

Herding throughout COVID-19 pandemic: evidence from Asian stock markets

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Abstract

This paper examines herding behavior in six Asian markets (China, Hong Kong, Japan, South Korea, Singapore and Taiwan) throughout the Covid-19 crisis (January 2019 to December 2023). By applying the CCK (2000) model to detect herding at the market level, we find that herding activities generally exist in these markets, although not significant in China and Singapore. When we test investors herding in the three sub-sample periods, we find that herding is the most pronounced during tranquil period, then in strict control period, and the least significant in the open-up period. The results also suggest that domestic investors herd towards the U.S. market more in the open-up period, but the U.S. market has little influence on domestic investors in the strict control period. The portfolio analysis shows that investors are more likely to herd in smaller stocks or value stocks during the pandemic. In addition, the conditional correlation analysis shows that herding in these Asian markets is highly correlated especially when alpha, beta and delta variants emerged.

Keywords: Herding behavior, Covid-19, Asian stock markets, contagion and spillover.

JEL classification: G14; G15; G40

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1. Introduction

Investors' herding behavior has been studied extensively in literature. In behavioral finance, herding is described as a group of investors who trade in the same direction over a period of time (Nofsinger and Sias, 1999). Herding happens when investors ignore stock market/fundamental information and intentionally follow the trading patterns from other investors (intentional herding, Bikhchandani, Hirshleifer, and Welch, 1992). It can also happen when investors take similar investment decisions when facing the same sets of information from the market (spurious herding, Bikhchandani and Sharma, 2000).

Herding can be observed among specific groups of investors.¹ It can also be observed at the aggregate market level. Due to different development stages of the capital market, investors compositions, and investment cultures, investors herding behavior vary in different countries. For example, Chang, Cheng, and Khorana, (2000) finds significant evidence of herding in South Korea and Taiwan and partial evidence of herding in Japan, but no evidence of herding is found in the US and Hong Kong. Tan et al. (2008) report that herding occurs in both Chinese A-share and B-share markets. In their international study, Chiang and Zheng (2010) conclude that investors herding exists mostly in European and Asian markets but is absent in Latin American and the U.S. markets.

Studies also show that investors herding activities change in different market conditions. Chiang and Zheng (2010) document that herding is asymmetrical between up and down market, and crisis can trigger herding activity in the crisis country of origin. When crisis spread from the country of origin to other countries, herding also can be contagious and spillover to neighboring markets (Boyer et al., 2006; Chiang et al., 2007). As one of the most serious crises after the 2008 financial crisis, the Covid-19 pandemic severely disrupted businesses globally. The pandemic started from early 2020, China was the first country that identified the virus and many regional countries kept certain levels of prevention and control measures till 2023. Thus, this paper investigates herding during the pandemic and tends to fill in the gap of literature from the following aspects.

¹ For example, herding activities are detected among amateur investors (Venezia, Nashikkar, and Shapira, 2011), institutional investors (Nofsinger and Sias, 1999), mutual fund managers (Grinblatt, Titman, and Wermers, 1995), and financial analysts (Welch, 2000), etc.

Firstly, the research on herding during the Covid-19 pandemic does not provide a comprehensive conclusion. Most of existing literature focuses on the impact of Covid-19 on investors behavior at the breakout of the pandemic. Ferreruela and Mallor (2021) study investors herding in Covid-19 crisis in Spain and Portugal, and their data ends May 2021. Wu, Yang, and Zhao (2020) investigate herding behavior in the Chinese stock markets, and their data ends October 2020. Bouri, Demirer, Gupta, & Nel (2021) study investor herding in international stock markets under Covid-19 pandemic, and their data ends August 2020. Our study has a longer span of sample covering before, during and after the pandemic. This will allow us to compare investor herding behavior before, during, and after the pandemic.

Secondly, we examine herding activities in a regional setting. Previous research on herding in Covid-19 crisis either only study individual markets, such as Spain and Portugal markets (Ferreruela, et al., 2021), the Chinese stock markets (Wu et al., 2020), Egyptian stock market (Allam, Abdelrhim, and Mohamed, 2020), Australian stock market (Espinosa-Méndez, C., & Arias, 2021), and the Borsa Istanbul exchange (Erdogan, 2021), etc. Or on the other hand, some research aims for the entire global markets. For example, Ghorbel, Snene, and Frikha (2023) study major developed stock markets and BRICS country indices. Loang and Ahmad (2023) select 15 markets in all regions including Europe, Asia, and America. Bouri et al. (2021) examines the BRICS and PIIGS nations. However, as the region that Covid cases were first identified, and the quarantine/prevention measures² were dropped the last compared to other regions, how Asian markets were impacted throughout the crisis was not thoroughly investigated.³

Thirdly, following Chang et al. (2000), we measure herding by testing the relation between the cross-sectional absolute deviation (CSAD) of stock returns and stock market returns (CCK model).⁴ However, different from most papers that directly apply the model, we utilize the rolling-window method to detect herding activities throughout the whole Covid-19 crisis. Since Covid-19 infections came several waves and government's policy response changed during the whole period,

² Discussions on how Covid-19 crisis was developed and how it affects stock markets can be found in section 2.

³ Jiang, Wen, Zhang, and Cui (2022) Investigate herding behavior in six Asian stock markets. However, their study also ends January 2021, when most Asian markets were still in strict herding prevention measures.

⁴ Discussions on the methodology of empirical analysis can be found in Section 3.

investors trading behavior could also change dramatically in a short period of time. Thus, it is more accurate to detect herding behavior with a smaller time frame and at rolling basis.⁵

Fourthly, we perform portfolio analysis to investigate what type of firms are more likely to herd during the Covid-19 period. Specifically, we divide firms in each market into three portfolios by firm's market value and price-to-book ratio and conduct the herding tests on each portfolio. The results show that investors intend to herd more on stocks with smaller market value and low price-to-book ratios.

Lastly, to our knowledge, this is the first research to investigate the herding spillover and contagion throughout the Covid-19 crisis in major Asian markets. Previous international/regional studies, such as Jiang et al. (2022), document evidence of herding activities in several Asian markets, but the interconnection between markets is missing. In our analysis, we adopt the GARCH model to test how stock returns are correlated among the markets, and investigate whether the herding spillover is associated with each Covid-19 wave and/or new Covid prevention measures placed by the government.

The remainder of this paper is organized as follows: Section 2 introduces the development of Covid-19 crisis, from the beginning to the end, and how it affected major Asian stock markets. Section 3 describes the data and explains the estimation models for testing herding behavior. Section 4 reports the empirical evidence of herding behavior in each market and the portfolio analysis for herding. Section 5 examines the spillover and contagion of herding activities across those markets. Section 6 summarizes our findings and concludes the analyses.

2. Covid-19 and Asian stock markets

Covid-19 cases started to show up in December of 2019 and broke out in January of 2020 in the city of Wuhan in China. However, the news of Covid-19 did not get much attention until the lockdown of Wuhan on January 23, 2020. After about two months' lockdown of cities and provinces around the country, new cases and deaths of Covid-19 were quickly under control and

⁵ Herding in general is short-lived, therefore it is important to examine the short-term dynamic effect. See, for example, Zhang and Giouvris (2022), Bogdan et al. (2022)

relaxation of lockdown measures was implemented so that the economy could get back to normal in China. However, the world was profoundly changed after the virus spread globally via travelers.

Since the initial outbreak in Wuhan, Covid-19 virus has had a few variants named by the World Health Organization: Alpha, Beta, Delta and Omicron variants, among others. Alpha cases started in November 2020 in Great Britain, and Beta was first discovered later that year in South Africa. Both were more contagious than the original strain and were more likely to lead to hospitalization and death. However, with the multi-stage implementation of vaccination starting in December 2020, the cases seemed to be under control. Then Delta, which was first identified in India in late 2020, became the dominant variant in June 2021. Even though vaccination could lessen the seriousness of infection, it couldn't stop the spread of the virus. The Omicron variant quickly prevailed in the world in December 2021 and has had several sub-variants emerging since then.⁶ All the Asian countries have been affected by these variants, even though each had its own public health and economic policies.

China continued to pursue zero-Covid policy since the initial outbreak, even facing the spread of the Delta and Omicron variants. It approved five of its own vaccines for emergency use by March 2021. Quarantine, mass testing and mask policies were still in place to control the spread of the virus in the next two years or so, until break out of Omicron cases in the financial center, the city of Shanghai in March 2022. This time, Shanghai was in strict lockdown for about two months until the situation was under control. Shanghai, where Shanghai Stock Exchange was located, was the major city for inbound travel, where international travelers were required to quarantine in hotels for two weeks before traveling to other cities in China. Its lockdown caused panic in the stock market and Shanghai Stock Exchange Composite Index dropped by about 13% in March 2022. Afterwards, however, China's strict quarantine policy was eased to 10 days (May 2022) and then 7 days (October 2022). In December 2022, Covid cases spread quickly around the country and the government finally lifted most stringent rules on quarantine and ended mass testing. This officially ended the zero-Covid policy in China. This can be seen in Figure 1, where the daily new cases peaked at the beginning and end of the whole period, with sub-peaks in April and December of 2022.

⁶ <https://www.yalemedicine.org/news/covid-19-variants-of-concern-omicron>

As an international financial center and a port for international trade, Hong Kong had a small breakout in January 2020, followed by another small breakout from returnees abroad in late March and imported cases such as air crew members in July. It pursued a similar zero-Covid strategy as mainland China with strict border control and partial shutdown when cases were discovered. Vaccination with both Chinese vaccines and Pfizer vaccines was introduced in February 2021. New cases were sparse as seen in Figure 1 until January and February 2022 when Omicron variant spread quickly across the world. Hong Kong eventually opened up its border on December 13, 2022, with only requirements on vaccination records.

Singapore, similar to Hong Kong, is a financial center and port for international trade. It adopted circuit breaker measures including stay-at-home order and cordon sanitaire to prevent spread of the virus. This nation-wide partial lockdown requested remote work and home-based learning and restricted social gatherings and dining in at restaurants. The circuit breaker measures were only used from April 7, 2020, to June 1, 2020, May 16, 2021, to June 13, 2021, and July 22, 2021, to August 9, 2021. Vaccines were available starting in December 2021. With the spread of Delta and Omicron variants, it finally lifted all restrictions in February 2023.

Japan, as the most advanced economy in our sample, has not had a full lockdown. When the pandemic broke out in January 2020, Japan closed all k-12 schools from late February to early April to prevent the virus from spreading too quickly. It declared a state of emergency for Tokyo and six other prefectures to restrict movement or travel domestically from early April 2020 until May 2020. Another state of emergency was declared for Tokyo and three prefectures from January 2021 to February 2021. The measures worked effectively as the death rate was one of the lowest despite its aging population. The vaccination began in February 2021. However, as the Omicron wave hit towards the end of 2021, Japan faced several spikes of new cases (seen in Figure 1) in 2022. It officially opened up in May 2023.

South Korea, like Japan, has never had a lockdown of a whole city due to its mass rapid testing and tracing program. There were a few break out cases in 2020 due to church gatherings. However, the situation was quickly under control without a major spike until it was hit by the Omicron variant in early 2022. It began relaxing rules in March 2022 and shifted to endemic status.

Taiwan, same as South Korea and Japan, has not implemented a strict lockdown. It had strict border control measures such as no foreigner entry and quarantine starting in March 2020, which proved

effective. However, in late April 2021, a spike of new cases occurred in Taipei area due to outbreak from airline crew members. Closures of schools and national borders were implemented at the time. Vaccination became available in June 2021. Then the Omicron variant hit Taiwan with the second outbreak from January to March 2022. Taiwan slowly opened since then, and dropped all health measures on May 1st, 2023⁷. It provided stimulus packages worth billions of dollars to businesses and used stimulus vouchers to encourage residents to buy commodities in 2020.

The pandemic greatly impacted the global economy and stock market, caused by supply chain disruptions due to border control, changes in new Covid cases and deaths and sentiment change from lockdowns. Herding in these Asian stock markets during this period has been documented by many studies (Yuan 2021; Wu et al, 2020; Jiang et al, 2022; Fei and Zhang, 2023; etc.) and most of them conclude that herding in China's stock market has become more prominent during the pandemic compared to before-pandemic measure with one exception from Wu et al (2020), who find significantly lower herding during the pandemic. Loang and Ahmed (2023) find evidence of herding in China and South Korea, but not in the U.S., Hong Kong and Japan. Yang and Chuang (2023), on the other hand, find slight herding in the U.S., China and Taiwan compared to previous market incidents such as dotcom bubble in 2001. Aslam et al (2022) compares Asian markets with European markets and only find herding in China and Japan in the third quarter of 2020.

Very few studies have looked at the spillover effect of herding between these markets. As the virus spread across these close neighboring countries, the fear and anxiety stemming from the initial outbreak in one country, such as China, could easily trigger the sentiment change in investors in other neighboring countries and lead to herding change in those stock markets. Loang and Ahmed (2023) show that the U.S. and China's cross-market herding had a significant impact on other markets' herding activities.

In following sections, we will perform empirical analysis to investigate herding in those Asian markets and the dynamics of the contagion effect.

[Figure 1]

⁷ Effective May 1, COVID-19 to be downgraded to Category 4 notifiable communicable disease and CECC to disband; Ministry of Health and Welfare to take charge of relevant preparation and response work (http://www.cdc.gov.tw/En/Bulletin/Detail/FW_1qpr_nCJoo0X1X5oDCw?typeid=158)

3. Data and Methodology

3.1 The data

The daily data employed in this study consists of stock price and market price indices. The sample covers six major Asian markets: China (CN), Hong Kong (HK), Japan (JP), Singapore (SG), South Korea (KR), and Taiwan (TW). We also collect the data from the United States (US) as an external control variable. The data range is from January 2019 to December 2023.⁸ The stock/index return is calculated as $R_t = 100 \times (\log(P_t) - \log(P_{t-1}))$; where P_t denotes either a stock price or a stock market index. All data are taken from DataStream International.

3.2 Herding measure

Investors herding activities can be measured from two aspects, specifically, herding to individual stocks and herding to market. The former measures mainly utilize the trading ratio of “buy trade” and/or “sell trade” to “total trade”, and it is best to test herding between different groups of investors.⁹ Our study, however, explores investors’ behavior at the aggregate market level. Thus, we follow one of the most cited CCK (Chang, Cheng and Khorana, (2000)) procedure and calculate the stock return dispersion as the market level herding measure.

According to the CCK (2000), market herding is detected when investors tend to mimic collective actions in the market and trade towards the same direction. When herding is absent, investors should trade more diversely, and the stock return dispersion (measured by the cross-sectional absolute deviation (CSAD)) has a linear relation with the absolute value of stock market return. On the other hand, when investors herd, the linear relationship doesn’t hold any more, and instead CSAD has a concave non-linear association with the market return square. CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

⁸ Because of the limited availability of data, the starting and ending dates vary across different markets, but only off by several days.

⁹ For example, Lakonishok, Shleifer, and Vishny (1992), Sias (2004), Kremer and Nautz (2013).

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{m,t}$ is the cross-sectional average return of N stocks in the portfolio at time t . The equation to test herding activities has the following specification:

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{m,t})^2 + \varepsilon_t \quad (2)$$

According to Chang et al. (2000), the coefficient λ_2 measures the herding behavior, and a significantly negative λ_2 is the evidence that herding exists at the aggregate market level.

Table 1 reports descriptive statistics for stock market returns and CSAD for all markets in our sample. Among the seven markets, Taiwan has the highest average daily return (0.0417%) and Hong Kong has the lowest average return (-0.0228%). For the CSAD measure, Hong Kong has the highest average return deviation (2.313) while Singapore has the lowest (1.2538).

[Table 1]

3.3 Contagion during the pandemic

During the pandemic, not only the herding within each market might change, but also there might be spillover effect among these Asian economies, possibly due to their close geographic locations, economic ties or similar investor sentiment towards these economies. Our purpose in this paper does not focus on which channel leads to the spillover or contagion, but more on the dynamics of their return correlation to see when the contagion occurs during the different stages of the pandemic.

The multivariate GARCH-DCC model proposed by Engle (2002) enables us to estimate the time-series conditional correlation so that we can have a clear view of the dynamic trajectories of the contagion. As China was the first market that Covid-19 cases were identified and also the largest economy in the region, we adopt a bivariate GARCH-DCC model to examine how the correlation between stock returns of China and one of the other economies changes over time. Following Equation (2), the mean equation of the bivariate GARCH model is specified as below:

$$R_{i,t} = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{m,t})^2 + \varepsilon_t \quad (3)$$

where $R_{i,t} = (R_{CN,t}, R_{i,t})'$, $R_{m,t} = (R_{CN,m,t}, R_{i,m,t})'$, $\varepsilon_t = (\varepsilon_{CN,t}, \varepsilon_{i,t})'$; $i = \text{HK, JP, KR, SG, or TW}$; and $\varepsilon_t | \mathfrak{F}_{t-1} \sim N(0, H_t)$.

Next, we specify a bivariate conditional variance/covariance matrix as:

$$H_t = D_t P_t D_t \quad (4)$$

where D_t is the (2x2) diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{jj,t}}$ on the j^{th} diagonal, $j = \text{CN}$ and i ; P_t is the (2x2) time-varying correlation matrix. The DCC model proposed by Engle (2002) involves two-stage estimation of the conditional covariance matrix H_t . In the first stage, univariate volatility models are fitted for each of the stock index returns and estimates of $\sqrt{h_{jj,t}}$ are obtained. In the second stage, CSAD residuals are transformed by their estimated standard deviations from the first stage. That is, $\mathbf{u}_{j,t} = \boldsymbol{\varepsilon}_{j,t} / \sqrt{h_{jj,t}}$, where $u_{j,t}$ is then used to estimate the parameters of the conditional correlation.

The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \quad (5)$$

where $Q_t = (q_{CN,i,t})$ is the 2x2 time-varying covariance matrix of u_t , $\bar{Q} = E[\mathbf{u}_t \mathbf{u}'_t]$ is the 2x2 unconditional variance matrix of u_t , and α and β are nonnegative scalar parameters satisfying $(\alpha + \beta) < 1$.¹⁰ The parameter α captures the responsiveness of conditional covariance to past shocks, while the parameter β reflects the persistence in volatility transmission. Since Q_t does not generally have ones on the diagonal, we scale it to obtain a proper correlation matrix R_t . Thus,

$$P_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2}, \quad (6)$$

where $(\text{diag}(Q_t))^{-1/2} = \text{diag}(1/\sqrt{q_{CN,CN,t}}, 1/\sqrt{q_{ii,t}})$.

Now P_t in equation (4) is a correlation matrix with ones on the diagonal and off-diagonal elements less than one in absolute value, as long as Q_t is positive definite. A typical element of $R P_t$ is of the form:

$$\rho_{CN,i,t} = q_{CN,i,t} / \sqrt{q_{CN,CN,t} q_{ii,t}}, \quad i = \text{HK, JP, KR, SG, TW}. \quad (7)$$

Expressing the correlation coefficient in a bivariate case, we have:

$$\rho_{CN,i,t} = \frac{(1-\alpha-\beta)\bar{q}_{CN,i} + \alpha u_{CN,t-1} u_{i,t-1} + \beta q_{CN,i,t-1}}{\sqrt{[(1-\alpha-\beta)\bar{q}_{CN,CN} + \alpha u_{CN,t-1}^2 + \beta q_{CN,CN,t-1}]} \sqrt{[(1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1}]}}. \quad (8)$$

¹⁰ A typical element of Q_t is given by: $q_{CN,i,t} = (1 - \alpha - \beta)\bar{\rho}_{CN,i} + \alpha u_{CN,t-1} u_{i,t-1} + \beta q_{CN,i,t-1}$, where $\bar{\rho}_{CN,i}$ is the unconditional correlations of $u_{CN,t} u_{i,t}$. $i = \text{HK, JP, KR, SG, or TW}$

As proposed by Engle (2002), the DCC model can be estimated by using a two-stage approach to maximizing the log-likelihood function. Let θ denote the parameters in D_t , and φ the parameters in P_t , then the log likelihood fund is:

$$l_t(\theta, \varphi) = [-\frac{1}{2}\sum_{t=1}^T(n \log(2\pi) + \log |D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t)] + [-\frac{1}{2}\sum_{t=1}^T(\log |P_t| + u_t' P_t^{-1} u_t - u_t' u_t)]. \quad (9)$$

The first part of the likelihood function in Equation (9) is volatility, which is the sum of individual GARCH likelihoods. The log-likelihood function can be maximized in the first stage over the parameters in D_t . Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage (the second part of Equation (9)) can be maximized to estimate correlation coefficients.

4. Empirical evidence of herding

In this section, we will perform various tests to investigate investors' herding behavior throughout our sample period that covers pre, during, and post of the Covid-19 crisis in the six major Asian markets. We start with the baseline model to test if herding activities are significant for the whole sample period. Next, we divide the whole sample into three subset periods, strict control, open-up, and tranquil periods, and test if there are differences in herding behavior among the three periods. We also further investigate how domestic investors' herding is affected by the external U.S. market.

4.1 Herding during the whole sample period

We first examine investors' herding activities during the whole sample period from January 2019 to December 2023. Since herding is a short-term investor behavior (Bikhchandani, Hirshleifer, and Welch, 1992; Kremer and Nautz, 2013), a shorter time window would be able to capture its dynamics more accurately. Thus, we apply the CCK model (Equation (2)) with a rolling-window regression at monthly basis.¹¹

¹¹ We follow Liu et al., (2023) to select the rolling window period as past 25 trading days prior to day t . We also try different time frames for the rolling window, such as 15 days or 60 days, and the main results are similar.

Table 2 reports the means of the herding measure from the rolling window regressions. Note that the herding measure is the estimate of λ_2 in Equation (2), and a negative λ_2 indicates evidence of herding. The results show that λ_2 is negative for all six Asian markets and the US, suggesting that investor herding generally exists during the sample period. The significance of herding activities varies across different markets. For example, λ_2 has the larger absolute value in Japan, Korea, and Hong Kong but is not significant in China and Singapore markets. It is also worth noting that our results are consistent with some previous findings such as those in Chiang and Zheng (2010), which document that herding is significant in Asian markets. But it is possible that the impact of the pandemic alters investors' herding behavior in different periods, therefore, we will analyze this in more detail in the next sections.

Figure 2 presents the dynamics of the herding measure throughout our sample period for all six Asian markets. It is evident that the herding measure follows certain patterns, and the patterns coincide with each other across the Asian markets. There are a few notable time points that the herding measure became more significant for most of the markets, which are consistent with the timeline of the Covid-19 development¹².

[Table 2]

[Figure 2]

4.2 Herding in different stages through Covid crisis

As we discussed in Section 2, the impacts of Covid-19 shock on stock markets and the economy were severe, and the government from each market implemented multiple health and economic measures to slow down the virus spread and support the economy. In this section, we investigate how investors' herding activities changed throughout the Covid crisis.

Specifically, we define the period that Covid and Covid variants (Initial breakout, Alpha, Delta, and Omicron) had major impacts on the economy as "strict control period", when most markets implemented strict public health measures (such as quarantine, lockdown, and work at home¹³).

¹² For example, in summer 2021 when the deadly Delta variant started to spread and spring/summer 2022 when Omicron became the dominant variant.

¹³ See Section 2 for details. Note Asian markets in general implemented stricter Covid control policies throughout the initial breakout period until Omicron variant breakout.

Since the Omicron variant became the prevalent Covid variant, however, strict public health measures didn't work well to slow down the virus spread, and as the Covid vaccine became widely available from late 2021, most markets started to ease Covid control measures till fully open-up. We define this period as "Open-up period". Finally, we define the pre- and post-Covid time as the tranquil period. In our analysis, strict control period is the period from Feb 2020 to May 2022, open-up period is from June 2022 to Jan 2023, and tranquil period is from Jan 2019 to Jan 2020 and from Feb 2023 to Dec 2023¹⁴. We still apply the same method (rolling window regression of Equation (2)) to detect herding in each sub-period.

The regression results are reported in Table 3. There are a few notable findings from the results. Firstly, the herding measure (λ_2) is negative and significant in most of the regressions, suggesting that herding generally exists in Asian markets during all three regimes (strict control, open-up and tranquil). The exceptions are China and Singapore during the strict control period and open-up period. The results are consistent with those in Table 1 that herd activities overall are not significant in these two markets. Secondly, including China, the herding measure (λ_2) is negative and significant in all markets (except for Singapore) during the tranquil period. In addition, for all markets, the absolute value of λ_2 is larger (more negative) in the tranquil period than that in the other two periods. Finally, if we compare the herding measure (λ_2) between the strict control and open-up periods, λ_2 has a larger absolute value (more negative) in the strict control period. The results indicate that investors are less likely to herd during the Covid crisis than in tranquil period and herd the least during the open-up period.

The results suggest that investors in Asian markets might search for a different set of information instead of domestic market consensus during the strict control and open-up period, possibly information from other markets, such as the US and China.

[Table 3]

4.3 The impact from the U.S. market

¹⁴ Specifically, Initial Covid impact started in early 2020, Covid Alpha variant wave dominated in late 2020 to early 2021, Delta variant wave dominated summer to fall of 2021, and Omicron variant wave dominated in spring of 2022. Most markets fully opened in spring 2023. Note for that each market, the Covid impact has slightly different time frames, but it doesn't affect our results.

The U.S. is often considered one of the most influential markets in global financial markets. In crisis such as the Covid-19 crisis, the U.S. market could play a significant role in Asian investor's trading decisions (Chiang and Zheng, 2010; Yang et al. 2015). Follow Chiang and Zheng (2010), we revise the CCK herding model Equation (2) by including the U.S. market return squared term as the following:

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{i,m,t})^2 + \lambda_3 (R_{us,m,t})^2 + \varepsilon_t \quad (2)'$$

where $R_{i,m,t}$ and $R_{us,m,t}$ are the cross-sectional average return of N stocks in the portfolio at time t in the domestic market and the US market, respectively. All other variables are defined as before. In this model, herding not only can be detected at domestic level (λ_2 is negative and significant), but also towards the U.S. market (λ_3 is negative and significant).

Table 4 reports estimated results from Equation (2)'. For the domestic herding measure (λ_2), the results are generally consistent with those in Table 3. Herding is detected most significantly during the tranquil period, and least significantly in the open-up period. Also, Domestic herding is not detected in China and Singapore during the strict control and open-up periods.

The herding coefficient from the U.S. market (λ_3), however, reveals different patterns. When the Covid crisis was at its peak and governments implemented strict control in health measures, none of λ_3 is negative and significant. The result suggests that when lockdown and quarantine measures were in place, Asian markets behave more isolated, and the U.S. market information has little impact on domestic investors' trading decisions.

On the other hand, when Omicron became the dominant Covid variant, and Asian markets slowly opened and loosened strict health measures, λ_3 is negative and significant for all markets except for Hong Kong, indicating that domestic investors look for external information to trade and herd during that period, especially information from the U.S. market. The results also show that during the open-up period, even though herding is not detected in China and Singapore domestic markets, investors from these two markets did herd with the U.S. market.

During the tranquil period when Covid is not the concern for investors, the domestic herding coefficient (λ_2) is negative and significant for all Asian markets except Singapore, but investors from Japan, Korea, and Taiwan also herd with the U.S. market, although to a less extent (λ_3 is less than λ_2 in absolute value).

Findings from Panel A (the strict control period) suggest that investors didn't herd with the U.S. market, but it is still possible that as closely related markets in the region, these markets might have stronger influence on each other during the pandemic and cause contagion and spillover effect (Chiang et al., 2007). We will further explore this issue in Section 5.

[Table 4]

4.4 Robustness test on market conditions

The literature suggests that investors tend to herd more under extreme market conditions when investors face more uncertainty. For example, Christie and Huang (1995) finds that herding is more prevalent during periods of market stress. Chiang and Zheng (2010) documents that herding is more profound in Asian markets during rising markets¹⁵. Since Asian stock markets experienced some extreme moves during the Covid-19 period¹⁶, it is important to examine if the herding activities detected in previous sections are associated with market extreme conditions.

To test whether investors herding activities vary under different market conditions, for each market, we sort the data by stock market returns, and divide the whole sample period into three groups, each of which represents the bottom one third (highest negative returns, group 1) of market returns days, middle one third (middle range returns, group 2) of market returns days, and the top one third (highest positive returns, group 3) of market returns days. Then we apply the augmented Equation (2)' and run the regression for each of the three groups¹⁷.

The regression results are reported in Table 5. The results are consistent with those in Table 2. For all three market return groups, domestic herding is detected significantly in Hong Kong, Japan, Korea, and Taiwan markets, but not in Singapore and China. The absolute values of herding coefficients are generally higher in group 2, suggesting that herding is more prominent when Asian markets are not experiencing extreme moves. In addition, Japanese and Korean investors herd more towards the U.S. market when domestic market is on the rise, and Korean and Taiwanese investors herd more towards the U.S. market when domestic market is down. The results are

¹⁵ Other research such as Hwang and Salmon (2004) find less herding behavior during the Asian crisis and the Russian crisis, which contradicts the findings from Chiang and Zheng (2010).

¹⁶ For example, Nikkei 225 in Japan and Hang Seng Index both fell by over 20% from January to March 2020.

¹⁷ We also divided the data into 5 groups and 10 groups by market returns and applied the same regression. The results among different groups are similar to those of the 3 groups we report in Table 5.

consistent with those in Table 4 and Chiang and Zheng (2010). However, domestic market herding still dominates as the domestic herding coefficient λ_2 has a much larger absolute value than the U.S. herding coefficient λ_3 . The results suggest that the previous findings on herding activities and patterns are not different due to extreme market conditions during the Covid-19 period.

[Table 5]

4.5 Portfolio analysis

The literature documents that investors exhibit different herding behaviors towards different types of stocks. For example, Wermers (1999) finds mutual fund herding is strongest in small and growth stocks. Demirel & Kutan (2006) show small firms in emerging markets have persistent herding. However, very few studies investigate investors' herding on different types of stocks during the Covid-19 period. In this section, we explore this issue by dividing all stocks in each market by their market value (size) and price-to-book ratio and perform the same herding tests as in the previous section for those portfolios.

For each market, at the beginning of every month, we sort the data by the stocks' market value (MV) or their price-to-book ratio (PB) and divide the data into three groups: the low MV (PB) group 1 (bottom one third), the high MV (PB) group 3 (top one third), and the middle MV (PB) group 2 (middle one third). Then we apply the augmented Equation (2)' and run the regression for each of the three groups¹⁸. The regression results are reported in Table 6, where Panel A reports the results for MV sorted portfolios and Panel B reports the results for PB sorted portfolios.

[Table 6]

The results reveal that herding tends to be more profound in small-cap and low price-to-book (value) stocks, as the herding coefficient λ_2 has a greater negative value in group 1 (bottom group) than group 3 (top group) for both size and price-to-book sorted portfolios in all Asian markets in our sample¹⁹. The results suggest that throughout the Covid-19 crisis, investors are more likely to herd in smaller stocks (due to information asymmetry) or value stocks (due to liquidity) which is

¹⁸ We also divided the data into 5 groups by MV (PB) and applied the same regression. The results among different groups are similar to those of the 3 groups we report in Table 6.

¹⁹ Except for China, where λ_2 is not negative in all portfolio results.

documented in some of the previous studies²⁰. On the other hand, the US effect on domestic investors' herding is mixed for different types of stocks.

5. Contagion effect in the region

During the pandemic, the impact of the U.S. market is non-existing from Table 4 results, especially during the strict control period. This section tries to investigate the possibility of contagion within the region as the pandemic started in early 2020. Given the geographic closeness and trade relationship of these economies and the nature of the Covid-19, it is possible that the stock market panic sentiment (and herding behavior) could spread to neighboring markets, which can be captured in the bivariate GARCH-DCC model.

The bivariate GARCH (1,1)-DCC model used in this study examines the dynamic correlation between China's market return and the other five Asian markets' returns, because China is the largest economy in the region and had implemented strict health measures earlier than other markets during the pandemic. The literature has found that GARCH (1,1) model is enough to model the volatilities of daily stock return (e.g. Miah and Rahman, 2016). Table 7 Panel A presents the GARCH results for each bivariate model and shows the mean equation, variance equation and covariance equation results for the whole sample period. In China's variance equation, the ARCH term and GARCH term are both positive and significant, suggesting the volatility is mainly coming from past variance as well as from past shocks. In other markets' variance equations, all ARCH and GARCH terms are also positive and significant, showing high persistence of the volatility ($\lambda_1 + \lambda_2$ close to 1) like China's case. The covariance equations, though, show lower degrees of persistence ($\alpha + \beta$ not close to 1) except for Singapore and Taiwan. The past covariances are positive and significant at 1% level while the products of past shocks are less significant (only significant at 1% level for China-Hong Kong and China-Taiwan pairs). The past covariance still dominates in the equation, suggesting that the transmission of the co-movement mainly comes from the past co-movement, but also absorbs the past shocks from each market.

²⁰ For example, Chang, Cheng, and Khorana, (2000); Shleifer & Vishny (1997); Chiang et al. (2010)

Next, the same GARCH model is run for the strict control sub-period.²¹ Results are reported in Table 7 Panel B. In the variance equations, each market is affected less by its past variance, but more by its past shocks compared to the whole sample period. This shows that during a major event like Covid-19, past shocks have more impact on the volatility in domestic market. This also applies to covariance equations for Japan, Singapore and Taiwan. However, Hong Kong and South Korea show different patterns in covariance equations. The β coefficient for the covariance equation is much larger during the strict control period, indicating strong interdependence of these two markets with China's market.

Next, the conditional correlation series are generated and presented in Figure 3 for the whole sample period and in Figure 4 for the strict control period. The line shows the conditional correlation between index returns of China and Hong Kong (or Japan, South Korea, Singapore, Taiwan) generated from the DCC-GARCH (1,1) model. China and Hong Kong conditional correlation seems to have the highest correlation among the five, given that China and Hong Kong's economies have the closest ties and many Chinese firms are cross listed on the Hong Kong Stock Exchange. All the correlation series show similar spikes in early 2020, mid-2020, late 2020, and early 2022. The first spike around March 2020 coincides with the breakout of the Covid-19 virus in China in late January 2020 and the panic sentiment was felt throughout the financial markets around the world. Right before the spike, we typically observe a drop in correlation (January to February 2020), which is termed the contagion stage (Chiang, Jeon and Li, 2007) as the financial markets around the region had not felt the immediate impact of the virus. However, as the virus spread gradually among the neighboring markets in March 2020, the panic sentiment seeped through their financial markets quickly. The correlations between these markets spiked to reflect the herding behavior of the investors due to sentiment changes (Chiang, Jeon and Li, 2007). As different forms of prevention and control measures were put into place, the market calmed down and the correlations came down. When more Covid cases emerged in mid-year 2020 as more markets began to open up, the correlations went up again.

The third spike comes towards the end of 2020 and beginning of 2021, showing that the herding in these Asian countries is elevated probably due to the emergence of the alpha, beta and delta

²¹ The GARCH model does not converge successfully for the open-up subperiod probably due to insufficient data points, therefore not reported here.

variants around that time. After that, the vaccination was rolled out gradually in these Asian economies. The spillover effect is not obvious until when Omicron hit hard and new cases rose in late 2021 and early 2022.

Note that none of these spikes has changed the correlation permanently, meaning that the impact of the Covid-19 pandemic on correlations between the index returns of these Asian countries is transitory. An investor who is aiming for long-term diversification of his/her portfolio should not change the strategy due to these incidents of higher correlation.

[Table 7]

[Figure 3]

[Figure 4]

6. Conclusion

This paper studies the herding behavior in six Asian markets (China, Hong Kong, Japan, South Korea, Singapore and Taiwan) throughout the Covid-19 pandemic. Herding activities are detected by the CCK (2000) model, and we divide the whole sample period into three subperiods: the strict control period when the government of all these markets implemented strict health measures to prevent spread of Covid-19 virus, the open-up period when most prevention measures eased till fully open-up, and the tranquil period before and after the pandemic.

The empirical results show that the herding coefficients (λ_2) is negative in all six Asian markets during the whole sample period, indicating that herding activities generally exist in these markets, although they are not significant in China and Singapore. When we test investor herding in the three sub-sample periods, we find that herding is the most pronounced during the tranquil period, then in strict control period, and the least significant in the open-up period, measured by the absolute value of the herding coefficients (λ_2).

After including the U.S. market return squared term in the equation, it is evident that domestic investors herd towards the U.S. market more in the open-up period when quarantine measures were eased, but the U.S. market has little influence on domestic investors in the strict control period when Asian markets are mostly isolated. We also divide firms in each market into three portfolios

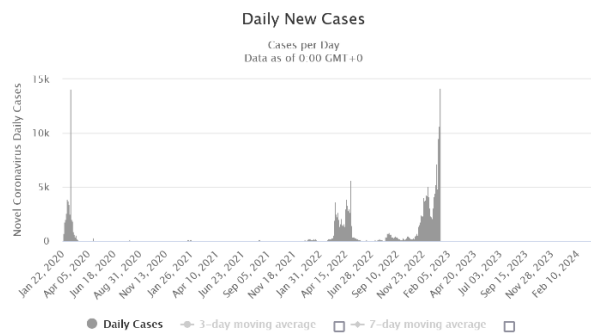
by their market value and price-to-book ratio and conduct the herding tests on each portfolio. It is evident that herding is more profound in small and value stocks during the pandemic.

In the robustness test, we test herding behavior under the highest 1/3 market return days and the lowest 1/3 market return days during the crisis. It reveals that there are no differences in herding activities and patterns due to the extreme market conditions. Stocks are also sorted into portfolios by their market value and price-to-book ratio to test whether investors herd more on specific types of stocks. The results suggest that during the pandemic, herding is more pronounced in smaller stocks or value stocks.

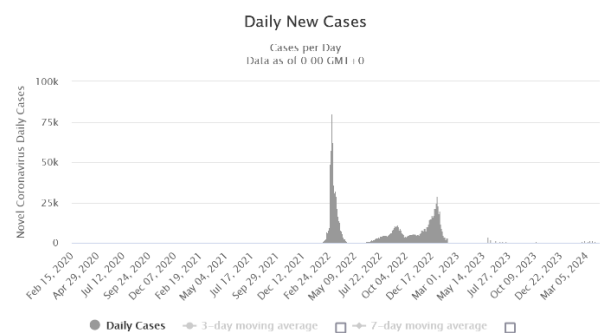
Finally, the GARCH (1,1)-DCC model examines the dynamic correlation between China stock market and the other five Asian markets during the pandemic. We find that during the strict control period, the volatility of stock returns in each market is persistent with less coming from past variance, but more coming from past shocks. The co-movement between China and other markets such as Hong Kong and South Korea, on the other hand, shows strong interdependence. The spikes of the conditional correlations generally coincide with the emergence of different new variants and rise of new cases and deaths, but the high correlations during the strict control period are transitory.

Figure 1 Daily new Covid cases during the pandemic period

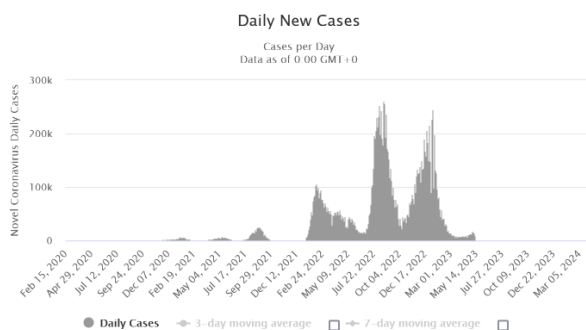
Daily New Cases in China



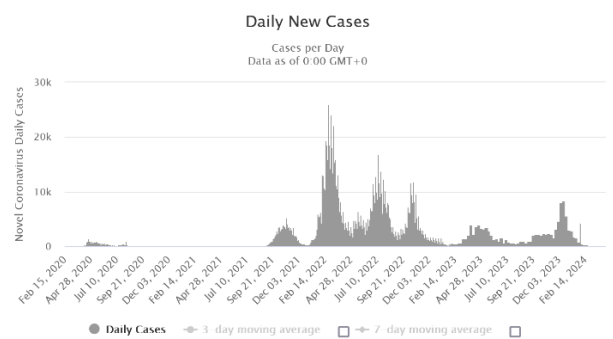
Daily New Cases in China, Hong Kong SAR



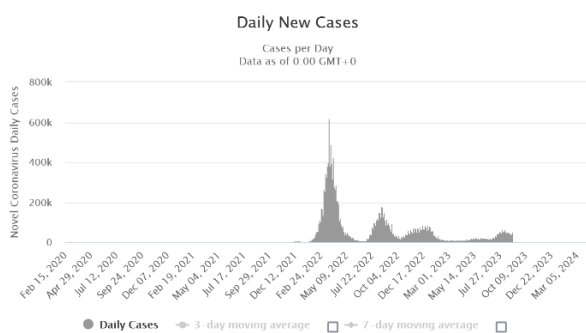
Daily New Cases in Japan



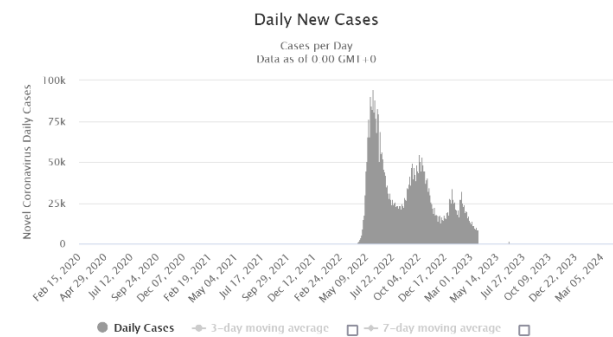
Daily New Cases in Singapore



Daily New Cases in South Korea



Daily New Cases in Taiwan



Source: <https://www.worldometers.info/coronavirus/>

Figure 2. Herding measure during the whole sample period

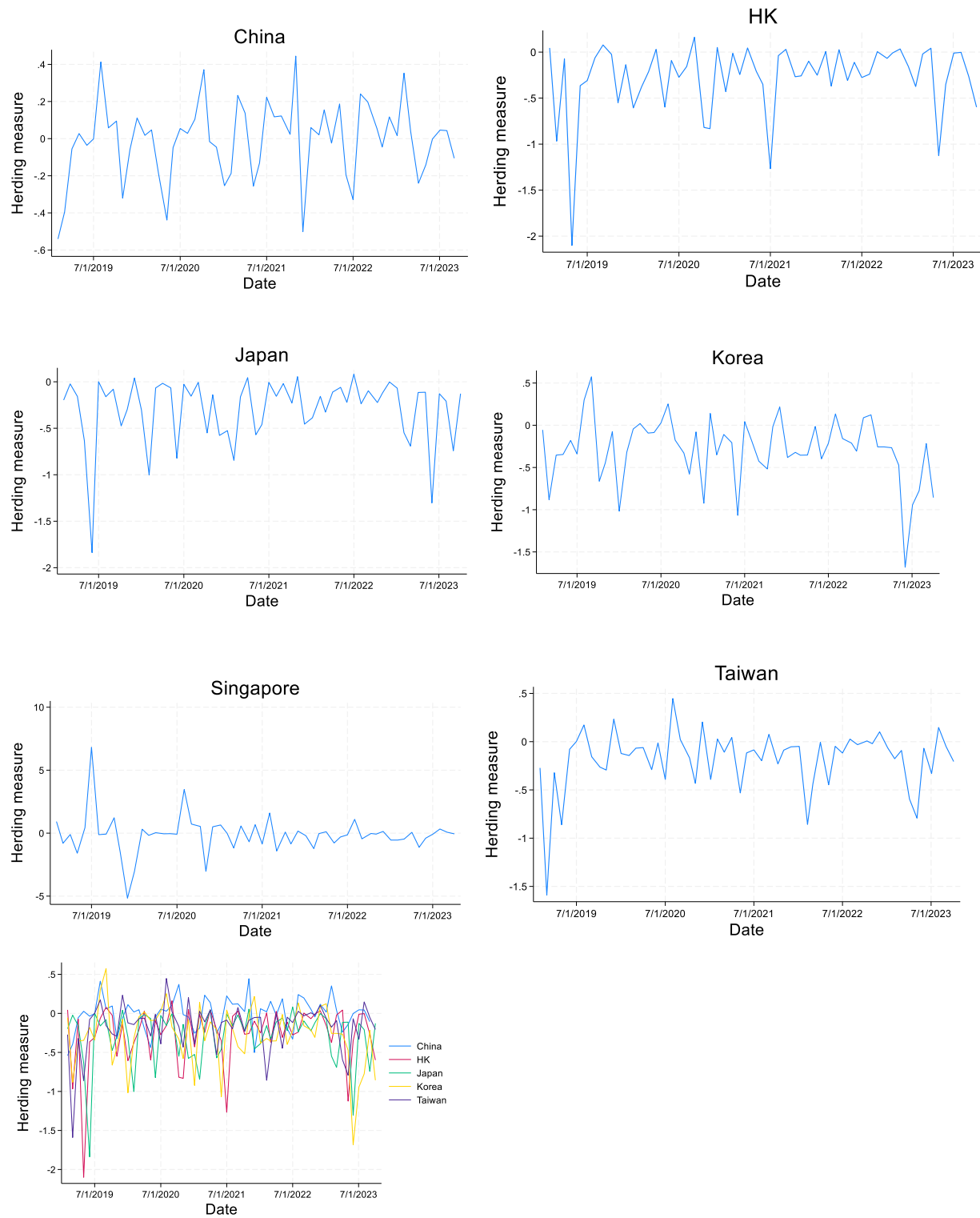


Figure 3. Conditional Correlation from bivariate GARCH-DCC models with local polynomial smoothing

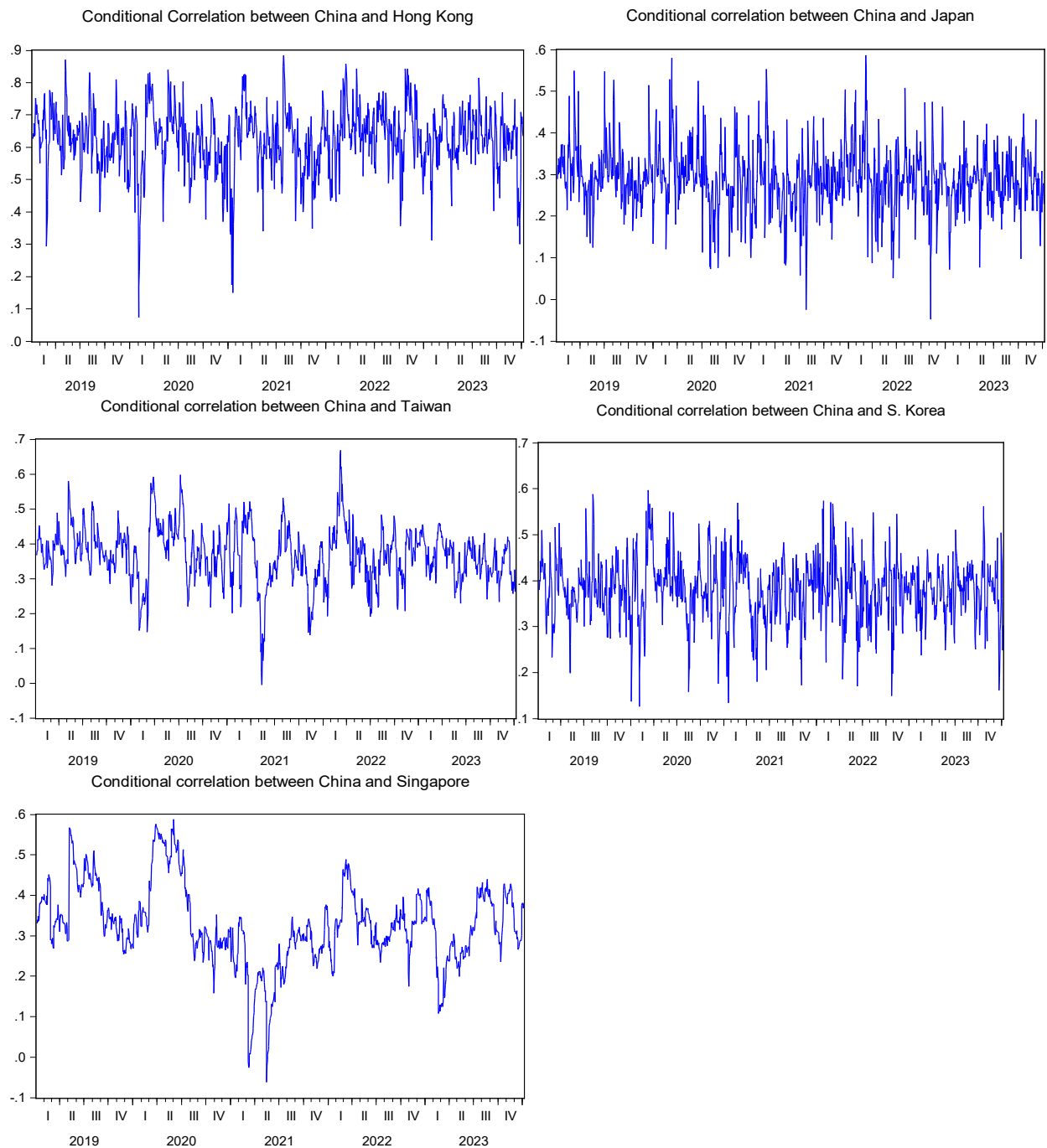


Figure 4 Conditional Correlation during the Strict Control Period (February 2020 – May 2022)

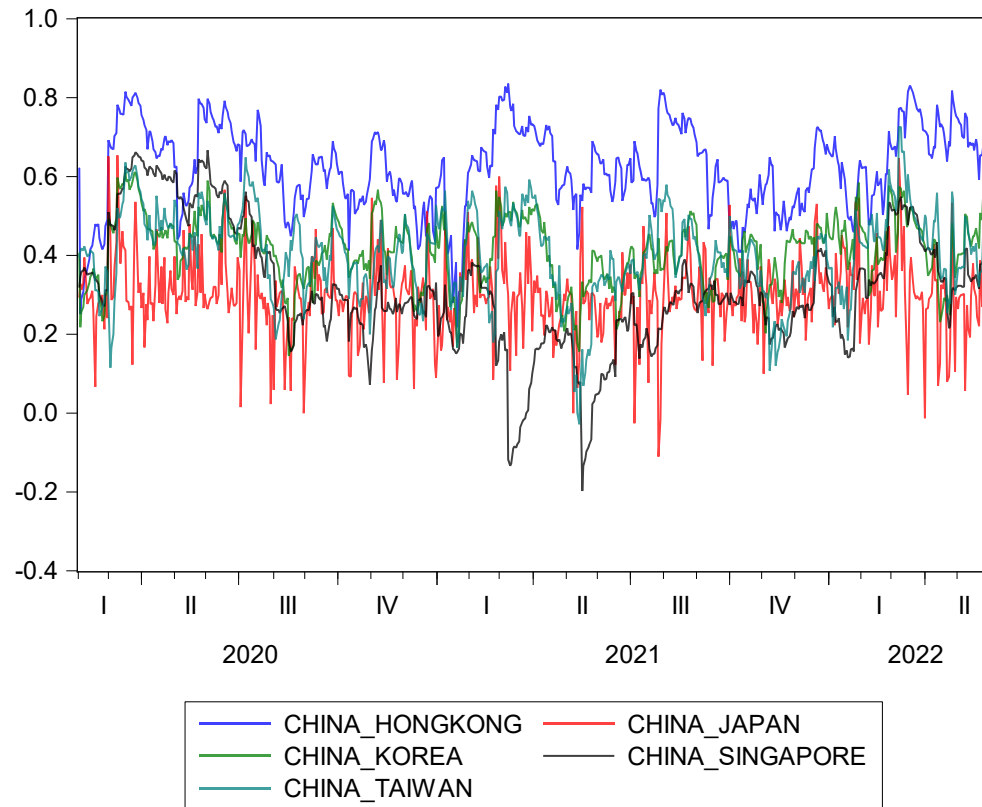


Table 1. Descriptive Statistics

This table reports descriptive statistics of daily, equally weighted stock market return and stock return cross-sectional absolute deviations (CSAD) for six Asian markets: China (CN), Hong Kong (HK), Japan (JP), South Korea (KR), Singapore (SG), and Taiwan (TW). The data ranges from January 2019 to December 2023. Calculations of the CSAD are based on equation (1). All stock and stock index returns are calculated as $R_t = 100 \times (\log(P_t) - \log(P_{t-1}))$, where P_t denotes either individual stock price or stock market index.

Panel A. Market return

Market	CN	HK	JP	KR	SG	TW
<i>Mean</i>	0.0162	-0.0228	0.0345	0.0158	-0.0070	0.0417
<i>Std.</i>	1.1585	1.4708	1.0097	1.1962	0.8383	1.1083
<i>Ske</i>	-0.4699	0.1248	-0.0849	-0.0128	-0.9551	-0.1486
<i>Obs.</i>	1158	1304	1304	1304	1304	1304

Panel B. CSAD

Market	CN	HK	JP	KR	SG	TW
<i>Mean</i>	1.6799	2.3113	1.2795	1.8383	1.2538	1.3593
<i>Std.</i>	0.4482	0.8889	0.5636	0.7950	1.2912	0.6396
<i>Ske</i>	-1.3144	-0.8459	0.0159	0.2408	3.3225	0.0628
<i>Obs.</i>	1158	1304	1304	1304	1304	1304

Table 2. Herding during the whole sample period

This table reports rolling window regression²² results for the following equation:

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{m,t})^2 + \varepsilon_t \quad (2)$$

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{m,t}$ is the cross-sectional average return of N stocks in the portfolio at time t . CSAD stands for Cross-Sectional Absolute Deviation and is introduced by Chang et al. (2000) (CCK model). CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW). Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Market	CN	HK	JP	KR	SG	TW
λ_1	0.1100** (2.16)	1.1484*** (10.93)	0.9159*** (11.28)	0.9570*** (9.62)	0.8722*** (3.94)	0.7956*** (10.40)
λ_2	-0.0070 (-0.25)	-0.2763*** (-5.46)	-0.2893*** (-6.18)	-0.2825*** (-5.58)	-0.1155 (-0.60)	-0.1760*** (-4.28)
λ_0	1.6254 (37.90)	1.6508*** (29.91)	0.9466*** (23.69)	1.4171*** (27.48)	0.8687*** (10.80)	0.9762*** (20.31)
<i>Obs.</i>	1174	1259	1244	1241	1272	1246
<i>Adj R</i> ²	0.1445	0.5871	0.5260	0.3566	0.3296	0.5641

²² based on past 25 trading days.

Table 3. Herding in sub-sample periods

This table reports rolling window regression²³ results for the following equation in the three stages of Crisis: Strict control period (Feb 2020 to May 2022), Open-up period (June 2022 to Jan 2023), and Tranquil period (Jan 2019 to Jan 2020 and Feb 2023 to Dec 2023)²⁴:

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{m,t})^2 + \varepsilon_t \quad (2)$$

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{m,t}$ is the cross-sectional average return of N stocks in the portfolio at time t . CSAD stands for Cross-Sectional Absolute Deviation and is introduced by Chang et al. (2000) (CCK model). CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW). Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Panel A. Strict control Period (Feb 2020 to May 2022)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0321** (2.02)	1.0262*** (36.66)	0.9148*** (42.26)	0.8269*** (30.05)	0.5496*** (8.47)	0.7333*** (31.43)
λ_2	0.0315*** (4.01)	-0.1884*** (-17.62)	-0.2586*** (-23.42)	-0.2058*** (-17.30)	0.0454 (1.13)	-0.1364*** (-12.34)
λ_0	1.7923*** (157.08)	1.7106*** (95.00)	1.0103*** (76.58)	1.4893*** (82.81)	1.1599*** (39.99)	1.0928*** (76.76)
<i>Obs.</i>	632	607	607	607	607	607
<i>Adj R</i> ²	0.2021	0.6095	0.5161	0.3758	0.2721	0.5218

Panel B. Open-up Period (June 2022 to Jan 2023)

Market	CN	HK	JP	KR	SG	TW
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²³ based on past 25 trading days.

²⁴ Note for that each market, the Covid impact has slightly different time frames, but it doesn't affect our results.

λ_1	-0.0462** (-2.20)	0.8560*** (22.53)	0.6457*** (22.96)	0.6207*** (14.17)	0.8820*** (21.54)	0.4897*** (19.63)
λ_2	0.0890*** (6.61)	-0.1182*** (-10.56)	-0.1086*** (-8.15)	-0.1118*** (-7.25)	0.0364 (0.91)	-0.0253*** (-2.82)
λ_0	1.6079*** (170.21)	1.7424*** (68.09)	0.8774*** (62.34)	1.4332*** (58.57)	0.5161*** (43.85)	1.0504*** (58.32)
<i>Obs.</i>	173	175	175	175	175	175
<i>Adj R</i> ²	0.2107	0.7000	0.5947	0.3324	0.5945	0.6905

Panel C. Tranquil Period (Jan 2019 to Jan 2020 and Feb 2023 to Dec 2023)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.1991*** (11.66)	1.1412*** (32.01)	0.9819*** (30.67)	1.0134*** (24.76)	0.0151 (0.02)	0.8924*** (31.85)
λ_2	-0.0429*** (-3.42)	-0.2959*** (-18.12)	-0.3703*** (-18.70)	-0.3520*** (-14.75)	-0.5604 (0.91)	-0.2401*** (-13.27)
λ_0	1.3476*** (126.45)	1.5923*** (91.65)	0.8643*** (87.96)	1.4395*** (82.86)	0.9434*** (3.16)	0.8395*** (71.25)
<i>Obs.</i>	469	477	462	459	490	464
<i>Adj R</i> ²	0.1505	0.5573	0.4897	0.3306	0.3296	0.5796

Table 4. Impact from the US market

This table reports rolling window regression²⁵ results for the following equation in the three stages of Crisis: Strict control period (Feb 2020 to May 2022), Open-up period (June 2022 to Jan 2023), and Tranquil period (Jan 2019 to Jan 2020 and Feb 2023 to Dec 2023)²⁶:

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{i,m,t})^2 + \lambda_2 (R_{US,m,t})^2 + \varepsilon_t \quad (2)'$$

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{i,m,t}$ and $R_{US,m,t}$ are the cross-sectional average return of N stocks in the portfolio at time t in the domestic market and the US market. CSAD stands for Cross-Sectional Absolute Deviation and is introduced by Chang et al. (2000) (CCK model). CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW) and the US. Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Panel A. Strict control Period (Feb 2020 to May 2022)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0427** (2.45)	1.0324*** (36.63)	0.9313*** (42.54)	0.8323*** (29.01)	0.6280*** (9.66)	0.7130*** (30.86)
λ_2	0.0245*** (2.87)	-0.1917*** (-17.62)	-0.2659*** (-24.39)	-0.2079*** (-16.89)	-0.0270 (-0.63)	-0.1335*** (-12.24)
λ_3	-0.0041 (-0.96)	0.0017 (0.48)	0.0017 (0.66)	0.0081** (1.95)	0.0827*** (4.87)	0.0065* (1.67)
λ_0	1.7867*** (144.47)	1.6990*** (91.81)	0.9943*** (79.45)	1.4882*** (81.58)	1.1127*** (40.06)	1.1046*** (76.37)
<i>Obs.</i>	632	607	607	607	607	607
<i>Adj R</i> ²	0.2571	0.6283	0.5367	0.4034	0.3052	0.1712

²⁵ based on past 25 trading days.

²⁶ Note for that each market, the Covid impact has slightly different time frames, but it doesn't affect our results.

Panel B. Open-up Period (June 2022 to Jan 2023)

Market	CN	HK	JP	KR	SG	TW
λ_1	-0.1110*** (-4.30)	0.8716*** (22.77)	0.6505*** (23.23)	0.5600*** (11.61)	0.8480*** (18.87)	0.4872*** (18.97)
λ_2	0.1277*** (7.52)	-0.1214*** (-10.78)	-0.1135*** (-8.58)	-0.0763*** (-4.41)	0.1003** (2.06)	-0.0217** (-2.36)
λ_3	-0.0108*** (-5.24)	0.0161*** (5.10)	-0.0094*** (-6.24)	-0.0377*** (-7.97)	-0.0122*** (-4.12)	-0.0136*** (-10.90)
λ_0	1.6261*** (146.67)	1.7121*** (60.38)	0.8918*** (65.84)	1.5045*** (58.58)	0.5285*** (41.31)	1.0746*** (58.95)
<i>Obs.</i>	173	175	175	175	175	175
<i>Adj R</i> ²	0.3411	0.7129	0.6124	0.3766	0.6103	0.7010

Panel C. Tranquil Period (Jan 2019 to Jan 2020 and Feb 2023 to Dec 2023)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.3458*** (7.86)	1.1836*** (29.78)	0.9060*** (18.32)	1.0452*** (22.77)	0.8924*** (6.63)	0.8993*** (15.36)
λ_2	-0.1492*** (-5.59)	-0.3270*** (-16.35)	-0.3219*** (-7.56)	-0.3540*** (-12.93)	-0.1364 (-0.91)	-0.2469*** (-5.25)
λ_3	0.0530*** (6.07)	0.0919*** (8.87)	-0.0223*** (-2.71)	-0.0416*** (-4.73)	0.1029*** (4.45)	-0.0258*** (-3.97)
λ_0	1.2846*** (70.80)	1.5554*** (83.29)	0.8819*** (64.27)	1.4467*** (75.90)	0.6614*** (27.09)	0.8577*** (55.85)
<i>Obs.</i>	456	477	451	448	479	453
<i>Adj R</i> ²	0.2330	0.5755	0.5088	0.3676	0.3411	0.6017

Table 5. Robustness test on market conditions

This table reports rolling window regression²⁷ results for the following equation for three market return groups: For each market, we sort the data by stock market returns and divide the whole sample period into three groups: the high negative returns group 1 (bottom one third), the high positive returns group 3 (top one third), the and the middle returns group 3 (middle one third)²⁸.

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{i,m,t})^2 + \lambda_2 (R_{US,m,t})^2 + \varepsilon_t \quad (2)'$$

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{i,m,t}$ and $R_{us,m,t}$ are the cross-sectional average return of N stocks in the portfolio at time t in the domestic market and the US market. CSAD stands for Cross-Sectional Absolute Deviation and is introduced by Chang et al. (2000) (CCK model). CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW) and the US. Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Panel A. The high negative returns group 1 (bottom one third)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0495*** (2.76)	1.0537*** (28.54)	0.8507*** (28.02)	0.8143*** (20.90)	0.7660*** (8.45)	0.6846*** (27.84)
λ_2	0.0230** (2.49)	-0.2244*** (-13.22)	-0.2544*** (-14.58)	-0.2089*** (-10.61)	-0.0552 (-0.62)	-0.1245*** (-9.89)
λ_3	0.0119** (2.50)	0.0376*** (4.89)	0.0011 (0.24)	-0.0164*** (-2.46)	0.0610*** (3.37)	-0.0145*** (-2.60)
λ_0	1.6432*** (91.12)	1.6467*** (77.71)	0.9530*** (66.72)	1.4773*** (72.18)	0.8613*** (30.30)	1.0431*** (65.47)
<i>Obs.</i>	338	412	398	402	415	399
<i>Adj R²</i>	0.2060	0.6167	0.5402	0.3900	0.3723	0.5697

²⁷ based on past 25 trading days.

²⁸ We also divided the data into 5 groups and 10 groups by market returns and applied the same regression. The results among different groups are similar to those of the 3 groups we report in the table.

Panel B. The middle returns group 2 (middle one third)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0735*** (4.03)	1.1339*** (30.73)	0.9640*** (33.74)	0.9137*** (23.34)	0.8252*** (7.48)	0.8131*** (26.47)
λ_2	0.0235** (2.27)	-0.2678*** (-15.29)	-0.3288*** (-18.92)	-0.2739*** (-13.54)	-0.0272 (-0.23)	-0.1910*** (-11.05)
λ_3	0.0108*** (3.03)	0.0451*** (5.59)	-0.0091 (-1.38)	-0.0232*** (-3.20)	0.0720*** (3.00)	-0.0003 (-0.07)
λ_0	1.5470*** (91.95)	1.6063*** (80.41)	0.8837*** (87.22)	1.4457*** (74.02)	0.7664*** (29.45)	0.9505*** (59.02)
<i>Obs.</i>	333	409	407	402	410	407
<i>Adj R</i> ²	0.2379	0.5989	0.5394	0.3799	0.3515	0.6017

Panel C. The high positive returns group 3 (top one third)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0254 (1.49)	0.9993*** (28.98)	0.9061*** (30.73)	0.8146*** (21.03)	0.7402*** (7.47)	0.7290*** (26.45)
λ_2	0.0433*** (4.86)	-0.1903*** (-14.18)	-0.2777*** (-17.13)	-0.2052*** (-10.55)	-0.0888 (-0.93)	-0.1463*** (-10.07)
λ_3	0.0067 (1.50)	0.0235*** (3.15)	-0.0175*** (-2.98)	-0.0187*** (-2.93)	0.0839*** (3.97)	-0.0074 (-1.52)
λ_0	1.6632*** (91.06)	1.7074*** (77.12)	0.9594*** (65.17)	1.5306*** (71.52)	0.9499*** (27.74)	1.0509*** (64.67)
<i>Obs.</i>	335	403	404	402	412	405
<i>Adj R</i> ²	0.2015	0.6443	0.5369	0.3776	0.3514	0.5826

Table 6. Portfolio analysis

This table reports rolling window regression²⁹ results for the following equation for size sorted and price-to-book ratio sorted portfolios: For each market, at the beginning of every month, we sort the data by stocks' market value (MV, Panel A) or stocks' price-to-book ratio (PB Panel B) and divide the data into three groups: the low MV (PB) group 1 (lowest one third), the high MV (PB) group 3 (top one third), and the middle MV (PB) group 2 (middle one third)^{30,31}.

$$CSAD_t = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{i,m,t})^2 + \lambda_3 (R_{US,m,t})^2 + \varepsilon_t \quad (2)'$$

where $R_{i,t}$ is the stock return of stock i at time t , and $R_{i,m,t}$ and $R_{US,m,t}$ are the cross-sectional average return of N stocks in the portfolio at time t in the domestic market and the US market. CSAD stands for Cross-Sectional Absolute Deviation and is introduced by Chang et al. (2000) (CCK model). CSAD is defined as following:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW) and the US. Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Panel A1. The low market value group 1 (bottom one third)

Market	CN	HK	JP	KR	SG	TW
λ_1	-0.0117 (-1.59)	2.5145*** (44.92)	0.9524*** (40.34)	0.8509*** (35.38)	2.0152*** (137.72)	1.4018*** (30.08)
λ_2	0.0386*** (10.81)	-1.4064*** (-23.06)	-0.3217*** (-11.83)	-0.2331*** (-15.35)	-0.0152 (-1.27)	-1.1170*** (-14.80)
λ_3	0.0010 (0.70)	0.0432*** (8.20)	-0.0039 (-1.40)	-0.0182*** (-5.10)	-0.0257*** (-3.85)	0.0044* (1.77)
λ_0	1.4617*** (180.49)	1.9926*** (133.21)	0.9512*** (134.72)	1.5404*** (145.09)	0.1509*** (24.87)	1.0261*** (108.83)
<i>Obs.</i>	1033	1224	1209	1206	1237	1211

²⁹ based on past 25 trading days.

³⁰ We also divided the data into 5 groups by MV (PB) and applied the same regression. The results among different groups are similar to those of the 3 groups we report in the table.

³¹ To save space, we shall only report the results from the top and bottom portfolios.

<i>Adj R</i> ²	0.2245	0.4373	0.4823	0.4563	0.9423	0.5134
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Panel A2. The high market value group 3 (top one third)

Market	CN	HK	JP	KR	SG	TW
λ_1	0.0861*** (10.05)	0.7642*** (37.58)	0.7411*** (45.38)	0.6052*** (33.32)	1.3095*** (75.31)	0.8277*** (41.74)
λ_2	0.0187*** (3.76)	-0.2254*** (-20.62)	-0.2748*** (-28.82)	-0.1624*** (-16.70)	0.1002*** (3.98)	-0.3263*** (-21.32)
λ_3	0.0143*** (6.47)	0.0225*** (7.39)	-0.0006 (-0.15)	-0.0191*** (-6.49)	0.0027* (1.86)	0.0045* (1.79)
λ_0	1.4871*** (151.58)	1.3383*** (134.25)	0.8850*** (112.01)	1.3600*** (127.02)	0.3672*** (88.08)	0.8701*** (103.12)
<i>Obs.</i>	1033	1224	1209	1206	1237	1211
<i>Adj R</i> ²	0.2181	0.3926	0.3468	0.3440	0.7535	0.5196

Panel B1. The low price-to-book ratio group 1 (bottom one third)³²

Market	CN	HK	JP	KR	TW
λ_1	0.0355*** (4.71)	1.9503*** (45.36)	0.9306*** (51.49)	0.6947*** (35.92)	0.9776*** (37.03)
λ_2	0.0390*** (7.91)	-1.0013*** (-24.49)	-0.3993*** (-26.80)	-0.2204*** (-16.88)	-0.5819*** (-18.51)
λ_3	0.0033** (2.29)	0.0431*** (8.82)	-0.0043 (-1.37)	-0.0153*** (-6.36)	-0.0026 (-1.23)

³² Since price-to-book ratio data are mostly missing in Singapore, we dropped its results from this table.

λ_0	1.1371*** (162.13)	1.6166*** (136.80)	0.7452*** (113.45)	1.1603*** (135.05)	0.8221*** (103.97)
<i>Obs.</i>	1033	1224	1209	1206	1211
<i>Adj R</i> ²	0.2535	0.4575	0.4943	0.4262	0.4917

Panel B2. The high price-to-book ratio group 1 (top one third)

Market	CN	HK	JP	KR	TW
λ_1	0.0572*** (6.30)	1.5915*** (43.93)	0.9867*** (41.42)	0.6949*** (29.58)	1.0563*** (34.74)
λ_2	0.0092** (2.01)	-0.6924*** (-23.46)	-0.3772*** (-22.87)	-0.1673*** (-11.61)	-0.4673*** (-18.36)
λ_3	0.0188*** (6.46)	0.0238*** (7.04)	-0.0206*** (-4.33)	-0.0085** (-2.34)	0.0061** (1.97)
λ_0	1.8466*** (202.46)	1.7791*** (151.40)	1.2380*** (126.43)	1.7421** (128.95)	1.2178*** (104.27)
<i>Obs.</i>	1033	1224	1209	1206	1211
<i>Adj R</i> ²	0.1920	0.4192	0.3720	0.3612	0.4796

Table 7. Bivariate GARCH-DCC model results

This table reports the bivariate GARCH-DCC model results from the following mean equation:

$$R_{i,t} = \lambda_0 + \lambda_1 |R_{m,t}| + \lambda_2 (R_{m,t})^2 + \varepsilon_t \quad (3)$$

where $R_{i,t} = (R_{CN,t}, R_{i,t})'$, $R_{m,t} = (R_{CN,m,t}, R_{i,m,t})'$, $\varepsilon_t = (\varepsilon_{CN,t}, \varepsilon_{i,t})'$; $i = \text{HK, JP, KR, SG, or TW}$; and $\varepsilon_t | \mathfrak{I}_{t-1} \sim N(0, H_t)$.

The bivariate conditional variance/covariance matrix is specified as:

$$H_t = D_t P_t D_t \quad (4)$$

where D_t is the (2×2) diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{jj,t}}$ on the j^{th} diagonal, $j = \text{CN and HK, JP, KR, SG or TW}$; P_t is the (2×2) time-varying correlation matrix.

The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \quad (5)$$

where $Q_t = (q_{CN,i,t})$ is the 2×2 time-varying covariance matrix of u_t , $\bar{Q} = E[u_t u'_t]$ is the 2×2 unconditional variance matrix of u_t , and α and β are nonnegative scalar parameters satisfying $(\alpha + \beta) < 1$.

The data covers the whole sample period from January 2019 to December 2023 for six Asian markets (CN, HK, JP, KR, SG, TW). Numbers in parentheses are t-stats. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

Panel A: Whole Sample Period

	Mean Equation	Variance Equation			Covariance Equation	
	λ_0	constant	α	β	α	β
China	3.44E-05 (0.13)	3.53E-06** (2.29)	0.0675*** (3.95)	0.9056*** (41.58)	0.1228*** (4.51)	0.6439*** (7.28)
Hong Kong	-1.63E-05 (-0.04)	9.65E-06** (2.31)	0.0910*** (4.49)	0.8626*** (25.04)		
China	3.44E-05 (0.13)	3.53E-06** (2.29)	0.0675*** (3.95)	0.9056*** (41.58)	0.0797** (2.51)	0.5149** (2.20)
Japan	0.0006** (2.39)	6.98E-06 (1.26)	0.0984** (2.31)	0.8271*** (8.48)		
China	3.44E-05 (0.13)	3.53E-06** (2.29)	0.0675*** (3.95)	0.9056*** (41.58)	0.0705** (2.46)	0.6311*** (4.97)
South Korea	0.0003 (1.21)	7.36E-06*** (2.58)	0.1130*** (4.53)	0.8314*** (21.53)		
China	3.44E-05 (0.13)	3.53E-06** (2.29)	0.0675*** (3.95)	0.9056*** (41.58)	0.0230** (2.20)	0.9524*** (36.98)
Singapore	4.57E-05 (0.27)	3.95E-06 (4.00)	0.1231*** (4.83)	0.7983*** (26.36)		
China	3.44E-05 (0.13)	3.53E-06** (2.29)	0.0675*** (3.95)	0.9056*** (41.58)	0.0472*** (2.69)	0.8556*** (12.74)
Taiwan	0.0007*** (2.58)	5.41E-06 (1.36)	0.0633*** (2.94)	0.8881*** (17.42)		

Panel B: Strict Control Period

Mean Equation		Variance Equation			Covariance Equation	
	λ_0	constant	α	β	α	β
China	7.61E-05 (0.18)	6.96E-06* (1.74)	0.1036** (2.44)	0.8481*** (14.95)	0.0751*** (3.23)	0.8357*** (16.26)
Hong Kong	2.66E-05 (0.05)	3.38E-06** (2.31)	0.1496*** (4.14)	0.7127*** (10.44)		
China	7.61E-05 (0.18)	6.96E-06* (1.74)	0.1036** (2.44)	0.8481*** (14.95)	0.1289** (2.54)	0.2042 (0.62)
Japan	0.0005 (1.22)	1.65E-05 (1.33)	0.1405* (1.83)	0.7297*** (4.47)		
China	7.61E-05 (0.18)	6.96E-06* (1.74)	0.1036** (2.44)	0.8481*** (14.95)	0.0581* (1.89)	0.8133*** (6.75)
South Korea	0.0004 (0.93)	1.08E-05* (1.70)	0.1794*** (3.39)	0.7584*** (9.67)		
China	7.61E-05 (0.18)	6.96E-06* (1.74)	0.1036** (2.44)	0.8481*** (14.95)	0.0376*** (2.60)	0.9384*** (35.39)
Singapore	0.0001 (0.40)	5.93E-06**** (3.21)	0.1680*** (3.73)	0.7582*** (18.91)		
China	7.61E-05 (0.18)	6.96E-06* (1.74)	0.1036** (2.44)	0.8481*** (14.95)	0.0696** (2.55)	0.8053*** (9.50)
Taiwan	0.0011** (2.50)	1.52E-05* (1.67)	0.1312*** (2.81)	0.7566*** (7.20)		

References:

- Allam, S., Abdelrhim, M., & Mohamed, M. (2020). Determinants of herding behavior in the time of COVID-19: The case of Egyptian stock market sectors. Available at SSRN 3717995.
- Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, 100(5), 992-1026.
- Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. IMF Staff papers, 47(3), 279-310.
- Bogdan, S., Suštar, N., & Draženović, B. O. (2022). Herding behavior in developed, emerging, and frontier European stock markets during COVID-19 pandemic. *Journal of risk and financial management*, 15(9), 400.
- Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). COVID-19 pandemic and investor herding in international stock markets. *Risks*, 9(9), 168.
- Boyer, B. H., Kumagai, T., & Yuan, K. (2006). How do crises spread? Evidence from accessible and inaccessible stock indices. *The Journal of finance*, 61(2), 957-1003.
- Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679.
- Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and finance*, 26(7), 1206-1228.
- Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, 34(8), 1911-1921.
- Christie, W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market?. *Financial analysts journal*, 51(4), 31-37.
- Demirer, R., & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets?. *Journal of international Financial markets, institutions and money*, 16(2), 123-142.
- Espinosa-Méndez, C., & Arias, J. (2021). Herding Behaviour in Australian stock market: Evidence on COVID-19 effect. *Applied Economics Letters*, 28(21), 1898-1901.
- Erdogan, H. H. (2021). Beta herding in the COVID-19 era: Evidence from Borsa Istanbul. *Business and Economics Research Journal*, 12(2), 359-368.
- Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *The North American Journal of Economics and Finance*, 58, 101531.
- Ghorbel, A., Snene, Y., & Frikha, W. (2023). Does herding behavior explain the contagion of the COVID-19 crisis?. *Review of Behavioral Finance*, 15(6), 889-915.

- Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American Economic Review*, 1088-1105.
- Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of empirical finance*, 11(4), 585-616.
- Jiang, R., Wen, C., Zhang, R., & Cui, Y. (2022). Investor's herding behavior in Asian equity markets during COVID-19 period. *Pacific-Basin Finance Journal*, 73, 101771.
- Kremer, S., & Nautz, D. (2013). Short-term herding of institutional traders: New evidence from the German stock market. *European Financial Management*, 19(4), 730-746.
- Lakonishok, J., Shleifer, A. and Vishny, R., 'The impact of institutional trading on stock prices', *Journal of Financial Economics*, Vol. 32, 1992, pp. 23-43.
- Liu, T., Zheng, D., Zheng, S., & Lu, Y. (2023). Herding in Chinese stock markets: Evidence from the dual-investor-group. *Pacific-Basin Finance Journal*, 79, 101992.
- Loang, O. K., & Ahmad, Z. (2023). Empirical analysis of global markets herding on COVID-19 effect. *Vision*, 09722629221146653.
- Miah, M., & Rahman, A. (2016). Modelling volatility of daily stock returns: Is GARCH (1, 1) enough. *American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)*, 18(1), 29-39.
- Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of finance*, 54(6), 2263-2295.
- Sias, R. W. (2004). Institutional herding. *The review of financial studies*, 17(1), 165-206.
- Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, 16(1-2), 61-77.
- Venezia, I., Nashikkar, A., & Shapira, Z. (2011). Firm specific and macro herding by professional and amateur investors and their effects on market volatility. *Journal of Banking & Finance*, 35(7), 1599-1609.
- Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics*, 58, 369-396.
- Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *the Journal of Finance*, 54(2), 581-622.
- Wu, G., Yang, B., & Zhao, N. (2020). Herding behavior in Chinese stock markets during COVID-19. *Emerging Markets Finance and Trade*, 56(15), 3578-3587.

Yang, S. J., Hsu, A. C., Lai, S. Y., & Lee, C. C. (2015). Empirical investigation of herding behavior in East Asian stock markets toward the US market. *International Journal of Business and Finance Research*, 9(1), 19-31.

Zhang, H., & Giouvris, E. (2022). Measures of volatility, crises, sentiment and the role of US 'Fear' Index (VIX) on herding in BRICS (2007–2021). *Journal of Risk and Financial Management*, 15(3), 134.