A Study on Asymmetric Leverage Effects Based on GARCH: The Case of the Artificial Intelligence Sector

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Abstract: Financial asset returns often exhibit asymmetric reactions to positive and negative news, a phenomenon known as the leverage effect, which is particularly pronounced in high-tech growth sectors. This study examines the China Securities Artificial Intelligence Sector Index (931071) using daily return data from October 2020 to October 2025. GARCH, TGARCH, and EGARCH models are constructed to systematically investigate the volatility characteristics and asymmetry of returns in the AI sector. Findings reveal: The standard GARCH(1,1) model demonstrates optimal goodness-of-fit and diagnostic performance, indicating volatility clustering as the primary driver of sector fluctuations. However, TGARCH and EGARCH models exhibit divergent estimates for asymmetry parameters-the former showing a non-significant negative leverage effect, while the latter exhibits a significant positive effect, suggesting positive news may trigger stronger volatility in this sector. This anomalous effect may be closely linked to the sector's high valuations, sentiment-driven dynamics, and policy sensitivity. The findings provide theoretical and empirical support for understanding the volatility mechanisms of high-tech assets and optimizing risk management strategies.

Keywords: GARCH Model Family; Asymmetric Leverage Effect; TGARCH Model; EGARCH Model

1. Introduction

1.1 Research Context and Literature Review

In recent years, artificial intelligence (AI) technology has emerged as the core driving force behind the new wave of technological revolution, becoming a pivotal domain for global industrial upgrading and national strategic competition. Compared to traditional sectors, it is noteworthy that the AI sector exhibits a unique asymmetric leverage effect: negative policy shocks (such as regulatory tightening or technology export restrictions) significantly amplify volatility far more than equally potent favourable policies (such as tax incentives or R&D subsidies). This asymmetry stems from the sector's inherent characteristics: high valuations reliant on future expectations, lengthy R&D cycles, and substantial uncertainty in technology commercialization. Consequently, the market exhibits heightened sensitivity to policy risks, with bearish news readily triggering panic selling and volatility spillovers.

Traditional financial time series models struggle to adequately capture such complex volatility patterns: on one hand, sector volatility exhibits pronounced time-varying variance properties, necessitating quantitative modelling to decipher volatility patterns; On the other hand, the market's differential reaction to positive versus negative information necessitates models capable of identifying volatility asymmetry. Against this backdrop, GARCH family models, with their strong explanatory power for volatility clustering, alongside variants like EGARCH and TGARCH that specifically characterize leverage effects, provide effective methodologies for deconstructing the volatility mechanisms within the artificial intelligence sector.

The evolution of financial volatility modelling has undergone a significant shift from static assumptions towards dynamic capture. Early research primarily relied on simplistic statistical models and idealised market assumptions. For instance, Markowitz's (1952) mean-variance model was based on the assumption of constant variance, while the Black-Scholes option pricing model (1973) posited volatility as a constant. While theoretically groundbreaking, these models struggled to explain the pervasive leverage effect in financial markets-where negative news often triggers greater market volatility than equally intense positive news. This disconnect between theory and practice was partially addressed by Engle's 1982 introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model, though its lag order constraints still limited the capture of long-range memory.

Traditional econometric models exhibit clear inadequacies when addressing the complexity of financial time series. On one hand, time series models (Devi et al., 2013; Challa et al., 2020) can capture linear dependencies in return sequences but cannot handle time-varying variance characteristics [1][2]; on the other hand, factor analysis models (Green et al., 2017; Linnainmaa and Roberts, 2018) can integrate macroeconomic variables but struggle to quantify the impact of asymmetric shocks [3][4]. Particularly within high-tech sectors such as artificial intelligence, enterprises commonly face characteristics including rapid technological iteration, high policy dependency, and uncertain profit cycles. Compounded by market sentiment resonance, this results in financial volatility exhibiting more complex structural discontinuities. Traditional models demonstrate insufficient adaptability to such structural discontinuities, frequently leading to parameter estimation biases and predictive failures.

Subsequently, machine learning models were introduced into the field of volatility forecasting. Random forests (Gupta et al., 2019) can identify key volatility drivers through feature importance ranking [5], while SVMs (Huang et al., 2005) can partially fit non-linear relationships via kernel techniques. However, these methods retain fundamental flaws: firstly, they lack a rigorous financial theoretical foundation, with model outputs often diverging from economic logic; Second, they inadequately model volatility's long-memory properties, struggling to capture persistence characteristics; Third, they exhibit weak out-of-sample generalisation capabilities, particularly during market mechanism transitions where spot-futures instability arises [6].

In 1986, Bollerslev proposed the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. A higher-order ARCH model can be represented by a lower-order GARCH model, thereby facilitating model identification and estimation [7]. Subsequently, Crouhy and Rockinger (1997) utilised the AT-GARCH(1,1) model to demonstrate that volatility reacts more strongly to adverse news in financial markets than to favourable news, while long-term trends also exert a significant influence on the volatility of financial time series [8].

Domestically, Zhang Shiying et al. (2002) examined the fundamental characteristics of financial risk from a dynamic perspective, finding that volatility persistence in financial time series reflects correlations between different risks [9]. Additionally, Zhang Shiying and Li Handong (2002) proposed a coherence continuity theorem for stochastic volatility models based on single-integration theory, further exploring the conditions required for coherence continuity and its associated properties [10]. Xu Lixia (2010) applied the GARCH family of models to investigate volatility in the Chinese stock market. Results indicated that stock return sequences exhibit characteristics of heavy tails with spikes and volatility clustering, with the GARCH family models providing an excellent fit for stock market volatility [11]. Ren Chengke and Jiang Xiaogan (2012) analysed the existing issues and future development directions of GARCH models for domestic and international financial time series, proposing key avenues for their advancement and refinement [12].

In summary, compared to traditional models (such as ARIMa, which only describes return sequences, and SV models, which exhibit prediction delays and tracking lags), EGARCH and TGARCH modelling within the GARCH family can achieve asymmetric modelling of leverage effects. By incorporating thresholds and sign functions, these models directly translate micro-mechanisms of financial markets into mathematical expressions. This enables model outcomes to more closely align with the operational logic of real financial markets and distinguish between the impacts of positive and negative shocks.

1.2 Research Significance and Scope

This study aims to conduct an in-depth investigation into the asymmetric characteristics of stock index return volatility within the artificial intelligence sector and its underlying formation mechanisms. Firstly, it seeks to validate and quantify the ‘asymmetric leverage effect’ observed in the AI sector, specifically testing the core hypothesis that ‘negative news significantly amplifies market volatility more than positive news’. This endeavour aims to enrich and refine the financial volatility theory of high-tech growth sectors from an empirical perspective. Secondly, it constructs an econometric analytical framework tailored for studying volatility in the artificial intelligence sector. By systematically comparing the goodness-of-fit between symmetric GARCH models and asymmetric GARCH family models, it identifies the optimal model best suited to precisely capture the cluster, persistence, and asymmetry of volatility in this sector.

Specifically, a representative domestic artificial intelligence sector index (using the CSI Artificial Intelligence Sector Index as an example) is selected as the research subject. Daily closing price data is collected and logarithmic returns are calculated. The return series undergoes rigorous statistical description, with preliminary visual analysis observing typical phenomena such as volatility clustering and heavy tails. Building upon descriptive statistics, we constructed the GARCH(1,1) model (as a symmetry benchmark), the EGARCH(1,1) model, and the TGARCH(1,1) model (as core models capturing asymmetry). We focused on interpreting the leverage effect coefficient (γ) in the EGARCH model or the asymmetry term coefficient (γ) in the TGARCH model. The core innovation of this research lies in its approach to measuring asymmetric leverage. Traditional models assume symmetrical volatility responses to information, which significantly diverges from the actual behaviour observed in the artificial intelligence sector. By incorporating asymmetric terms within EGARCH/TGARCH models, we aim to construct a volatility equation capable of distinguishing between the impacts of 'positive news' and 'negative news'. This enables a rigorous mathematical definition and quantification of the existence and significance of this asymmetry.

2. Research Design

2.1 Asymmetric Leverage Effect

The asymmetric effect of returns refers to the differing sensitivities of financial asset yields to the direction of market information. Specifically, for certain assets, yield fluctuations triggered by positive information often exceed those induced by negative information; conversely, other assets exhibit more pronounced reactions to negative information, with yield variations under bearish shocks surpassing those under bullish shocks. This disparity in reaction intensity to market information of differing natures reflects the asymmetric characteristics of financial asset returns.

2.2 GARCH Family Models

2.2.1 GARCH model

Proposed by Bolleslev in 1986, the GARCH model is constructed based on the clustering property of volatility, wherein current volatility exhibits a relationship with past volatility. The Generalised Autoregressive Conditional Heteroskedasticity model builds upon the ARCH framework, positing that the variance of the error term depends not only on its past variance but also on the error term itself, thereby effectively capturing the long-memory nature of volatility. The most widely applied variant is the GARCH(1,1) model, whose general expression is as follows:

$$\sigma_t^2=\alpha_0+\alpha_1\epsilon_{t-1}^2+\beta\sigma_{t-1}^2 \quad (1)$$

$$r_t=\mu+\varepsilon_t \quad (2)$$

2.2.2 TGARCH model

As the GARCH model is unsuitable for addressing the non-symmetric effects in financial asset returns, Zakoian et al. proposed the threshold ARCH model, or TGARCH model. This type effectively studies the non-symmetric effects in financial asset returns. The general expression for the TGARCH(1,1) model is as follows:

$$\sigma_t^2=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\gamma\varepsilon_{t-1}^2 d_{t-1}+\beta\sigma_{t-1}^2 \quad (3)$$

2.2.3 EGARCH model

Nelson introduced another model for examining the asymmetric effects of financial asset returns in 1991: the EGARCH model. The EGARCH model employs a logarithmic transformation to ensure variance remains positive. The general expression for the EGARCH(1,1) model is as follows:

$$ln(\sigma_t^2)=\alpha_0+\alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|+\gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}+\beta ln\left(\sigma_{t-1}^2\right) \quad (4)$$

3. Descriptive Statistics and Correlation Tests for the Sample

3.1 Data Selection and Processing

To better analyse the effectiveness of model improvements, this study selected the CSI Artificial Intelligence Index (931071) as the research subject, with data sourced from the CSI official website. Considering data timeliness, the sample period was set from October 2020 to October 2025.

3.2 Descriptive Statistics of Sample Returns

This study utilised the seven-day annualised returns of the sample funds from 15 October 2020 to 14 October 2025, comprising 1,211 data points. To characterize the fundamental attributes of each sample fund, descriptive statistics were conducted using R Studio software. Key metrics including mean, median, maximum and minimum values, standard deviation, skewness, kurtosis, and J-B test values were employed for detailed analysis. The results are presented in Table 1.

Table 1. Descriptive Statistics of Sample Returns

name	mean	median	maximum	minimum	Standard deviation	skewness	kurtosis	J-Btest values	P
AI index	0.00025	-0.00057	0.1319	-0.1282	0.02	0.2764	4.5439	1063	0.00

Table 1 shows that the CSI Artificial Intelligence Index had a positive mean and a standard deviation of 0.02 during the sample period, indicating high volatility and elevated risk for this sector. Additionally, the skewness value reflects the degree of asymmetry in the return distribution. A normally distributed dataset is perfectly symmetric, hence exhibiting zero skewness. A skewness value greater than zero indicates right skewness, while a value less than zero indicates left skewness. Table 1 shows that the returns for this sector exhibit right skewness, with all skewness values below 1. The kurtosis value for a normal distribution is 3. The kurtosis data in the table above indicates that this sector's kurtosis exceeds 3, classifying it as leptokurtic. The J-B test is used to determine whether a sample can be considered derived from a normal population. As shown in Table 1, the J-B test values for the samples are all greater than the critical value for a normal distribution, indicating non-normality. The value of 1063 suggests a strong degree of non-normality.

The daily returns of the sample generate a sample time series. Basic statistical analysis of the series is performed. The basic characteristics of the 1211 sample data points are summarized in the figure 1 below.

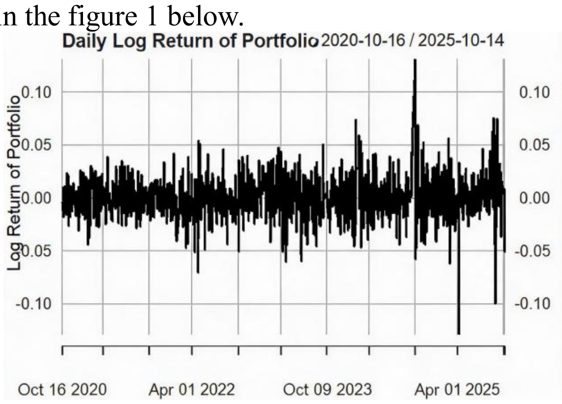

Figure 1. Daily Log Return of Portfolio

3.3 Stationarity Tests

Regarding stationarity tests, the ADF test-also known as the unit root test-is currently the most widely used and mainstream method. Therefore, this study employs the ADF test to assess the stationarity of the data. Stationarity refers to the requirement that the curve derived from a sample time series can continue in the future along the projected path of its current form. In a unit root test, the null hypothesis is that the yield series contains a unit root, while the alternative hypothesis is that the yield series does not contain a unit root. Therefore, when the p-value is less than the significance level α, the null hypothesis can be rejected, concluding that the yield series does not contain a unit root and that the time series is stationary.

The results of the ADF test on the sample data are shown in Table 2.

Table 2. Sample ADF Test Results

	t-value	p-value
ADF test	-9.615	0.01

As shown in Table 2, the unit root test conducted on the CSI AI Index yielded a t-value of -9.615 and a p-value of 0.01, which is less than the commonly used significance level of 0.05. Therefore, we can reject the null hypothesis and conclude that the time series is stationary.

3.4 Autocorrelation Test

For the autocorrelation test, the analysis was performed using the Ljung-Box Q statistic,

$$Q_{LB}=T(T+2)\sum_{j=1}^{p}\frac{r_j^2}{T-j} \quad (5)$$

The calculation of the Ljung-Box Q statistic is based on the autocorrelation coefficients of the residual series, the sample size, and the specified lag order. Its specific construction involves three key parameters: the jth-order autocorrelation coefficient (γ_j) of the residual series, the total sample size (T), and the pre-specified lag order (p).

The primary function of the Ljung-Box Q statistic is to test for autocorrelation in a time series. For the Q statistic at lag p, if the Q statistics at all lag orders do not exceed the critical values determined by the specified significance level, the null hypothesis is accepted, meaning the residual series is deemed to be free of autocorrelation. In this case, the autocorrelation coefficients and partial correlation coefficients for each lag order will also be close to 0. If, at a certain lag order p, the Q-statistic exceeds the critical value corresponding to the specified significance level, the null hypothesis must be rejected, indicating that the residual series exhibits p-order autocorrelation.

The results of applying the above test to the sample data are shown in Table 3.

Table 3. Ljung-Box Autocorrelation Detection Results

Lag order	Q statistic	p-value
5	10.154	0.07099
10	17.593	0.06223
15	20.67	0.1477

As shown in Table 3, all p-values are greater than 0.05, so the null hypothesis is not rejected. For lags ranging from 1 to 5, 1 to 10, and 1 to 15, there is insufficient evidence to support the hypothesis that “the series exhibits autocorrelation.” This indicates that the series has weak overall autocorrelation and is suitable for subsequent analyses such as ARCH tests and GARCH modeling.

Based on the stationarity and autocorrelation tests conducted above, it is confirmed that the Shanghai Composite Index return series meets the conditions for ARIMA modeling. The next section will perform mean ARIMA modeling on the Shanghai Composite Index returns, conduct an ARCH test on the residuals, and further introduce a GARCH model to characterize the volatility of the Shanghai Composite Index returns.

3.5 Establishing the Mean Equation ARIMA(0,0,2)

3.5.1 Model selection and interpretation

The order of the ARIMA model (Ma) was determined based on the AIC value; the smaller the AIC value, the better the model fit. After iterative tuning, the model was finalized as ARIMA(0,0,2), i.e., a zero-order autoregressive, zero-order differenced, and second-order moving average model. The core parameters of the model are shown in Table 4.

Table 4. Core Parameters of the ARIMA (0,0,2) Model

	Parameter
Ma1	0.0501
Ma2	0.0620
standard error	0.0288

As shown in Table 4, the absolute values of both Ma1 and Ma2 are greater than the standard error, indicating that the results are statistically significant. Furthermore, the log-likelihood value obtained is 2995.21, which measures the model’s explanatory power; a higher value indicates better model fit. The AIC value is -5986.41, which is the minimum among all AIC values considered and serves as a key supporting factor for constructing the ARIMA(0,0,2) model.

3.5.2 Model testing

After completing the modeling of the mean equation, the Ljung-Box Q statistic was used to further test whether the residuals of the mean equation still exhibit correlation, thereby verifying whether the model has fully extracted the information from the data. The results are shown in Table 5.

Table 5. Model Fitting Results

Lag order	Q statistic	p-value
5	2.8233	0.7272
10	8.774	0.5537
15	11.623	0.7073

As shown in Table 5, the residuals exhibit no autocorrelation at lags of 5, 10, and 15, indicating that the mean equation has adequately captured the autocorrelation in the series and that the model fits the data well.

3.6 Heteroskedasticity and ARCH Tests

The most common methods for testing for ARCH effects are the residual squared correlation plot and the LM test. Therefore, this paper uses the residual squared correlation plot to test for ARCH effects in the artificial intelligence sector. In the RSC plot test, the null hypothesis is that the sample fund return series does not exhibit an ARCH effect. If the test statistic exceeds the specified significance level and degrees of freedom, the null hypothesis is rejected, indicating that the return series exhibits an ARCH effect; conversely, if the test statistic does not exceed these thresholds, the null hypothesis cannot be rejected, indicating that the return series does not exhibit an ARCH effect.

The Ljung-Box Q-test was performed on the squared residuals with lags of 5, 10, and 15 periods, and the results are shown in Table 6.

Table 6. Ljung-Box Q-Test (Square Residuals with Lags of 5, 10, and 15 Periods)

Lag order	Q statistic	p-value
5	211.42	0.001
10	232.7	0.001
15	233.77	0.001

As shown in Table 6, the p-value is significantly less than 0.05, indicating that the squared residuals exhibit significant serial correlation. This suggests a pronounced ARCH effect in the data, making it appropriate to use GARCH-type models for further volatility modeling.

4. Empirical Study of Asymmetric Effects in the Sample

The data were tested using GARCH, EGARCH, and TGARCH models, and the results are presented in Tables 7-10:

4.1 Analysis of Mean Equation Parameters (Table 7)

Table 7. Analysis of Mean Equation Parameters

Parameter	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)
Ma1	-0.0101	-0.0091	-0.0099
Ma2	0.0513	0.0490	0.0494
omega	0.000032	0.000979	-0.415368
alpha1	0.1035	0.0886	0.0207
beta1	0.8182	0.8836	0.9473
asymmetry	-	-0.1331	0.1822
shape	1.3695	1.3485	1.3498

The mean equation adopts the ARMa(0,2) form, excluding the constant term to focus primarily on the explanatory power of the moving average terms for returns. The moving average parameters across the three models show a high degree of consistency:

Ma1 parameter: -0.0101 for the GARCH model, -0.0091 for the TGARCH model, and -0.0099 for the EGARCH model; all three are negative and closely similar in value. In terms of statistical significance, the p-values for the Ma1 parameter in all three models are greater than 0.05 (0.6852, 0.7402, and 0.7322, respectively), indicating that the first moving average term is not statistically significant. This result suggests that the impact of the one-period lag shock on the current-period return may be relatively limited.

Ma2 parameter: The GARCH model yields 0.0513, the TGARCH model yields 0.0490, and the EGARCH model yields 0.0494; all are positive and remain relatively stable across the three models. In terms of significance, the p-values for the Ma2 parameter in the three models are 0.0815, 0.0972, and 0.1043, respectively, all of which are at the 10% significance level threshold, indicating a certain degree of statistical significance. This suggests that a two-period lagged shock has a positive impact on the current-period return, consistent with the characteristics of short-term memory effects in financial time series.

4.2 Analysis of Volatility Equation Parameters

Volatility equation parameters are the core of GARCH-type models, reflecting the dynamic characteristics of conditional variance:

Constant term (omega): The three models exhibit completely different characteristics. The omega of the standard GARCH model is 0.000032, a very small positive value; The omega of the TGARCH model is 0.000979, approximately 30 times higher than that of the GARCH model; while the omega of the EGARCH model is -0.415368, a negative value. In terms of significance, the omega of both the GARCH and TGARCH models is not significant under conventional standard errors ($p > 0.05$), whereas the omega of the EGARCH model is highly significant at the 1% level.

ARCH effect parameter (alpha1): This parameter measures the impact of past volatility shocks on the current conditional variance. The alpha1 value in the EGARCH model is significantly smaller than in the other two models, reflecting that the symmetric effects of volatility shocks in the EGARCH model are separated into the asymmetric parameters. In terms of significance, alpha1 is significant at the 1% level for both the GARCH and TGARCH models, while alpha1 is not significant for the EGARCH model, indicating a weaker effect of symmetric volatility shocks.

GARCH Effect Parameter (beta1): This parameter measures the persistence of conditional variance. All three models exhibit high volatility persistence, with the EGARCH model having the highest beta1, indicating that the logarithm of conditional variance exhibits extremely strong persistence. The beta1 values for all models are highly significant at the 1% level, confirming the widespread existence of the 'volatility clustering' phenomenon in financial markets.

Asymmetry parameters: The TGARCH model's eta11 is -0.1331, with a negative sign consistent with the expected traditional 'leverage effect,' but it is not statistically significant. The EGARCH model's gamMa1 is 0.1822, with a positive sign contrary to expectations, but it is highly significant at the 1% level. This may indicate that different asymmetry models capture different aspects of volatility dynamics.

Distribution shape parameters: The values for the three models are 1.3695, 1.3485, and 1.3498, respectively, all significantly greater than 1 (p = 0.0000), confirming that the return distribution exhibits fat-tailed characteristics, consistent with typical financial data.

4.3 Comparative Analysis of Model Fit (Table 8)

Table 8. Comparative Analysis of Model Fit

Statistics	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
Log-likelihood	3090.8	3088.4	3088.4
AIC	-5.0947	-5.0890	-5.0890
BIC	-5.0694	-5.0596	-5.0596
Mean-Volatility	0.019693	0.019708	0.019725

Log-likelihood: The log-likelihood of the GARCH model is 3090.8, which is the highest among the three; both the TGARCH and EGARCH models are 3088.4. This result indicates that, in terms of in-sample fit, the standard GARCH model provides the best overall fit, while models incorporating asymmetric effects, despite having more parameters, do not significantly improve the goodness of fit.

Comparison of Information Criteria: Under the AIC criterion, the GARCH model has a value of -5.0947, the TGARCH model has -5.0890, and the EGARCH model has -5.0890. The GARCH model has the lowest AIC value, making the standard GARCH model the optimal choice. The BIC criterion also shows the same ranking: GARCH is optimal, with TGARCH and EGARCH tied.

Conditional Volatility Comparison: The estimated mean volatilities of the three models are very close, indicating that their basic estimates of volatility levels are consistent.

4.4 Analysis of Model Results (Table 9)

Table 9. Analysis of Model Results

Test Item	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	Passes·Test·
LB Test for Standardized Residual (p)	0.3919	0.0092	0.0464	>0.05
Joint Test for Sign and Trend (p)	0.7825	0.1283	0.3040	>0.05
Nyblom Stability Test Statistic	1.6974	1.9579	1.9234	<1.68(5%)

Ljung-Box test for standardized squared residuals: Used to assess whether the model adequately captures the dynamic characteristics of volatility, with the null hypothesis being that there is no autocorrelation in the standardized squared residuals. The p-value for the GARCH model is 0.3919, which is significantly greater than 0.05; therefore, the null hypothesis cannot be rejected, indicating that the model adequately captures the dynamic characteristics of volatility; The p-value for the TGARCH model is 0.0092, which is less than 0.01; the null hypothesis is rejected at the 1% level, indicating that the model fails to adequately capture the dynamics of volatility and that there is significant clustering of residual volatility; the p-value for the EGARCH model is 0.0464, which is slightly less than 0.05; the null hypothesis is rejected at the 5% level, indicating that the model has some shortcomings in capturing volatility, but the issue is less severe than in the TGARCH model. These test results indicate that the TGARCH and EGARCH models are less effective than the simple GARCH model in capturing volatility dynamics.

Joint test for sign bias: This evaluates the models' ability to capture asymmetric effects. The p-value for the joint effect of the GARCH model is 0.7825, which fails to reject the null hypothesis of no sign bias, consistent with expectations since GARCH is a symmetric model. Although both the TGARCH and EGARCH models passed the sign bias test, their parameter estimates for the asymmetric effect differ, which may imply that the two models capture the asymmetric effect in different ways.

Nyblom parameter stability test: All models exhibit some degree of parameter instability, which is common in financial time series analysis and reflects the changing nature of market conditions over time.

4.5 Analysis of Asymmetric Volatility Effects (Table 10)

Table 10. Analysis of Asymmetric Volatility Effects

Model	Asymmetric Parameter	Estimate	Standard Error	t-value	p-value	Direction/Interpretation
GARCH(1,1)	-	-	-	-	-	Symmetric Models
TGARCH(1,1)	eta11	-0.1331	0.1658	-0.803	0.4222	Negative (Leverage Effect)
EGARCH(1,1)	gamMa1	0.1822	0.0439	4.148	0.00003	Positive(Anomalous Effect)

Asymmetric Effects in the TGARCH Model: The TGARCH model captures asymmetric effects through the eta11 parameter, which is estimated at -0.1331. This negative sign aligns with traditional financial theory's expectations regarding the "leverage effect," but the result is not statistically significant ($p = 0.4222$). If the parameter were significant, a negative value would imply that bad news of equal magnitude leads to a greater increase in volatility than good news, which is consistent with the leverage effect theory proposed by Black (1976) and Christie (1982): a decline in stock prices increases a company's financial leverage, thereby raising equity risk and leading to increased volatility.

Asymmetric effects in the EGARCH model: The EGARCH model captures asymmetric effects through the γ_m1 parameter, with an estimated value of 0.1822. The sign is positive, contrary to expectations under traditional leverage theory, but highly significant at the 1% level. A positive value implies that good news leads to a greater increase in volatility than bad news. This "anomalous effect" has also been discussed in the financial literature, with possible explanations including: First, the volatility feedback effect (Engle and Ng, 1993) suggests that when volatility is expected to rise, risk-averse investors demand higher expected returns, leading to a decline in stock prices; thus, the increase in volatility caused by good news may manifest through this mechanism; Second, market sentiment plays a role: in bull markets or markets dominated by optimism, good news may trigger excessive trading and herd behavior, leading to increased volatility.

5. Research Conclusions and Outlook

5.1 Research Conclusions

Through systematic modeling and comparative analysis of the volatility of stock index returns in the artificial intelligence sector, this study has drawn a series of conclusions. Empirical results indicate that the volatility dynamics of the AI sector exhibit both consistency with and distinct characteristics from traditional financial market theories. In terms of model selection, the symmetric standard GARCH(1,1) model demonstrated the optimal overall fit, with the lowest AIC and BIC values, the highest log-likelihood, and the most ideal diagnostic results, indicating that this model provides the most comprehensive and reliable description of volatility clustering and persistence. This finding reveals a key characteristic of the volatility generation mechanism in the AI sector: the core driving force of its volatility dynamics is closer to a symmetric clustering effect rather than a strong asymmetric leverage effect.

However, in our in-depth exploration of asymmetric effects, we discovered a thought-provoking contradiction. The asymmetric parameters estimated by the TGARCH model are negative, consistent with the direction of traditional "leverage effect" theory-namely, that negative news has a greater impact on volatility-but their statistical significance is not significant. In stark contrast, the EGARCH model yields significantly positive estimates for the asymmetric parameters. This "anomalous effect" suggests that in the AI sector, positive news may actually trigger stronger market volatility. As a typical high-tech growth sector, the valuation of the AI sector often relies heavily on optimistic expectations regarding future technological breakthroughs, commercial application prospects, and the extent of policy support. Consequently, the release of positive news may rapidly intensify market enthusiasm, attracting a flood of trend-following investors and thereby amplifying volatility in the short term. Conversely, the impact of negative news may have already been partially priced in by the market, or it may be interpreted differently by investors due to the complexity of the technology, leading to a dispersion of the impact. Furthermore, companies within the sector generally exhibit characteristics such as high valuation premiums and substantial R&D expenditures, making investor sentiment more susceptible to being driven by positive catalysts toward excessive optimism.

The practical value of this study is evident on multiple levels. For investors, recognizing that volatility in the AI sector may be more sensitive to positive news implies that when major breakthroughs or policy support emerge in the industry, they must be vigilant about the risk of rising volatility and adjust their risk budgets and hedging strategies in a timely manner.

5.2 Outlook

Looking ahead, there remains room for further expansion of this study. First, at the model level, we can incorporate a wider variety of asymmetric GARCH models (such as

GJR-GARCH and APARCH) as well as GARCH-M models that account for the correlation between volatility and returns to conduct a more comprehensive model analysis. We can also explore hybrid forecasting frameworks that leverage machine learning methods to integrate the strengths of multiple models. Second, at the data level, higher-frequency intraday data could be used to capture the immediate effects of news shocks with greater precision, or alternative data such as online search trends and social media sentiment could be introduced to quantify market sentiment and directly test the "sentiment leverage" hypothesis. Furthermore, regarding mechanism analysis, future research could combine micro-level financial data from AI companies with macro-level policy text data to construct panel data models, empirically testing how firm heterogeneity and policy shocks interact to influence the asymmetry of stock price volatility.

In summary, through an empirical exploration of the asymmetric volatility in the AI sector, this study reveals a unique volatility formation mechanism distinct from traditional industries, challenges the universal perception of the leverage effect, and establishes an effective analytical framework. The findings contribute theoretically to the development of financial volatility theories better suited to the characteristics of the new economy sector, and practically provide decision-making support for risk assessment and strategy formulation among various market participants.

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