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Volatility Characteristics of CSI 300 Index Returns: Evidence from GARCH-Family Models

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Abstract: Financial asset returns exhibit volatility clustering, heavy tails, and conditional heteroskedasticity commonly. Modeling the volatility process is therefore important for understanding risk in equity markets. This study examines the log returns of the CSI 300 Index from April 8, 2005, to December 31, 2025, using GARCH-family models. The results reveal pronounced non-normality, heavy tails, and volatility clustering. Market volatility is also highly persistent. The magnitude of market shocks has a significant effect on conditional volatility, whereas the asymmetric term that captures differences between positive and negative shocks is not statistically significant. Thus, the sample provides insufficient evidence of a significant leverage effect in CSI 300 Index returns. The main findings remain robust to alternative conditional distributions, mean-equation specifications, and subsample periods. Using data spanning more than two decades, this study re-examines the dynamic volatility of CSI 300 Index returns and provides new empirical evidence on volatility persistence and asymmetry in China's equity market.

Keywords: CSI 300 Index; Log returns; Volatility persistence; GARCH model; EGARCH model; Asymmetric volatility

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1. Introduction

The CSI 300 Index is a major broad-market benchmark for China's A-share market. Fluctuations in its returns matter not only for assessing market risk but also for asset allocation and risk management. Since 2005, China's equity market has undergone several pronounced bull-bear cycles and alternating periods of high and low volatility. Against this background, the present study asks whether CSI 300 Index volatility remains highly persistent over a long sample spanning multiple market cycles and whether positive and negative shocks generate systematically different volatility responses over the long sample.

Previous research has established that returns in China's equity market exhibit volatility clustering and conditional heteroskedasticity, commonly modeled with GARCH and its extensions. Unlike volatility clustering, which is a relatively stable empirical regularity, estimates of volatility persistence and asymmetric effects often depend strongly on the sample. Over the past two decades, China's equity market has experienced

repeated regulatory changes, bull-bear cycles, and external shocks. Conclusions drawn from earlier samples therefore warrant re-examination over a longer period.

Accordingly, this study uses daily observations on the CSI 300 Index from April 8, 2005, to December 31, 2025, constructs a log-return series, and applies GARCH-family models to examine its volatility characteristics. Descriptive statistics, the Jarque-Bera test, the Ljung-Box test, and the ARCH-LM test are first used to characterize the return series. Information criteria are then compared across GARCH specifications to select the baseline model. Finally, an EGARCH model tests whether positive and negative information shocks have asymmetric effects on conditional volatility. The results show that CSI 300 Index returns are distinctly non-normal and exhibit volatility clustering and conditional heteroskedasticity, together with strong volatility persistence. By contrast, the asymmetric term in the EGARCH model is not statistically significant, leaving insufficient evidence of a significant leverage effect over the long sample. By covering more than two decades of market development, the study provides updated evidence on whether two widely documented features of equity-market volatility—persistence and asymmetry—remain stable across a substantially longer sample of the Chinese stock market.

2. Literature review

2.1. Volatility persistence

Financial asset return volatility is time-varying and persistent, two empirical regularities that underpin the use of GARCH-family models. Engle introduced the ARCH model, linking conditional variance to past shocks [1]. Bollerslev subsequently incorporated lagged conditional variance into the model, creating the GARCH framework and providing a more parsimonious account of volatility clustering and persistence in financial markets [2]. GARCH and its extensions have since become central tools in financial-market volatility analysis.

Studies of China's equity market generally find strong persistence in return volatility. Zhou *et al.* incorporated GARCH structures into HAR, ARFIMA, and ARFIMAX models of realized volatility for the CSI 300 and document pronounced long memory; they also showed that the assumed error distribution materially affects forecasting performance [3]. Wang *et al.* compared several GARCH models for China's equity market and found that the GARCH family captures the dynamics of Chinese stock-return volatility well [4].

Recent research has moved beyond conventional GARCH models of daily returns to incorporate high-frequency information, realized volatility, and mixed-frequency methods. Wu *et al.* introduced option-implied risk aversion into a Realized EGARCH-MIDAS framework and found that risk aversion significantly explains and predicts long-run volatility in China's equity market [5]. Tian *et al.* combined several symmetric and asymmetric GARCH models with LSTM to forecast CSI 300 Index volatility, showing that GARCH-based models continue to supply useful volatility information to more complex forecasting frameworks [6].

The literature has therefore reached broad agreement that China's equity market exhibits volatility clustering and strong persistence, although the estimated parameters remain sample-dependent. As the market's institutional setting and structure continue to change, it remains useful to reassess the persistence of CSI 300 Index return volatility over a longer sample.

Volatility persistence indicates how long the effect of a market shock lasts, but it does not reveal whether shocks in opposite directions elicit the same volatility response. Differences between positive and negative shocks thus form a second important dimension of financial-market volatility.

2.2. Asymmetric volatility

A further question is whether positive and negative information shocks generate different levels of market volatility. The standard GARCH model does not distinguish the direction of a shock. Nelson developed the EGARCH model, which specifies conditional variance in logarithmic form and incorporates both shock magnitude and direction, allowing volatility to respond asymmetrically [7].

Asymmetric GARCH models have also been widely applied to China's equity market. Ausloos *et al.* used a TGARCH model to examine the relationship between CSI 300 stock-index futures trading and spot-market volatility, explicitly considering asymmetric responses in Chinese equity volatility [8]. Comparing GARCH, TGARCH, EGARCH, and related specifications, Wang *et al.* provided a systematic assessment of volatility persistence and asymmetry in China's equity market and showed that asymmetric GARCH models provide additional information beyond the standard GARCH specification [4].

Research on asymmetric volatility has recently expanded into high- and mixed-frequency settings. Wu *et al.* developed a Realized EGARCH-MIDAS model that jointly incorporates realized volatility, long-run volatility, and risk-aversion information [5]. The literature has thus moved from isolating differences between positive and negative shocks to jointly modeling multiple information sources and long-horizon risk factors. Tian *et al.* likewise included several asymmetric GARCH specifications when forecasting CSI 300 volatility, further indicating that leverage effects and asymmetric responses to news remain important considerations in current volatility modeling [6].

Evidence of asymmetric effects, however, is generally more sensitive to the sample period and model specification than evidence of volatility persistence. After using a GARCH model to characterize persistence, this study therefore applies an EGARCH model to test whether positive and negative information shocks have significantly different effects on the conditional volatility of CSI 300 Index returns. The aim is not to propose a new volatility model. Instead, the 2005–2025 sample is used to revisit two basic properties of CSI 300 Index returns: whether volatility persistence remains statistically significant and whether asymmetric effects remain stable over a long sample.

3. Data and methodology

3.1. Data and variables

The sample consists of daily closing values of the CSI 300 Index from April 8, 2005, to December 31, 2025, obtained from Wind. The index broadly represents the performance of large-cap stocks listed in Shanghai and Shenzhen and is a widely used benchmark for price fluctuations in China's equity market. The raw observations are ordered by trading date, with non-trading days excluded. To mitigate trend effects in the price series and measure daily market returns, daily log returns are calculated as follows:

$$R_t = 100 \times \left[ln\left(P_t\right) - ln\left(P_{t-1}\right) \right]$$

where P_t and P_{t-1} denote the closing values of the CSI 300 Index on trading day t and the preceding trading day, respectively, and R_t is the daily log return expressed as a percentage. The differenced series contains 5,039 valid return observations.

Before estimation, descriptive statistics and the Jarque-Bera test are used to examine the distribution of returns, and the augmented Dickey-Fuller (ADF) unit-root test is used to assess stationarity. Ljung-Box tests are then applied to the returns and squared returns to test for serial correlation, while the ARCH-LM test is used to detect conditional heteroskedasticity.

3.2. GARCH model

Because financial asset returns typically exhibit volatility clustering and conditional heteroskedasticity, a GARCH model is used to characterize the dynamic volatility of CSI 300 Index returns. The return mean equation is specified as:

$$R_t = \mu + \varepsilon_t$$

where μ is the conditional mean of returns and ε_t is a random disturbance satisfying:

$$\varepsilon_t = \sigma_t z_t$$

where σ_t^2 denotes the conditional variance in period t and z_t is a standardized innovation.

The conditional variance equation for a general GARCH(p,q) model is:

$$\sigma_t^2 = \omega + \Sigma \alpha_t \varepsilon_{t-i} \ + \Sigma \beta_j \sigma_{t-j}$$

where ω is the constant; α_i is an ARCH coefficient measuring the effect of new information shocks on current volatility; and β_j is a GARCH coefficient measuring the persistence of past volatility in current volatility.

To select an appropriate variance specification, this study compares GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2) models using the Akaike information criterion (AIC), Bayesian information criterion (BIC), Shibata criterion, and Hannan-Quinn information criterion. Lower values indicate a better trade-off between fit and complexity.

After estimation, Ljung-Box tests are applied to the standardized residuals and their squares. The ARCH-LM test is also used to determine whether unexplained conditional heteroskedasticity remains, thereby assessing how well the GARCH model captures the volatility process.

3.3. EGARCH model

The standard GARCH model captures volatility clustering and persistence but assumes that positive and negative shocks of equal magnitude have symmetric effects on conditional volatility. To investigate whether information shocks in opposite directions affect the volatility of CSI 300 Index returns differently, this study further estimates an EGARCH(1,1) model.

The conditional variance equation for the EGARCH(1,1) model is:

$$ln\left(\sigma_t^2\right) = \omega + \alpha_1 z_{t-1} + \gamma_1\left(\left|z_{t-1}\right| - E\left|z_{t-1}\right|\right) + \beta_1 ln\left(\sigma_{t-1}^2\right)$$

where:

$$z_{t-1} = \varepsilon_{t-1} / \sigma_{t-1}$$

β_1 captures the persistence of conditional volatility, γ_1 measures the effect of shock magnitude on market volatility, and α_1 captures asymmetry across shocks of different signs. If α_1 differs significantly from zero, positive and negative information shocks of equal magnitude have significantly different effects on conditional volatility. Under the parameterization used in this study, a significantly negative α_1 implies that a negative shock produces a stronger volatility response than an equally large positive shock.

Because EGARCH specifies the logarithm of conditional variance, its variance-equation parameters need not be constrained to be nonnegative. The model also offers a flexible representation of asymmetric volatility in financial markets. This study uses the EGARCH(1,1) specification primarily to test for a significant leverage effect in CSI 300 Index returns and evaluates model performance using parameter significance and standardized-residual diagnostics.

4. Empirical results

4.1. Return dynamics and descriptive statistics

Figures 1 and **2** plot the CSI 300 Index and its log returns, respectively. **Figure 1** reveals clear phases in the index over the sample period. Rather than fluctuating around a fixed mean, the index experienced several pronounced rises and declines. Distinct local peaks occurred around 2007, 2015, and 2021, each followed by an adjustment of varying magnitude. The price level therefore exhibits a marked trend, and direct volatility modeling of the level series may be affected by non-stationarity. The index is consequently transformed using log differences.

Figure 2 shows that CSI 300 log returns fluctuate around zero without a clear trend, although the magnitude of the fluctuations varies across periods. Large movements are concentrated in several intervals, displaying the familiar pattern of volatility clustering. The series also contains a number of large positive and negative shocks. These observations suggest that the return series may be conditionally heteroskedastic, a possibility examined below using tests for ARCH effects and GARCH models.

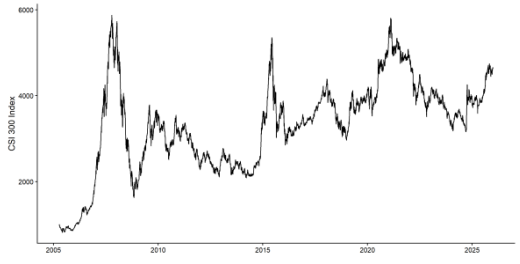


Figure 1. CSI 300 Index

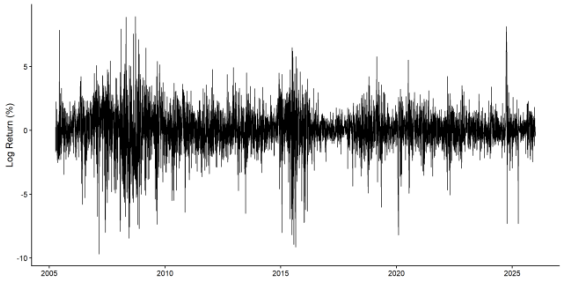


Figure 2. CSI 300 Index log returns

Table 1 reports descriptive statistics for CSI 300 Index log returns. Skewness is -0.497, indicating a moderately left-skewed distribution. Kurtosis is 7.619, well above the normal-distribution benchmark of 3 and consistent with pronounced leptokurtosis and heavy tails. The Jarque-Bera statistic is 4,686.1, rejecting normality at the 1% level. Overall, the distribution of CSI 300 Index log returns is distinctly non-normal. The ADF statistic is -50.4695, rejecting the unit-root null at the 1% level. The return series is therefore stationary and suitable for estimation with GARCH-family models.

Table 1. Descriptive statistics for CSI 300 Index log returns

N	Mean	SD	Min	Max	Skewness	Kurtosis	Jarque–Bera	ADF
5,039	0.030	1.594	-9.695	8.931	-0.497	7.619	4686.1***	−50.4695***

Note: *** denotes significance at the 1% level.

4.2. Serial correlation and ARCH-effect tests

Table 2 reports the Ljung-Box and ARCH-LM test results. At lags 10 and 20, the Ljung-Box tests for both returns and squared returns significantly reject the null hypothesis of no autocorrelation. The Q statistics are much larger for squared returns, indicating strong serial dependence and persistence in volatility. The ARCH-LM tests likewise significantly reject the null of no ARCH effects at both lag orders. CSI 300 Index log returns therefore exhibit significant conditional heteroskedasticity, supporting the use of GARCH-family models.

Table 2. Serial correlation and ARCH effects in CSI 300 Index log returns

Lag	Return Q	*P*-value	Squared Return Q	*P*-value	ARCH-LM	*P*-value
10	42.924	<0.001	1383.616	<0.001	559.810	<0.001
20	71.933	<0.001	2186.217	<0.001	627.877	<0.001

4.3. GARCH model selection and estimation results

To select the lag orders for the conditional variance equation, GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2) models are estimated and compared using the AIC, BIC, Shibata, and HQIC criteria. As shown in **Table 3**, GARCH(1,1) has the lowest value under all four criteria. Although the differences across models are generally small, every criterion favors the same specification. Balancing goodness of fit and parsimony, the GARCH (1,1) model is therefore selected as the baseline.

Table 3. Information criteria for alternative GARCH models

	AIC	BIC	Shibata	HQIC
GARCH(1,1)	3.467174	3.472353	3.467172	3.468988154
GARCH(1,2)	3.46746	3.473935	3.467458	3.469728627
GARCH(2,1)	3.467571	3.474045	3.467569	3.469838842
GARCH(2,2)	3.467857	3.475627	3.467854	3.470579209

Note: AIC, BIC, and HQIC denote the Akaike, Bayesian, and Hannan-Quinn information criteria, respectively. Lower values indicate a better balance between model fit and parsimony.

Table 4 reports parameter estimates for the GARCH (1,1) model. The ARCH coefficient α_1 is 0.0701 and significant at the 1% level, indicating that new market shocks significantly affect current conditional volatility. The GARCH coefficient β_1 is 0.9250, also significant at the 1% level and substantially larger than the ARCH coefficient. Current volatility is therefore driven mainly by persistent effects from past volatility. Moreover, $\alpha_1 + \beta_1 = 0.9951 < 1$, satisfying the covariance-stationarity condition. Because the sum is very close to 1, however, volatility in CSI 300 Index returns is highly persistent and the effects of market shocks decay slowly.

Table 4. GARCH (1,1) parameter estimates

Parameter	Estimate	Robust SE	*t*-statistic	*P*-value
μ	0.0337	0.0183	1.844	0.065
ω	0.0175	0.0072	2.415	0.016
α1	0.0701	0.0130	5.396	<0.001
β1	0.9250	0.0131	70.441	<0.001

The resulting mean and conditional variance equations are:

$$r_t = 0.03375 + \varepsilon_t$$

$$\sigma_t^2 = 0.01748 + 0.07014\varepsilon_{t-1}^{\ 2} + 0.92505\sigma_t^2$$

Figure 3 plots the conditional volatility series estimated by the GARCH(1,1) model. Conditional volatility varies considerably over time and across sample periods. It rose sharply during 2007–2009, around 2015, and around 2024, reaching one of its highest levels near 2015. High-volatility episodes typically persisted before gradually subsiding, while low-volatility periods also displayed persistence. The persistence of both high- and low-volatility episodes is consistent with the large persistence parameter estimated by GARCH (1,1): after a market shock, the effect on volatility dissipates slowly rather than disappearing immediately.

Figure 4 plots the standardized residuals from the GARCH(1,1) model. Compared with the raw returns, these residuals fluctuate around zero with a more even amplitude across the sample. The pronounced volatility clustering in the original return series is substantially attenuated, indicating that the GARCH(1,1) model

captures its time-varying volatility reasonably well.

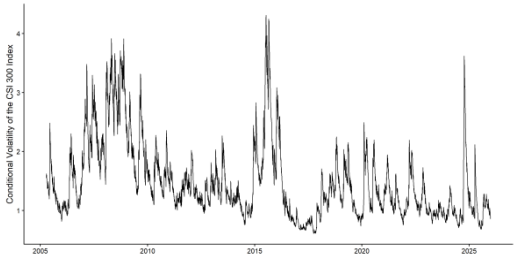


Figure 3. Conditional volatility

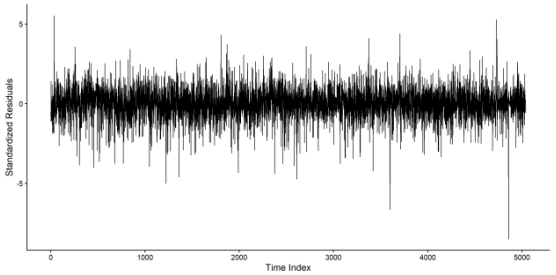


Figure 4. Standardized residuals

4.4. GARCH model diagnostics

To assess the fit of the GARCH(1,1) model, Ljung–Box tests are applied to the standardized residuals and their squares, and an ARCH-LM test is used to detect any remaining ARCH effects. As shown in **Table 5**, the Ljung–Box tests for the standardized residuals are statistically significant at the reported lag orders, indicating some remaining serial correlation in the mean equation. In contrast, the Ljung–Box tests for the squared standardized residuals and the ARCH-LM tests are insignificant at all reported lag orders. These results suggest that the GARCH(1,1) specification adequately captures the conditional heteroskedasticity and volatility clustering in CSI 300 Index returns, although some serial dependence remains in the standardized residuals. Because this remaining autocorrelation may reflect mean-equation misspecification, an AR(1) term is added in the robustness analysis to assess the sensitivity of the main results.

Table 5. GARCH (1,1) model diagnostics

Lag	LB Q (Std. Resid.)	*P*-value	LB Q (Std. Resid. ²)	*P*-value	ARCH-LM	*P*-value
5	18.365	0.003	2.078	0.838	2.039	0.844
10	36.472	<0.001	4.880	0.899	4.868	0.900
20	44.841	0.001	8.725	0.986	8.520	0.988

Note: Std. Resid. denotes standardized residuals, and Std. Resid. ² denotes squared standardized residuals.

4.5. EGARCH model and asymmetric volatility

The baseline GARCH model indicates statistically significant persistence in CSI 300 Index return volatility, but the standard specification cannot distinguish positive from negative information shocks. To determine whether shocks of different signs generate asymmetric volatility responses, an EGARCH(1,1) model is estimated. The results appear in **Table 6**.

Table 6. EGARCH (1,1) parameter estimates

Parameter	Estimate	Robust SE	*t*-statistic	*P*-value
μ	0.0370	0.0143	2.597	0.009
ω	0.0161	0.0036	4.451	<0.001
α_1	-0.0036	0.0097	-0.373	0.709
β_1	0.9894	0.0012	834.881	<0.001
γ_1	0.1592	0.0289	5.510	<0.001

The estimated variance equation for the EGARCH (1,1) model is:

$$ln\left(\sigma_t^{\,2}\right) = 0.01611 - 0.00364 z_{t-1} + 0.15919\left(\left|z_{t-1}\right| - E\left|z_{t-1}\right|\right) + 0.98937 ln\left(\sigma_{t-1}^{\,2}\right)$$

where $z_{t-1} = \varepsilon_{t-1} / \sigma_{t-1}$, and the mean equation is $r_t = 0.03700 + \varepsilon_t$.

The EGARCH(1,1) estimates show that the volatility-persistence parameter β_1 is 0.9894 and significant at the 1% level, indicating strong persistence in CSI 300 Index return volatility. The shock-magnitude parameter γ_1 is 0.1592 and significantly positive, indicating that larger market shocks significantly raise subsequent conditional volatility. The estimated asymmetric parameter α_1 is -0.0036, but its *P*-value is 0.709 and it is not significant at conventional levels. Although the sign suggests a slightly stronger response to negative shocks, the difference is not statistically significant. The evidence is therefore insufficient to conclude that CSI 300 Index returns exhibit a significant leverage effect.

4.6. Robustness checks

4.6.1. Robustness to the conditional distribution

The Jarque-Bera test above shows that CSI 300 Index log returns depart significantly from normality. To test whether the baseline findings are sensitive to the conditional distribution, the GARCH(1,1) and EGARCH(1,1) models are re-estimated under a Student-*t* distribution. As shown in **Table 7**, under the Student-*t* GARCH(1,1) model, the ARCH and GARCH coefficients are 0.0633 and 0.9336, respectively, and sum to 0.9969, close to 0.9951 under the normal distribution. The estimated persistence is therefore highly robust to the alternative conditional distribution. In the Student-*t* EGARCH(1,1) model, both the persistence and shock-magnitude parameters are significant, whereas the asymmetric term remains insignificant, matching the baseline results. The estimated degrees of freedom are approximately 5 in both models, which is consistent with the heavy-tailed return distribution. Changing the conditional error distribution does not alter the main conclusions of strong volatility persistence and no statistically significant asymmetry.

Table 7. Estimates of GARCH-family models under alternative conditional distributions

Model	Distribution	α_1	β_1	$\alpha_1+\beta_1$	γ_1	Degrees of freedom
GARCH (1,1)	Normal	0.0701***	0.9250***	0.9951	—	—
GARCH (1,1)	Student-t	0.0633***	0.9336***	0.9969	—	5.1709***
EGARCH (1,1)	Normal	-0.0036	0.9894***	—	0.1592***	—
EGARCH (1,1)	Student-t	-0.0014	0.9929***	—	0.1407***	5.1560***

Note: *** denotes significance at the 1% level. Significance in the Student-*t* models is based on robust standard errors.

4.6.2. Robustness to the mean-equation specification

To assess sensitivity to the mean-equation specification, an AR(1) term is added to the mean equation. As shown in **Table 8**, the volatility-persistence parameter in the AR(1)-GARCH(1,1) model is 0.9952, almost identical to its baseline value. The asymmetric term in the AR(1)-EGARCH (1,1) model remains insignificant ($P = 0.738$). Adding a first-order autoregressive term therefore leaves the main conclusions of strong volatility persistence and no statistically significant asymmetry unchanged.

Table 8. Estimates of GARCH-family models under alternative mean equations

Model	Mean-equation specification	α_1	β_1	$\alpha_1+\beta_1$	γ_1
GARCH (1,1)	Constant only	0.0701***	0.9250***	0.9951	—
AR (1)-GARCH (1,1)	AR (1)	0.0702***	0.9250***	0.9952	—
EGARCH (1,1)	Constant only	-0.0036	0.9894***	—	0.1592***
AR (1)-EGARCH (1,1)	AR (1)	-0.0034	0.9894***	—	0.1597***

Note: *** denotes significance at the 1% level.

Residual diagnostics show that, after the AR(1) term is added, the Ljung-Box statistics for the standardized residuals from the AR(1)-GARCH(1,1) model decline from the baseline values of 18.365, 36.472, and 44.841 to 11.243, 29.376, and 37.671 at lags 5, 10, and 20, respectively. Linear dependence in the residuals is reduced but not eliminated. The Ljung-Box tests on the squared standardized residuals remain insignificant at all three lags, with *P*-values of 0.834, 0.904, and 0.988. The AR(1)-EGARCH(1,1) model yields a similar pattern, with *P*-values of 0.110, 0.290, and 0.772 for the squared standardized residuals. After the mean-equation adjustment, both models continue to capture conditional heteroskedasticity reasonably well, and the main findings remain unchanged.

4.6.3. Subsample robustness of the EGARCH model

Because China's equity market experienced severe volatility and a marked change in market conditions around 2015, the sample is divided into 2005–2015 and 2016–2025, and the EGARCH(1,1) model is re-estimated for each period. As shown in **Table 9**, the volatility-persistence parameter β_1 is significantly positive in both subsamples, at 0.9909 and 0.9683, indicating strong persistence in CSI 300 Index return volatility in both periods. The shock-magnitude parameter γ_1 is also significantly positive in both subsamples. By contrast, the asymmetric parameter α_1 is -0.0025 and -0.0172, with *P*-values of 0.795 and 0.505, respectively; neither estimate is significant at conventional levels. Subsample estimation therefore leaves the full-sample conclusion of no statistically significant asymmetry unchanged, indicating that the finding is stable across periods. At the same time, the persistence and shock-magnitude parameters differ between the two periods, suggesting some period-specific variation in the degree of volatility persistence and in the response to shocks.

Table 9. EGARCH (1,1) estimates by sample period

Model	Sample	α_1	β_1	γ_1
EGARCH (1,1)	2005–2015	-0.0025	0.9909***	0.1262***
EGARCH (1,1)	2016–2025	-0.0172	0.9683***	0.2037***

Note: *** denotes significance at the 1% level.

5. Conclusion

Using daily observations on the CSI 300 Index from April 8, 2005, to December 31, 2025, this study applies GARCH-family models to examine the dynamic volatility of index returns. The results show that CSI 300 Index log returns are distinctly leptokurtic, heavy-tailed, and non-normal and display clear volatility clustering. The Ljung-Box and ARCH-LM tests further indicate significant conditional heteroskedasticity in the return series.

Across the alternative GARCH specifications, the AIC, BIC, Shibata, and Hannan-Quinn criteria all favor GARCH(1,1). The sum of the estimated ARCH and GARCH coefficients is 0.9951, indicating strong volatility persistence and a slow decay in the effects of external shocks. Ljung-Box tests of the squared standardized residuals and the ARCH-LM tests find no evident residual ARCH effects, suggesting that GARCH(1,1) captures the conditional volatility process of CSI 300 Index returns reasonably well.

The EGARCH(1,1) results likewise indicate strong volatility persistence and a significant effect of shock magnitude on conditional volatility. The asymmetric term that captures differences between positive and

negative information shocks is negative but statistically insignificant. The sample therefore provides insufficient evidence of a significant leverage effect in CSI 300 Index returns. Taken together, the results identify strong volatility persistence as a robust feature of CSI 300 Index returns, while providing no statistically significant evidence of asymmetric volatility over the full sample.

This study compares only the normal and Student-*t* distributions and does not consider more flexible conditional distributions such as the skewed Student-*t* or generalized error distribution (GED). Although broad subsample estimates are used to examine stability across periods, market regimes are not identified using structural-break tests or endogenous methods. Future research could incorporate regime-switching behavior, structural breaks, or alternative volatility models to provide a more granular analysis of CSI 300 Index volatility.

Disclosure statement

The author declares no conflict of interest.

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