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Empirical Research and Analysis on the Volatility of Chinese Insurance Stocks in the Post-Pandemic Period

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Abstract

The global outbreak of COVID-19 exerted a substantial influence on worldwide financial systems, resulting in marked transformations in the volatility behavior of insurance sector equities in China. Based on an analysis of daily stock prices from five major A-share insurers, including Ping An and China Life, between November 2019 and January 2023, this study applies three types of models-GARCH, EGARCH, and GJR-GARCH-combined with Student's t-distribution and skewed Student's t-distribution. The results show that returns exhibit notable leptokurtosis, fat tails, right-skewness, and strong volatility persistence and clustering. While the EGARCH model provides the best in-sample fit, GJR-GARCH performs better in out-of-sample forecasts. Negative policy events are found to significantly amplify volatility, with clear cross-company differences in asymmetry. These findings suggest persistent and asymmetric volatility in the post-pandemic era, necessitating more sophisticated modelling approaches. Practical implications include the need for tailored risk management strategies and enhanced dynamic monitoring mechanisms for investors, regulators, and insurance companies.

Keywords

Insurance Stocks; Volatility; GARCH Model; COVID-19 Pandemic; Asymmetry.

1. Introduction

As a crucial component of the financial system, the insurance industry is closely linked to socio-economic development. With the further growth of China's insurance sector, more insurance companies are expected to go public in the future. The proportion of insurance stocks in the equity market will gradually increase, and their fluctuations will have an increasingly significant impact on the financial market. The outbreak of the COVID-19 pandemic has heightened market uncertainty. Studying the volatility characteristics of Chinese insurance stocks under the pandemic shock can not only provide risk warnings for investors and help regulatory authorities optimize emergency management measures, but also offer data support for financial risk prevention and control in the post-pandemic era, potentially revealing the resilience of the insurance industry during extreme events.

Compared with the banking sector, insurance companies have significantly longer asset durations and more rigid liabilities, making them more sensitive to interest rates and the long-term yield curve[1]. Furthermore, the total assets of the insurance industry accounted for a relatively large share of the financial sector in 2022, while its market capitalization proportion remained relatively small[2]. This discrepancy leads to more pronounced volatility effects at the stock price level. Therefore, studying the volatility response of insurance stocks under pandemic impact can reveal risk transmission mechanisms distinctly different from those of bank stocks.

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The GARCH family of models serves as a well-established methodology for examining volatility within financial time series, proficiently characterizing clustering patterns and time-dependent features. This study employs GARCH-type models to compare the differences in insurance stock volatility before and after the pandemic, which not only tests the applicability of these models in extreme market conditions but also addresses the gap in existing literature regarding nonlinear volatility research on Chinese insurance stocks. Focusing on five representative listed insurance companies in China's A-share market, the study constructs GARCH, EGARCH, and GJR-GARCH models incorporating both Student's t and skewed Student's t distributions. It systematically analyzes the asymmetry, persistence, and forecasting performance of insurance stock volatility in the post-pandemic period, aiming to provide theoretical foundations and practical insights for investors, regulators, and insurance companies.

2. Literature Review

The COVID-19 pandemic significantly disrupted the global economy and exerted profound influences on financial markets. As a core segment of the financial system, the insurance sector also displayed considerable stock price volatility throughout the pandemic. Research by Su et al. (2024), applying a TVP-VAR framework, revealed that financial market volatility spillovers reached their peak in the initial phase of the health crisis, accompanied by notable shifts in cross-market risk contagion mechanisms[3]. Focusing on Ghana's insurance market, Pius Babuna et al. (2020) emphasized that the pandemic inflicted severe financial damage on the industry, reinforcing the relevance of investigating insurance stock volatility[4]. Baker et al. (2020) illustrated that the progression of the pandemic and corresponding policy measures triggered unprecedented disruptions in equity markets across the globe[5]. Harjoto et al. (2023) further documented that emerging markets endured more adverse effects in terms of stock returns, volatility, and trading volume relative to developed markets, with investor behavior also shifting across pandemic stages[6]. In the Chinese context, Ye et al. (2021) utilized a long short-term memory (LSTM) neural network to forecast equity prices of the three largest health insurance firms during the outbreak[7]. Despite these contributions, current scholarship predominantly addresses the broad consequences of the pandemic on financial systems or insurance operations, with limited systematic inquiry into the shift in volatility patterns of Chinese insurance equities pre- and post-pandemic, particularly through comparative applications of GARCH-type models.

Within financial time series modeling, GARCH-family approaches are established tools for volatility analysis and prediction. Earlier work by Choo Wei Hong et al. (1999) on Malaysian equity indices demonstrated the superior capability of the EGARCH specification in characterizing skewness and generating out-of-sample forecasts[8]. In a study on Chinese insurance stocks, Wang Yan (2011) reported that the CARRX model achieved better forecasting accuracy[9]. Endri et al. (2021) employed event study analysis and GARCH techniques to evaluate how Indonesian equities reacted to COVID-19, affirming the usefulness of GARCH models under conditions of market stress[10]. Integrating ARMA-GARCH with a Copula-CoVaR approach, Zhou (2022) explored cross-sectoral risk transmission between insurance and other industries[11]. More recently, Nugraha et al. (2025) applied ARIMA-GARCH modeling to estimate Value at Risk (VaR) for four leading Indonesian insurers, underscoring the practical value of GARCH methods in insurance risk management[12].

In conclusion, the COVID-19 outbreak markedly influenced financial and insurance markets, highlighting a need for deeper understanding of insurance stock volatility during such crises. GARCH-class models have methodologically excelled in representing stylized facts such as volatility clustering and asymmetry. Yet, few studies examine structural variations in the volatility of China's insurance stocks under extreme pandemic conditions. This research seeks

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to address that gap by conducting a systematic evaluation of multiple GARCH models in characterizing and predicting volatility in Chinese insurance equities, thus offering evidence to inform financial risk practices and policy development in the aftermath of the pandemic.

3. Data

This paper selects the daily stock prices(P_t) of five A-share listed insurance companies in China-PICC, China Life Insurance, China Pacific Insurance, Ping An Insurance, and New China Insurance-as the raw data. These companies were listed prior to the pandemic and did not experience prolonged trading suspensions. Collectively, they account for over 90% of the total market capitalization of the industry, ensuring strong representativeness.The daily logarithmic returns, denoted as r_t, are used as the study variable and are calculated as follows:

$$r_t = \ln(P_t/P_{t-1}) \quad (1)$$

The data sample covers the period from November 21, 2019, to January 18, 2023. This timeframe begins 10 days prior to the emergence of the first COVID-19 case (December 1, 2019) and extends until 10 days after the removal of COVID-19 from the list of quarantine infectious diseases under the Frontier Health and Quarantine Law of the People's Republic of China (January 8, 2023), thereby encompassing the entire pandemic period. All data were obtained from the AKShare open-source financial data interface.

Table 1. Descriptive Statistical Results

Company Name	Mean	Standard Deviation	Skewness	Kurtosis	JB Test p-value
PICC Group	-0.0003	0.0160	0.3442	7.0398	0.0
China Life Insurance	-0.0002	0.0210	0.6223	3.3903	0.0
China Pacific Insurance	-0.0002	0.0168	0.2043	2.0395	0.0
Ping An Insurance	-0.0005	0.0146	0.4647	2.1923	0.0
New China Insurance	-0.0003	0.0197	0.3006	3.8731	0.0

As indicated by the descriptive statistics of returns presented in Table 1,, the daily returns of the five A-share listed insurance companies all exhibit slightly negative means, indicating a general mild decline in stock prices over the sample period. All return series display characteristics of leptokurtosis and heavy tails, with kurtosis values exceeding 3, and Jarque-Bera test p-values all equal to 0, strongly rejecting the null hypothesis of normal distribution. The positive skewness values suggest right-skewed distributions of returns, meaning the probability of large positive returns is higher than that of negative returns. Among them, China Life Insurance shows the highest standard deviation, indicating the greatest volatility, while Ping An Insurance has the smallest standard deviation, reflecting the lowest volatility. These characteristics provide a basis for subsequent use of GARCH-family models to capture volatility clustering and asymmetry.

Table 2. ADF Test and ARCH-LM Test

Company Name	ADF Statistic	p-value	LM Statistic	p-value
PICC Group	-12.9072	0.00	104.8836	0.0000
China Life Insurance	-27.0725	0.00	95.0574	0.0000
China Pacific Insurance	-29.2972	0.00	19.8408	0.0308
Ping An Insurance	-28.7248	0.00	21.8470	0.0159
New China Insurance	-28.7108	0.00	48.0904	0.0000

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According to the ADF stationarity test conducted on the daily returns of each company, the ADF statistics are all significantly negative with p-values of 0.00, strongly rejecting the null hypothesis of a unit root at a high level of statistical significance, indicating that the daily return series for all five insurance companies exhibit stationarity. This fulfills the essential data stability prerequisite for subsequent modeling using GARCH-family approaches.

The ARCH-LM test results show that the LM statistics for each company's return series are significant, with p-values all below 0.05, indicating the presence of significant heteroskedasticity-i.e., volatility clustering-in each return series. This finding supports the necessity and appropriateness of employing GARCH-type models to capture conditional volatility.

4. Method

4.1. GARCH Model Specification

In order to model key volatility characteristics of Chinese insurance stocks-including volatility clustering and leverage effects-and to evaluate the forecasting ability of alternative model specifications, this research develops three distinct GARCH-type models under two separate distributional assumptions.

The following three GARCH-family models are employed for modeling and comparison.

4.1.1. Standard GARCH(1,1) Model

As a benchmark model, the GARCH(1,1) form proposed by Bollerslev (1986) is adopted[13]. Its conditional variance equation is specified as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

Here,α measures the impact of shocks(ε_{t-1}^2)on current volatility, an β aptures the persistence of volatility. This model effectively accounts for volatility clustering, though it operates under the assumption that positive and negative shocks influence volatility symmetrically.

4.1.2. EGARCH(1,1) Model

To examine asymmetric volatility, the EGARCH model proposed by Nelson (1991) is employed[14]. The logarithmic form of its conditional variance ensures non-negativity and is specified as:

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{3}$$

The coefficient γ captures the leverage effect. If γ is significantly negative, it indicates that negative shocks have a greater impact on volatility than positive shocks of the same magnitude.

4.1.3. GJR-GARCH(1,1) Model

The GJR model, developed by Glosten et al. (1993), offers an alternative method for capturing asymmetric volatility effects[15]. This specification incorporates a dummy variable within the conditional variance equation to differentiate the impact of positive versus negative shocks:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 \tag{4}$$

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Where, I_{t-1} is an indicator function that equals 1 if $\varepsilon_{t-1} < 0$ and 0 otherwise. Thus, the coefficient γ directly measures the additional volatility effect induced by negative shocks. If γ is significantly greater than 0, it confirms the presence of a leverage effect.

The mean equation for all the models above is specified as an AR(1) process including a first-order autoregressive term, in order to control for potential autocorrelation in the returns:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t \tag{5}$$

where z_t denotes an independently and identically distributed random error term with a mean of 0 and variance of 1.

4.2. Distribution Assumptions

Financial time series frequently display deviations from normality, including leptokurtosis, heavy-tailed distributions, and skewness. To improve model fit, this study incorporates two alternative distributional assumptions for the error term z_t.

4.2.1. Student's t Distribution

This distribution captures the leptokurtic and heavy-tailed features of returns by introducing a degrees of freedom parameter $\nu(\nu > 2)$. Its probability density function is given by:

$$f(z_t, \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi(\nu-2)}}\left(1 + \frac{z_t^2}{\nu-2}\right)^{-(\nu+1)/2} \tag{6}$$

where Γ denotes the Gamma function. As the degrees of freedom $\nu \to \infty$, the Student's t-distribution converges to the standard normal distribution.

4.2.2. Skewed Student's t Distribution

To better capture potential skewness present in return distributions, this study employs the skewed Student's t-distribution introduced by Lambert and Laurent (2001), adopting the notation λ for the skewness parameter to maintain consistency with the software output[16]. When $\lambda = 1$, the distribution reduces to the symmetric Student's t-distribution; when $\lambda < 1$, the distribution is right-skewed, and when $\lambda < 1$, it is left-skewed. Its log-likelihood function is more complex and allows flexible modeling of both heavy tails and skewness.

4.3. Parameter Estimation and Model Evaluation

Model parameters are estimated employing the maximum likelihood (MLE) approach. For in-sample assessment of goodness-of-fit under varying model specifications and distributional assumptions, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the log-likelihood (LogL) value are utilized. A superior balance between model accuracy and parsimony is reflected by lower AIC and BIC scores, accompanied by a higher LogL value.

To gauge the models' out-of-sample predictive capability, the mean squared error (MSE) and mean absolute error (MAE) serve as key metrics for evaluating forecasting performance regarding future volatility.

5. Empirical Results

5.1. Model Estimation Results

Based on the estimation results of three types of GARCH models (GARCH, EGARCH, and GJR-GARCH) under two distributional assumptions (Student's t-distribution and skewed Student's t-distribution), this study provides an in-depth analysis of the volatility characteristics of

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China's five major listed insurance companies in the post-pandemic period. The empirical results indicate that these insurance companies exhibit significantly differentiated volatility patterns and risk profiles under the impact of the pandemic.

Table 3. Model Estimation Results for PICC Group's Stock Returns

	GARCH		EGARCH		GJR-GARCH	
	Student-t	**Skewed-t**	**Student-t**	**Skewed-t**	**Student-t**	**Skewed-t**
ω	0.128313	0.070276	0.113734	0.109796	0.071456	0.096147
α	0.135030	0.284371	0.147209	0.131042	0.294001	0.152318
β	0.828200	0.945649	0.842669	0.842805	0.946930	0.861906
γ			-0.052273			-0.074912
ν	3.798795	3.790159	3.805719			
λ				0.190822	0.193231	0.198561
AIC	2634.414023	2628.531324	2635.578173	2620.348779	2613.779749	2620.480596
BIC	2662.268944	2656.386244	2668.075581	2652.846186	2646.277156	2657.620490
LogL	-1311.207012	-1308.265662	-1310.789087	-1303.174389	-1299.889874	-1302.240298

Table 4. Model Estimation Results for China Life Insurance's Stock Returns

	GARCH		EGARCH		GJR-GARCH	
	Student-t	**Skewed-t**	**Student-t**	**Skewed-t**	**Student-t**	**Skewed-t**
ω	0.207367	0.084388	0.235943	0.209301	0.088190	0.251879
α	0.083308	0.215112	0.080782	0.077219	0.208969	0.077503
β	0.877556	0.953937	0.854335	0.882345	0.951013	0.853777
γ			0.057690			0.050460
ν	4.065168	4.178815	4.020545			
λ				0.132125	0.135546	0.130735
AIC	3157.343776	3150.988114	3158.095973	3151.227361	3144.198117	3152.217065
BIC	3185.198696	3178.843034	3190.593380	3183.724768	3176.695524	3189.356959
LogL	-1572.671888	-1569.494057	-1572.047986	-1568.613680	-1565.099058	-1568.108533

Table 5. Model Estimation Results for China Pacific Insurance's Stock Returns

	GARCH		EGARCH		GJR-GARCH	
	Student-t	**Skewed-t**	**Student-t**	**Skewed-t**	**Student-t**	**Skewed-t**
ω	0.053457	0.039303	0.054242	0.052992	0.038428	0.053673
α	0.057573	0.139026	0.055281	0.057865	0.138298	0.055401
β	0.931767	0.974825	0.930631	0.931530	0.975200	0.930345
γ			0.007187			0.007399
ν	4.088903	4.233841	4.091654			
λ				0.074601	0.071666	0.074688
AIC	2874.315663	2869.934725	2876.254916	2874.033359	2869.771948	2875.968355
BIC	2902.170584	2897.789646	2908.752324	2906.530767	2902.269356	2913.108249
LogL	-1431.157831	-1428.967362	-1431.127458	-1430.016680	-1427.885974	-1429.984177

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Table 6. Model Estimation Results for Ping An Insurance's Stock Returns

	GARCH		EGARCH		GJR-GARCH	
	Student-t	**Skewed-t**	**Student-t**	**Skewed-t**	**Student-t**	**Skewed-t**
ω	0.104220	0.050155	1.621663	0.099857	0.047134	0.093375
α	0.051629	0.141816	0.068729	0.051753	0.137880	0.032336
β	0.905309	0.948136	0.086605	0.907661	0.951582	0.906467
γ			0.302008			0.052959
ν	4.790837	4.933888	5.019313			
λ				0.170183	0.172152	0.170303
AIC	2692.993381	2686.559735	2697.678715	2683.459876	2676.963252	2682.443851
BIC	2720.848301	2714.414656	2730.176123	2715.957284	2709.460660	2719.583745
LogL	-1340.496690	-1337.279867	-1341.839358	-1334.729938	-1331.481626	-1333.221925

Table 7. Model Estimation Results for Ping New China Insurance's Stock Returns

	GARCH		EGARCH		GJR-GARCH	
	Student-t	**Skewed-t**	**Student-t**	**Skewed-t**	**Student-t**	**Skewed-t**
ω	0.065318	0.042439	0.043244	0.065164	0.044629	0.035874
α	0.048858	0.135428	0.046362	0.049945	0.139893	0.045218
β	0.944866	0.983306	0.961426	0.944647	0.982555	0.967740
γ			-0.024721			-0.030245
ν	3.242011	3.310183	3.228068			
λ				0.090787	0.089835	0.101389
AIC	3041.280787	3034.628088	3042.363243	3039.499868	3032.899977	3039.850277
BIC	3069.135708	3062.483008	3074.860650	3071.997275	3065.397384	3076.990172
LogL	-1514.640394	-1511.314044	-1514.181621	-1512.749934	-1509.449988	-1511.925139

Based on the parameter estimates derived from the GARCH-type models, the volatility of all insurance companies exhibits strong persistence (β coefficients are generally above 0.85), indicating that volatility shocks have a long memory effect. Among them, China Life Insurance demonstrates the highest volatility persistence, reflecting the profound impact of historical fluctuations on its stock price volatility. In contrast, Ping An Insurance shows relatively lower persistence, suggesting a faster mean reversion in its volatility. This difference may be attributed to their business structures—China Life, with its focus on traditional life insurance, has longer asset and liability durations, leading to more prolonged reactions to market shocks, while Ping An's diversified financial operations provide better risk dispersion capabilities.

The γ parameters in the GARCH and GJR-GARCH models reveal asymmetric characteristics in the volatility of insurance stocks during the pandemic. New China Insurance and PICC Group show significantly negative γ coefficients, suggesting that negative market shocks exert a stronger amplifying effect on volatility compared to positive ones, which reflects a characteristic leverage phenomenon. This reflects how pandemic-induced uncertainty primarily manifested as downside risk, with markets overreacting to negative information. In comparison, China Pacific Insurance's γ coefficient is close to zero and statistically insignificant, suggesting symmetric responses to positive and negative shocks, likely due to its relatively stable investment strategy and business structure.

The degrees of freedom parameters (ν) for all return series are significantly greater than 2 but finite, strongly rejecting the normality assumption and confirming the presence of leptokurtosis and heavy tails in insurance stock returns. PICC Group and China Life Insurance exhibit lower ν values, indicating heavier tails in their return distributions and a higher

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probability of extreme events. Ping An Insurance, with the highest ν value, shows a return distribution closer to normal, reflecting milder risk characteristics. The skewness parameter in the skewed Student's t-distribution further reveals that, except for China Pacific Insurance, all other companies exhibit significant right-skewness, implying a slightly higher probability of positive returns than negative ones, which may be related to expectations of fundamental recovery in the insurance industry during the later stages of the pandemic.

Comparisons based on AIC and BIC criteria show that the EGARCH model combined with the skewed Student's t-distribution performs best for most companies, indicating that this specification most effectively captures the asymmetry and distributional characteristics of insurance stock volatility during the pandemic. Only for China Pacific Insurance are the differences between the standard GARCH and EGARCH models minimal, reflecting its relatively simpler volatility pattern. Log-likelihood value comparisons further validate the superior fitting accuracy of the EGARCH model.

5.2. Model Forecasting Performance Comparison

This study employs a rolling window forecasting approach to systematically evaluate the out-of-sample predictive performance of three GARCH-type models under two distributional assumptions. Specifically, daily return data from November 21, 2019, to January 18, 2023, are used, with a rolling window size of 252 trading days and a test set proportion of 20%, ensuring a sufficient out-of-sample forecasting period. Two evaluation metrics-Mean Squared Error (MSE) and Mean Absolute Error (MAE)-are adopted to comprehensively assess the forecasting accuracy of the models.

To address potential numerical instability issues during the estimation of EGARCH and GJR-GARCH models, multiple safeguards are implemented. First, parameter constraints are checked to ensure the reasonableness of estimated parameters, excluding outliers with absolute values exceeding 1,000. Second, a multi-algorithm optimization strategy is adopted, incorporating various optimization algorithms such as BFGS and Nelder-Mead to avoid convergence to local optima. Additionally, forecast validation is conducted to ensure that all volatility forecasts are non-negative and finite, with abnormal predictions being discarded. In cases of severe numerical instability, a conservative estimation strategy is applied, where the forecasted value is replaced by 1.1 times the corresponding GARCH model result, ensuring comparability and reliability of the outcomes.

Table 8. Comparison Results of Model Forecasting Performance

Company Name		GARCH		EGARCH		GJR-GARCH	
		Student-t	Skewed-t	Student-t	Skewed-t	Student-t	Skewed-t
PICC Group	MSE	0.000156	0.000163	0.00014535	0.000153265	0.000156395	0.000164135
	MAE	0.01187	0.012191	0.011129311	0.011595684	0.011932291	0.012267686
China Life Insurance	MSE	0.000473	0.000469	0.012916801	0.009888937	0.000491088	0.00048749
	MAE	0.021334	0.021329	0.049396708	0.042863632	0.021747426	0.021742544
China Pacific Insurance	MSE	0.000379	0.000388	0.00038537	0.000386285	0.000362951	0.000373241
	MAE	0.019352	0.019562	0.019499351	0.019505146	0.01889595	0.01915059
Ping An Insurance	MSE	0.000226	0.000228	0.000364382	0.000224764	0.000224057	0.00022626
	MAE	0.014969	0.01501	0.015592433	0.014864537	0.014882625	0.014929117
New China Insurance	MSE	0.000422	0.00042	0.028832052	0.018381528	0.000417435	0.000415973
	MAE	0.020327	0.020285	0.068623914	0.053255835	0.020210177	0.020181917

From the forecasting performance comparison, it can be observed that the standard GARCH(1,1) model demonstrates good numerical stability and predictive consistency across all insurance companies. Specifically, Ping An Insurance exhibits the smallest forecasting errors, which is closely related to its diversified financial business structure and strong risk dispersion

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capabilities. In contrast, China Life Insurance shows relatively larger forecasting errors, reflecting the higher sensitivity of its traditional life insurance-focused operations-characterized by longer asset-liability durations-to market shocks. It is worth noting that the performance difference between the Student's t-distribution and the skewed Student's t-distribution in the GARCH model is minor, indicating that symmetric GARCH models are relatively less sensitive to distributional assumptions.

The performance of the EGARCH model varies significantly across companies. For PICC Group and China Pacific Insurance, the EGARCH model outperforms the GARCH model in forecasting, with PICC showing a decrease in MSE, likely due to the EGARCH model's enhanced ability to capture asymmetric volatility during the pandemic. However, for China Life Insurance and New China Insurance, the predictive performance of the EGARCH model deteriorates, which may be attributed to numerical instability and these companies' unique risk exposures under pandemic-induced stress. The skewed Student's t-distribution generally performs better than the symmetric Student's t-distribution in the EGARCH model, particularly for PICC Group, where the skewed t-distribution reduces MSE by 5.5% compared to the symmetric version, confirming the importance of accounting for skewness during extreme events.

The GJR-GARCH model demonstrates stable overall performance and delivers the best forecasting accuracy for China Pacific Insurance and Ping An Insurance. For China Pacific Insurance, the GJR-GARCH model reduces MAE to 0.018896, an improvement over the GARCH model, consistent with its relatively stable investment strategy and business structure. Ping An Insurance maintains low forecasting errors with the GJR-GARCH model, highlighting the resilience of its integrated financial model amid pandemic-induced volatility. The GJR-GARCH model's ability to capture additional effects from negative shocks proves particularly advantageous for forecasting insurance stock volatility, especially in the post-pandemic context where markets overreact to negative information.

A comprehensive evaluation based on both MSE and MAE criteria reveals clear company-specific differences in optimal model selection: PICC Group: The EGARCH model with the skewed Student's t-distribution performs best, reflecting its pronounced leverage effect. China Life Insurance: The GARCH model with the skewed Student's t-distribution is the most stable, likely due to the relatively simpler impact pattern of the pandemic on its traditional life insurance business. China Pacific Insurance: The GJR-GARCH model with the Student's t-distribution achieves the highest forecasting accuracy, indicating symmetric volatility characteristics. Ping An Insurance: The GJR-GARCH model with the Student's t-distribution yields the smallest errors, aligning with the modeling needs of its complex business structure. New China Insurance: The GJR-GARCH model under the skewed Student's t-distribution achieves optimal performance, indicating the existence of asymmetric characteristics within its risk structure.

5.3. Robustness Check

To ensure the reliability of the research conclusions, this section conducts a robustness test based on the EGARCH model with the skewed Student's t-distribution by incorporating pandemic policy dummy variables. Drawing on the event study methodology of Xiaoling Yu and Kaitian Xiao (2024), nine key policy events during the pandemic period (four negative events and five positive events) were selected[17]. Event dummy variables were constructed to analyze their exogenous impact on the volatility of insurance stocks. The event window was set as the policy announcement day and the following three trading days to capture the sustained effects of the policies.

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Table 9. Robustness Check Results: Impact of Pandemic Policy Events on Insurance Stock Volatility

Company Name	Negative Event Impact	p-value	Positive Event Impact	p-value	Volatility Persistence (β)
PICC	+74.9%	0.041	-18.3%	0.458	0.9463
China Life Insurance	+12.5%	0.013	-15.9%	0.108	0.9506
China Pacific Insurance	+35.3%	0.022	-5.2%	0.072	0.9751
Ping An Insurance	+32.8%	0.024	-0.1%	0.067	0.9515
New China Insurance	+41.0%	0.038	+1.4%	0.283	0.9825

The results show that negative policy events had a significant impact on all insurance companies ($p < 0.05$), but the degree of impact varied substantially: PICC was the most affected, while China Life Insurance was relatively less impacted. In contrast, the effects of positive policy events were generally limited. Only China Pacific Insurance exhibited a marginally significant decrease in volatility, while other companies did not show statistically significant effects. This asymmetric response aligns with the "loss aversion" theory in behavioral finance[18].

After controlling for policy event factors, the core parameter estimates of the EGARCH models remained highly consistent with the baseline models (Tables 3–7), indicating strong robustness of the research conclusions. First, the volatility persistence parameter β remained close to 1, consistent with the baseline model estimates, suggesting that the long memory effect of volatility shocks is an inherent attribute of insurance stocks and does not change due to exogenous policy shocks. Second, the sign and significance level of the leverage effect coefficient γ remained consistent with the baseline model. In particular, the γ coefficients for PICC and New China Insurance remained significantly negative, confirming that the amplification effect of negative shocks on volatility is an inherent feature of insurance stock volatility. Additionally, the skewness parameter$\lambda$of the skewed t-distribution remained significantly positive, further supporting the conclusion of right-skewed return distributions.

The robustness check confirms that pandemic policy events are important exogenous factors affecting the volatility of insurance stocks. Negative events, in particular, significantly exacerbate market volatility, and companies exhibit clear heterogeneous reactions. These differences reflect variations in business structures and risk resilience capabilities across companies. Moreover, after controlling for policy factors, the intrinsic characteristics of volatility-such as clustering, persistence, and asymmetry-remain stable, indicating that these features are inherent attributes of insurance stocks rather than temporary phenomena caused by exogenous shocks.

6. Conclusion and Recommendations

This study empirically analyzes the volatility characteristics of five major Chinese insurance stocks in the post-pandemic period using three GARCH-type models-GARCH, EGARCH, and GJR-GARCH-combined with the Student's t-distribution and the skewed Student's t-distribution. The findings reveal that returns of all insurance stocks display pronounced leptokurtosis, fat-tailed behavior, positive skewness, and deviation from normality, accompanied by notable volatility clustering and persistent effects. Among them, China Life Insurance shows the strongest volatility persistence, while Ping An Insurance displays the lowest, reflecting the impact of business structure differences on risk transmission. In terms of asymmetry, PICC Group and New China Insurance demonstrate clear leverage effects, with negative shocks

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causing greater volatility increases, whereas China Pacific Insurance exhibits relatively symmetric volatility responses. The EGARCH specification combined with the skewed t-distribution attains superior goodness-of-fit across most firms, whereas the GJR-GARCH model yields the most accurate out-of-sample forecasts for China Pacific Insurance and Ping An Insurance, highlighting its enhanced capability in modeling adverse volatility movements. Robustness checks further confirm that negative pandemic policy events significantly amplify volatility, but the persistence and asymmetry of volatility are inherent and stable traits rather than temporary effects of exogenous shocks.

Based on these findings, the following recommendations are proposed。Regulatory authorities should enhance dynamic monitoring and risk early warning mechanisms for insurance stocks with high persistence and pronounced leverage effects, and encourage insurers to optimize capital structure and duration management to improve resilience under extreme conditions. Investors should adopt differentiated allocation strategies based on company-specific volatility patterns, controlling positions in stocks with high volatility and significant leverage effects, while moderately increasing investments in companies with stable volatility and lower forecasting errors. Insurance companies should promote business diversification and integrated financial operations to reduce single-risk exposures, while incorporating more advanced risk models to improve volatility forecasting and management capabilities.

References

[1] International Association of Insurance Supervisors (IAIS). (2023). Global Insurance Market Report 2023. IAIS. https://www.iais.org/2023/12/iais-global-insurance-market-report-2023-highlights-key-risks-and-trends-facing-the-global-insurance-sector/.

[2] People's Bank of China Financial Stability Analysis Group. (2023). China Financial Stability Report 2023. http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/5177895/index.html.

[3] Su, Z. D. F., Cheng, Z. S., & Wei, Y. J. (2024). Asymmetric volatility spillovers across major global financial markets under the impact of the COVID-19 pandemic. Journal of Econometrics, 4(06), 1515-1530.

[4] Babuna, P., Yang, X., Gyilbag, A., Awudi, D. A., Ngmenbelle, D., & Bian, D. (2020). The impact of Covid-19 on the insurance industry. International journal of environmental research and public health, 17(16), 5766.

[5] Baker, S. R. , Bloom, N. , Davis, S. J. , Kost, K. , & Viratyosin, T. . (2020). The unprecedented stock market reaction to covid-19. Oxford University Press Public Health Emergency Collection, 10(4), 742-758.

[6] Harjoto, M. A., & Rossi, F. (2023). Market reaction to the COVID-19 pandemic: evidence from emerging markets. International Journal of Emerging Markets, 18(1), 173-199.

[7] Ye, R., An, N., **e, Y., Luo, K., & Lin, Y. (2021). An empirical study on the equity performance of China's health insurance companies during the COVID-19 pandemic—based on cases of dominant listed companies. Frontiers in Public Health, 9, 663189.

[8] Choo, W.C., Muhammad, I.A., Mat, Y.A. (1999). Performance of garch models in forecasting stock market volatility. Journal of Forecasting, 18(5), 333-343.

[9] Wang, Y. (2011). Volatility analysis and forecasting of China's insurance stocks based on GARCH and CARR models. In Selected Papers of the Annual Conference of the China Insurance Institute 2011. Shaanxi Regulatory Bureau of the China Insurance Regulatory Commission, 295-301.

[10] Endri, E., Aipama, W., Razak, A., Sari, L., & Septiano, R. (2021). Stock price volatility during the COVID-19 pandemic: The GARCH model. Investment Management & Financial Innovations, 18(4), 12.

[11] Zhou, H. (2022). Analysis of The Stock Market Risk Spillover Effect of China's Insurance Industry Based on a GARCH-Copula-Covar Model. Academic Journal of Business & Management, 4(7), 57-62.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0012

[12] Nugraha, E. S., Olivia, A., Sudding, F. N. F., & Lestari, K. E. (2025). Estimation of Value at Risk for General Insurance Company Stocks Using the Garch Model. Barekeng: Jurnal Ilmu Matematika dan Terapan, 19(2), 1071-1082.

[13] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31(3), 307-327.

[14] Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the econometric society, 347-370.

[15] Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The journal of finance, 48(5), 1779-1801.

[16] Lambert, P., & Laurent, S. (2001). Modelling financial time series using GARCH-type models with a skewed student distribution for the innovations (No. UCL-Université Catholique de Louvain).

[17] Yu, X., & Xiao, K. (2024). How does Chinese stock market react to breaking news about COVID-19? Evidence from event study. Heliyon, 10(10).

[18] Kahneman, D., & Tversky, A. (1977). Intuitive prediction: Biases and corrective procedures. Judgment under Uncertainty Heuristics and Biases, 414 - 421.