as the most important features. The pie chart clearly illustrates that economic indicators are consistently selected as the primary drivers of volatility forecasting, with a remarkable majority of approximately 95% of the cases. This substantial preference for economic variables over return-volatility values suggests a robust influence of economic conditions and macroeconomic factors in shaping the volatility dynamics of each asset within the ANN-E model. The findings imply that market conditions, as captured by economic variables, may have a more significant impact on volatility than the individual movement of each asset. This highlights the importance of considering broader market factors when forecasting and managing volatility in financial markets.

Moving to the ANN-SE model depicted in Figure 4.1c, the results reveal a distinct selection pattern. Only exogenous variables are chosen as the most important features, with sentiment and economic categories being considered. This is an interesting finding since it demonstrates that exogenous variables are actually the key drivers, while the endogenous factors, represented by return and volatility, are not given prominence. Interestingly, among these categories, economic variables have a higher frequency of selection compared to sentiment-related variables. This implies that the model relies more heavily on economic factors, such as economic indicators and market fundamentals, when forecasting volatility. The relatively limited emphasis on sentiment-related variables in this model configuration implies that market sentiment and psychological factors may be considered less influential in shaping volatility dynamics. Instead, the model emphasizes the importance of economic conditions and external factors in driving volatility patterns.

Lastly, the ANN-T model depicted in Figure 4.1d, the analysis of feature importance reveals a distinctive pattern. Economic variables maintain their dominance as the most frequently selected features, affirming their crucial role in capturing volatility patterns within this model. Furthermore, sentiment-related variables, encompassing both individual stock sentiment and macroeconomic sentiment, are also given considerable importance. This highlights the value of incorporating sentiment indicators in enhancing volatility forecasts. The significant presence of economic variables combined with the inclusion of sentiment variables underscores the comprehensive approach of the ANN-T model in considering both economic and sentiment factors for accurate volatility predictions.

By integrating the findings from the feature importance analysis with the results from the forecasting results analysis, a deeper understanding of the driving factors behind volatility in non-linear models is obtained. The incorporation of exogenous variables goes beyond improving the performance of the models. It reveals that these variables play a fundamental role as the primary drivers of volatility dynamics.

In the previous section, it was discovered that the ANN-S model did not statistically outperform the baseline ANN model, while the ANN-E model demonstrated superior performance. This finding aligns with the overarching observation that economic variables dominate as drivers of volatility dynamics. The stronger forecasting performance of the ANN-E model, along with the emphasis on economic variables in the feature importance analysis, provides valuable insight into the critical role of economic conditions in accurately predicting asset volatility.

Furthermore, the integration of sentiment and attention variables alongside economic factors in the ANN-SE model resulted in more robust forecasting outcomes. This suggests that the inclusion of multiple exogenous variables, encompassing both economic and psychological factors, enhances the predictive capabilities of the models. Not only does this integration amplify performance, but it also establishes these exogenous variables as key drivers of the forecast, surpassing the significance of return and volatility values. A similar pattern is observed in the ANN-T model, where the comprehensive use of variables further improves predictive performance, with economic variables and sentiment-attention variables playing a central role in driving volatility dynamics. This insight highlights the importance of considering a comprehensive set of exogenous variables when developing volatility forecasting models, as they play a critical role in capturing and explaining volatility patterns in financial markets.

Chapter 5

Conclusion

This chapter concludes the paper and highlights potential avenues for future research and areas that can be explored to further enhance the understanding and application of the study's findings.

5.1 Conclusion

This study aimed to investigate the enhancement of non-linear asset volatility forecasting models by integrating exogenous variables and utilizing explainable AI technique, SHAP. The empirical analysis encompassed two main aspects: forecasting results and feature importance analysis. In the forecasting results analysis, we compared the performance of non-linear neural network models with the widely used HAR (Heterogeneous Autoregressive) model. The results demonstrated the superior predictive capabilities of the non-linear neural network model, as evidenced by its lower Mean Squared Error (MSE) loss metric.

The forecasting results of this study highlight the effectiveness of incorporating different variables in volatility forecasting models. Specifically, the inclusion of economic variables significantly improved model performance, emphasizing the importance of considering macroeconomic conditions when predicting asset volatility. In contrast, models relying solely on sentiment variables did not exhibit statistically superior performance. However, a noteworthy finding emerged when economic and sentiment variables were combined, resulting in enhanced forecasting accuracy. The integration of sentiment variables at the macro level also played a meaningful role in augmenting model performance, highlighting the significance of capturing market sentiment and psychological factors. By comprehensively including both economic and sentiment variables, a more robust approach to volatility modeling was achieved, leading to heightened accuracy and predictive power. These findings collectively emphasize the value of variable selection and the incorporation of diverse factors in non-linear asset volatility forecasting models.

The feature importance analysis revealed distinct patterns in the key drivers of asset volatility forecasting across different model types and variable categories. In the ANN-S model, market sentiment and investor attention emerged as influential factors, underscoring the importance of incorporating psychological factors. The dominance of economic variables in the ANN-E model highlighted the significance of macroeconomic conditions. The ANN-SE model demonstrated the substantial impact of exogenous variables, with a relatively lesser emphasis on sentiment-related variables and a stronger focus on economic factors. Similarly, the ANN-T model showcased the comprehensive role of exogenous variables, with economic variables and sentiment indicators as the main drivers, surpassing the influence of return-volatility values. These findings underscore the significance of incorporating exogenous variables in volatility forecasting models, as they not only amplify the forecasting performance but also serve as the primary drivers of volatility dynamics.

5.2 Future Work

In addition to the findings and contributions of this study, there are several avenues for future research in the field of asset volatility forecasting. Firstly, exploring a broader range of exogenous variables could provide a deeper understanding of their impact on volatility dynamics. This could involve incorporating additional economic, financial, and sentiment indicators to assess their predictive power. Furthermore, applying feature selection techniques can help identify the most influential variables and reduce dimensionality in the models. Additionally, investigating different types of neural networks, such as RNNs or Transformers, can offer insights into their effectiveness in capturing temporal dependencies and long-term patterns in volatility. Lastly, exploring alternative explainability techniques and testing the robustness of the models across different market conditions would further enhance their reliability and applicability.

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국문초록

본 논문에서는 투자자 심리로 대표되는 외생변수의 활용과 SHAP 분석을 활용한 설명 가능 인공지능 기법 적용을 통해 비선형 자산 변동성 예측 모형을 개선하는 방법을 제시한다. 자산 변동성 예측 분야에 있어 비선형 모형의 개발은 주로 정확도 향상에 초점을 맞춰 왔지만, 모델 내 각 변수의 중요도와 영향에 대한 이해가 제한되어 있어 잠재적인 신뢰성 저하로 이어졌다. 이러한 한계를 극복하기 위해 본 연구에서는 모델의 예측 능력을 개선하는 것뿐만이 아니라 외생변수의 중요성에 대한 분석을 통해 신뢰할 수 있는 예측 모형을 제시한다. 이를 위해, 우선적으로 자산 변동성 예측에 널리 사용되는 이질적 자기회귀 (HAR) 모형에 비해 신경망 구조를 활용한 비선형 예측 모형이 우수한 성능을 가지는 것을 확인한다. 또한 이 과정에서 다양한 외생변수를 포함하였을 때, 외생변수의 실제 영향력을 분석하여 비선형 모델 내에서 외생변수의 중요성과 영향력에 대한 분석을 제공한다. 분석 결과, 경제 상황과 관련된 변수가 지배적인 역할을 하며 변동성 역학에 상당한 영향을 미치는 것을 확인하였다. 또한 투자자의 심리와 관심 역시 비선형 변동성 예측에 유의하게 기여하는 것을 확인하였다. 본 연구는 예측 정확도의 향상과 더불어 변수의 중요성에 대한 이해 심화를 통해 보다 더 신뢰할 수 있는 예측 모형을 제시하였다는 점에서 기존의 자산 변동성 예측 모델을 개선한다. 외생변수의 활용과 설명 가능 인공지능 기법의 활용을 통해 본 연구는 리스크 관리 및 투자 전략에 대한 귀중한 인사이트를 제공할 수 있는 신뢰할 수 있고 효과적인 비선형 변동성 예측 모형 개발 방향성을 제시한다.

주요어: 변동성 예측, 설명 가능 AI, 투자자 심리, SHAP, 산업공학

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