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The Correlation between Returns and Volatility in China's Low Altitude Economy Stock Market

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Abstract:

Low altitude economy refers to a new economic form of integrated development of low altitude flight activities and their derivative industries. Currently, China's general aviation industry is constantly developing, the drone industry remains globally leading, emerging concepts such as flying cars are frequently emerging, and downstream application scenarios are constantly increasing. Low altitude economy has become a fertile ground. This article uses the closing price data of China's Low Altitude Economy Index, Tourism Travel Index, General Aviation Index, Drone Index, and New Energy Index from January 2015 to August 2024, and uses a multivariate dynamic conditional correlation-generalised autoregressive conditional heteroskedasticity(DCC-GARCH) model to explore the dynamic stock returns and volatility correlations between China's low altitude economy companies and tourism travel companies, general aviation companies, drone companies, and new energy companies. By studying the correlation between the returns and volatility of the low altitude economy stock market, it can reflect the correlation between the development of the low altitude economy industry and other industries. Investors can identify risks based on this, make more informed investment allocations, and also predict the development trend of the industry. The government and regulatory agencies can also formulate and adjust relevant policies based on this to promote the healthy development of the low altitude economy industry.

Keywords: Low altitude economy; stock market; conditional mean regression; volatility analysis; multivariate GARCH model.

1. Introduction

Low altitude economy refers to an economic form dominated by civil aircraft, with multi scenario low altitude flight activities such as manned, cargo, and other operations as the driving force, radiating and driving the development of related fields. In 2021, the concept of low altitude economy was first mentioned and included in national planning. In December 2023, the Central Economic Work Conference once again proposed the development of low altitude economy and listed it as a strategic emerging industry. Starting from January 1, 2024, the Interim Regulations on the Flight Management of Unmanned Aerial Vehicles issued by the Central Military Commission of the State Council will officially come into effect, which is conducive to better releasing the demand for unmanned aerial vehicle industry applications and promoting the development of low altitude economy. Under the strategic goal of vigorously promoting the construction of a modern industrial system and accelerating the development of new quality productivity, China's low altitude economy, as a representative of new quality productivity, is accelerating its takeoff and becoming a remarkable new industry engine.

This article studies China's low altitude economy industry and finds that its impact on the stock market is significant. This indicates that as an emerging industry with good economic benefits, high growth potential, and strong integration, the low altitude economy industry will also have an important impact on China's industrial structure upgrading and economic development. A deep understanding of the returns and the correlations of volatility of China's low altitude economy stock market is not only helpful for the horizontal integration of capital among various industries in our country, improving the level of the national economy and resource allocation efficiency, but also broadens investors' investment channels and provides decision-making basis for obtaining higher returns. At the same time, studying the returns and volatility correlations of China's low altitude economic stock market is of great significance for investment decision-making, capital market reform, economic structure optimization, and resource allocation in China's capital market. The research of this project will help to better understand and grasp the current situation of China's low altitude economy development, and provide theoretical basis for the policy-making and policy-making of various stakeholders.

2. Literature References

Zhang and Pan pointed out that the low altitude economy industry refers to the emerging industries associated with various low altitude aircraft in flight activities, and is an economic format that reflects the orientation of national and market demand [1]. The "Research Report on the Development of China's Low altitude Economy" released by the CCID Research Institute of the Ministry of Industry and Information Technology on April 1, 2024, pointed out that the low altitude economy mainly includes four links: low altitude infrastructure, low altitude aircraft manufacturing, low altitude operation services, and low altitude flight support. Liu and Ma conducted a statistical analysis of the industrial scale, and the data showed that from 2017 to 2023, the scale of China's low altitude economy industry increased from over 190 billion yuan to over 500 billion yuan. It is expected to exceed one trillion yuan in 2026 and reach 2 trillion yuan in 2030, with an average compound annual growth rate of about 20%, which is a very rapid growth [2]. Therefore, studying the correlation between the returns and volatility of China's low altitude economy stock market is of great significance for investors' investment decisions and the optimization of economic structure.

Liang proposed that with the advancement of technology and the upgrading of people's consumption concepts, low altitude tourism, as an emerging form of tourism, is gradually entering the public eye. There are various forms of low altitude tourism, including helicopter tours, powered paragliding, hot air balloon rides, etc. These experiences provide tourists with unique perspectives and new ways of travel [3]. Zhang proposed that low altitude economy plus tourism is flourishing in many parts of the country. Whether it is drone photography or new projects such as helicopter tours and powered paragliding launched by major scenic spots across the country, low altitude economy is bringing new perspectives to the cultural and tourism industry and tourists who dare to try new things [4]. In the "Opinions on Promoting the High Quality Development of Service Consumption" issued by the State Council, it is explicitly proposed to promote the integrated development of business travel, culture, sports and health, enhance project experience and interactivity, and encourage the development of new formats including low altitude flights. Based on the above literature, the returns of China's low altitude economy stock market may be closely related to the returns of tourism and travel stocks.

Zhou defines low altitude economy as the emerging industry associated with various low altitude aircraft in flight activities, with transportation systems driven by multiple scenarios such as manned, cargo, and other operations as the core content. It consists of low altitude transport equipment (aircraft), air ground infrastructure (airports, routes, etc.), integrated management equipment and service systems for air and ground [5], and is similar to general aviation facilities. Zhu proposed that general airports are key infrastructure for general aviation, providing important support for the development of low altitude economy [6]. Tian pointed out that the low altitude economy is a new economic form formed by integrating advanced manufacturing, research and development design, operation services and other industries based on the general aviation industry [7]. Song and Xu pointed out that as a new economic model, the low altitude economy is dominated by high-tech, efficient operation, and high-quality development, which are the core characteristics of new quality productivity. It fully utilizes low altitude airspace resources and covers multiple fields such as aviation manufacturing, aviation transportation, general aviation, and aviation technology, demonstrating enormous market potential and development prospects [8]. In the State Council Executive Meeting, it was clearly stated that low altitude opening should be expanded, participation in the construction of general airports should be encouraged, and the economic development of the general aviation industry should be promoted, indicating the important role of low altitude opening in the development of the general aviation industry.

Guo et al. pointed out that the drone industry has become the dominant industry in the low altitude economy. Because the drone industry is a highly growing and innovative industry that can effectively drive the rapid development of other related industries [9]. Tian pointed out that drones are a typical form of low altitude economy, and the drone industry is currently in a rapid development stage, with the market size constantly expanding, technology constantly advancing, and application fields becoming increasingly widespread [10]. Hou proposed that the development of drones has not only brought many conveniences to human society, but also spawned a new economic field with enormous potential - the low altitude economy. There is a close interdependence between the development of drones and the rise of the low altitude economy [11].

Qiao mentioned that electric vertical takeoff and landing aircraft(eVTOL) is a new concept in the low altitude economy. It hopes to use aviation electrification to achieve a new type of transportation format that is vertical takeoff and landing, highly environmentally friendly, and intelligent [12]. Zhang et al. used a time-varying parameter stochastic volatility vector autoregression model to examine the interactive relationship between the stock prices of Chinese new energy companies, high-tech companies, and fossil fuel companies. The results showed that the stock prices of new energy companies were highly correlated with those of high-tech companies, and higher than those of coal and oil companies [13]. Uddin et al. analyzed the correlation and dependence between the returns of renewable energy stocks and other asset returns using a cross quantification graph method [14]. Niu used the time-dependent intrinsic correlation method to report the time-varying correlation between renewable energy stock prices and technology company stock prices [15].

Xiong et al. used three multivariate GARCH models (CCC-GARCH, DCC-GARCH, and ADCC-GARCH) to explore the dynamic stock returns and volatility correlations between Chinese new energy companies and airlines, pharmaceutical and health companies, agricultural companies, and non-ferrous metal companies [16]. Godfred et al. examine the co-movement and time-varying integration between equity, exchange rate, and international market volatility indices across different time–frequency domains using - bi-partial wavelet, - supplemented by DCC-GARCH, and BEKK GARCH model for selected African countries. The findings indicate that the co-movement between equity and exchange rates during the pandemic was exacerbated by global COVID-19 media coverage [17].

3. Methodology and Data

3.1 Methodology

In order to understand the dynamic interdependence between asset returns and volatility, this paper uses the DCC-GARCH model to analyze the dynamic correlation between the stock prices of Chinese low altitude economy companies and tourism companies, general aviation companies, drone companies, and new energy companies. The modeling steps of DCC-GARCH model can be roughly divided into three steps: Step 1, establish a conditional mean equation to extract residuals; Step 2: Verify whether there is autoregressive conditional heteroscedasticity (ARCH) effect in the residuals and standardize the residuals; Step 3, establish a DCC-GARCH model for the obtained residual sequence. There are two main methods for setting the DCC-GARCH conditional mean equation: (1) establishing autoregressive moving average (ARMA) models for each asset's time series separately; (2) Use vector autoregression (VAR) model to model multiple asset time series. The advantage of VAR model is that it abandons the causal relationship of economic significance and simply seeks the causal relationship between variables from a statistical perspective. In addition, it can also analyze whether there is mean spillover effect between assets based on the significance level of VAR model estimated parameters. Therefore, this article adopts the VAR model proposed by Sims [18] to establish the conditional mean equation.

Assuming that r_t is an $n \times 1$ dimensional asset logarithmic return time series, the conditional mean equation can be described as

$$r_t = \theta_0 + \sum_{i=1}^{p} \theta_i r_{t-i} + \epsilon_t \qquad \epsilon_t \setminus \Omega_{t-1} N\left(0, H_t\right) \tag{1}$$

In the equation: θ_0 is a constant vector; p is the optimal lag length selected based on information standards; θ_i represents an $n \times n$ dimensional coefficient matrix; ϵ_t is the residual term, and $\epsilon_t = H_t^{1/2} e_t$, where H_t is the conditional covariance matrix and e_t represents the $n \times 1$ dimensional independent and identically distributed error vector; Ω_{t-1} is the information set before the t-th period.

The DCC-GARCH model proposed by Engle [19] relaxes the assumption of constant conditional correlation, and the conditional covariance matrix H_t can be expressed as

$$H_t = D_t R_t D_t \tag{2}$$

In the equation, R_t is the matrix of dynamic conditional correlation coefficients, and

$$R_t = diag\left(Q_t\right)^{-\frac{1}{2}} Q_t diag\left(Q_t\right)^{-1/2} \tag{3}$$

$$Q_t = q_{ij,t} = (1-a-b)Q + a\mu_{t-1}\mu_{t-1}' + bQ_{t-1} \tag{4}$$

$$q_{ij,t} = (1-a-b)\bar{q}_{ij} + a\mu_{t-1}\mu_{t-1}' + bq_{ij,t-1} \tag{5}$$

In the equation: a and b are non negative impact and persistence parameters, satisfying $a+b<1$, and $a>0$, $b>0$; Q_t, $\bar{Q}$ and $\bar{q}_{ij}$ are all $n \times n$ dimensional positive definite matrices, Q_t is the conditional normalized residual matrix, and $\bar{Q}$ and $\bar{q}_{ij}$ are the covariance matrices of the conditional normalized residuals; μ_{t-1} is a standardized residual vector. Therefore, R_t changes over time.

Therefore, under the DCC-GARCH model framework, the dynamic correlation coefficient $r_{ij,t}$ between different asset returns can be expressed as

$$r_{ij,t} = \frac{q_{ii,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{6}$$

The parameter estimation of this model can be obtained by maximizing the following logarithmic likelihood function:

$$L = \frac{1}{2} \sum\nolimits_{t=1}^{T} (nln\left(2\pi\right)) + 2ln\left|D_t\right| + ln\left|R_t\right| + \mu_t R_t^{-1} \mu_t' \tag{7}$$

3.2 Data

The sample data used in this article includes the Low Altitude Economy Index (LAE), Tourism Travel Index (LY), General Aviation Index, Drone Index (WRJ), and New Energy Index (XNY), and the daily closing prices (denoted as P) of these five indices are taken as the research objects. All data is sourced from the Wind database. Our study covers a time range of 2352 trading days from January 1, 2015 to August 30, 2024. For estimation purposes, we convert all indices to natural logarithms. Figure 1 shows the time trend of the daily closing prices of five indices. We found that the trends of the five indices are very similar.

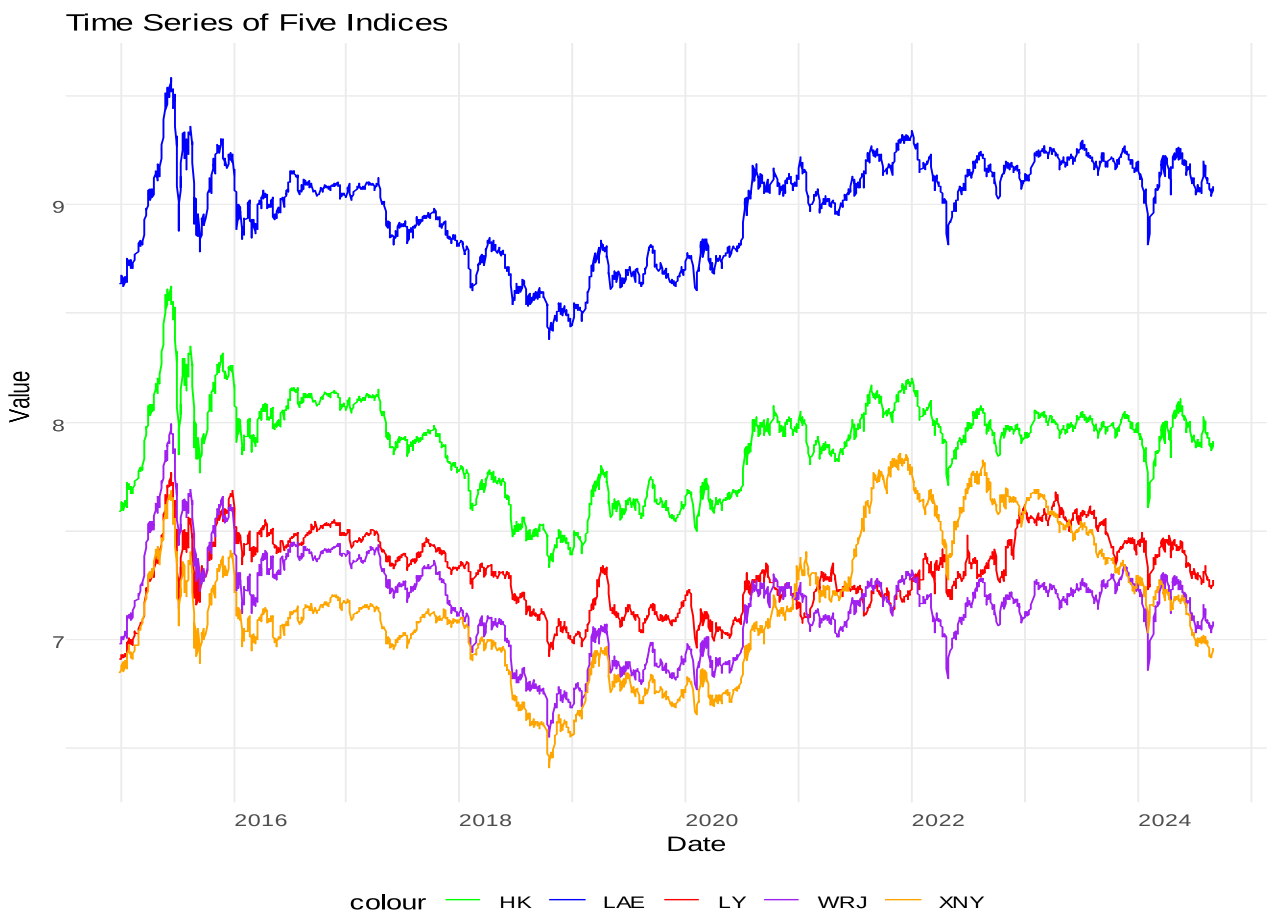

Fig. 1 Daily closing price trend of five indices

We performed first-order differencing on 5 closing price data and obtained 5 sets of daily return data. Figure 2 shows the time trend of daily returns for five indices. We observed that the daily return sequences of the five class indices all experienced significant volatility clustering in the third quarter of 2015.

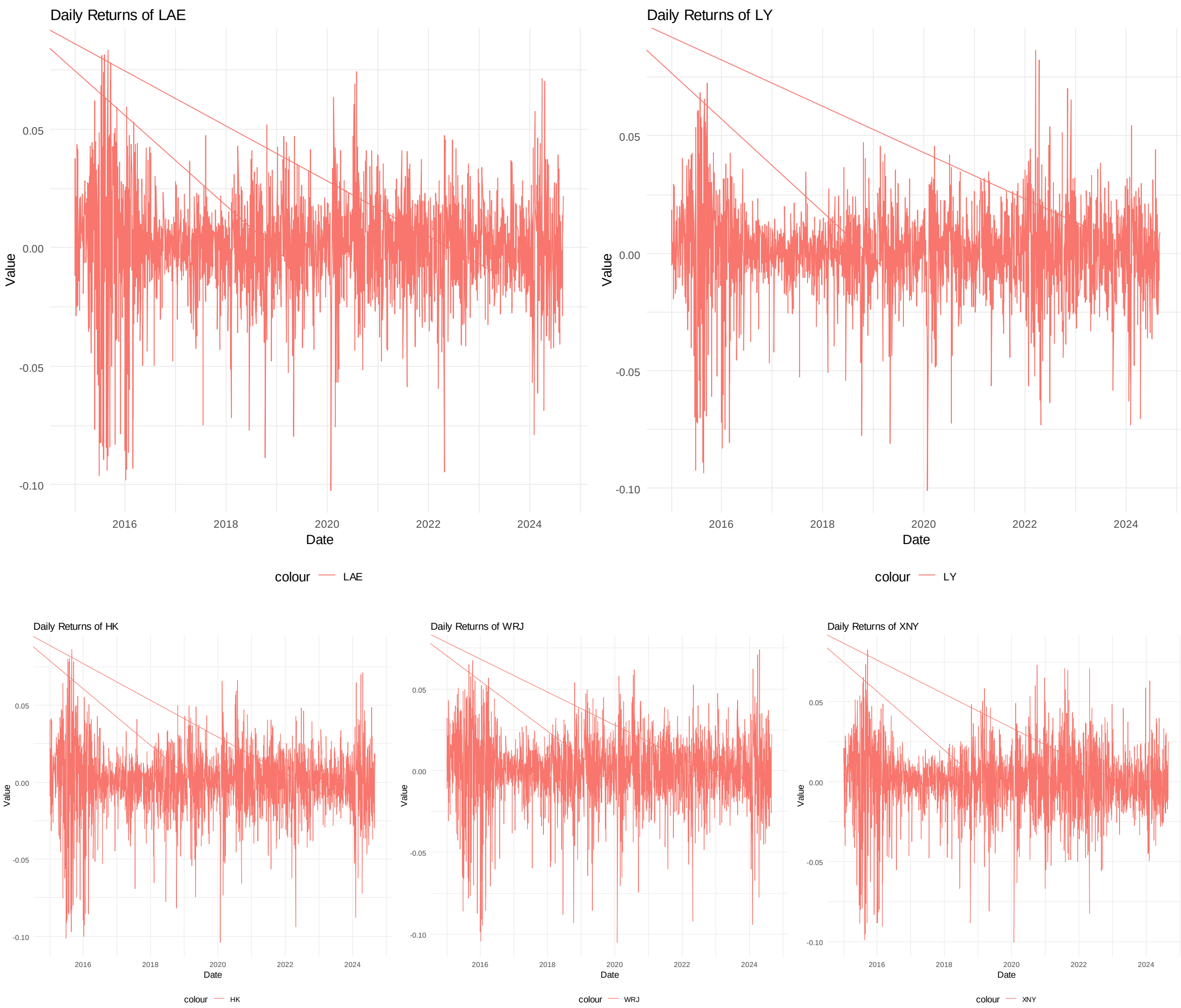

Fig. 2 Time trend of daily returns for five indices

Table 1 summarizes the descriptive statistics of daily returns for five indices. It can be seen that the average return rate of the low altitude economy index and tourism travel index is the highest, reaching 0.02%, while the average return rate of other indices is 0.01% or below. Among them, white (p) is the P-value after White's test, which also indicates that all five indices are stable.

Table 1. Descriptive Statistical Results

	LAE	LY	HK	WRJ	XNY
Mean	0.0002	0.0002	0.0001	0.0000	0.0000
Median	0.0010	0.0007	0.0009	0.0008	0.0008
Maximum	0.0834	0.0865	0.0862	0.0741	0.0826
Minimum	-0.1024	-0.1011	-0.1039	-0.1051	-0.1005
Std. Dev.	0.0216	0.0186	0.0211	0.0204	0.0203
Skewness	-0.6638	-0.6241	-0.7598	-0.7969	-0.5925
Kurtosis	3.3868	3.7581	3.9007	3.2831	3.1814
White(p)	0.0960	0.2950	0.1374	0.0531	0.5753

4. Empirical result

4.1 Analysis of Conditional Mean Equation

Table 2 shows the estimated coefficients of the conditional mean equation. The results indicate that the return of the XNY index lagged by one period has a positive impact on the current return of the LAE index, and is significant at the 5% level. This may be because the industries or company types represented by these two indices have a certain degree of similarity, and are jointly influenced by certain factors in the market, resulting in similar trends in returns. From Table 2, it is also found that the lagged return of the LAE index by one period has a negative impact on the current returns of other indices, but it is not statistically significant.

Table 2. Estimation coefficients of conditional mean equation

Index	$\beta_{LAE,t-1}$	$\beta_{LY,t-1}$	$\beta_{HK,t-1}$	$\beta_{WRJ,t-1}$	$\beta_{XNY,t-1}$	c
LAE	-0.0402	0.0208	0.1479	-0.0917	0.0842**	0.1427
LY	-0.0579	0.0433	0.2159**	-0.1213**	0.0030	0.0738
HK	-0.1017	0.0155	0.2365**	-0.1034	0.0827**	0.0738
WRJ	-0.1044	0.0019	0.1291	0.0075	0.0694	0.0314
XNY	-0.0394	-0.0137	0.0840	-0.0471	0.0728**	0.0002

Note: $\beta_{LAE,t-1}$ represents the estimated coefficient of the return lagged by one period of the LAE index; $\beta_{LY,t-1}$ represents the estimated coefficient of the return of LY index lagged by one period; $\beta_{HK,t-1}$ represents the estimated coefficient of the lagged return of the HK index for one period; $\beta_{WRJ,t-1}$ represents the estimated coefficient of the return lagged by one period of the WRJ index; $\beta_{XNY,t-1}$ represents the estimated coefficient of the return of the XNY index lagged by one period, and c represents the constant term. ** means Significant at the 5% significance level.

4.2 Analysis of Multivariate DCC-GARCH Model

Table 3 shows the estimation results of the DCC-GARCH model based on the VAR model. The results indicate that, except for HK, the daily return sequences of the other four indices exhibit ARCH effects at the 1% significance level, and the five indices exhibit GARCH effects at the 1% significance level. The significance of α and β further confirms the clustering characteristics of asset return volatility observed in Figure 2. We can also find that the alpha and beta of all asset returns are less than 1, indicating that the fluctuation process of all index returns is mean regression, that is, the fluctuation of returns will return to their average level. When the yield deviates significantly from the average level, the long-term GARCH effect will play a moderating role, gradually returning the volatility of the yield to the average level. This mean regression characteristic may reflect a feedback mechanism in the market, where high volatility of returns helps to compress the volatility of returns back to the mean, while low volatility of returns promotes increased volatility of returns. If α is less than β, it indicates that the GARCH effect plays a greater role than the short-term ARCH effect. Specifically, α represents short-term effects, while β represents long-term effects. If α is small, it indicates that the current volatility of returns is relatively less affected by past volatility of returns, and the contribution of short-term volatility of returns to overall volatility is relatively small. If β is large, it indicates that the volatility of long-term returns contributes more significantly to the overall volatility of returns, and the long-term trend plays a dominant role in the volatility of returns. We observed that the $\beta^{(1)}$ parameter of all sequences is significantly greater than 0 and close to 1, indicating that past volatility has a strong impact on current volatility. Therefore, LAE, LY, WRJ, and XNY all have long-term persistence, with WRJ showing greater long-term persistence.

Table 3. Estimation Results of DCC-GARCH Model

Variable parameters	$\beta^{(1)}$	$sd^{(2)}$	$t^{(3)}$	$p^{(4)}$
ω_{LAE}	0.0000	0.0000	1.6472	0.0995

α_{LAE}	0.0733	0.0167	4.3782	0.0000
β_{LAE}	0.9066	0.0106	85.1767	0.0000
γ_{LAE}	0.0000	0.0004	0.0371	0.9704
ω_{LY}	0.0000	0.0000	1.7414	0.0816
α_{LY}	0.1132	0.0239	4.7422	0.0000
β_{LY}	0.8598	0.0222	38.7857	0.0000
γ_{LY}	0.0002	0.0003	0.5518	0.5811
ω_{HK}	0.0000	0.0000	0.1414	0.8876
α_{HK}	0.0693	0.0795	0.8710	0.3837
β_{HK}	0.9145	0.0783	11.6849	0.0000
γ_{HK}	-0.0001	0.0004	-0.1948	0.8455
ω_{WRJ}	0.0000	0.0000	0.3860	0.6995
α_{WRJ}	0.0582	0.0141	4.1202	0.0000
β_{WRJ}	0.9290	0.0294	31.5840	0.0000
γ_{WRJ}	-0.0002	0.0004	-0.4237	0.6718
ω_{XNY}	0.0000	0.0000	0.4380	0.6614
α_{XNY}	0.0727	0.0155	4.6940	0.0000
β_{XNY}	0.9133	0.0346	26.4313	0.0000
γ_{XNY}	-0.0002	0.0004	-0.6180	0.5366
θ_1	0.0222	0.0031	7.1777	0.0000
θ_2	0.9746	0.0040	241.5163	0.0000

Note: (1) represents the estimated coefficient; (2) Representing Std Error; (3) Representing the t-statistic; (4) Indicate the p-value of the test. The DCC-GARCH model satisfies the stability condition: $\alpha+\frac{\gamma}{2}+\beta<1$.

From the estimation results of the DCC-GARCH model, it can be seen that the estimation coefficients θ_1 and θ_2 are significantly positive at the 1% level, and $\theta_1+\theta_2<1$. This indicates that the dynamic conditional correlation of the model estimation is mean regression, that is, the correlation between asset return series tends to be balanced after a period of time. The estimated value of θ_1 is 0.0222, indicating that the impact of new information on correlation is relatively small. The estimated value of θ_2 is 0.9746, indicating a strong long-term correlation between sequences.

Tables 4 and 5 present the diagnostic test results for univariate and multivariate standardized residuals, respectively. The results indicate that there is no sequence correlation or heteroscedasticity in the residual terms estimated by the DCC-GARCH model, which further confirms the effectiveness of the dynamic conditional correlation shown in Figure 3.

Table 4. Standardized univariate residual diagnostic test

Index	$Q(20)r$	P
LAE	24.8940	0.2055
LY	39.5520	0.0569

HK	27.7650	0.1151
WRJ	28.5740	0.0965
XNY	22.2090	0.3293

Note: $Q(20)r$ represents the statistical measure used in Box and Pierce's univariate Portmanteau test method; P represents the probability of the observed statistic appearing.

Table 5. Standardized Univariate Residual Diagnostic Test

lags	statistic	df	p-value
5	134.4263	125	0.2664

Note: Hosking's multivariate Portmanteau test method is used.

From the dynamic conditional correlation shown in Figure 3, it can be seen that in the DCC-GARCH model, the dynamic conditional correlation coefficient between LAE and LY is between 0.0670 and 0.9121, and the two have been positively correlated throughout the sample period. The mean dynamic conditional correlation coefficient during the sample period was 0.6333, and reached its peak from the first quarter of 2016 to the first quarter of 2017, followed by a downward trend. This means that before 2020, when the stock returns of China's low altitude economy rose, the stock returns of Chinese tourism companies often also rose, and vice versa. This positive correlation may reflect common economic factors or market influences between two industries. However, after 2020, their correlation coefficients significantly decreased, indicating that the correlation between the two indices was weak during that time period, and the related stock returns no longer showed a clear positive or negative correlation. It may be that at the beginning of the COVID-19 outbreak, the impact on the two is different.

The dynamic conditional correlation coefficient between LAE and HK during the sample period is between 0.9466 and 0.9929, with a mean of 0.9789. The correlation coefficient between the two has remained at a very high level, which means that there is a strong correlation between the two indices during this time period, and the related stock returns show a clear positive or negative correlation. This means that when the stock returns of China's low altitude economy rise, the stock returns of China General Airlines often also rise, and vice versa. This strong positive correlation may reflect common economic factors or market influences between the two industries. This also means that the low altitude economy sector in China is highly overlapping with companies within the general aviation sector, which verifies Zhu and Tian's viewpoint that the relationship between low altitude economy and general aviation is inseparable.

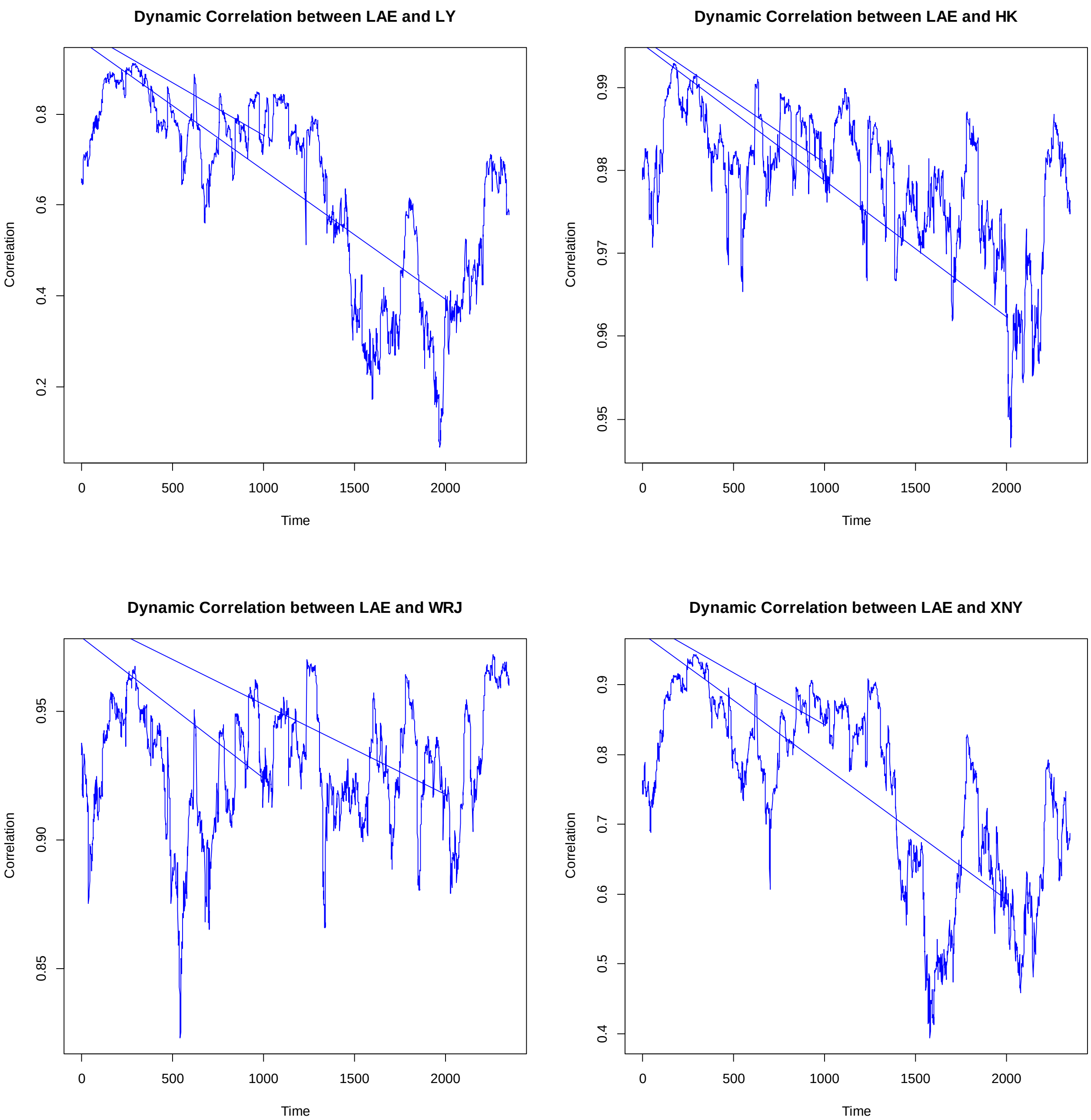

Fig. 3 Dynamic conditional correlations between LAE and LY, HK, WRJ, XNY

Similarly, the dynamic conditional correlation coefficient between LAE and WRJ during the sample period was between 0.8229 and 0.9723, with a mean of 0.9291, and the correlation coefficient between the two remained at a very high level. It may also mean that the low altitude economy sector in China is highly overlapping with companies within the drone sector, which verifies the close mutual influence between the development of drones and the rise of the low altitude economy mentioned by Hou. Therefore, investors can consider the overall financial performance of China General Airlines and drone companies as an extremely important indicator for predicting the stock price returns of China's low altitude economy companies.

The dynamic conditional correlation coefficient between LAE and XNY during the sample period is between 0.3934 and 0.9438, with a mean of 0.7503. The correlation coefficient between the two is also high, but shows a large amplitude. This means that when the stock returns of Chinese low altitude economic companies rise, the stock returns of Chinese new energy companies often also rise, and vice versa. This positive correlation may reflect the existence of common economic factors, industry factors, or market influences between the two types of companies. During the sample period, the average correlation between the two was relatively high. This higher average conditional correlation coefficient further supports the observation of a stable positive correlation between them. Therefore, investors can also consider using the overall financial performance of Chinese new energy companies as an indicator to predict the stock price returns of Chinese low altitude economy companies, but there is no close relationship between general aviation, drone companies, and low altitude economy companies.

5. Conclusion

This article uses a multivariate DCC-GARCH model to study the dynamic stock returns and their volatility correlations between Chinese low altitude economy companies and tourism travel companies, general aviation companies, drone companies, and new energy companies. The following conclusions are drawn:

Firstly, the estimation results of the conditional mean equation show that the lagged stock returns of new energy companies by one period significantly affect the current stock returns of low altitude economic companies. However, statistically speaking, we did not find that the lagged stock returns of low altitude economic companies by one period have an impact on the current stock returns of the other four types of companies. Secondly, the average dynamic conditional correlation coefficients estimated based on the DCC-GARCH model are 0.6333, 0.9789, 0.9291, and 0.7503, respectively. The results indicate that the conditional correlation between the stock returns of Chinese low altitude economy companies and general aviation companies during the sample period is the highest, followed by drone companies, new energy companies, and tourism companies. Thirdly, the model estimation results of DCC-GARCH show that the stock returns of Chinese low altitude economy companies during the sample period are positively correlated with the stock returns of tourism companies, general aviation companies, drone companies, and new energy companies.

The research findings of this article can provide important information about China's low altitude economy stock market for investors, financial institutions, and policy makers to help optimize investment portfolios, manage risks, and develop corresponding investment strategies. At the same time, government departments and regulatory agencies can also draw on the research results of this article to evaluate the development status and market prospects of the low altitude economy industry.

Firstly, the research findings of this article can assist investors in diversifying their investments. Investors can consider diversifying their investment portfolio, including low altitude economy companies, tourism travel companies, general aviation companies, drone companies, and new energy companies, to leverage their positive correlations to balance risk and return. For example, investors can consider combining stocks of low altitude economy companies with stocks of general aviation companies to leverage their strong conditional correlations for risk management and capture potential growth opportunities.

Secondly, policy makers can consider more fully considering the interrelationships between different industries when formulating relevant policies and development strategies. Especially the strong conditional correlation between China's low altitude economy companies and general aviation companies may indicate a certain degree of linkage and mutual influence between these two industries. Therefore, policy makers can encourage innovation and technological development in the low altitude economy sector, especially in general aviation and drone companies, through policy support and incentive measures. At the same time, close attention should be paid to the development and changes in the general aviation and drone markets in order to better predict and manage risks in the low altitude economy industry.

Thirdly, due to the conditional correlation between different industries, government departments and regulatory agencies can adopt cross industry regulatory measures and strengthen monitoring and evaluation of risk transmission and spillover effects between related industries. For example, in extreme cases, if the stock returns of tourism companies have a weak negative impact on low altitude economy companies, policy makers can closely monitor potential risk contagion issues between the two industries and take appropriate regulatory measures to reduce systemic risks.

In addition, in response to the potential impact of other industries, particularly general aviation and drones, on the development of the low altitude economy industry, policy makers may consider providing innovative policy support to promote cooperation between low altitude economy companies and industries such as tourism, general aviation, drones, and new energy, in order to achieve synergies and economic growth. It is also possible to accelerate the development and commercial application of low altitude economy related technologies by encouraging cross industry cooperation and knowledge sharing, such as investing in related infrastructure construction, such as drone flight corridors, low altitude economy demonstration zones, etc., to support industry expansion and promote the coordinated growth of the entire industry chain.

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