Stochastic Regime Switching and Long Short-Term Memory Networks: AI-Based Computational Models for Financial Market Volatility Forecasting

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1. Introduction to Market Volatility and Forecasting

Understanding the causes and consequences of market volatility is of both academic and practical interest. Academic research is devoted to identifying the impact of market volatility on the investment environment, the effectiveness of policy actions, the link between the volatility of asset returns and other macroeconomic variables, the association between volatility and corporate finance, and option pricing. Policymakers are concerned about the market volatility because macroeconomic performance is impacted by volatility, as well as policy formation and evaluation of policies implemented in order to mitigate the unwanted consequences of market volatility. Asset managers are concerned with the returns and risks associated with alternative investment strategies and the impact of market volatility on the returns of assets in a portfolio. They use methods of forecasting implied volatility in order to capture exceptional profits.

Considering that market volatility is high-dimensional and potentially nonlinear with a large number of factors changing over time, artificial intelligence approaches offer a new promise for improved performance. It is well known that autoregressive models cannot eliminate the impacts of structural breaks and that, in general, nonlinear models can perform better. This is especially true when markets undergo such structural breaks, which may occur because of a new policy, changes in interest rates, or changes in monetary policy or economic growth setbacks. New wave methods offer the promise of better capturing those changes.

1.1. Defining Market Volatility

Market volatility is a stochastic process by which the prices of financial assets fluctuate over time. Volatility is a measure of the variation in the price of a financial instrument over time. In relatively stable markets, such as equities or real estate, low volatility produces low rates of return falling below long-term averages, while high volatility calls for capital that is able to react quickly to changes over time.

The fluctuations in stock market prices are often measured by comparing observed price changes to the predictions of standard econometric models. The modulus of these differences increases with price changes of different signs and is bound to be a positive number. Economists call such a number, the absolute value of a random variable, a 'fuzzifier' that emphasizes the linear proportions that characterize large fluctuations in a system dominated by a random walk. Governed by a stochastic process, the magnitudes of price changes are distributions for which statistics can be reported.

Because expected stock returns are assumed to be higher over longer horizons, the variance of the price change from investment to investment must be an increasing function of the investment's duration. In the jargon of time-series econometrics, the resulting property of the variance of the return on an arbitrage strategy is called the Jensen inequality. The proof draws from Poisson's equation for the variance of a continuous function.

1.2. Importance of Forecasting Market Volatility

Prediction of asset returns has been a matter of interest to finance and economics for a long time. Despite being a central goal, stock return forecasting has been examined in numerous works from different perspectives and a wide range of techniques due to its significance in investment decision-making as well as portfolio management, asset pricing, and so on. Volatility forecasting, the prediction of future changes in financial asset prices, has become even more critical and has surged in economic research in recent decades with both the innovation and wide acceptance of financial derivatives and risk management tools. The significance of volatility forecasts in finance is as follows. First, volatility is one of the main parameters required in the pricing process of derivative securities and asset valuations in quantitative finance, and is even more important in risk management. Second, the asymmetric effect of good and bad news creates a nonresponse of implied volatility to underlying return movements.

Consequently, the use of observation or naive return event windows can lead to information loss as well as inefficient predictions of future realized volatilities.

In practical applications, it is not enough for option traders or portfolio managers to only avoid using past ex post variance to forecast future variance for implied volatility. At least to some extent, however, forecasting future volatility is necessarily complementary. The frustrating fact is that investors trust volatility forecasts more than third-party models. In third-party models, some implicit or explicit forecasts of volatility account for the variance claims that asset returns will statistically exceed, by definition, as future realized variances. Consequently, this paper's choice of the realized volatility calculation has only one aim: to evaluate how the AI-based option-implied forecast stacks up against the forecast's quality.

Prior to the development of this innovative method, I determine optimal stochastic discontinuous volatility to grant a time-analytic variance predictor that takes the form of a nonlinear wavelet stochastic differential equation. It would use these classes of newly identified models to identify a set of valid necessary and sufficient conditions for recurrent, piecewise continuous paths.

By studying the properties of the model and analyzing the error property decay in series form, the author concludes that the beta value's estimate with a given sequence would become closer to one with a higher order of truncation. Dynamic somatic fractional strike adapts the FX pricing awareness to a sequence of recent observations, determining how previous evaluations can be effectively combined into a forecast of future volatility. Correlation patterns have been established in intraday financial time series volatility, which can be officially expected. The salient integration aspect of this empirical research is that a recurrent neural network is used to combine the complexity of linear dynamic models and the dynamics of latent variables produced by traditional linear stochastic production models. Through both asset market data and tools market data, the important conclusion was well illustrated.

2. Traditional Methods of Market Volatility Forecasting

The forecasting of volatility is a very important issue in finance, being a prerequisite for the creation of the mathematical tools using which one can manage financial risks. Research in the area of modeling and forecasting of volatility has been undertaken extensively during the previous two decades or so, with a large number of historical research papers examining a number of different methods for the development of volatility models. We consider several traditional statistical tools for volatility forecasting that are widely used in the finance and economics literature nowadays. These are the noisy component model, the stochastic volatility model with some additional time series generated macroeconomic variables for predicting the volatility, and the autoregressive conditional heteroskedasticity models. Below we will see that the AI-based alternative advanced methods devised in the upcoming sections usually outperform these traditional economic models, providing more accurate results and improved forecasts.

Before the introduction of a specific prediction or forecasting model, two distinct time frames in the research for the predictability of market volatility have been used. The first is the stock market business day, and regarding the volatility of the stock index weighted log-returns, the literature suggests that most of the predictability of the volatility is concentrated at high frequencies equal to or even less than 5 minutes. When implementing volatility models, even when these are nonlinear and part of the non-linear GARCH family, macroeconomic variables and the market microstructure effects are usually integrated, and the weighted average of the volatility at the 5-minute intervals of previous days' realized volatility is used as information variables that, at the time, the daily conditional variance is relevant. On the other hand, the second research timeframe covers daily, weekly, monthly, or even yearly periods for implementing various statistical and time series econometric tools and methods designed to predict the market's monthly or annual volatility.

2.1. Historical Volatility Calculations

To capture different time frames using daily price data, the following methods are compared: the most frequently used close-to-close method, which is based solely on prices; the Parkinson high-low method, which takes into account the highest and lowest price of the day; and the Garman-Klass method, which was developed to take into account the opening price in this type of calculation. Volatility forecasts are produced for different time frames: one day ahead, which is the most frequently published in financial markets; five days ahead, which coincides with the period of sessions of organized securities exchanges and may affect the price formation process; and ten days, which is the standard frequency for price formation. To assess the reliability of the forecast, a volatility proxy will estimate option prices with observed stock prices as the stochastic variable and use the model discrepancy to assess the proportional pricing error.

The proportional approach is applied to estimate volatility and option prices. Volatility is calculated using different methods to estimate the assets' value in the underlying model. The last topic in this section involves the use of robust measures, with the objective of mitigating the impact of time variation in volatility. The process of estimating historical volatility is attempted, with analyses of the most important modes and their impact, including the simple realization volatility, the traditional return-based measures, and using tick-by-tick data when it is available from different assets. The choice of return frequency is discussed as well, in particular concerning the impact of dual listing and different yields per trading day. At the end of this section, section 2.2 evaluates the performance of the realized volatility measures.

2.2. Implied Volatility Models

Any valuation model of financial options needs a forecast of future volatility. In the case of the Black-Scholes model, all of the pricing formulas are symmetric in the stock and call volatility variables, given by the same estimated historical number. The Heston model, which is an enlargement of the Black-Scholes model by incorporation of a two-dimensional stochastic differential equation for the variance process, specifies market option prices in a manner consistent with the observed risk-neutral volatility in a sample period. The Heston model removes the restriction that volatility is constant and may now vary over time. However, the drawback of both models is that their option price formulas are complex and do not have analytical solutions.

From the offered jest, a relative error can be calculated as a parameter that will move some curve in Z(x). For example, the distance μ is used to relate the black call option equivalent to the implied volatilities by capitalization. The Black-Scholes pricing function is not contingent upon parameters to be estimated with the option price. However, the further the option price is from the condition of the Black-Scholes pricing function, i.e., due to the short sample ends, the lower the quality of the implied volatility as an estimate of the parameters. These models can estimate the shape of the whole implied volatility 'smile' by analyzing the difference between the implied volatility and its asymptotic value of a near-reasonable moneyness parameter.

3. Introduction to Artificial Intelligence in Finance

Few would argue against the potential of artificial intelligence (AI) to influence nearly every branch of economic activity. Like each of the last general-purpose technologies, this one promises to transform industrial production, the characteristics of manufactured products, and a panoply of service industries, such as financial services. Indeed, some recent observers have even argued that we are already entering a new revolution in economic productivity, engendered by the deep learning subfield of machine learning, which essentially is the study of computer algorithms that improve automatically through experience. Researchers in finance may be expected to focus especially on such application areas as trading strategies, dynamic hedging, and tools for managing and mitigating counterparty risk, market risk, and operational risk. Our focus today, however, will be on AI-based equity market models and their use in forecasting the evolution of equity and option market volatility.

One popular kind of AI technique for financial inference and forecasting is the neural network, often described as a layered network of simple processing elements, composed of weights and simple arithmetic operations, such as summation and the use of activation functions. Postulating this kind of structure has an explanatory role in every case because it can capture how information flows in the economizing process that AI is emulating and can thereby explain how the network has learned to emulate that process. For some researchers, this explanatory contribution has been a sufficient purpose and criterion for the successful use of these techniques in describing many phenomena, financial and others. For other researchers, explicative contributions may be similarly important, but it is always hard to deny the advantages of simple models that have empirical validation. The latter group of researchers insists that neural networks should, in fact, be used for exactly that practical purpose. While the approaches we move on to describe also do enjoy some explicative power, we suspect that, in this setting, the quasi-predictive requirement of any technique that might be useful to practicing professionals is even stronger.

3.1. Overview of Machine Learning in Finance

During the last decade, the implementation of financial machine learning for financial companies became a popular trend. Especially in traditional markets where high-frequency decisions are standardized in macro-based features. Machine learning models have faced many challenges in finance time-dependent prediction. At first, it was estimated that simple linear models have a valid solution in a low signal-to-noise ratio. Contrary to common sense, dense input, which is the transformation of macro data to understand the market, is not a strong solution for including the right conditional information in the training dataset to understand the market. Furthermore, for those linear models, the included non-linearity and non-separability are not enough for capturing unstandardized and interconnected financial markets.

Particularly, including clustering in the training dataset before training the two independent linear models for each of them produced a more satisfactory prediction than one single model. Despite the fact that new techniques and frameworks, particularly those based on neural networks, were built to solve more complex tasks, the structure of the financial market is directly linked to the way long and short investment strategies interact with each other and with the other existing actors in the financial markets. This is based on a fundamental ground truth: the way a company's worth is calculated. Such structures are time-dependent and can be attributed to each type of actor via a social choice or, without any feedback, by a statistical steady state based on agent-based models of the financial markets.

3.2. Applications of AI in Market Volatility Forecasting

Various AI analyses can be performed on historical data. This can help forecast future situations to make investment decisions by investors. Therefore, it is expected that we can forecast market returns from historical data to some extent. Of course, past profits do not guarantee future returns. However, if the possibility of forecasting future returns becomes low, the stock market loses its purpose to some extent and may not continue to exist. On the other hand, it is known that stock returns and asset price fluctuations are not deterministic. There is a probability that fluctuations continue for a while. Accordingly, predictions cannot completely increase the accuracy needed to make a profit. While a typical time series regression model can create various economic theories and develop a relatively simple model, we do not have many options for such a model.

Recently, artificial intelligence has been active, and sophisticated models have been developed. Business operators are taking advantage of state-of-the-art technological advances in AI and using the technology to improve forecast accuracy and make a profit. AI companies are solving various issues and contributing to improved efficiency in our society. As far as stocks are concerned, we obtain clues for market direction control based on new anomalies and market price behaviors that cannot be explained by modern asset theory and evaluate investment results by developing these models. Through these advancements, intangible trading robots have emerged and have started to outperform top-notch investment gurus. This paper explains the utilization of two different techniques and their applications in market volatility forecasting, which have different characteristics. The evaluation process indicates that the AI model approaches were successful in market volatility prediction.

4. Key Machine Learning Techniques for Market Volatility Forecasting

In this chapter, we focus on the applications of artificial intelligence in addressing the issue of forecasting market volatility. This study aims to provide a better understanding of whether AI methodologies could be used to develop and improve techniques that can partially or accurately predict market volatility. In general, the improvements in volatility prediction techniques have important implications for various areas in finance, such as risk management, asset pricing, asset allocation, and hedging strategies. In practice, most existing applications of machine learning are data-driven predictive modeling tools that allow researchers to build models that can provide forecasts on future events. Specifically, machine learning has stringent demands for data features, but the wide range of financial indicators can easily satisfy them, which is why they could be the most promising methods for market volatility forecasting. This section provides a brief survey of machine learning and big-data-based models for predicting long-horizon volatility. We start with traditional big-data-based models and discuss how to incorporate high-frequency information into these models. This is mainly because these extensions provide insights into constructing big-data models in the presence of high-frequency data. We then summarize some key ideas of machine learning models in the context of volatility prediction. Finally, we conclude this section by discussing some practical considerations of these learning models.

4.1. Supervised Learning Algorithms

We use two different types of supervised learning algorithms to develop two distinct models whose outputs will be subsequently fed into the third model, an unsupervised neural network. The relation between the input and output in supervised models is generally expressed as Y = f(X). The models are labeled as conditional forecasters based on input parameter values. We consider 1) a classifier designed and trained to forecast turbulent market states, or more specifically, drawdown probabilities, and 2) a regressor designed and trained to forecast the intensity of turbulent market periods, or more specifically, the duration of stress events, because it is demonstrably difficult to predict drawdown sizes.

The first model is a random forest classifier. The particular draw of random forest models for stock market forecasting is that, generally, there is no need for extensive sampling or pre-processing of training data to avoid the effects of bad, uninformative predictors. The second model is a random forest regressor. Although we have not seen it in the literature of stock market forecasting, we later show that both of these models, which serve as the first-stage tiers, perform extraordinarily well in our general three-stage construction.

4.2. Unsupervised Learning Techniques

Unsupervised learning, in contrast to supervised learning, involves training methods and model structures that require no additional data to find the complex structure within it. As trading datasets grow rapidly, it is more expensive and time-consuming to label data using expertise or simply validate the entire set of data. Standard unsupervised techniques include clustering and community detection models, identification of anomalies, and density estimation. Furthermore, some artificial neural network models with few adjustments can be used to address data clustering problems. These models can find patterns in the features of the time series data by decomposing it, then output a categorization of the data. Many conventional unsupervised models can be applied to time series features. For example, K-means clustering, with careful construction of features expressed as a result of the time series data, can capture some latent and possibly critical features of the market.

5. Challenges and Limitations of AI-Based Market Volatility Forecasting

In recent times, there has been a lot of research interest in forecasting market volatility, and different forecasting models have been employed. AI-based forecasting models, including machine learning and deep learning algorithms, are becoming increasingly popular, especially in this domain due to the models' high power to learn vast amounts of data and capture hidden patterns. In this section, we discuss and outline several limitations and challenges regarding the application of AI-based forecasting models in forecasting market volatility.

A prominent challenge of AI techniques is the tremendous computational cost they require. Especially in training models, as it is time-demanding, it also requires a massive amount of data and fast processors, as well as related technology. The huge computational cost puts some constraints on applying these methodologies for forecasting market volatility in real markets. While this obstacle has been increasingly overcome thanks to improvements in technology, comparisons between the computational effectiveness of AI and that of traditional methodologies would be worth investigating. Further, the theoretical framework is still underdeveloped. Since AI models cannot be completely understood in terms of the internal mechanisms they have, it is very difficult to obtain new insights from the point of view of market volatility. The black-box effect of AI models thus restricts the potential benefits from these models. It is another barrier to explaining the forecasting output of AI models in forecasting market volatility. For this reason, researchers may not draw upon the meaningful implications for the direction of changes, or the size of shock, and so on.

In addition, the high performance of AI models can be sensitive to specific numerical architecture as well as parameters, which increases the difficulty of applying AI models to market volatility forecasting. The debate on the data mining effect has caused doubts about the reliability of findings with the use of AI. The data mining effect suggests that when growing amounts of data are examined, researchers are more likely to make erroneous inferences. Some researchers have shown an overfitting problem when using AI techniques for forecasting, by finding that there is a collection of investors who seek complicated models in order to exaggerate their own forecasting as a sign of expertise. This would make adaptive AI models overweight complex models in either the risk manager or investor. Meanwhile, others seem to regard the issue as less acute. Market microstructure effects may complicate forecasting the true market volatility. For example, it was shown that the simple models of realized volatility can lead to biased estimates of the order flow variance, as well as to consistent volatility estimates and provide a consistent realized volatility model.

5.1. Data Quality and Quantity

In a recent study, attention was given to alternative data sources and computing power for empirical financial research. It was shown that varying data quality not only affects data reliability but also dependent test statistics and, therefore, the stability of empirical results. Because of these reasons, out-of-sample validations of AI-based models in finance are highly important for issues of data quality and data quantity. In order to have a dynamic risk management and automated forecasting model, it is of utmost importance not only to consider the quantity aspect of data but also the quality aspect. For detecting complex market patterns, sometimes even small amounts of data may help some models better anticipate future market movements. When available analyzable data are very sparse, more complex modeling techniques may exhibit superior dynamic market volatility computation when compared with traditional econometric models.

Additionally, quality data will allow models to be sensitive and even assess changes in dependencies of economic and financial phenomena in order to help anticipate future market conditions. It is not only important to have the most current high-quality data, where access to alternative data sources, faster computing power, and better empirical models are valuable for forecasting market volatility and performance, but also the linking of these data sets with the most relevant variables is important in models. Moreover, heuristics and judgmental reasoning can have predictive power. Establishing a structure for linking all these data sources together to the most important variables in a financial context will sometimes allow the extraction of essential features for dynamic financial market volatility forecasting, opening new research horizons for the fast-growing and evolving field of AI in Big Data Finance.

5.2. Interpretability and Explainability

Even though a model has strong predictive performance, we still need to ask why it has such performance. Interpretability in this context refers to the fact that the model should be interpretable to the extent that the analyst can answer questions regarding why a given instrument is predicted to have a certain level of volatility. For most financial AI-based models, they are not designed with such interpretability.

In the case of the tag-tagger boosting model, given the tools and a model-agnostic method, it can offer significant explainability for the final model. In the case of the multiscale finance model, the analyst can examine the feature importance for the particular instruments in question to form their own rationalizations for the potential market participants and mechanisms at work, and researchers can filter features of prior economic theory. With either of these models, market participants can more confidently trade in the market, knowing that the model contains a degree of rationality and explanation. Using the prior underlying theory or explaining the model's focus on relevant financial and economic theory can limit the potential for model overfitting.

6. Future Direction

The analysis presented opens up several directions for future research. We take up only two of these possible insights. There is wide scope for the introduction of further factors into our data on market variables. Many could be of considerable interest in their predictive effects. For example, we have taken account of the volatility-of-volatility effect in introducing measures of generalized implieds and skewness, but, as is well known, these are important aspects of the market data time series. These indicators are readily available; their forecasting power is known, and expression-based measures may be available for direct assignment to the corresponding locations in the economic data set. Moreover, we employ their effects in surveys of market participants. Once an indication of the direction of causation is defined via the application of suitable models of option pricing, it becomes very instructive to evaluate to what extent these effects may be discernible in impacts upon established relationships – this, indeed, is one means of answering the 'chicken and egg' question. These data are straightforwardly consumed by the AI models we employ. Another area in which syntactic pattern recognition has been effective takes the form of analysis of individual option prices on the face of securities pricing or indeed reliability aspects. For example, credit risk is a major component in the pricing of options and suggests a generalizing factor into wider investment analysis.

This aspect is explored. Again, such data are available and are ecologically simple to add to the mix of explanatory variables for structural forecasting models. Do they provide that missing 'x' in the equation street practitioners demand? That the data permit this to be established in terms of modeled as well as descriptive abilities is an obvious complement to our analysis. Secondly, there is work to be done in extending the formalism employed. The boilerplate model used is somewhat opaque. An aspect of the use of statistics (or artificial intelligence generally) is that dependence of inferences upon any model of the process being investigated can be largely eliminated. The relationships are learned from the data. Our technique – survival analysis – may rather obscure the relationships learned, as it is complex and not always interpretable in the standard manner of AI technologies.

7. Conclusion

In light of the rapid pace of global financial market developments, forecasting financial market volatility plays a crucial job for the market participants. Especially, for the individual investor, forecasting market volatility well might affect their investment objectives. In this chapter, using the well-known GARCH model, and LSTM and GRU models then predicting market volatility. In the analysis, monthly price data of IBEX 35 market index futures which are related to Madrid Stock Exchange from 2001 to 2019 were used. We chose the global financial crisis period of 2008 and the health crisis as the COVID-19 period of 2020 and 2021 to better model possible future crises and to help investors manage their risk limits for the period. With the findings obtained in the analysis, the forecasting performance of GARCH, LSTM and GRU models were evaluated and compared on the basis of Root Mean Squared Error. The findings of the empirical study showed that AI based models have the ability to forecast better than traditional econometric models.

Furthermore, our analysis has certain policy implications. When using other financial assets, investors can apply the method to make more informed decisions. In addition, AI-based forecasting models not only outperform the well-known GARCH model, but also that they possess excellent characteristics in predicting fake volatilities during the crisis periods of interest. In sum, the latest findings from this study will serve as a warning to investors who are active in the futures markets. Due to the enhanced prediction and bursty nature from LSTM and GRU, they are ideal. In stock market forecasting of other types of futures indices and also of other financial assets, its applicability can also be verified.