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Volatility Study of AI Investment Products

-- AIEQ Fund as an Example

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Abstract: In recent years, with the development of science and technology, artificial intelligence is applied in various fields of society. Among them, the application in financial market prediction has attracted a lot of attention. Artificial intelligence combined with machine learning, deep learning and other models has helped investors solve many problems related to financial investment. It improves the efficiency of investment and saves the cost of investment. However, while gaining benefits, there are also disadvantages of AI investment. In this paper, the volatility of the AIEQ fund is predicted using the Garch model, based on the AIEQ fund data, and the AI stock returns from January 2019 to July 2024 are used. The empirical results show that the volatility of the GARCH model under the t-distribution assumption of the fund is significant, and there are still some problems in the prediction, although the AIEQ fund has an advantage in processing data and executing the trading strategy, but there is still instability in still has a certain market risk. When considering investing in AIEQ funds, investors should fully understand their operating mechanisms and potential risks, and make decisions based on their risk tolerance and investment objectives. This study enhances the knowledge and understanding of AI investment, enabling future investors and financial institutions to make more reasonable investment choices when utilizing AI for investment decisions.

Keywords: Artificial intelligence, Garch model, Financial investment.

1. Introduction

With the continuous development of the economy, investment in the financial market has gradually become a new means of financial management, and the financial industry continues to develop. Funds play an important role in the financial industry, the investment object of the fund is mainly stocks, through the purchase of shares to track a specific index. It can help investors realize diversified investment indirectly through the purchase of fund shares, effectively avoiding some investment risks. At the same time, the liquidity and flexibility of the fund also promote the development of the economic market, and can reflect the overall situation of the market through investment decisions. Therefore, financial investment plays an indispensable role in providing effective resource allocation, reducing investment risks and promoting economic development. However, due to factors such as the instability and volatility of the financial market, problems such as how to more accurately obtain analytical data and build better models to predict complex situations pose a certain obstacle to predicting the volatility of investment products and market trends. With the continuous upgrading of computer technology, artificial intelligence is applied in various fields of society. Among them, the application in financial market prediction has attracted wide attention. Taking AIEQ Fund as an example, AIEQ Fund is the world's first ETF that applies artificial intelligence and machine learning for investment. Al model is able to capture market dynamics and trends by learning historical data, thus improving the accuracy of volatility prediction of financial markets. Deep learning models such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Gated Recursive Units (GRU) built through AI are able to process sequential data, effectively capturing long-term dependencies in the data, which can better improve the accuracy of market price forecasts. Machine learning forecasting models can better predict future financial market volatility based on past market trends. In order to explore the effectiveness of AI investment in the financial market, this study attempts to predict the volatility of AIEQ fund using Garch model. By giving an analysis of intuitive data through empirical results, it shows the effectiveness of AI investment, while assisting future investors and financial institutions to make more accurate decisions when utilizing AI for investment decisions.

2. Literature Review

Stock market investment is the main way for investors to gain excess returns, and one of the most important aspects is to predict the volatility of stock prices. Many researchers keep exploring the changes of financial market volatility, expecting to get the rules from it. After a long period of research, professional scholars have summarized many theoretical knowledge and basic models. Among them, the most famous ones are the portfolio theory proposed by American economist Markowitz (1952), the capital asset pricing model derived from the CAPM model, Ross's arbitrage pricing theory and Farmer's market efficient hypothesis. Numerous financial theories have been proposed to lay the foundation for the establishment of quantitative investment models.

In traditional stock price forecasting models, the main reliance is on fundamental and technical analysis. Most of them rely on the company's financial research and analysis and the knowledge and experience of investment managers. This kind of prediction is biased towards qualitative investment and contains subjective judgment. With the combination of financial knowledge and mathematical theory, the earliest model that reflects the volatility agglomeration and conditional heteroskedasticity characteristics of financial time series - autoregressive conditional heteroskedasticity model (ARCH model). GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is an extension of the ARCH model, the GARCH model is more reflective of market data information than the ARCH model. The traditional GARCH model can effectively characterize the aggregation effect and long memory of volatility. However, traditional forecasting models have some drawbacks. Traditional models are often based on linear models, which are difficult to capture complex nonlinear relationships. With the development of technology, modern people have introduced machine learning on traditional models to improve the accuracy of forecasting. Jingnan et al. (2019) used the HMM-GARCH model to predict the volatility of the CSI 300 stock index futures market, and combining the GARCH model with the HMM can better predict the volatility of the Chinese futures market.

With the continuous development of computer technology and big data on the Internet, neural networks are widely studied. Neural networks are mainly used for loan evaluation, risk assessment and trading decisions. Serrano (2022) concluded that investors and financial institutions use stochastic neural networks to build financial models and train them to be more efficient and intelligent in predicting stock indices, property prices, etc. In the 1990s, on the basis of neural networks Cortes& Vapnik (1995) proposed support vector machines, which are outstanding in solving small sample, nonlinear problems. Ouyang Tianhao, Lu Xiaoyong (2019) used SVM to predict the price change of Chinese securities market, combined with the value of arbitrage (VaP), and concluded that SVM predicts well.

With the accumulated development of datasets, machine learning is widely used, and machine learning is the core field of artificial intelligence. The main algorithms of machine learning include Decision Number, Park Bayes, Random Forest and so on. Summarizing the main development history and applications in this field, Hao-Ran Xu et al. (2020) proposed the significant role of machine learning in stock prediction. Meanwhile, in financial risk management, machine learning algorithms can be used for prediction model building and optimization, as well as risk management implementation. Li, Bin and Long, Zhen (2023) used regression tree model to predict the return and volatility of Chinese stock market, and the combination of machine learning method and stock market risk premium can get the riskiest asset portfolio and obtain better investment decision. Chen Menglong et al. (2024) used a random forest model to predict the A-share new energy automobile industry index, comparing the three machine learning methods, random forest, bagging method and decision tree, the random forest model performs better in predicting the price of new energy stocks.

Machine learning includes deep learning. Deep learning mainly includes convolutional neural networks, recurrent neural networks and natural language processing. There are also many research findings on deep learning for financial series data prediction, which is applied in various aspects such as predicting changes in financial market trends and credit assessment. Juping Zhang and Lu Li (2024) used the IMGAF-RLNet model to predict the trend of large and mid-cap indices in the Chinese stock market. The IMGAF-RLNet model is based on deep learning algorithms of convolutional neural network (CNN) and long and short-term memory network (LSTM), and compared with a single LSTM model and ResNet model, the IMGAF-RLNet model has a better prediction performance than the single LSTM model and ResNet model. RLNet model with better prediction effect compared with single LSTM model and ResNet model. Han Ying et al (2023) used CEEMD-LSTM-BLS (C-L-B) model to predict the stock prices of stock agriculture, forestry and fishery industries. The LSTM model has some errors in prediction, especially the location of inflection points, while the BLS module in the C-L-B model is able to solve these kinds of problems. Gunnarsson et al (2021) used a credit risk prediction sub model and found that the deep learning credit assessment model is able to accurately obtain information from the dataset and manage the credit data by utilizing the powerful feature extraction and recognition capabilities of CNN.

Based on the excellent ability to process data with the use of machine learning, deep learning and other algorithms, artificial intelligence is widely used in the financial field. Gaoke Liao and Tinghui Li (2023) describe the effects and future prospects of AI application in financial development impact, financial field utility, risk management and other aspects from various aspects. With the continuous development of science and technology, compared with traditional algorithms, artificial intelligence has better performance in model building and financial risk prediction. Huang et al (2021) proposed that artificial intelligence can build more complex nonlinear models, such as neural networks, support vector machines, etc., which effectively improves the prediction accuracy in the assessment of portfolio risk, financial data prediction and so on.

With the development of artificial intelligence technology, the application of machine learning based predictive modeling in the financial field is becoming more and more widespread. The use of machine learning and deep learning algorithms to develop quantitative investment strategies, as well as the use of intelligent and efficient scientific methods to guide stock trading can improve the accuracy of stock price prediction. Shanmuganthan (2020) suggests that with the application of AI in the field of finance, many financial institutions have combined with AI to provide a wide range of AI financial products to satisfy the needs of different investors. It improves investment effectiveness and promotes investment efficiency. But there is also a certain risk of artificial intelligence in stock market investment. He Chengying (2020) combined with AI overseas stock market and A-share market performance to make an overview analysis, artificial intelligence can only be used as an auxiliary means to help investors in stock market investment.

In conclusion, AI combined with machine learning, deep learning and other models can identify and utilize complex models in the stock market such as trends, volatility, correlation of financial indicators compared to traditional forecasting methods. However, despite the significant advantages and potential of AI in stock market forecasting, there is a need to be cautious about the risks and challenges it may pose. This study refines the theory of AI-enabled financial investment. Meanwhile, in terms of AI forecasting stock prices, based on the AIEQ fund, a GARCH model is constructed to analyze the impact of its volatility, predict the effectiveness of AI investment, and at the same time forecast its future performance to provide empirical evidence for the actual effect of AI investment products, which is the innovative direction of this study.

3. GARCH Model Definition

The GARCH model is a statistical model used to estimate the volatility of time series data. The model is an extension of the ARCH model, which predicts the conditional variance of the dependent variable. The current heteroskedasticity function values are fitted in a qth order moving pan using the squared residual series, but the moving pan model has a qth order truncation of the autocorrelation coefficients, so the model is only applicable to the short-term autocorrelation coefficients of the heteroskedasticity function. Its variance equation is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \cdots + \alpha_p \mu_{t-p}^2$$

However, in practice, the heteroskedasticity functions of some residual series have long-term autocorrelation, and the utilization of the ARCH model will produce a high moving average order, which not only increases the difficulty of parameter estimation, but also affects the fitting effect of the model. Therefore, the GARCH (p, q) model takes into account the p-order autoregressivity of the heteroskedasticity function to effectively fit the heteroskedasticity function with long-term memory. The GARCH (p, q) model is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \, \sigma_{t-i}^2$$

Where $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ are constant parameters, and $\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i < 1$. where ε_t denotes the independently and identically distributed random error term, and σ_t^2 denotes the stock price volatility in period t. The parameters of the GARCH model are obtained by the great likelihood estimation function method.

The GARCH (1, 1) model is: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

4. Authentic Proof Analysis

4.1. Sample Selection and Descriptive Statistics

In this paper, the daily closing returns data of AIEQ funds for the period from January 1, 2019 to July 31, 2024, totaling 1,405 data, are selected as sample data for empirical analysis. Calculate its daily return, the return formula is: R(t)=ln (p_t/p_{t-1}), and the GARCH model is established with the daily return as the research object. All data are obtained from Flush database.

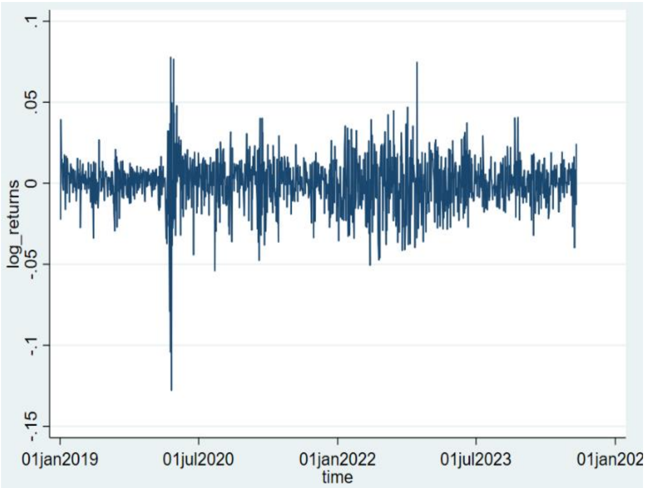

Figure1. Time series plot of daily log returns of AIEQ funds

As seen in Figure 1, the daily logarithmic returns of AIEQ funds fluctuate up and down centered on 0. And most of the data are between -0.5 and 0.5, indicating the existence of volatility clustering in this time series.

Table1. Descriptive Statistics of AIEQ Daily Log Returns

sequences	Average value	maximum values	minimum value	standard deviation	kurtosis	skewness	J-B statistic	J-B p-value
logarithmic yield	0.00036	0.07779	-1.27833	0.01538	9.71878	-0.69257	2665.06723	0.00000

As can be seen from Table 1, the mean of the daily logarithmic return series of AIEQ Fund is about 0.00036, the standard deviation is about 0.01538, and the skewness is -0.69257, which indicates that this series is characterized by a left-skewed distribution. The kurtosis of the series is 9.71878, which is much larger than 3, indicating that its probability density curve is a spike distribution, and its spike is steeper than that of the normal distribution, which can be seen that the probability density curve of the yield series has the characteristic of "spike and thick tail". On the other hand, the Jarque-Bera test statistic is 2665.0672, which is much larger than 0, and its corresponding P-value is about 0, which also proves that the series does not satisfy the assumption of normal distribution.

4.2. Smoothness, Autocorrelation and ARCH Effect Tests

4.2.1. Smoothness test

In order to verify the applicability of the data, this paper uses the test of ADF to perform a unit root test on the daily logarithmic return series of the AIEQ fund, and the results are shown in Table 2.

Table 2. Unit root test for AIEQ daily logarithmic yield series

sequences	t-statistic	1% threshold	5% threshold	10% threshold	p-value
logarithmic yield	-39.292	-3.430	-2.860	-2.570	0.000

As can be seen in Table 2, the critical values of the daily logarithmic return series of the AIEQ Fund at 1%, 5% and 10% significance levels are -3.430, -2.860, and -2.570, respectively. t-statistics are less than the critical values, then the unit root test can be rejected, i.e., it indicates that the time series is smooth. Meanwhile, the significance p-value is 0.000 at the difference of order 0, which is less than 0.05. The significance is presented at the level of significance, and the original hypothesis is rejected, and the series is a smooth time series.

4.2.2. Autocorrelation test

From Table 3, the lagged order of the daily logarithmic return series of the AIEQ fund, the p-value accompanying the Q-statistic for the first 5 orders is greater than 0.05 except for the lagged 2nd order, so there is no autocorrelation in the series when the lagged order is 1, 3, 4, and 5. And from lag order 6, the probability value accompanying the Q statistic is less than 0.05, which rejects the original hypothesis. And the absolute values of AC and PAC are more than 0.05 at lag order 6, indicating that there is significant autocorrelation at lag order 6, and the effect of lag order 6 needs to be considered in the subsequent model construction.

Table 3. Autocorrelation test of AIEQ fund daily log return series

hysteresis order	Autocorrelation coefficient	Partial Autocorrelation Coefficient	Q-stat	Prob
1	-0.476834176	-0.476834176	3.4054	0.0650
2	-0.009006686	-0.305939157	6.4987	0.0388
3	-0.026285578	-0.253853178	6.6223	0.0850
4	0.078154277	-0.0999427	8.5871	0.0723
5	0.024996635	0.027331514	9.5482	0.0891
6	-0.207960556	-0.226064654	15.4902	0.0168
7	0.130214683	-0.146793151	22.0841	0.0025
8	0.092948948	0.049049488	28.3010	0.0004
9	-0.100932962	-0.018569544	47.5856	0.0000
10	0.012540059	0.011076816	49.2241	0.0000

4.2.3. ARCH effect test

The presence of ARCH effect in the series is confirmed using ARCH-LM test, which is used to determine the presence of conditional heteroskedasticity, i.e., the phenomenon of volatility aggregation, in the time series. In Table 4, it is observed that the concomitant p-value of 0.024 less than 0.05 level of significance for the daily log returns of AIEQ funds at lag 1 order indicates the presence of a significant ARCH effect at lag 1 order at 5% level of significance. This result supports the existence of conditional heteroskedasticity in the residual series, i.e., the squared residuals of the previous period have a significant effect on the current residual variance, which is in line with the assumptions of the GARCH model modeling. Therefore, this paper can reasonably use the GARCH model to analyze the volatility of the AIEQ fund.

Table 4. ARCH effect test for daily log return series of AIEQ funds

sequences	R^2	F-statistic	contingent probability	reach a verdict
Daily logarithmic yield	0.0037	0.52	0.024	Presence of ARCH effect

4.3. GARCH Model Construction and Evaluation

Next, the daily log returns of the AIEQ fund are compared by model simulation using GARCH (1, 1), GARCH (1, 2), GARCH (2, 1), GARCH (2, 2), respectively, and according to the simulation results, it is concluded that only the p-value of the coefficients of the GARCH (1, 1) model is more significant at the 5% level of significance. Since the GARCH (1, 1) model can capture the financial time series characteristics, the empirical part of this paper adopts the GARCH (1, 1) model in the GARCH model parameter estimation, from Table 5 observed that the constant term coefficients of 0.000007, then the long-term equilibrium level of the conditional variance of 0.000007. The past fluctuations of the current impact on the smaller, and the conditional variance in time has a strong persistence. The volatility impact GARCH model equation is:

$$r_t = 0.000633 r_{t-1} + \mu_t$$

$$\sigma_t^2 = 0.000007 + 0.016844 \varepsilon_{t-1}^2 + 0.808091 \sigma_{t-1}^2$$

Table 5. Estimates of GARCH (1, 1) model effects

parameters	ratio	standard error	Z-statistic	p-value	reach a verdict
constant term	0.000007	0.000002	4.440000	0.000000	statistically significant
ARCH	0.016844	0.217096	7.760000	0.000000	statistically significant
GARCH term	0.808091	0.022948	35.210000	0.000000	tatistically significant

Table 6. GARCH (1, 1) model L-B test

hysteresis order	LB statistics	p-value
1	1.244	0.265
2	1.357	0.507
3	1.371	0.712
4	3.383	0.496
5	3.438	0.633
6	5.619	0.467
7	7.886	0.343
8	11.167	0.192
9	11.192	0.263
10	11.193	0.343

The GARCH (1, 1) model is then subjected to a standardized residual purely stochastic test to assess whether the model adequately captures the volatility features in the data. As can be seen in Table 6, the LB statistic and its corresponding p-value for each lag order do not reach the traditional significance level. From order 1 to order 10, although the LB statistic increases with increasing lag order, all P-values are greater than 0.05 and the standardized residuals satisfy randomness. It shows that GARCH (1, 1) extracts the volatility of the series well. Therefore, it can be concluded that the GARCH model effectively removes the autocorrelation in the original time series, the model fits well and can reflect the characteristics more accurately, and the GARCH (1, 1) model is effective.

4.4. Volatility Projections

Next, the GARCH (1, 1) model is used to predict future volatility, and the AIEQ fund volatility is plotted by generating the conditional variance of the prediction. The AIEQ fund volatility is shown in Fig. 2, which demonstrates the trend of future volatility predicted by the model, and it can be seen that there is a significant price fluctuation in the AIEQ fund. This shows that there is instability and certain risks in the AI investment market, which requires investors to use it rationally.

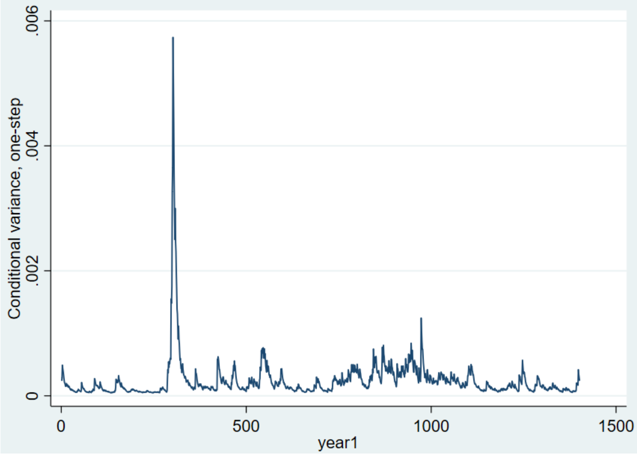

Figure 2. Volatility forecasting of AIEQ funds

5. Conclusion

This paper empirically analyzes the volatility of the AIEQ fund through the GARCH (1, 1) model, and the results show that the fund's volatility has significant persistence, and the AI-driven AIEQ fund is still more volatile despite its data-driven advantages. With respect to the current technology and research, it can be seen that there is a certain risk in fully utilizing AI for investment, and investors should use AI as an auxiliary investment tool rather than relying on it completely for investment.

AI investing continues to evolve, and the trend of AI applied to equity investing will not change. Future research could further explore the performance of AI investment products in different market environments, especially in conjunction with other AI-driven ETFs, and conduct more extensive comparative analyses to better understand the prospects for the application of AI in the financial market.

References

[1] Cortes, C. & Vapnik, V. Support-vector networks. Machine learning, 1995, 20(3):273-297.

[2] Chen Menglong, Fan Cheng, Wu Zhipeng. Research on stock price prediction of new energy vehicle industry_Based on machine learning algorithm. Journal of Jilin Industry and Business College, 2024, 40 (01): 93-100.

[3] Gunnarsson, B.R. et al. Deep learning forcredit scoring: Do or don't? Eurpean Journal of Operational Research, 2021, 295(1):292-305.

[4] Harry Markowitz. "Portfolio Selection." Journal of Finance, 1952, 7(1):77-91.

[5] Huang, Y. et al "A new financial data forecasting model using genetic algorithm and long short-term memory network", Neurocomputing 2021, 425:207-218.

[6] Han Ying, Zhang Dong, Sun Kaiqiang, et al. A new model of stock prediction combining long and short-term memory network and width learning. Operations Research and Management, 2023, 32 (08): 187-192.

[7] He Chengying. Can artificial intelligence fry stocks to outperform the stock market? The Academic Frontier of the People's Forum, 2020, (16): 92-101.

[8] Jing Nan, Lu Shanshan, Jiang Tao. Study on the volatility of China futures market based on HMM and GARCH models. Management Science, 2019, 32 (05): 152-162.

[9] Li Bin, Long Zhen. Research on predictability of China: A perspective based on Machine Learning. Journal of Management Science, 2023, 26 (10): 138-158.

[10] Liao Gaoke, Li Tinghui. Progress in the application of artificial Intelligence in finance. Economic Dynamics, 2023, (03): 141-158.

[11] Ouyang Tianhao, Lu Xiaoyong. A new method of securities market stability measurement under the background of financial security_Research on market prediction and arbitrage value measurement based on big data support vector machine. Financial Theory and Practice, 2019, 40 (01): 77-83.

[12] Serrano, W. "The random neural network in price predictions", Neural Computing and Applications, 2020, 34(2):855-873.

[13] Shanmuganthan, M. "Behavioural finance in an era of artificial intelligence: Longitudinal case study of roboadvisors in investment decisions", Journal of Behavioral and Experimental Finance 2020, 27, no.100297.

[14] Xu Haoran, Xu Bo, Xu Kewen. Review of the application of machine learning in stock forecasting. Computer Engineering and Application, 2020, 56 (12): 19-24.

[15] Zhang Juping, Li Lu. Research on the stock index trend prediction of the IMGAF-RLNet Model. Computer Engineering and Application, 2024, 1-18.