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Investor’s herding behavior in Asian equity markets during COVID-19 period

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\begin{abstract}
In this paper we investigate herding behavior triggered by the COVID-19 outbreak in 2020 by considering six typical Asian stock markets. Cross-sectional Standard Deviation (CSSD) and Cross-sectional Absolute Deviation (CSAD) have been employed as the key indicators, which are aligned with the Markov-switching regression and HS model to identify the presence and magnitude of herding. We then elaborate our study by examining herding in specific time slots and markets with different idiosyncratic volatility. Our empirical results show a clear presence of herding in the “Feb 2020-Jan 2021” time window and we have captured a sharp rise of the magnitude of herding during the market crash in March 2020, and found herding emerged in these markets with shocks and fierce fluctuations.
\end{abstract}

\section{Introduction}

In his efficient market hypothesis, Fama (1970) describes an ideal setting for the finance market, where investors always make rational decisions, and share prices would reflect all available information and stay unpredictable. These assumptions, however, often fail in practice (Shiller, 1989; Summers, 1986) because it is a part of human nature to act as a group and follow socioeconomic norms. Herding in finance, also known as herd instinct, is the phenomenon where investors tend to mimic trading actions from others who they believe are better-informed, while their own intelligence is overlooked (Bikhchandani & Sharma, 2000). As one of the key points in the field of behavioral finance, herding is a significant driving factor of asset bubbles and thus by conducting thorough studies, people hope to detect its presence and further, make proper justifications on the assets pricing and reduce irrational transactions.

It is well observed that financial markets are usually sensitive to political and social unrest, for instance, wars and disease. Therefore, the impact triggered by the outbreak of COVID-19 has been closely watched since the beginning of 2020. Share prices crashed in the US stock market in March 2020, shown by the fact that the S&P 500 index slumped from 3386.19 points on February 19, 2020 to 2237.40 on March 23, 2020. Influenced by both the US market and the passive market expectation under pandemic, stock markets in East and Southeast Asia showed fierce fluctuation. For instance, in Hong Kong, the Hang Seng Index (HSI) experienced the worst drop in a year by falling from 26,356.98 on February 3, 2020 to 21,696.13 on March 23, 2020. Moreover, the COVID-19 epidemic has severely reduced the efficiency of information transmission of the capital markets in Asia. Massive rumors, the spread of COVID-19, and investors’ sentiments (positive or negative) have certainly affected Asian stock markets, and further, they are likely

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to trigger herding. In this paper, we conduct rigorous statistical analysis based on a large volume of data, in order to identify the presence and magnitude of herding.

Despite the previous efforts on giving a conclusion of herding detection in certain observed periods and possible reasons behind, the detailed features of herding in markets have been overlooked. Therefore, we aim to conduct a comprehensive study to make a deeper investigation of herding beyond a conclusion, and make a connection of market movements and influential events. Particularly, our research ideas are implemented in the following steps: (1) Observe the variation of the cross sectional dispersion in the markets and the correlation between market herding and COVID-19 to provide reference for model selection. (2) Identify emergence of herding in general. As introduced by Christie and Huang (1995), and Sanders and Irwin (1997), two indicators, Cross-sectional Standard Deviation (CSSD) and the Cross-sectional Absolute Deviation (CSAD) are employed. (3) Gain more precise insights on the specific timing, cause and magnitude of herding by considering idiosyncratic volatility, Markov switching regression and Hwang and Salmon (2001)'s herding measurement model (i.e., the HS model). The step (2) and (3) constitute the main frame work of the analysis, which has been shown in Fig. 1. In this study, we investigated six major East and Southeast Asian stock markets in Chinese Mainland, Japan, South Korea, Singapore, Hong Kong, and Taiwan, and our experimental results show that there is a clear presence of herding in Japan, Singapore, Taiwan, Hong Kong stock markets, and in some market sections in South Korea and Chinese Mainland in the period during COVID-19, and this has reinforced our intention, and stocks with large idiosyncratic volatility is more likely to have larger magnitude of herding in Hong Kong, Japan, and South Korea. It is also found that the magnitudes of herding are enlarged in the six Asian markets around the market crash in 2020. The road map aims to demonstrate which model or indicator is used for which purpose. The rest of the paper is organized as follows. Section 2 overviews how the COVID-19 and the authorities' responses impact the stock markets globally. Section 3 reviews the existing research on herding. In Section 4 we explain the methodology involving CSSD, CSAD, the adaption of classical linear herding detection model, Markov-switching regression, HS model and idiosyncratic volatility to test herding behavior. Section 5 derives the baseline analysis and we then present the empirical results along with reasoning in Section 6. Concluding remarks are made in Section 7.

2. COVID-19, policy measures, and markets trends

The outbreak of COVID-19 caused a significant impact on global economy, and each country took a series of actions for anti-epidemic and economic stimulation, which changed investors' expectation and caused fluctuations in global equity markets. Therefore, it is necessary to overview the anti-epidemic actions, monetary policies and the spread of COVID-19 and the market response, for a deeper exploration of the relationship between these factors and the possible irrationality and herding in the six Asian markets. Fig. 2 reports the trends of the six Asian equity markets, and the daily new cases from January 2020 to January 2021. For Chinese Mainland, the intensive emergence of COVID-19 cases was generally from late January to early March 2020, and the daily increase of new cases in the most serious period, i.e., February 2020, was up to 2398. To prevent the spread of COVID-19, Hubei province was locked down in January, and containment measures were imposed nationally. Affected by the outbreak of COVID-19, the Shanghai Composite index fell by 7.72% on February 3 in one day, and the Chinese Mainland stock market decreased from 3071.68 points to 2660.17 from March 5 to March 23 along with the crash of US stock markets. Meanwhile, the government took policy measures to stimulate the economic recovery and support the market, mainly by reversing repo operations (e.g., CNY900 billion for 7-day maturity on February 3, 2020), encouraging financial institutions to provide CNY 1.5 trillion (about $212 billion) with lower interest rates or

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1 The abnormal increase of new cases in 13 February was due to the adjustment of statistic criteria.
other allowances for firms' financing in June 17, 2020, and reducing tax and fee for another CNY 1.5 trillion (about USD 213 billion) in August 8 (Asian Development Bank, 2021). Under the policy measures and the control of COVID-19, the economic activities started to recover, shown by the 10.1% GDP growth rate in the second quarter compared with the -6.8% growth rate in previous quarter (National Bureau of Statistics of China, 2021). The Chinese Mainland stock markets also showed a mild upward trend since the late March 2020, and the market went up in the end of June 2020 due to the quantitative easing along with the imminent application of registered system in Chinese Growth Enterprise Market (GEM) board, and followed by a relatively stable move in the second half of 2020.

Meanwhile, with the spread of COVID-19 in Asia, Japan announced that their seven major prefectures were in emergency state on April 7, 2020, and both the entry-exit and domestic travels were restricted. The measures have effectively blocked the spread of COVID-19, but also imposed pressure on economy. For example, the tourist industry was hit badly. Under the impact of COVID-19, the GDP growth rate of Japan in the first and second quarters were 0.5%, and 8.1% lower than the previous quarters (Cabinet Office,
markets generally revealed an upward trend from mid-March 2020 to the end of the year. We thus believe that the fluctuation of Asian six countries or regions started in different time spots in 2020. A significant slump has been observed from mid-February to mid-March in all, directly triggered by the dramatic drop in US stock market under the widespread passive sentiments of investors. A series of and the local economic condition.

Korea, the Taiwan stock market, represented by Taipei Weighted Index (TWII) showed an upward trend in the rest of 2020. The number of daily new cases for the Taiwan region was generally less than 30 in 2020, possibly because of the entry restrictions, 14-day home quarantine for inboard travelers, and compulsive mask-wearing in some public venues. In April 2020 the monetary Authority (HKMA) implemented policies to improve the liquidity of financial institutions, encourage banks to deploy their liquidity buffers more flexibly, and cut the issuance scale of Exchange Fund Bills. After the market crash during February and mid-March, the Hang Seng Index (I) fluctuated in the range between 23,000 and 26,000 from mid-March to the end of 2020.

The GDP growth of South Korea dropped by 1.3% and 3.2% respectively in the first two quarters, but recovered and increased by 2.2% and 1.1% in the third and fourth quarters (KOSIS, 2021). The Korea Composite Stock Price Index (KOSPI) dropped significantly since February 2020, along with the crash of US financial markets, and then experienced a long bull from mid-March 2020 to January 2021.

As for Singapore, the government responded quickly in the early stage of COVID-19. The force of police investigators and surveillance cameras were applied for tracking and isolation. Meanwhile, the authorities kept identifying and monitoring COVID-19 and other respiratory cases, so the spread of COVID-19 was controlled at a very early stage. However, the country suffered a big outbreak in late-March 2020, caused by the contagion among foreign labors. The government then prohibited all cruise from docking and restricted the entry of short-term foreign passengers since April 2020, and the spread of COVID-19 was controlled in August. Different from the policy measures of other Asian central banks, the operations of Monetary Authority of Singapore (MAS) mainly concentrated on foreign exchange, such as providing the liquidity of USD in bank system and conducting a USD 60 billion swap facility with the US Fed (Asian Development Bank, 2021). Additionally, the Singapore stock market went up significantly after the American presidential election.

It is noted that the outbreak of coronavirus in Hong Kong is mainly in three periods, which are similar to the epidemic trend in South Korea and Japan, but the daily new cases in Hong Kong were normally around 150, as shown in Fig. 2. The Hong Kong Monetary Authority (HKMA) implemented policies to improve the liquidity of financial institutions, encourage banks to deploy their liquidity buffers more flexibly, and cut the issuance scale of Exchange Fund Bills. After the market crash during February and mid-March, the Hang Seng Index (I) fluctuated in the range between 23,000 and 26,000 from mid-March to the end of 2020.

The number of daily new cases for the Taiwan region was generally less than 30 in 2020, possibly because of the entry restrictions, 14-day home quarantine for inboard travelers, and compulsive mask-wearing in some public venues. In April 2020 the monetary authority of Taiwan preliminarily supported financial institutions by funding about TWD 200 billion in order to mitigate the financing difficulty of small and medium-scale enterprises (Asian Development Bank, 2021). Similar to the market trend in Japan and South Korea, the Taiwan stock market, represented by Taipei Weighted Index (TWII) showed an upward trend in the rest of 2020.

In general, the fluctuations of the six equity markets have displayed a strong consistency although the spread of COVID 19 in these six countries or regions started in different time spots in 2020. A significant slump has been observed from mid-February to mid-March in all, directly triggered by the dramatic drop in US stock market under the widespread passive sentiments of investors. A series of monetary actions have been enacted to support their local financial markets and stimulate the economic recovery, and their stock markets generally revealed an upward trend from mid-March 2020 to the end of the year. We thus believe that the fluctuation of Asian stocks markets in 2020 was affected by the Coronavirus, the movement of US financial markets, the local and US monetary policies, and the local economic condition.

The figure shows the market trends in six Asian stock markets and the variation of daily new cases of COVID-19 from January 2020 to January 2021.

3. Literature review

There are a series of papers studying the herding behavior in the finance literature. Keynes (1936) publishes a pioneering work that lays the foundation in the field. He indicates that investors have the tendency to follow others instead of making decisions by their own. Thus, studying herding behavior usually is to explore the impact of group behavior on individual decisions. Whereas the emergence of irrational behaviors shows some diversities in markets, and it seems to be different in time periods, countries or regions, and market sectors, indicating the necessity of a comprehensive detection.

Studies have also found the impact of volatility in different time periods on herding behavior. Diamandis (2008) analyzes the dynamic feature of stock market volatility along with herding behavior in Argentina, Brazil, Chile, Mexico and the US stock markets. The empirical results show that stock returns are highly associated with their volatility, and the herding behaviors are detected in these markets. Demirer, Lee, and Lien (2015) tests the herding behavior in an emerging market (Borsa Istanbul) based on a time-varying transition probability Markov-switching model, and finds that herding behavior occurs in the periods under high or extreme market volatility which can be measured by realized volatility indicators (Jiang & Wen, 2021). Additionally, the Capital Asset Pricing Model (CAPM) specifies that volatility of a stock has two components: systematic volatility and idiosyncratic volatility. Some studies
also focus on the relationship between idiosyncratic volatility and herding. Chang and Dong (2006) test companies’ idiosyncratic volatility and herding in Japan stock market, and they show that institutional herding emerges during transactions of stocks with high idiosyncratic volatility. Tan and Henker (2010) investigate the Australia stock market and also prove a positive correlation between idiosyncratic volatility and herding behavior. Huang, Lin, and Yang (2015) analyze the herding behavior and idiosyncratic volatility based on the stock market data in Taiwan region from 2004 to 2013, and they find a similar relationship between idiosyncratic volatility and herding. Whereas they also state that financial crisis enhances investors’ herding behavior, and the effect is particularly obvious for high idiosyncratic volatility portfolios. Inspired by these work, we would conduct the volatility analysis based on Markov-switching and idiosyncratic volatility in this paper.

Herding behavior also displays various features in different countries or areas. In Chinese Mainland, Tan, Chiang, Mason, and Nelling (2008) propose that both Shenzhen and Shanghai A shares stock market exist herding behavior no matter market goes up or down. Yao, Ma, and He (2014) find that the phenomenon also exists in Shenzhen and Shanghai B shares stock market. Wen, Yang, and Jiang (2021) discover the mild herding in Hong Kong stock market based on quantile regression and the measurement of herding’s magnitude. Wang and Huang (2018) state that herding generally exists in the Taiwan stock market and it is more serious during financial crisis than in normal period. In South Korea, Hwang and Salmon (2004) discover that herding emerges in the local stock market no matter in bear or bull market. In Italy, herding always exists in some large-cap companies (Caparrelli, D’Arcangelis, and Cassuto (2004)). In United States, Babalos, Balcilar, and Gupta (2015) find that herding cannot be detected by a static model in Real Estate Investment Trusts (REITs) markets, but it appears when a Markov-switching model is used in the crash regime for almost all sectors. Balagoyzan and Cakan (2016) conclude that herding is more obvious in periods when US stock market rise than collapse under dot-com bubble of the 1990s. Stavroyiannis and Babalos (2017) detect anti-herding behavior, i.e., the intention to make inverse choice based on other investors’ option, among the components of the US Islamic Dow Jones index from January 2007 to December 2014. The level of anti-herding behavior is strengthened in the US Islamic Dow Jones index during the periods with high market fluctuation.

Besides looking into herding in aggregated markets, it is also necessary to consider different divisions (Lee, Chen, & Hsieh, 2013). Christie and Huang (1995) and Choi and Sias (2009) state that only a few work have studied herding behavior in different industry sectors. Xu, Lu, and Gu (2014) find that herding is more serious in cyclical than non-cyclical industry sectors in Chinese Mainland since the fluctuation of the former is more severe than the latter. Henker, Henker, and Mitsios (2006) find that herding is obvious in materials, consumer staples and financial field in the Australia stock market. Besides, Gebka and Wohar (2013) state that both gas and oil industries have significant herding behavior. Litiimi, Bensaida, and Bouraoui (2016) state that consumer non-durables, energy, health care, public utilities, technology and transportation industries exist herding in the American stock market. Zheng, Li, and Chiang (2017) also find that in each market, herding activities are stronger in technology than utilities industry, especially in the East Asian markets including Chinese Mainland, Japan, South Korea, and Hong Kong. Therefore, in this study we specifically investigate the herding in a few industry sectors directly influenced by COVID-19.

4. Methodology

4.1. Indicators of herding behavior

When market shocks, crisis and other extreme conditions would occur in the equity market, and thus investors may learn from each other to trade. Consequently, herding could cause a decrease of the cross-sectional deviation of stocks. Christie and Huang (1995) put forward the Cross-sectional Standard Deviation (CSSD) of returns to measure the dispersity of stock returns which can be used to detect herding behavior. The formula can be expressed as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{it} - \bar{R}_t)^2}{N - 1}}$$

where $R_{it}$ and $\bar{R}_t$ represent the returns of stock $i$ at time $t$, and the whole market return at time $t$, respectively. Sanders and Irwin (1997) adopt another indicator, the Cross-Sectional Absolute Deviation (CSAD), to measure the consistency of investors’ behavior, it is computed as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{it} - \bar{R}_t|$$

CSSD and CSAD can reflect the dispersion of stock returns in market, and their changes can be used to reveal the level of herding, i.e., the smaller of CSSD or CSAD, the more obvious the herding is. Although both indicators measure deviations, the results derived from them are not always consistent, so we employ both in this paper.

4.2. Linear model for herding detection

Based on the theory of the Capital Asset Pricing Model (CAPM), Chang, Cheng, and Khorana (2000) have proposed a pathbreaking herding detection approach, referred as CCK model by the subsequent studies. They detect the presence of herding in stock markets by observing whether the value of CSAD decrease with the increase of the absolute value of market return. If investors’ behavior presents a
growing consensus during the market fluctuation, the existence of herding can be proved in the market. We make several modifications on the CCK model, such as disaggregating the market return into upward and downward processes, and adopting both CSAD and CSSD as dependent variables. The refined indicator, CSD, is written below and it would become CSSD or CSAD depending on different values of $D_i$.

$$CSD_i = \alpha + \gamma_1(1 - D_i)|R_{m,i}| + \gamma_2D_i|R_{m,i}| + \gamma_3(1 - D_i)R_{m,i}^2 + \gamma_4D_iR_{m,i}^2 + \epsilon_i \quad \text{(3)}$$

In Eq. (3), $D_i$ is a dummy variable with value 0 if $R_{m,i} > 0$, and 1 otherwise. $\gamma_1$, $\gamma_2$ and $\gamma_3$ are the parameters of independent variables. If $\gamma_1$ or $\gamma_3$ is significantly negative, the herding behavior exists when the market has an upward trend. Similarly, a significantly negative $\gamma_2$ means that the herding behavior exists when the market has a downward trend.

On the other hand, $|R_{m,i}|$ and $R_{m,i}^2$ are highly correlated with each other, and thus they are very likely to have multicollinearity issue. In this case, the result may have a relatively high standard error. Removing the mean value from market return could resolve this issue, thus we reduce the standard errors of regression parameters and increase the validity of (3). Therefore, we transform $R_{m,i}$ into $R_{m,i} - \bar{R_m}$, where $\bar{R_m}$ represents the mean value of market return at time $t$. Moreover, high-frequency time series data in financial market is generally highly sequentially autocorrelated, which will reduce the precision of $CSD$. Considering the autocorrelation property of data, the previous lag term of $CSD$ or $CSAD$ is added into the model as independent variable. After these modifications, the equation is given as following:

$$CSD_i = \alpha + \gamma_1(1 - D_i)|R_{m,i} - \bar{R_m}| + \gamma_2D_i|R_{m,i} - \bar{R_m}| + \gamma_3(1 - D_i)(R_{m,i} - \bar{R_m})^2 + \gamma_4D_i(R_{m,i} - \bar{R_m})^2 + \epsilon_i \quad \text{(4)}$$

4.3. A dynamic model for detecting herding in different market states

We adopt a nonlinear model which can capture the dynamic relationships between the cross-sectional dispersion and market returns is introduced. Based on the idea of Balcilar, Demirer, and Hammoudeh (2012), we conduct a three-regime Markov-switching model and it can be represented as:

$$CSAD_i = \alpha + \gamma_{1,5}(1 - D_i)|R_{m,i} - \bar{R_m}| + \gamma_{2,5}D_i|R_{m,i} - \bar{R_m}| + \gamma_{3,5}(1 - D_i)(R_{m,i} - \bar{R_m})^2 + \gamma_{4,5}D_i(R_{m,i} - \bar{R_m})^2 + \epsilon_i \quad \text{(5)}$$

where $S_t$ refers to the regimes in the Markov-switching model including Regime 0, 1 and 2. $\epsilon_t$ follows i. i. d. $N(0, \sigma^2)$. The probability of regime transition can be defined as $p_{ij} = P(S_{t+1} = j|S_t = i)$, where the $p_{ij}$ is to the probability of transforming from state $i$ to $j$. Different from Balcilar et al. (2012), we cannot adopt a heteroscedastic Markov-switching model because no significant heterogeneity is observed in most markets. For simplicity, we follow Chang et al. (2000) to employ CSAD to demonstrate the dynamic structure.

4.4. Model for measuring herding magnitude

To further measure the magnitude of herding, we consider the HS model introduced by Hwang and Salamon (2001) as it adopts the spirit of CAPM model and optimizes the CCK model. As shown in the following formula, we compute $H_t$ as

$$H_t = \frac{1}{N} \sum_{i=1}^{N} \left( \beta_{i,t} - 1 \right)^2 \quad \text{(6)}$$

where the model adopts the same parameter $\beta_{i,t}$, the cross-sectional dispersion of regression, as that in CAPM return model (Markowitz, 1959). The key idea is to use variance of $\beta_{i,t}$ as an indicator of herding. When herding appears in the market, the similar decisions of investors can reduce the dispersion of $\beta_{i,t}$ cross sections of the stock market, i.e., the variance of $\beta_{i,t}$ will decrease. Ultimately, a smaller $H_t$ reflects a lower dispersion of $\beta_{i,t}$, and reveals a stronger herding. Besides, the basic idea of HS model is also consistent with the study of Cho and Engle (1999) who find that the bad news of individual stocks or market can cause the reduction of $\beta_{i,t}$.

4.5. The application of idiosyncratic volatility

Idiosyncratic volatility can be recognized as the external expression of idiosyncratic risk. Together with systematic risk, they are both derived from the CAPM theory. Vo and Phan (2019) explain that the idiosyncratic volatility is an essential factor that affects the test of herding behavior. Hence, we investigate herding of stock portfolios with different idiosyncratic volatilities. Idiosyncratic risk refers to the uncertainty of a certain company, and the risk can be diversified in an investment portfolio. In this paper, we also study how idiosyncratic volatility affects herding behavior in Asian stock markets. To estimate idiosyncratic volatility, we employ a single-factor model put forward by Bali and Cakici (2008):

$$R_{i,t} = \alpha + \beta_i R_{m,t} + \epsilon_{i,t} \quad \text{(7)}$$
where $R_{i,t}$ is the return of stock $i$ at time $t$, $R_m,t$ is the aggregated market return at time $t$, $\epsilon_{i,t}$ is regression residuals, and $IV_{i,t}$ is the idiosyncratic volatility of individual stock $i$ which is the standard deviation of residuals. We sort all samples by their magnitudes of idiosyncratic volatility and take the ones with the largest and smallest 20% values for further analysis. By comparing the two groups, we can explore the impact of idiosyncratic volatility on detecting herding behavior.

5. Baseline analysis

5.1. Data

In this study, we obtain the data of daily stock prices for major East Asian and South East Asian stock markets’ main boards, including: Tokyo Stock Price Index (TOPIX) components in Japan, South Korea Securities Dealers Association Quotations (KOSDAQ) components in South Korea, The Shanghai A-shares in Chinese Mainland, the main board market in Hong Kong, and the entire market in Singapore and Taiwan to ensure adequacy of samples. Besides, we also briefly investigate another two essential international markets for comparison: the main board of New York Stock Exchange (NYSE) in United States and London stock exchange (LSE) in United Kingdom. The closing prices of the above 8 stock markets are all collected from the wind database (Wind Information Co., Ltd, 2020). Focusing on the detection of herding and the measurement of its magnitude during the COVID-19 period, we collect the data from February 1, 2020 to January 31, 2021. In Section 6.4, we extend the time span to include one year before the outbreak of COVID-19, i.e., from February 1, 2019 to January 31, 2021 which can be helpful to reveal the cross-period variation of herding behavior in the market.

5.2. Descriptive statistics

For a better understanding of the observed samples, we review the descriptive statistics of log returns for 6 Asian stock markets, shown in Table 1. We calculate the mean, standard deviation, and median of the market returns for the observed Asian stock markets.

Table 1
Descriptive statistics of the log returns of stocks in six Asian markets.

| Countries & regions | Count | Before COVID-19 | During COVID-19 |
|---------------------|-------|----------------|-----------------|
|                     |       | Mean  | Std.Dev | Median | Mean  | Std.Dev | Median |
| Singapore           | 696   | 0.0003 | 0.0075 | 0.0003 | -0.0001 | 0.0096 | 0.0009 |
| Taiwan              | 950   | 0.0004 | 0.0105 | 0.0013 | 0.0006  | 0.0132 | 0.0023 |
| Hong Kong           | 2204  | -0.0005 | 0.0078 | 0.0002 | -0.0001 | 0.0085 | 0.0007 |
| Chinese Mainland    | 1835  | 0.0001 | 0.0142 | 0.0006 | 0.0030  | 0.0128 | 0.0000 |
| Japan               | 2190  | 0.0000 | 0.0131 | 0.0000 | -0.0001 | 0.0160 | 0.0000 |
| South Korea         | 1465  | 0.0002 | 0.0182 | 0.0016 | 0.0009  | 0.0224 | 0.0026 |

The table reports observed number of stocks and the mean, standard deviation, and median of the market returns for the observed Asian stock markets.

IV_{i,t} = \sqrt{\text{Var}(\epsilon_{i,t})}

where $R_{i,t}$ is the return of stock $i$ at time $t$, $R_m,t$ is the aggregated market return at time $t$, $\epsilon_{i,t}$ is regression residuals, and $IV_{i,t}$ is the idiosyncratic volatility of individual stock $i$ which is the standard deviation of residuals. We sort all samples by their magnitudes of idiosyncratic volatility and take the ones with the largest and smallest 20% values for further analysis. By comparing the two groups, we can explore the impact of idiosyncratic volatility on detecting herding behavior.

5.3. Correlation test between herding and COVID-19

To test the impact of COVID-19 on the emergence of herding, we examine the correlation between variables reflecting herding and indicators of COVID-19, including the total case per million, new case per million, total death per million, and reproduction rate along with the 7 days smoothed ones, and their 3 days increase rate. It is demonstrated by Fig. 4 that two representative COVID-19 indicators - total case per million and total death per million have the highest correlation with the herding variables.

Apart from Asian markets, we also implement the correlation test in United Kingdom and United States for comparison. It seems that CSAD and CSSD in all eight stock markets are negatively correlated with COVID-19 indicators. This means that the severity of
COVID-19 usually accompanies with the shrink of the cross sectional dispersion in the stock markets, i.e., the possible emergence of herding. Specifically, the negative correlations are stronger in Japan and Singapore stock markets than the other observed Asian markets, where the correlation between CSAD and COVID-19 indicators ranges from −0.3 to −0.2. Herding and COVID-19 in Hong Kong and Taiwan region seem to be the least correlated, where the correlations between those two indicators range from −0.1 to 0. Relatively, the correlations between CSAD and COVID-19 indicators in Chinese Mainland and South Korea generally range from −0.16 to −0.07. In addition, the correlation between CSSD and COVID-19 indicators is not that significant in Asian markets, and the difference is shown in Section 6.1. Interestingly, herding and COVID-19 indicators are more correlated in United Kingdom and United States markets than all observed Asian stock markets. Especially, the correlation between total death (new case) per million and CSAD reaches −0.41 and −0.38 (−0.33 and −0.23), respectively.

Fig. 3. The movement of CSAD and CSSD for six Asian stock markets.
The figure shows the correlation between herding indicators and COVID-19 indicators in six Asian stock markets and two essential international stock markets. The results shows that cross sectional dispersions in stock markets is negatively correlated with severity of COVID-19.

6. Empirical analysis

Using the dataset described in Section 5, we now estimate the parameters in Asian equity markets based on both linear herding detection model and Markov-switching model, conduct a subsample test according to the levels of idiosyncratic volatility, and adopt the HS model to investigate magnitude of herding.

6.1. Detection of herding in equity markets during COVID-19

We firstly focus on Singapore, the Taiwan, Hong Kong, Japan, Chinese Mainland, South Korea and two international stock markets.
and apply linear regression technique (based on Eq. (4)). Table 2 shows the estimated parameters. To detect herding, we search for significantly negative $\gamma_1, \gamma_2$ when these market rise, and significantly negative $\gamma_3, \gamma_4$ when they fall. As for Singapore, $\gamma_4 = -8.8957$ in CSAD at 5% significance level, $\gamma_3 = -47.1130$ and $\gamma_4 = 21.2416$ in CSSD at 5% significance level, both of which imply the existence of

Table 2
Regression results of CSSD and CSAD in stock markets.

|          | Singapore | Taiwan | Hong Kong | Japan |
|----------|-----------|--------|-----------|-------|
|          | CSAD      | CSSD   | CSAD      | CSSD  |
| $\alpha$ | 0.0120*** | 0.0410*** | 0.0081*** | 0.0164*** |
| $\gamma_1$ | 1.2770*** | 2.3055*** | 0.2266*** | 0.4328*** |
| $\gamma_2$ | 1.2543*** | 1.7823*** | 0.2730*** | 0.2973*** |
| $\gamma_3$ | -10.0977*** | -47.1130*** | -0.2958 | -4.7274 |
| $\gamma_4$ | -8.8957*** | -21.2416*** | -1.2864*** | -1.4229 |
| $\gamma_5$ | 0.1715*** | 0.2144*** | 0.3219*** | 0.1948*** |

Significant parameters revealing the presence of herding. ****, ** and * indicate that the parameters are significant at 1%, 5%, and 10% level, respectively. Terms in boldface are significantly negative parameters reflecting the presence of herding.

Table 3
Regression results under different levels of idiosyncratic volatility.

| Small idiosyncratic volatility | Singapore | Taiwan | Hong Kong |
|--------------------------------|-----------|--------|-----------|
|      | CSAD      | CSSD   | CSAD      | CSSD  |
| $\alpha$ | 0.0052*** | 0.0097*** | 0.0032*** | 0.0045*** |
| $\gamma_1$ | 0.7456*** | 0.6901*** | 0.2334*** | 0.2385*** |
| $\gamma_2$ | 0.7166*** | 0.6847*** | 0.2008*** | 0.1965*** |
| $\gamma_3$ | -5.6980*** | -3.3989 | -0.8898 | -0.7104 |
| $\gamma_4$ | -6.7249*** | -5.1765 | 0.8275 | 1.2156 |
| $\gamma_5$ | 0.1699*** | 0.1524*** | 0.3499*** | 0.4103*** |

Largest idiosyncratic volatility

| Largest idiosyncratic volatility | Singapore | Taiwan | Hong Kong |
|--------------------------------|-----------|--------|-----------|
|      | CSAD      | CSSD   | CSAD      | CSSD  |
| $\alpha$ | 0.0178*** | 0.0655*** | 0.0131*** | 0.0286*** |
| $\gamma_1$ | 1.1818*** | 1.1072* | 0.3287** | 0.5898* |
| $\gamma_2$ | 1.3869*** | 1.6445** | 0.2197*** | 0.2138 |
| $\gamma_3$ | 9.2552 | 20.2344 | -2.4003 | -10.8064 |
| $\gamma_4$ | -3.7958 | -12.0155 | -1.2555 | -0.8685 |
| $\gamma_5$ | 0.2108** | 0.2178** | 0.3782** | 0.1499** |

Smallest idiosyncratic volatility

| Smallest idiosyncratic volatility | Singapore | Taiwan | Hong Kong |
|--------------------------------|-----------|--------|-----------|
|      | CSAD      | CSSD   | CSAD      | CSSD  |
| $\alpha$ | 0.0048*** | 0.0067*** | 0.0052*** | 0.0074*** |
| $\gamma_1$ | -0.0311 | -0.0323 | 0.3775*** | 0.4885*** |
| $\gamma_2$ | 0.1488*** | 0.1213** | 0.3384*** | 0.4085*** |
| $\gamma_3$ | 4.1966*** | 4.1748*** | -0.0334 | -2.3620 |
| $\gamma_4$ | 0.4471 | 1.9888 | -3.4100** | -3.9978** |
| $\gamma_5$ | 0.4097*** | 0.4622** | 0.2028** | 0.1810*** |

Largest idiosyncratic volatility

| Largest idiosyncratic volatility | Singapore | Taiwan | Hong Kong |
|--------------------------------|-----------|--------|-----------|
|      | CSAD      | CSSD   | CSAD      | CSSD  |
| $\alpha$ | 0.0145*** | 0.0198*** | 0.0146*** | 0.0257*** |
| $\gamma_1$ | -0.0759 | -0.1362 | 0.5834*** | 0.8810*** |
| $\gamma_2$ | 0.1271* | 0.0582 | 0.4693*** | 0.7877*** |
| $\gamma_3$ | 0.9902 | 0.3058 | -4.6960*** | -8.6271** |
| $\gamma_4$ | -0.8105 | 0.4706 | -3.1553** | -5.3872** |
| $\gamma_5$ | 0.3762** | 0.4292** | 0.0782 | -0.0053 |

In this table, we investigate the impact of idiosyncratic volatility on the herding behavior in the Asian stock markets. The market data is equally divided into two groups based on the level of idiosyncratic volatility. Herding is detected among samples with the smallest 20% and the largest 20% idiosyncratic volatility. ****, ** and * indicate that the parameters are significant at 1%, 5%, and 10% level, respectively. Terms in boldface are significant parameters revealing the presence of herding.

The table presents the test of herding in eight stock markets. ****, ** and * indicate that the parameters are significant at 1%, 5%, and 10% level, respectively.
Table 4
Regression results of Markov-switching model under three regimes.

| Regime | Japan | South Korea | Hong Kong | Singapore | Taiwan | Chinese Mainland |
|--------|-------|-------------|-----------|-----------|--------|-----------------|
|α      | −0.0095 | −0.0314*** | 0.0029    | −0.0034   | −0.002 | 0.0155          |
|γ1     | 2.4871*** | 4.6194      | 14.3967***| 17.4106***| 5.8943***| −0.2378***      |
|γ2     | 2.8487*** | 2.5841***   | 16.2425***| 11.7150***| 3.7153***| −0.1107***      |
|γ3     | −64.1733***| −206.199    | −1748.8804***| −2203.5993***| −500.9323***| 6.0043***       |
|γ4     | −51.7492***| −124.9949***| −1753.1732***| −924.2484***| −158.8699***| 5.3336***       |
|γ5     | −0.0004 | 1.4821***   | −0.1483***| 0.0781    | −0.0088 | 0.2954***       |

Regime 1

|α      | 0.0127*** | 0.0129*** | −0.0014 | 0.0211*** | 0.0001 | 0.011           |
|γ1     | −0.3263** | 0.1382*** | 8.2455***| 5.7276*** | −0.5219**| −0.0335         |
|γ2     | 0.2640*** | 0.1627*** | 6.1662***| 4.2722*** | 1.2807* | 0.0013          |
|γ3     | 38.2610***| −3.1858* | −644.2007***| −271.4964***| −27.8238***| 0.5273          |
|γ4     | −4.8740***| 0.4232    | −381.9994***| −201.5313***| −2.3005***| 2.3745          |
|γ5     | 0.0532    | 0.3117*** | 0.0384   | −0.0071   | 1.6055***| 0.308           |

Regime 2

|α      | 0.0029*** | 0.0210*** | 0.0151***| 0.0112*** | 0.0085***| 0.0021          |
|γ1     | 0.005     | 0.5381*** | 0.7980***| 1.0438*** | 0.1999***| −0.109          |
|γ2     | −0.0176   | 0.4555*** | 0.5710***| 1.0427*** | 0.2479***| 0.2785***       |
|γ3     | 0.8019    | −2.7166***| −0.7808  | −2.255    | 0.3424   | 5.1322***       |
|γ4     | 2.3811**  | −0.8759***| −2.8781  | −4.5497***| −0.8779  | −2.8332***      |
|γ5     | 0.8081*** | −0.0803***| 0.2142***| 0.2263*** | 0.3037***| 0.8314          |

The table presents the estimation results for the six Asian stock markets. The Eq. (5) is adopted for parameters estimation, where γ1, γ2, γ3, γ4, γ5 represent the parameters. Regime 0, 1 and 2 refer to the three market states generated from Markov-switching regression. ***, ** and * indicate that the parameters are significant at 1%, 5%, and 10% level, respectively. Terms in boldface are significantly negative parameters at 5% significance level revealing the presence of herding.

We attempt to add COVID-19 variables (total case per million and total death per million) into Equation (4), one at a time, but these variables are not significant in most markets, so the results are not included in the table.

Herding. Similarly, in both Hong Kong and Taiwan stock markets, the significantly negative γ4 by CSAD indicates the emergence of herding when stock market went downward. Significantly visible herding is also detected in both upward and downward markets in Japan: γ3 and γ4 in CSAD are significantly negative (−3.5312 and −3.5926). To summarize, herding is detected in both upward and downward markets in Singapore and Japan, and in downward markets in Taiwan and Hong Kong.

Table 2 presents the test results of herding in South Korea, Chinese Mainland, United States, and UK equity markets.2 For the first three, neither CSAD nor CSSD displays significantly negative parameters, implying little evidence on herding existence. For United Kingdom, herding is discovered in both upward and downward markets. In general, herding emerged in Singapore, Taiwan, Hong Kong, Japan and United Kingdom, when the markets went downward, but it appeared in upward markets only in Singapore and Japan, showing that the herding behaviors widely arise among Asian stock market during the epidemic period, and investors are more hardheaded when the market declines. However, for a deeper understanding of market herding during and after the global market crash in 2020, we investigate the specific time spans that herding occurred based on Markov-switching regression in Section 6.3.

6.2. Herding in companies with different levels of idiosyncratic volatility

Inspired by the method introduced by Vo and Phan (2019), we collect stocks with the smallest 20% and the largest 20% idiosyncratic volatility from each Asian market (referred as Groups 1 and 2, respectively). Parameters of Eq. (4) for the two groups are shown in Table 3. In Singapore, the regression results of Group 2 include significantly negative γ3 and γ4, indicating the emergence of herding among the stocks in this group. As for Chinese Mainland and the Taiwan stock markets, the regression results show no significantly negative γ3 or γ4 by CSAD and CSSD measures, so no significant herding is detected in either group. Similarly, we found herding in Group 1 in Hong Kong and South Korea, and in Groups 1 and 2 in Japan.

The regression results reflect the robustness of the CCK model, and it is also suggested that higher idiosyncratic volatility in stock markets is more likely to be accompanied by more pronounced herding. We find that the herding is generally more serious in Group 1 than Group 2 in Hong Kong, Japan and South Korea markets. The idiosyncratic volatility of a company can be affected by many factors such as fundamental information of a company (including financial and operating conditions), stock price, the noisy trading caused by investors’ irrational investment.

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2 We attempt to add COVID-19 variables (total case per million and total death per million) into Equation (4), one at a time, but these variables are not significant in most markets, so the results are not included in the table.
6.3. Herding in different market states based on Markov-switching regression

Table 4 shows the Markov-switching regression results of six Asian equity markets based on Eq. (5). The parameters help to determine whether herding emerges in a certain market state, and the movement of smoothed probabilities shown in Fig. 5 can track specific time spots at what herding occurs. It is worthy to notice that herding becomes more obvious in different regimes/states based on Markov-switching regression than in the whole observed period based on static model regression. In Japan, strong herding appeared in Regime 0 in both upward and downward markets, and it became mild in Regime 1, which is consistent with the regression result.
During the market crash in March, herding suddenly emerged in the downward market in the mid-March shown by the market state switched from Regime 1 to Regime 2 in South Korea, as it is revealed in the figure. During the investigation of herding in Hong Kong stock market, the significantly negative parameters are principally detected in Regime 0 and 2 in South Korea, and Fig. 5 shows that the total length of these two regimes were much shorter than that of Regime 1 where no herding was detected. This may explain why linear regression did not find herding for the whole time period. The significant negative parameters in boldface are significantly negative parameters at 5% significance level revealing the presence of herding.

Table 5 summarizes the result of herding detection based on Markov-switching regression, and Fig. 6 gives the time spots that herding was observed in Regimes 0 and 1 in Taiwan stock market. However, the Regime 2, where herding was detected. Meanwhile, herding was observed in Regimes 0 and 1 in Taiwan stock market. However, the Regime 2, when no herding was detected, occupied the longest time span, which may explain why weak herding was detected in a downward market based on CSAD approach by static model. It is shown in the subplot of Taiwan that before the market crash in March 2020, there was a short period in Regime 2 when herding happened in both upward and downward market.

Table 5: Markov-switching model results of market sectors.

| Regime 0 | Healthcare | Tourism & Hospitality | Chinese Mainland | Healthcare | Tourism & Hospitality |
|----------|------------|----------------------|-----------------|------------|----------------------|
|          |            |                      |                 |            |                      |
| α        | 0.0042     | 0.0159***            | 0.0291***       | 0.0532***  | 0.0060               |
| γ1       | 3.6654***  | 0.6066**             | −1.1428***      | 0.0600     |                     |
| γ2       | 3.1992***  | 0.3422               | −0.3444***      | −0.4661*** |                     |
| γ3       | −93.4754*** | 2.6381              | 3.9010***       | −5.7155    |                     |
| γ4       | −45.9161*** | 1.5197              | 1.2420***       | 0.5420     |                     |
| γ5       | −0.3461*** | −0.3291***           | 0.1423          | −1.5658    |                     |

The table presents the estimation results for the healthcare and tourism & hospitality industries in South Korea, and Chinese Mainland stock markets. The Eq. (5) is adopted for parameters estimation, where $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ represent the parameters. Regime 0, 1 and 2 refer to the three market states generated from Markov-switching regression. ***, ** and * indicate that the parameters are significant at 1%, 5%, and 10% level, respectively. Terms in boldface are significantly negative parameters at 5% significance level revealing the presence of herding.

Based on the static model, and herding is discovered in several days during the march crash in March 2020. While herding was principally detected in Regime 0 and 2 in South Korea, and Fig. 5 shows that the total length of these two regimes were much shorter than that of Regime 1 where no herding was detected. This may explain why linear regression did not find herding for the whole time period. During the market crash in March, herding suddenly emerged in the downward market in the mid-March shown by the market state switched from Regime 1 to Regime 2 in South Korea, as it is revealed in the figure. During the investigation of herding in Hong Kong stock market, the significantly negative $\gamma_3$ and $\gamma_4$ were observed in Regimes 0 and 1. The detection results based on Markov-switching can possibly explain, since herding did not exist in Regime 2 which occupies the largest proportion among all three states.

As shown in Table 4, herding was found in Singapore stock market in all three regimes, which is consistent with the results of linear regression model. Shown in Fig. 5, the market state was located in the Regime 2 during the market crash, indicating that herding presented when the market showed a downward trend. As for Chinese Mainland, herding was detected in Regimes 0 and 2, including the market crash period. The absolute values of significantly negative parameters seem to be less than that in most other Asian markets where herding was detected. Meanwhile, herding was observed in Regimes 0 and 1 in Taiwan stock market. However, the Regime 2, when no herding was detected, occupied the longest time span, which may explain why weak herding was detected in a downward market based on CSAD approach by static model. It is shown in the subplot of Taiwan that before the market crash in March 2020, there was a short period in Regime 2 when herding happened in both upward and downward market.

The figure presents the market returns and the smoothed regime probability calculated based on Markov-switching regression in the six equity markets.

Since a few signs of herding have been detected in South Korea and Chinese Mainland stock markets, we further explore whether the market sectors directly affected by COVID-19 shows any sign of herding. Therefore, we investigate two essential market sectors: healthcare and tourism & hospitality, which are highly affected by the COVID-19. The first contains pharmaceuticals, biotechnology, medical devices, and medical & aesthetic services, while the second includes hotels, restaurant, resorts, travel agencies, and casinos. Table 5 summarizes the result of herding detection based on Markov-switching regression, and Fig. 6 gives the time spots that herding was detected by regime switching. As for the healthcare sector in South Korea, Regime 1 occupied the longest time span, and $\gamma_3 = −7.2602$ at 0.05 significant level, which means significant herding was discovered in the upward market. The result shows investors’ positive expectation on healthcare stocks. As for the tourism & hospitality stocks in South Korea stock market, there were even more divergent views, revealed by the results that no herding was detected in all three states but anti-herding was detected principally in Regimes 1 and 2.

In Chinese Mainland market, the price of healthcare stocks generally showed an upward trend in 2021, but the opposite trend has been observed on tourism & hospitality. However, the prices of medical products are restricted and the profit of pharmaceuticals and medical devices companies may be cut as the Chinese government implemented the centralized procurement of medicines and medical devices in 2020. Herding occurred in Regime 2 among the healthcare stocks in a downward market. Besides, the tourism & hospitality...
stocks seem to be seriously affected by the speculation since herding was detected in the upward market in Regime 1. As the tourism & hospitality industry is seriously hit by the COVID-19, the appearance of herding in different regimes reveals the existence of speculation and the “wait-and-see” attitude of market participants.

The figure presents the industry returns and the smoothed regime probability calculated based on Markov-switching regression for the healthcare and tourism & hospitality industries in South Korea, and Chinese Mainland stock markets.

6.4. The measurement of herding’s magnitude in Asian stock markets

We then adopt HS model to reflect the strength of herding behavior and make a comparison in two periods: before and during COVID-19, to reflect potential impact of COVID-19 on herding in the markets. Fig. 7 shows the movement of $H_t$, which is calculated by HS model. As being analyzed in Section 4.4, a smaller $H_t$ value implies a stronger herding in the market. Monthly $H_t$ is calculated based on daily stock returns and daily market returns collected in the six Asian markets we considered, and the time window is from February 2019 to January 2021.

It is phenomenal that for all six markets, the lowest $H_t$ is obtained in the periods around either the global market crash or the first peak of COVID-19 new cases in these countries or regions - February 2020 in Chinese Mainland when the market experienced a rapid growth of cases, March 2020 in Singapore, Taiwan, Japan, Hong Kong and South Korea possibly because of the pessimism in markets. Especially the movement of $H_t$ in Singapore showed a general downward trend in the observed periods and there was a distinct difference of magnitude of herding “Before” and “During” the outbreak of COVID-19. The change of magnitude of herding in Chinese Mainland stock market has shown some uniqueness that a large magnitude of herding was detected from January to August in 2019 and from February to March in 2020. Whereas the level of herding decreased significantly from April to June in 2020, possibly because the market tended to be stable along with the COVID-19 generally getting controlled and the resumed production. In general, the largest magnitudes of herding in investigated Asian stock markets were mainly observed from February to April in 2020.

The figure displays the results of $H_t$ from HS model. The sample range is from February 2019 to January 2021. A smaller $H_t$ implies a higher magnitude of herding in the market.
In this study, we investigate the herding behavior under the impact of COVID-19 by considering six typical Asian equity markets in Japan, South Korea, Chinese Mainland, Hong Kong, Singapore and Taiwan, respectively. We have found that when a destructive worldwide public crisis such as COVID-19 largely exacerbates the market uncertainty, investors tend to mimic others who are believed to have valuable private information. To deeply understand the herding under different circumstances, we test the herding behavior in groups of different levels of idiosyncratic volatility, whose results are also robust with the entire sample tests. The empirical results show that herding is more likely to be more intensive in stocks with large idiosyncratic volatilities. Afterwards, we adopt the Markov-switching regression to determine the specific time spots that herding occurs, and we observe the presence of herding in Chinese Mainland, Japan, South Korea and Singapore stock markets during the market crash in March 2020, and herding is also detected in

Fig. 7. The movement of $H_t$ in Asian stock markets.

7. Conclusion

In this study, we investigate the herding behavior under the impact of COVID-19 by considering six typical Asian equity markets in Japan, South Korea, Chinese Mainland, Hong Kong, Singapore and Taiwan, respectively. We have found that when a destructive worldwide public crisis such as COVID-19 largely exacerbates the market uncertainty, investors tend to mimic others who are believed to have valuable private information. To deeply understand the herding under different circumstances, we test the herding behavior in groups of different levels of idiosyncratic volatility, whose results are also robust with the entire sample tests. The empirical results show that herding is more likely to be more intensive in stocks with large idiosyncratic volatilities. Afterwards, we adopt the Markov-switching regression to determine the specific time spots that herding occurs, and we observe the presence of herding in Chinese Mainland, Japan, South Korea and Singapore stock markets during the market crash in March 2020, and herding is also detected in
healthcare industry in South Korea, and in both healthcare and the tourism & hospitality industries in Chinese Mainland. Meanwhile, we adopt the HS model to study the variation of herding's magnitude in different time spots, and find the magnitude of herding during the global market crash in March 2020 is significantly larger than that in the rest in most observed Asian stock markets. Future research can be conducted to examine the modified model for other economic events that would cause herding and derive comprehensive measures to monitor investors' behavior.

Contribution of the authors

Study conception and design: Conghua Wen, Ruonan Zhang; data collection: Rui Jiang, Yu Cui; analysis and interpretation of results: Rui Jiang, Yu Cui, Conghua Wen; draft manuscript preparation: Rui Jiang, Ruonan Zhang, Conghua Wen; Funding Acquisition: Conghua Wen. All authors reviewed the results and approved the final version of the manuscript. The research is supported by Research Development Funding of Xi’an Jiaotong-Liverpool University, Code: RDF-18-02-08.

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