

# COVID-19 Pandemic and Stock Market Contagion Between the Chinese Mainland and Hong Kong

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**Abstract:** This study utilizes stock market data from March 2020 to December 2022, employing VAR models and Granger causality models to investigate the daily returns and contagion effect of the CSI 300 and the HSI in Hong Kong. Based on this, the analysis explores the impact of the pandemic on the contagion effect between the mainland Chinese and Hong Kong stock markets. The research findings indicate that during the pandemic period, there exists a unidirectional Granger causality relationship from the Hong Kong stock market to the mainland Chinese stock market. The pandemic has intensified the connection between mainland China and Hong Kong, significantly increasing their mutual influence. The overall trends of the two stock markets are consistent, with the mainland Chinese market exhibiting smoother fluctuations during this period.

**Keywords:** COVID-19 pandemic; Contagion effect; Granger causality model; Stock market.

## 1. Introduction

At the end of 2019, the outbreak of the novel coronavirus brought serious health challenges to residents across China and posed significant challenges to the global financial markets. As a crucial indicator of a nation's economy, the development and operation of the stock market reflect the country's economic trends. Therefore, a thorough analysis and exploration of the interconnection between stock markets will provide essential reference points for the government and investors.

In recent years, with the introduction of policies such as the Shanghai-Hong Kong Stock Connect and the Shenzhen-Hong Kong Stock Connect, China has actively promoted the internationalization of its capital markets, striving to eliminate internal and external barriers, promote integration, and advance economic globalization for sustainable development. According to Granger's causality analysis, the implementation of the Shanghai-Hong Kong Stock Connect has intensified stock trading between the two sides and increased the frequency of transactions. This development has made the connection between the mainland and Hong Kong markets even closer. Against this backdrop of the COVID-19 pandemic, this paper conducts research on the contagion effect between mainland A-share market and the Hong Kong stock market in China.

From an academic perspective, existing research on the contagion effect between China's mainland A-share market and the Hong Kong stock market is mostly concentrated around the year 2000, the periods surrounding the opening of the Shanghai-Hong Kong Stock Connect and the Shenzhen-Hong Kong Stock Connect, as well as the early stages of the pandemic. Research on the contagion under the backdrop of the COVID-19 pandemic has focused on specific sectors within the stock market, as well as the interconnectivity between stocks and bonds. The overall impact of the pandemic on the contagion between the two markets is still in a relatively unexplored state. This paper chooses to analyze the contagion effect between the mainland A-share market and the Hong Kong stock market throughout the entire duration of the pandemic, filling this gap, enriching the

research content, and enhancing the research framework.

In terms of practical significance, given the current situation, focus on the trends in the contagion effect between the mainland and Hong Kong can assist enterprises in both regions in better seizing international opportunities, serving the national economy and life more effectively. Simultaneously, it can alleviate uncertainty between the mainland and Hong Kong stock markets, reducing the impact on both markets and mitigating the negative effects brought about by the pandemic.

This paper employs literature research and quantitative analysis methods, utilizing ADF (Augmented Dickey-Fuller) tests, Granger causality tests, and VAR (Vector Autoregression) models to analyze the contagion effect between China's mainland A-share market and the Hong Kong stock market. The daily returns of the CSI 300 in the mainland and the HSI in Hong Kong are selected as the research objects, studying the daily returns between the two markets from March 2, 2020, to December 30, 2022. The research findings indicate that, before the pandemic from 2010 to January 2020, there was a unidirectional Granger causality relationship from the mainland A-share market to the Hong Kong stock market. During the pandemic period from January 2020 to December 2022, there existed a unidirectional Granger causality relationship from the Hong Kong stock market to the mainland A-share market.

## 2. Literature Review

In the methodology of studying contagion effect, Marinko and Skare (2019) employed frequency-domain Granger causality tests to investigate the financial-growth relationship in 19 Central and Eastern European and Southeastern European (CESEE) countries from 1991 to 2017. Seyi Saint (2020) and Akadiri (2018) utilized Granger causality tests to examine the causal relationships among the tourism industry, economic growth, and carbon emissions within a multivariate framework. Mishra et al. (2021) used the quantile autoregressive distributed lag method to study the contagion between clean energy and oil prices in Europe and the United States, investigating the impact of changes in clean energy

stock returns on oil and gold price movements.

Regarding the research subjects, Nuhu A Sansa (2020) found, during the period from March 1, 2020, to March 25, 2020, a significant positive correlation between all financial markets in China and the United States (Shanghai Stock Exchange and the New York Dow Jones Index) and confirmed COVID-19 confirmed cases. Zhifeng Dai et al. (2020), through the analysis of a linear autoregressive model, affirmed that internal changes in the stock market lead to corresponding external changes, a phenomenon confirmed through Granger causality. Karamat KHAN et al. (2020) combined OLS regression, conventional t-tests, and Mann-Whitney tests to estimate research results, investigating the impact of the COVID-19 pandemic on the stock markets of 16 countries. The results showed that all stock market indices responded negatively to this news in both short-term and long-term event windows.

In theoretical studies on stock market contagion, Wang Tao and Dong Meisheng (2018) employed the GJR-GARCH-DCC model, Zhao Shanshan and Yin Guangwei (2020) utilized ADF, Johansen, and Granger tests, while Jin Jiaqi (2019) applied various methods, including Granger tests and GARCH models, to investigate the changes in interconnectivity between the Shanghai, Shenzhen, and Hong Kong stock markets. They found that the mutual access mechanism between mainland China and Hong Kong has a promoting effect on the contagion between the Shanghai-Hong Kong and Shenzhen-Hong Kong stock markets. Wu Xiaofei et al. (2020) used SJC-Copula, Markov state transition, and an improved ICSS algorithm, along with variance structure change-point tests, to discover that the relationship between the mainland and Hong Kong stock markets is nonlinear and asymmetric, with frequent shifts between high and low states. Lan Bo and Zhuang Lei (2021) delved into the profound and lasting changes brought by the COVID-19 pandemic to various segmented financial markets, employing VAR, VCC-M-GARCH, TGARCH models, and a dynamic Markov switching model. They found that the impact of the COVID-19 pandemic on financial markets exhibits dynamic lag effects, distinct threshold effects, and state transition effects.

### 3. Basic Theory

#### 3.1. Contagion effect

The term 'contagion' was first introduced by Lucas (1977) in his book 'Studies in Business-Cycle Theory.' Contagion is typically defined as the occurrence of interrelated phenomena. In the context of stock markets, market contagion refers to the simultaneous or opposite movements in the returns of different assets. This phenomenon can occur globally between stock markets and within the stock market of a single country. The stock market contagion defined in this paper refers to the co-movements or changes among stock market indices in different stock markets.

Zhang Qian wei (2021) points out that there are two basic hypotheses regarding stock market contagion: the economic fundamentals hypothesis and the market contagion hypothesis.

The economic fundamentals hypothesis traces its theoretical origins back to the Efficient Market Hypothesis proposed by Eugene Fama (1970). According to this hypothesis, stock prices in different regions are influenced by common factors such as government macroeconomic policies

and fiscal policies, resulting in an inherent connection. If there is a high degree of correlation between the fiscal policies and macroeconomic data of different countries, investors may make similar investment decisions, leading to a certain degree of contagion effect between the stock markets of different nations.

The market contagion hypothesis, proposed by King and Wadhvani (1990), suggests that, even in the absence of changes in economic fundamentals, fluctuations in one country's stock market caused by trading noise can transmit to another country's stock market. This hypothesis asserts that the contagion between stock markets depends not only on macroeconomic fundamentals but also on the irrational behavior of investors. It considers factors such as investor preferences, emotions, and the impact of global capital flows in financial markets. In other words, when investors receive similar information, they tend to form consistent, directionally similar expectations and take similar actions simultaneously. This leads to the contagion observed among stock markets in different countries.

#### 3.2. Stationarity test

Stationarity assumes that a time series is generated by a series of random processes. In other words, for each parameter in the time series  $X_t$  ( $t=1,2,3,4,5$ ), it is assumed that they all come from the same probability distribution and are randomly obtained. The time series is considered stationary if it satisfies the following conditions:

- 1) The mean  $E(X_t) = u$  is a constant independent of time  $t$ .
- 2) The variance  $Var(X_t) = \sigma^2$  is a constant independent of time  $t$ .
- 3) The covariance  $Cov(X_t, X_{t+k}) = rk$  is a constant only dependent on the time interval  $k$  and is independent of time  $t$ .

In this case, the random time series is termed stationary, and the random process is referred to as a stationary stochastic process. The determination of stationarity involves examining whether the series has a unit root. If the series is stationary, no unit root exists; otherwise, a unit root is present.

The Augmented Dickey-Fuller test (ADF test) is an extension of the Dickey and Fuller (1981) test. The ADF test is conducted through three models:

Model 1:

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^m \beta_i \Delta Y_{t-i} + \varepsilon_t$$

Model 2:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^m \beta_i \Delta Y_{t-i} + \varepsilon_t$$

Model 3:

$$\Delta Y_t = \alpha + \beta T + \delta Y_{t-1} + \sum_{i=1}^m \beta_i \Delta Y_{t-i} + \varepsilon_t$$

Model 1 does not include any deterministic trend; Model 2 includes only the intercept  $\alpha$ ; Model 3 introduces the variable  $T$  as a time variable representing some trend in the time series over time, along with the intercept  $\alpha$ . This model aims to remove all deterministic trends from the time series.

All three models, Model 1, Model 2, and Model 3, include lagged terms of  $\Delta Y$  to eliminate serial correlation in the disturbance term of the model when the time series is generated by higher-order autoregressive processes, ensuring

that the disturbance term is white noise.

The null hypothesis (H0) of the ADF test is  $\delta=0$ . As long as the test result of any of these models rejects the null hypothesis, it can be concluded that the time series is stationary. If none of the three models rejects the null hypothesis, it is considered that the time series is non-stationary. In other words, the null hypothesis (H0) is that a unit root exists. If the obtained test statistic is below the critical values at three confidence levels (10%, 5%, 1%), there is a (90%, 95%, 99%) confidence level to reject the null hypothesis.

In the subsequent ADF test used, the basic assumption is that the HSI daily return time series and the CSI 300 daily return time series are non-stationary. When the p-value is  $>0.05$ , the null hypothesis is accepted, and when the p-value is  $<0.05$ , the null hypothesis is rejected. That is, the HSI daily return time series and the CSI 300 daily return time series are stationary. The stationarity of the time series is a prerequisite for conducting the Granger test.

### 3.3. Granger causality test

The Granger Causality test is a method used in econometrics and time series analysis to detect causal relationships. It assesses whether changes in the dependent variable are influenced by changes in the independent variable and quantifies the magnitude of this influence. The test examines the causal relationship between two variables by comparing their relationships in different time periods. A prerequisite for the Granger Causality test is that the time series must be stationary.

Basic Principles:

Suppose there are two variables,  $X_t$  and  $Y_t$ , in the time series data. Consider the following three situations:

1. Predicting  $X_{t+1}$  based on  $X_t$
2. Predicting  $X_{t+1}$  based on  $X_t$  and  $Y_t$
3. Predicting  $X_{t+1}$  based on  $X_t$ ,  $Y_t$ , and  $W_t$ , where  $Y_t$  directly depends on  $W_t$

Situation 1 involves a univariate autoregressive model, represented mathematically as:

$$X_t = \alpha + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \dots + \gamma_p X_{t-p}$$

where p is the order.

In Situation 2, if the data of Y contains information predicting  $X_{t+1}$ , then Y t is considered a G-Cause for  $X_{t+1}$ . The mathematical model is:

$$X_t = \alpha + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \dots + \gamma_p X_{t-p} + \alpha_1 Y_{t-1} + \dots + \alpha_p Y_{t-p}$$

with 2p degrees of freedom.

If Yt is a G-Cause for X<sub>t</sub>, it implies that Y precedes X, and:

- The lagged values of Y should have a statistically significant correlation with the values of X at previous time points.
- The lagged values of X should not have a statistically significant correlation with the values of Y.

Situation 3 is not suitable for discovering Granger causality because Yt is influenced by Wt.

Hypothesis Testing:

Null Hypothesis: There is no Granger causality from Yt to  $X_{t+1}$ .

Alternative Hypothesis: There is Granger causality from Yt to  $X_{t+1}$ , or at least one lagged value is statistically significant.

The Granger causality test only examines the relationship between two variables, while real dependency relationships often involve multiple variables.

### 3.4. Vector autoregressive model

The Vector Autoregressive Model (VAR model) was introduced by Sims (1980). This model adopts a simultaneous equation format and is not grounded in economics. In each equation of the model, the endogenous variable regresses on the lagged terms of all endogenous variables in the model. This allows the estimation of the dynamic relationships among all endogenous variables. The VAR model is commonly used to forecast interconnected time series systems and analyze the dynamic impacts of random disturbances on variable systems.

Assuming there is a relationship between  $y_{1,t}$  and  $y_{2,t}$ , if two separate autoregressive models are constructed for each, the relationship between the two variables cannot be captured. By adopting a simultaneous equation format, the relationship between the two variables can be established. The structure of the VAR model is determined by two parameters: the number of variables N and the maximum lag order k.

Taking the example of a VAR model with a lag of 1 for two variables,  $y_{1,t}$  and  $y_{2,t}$ :

$$\begin{cases} y_{1,t} = \mu_1 + \pi_{11.1}y_{1,t-1} + \pi_{12.1}y_{2,t-1} + u_{1t} \\ y_{2,t} = \mu_2 + \pi_{21.1}y_{1,t-1} + \pi_{22.1}y_{2,t-1} + u_{2t} \end{cases}$$

, above  $u_{1t}, u_{2t} \sim IID(0, \sigma^2)$ ,  $Cov(u_{1t}, u_{2t}) = 0$ . Written in matrix form is:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.1} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$

Hypothesis,

$$Y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Pi_1 = \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.1} \end{bmatrix}, u_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$

Thus, the VAR model with a lag of k periods for N variables is represented as follows:

$$Y_t = \mu + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \dots + \Pi_k Y_{t-k} + u_t, u_t \sim IID(0, \Omega)$$

In this formula,  $Y_t = (y_{1,t} \ y_{2,t} \ \dots \ y_{N,t})'$ ,  $\mu = (\mu_1 \ \mu_2 \ \dots \ \mu_N)'$ ,  $u_t = (u_{1t} \ u_{2t} \ \dots \ u_{Nt})'$ ,

$$\Pi_j = \begin{bmatrix} \pi_{11.j} & \pi_{12.j} & \dots & \pi_{1N.j} \\ \pi_{21.j} & \pi_{22.j} & \dots & \pi_{2N.j} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{N1.j} & \pi_{N2.j} & \dots & \pi_{NN.j} \end{bmatrix}, j = 1, 2, 3, \dots, k$$

where  $Y_t$  is an  $N \times 1$  order time series column vector,  $\mu$  is an  $N \times 1$  order constant term column vector,  $\Pi_1, \dots, \Pi_k$  are  $N \times N$  order parameter matrices, and  $u_t \sim IID(0, \Omega)$  is an  $N \times 1$  order vector of random errors. Each element is non-autocorrelated, but there may be correlations between the random error terms corresponding to different equations. Since each equation in the VAR model only includes lagged terms of endogenous variables on the right-hand side, it is uncorrelated with  $u_t$ . The Ordinary Least Squares (OLS) method can be employed to sequentially estimate each equation, and the resulting parameter estimates are consistently obtained.

## 4. Empirical Analysis

### 4.1. Variables and hypothesis

Based on previous studies by scholars, within the context of the development of economic globalization, the mainland and Hong Kong stock markets have close relationships, and capital flows frequently. With the successive opening of the Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect, the contagion between the two stock markets has strengthened. In light of this, the following

hypotheses are proposed:

Hypothesis 1: There is no Granger causality relationship from the Hong Kong stock market to the mainland stock market.

Hypothesis 2: There is a Granger causality relationship from the Hong Kong stock market to the mainland stock market.

When the p-value is greater than 0.05, it indicates that the null hypothesis cannot be rejected, thus supporting Hypothesis 1. When the p-value is less than 0.05, the null hypothesis can be rejected, supporting Hypothesis 2.

The selected variables in this study are the daily closing prices of the CSI 300 (representing the mainland stock market) and the HSI (representing the Hong Kong stock market). The data are sourced from the Wind database. The research period is set from March 2, 2020, to December 30, 2022, focusing on the daily returns between the two stock markets against the backdrop of the COVID-19 pandemic.

Due to slight differences in holidays and customs between

the mainland and Hong Kong, dates where the mainland market was open while Hong Kong was closed, and vice versa, were excluded. Only dates where both markets traded normally were chosen for the analysis.

## 4.2. Causality test between chinese mainland a-share market and hong kong stock market

### 4.2.1. Descriptive statistics

The calculation method for daily stock index returns is as follows:

$$\text{Daily return} = \frac{\text{Closing Price} - \text{Opening Price}}{\text{Opening Price}} * 100\%$$

During the pandemic period, statistical analysis of the daily returns of the CSI 300 and the HSI can be conducted using indicators such as the mean, median, maximum, minimum, and standard deviation. This allows for a better understanding of the market's trends, as shown in Table 1.

**Table 1.** Descriptive statistics of the CSI 300 and the HSI during the pandemic

	Daily yield of HSI	CSI 300-day yield
Statistics	691.0000	691.0000
average	-0.000720	0.000610
standard deviation	0.011811	0.011411
minimum	-0.044924	-0.047512
25% quantile	-0.007093	-0.006045
50% quantile	-0.001121	0.000447
75% quantile	0.005797	0.006936
maximum	0.067213	0.045743

From the basic statistics of descriptive statistics, for the period from February 3, 2020, to December 30, 2022, 691 data points were selected for both the daily returns of the HSI and the CSI 300, representing the mainland stock market. The daily average return of the CSI 300 is slightly higher than that of the HSI, and both are overall positive. The daily average return of the HSI, representing Hong Kong, is in a slightly

negative state. The standard deviations of the two are similar, and the 25%, 50%, and 75% quantiles of the daily returns of the CSI 300 are slightly higher than those of the HSI.

Next, the daily closing prices of the CSI 300 and the HSI will be plotted for visual analysis. Figure 1 shows the trend chart of the closing prices of the CSI 300 and the HSI from 2010 to 2019.

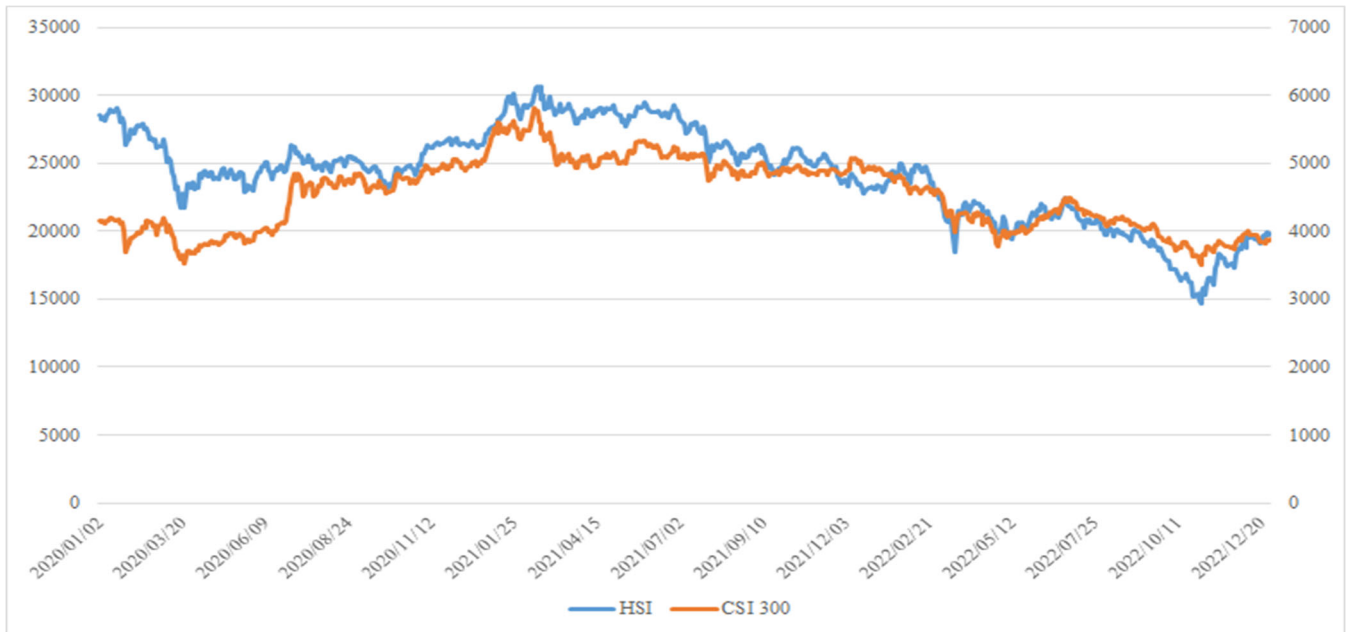


**Figure 1.** Daily closing price chart of the HSI and the CSI 300 from 2010 to 2019

From Figure 1, it can be observed that from 2010 to the end of 2014, the trends of the HSI and the CSI 300 were similar. From the end of 2014 to March 2016, during the period when the Shanghai-Hong Kong Stock Connect and Shenzhen-Hong

Kong Stock Connect were opened, the CSI 300 experienced a rapid rise, with a much larger increase than the HSI. From 2017 to 2018, the CSI 300 exhibited a stable upward trend, slightly smaller than the increase in the HSI. Overall, from

2010 to 2019, there was a general trend of rising and falling together.

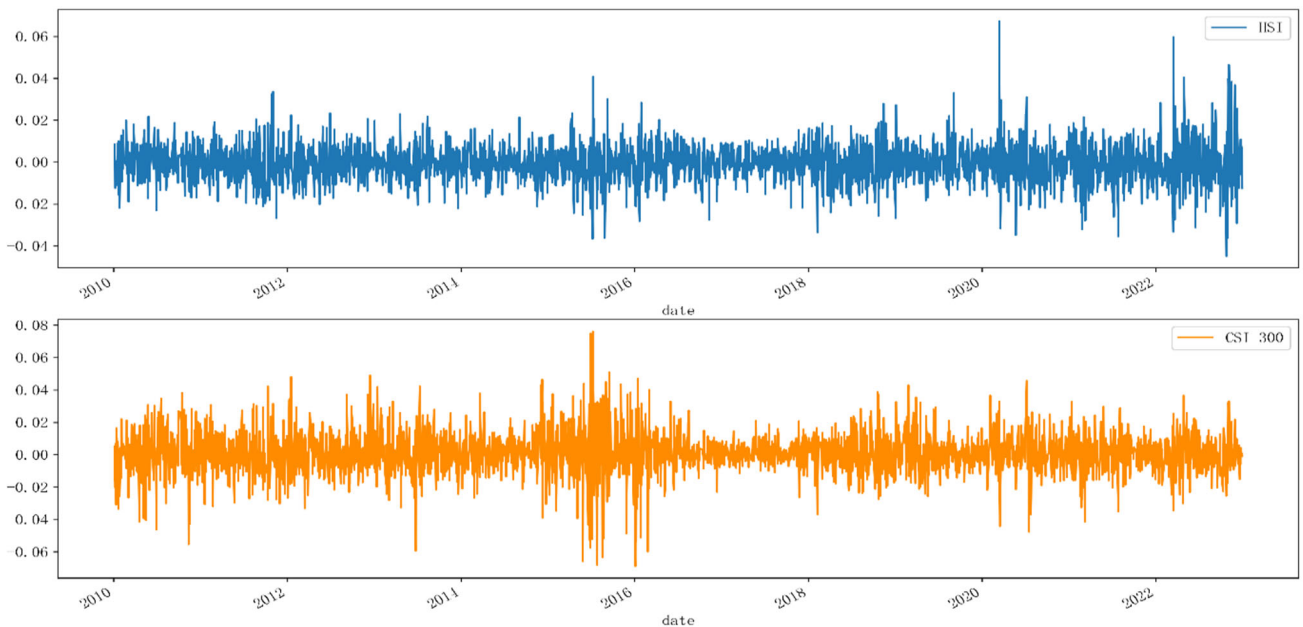


**Figure 2.** Daily closing price chart of the HSI and the CSI 300 from 2020 to 2022

Figure 2 depicts the closing price trends of the HSI and the CSI 300 from the beginning of 2020 to the end of 2022, representing the trends during the COVID-19 pandemic. From the chart, it is evident that in the early stages of the pandemic, from January to June 2020, the HSI experienced a larger decline compared to the CSI 300. Starting from July 2020, the two indices maintained similar fluctuations, and

there was a strong correlation in their closing price trends.

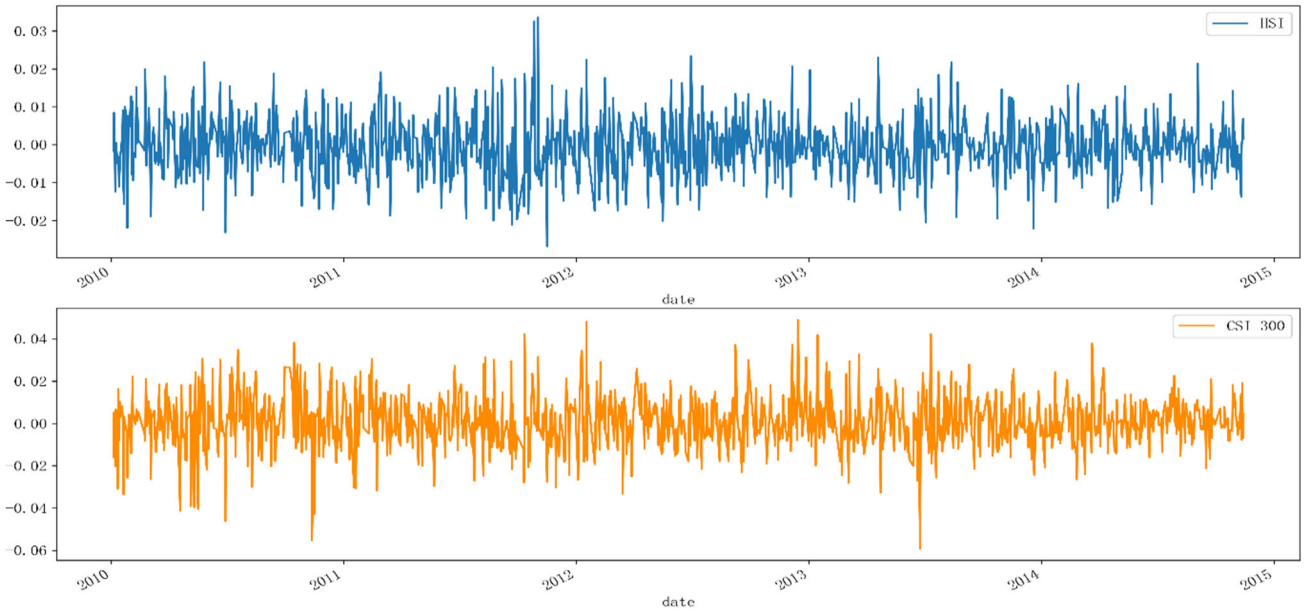
The sequence plot of daily returns for the stock indices provides further insight into whether there is clustering and a trend of rising and falling together in the daily returns. The daily return series for the CSI 300 and the HSI from 2010 to the outbreak of the pandemic are illustrated in Figure 3.



**Figure 3.** Daily return series chart of the HSI and the CSI 300 from 2010 to 2022

Figure 3 displays the time series plot of daily returns for the HSI and the CSI 300 from 2010 to December 2022. The orange line represents the daily returns of the CSI 300, while the blue line represents the daily returns of the HSI. The chart

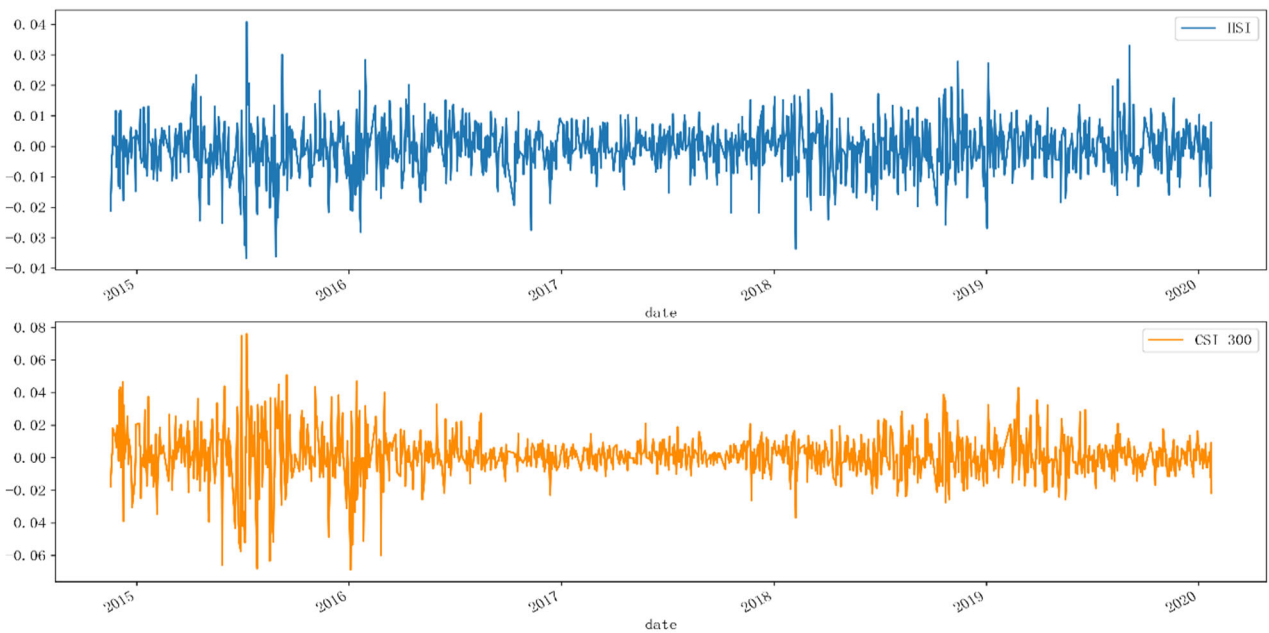
illustrates that, during the period from 2010 to 2022, the daily returns of the CSI 300 exhibited more pronounced fluctuations compared to the daily returns of the HSI.



**Figure 4.** 2010 - HSI and CSI 300 daily return series chart before the launch of Shanghai-Hong Kong Stock Connect

Figure 4 illustrates the time series plot of daily returns for the HSI and the CSI 300 from 2010 to November 2014. The orange line represents the daily returns of the CSI 300, while the blue line represents the daily returns of the HSI. The chart

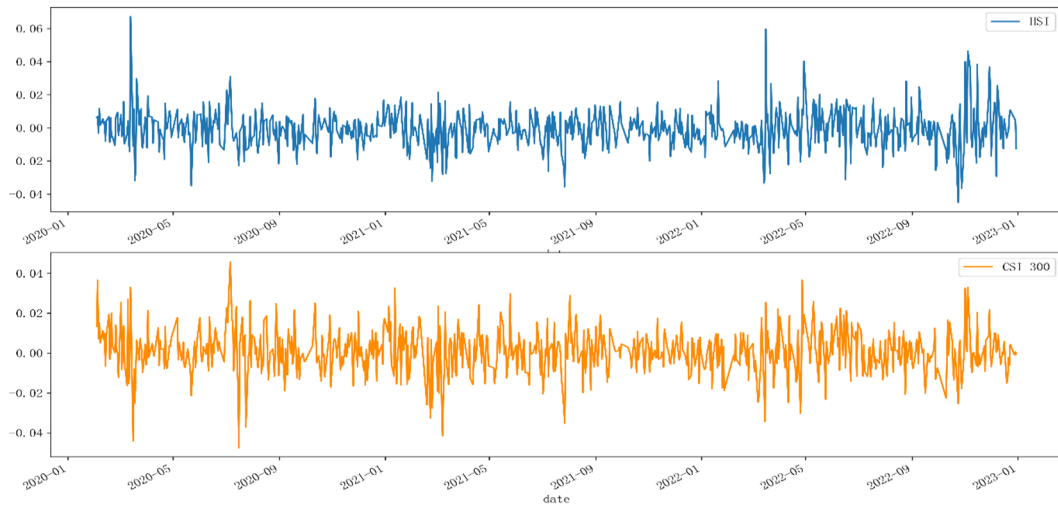
demonstrates that, during the period from 2010 to 2014, the daily returns of the CSI 300 exhibited more pronounced fluctuations compared to the daily returns of the HSI.



**Figure 5.** After the launch of Shanghai-Hong Kong Stock Connect - the daily return series of the HSI and the CSI 300 before the pandemic

Figure 5 illustrates the period from November 2014, when the Shanghai-Hong Kong Stock Connect was initiated, until the opening of the Shenzhen-Hong Kong Stock Connect in 2016. During this period, the daily returns of the CSI 300 exhibited increased volatility compared to the preceding

period, with a range of daily returns between -0.06 and 0.08. Following the opening of the Shenzhen-Hong Kong Stock Connect in December 2016, the volatility of daily returns for the CSI 300 gradually expanded until the pre-pandemic period.



**Figure 6.** Chart of the daily return series of the HSI and the CSI 300 during the pandemic

Figure 6 depicts the daily return series of the CSI 300 and the HSI during the pandemic period. From Figure 6, it can be observed that from December 2019 to December 2022, the trend of daily returns for the CSI 300 closely mirrored that of the HSI. The volatility of daily returns for the HSI was slightly higher than that of the CSI 300.

#### 4.2.2. Correlation analysis

Correlation analysis involves examining the relationship between two or more variables to measure the degree of association between them. For correlation analysis to take place, there must be a certain level of connection or probability between the elements being studied. The Pearson

correlation coefficient, also known as the Pearson product-moment correlation coefficient, is commonly used to analyze the relationship between two continuous variables. Its formula is as follows:

$$r(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var[X]Var[Y]}}$$

The correlation coefficient 'r' ranges from -1 to 1, where  $r > 0$  indicates a positive correlation,  $r < 0$  indicates a negative correlation,  $|r| = 0$  signifies no linear relationship, and  $|r| = 1$  represents a perfect linear relationship. In the formula, 'X' and 'Y' represent the daily returns of the CSI 300 and the HSI, respectively.

**Table 2.** The correlation coefficient between the daily return of the CSI 300 and the daily return of the HSI

	CSI 300-day yield	Daily yield of HSI
CSI 300-day yield	1	0.643
Daily yield of HSI	0.643	1

Table 2 displays the correlation coefficient between the daily returns of the CSI 300 and the HSI. The data indicates a positive correlation and a linear relationship between the daily returns of the two indices, with a correlation coefficient of 0.643. This suggests that as the daily returns of the CSI 300 increase, the daily returns of the HSI also tend to increase.

#### 4.2.3. Stationarity test

Stationarity refers to a state in a stochastic process where both the mean and variance are constant, and the covariance between any two time periods depends solely on the time lag

between them. Testing for stationarity is a prerequisite when employing the Granger causality model.

This paper utilizes the Augmented Dickey-Fuller (ADF) unit root test method. The null hypothesis of the ADF unit root test assumes the presence of at least one unit root. If the ADF test statistic in the result is less than the critical value at a given significance level, the null hypothesis is rejected, suggesting that the examined time series is stationary. Otherwise, it is considered a non-stationary time series. The ADF test results for the daily returns of the HSI and the CSI 300 during the pandemic period are presented in Table 3.

**Table 3.** ADF test results for CSI 300 and HSI during the pandemic

ADF Test:	Daily yield of HSI
ADF Statistics:	-11.559555
p-value:	0.000000
Critical values:	
1%:	-3.440
5%:	-2.866
ADF Test:	Daily yield of HSI
10%:	-2.569
ADF Test:	CSI 300-day yield
ADF Statistics:	-26.671443
p-value:	0.000000
Critical values:	
1%:	-3.440
5%:	-2.866
10%:	-2.569

Looking at the ADF test results for both the HSI and the CSI 300, the p-values are extremely low, approaching zero. With p-values < 0.05, rejecting the null hypothesis is valid, indicating the stationarity of these two time series. Consequently, conducting further Granger causality tests is feasible. Omitting the ADF testing process from 2010 until the pre-pandemic period, the p-values consistently approach zero, confirming the stationarity of the time series and

allowing for Granger causality analysis.

#### 4.2.4. Granger causality test

1) The Granger causality test results for the daily returns of the HSI and the CSI 300 from 2010 to November 2014 (pre-Shanghai-Hong Kong Stock Connect) are presented in Table 4.

**Table 4.** Granger causality test results of CSI 300 and HSI from 2010 to 2014

	HSI x	CSI 300 x
HSI y	1.000	0.0337
CSI 300 y	0.1047	1.000

In the table above, 'y' represents the response variable, and 'x' represents the predictor variable. Each cell contains a p-value. In the second row and third column, the p-value is  $0.0337 < 0.05$ , indicating the rejection of the null hypothesis, suggesting a Granger causal relationship from the CSI 300 ('x') to the HSI ('y'). In the third row and second column, the p-value is  $0.1047 > 0.05$ , suggesting a failure to reject the null

hypothesis, indicating that the HSI ('x') does not have a Granger causal relationship with the CSI 300 ('y').

2) From November 2014 to January 2020, after the opening of the Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect until the pre-pandemic period, the Granger causality test results for the daily returns of the HSI and the CSI 300 are presented in Table 5.

**Table 5.** The results of the Granger causality test of the CSI 300 and the HSI from 2014 to before the pandemic

	HSI x	CSI 300 x
HSI y	1.000	0.0153
CSI 300 y	0.1287	1.000

The p-value in the second row and third column is  $0.0153 < 0.05$ , indicating the rejection of the null hypothesis, suggesting a Granger causal relationship from the CSI 300 ('x') to the HSI ('y'). In the third row and second column, the p-value is  $0.1287 > 0.05$ , indicating a failure to reject the null

hypothesis, suggesting that the HSI ('x') does not have a Granger causal relationship with the CSI 300 ('y').

3) During the pandemic period, the Granger causality test results for the daily returns of the HSI and the CSI 300 are presented in Table 6.

**Table 6.** Granger causality test results for CSI 300 and HSI during the pandemic

	HSI x	CSI 300 x
HSI y	1.000	0.2527
CSI 300 y	0.009	1.000

**Table 7.** Weekly VAR model results for the CSI 300 and the HSI before and after the pandemic

\	Pre-pandemic coefficients	Pre-pandemic p-value	Post-pandemic coefficients	Post-pandemic p-value
The result of the HSI (Y).				
constant	0.000189	0.547	-0.000398	0.632
The weekly returns of the HSI with first-order lag	0.966446	0.000	0.860520	0.000
The weekly returns of the CSI 300 with first-order lag	-0.048903	0.009	-0.003680	0.954
The weekly returns of the HSI with second-order lag	-0.184018	0.000	-0.073881	0.163
The weekly returns of the CSI 300 with second-order lag	0.044479	0.017	-0.037597	0.558
CSI 300 (X) results				
The result of the HSI (Y).				
constant	0.000199	0.627	0.000063	0.926
The weekly returns of the HSI with first-order lag	0.036759	0.250	-0.052198	0.229
The weekly returns of the CSI 300 with first-order lag	0.910438	0.000	0.954463	0.000
The weekly returns of the HSI with second-order lag	-0.015005	0.639	0.089022	0.040
The weekly returns of the CSI 300 with second-order lag	-0.152519	0.000	-0.218300	0.000

The p-value in the second row and third column is  $0.2527 > 0.05$ , indicating a failure to reject the null hypothesis, suggesting that the CSI 300 ('x') does not have a Granger causal relationship with the HSI ('y'). In the third row and second column, the p-value is  $0.009 < 0.05$ , indicating the rejection of the null hypothesis, suggesting a Granger causal relationship from the HSI ('x') to the CSI 300 ('y').

### 4.3. Var model empirical study

The VAR model, excluding contemporaneous variables such as interfering factors, has played a facilitating role in studying the interrelationship between the returns of the CSI 300 and the HSI. Following the conclusion of the Granger causality test, empirical research was conducted using the VAR model to demonstrate the contagion effect between the Chinese mainland A-share market and the Hong Kong stock market, and to forecast the time series systems of both regions. Below presents the weekly VAR model results for the Chinese mainland A-share market and the Hong Kong stock market before and after the pandemic:

Observing that the p-values of the autoregressive coefficients are less than 5%, the VAR model is significant at a 5% significance level. Based on the aforementioned regression results, assuming the weekly returns of the HSI as 'Y' and the weekly returns of the CSI 300 as 'X', the constructed autoregressive model for the HSI's weekly returns before the pandemic, spanning from 2010 to 2019, is as follows:

$$Y_t = 0.966446Y_{t-1} - 0.048903X_{t-1} - 0.184018Y_{t-2} + 0.044479X_{t-2}$$

, the autoregressive model for the weekly returns of the CSI 300 from 2010 to 2019 is as follows:

$$X_t = 0.910438X_{t-1} - 0.152519X_{t-2}$$

, During the pandemic from 2020 to 2022, the autoregressive model for the weekly returns of the HSI is as follows:

$$Y_t = 0.860520Y_{t-1}$$

, During the pandemic from 2020 to 2022, the autoregressive model for the weekly returns of the CSI 300 is as follows:

Through empirical analysis of the daily, weekly, and monthly returns of the CSI 300 and the HSI from 2010 to 2022, it is observed that the CSI 300 can account for the variations in the HSI. This validates that from 2010 to 2022, the CSI 300 has influenced the HSI. In the monthly VAR model results, it's evident that the CSI 300 returns exert the most significant influence on the HSI returns. The relationship between the two can be represented as:  $Y_t = 1.027407Y_{t-1} - 0.066210X_{t-1} - 0.076892Y_{t-2} + 0.062597X_{t-2}$ .

Before the pandemic, from 2010 to the end of 2019, the CSI 300 was the cause of variations in the HSI, while the HSI did not have an impact on the CSI 300. However, during the pandemic period from 2020 to the end of 2022, the CSI 300 ceased to be the sole cause of variations in the HSI. Instead, the HSI began to influence the CSI 300. The relationship between the two can be described as  $X_t = 0.954463X_{t-1} + 0.089022Y_{t-2} - 0.218300X_{t-2}$ . The results from the VAR model analysis align with the findings of the Granger causality test.

## 4.4. Contagion effect analysis

### 4.4.1. From pre- and post-pandemic perspectives

Against the backdrop of the COVID-19 pandemic, a comparative study was conducted on the contagion changes before and during the pandemic between the CSI 300 and the HSI. Daily opening and closing price data were analyzed for the periods: January 4, 2010, to January 23, 2020, representing pre-pandemic data, and February 3, 2020, to December 30, 2022, representing the pandemic period.

The main research objectives aimed to observe the interconnection between the Hong Kong and mainland Chinese stock markets during the COVID-19 pandemic and compare it with the contagion effect before the pandemic. The findings are summarized as follows:

(1) Before the launch of the Shanghai-Hong Kong Stock Connect, the mainland market had a certain influence on the Hong Kong market, showing a unidirectional Granger causal relationship from the Chinese mainland A-share market to the Hong Kong stock market.

(2) Following the successive openings of the Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connect programs until pre-pandemic times, while the Granger causal relationship remained unchanged, the external market environment gradually intensified its impact on the mainland market. The openings of the stock connect programs had a notable effect on the price differences between the mainland A-share market and the Hong Kong stock market, leading to a gradual reduction in these differences. This indicates that the openings of these programs effectively improved the market segmentation between the two regions, tightening their market connections.

(3) During the COVID-19 pandemic, the trends in the mainland stock market were generally similar to those in the Hong Kong stock market, with the HSI displaying slightly larger fluctuations compared to the CSI 300. The Hong Kong stock market exhibited a unidirectional Granger causal relationship with the Chinese mainland A-share market. Descriptive statistics show that the daily average returns of the CSI 300, representing the mainland market, were slightly higher than those of Hong Kong. Overall, the mainland market remained in a positive return state, while the HSI recorded slightly negative average daily returns. Since the onset of the COVID-19 pandemic, the ties between mainland China and Hong Kong have strengthened, showing a notable increase in mutual influence, resulting in overall consistent trends between the two markets, with the mainland market displaying a more stable trajectory.

### 4.4.2. View of economic development

From the perspective of promoting economic development, the changes in the contagion between the mainland Chinese stock market and the Hong Kong stock market have profound implications for the macroeconomy. Despite the impact of the pandemic, the two markets have maintained a unidirectional Granger causal relationship, indicating their inseparable economic ties and a deepening level of mutual influence under the pandemic's influence. Monitoring the evolving trend of the interconnectedness between these regions, both mainland China and Hong Kong capital markets, while closely intertwined, are collectively exploring international development. Their economic interdependence is expanding globally, enhancing the nation's macroeconomic resilience and fostering stable economic growth.

The enduring correlation between mainland China and Hong Kong's stock markets, where their market changes tend to converge, allows listed companies to better seize international opportunities. This diminishes the impact and uncertainties arising from stock market fluctuations, elevates resilience, and mitigates the negative impacts of uncertainties such as the pandemic, ensuring market stability and safeguarding enterprise economic performance.

As the flow of funds between mainland China's A-share market and Hong Kong's stock market intensifies and their internationalization progresses, international capital is drawn, injecting substantial funds into the market. This stimulates the prosperity of the stock market, offering investment opportunities across various sectors and industries. Coupled with robust policy support, the country's economy revitalizes amid the pandemic's challenges, compensating for losses and fostering stable and healthy development.

## 5. Suggestion

For individual investors, further education in fundamental stock knowledge, maintaining a high sensitivity to market trends, and enhancing risk management capabilities are essential. Proper allocation within their securities accounts to diversify risk and the ability to maintain rational thinking are crucial. When investing in stocks, they can opt for products like funds and bonds for risk hedging.

Institutional investors need in-depth research and assessment of different markets, industries, and enterprises to ensure investment returns and risk control. Active participation in promoting the development of securities, futures, and other financial derivatives in both regions under controlled risks injects vitality into the economies and offers increased financial support.

Market regulators must recognize the distinct regulatory mechanisms and legal frameworks between mainland China's A-share market and Hong Kong's stock market. With increased interconnectedness, there's a need for strengthened regulatory coordination and the integration of legal frameworks to enhance market transparency and stability. Regulators should focus on improving information disclosure and risk management to ensure market stability and healthy development. Additionally, enhancing mechanisms for information disclosure by listed companies improves transparency and reduces the risk spillage in the mainland stock market.

For policymakers, government departments should continue expanding market openness, fostering cross-border cooperation in various domains such as economics, culture, and technology. Actively promoting connectivity between the two markets, relaxing investment restrictions, and encouraging more mainland and Hong Kong investors to engage in each other's markets stimulate the flow and optimal allocation of capital, technology, and other factors, promoting mutual benefits and furthering economic development in both regions.

## 6. Conclusions

This article selects the daily returns of the CSI 300 to represent the mainland market and the daily returns of the HSI to represent the Hong Kong market. Data were sourced from the Wind database to investigate the contagion effect between the two stock markets amidst the backdrop of the pandemic.

Utilizing methods such as descriptive statistics, ADF tests,

correlation analysis, and Granger causality tests, this study explores the contagion effect between the mainland Chinese A-share market and the Hong Kong stock market before and after the pandemic. Empirical research using VAR regression was conducted to substantiate the findings. The results indicate a strong contagion between the mainland and Hong Kong markets, with stock index fluctuations showing convergence and mutual influence.

Specifically, before the pandemic from 2010 to January 2020, there was a unidirectional Granger causal relationship from the mainland A-share market to the Hong Kong stock market. During the pandemic period from January 2020 to December 2022, there existed a unidirectional Granger causal relationship from the Hong Kong stock market to the mainland A-share market.

With the acceleration of globalization, the heightened contagion between the mainland A-share market and the Hong Kong stock market is an inevitable trend. This interconnectivity not only fosters mutual learning and benchmarking between the two markets but also propels the Chinese capital markets toward internationalization, marketization, and standardization, thereby enhancing their international competitiveness. Simultaneously, it urges investors and regulatory authorities to collaboratively reinforce aspects like information disclosure and risk management, ensuring market stability and healthy development.

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