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Discover the Impact by COVID-19 Pandemic on Biopharmaceutical Index and Its Related Industry Portfolio

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Abstract: This research is trying to explore the changes in biopharmaceutical and other medically related indices under the impact of the pandemic, and how pharmacy related portfolio impact by the pandemic. The research utilizes EGARCH and VAR models to analyze the volatility of the biopharmaceutical index and the dynamic relationships among various related indices. The research mainly demonstrates the changes in risk of the biopharmaceutical index before and during the pandemic, providing a certain degree of alert to investors who are interested in investing in biopharmaceutical-related stocks but are relatively risk-averse. It also explores the impact of the biopharmaceutical index on other pharmaceutical-related indices, verifying its influence on other indices and whether it has predictive capabilities. Finally, by comparing the portfolios constructed using the biopharmaceutical index and its related industry indices before and during the pandemic, it provides recommendations for investors interested in investing in pharmaceutical stocks during large-scale health events.

Keywords: COVID-19, Biopharmaceutical index, EGARCH model, VAR model, Portfolio

1. Introduction

1.1. Research background and Motivation

Influenced by the COVID-19 pandemic, the Chinese stock market experienced significant volatility during this period, particularly in the medical-related industries which were specially affected by the pandemic. Consequently, many investors sought to profit from investing in medical-related stocks during this wave of the pandemic. However, many overlooked the potential issues behind the sharp rise in some medical stocks.

1.2. Literature Review

Some researchers have also conducted studies on the impact of the pandemic on stocks. Some of them focus on the short-term effects of the pandemic on stock returns. By establishing regression models, they have found that the pandemic has a negative correlation with stock returns and a positive correlation with stock volatility [1]. Other researchers have explored the impact of the pandemic on the interdependence and risk spillover effects in the stock markets of China, Europe, the US, and

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Hong Kong, using models such as DCC-GARCH, MS, BEKK and MSGARCH-EVT-Copula for analysis [2-4]. And some also focus on empirical study of volatility leverage effect and contagion [5]. Additionally, some researchers have studied the influence of investors' sentiment and decisions in the context of the COVID-19 pandemic on stock market returns, including analyzed the mechanism of the impact of the COVID-19 pandemic on the Chinese stock market, the causal relationship between emotions and stock index returns, shock effects, and contribution levels [6,7]. Other researchers have also investigated the interconnectivity among stock markets, bond markets, and currency markets during the pandemic, using VAR models to explore their dynamic relationships [8].

2. Methodology

2.1. Model Establish

2.1.1. GARCH and EGARCH Model

GARCH model using the mean equation (1) and conditional variance equation (2) to model the variable's mean and its volatility. Normal GARCH (1,1) model:

$$y_t = x_t^{'}\gamma + \mu_t, \ \ t = 1,2, \dots, T \tag{1}$$

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

EGARACH model have difference in its residual's distribution, it chooses generalized error distribution rather than normal distribution, making the conditional variance (3) have a more flexible mapping relation than the previous equation [9].

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

2.1.2. VAR Model

The VAR model is suitable for analyzing dynamic relationship among multiple variables, it uses the linear relationship between the past value to indicate how each variable influence others (4) . The mathematical expression of a VAR(p) model:

$$y_t = \Phi_1 y_{t-1} + \cdots + \Phi_P y_{t-p} + Hx_t + \varepsilon_t, \ \ t = 1, \dots, T \tag{4}$$

2.2. Data Origin and Processing

The data in this research is sourced from Choice Financial Terminal. The main subject is the weekly data of biopharmaceutical index between July 6, 2012, to February 2, 2024. In the portfolio the subject including the weekly data of pharmaceutical service, pharmaceutical equipment, and chemical raw material index between July 6, 2012, to February 2, 2024. But due to the pandemic, the research divided the data in to three parts, which is the data before pandemic corresponding to the data between July 6, 2012, to November 29, 2019, the data during the pandemic related to the data between November 29, 2019to January 6, 2023, and the data after pandemic which only use in aggregate analysis.

For the GARCH and VAR part, the data needs to be a white noise series, which means that it must be normal distribution and zero variance. The research uses the Augmented Dickey-Fuller (ADF) Test to verify the stability of the series. Before testing the series, this paper first logs the data to reduce the range and stabilize the variance, then use the ADF test to exam each logarithm data series. This

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research wants to examine the relationship between different index returns. According to the formula (5).

$$r = ln\left(\frac{P_{t_0}}{P_{t_0-1}}\right) = ln(P_{t_0}) - ln(P_{t_0-1}) \tag{5}$$

It can find out that the log return series is coincident with the log price series after difference operation. The research uses the closing price to establish the price series, and the closing price series after log and difference operation represents the index's return.

3. Empirical Result Analysis

3.1. GARCH Model Result Analysis

During the pandemic most investors might have a positive prospective towards pharmaceutical stocks, thinking that those pharmacy companies may have earn profit and incentive their stock price to rise. But is investing pharmaceutical stocks a wise choose for rational investors? This research using GARCH to model the risk of the biopharmaceutical index to find out answer.

The research use ADF test to check out whether the series of the return of biopharmaceutical index (RPHAR) is stable.

Table 1: RPHAR's ADF test results

Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-22.39282	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

The P-value in table 1 is less than the critical value, so the series RPHAR is a white noise series. Establishing the ACF and PACF to confirm the lags of biopharmaceutical index series.

Table 2: ACF and PACF results

Lag	AC	PAC	Q-Stat	Prob
1	0.069	0.069	2.8290	0.093
2	0.017	0.012	2.9992	0.223
3	-0.002	-0.004	3.0012	0.391
4	0.017	0.017	3.1741	0.529
5	-0.078	-0.080	6.7786	0.238
6	-0.024	-0.014	7.1342	0.309
7	-0.005	0.000	7.1484	0.414
8	0.043	0.044	8.2866	0.406
9	0.083	0.082	12.480	0.188
10	-0.002	-0.020	12.484	0.254
11	-0.030	-0.035	13.042	0.291
12	-0.051	-0.050	14.617	0.263

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Table 2: (continued).

13	-0.085	-0.077	18.997	0.123
14	-0.058	-0.032	21.072	0.100
15	-0.066	-0.055	23.716	0.070
16	0.005	0.010	23.729	0.096
17	-0.029	-0.040	24.239	0.113
18	0.034	0.020	24.945	0.126
19	0.009	0.004	24.996	0.161
20	0.029	0.025	25.529	0.182

According to table 2, it can't determine the lags that the series is related. Furthermore, this paper builds the mean equation for the GARCH model. The results are shown in table 3.

Table 3: The results of experimental mean equation

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	0.001220	0.001523	0.800488	0.4238
AR (1)	0.520323	0.194357	2.677154	0.0076
AR (2)	0.485272	0.282732	1.716364	0.0866
AR (3)	-0.871204	0.186023	-4.683313	0.0000
MA (1)	-0.479157	0.207029	-2.314444	0.0210
MA (2)	-0.476314	0.290191	-1.641382	0.1013
MA (3)	0.819402	0.192112	4.265244	0.0000
SIGMASQ	0.001215	5.38E-05	22.57125	0.0000

Based on the P-value in table 3, AR (2) MA (2) and the constant term are not significant, so eliminate these variables and rebuild the equation.

Table 4: The results of mean equation

Variable	Coefficient	Std.Error	t-Statistic	Prob.
AR (1)	0.838342	0.057903	14.47840	0.0000
AR (3)	-0.572711	0.059824	-9.573334	0.0000
MA (1)	-0.798474	0.067893	-11.76079	0.0000
MA (3)	0.536445	0.073746	7.274259	0.0000
SIGMASQ	0.001218	5.11E-05	23.81251	0.0000

In table 4 the P-values are significant, means that the equation is plausible. Because establishing a GARCH model requires the data series to exhibit volatility clustering, namely having ARCH effects, it is necessary to perform an Heteroskedasticity test on the mean equation's residual to make sure it have ARCH effects.

Table 5: Heteroskedasticity Test of RPHAR

F-statistic	37.42249	Prob. F (1,586)	0.0000
Obs*R-squared	35.29616	Prob. Chi_Squar (1)	0.0000

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The P-value is lower than the significant value, so it can reject the null hypothesis, means that RPHAR series have ARCH effect. Next the research uses residual normality test to ensure the residual distribution.

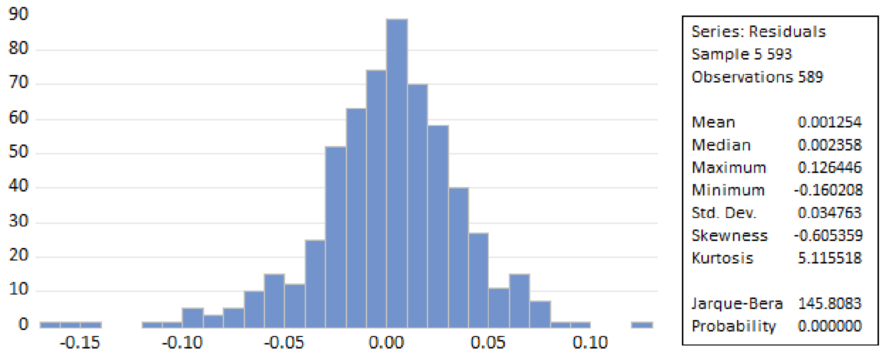


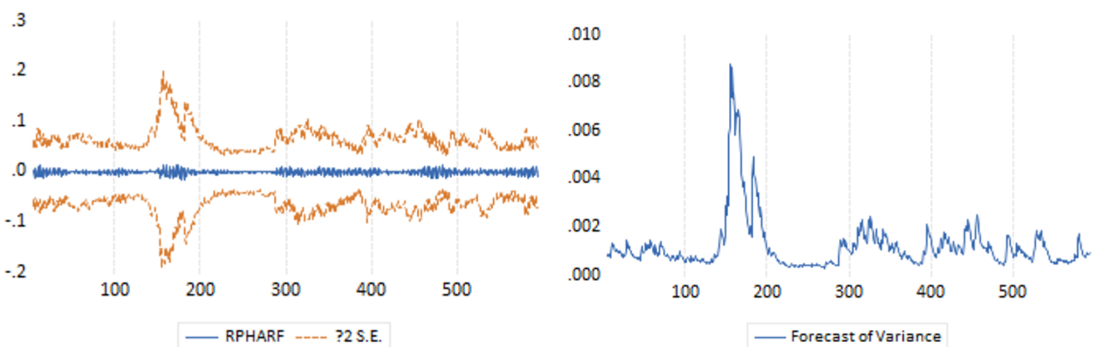
Figure 1: residual normality test

Based on the test results, the Jarque-Bera statistic for the data is very high, and the corresponding probability is close to zero, hence the residuals of the data do not follow a normal distribution. And the kurtosis is 5, which is greater than the kurtosis 3 for a normal distribution. Therefore, the residuals are more inclined towards a t-distribution or a generalized error distribution.

Using the mean equation in table 3, and choose generalized error as the residual's distribution, to build up the EGARCH (1,1) model. The results of EARCH(1,1) are shown in Table 6.

Table 6: Biopharmaceutical index EGARCH(1,1) model

Variable	Coefficient	Std.Error	z-Statistic	Prob.
AR (1)	-0.412345	0.016282	-25.32576	0.0000
AR (3)	0.762802	0.015993	47.69720	0.0000
MA (1)	0.456253	0.005977	76.33138	0.0000
MA (3)	-0.785281	0.004580	-171.4627	0.0000
Variance Equation				
C	3.82E-05	1.81E-05	2.110457	0.0348
RESID (-1) 2	0.140765	0.036041	3.905693	0.0001
GARCH (-1)	0.833005	0.037231	22.37413	0.0000
GED PARAMETER	1.724140	0.153317	11.24557	0.0000



(1) conditional mean (2) volatility outputs

Figure 2: the model's conditional mean (1) and volatility outputs (2)

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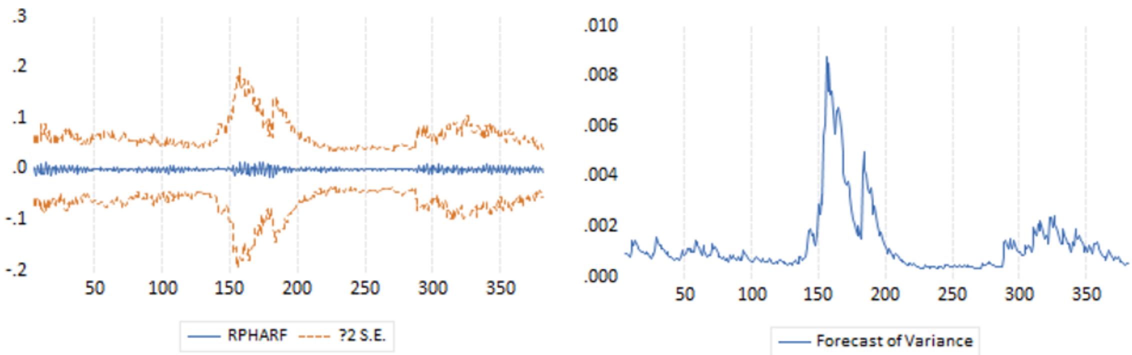
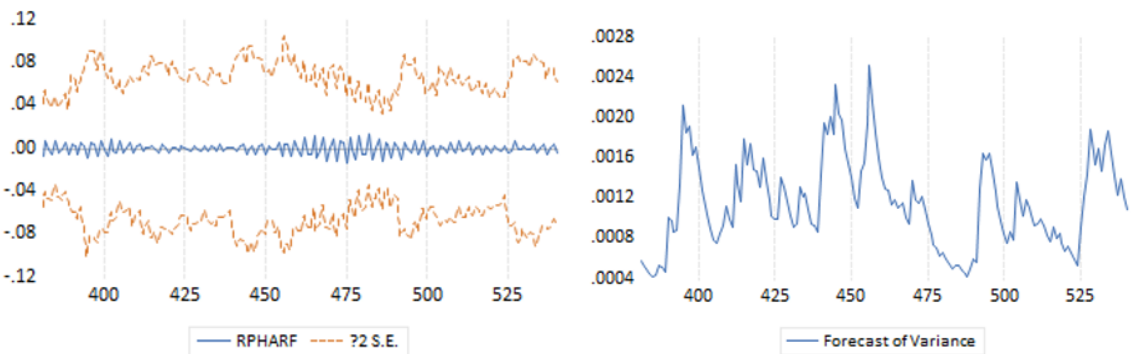
The overall average volatility in Figure 2 is about 0.0012. The pandemic started on 2019-12-1, so the dividing line will be December 6, which marks the end of the week in which December 1 falls, with the corresponding data index being 381. Therefore, the data is divided into pre-pandemic data and pandemic data. The end of the pandemic is benchmarked to the first week of January 2023, corresponding to the 540th data point. So, the paper divides the data into two parts, pre-pandemic part 1-381 data point, and pandemic part 381 to 540 data point.



(1) conditional mean (2) volatility outputs

Figure 3: the model's conditional mean (1) and volatility outputs (2) before pandemic

Figure 3 represent the output before pandemic. The average volatility in Figure 3 is about 0.0013.



(1) conditional mean (2) volatility outputs

Figure 4: the model's conditional mean (1) and volatility outputs (2) during pandemic

Figure 4 shows the result during pandemic. The average volatility in Figure 4 is about 0.0012. Despite the volatility during the pandemic is expected to be lower than pre-pandemic levels, but there is a significant increase in volatility around the 150th data point. This is because in 2015, corresponding to the data, there was a stock market crash where the overall stock market experienced sharp declines and rises [10]. The pharmaceutical stocks also saw a significant increase in volatility due to the influence of the overall market. Therefore, considering the direct impact of the overall market trends, a further analysis of the pharmaceutical index is conducted.

The research tends to build up the EGARCH model which eliminate the impact of market volatility on the volatility of the pharmaceutical index itself. This paper uses the HuShen 300 Index to represent the overall market, and name the series as hs300, the return series name as rhs300.

Using ADF to test wheatear the rhs300 series is stable.

Table 7: RHS300's ADF test

Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-23.28367	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

According to table 6, the P-value is nearly zero means that the series is stable. Establish the mean equation, which only consider the return of HuShen 300 index.

Table 8: RHS300 mean equation

Variable	Coefficient	Std.Error	t-Statistic	Prob.
RHS300	0.000229	9.19E-06	24.92734	0.0000

The equation is effective, so it can continue to test the ARCH effect and the residual normality.

Table 9: Heteroskedasticity Test of RHS300

F-statistic	19.67414	Prob.F (1,589)	0.0000
Obs*R-squared	19.10286	Prob. Chi_Square (1)	0.0000

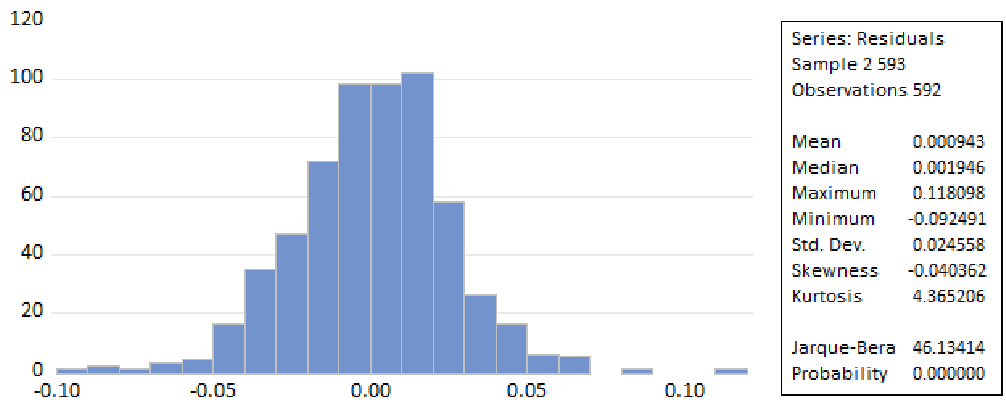


Figure 5: residual normality test

The P value means that it has ARCH effect, and according to the figure 5, it still chooses generalized error as the residual's distribution. Establish the EGARCH (1,1) model and the results are shown in table 10.

Table 10: Biopharmaceutical index EGARCH (1,1) model consider the RHS300

Variable	Coefficient	Std.Error	z-Statistic	Prob.
RHS300	0.000226	8.60E-06	26.32244	0.0000
Variance Equation				
C	3.41E-05	1.58E-05	2.160191	0.0308
RESID (-1) 2	0.158415	0.031935	4.960636	0.0000
GARCH (-1)	0.796953	0.035855	22.22734	0.0000
GED PARAMETER	1.714747	0.134987	12.70310	0.0000

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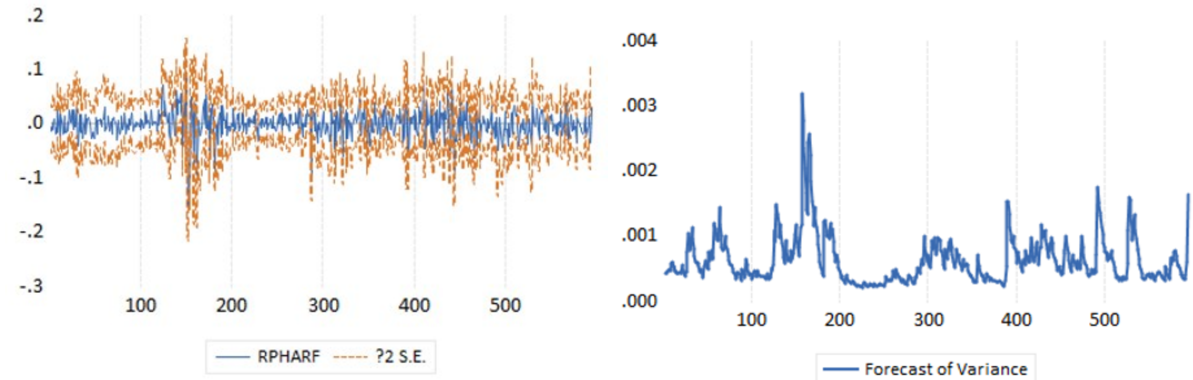
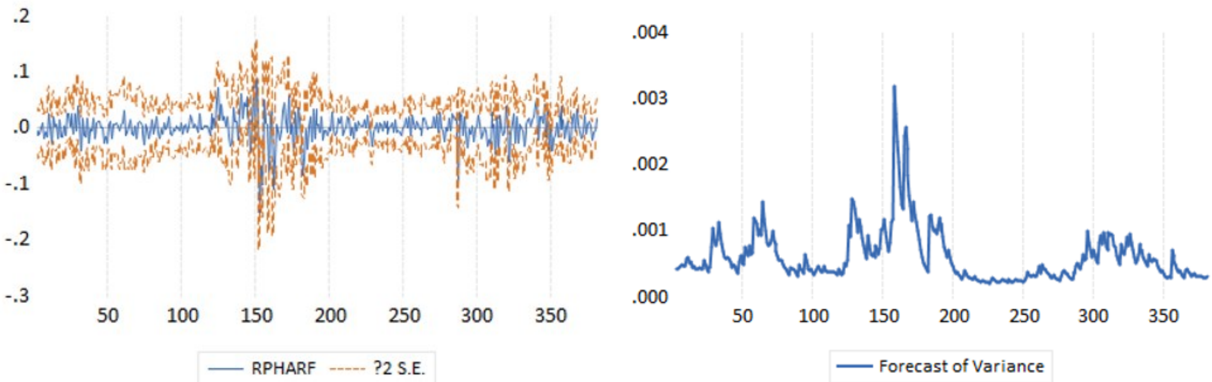


(1) conditional mean (2) volatility outputs

Figure 6: The model's conditional mean (1) and volatility outputs (2)

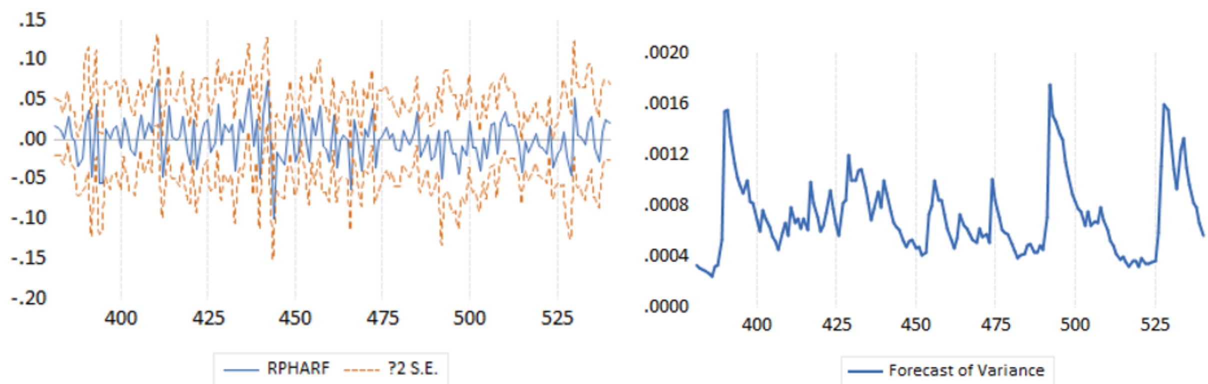
The overall average volatility in Figure 6 is about 0.0006.



(1) conditional mean (2) volatility outputs

Figure 7: The model's conditional mean (1) and volatility outputs (2) before pandemic

Figure 7 indicate the output before pandemic that after considering the HuShen 300 index. The average volatility in Figure 7 is about 0.0006.



(1) conditional mean (2) volatility outputs

Figure 8: The model's conditional mean (1) and volatility outputs (2) during pandemic

Figure 8 present the result during pandemic that after considering the HuShen 300 index. The average volatility in Figure 8 is about 0.0007.

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The model only considers the direct impact brought by the market, although around the 2015 year, there must still exist indirect effects from the market and other unaccounted-for anomalies. However, even during the 15th year when there was a notable increase in volatility in the pharmaceutical index, the volatility before the pandemic remained lower than during the pandemic. This indicates that the volatility of the biopharmaceutical index increased due to the impact of the pandemic, raising the risk of investing in biopharmaceutical stocks. Investors should not only focus on the increased revenue of various pharmaceutical companies during the pandemic, thinking they can blindly ride the wave of a major event by purchasing biopharmaceutical-related stocks. Instead, they should be more cautious in their investment choices when faced with such a situation.

3.2. VAR Model Result Analysis

For some more aggressive investors with a higher risk appetite, they aim to profit from investing in pharmaceutical-related stocks during this pandemic. This report selects the biopharmaceutical index and several related industry indices, including medical services, medical equipment, and chemical raw material. These industries are of particular interest to investors looking to profit from the pandemic. Therefore, this paper uses a VAR model to clarify the dynamic relationships among their returns, helping investors infer the approximate short-term changes in other indices based on the changes in the biopharmaceutical index return, thus increasing the likelihood of profitable investments.

After conducting the ADF test, it was found that the return series of the biopharmaceutical, medical services, medical devices, and chemical industries indices are all stationary series.

Table 11: Select the best lag for the VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	5102.084	NA	3.36e-13*	-17.36996*	-17.34015*	-17.35835*
1	5115.492	26.58832*	3.39e-13	-17.36113	-17.21207	-17.30305
2	5127.787	24.21253	3.43e-13	-17.34851	-17.08019	-17.24396
3	5136.577	17.18964	3.52e-13	-17.32394	-16.93637	-17.17292
4	5147.436	21.08976	3.58e-13	-17.30643	-16.79961	-17.10894
5	5160.375	24.95324	3.62e-13	-17.29600	-16.66993	-17.05204

According to table 10, since a VAR model requires a lag order to be established, so ignored the zero order, which is optimal according to information criteria. By comparing the information criteria values like AIC, SC and HQ for different lag orders, those values in lag one was the lowest, so it was determined that the optimal lag order is one.

Table 12: VAR Model

	RPHAR	RCHEM	RMEDEQU	RMEDSER
RPHAR (-1)	0.145679	0.148486	0.190766	0.213309
	(0.11198)	(0.13050)	(0.14418)	(0.14845)
RCHEM (-1)	-0.078903	-0.012289	-0.074345	-0.145720
	(0.05067)	(0.05905)	(0.06524)	(0.06717)
RMEDEQU (-1)	-0.061131	-0.063766	-0.087381	-0.169936
	(0.07108)	(0.08284)	(0.09152)	(0.09423)
RMEDSER (-1)	0.057953	0.077772	0.068609	0.118984
	(0.05254)	(0.06123)	(0.06765)	(0.06965)

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Table 12: (continued).

C	0.001063	0.001112	0.001641	0.002425
	(0.00145)	(0.00169)	(0.00186)	(0.00192)

Note: RPHAR: biopharmaceutical index's return RCHREM: chemical raw material index's return RMEDEQU: medical equipment index's return RMEDSER: medical services index's return

Table 12 is the VAR model which can observe the linear relationships between each variable and other variable, including their own first-order lag. For example, the linear equation of the biopharmaceutical index's return is show as:

$$RPHAR = 0.145679RPHAR(-1) - 0.078903RCHEM(-1) - 0.061131RMEDEQU + 0.057953RMEDSER + 0.001063 \tag{6}$$

Next, the paper focus on Granger causality tests and impulse response analysis. Granger causality tests help us determine whether there is a Granger causal relationship between variables, meaning whether the past values of one variable can predict the current value of another variable. On the other hand, impulse response analysis helps us understand the impact of a one-unit positive impulse in one variable on other variables.

Table 13: Granger causality tests

Dependent variable: RPHAR			
Excluded	Chi-sq	df	Prob.
RCHEM	2.424945	1	0.1194
RMEDEQU	0.739584	1	0.3898
RMEDSER	1.216693	1	0.2700
All	4.432692	3	0.2184
Dependent variable: RCHEM			
Excluded	Chisq	df	Prob.
RCHEM	1.294729	1	0.2552
RMEDEQU	0.592572	1	0.4414
RMEDSER	1.613514	1	0.2040
All	7.510340	3	0.0573
Dependent variable: RMEDEQU			
Excluded	Chi-sq	df	Prob.
RPHAR	1.750625	1	0.1858
RCHEM	1.298677	1	0.2545
RMEDSER	1.028676	1	0.3105
All	4.905283	3	0.1789
Dependent variable: RMEDSER			
Excluded	Chi-sq	df	Prob.
RPHAR	2.064612	1	0.1508
RCHEM	4.706169	1	0.0301
RMEDSER	3.252005	1	0.0713
All	8.960499	3	0.0298

According to the result of granger causality tests, there is a Granger causal relationship between medical services and medical devices, as well as between medical services and the overall dataset.

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This means that the past values of medical services have predictive power on the current values of medical devices and the overall dataset (see Table 13).

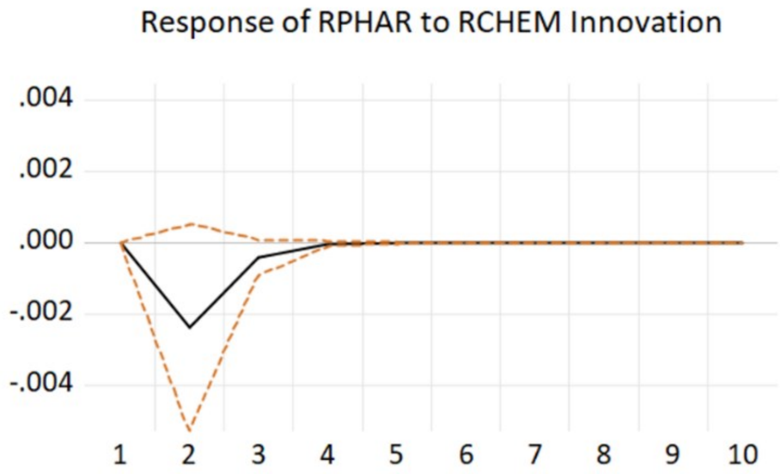

Figure 9: Response of RPHAR to RCHEM Innovation

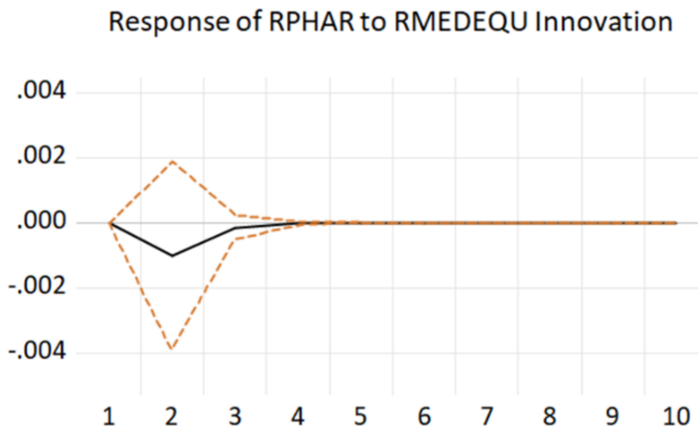

Figure 10: Response of RPHAR to RMEDEQU Innovation

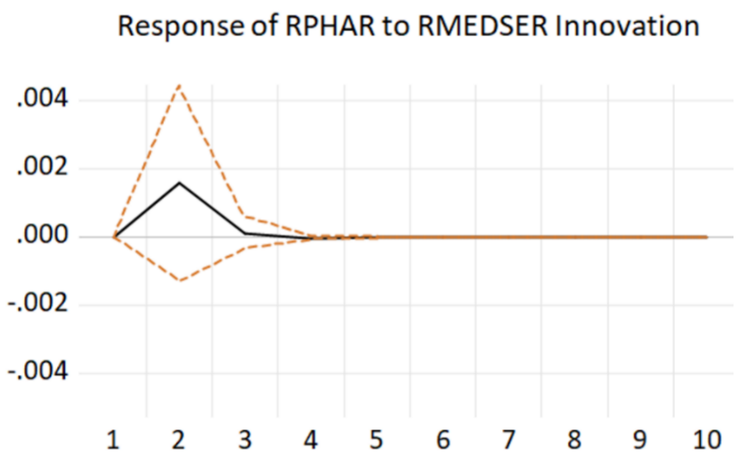

Figure 11: Response of RPHAR to RMEDSER Innovation

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The change in the medical services index's return following a one-unit positive impulse in the biopharmaceutical index's return is analyzed. From Figure 9 and Figure 10, it can be observed that both the chemical raw material index's return and the medical equipment index's return experience a decline and rebound process after the, indicating a negative impact of the biopharmaceutical index's return changes on these indices. Figure 11, on the other hand, shows that the changes in the biopharmaceutical index's return have a positive effect on the medical services index's return. Combining this with the analysis of volatility earlier, the increase in volatility of the biopharmaceutical index's return during the epidemic suggests a potential increase in its short-term fluctuations. The positive feedback of the medical services index's return to such changes implies that investors should lean towards investing in stocks related to medical services in the short term.

4. Investment Strategy

To reduce risk, investors can construct an investment portfolio. When constructing a portfolio, selling stocks would require buying options. Therefore, to make it more suitable for majority of ordinary investors, this paper will only consider buying stocks. And by segmenting the data into pre-pandemic and pandemic periods, this paper has established two investment portfolios that are suitable for both pandemic and non-pandemic times.

After splitting the data of the four industry indices into two parts pre-pandemic (July 6, 2012, to November 29, 2019) and pandemic period (December 6, 2019, to January 6, 2023) and separately importing them into Excel, then calculated the weekly returns by dividing the closing price by the opening price. After that computed the average weekly return and the population standard deviation of the returns. Since a year roughly consists of 52 weeks, this paper multiplied the average weekly return by 52 to obtain the annual return. The annual population standard deviation was calculated by multiplying the population standard deviation of the returns by the square root of 52. And the results are as Tables 14-15.

Table 14: stock’s return and stander deviation before pandemic

	r(year)	sd(year)
bioengineering and pharmaceutical	0.1745	0.2516
medical service	0.3643	0.3192
medical equipment	0.2582	0.3398
chemical raw material	0.1324	0.3243

Table 15: stock’s return and stander deviation during pandemic

	r(year)	std(year)
bioengineering and pharmaceutical	0.0709	0.2506
medical service	0.2886	0.3601
medical equipment	0.0733	0.3025
chemical raw material	0.2472	0.2871

Subsequently, calculate the correlation coefficients between each pair of variables, the results are show in Tables 16-17.

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Table 16: correlation coefficients between stocks before pandemic

	correlation coefficients
Biopharmaceutical& Medical services	0.7766
Biopharmaceutical& Medical equipment	0.8919
Biopharmaceutical& Chemical raw material	0.8167
Medical services& Medical equipment	0.7787
Medical services& Chemical raw material	0.5548
Medical equipment & Chemical raw material	0.7271

Table 17: correlation coefficients between stocks during pandemic

	correlation coefficients
Biopharmaceutical& Medical services	0.8552
Biopharmaceutical& Medical equipment	0.9064
Biopharmaceutical& Chemical raw material	0.4929
Medical services& Medical equipment	0.7938
Medical services& Chemical raw material	0.4787
Medical equipment & Chemical raw material	0.3552

Generate 2000 sets of four numbers that sum up to 1, representing the weights of each index in the investment portfolio. Calculate the portfolio's return and standard deviation for each set, then plot these 2000 points on a graph with standard deviation on the x-axis and return on the y-axis to obtain the feasible set of the investment portfolio (see Figures 12-13).

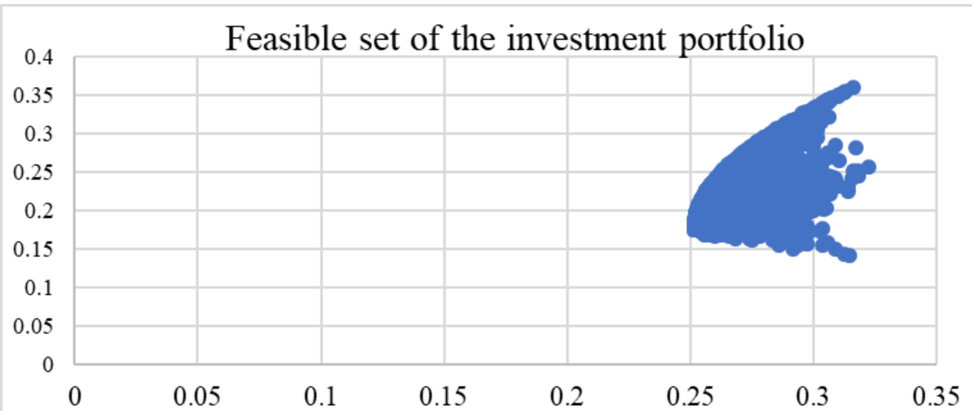

Figure 12: portfolio before pandemic

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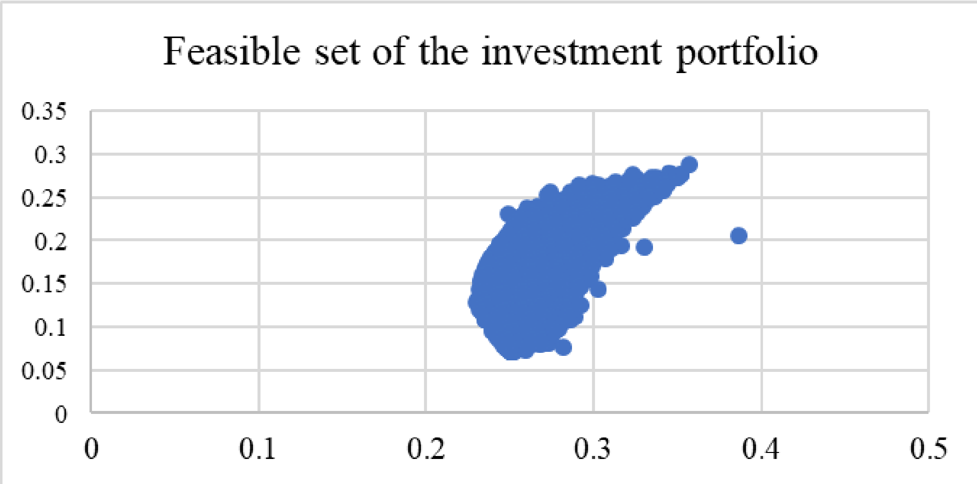

Figure 13: portfolio before pandemic during pandemic

Using the average yield of government bonds to determine the risk-free rate at 2.18%, calculate the Sharpe ratio using the formula,

$$\text{Sharpe ratio} = \frac{E(r)-r_f}{SD} \tag{7}$$

Select the 2000 points with the highest Sharpe ratios and plot the Capital Allocation Line (CAL) using their corresponding portfolio returns and standard deviations. (see Figures 14-15)

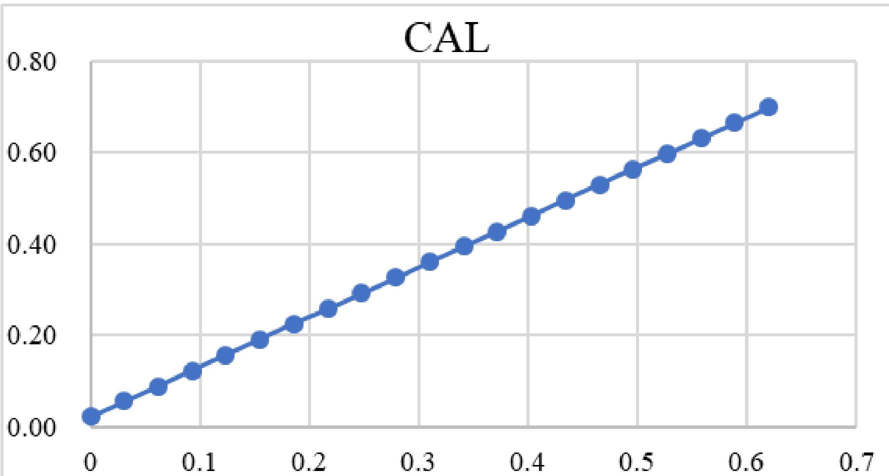

Figure 14: Capital Allocation Line (CAL) before pandemic

In CAL line before pandemic the expect return is 0.31 the stander deviation is 0.36.

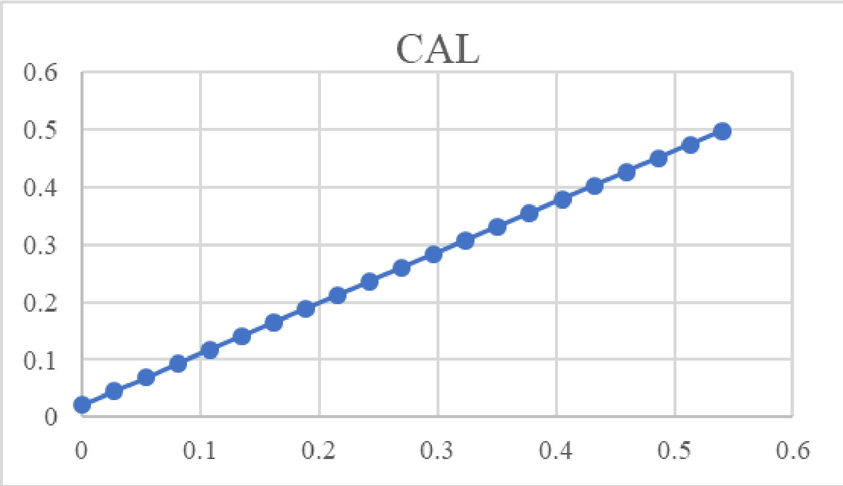

Figure 15: Capital Allocation Line (CAL) during pandemic

In CAL line during pandemic the expect return is 0.31 the stander deviation is 0.36. Combine CAL and the feasible set of the investment portfolio plot. The results of optimal portfolio are shown in Figures 16-17.

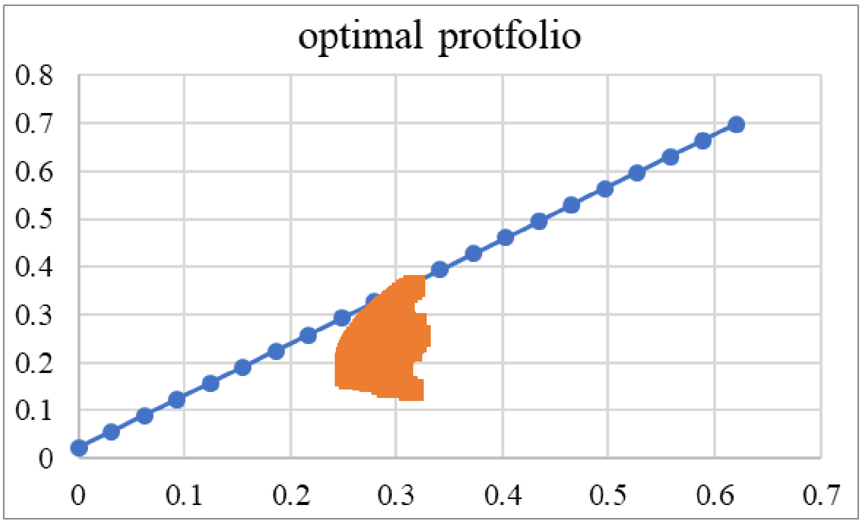

Figure 16: optimal portfolio before pandemic

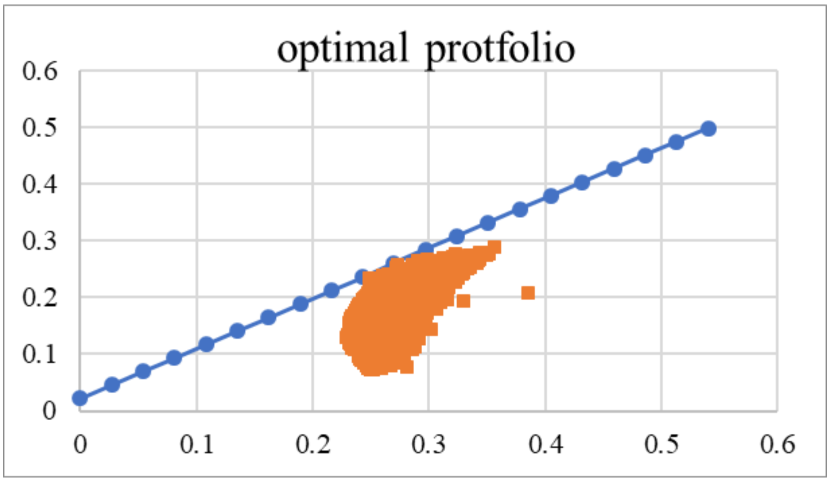

Figure 17: optimal portfolio during pandemic

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At the optimal portfolio position, the allocation to the risk-free asset is almost zero. Therefore, this paper ignores the risk-free asset and obtains the optimal portfolio.

Table 18: optimal portfolio before pandemic

Biopharmaceutical	medical service	medical equipment	chemical raw material
0.01	0.97	0.01	0.01

Table 19: optimal portfolio during pandemic

Biopharmaceutical	medical service	medical equipment	chemical raw material
0.02	0.45	0.01	0.52

Before the pandemic, the medical service sector dominated most of the weight, indicating a higher expected return for stocks in this industry. This also suggests a lack of diversification among these industries before the pandemic, making it less suitable for building a diversified portfolio. However, after the pandemic, the weight of chemical raw materials has taken over from medical services, with a value surpassing that of medical services (see tables 18-19). This indicates that the expected returns for stocks in these two industries are high, and the correlation between the two industries has decreased, leading to diversification between the industries.

5. Conclusion

Based on the conclusions drawn from the research, in the context of major health events such as the COVID-19 pandemic, the stock volatility and risks of pharmaceutical and related industries increase. Investors should make more rational choices when investing in corresponding stocks. Furthermore, most pharmaceutical-related stocks do not have the ability to predict the current values of other stocks based on past values. Investors should choose more suitable forecasting methods to help determine their investment decisions. According to the results of the impulse response in the report and combined with the previous conclusion of increased volatility during the pandemic, investors are more suitable for investing in medical services-related stocks in the short term. In the portfolio section, the author can see that in the absence of a pandemic, due to the relative stability of the stock market, the biopharmaceutical and related industries have low diversification, making it unsuitable for portfolio construction. However, during the pandemic, the industry becomes more diversified, allowing investors to construct portfolios related to the relevant industries.

This report also has some shortcomings. Firstly, the EGARCH and VAR models used in this report are relatively simple, leading to a low degree of fit with the data. Secondly, when constructing the portfolio, the report only involves buying stocks and includes only indices related to the biomedicine industry, which is not a typical investment portfolio and is not suitable for a wide range of investors. In future research, higher fitting models can be used to model the volatility of the biopharmaceutical index and the dynamic relationships between several industries, providing more accurate predictions and more reasonable investment advice for investors. The construction of investment portfolios can also include more industry indices and incorporate short-selling operations to make the portfolio closer to the ideal.

References

[1] Yongjing He, Ning He. (2023). The Short-term Impact of the Pandemic on Stock Market Returns in China: An Empirical Analysis Based on Event Study Methodology. Management and Administration, 1-10.

[2] Xiuwei Wang. (2023). Research on the Linkages and Risk Spillover Effects Between Mainland China's Stock Market and the Stock Markets of Europe, the US, and Hong Kong in the Context of the Pandemic. Shandong University.

DOI: 10.54254/2754-1169/84/20240808

[3] *Lulu Wang.(2022). A study on the impact of the COVID-19 pandemic on the stock markets of Shenzhen and Hong Kong. Xidian University.*

[4] *Zhi Su, Hongyan Fu. (2022). Interdependence Structure and Risk Spillover Effects of Chinese and Global Stock Markets under the Impact of the COVID-19 Pandemic - An Empirical Study Based on the MSGARCH-EVT-Copula Model. Journal of Shanghai University of Finance and Economics,*

[5] *Liqi Shen, Jie Zhang, Yumeng Ye. (2022). Empirical Study on Volatility Leverage Effect and Contagion - Evidence from the Chinese and American Stock Markets under the Impact of the COVID-19 Pandemic. National Circulation Economy, September 2022.*

[6] *Guangqiang Huang. (2023). Study on the Impact of Investor Sentiment on Stock Market Returns in the Context of the COVID-19 Pandemic. Guizhou University of Finance and Economics.*

[7] *Yuanlong Lin. (2022). A Study on the Impact of the COVID-19 Pandemic on the Chinese Stock Market. Jilin University.*

[8] *Hu Yue, Yanxia Jiang, Houjuun Xia. (2023). Research on the Interconnectivity Among Stock Market, Bond Market, and Foreign Exchange Market During the COVID-19 Pandemic. School of Science, Zhejiang University of Science and Technology.*

[9] *Tiemei Gao. (2016). Econometric Analysis Methods and Modeling: EViews Applications and Examples 3rd Edition. Beijing: Tsinghua University Press*

[10] *Chengxuan Guo. (2022). Based on the topological characteristics and node influence analysis of the Shanghai and Shenzhen 300 stock market - A study on the stock market crash and the period of the COVID-19 pandemic. Jiangsu University.*