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Herding behavior in Hong Kong stock market during the COVID-19 period: a systematic detection approach

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ABSTRACT
The study intends to conduct a systematic mechanism for herding detection in the Hong Kong stock market. We take stocks from three market sectors as samples and investigate the existence of herding in the two periods: before and during the outbreak of COVID-19 in Hong Kong, from August 2019 to July 2020. We adopt CCK model-based OLS and quantile regression to examine herding in each observed period and employ HS model to measure the magnitude of herding during the time. The empirical results indicate the emergence of mild herding from August 2019 to January 2020, and the herding phenomenon is generally weakened between February and July 2020. Our study confirms the implication of the systematic herding detection mechanism that can improve the sensitivity of detection and capture the magnitude and variation of herding.

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Herding; Hong Kong stock market; CCK model; quantile regression; HS model; COVID-19

1 Introduction

The efficient market hypothesis (EMH) lays the foundation for classical financial theories. One of its fundamental assumptions is that all investors are rational. However, the hypothesis usually cannot be held in financial markets because investors tend to behave irrationally (Shiller 1989; Summers 1986). The herding is a typical reflection of the irrationality in financial markets. Avery and Zemsky (1998) find that a proportion of investors hold a belief that other investors in the market have unpublished information, so they would follow others' investment behavior. Pretcher (2001) analyzes investors' herding behavior from the perspective of neuroeconomics and finds that investors' herding behavior is the same as other primitive instincts of human beings for survival. Devenow and Welch (2006) believe that investors have an inherent preference to follow market consensus, which is likely to lead them to blindly mimic other investors. Such herd-like buying and selling, chasing the rising and falling of asset price will intensify the deviation of assets price from their basic value, resulting in asset bubbles, aggravating market risks, and thus affecting the stability of financial markets (Lakonishok, Shleifer, and Vishny 1992; Jegadeesh and Kim 2009).

For both individual and institutional investors, a major ground of the mimicry is information asymmetry. The higher opaqueness and immaturity of financial markets are

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often followed with the higher possibility of the existence of herding. Except for the information asymmetry, financial crisis and influential market shocks usually are accompanied by investors' irrationality, which leads to heightened volatility in financial markets. In the first half year of 2020, the outbreak of COVID-19 hit the global financial markets. Under the strike of COVID-19 and other social or political events, share prices crashed in the U.S. stock market. The Dow Jones, S&P 500, and the Nasdaq index slumped from 29348.03, 3386.19 and 9817.18 points on 19 February 2020 to 18591.93, 2237.40 and 6860.67 on 23 March 2020, respectively. After the U.S. released a series of regulatory policies, the three indices rebounded. Influenced by the COVID-19 and U.S. market, the Hong Kong stock market fell by 1,637 points in the first three trading days. Then, the Hang Seng Index (HSI) experienced a huge violation from February to June in 2020, dropping from 26356.98 on February 3 to 21696.13 on March 23, which is the lowest in recent 5 years. Then, the index rose up and fluctuated around 26000. The huge fluctuation increases the probability of the presence of herding.

In previous research, Chang, Cheng, and Khorana (2000) find that normally the obvious herding behavior does not exist in mature stock markets such as America, Japan, and Hong Kong markets. However, the spread of COVID-19 and other social and political events can influence investors behaviors and emotions, which can stimulate irrational actions. In this paper, we choose to focus on detecting herding in Hong Kong stock market, because of the following two reasons. Firstly, we take the time window from February to July 2020, that is, the beginning of the COVID-19 outbreak in the world, to study the finance market so that the herding behavior could be detected at an early stage. There is a reasonably number of confirmed and suspected cases in Hong Kong in this time window. Secondly, the Hong Kong finance market perfectly integrates internationality and locality. For a long time, international investment from USA and Europe, especially the institutional investment, makes up a large proportion of capital in Hong Kong market, and it is considered to be fairly mature after being developed for over a hundred years. The Hong Kong and US markets are particularly close in a sense that their currencies hold a fixed exchange rate and they resonance obviously (Cha and Oh, 2000). On the other hand, the Hong Kong stock market has been increasingly affected by stock markets from mainland China (Cheng et al. 2019) after absorbing a large number of investments from the latter and accepting a set of promotional policies from the Chinese government. As the ones earliest hit by the COVID-19, the investors in the Chinese markets would display special behaviors, typically, herding, in the Hong Kong market.

Therefore, we intend to explore whether and to what extent COVID-19 has an impact on the herding phenomena in the Hong Kong market, contributing to understanding of abnormal movements of asset prices. Choi and Sias (2009) find that individuals turn to extrapolate and evaluate the condition of a company based on information about other companies in the same industry and make trading decision based on sectoral analysis. Hence, we concentrate on the herding detection from the perspective of market sectors. Stocks of real estate, banking, and state controlled are sampled and analyzed for their significant influence on both the economy and the stock market. Cross-sectional dispersion, represented by the cross-sectional absolute dispersion (CSAD) and cross-sectional standard dispersion (CSSD), is commonly adopted in the study of volatility and market consensus (Fei, Liu, and Wen 2019). The cross-sectional dispersion is also widely applied in measurements of herding (Lee, Chen, and Hsieh 2013; Chong et al. 2020). We follow

Chang, Cheng, and Khorana (2000) to apply the CSAD as the indicator of herding in this paper. Based on the cross-sectional dispersions, scholars propose various models for herding detection. CH model (Christie and Huang 1995), CKK model (Chang, Cheng, and Khorana 2000), and HS model (Hwang and Salmon 2001) are the fundamental models for herding investigation, and numerous extended models are put forward to improve the accuracy of herding detection. Luo (2019) uses American Depository Receipts (ADRs) of Chinese companies to study herding and financial crisis, and Xiong, Wang, and Shen (2020) adopt CH model to study emerging markets and analyze investors' herding. In this paper, we primarily apply the CCK model based on ordinary least squares (OLS) regression to detect the existence of herding, and use the quantile regression to further verify the presence of herding. Subsequently, we adopt the HS model to reveal the variation of the magnitude of herding in different periods. We find that the systematic combination of these three herding detection methods can better reflect the herding behavior than merely use one approach, and greatly improves the accuracy of the detection. The HS model is proved to reveal the variation of herding that cannot be explained by CCK model. The empirical results show that mild herding is detected among all three groups in the observed period before COVID-19, while the herding phenomena seem to be weakened in all groups during COVID-19.

The subsequent sections are organized as the follows: In Section 2, we introduce the classical models adopted in herding detection. Section 3 explains the collection of data and baseline analysis to confirm the feasibility of modeling. The empirical study to detect the herding and determine the magnitude of herding is discussed in Section 4 and then we conclude the paper in Section 5 with discussions.

2 The model of herding

2.1 CH model

Christie and Huang (1995) propose a pioneer model in the detection of herding. They analyze the feasibility to characterize the herding behavior based on cross-sectional dispersion. Specifically, they adopt the cross-sectional standard dispersion (CSSD) as the indicator of herding and attempt to reveal the existence herding based on the regression between CSSD and extreme market returns. CSSD is defined as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-R_{m,t}\right)^2}{N-1}}$$

where N is the total number of stocks, $R_{i,t}$ represents the return of stock i at the time t, and $R_{m,t}$ represents the market return at time t.

Different from the traditional CAPM model hypothesis, Christie and Huang (1995) believe that the violent fluctuation of stock price reveals the abnormally high and low pressure of the market return. Represented by the decrease of CSSD, the shrink of the variety of returns between different stocks implies the growing consensus of market expectation and the emergence of herding. Based on the mechanism, the CH model can be represented as:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^H + \mu_t \#(2.)$$

where D_t^L and D_t^H are two dummy variables screening the emergence of extremely high and low market return, and represent the dispersion coefficient outside the extreme volatility of the market, respectively. They also define the extreme (both the maximum and minimum) 1% and 5% market returns, as two different ranges of independent variables D_t^L and D_t^H. The concision and simplicity are two advantages of CH model but the model fails to provide sensitive detection of herding. In other words, it can merely detect serious herding.

2.2 CCK model

In order to overcome the defects of CH model, Chang, Cheng, and Khorana (2000) propose another model for the detection of herding, called CCK model by subsequent studies. They introduce cross-sectional absolute dispersion (CSAD) as dependent variable and derived the herding detection model form CAPM return model, where the sign (positive or negative) of its quadratic term indicates whether the herding exists. If the coefficient of quadratic term is significant, it is proved that the herding exists.

As for the indicator of herding in CCK model, the absolute deviation degree of cross-section between individual stock return and market average return at time t is:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \left| R_{i,} - R_{m,t} \right| \#(3.)$$

where N represents the number of stocks, $R_{i,t}$ is the return of stock i at the time of t, and $R_{m,t}$ represents the average return of N stocks at the time of t.

Chang, Cheng, and Khorana (2000) believe that the linearly increasing relationship between $E(CSAD_t)$ and $E(R_{m,t})$ in CAPM return model cannot be held in real world. In order to test the existence of herding, a quadratic parameter is introduced. In the model, measurable CSAD and R_m are used instead of unmeasurable $E(CSAD_t)$ and $E(R_{m,t})$. The regression equation is as follows:

$$CSAD_t = \alpha + \beta_1 R_{m,t} + \beta_2 R_{m,t}^2 + \mu_t \#(4.)$$

If the β_1 or β_2 is significantly negative, the existence of herding can be proved.

2.3 HS model

Hwang and Salmon (2001) propose another herding detection model to detect and measure herding. The model contributes to the measurement of the magnitude of herding. In HS model, the cross-sectional dispersion is applied to reveal the existence of herding and measure the degree of herding. Based on the CAPM return model, initially they derive the following indicators to measure the degree of herding effect. Assume the individual stocks in the market portfolio are equally weighted:

$$H_t = \frac{1}{N}\sum_{i=1}^{N} \left(\beta_{\mathrm{i,t}} - 1\right)^2 \#(5.)$$

where the model adopts the same β coefficient as that in CAPM return model (Markowitz 1959). A smaller H_t reflects a lower dispersion of $\beta_{\mathrm{i,t}}$ and reveals a stronger herding effect. Afterwards, standardizing the above equation, the formula of HS model is:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left(\widehat{\beta_{i,t}}-1\right)}{std\left(\beta_{i,t}\right)}\right)^2 \#(6.)$$

Cho and Engle (1999) find that the bad news of individual stocks or market can cause the reduction of β. Therefore, the market shocks including Hong Kong social chaos and COVID-19 from 2019 to 2020 are likely to encourage the herding in the market, which is explored in the following analyses.

3 Baseline analysis

3.1 Data

In this paper, analysis is conducted to test the herding in three market sections in the Hong Kong stock market. We collect the daily closing prices of around 900 representative stocks among the main board of the Hong Kong stock market from the wind database (Wind Information Co., Ltd 2020). The subsamples include 327 state-controlled stocks, 305 real estate stocks and 249 banking stocks.

Based on the suggestion from Song and Wu (2001), it is necessary to examine the herding behavior in different periods and make a comparison. Therefore, we investigate two different time spans: the period before the outbreak of COVID-19 and the period under the impact of COVID-19. We regard the end of January as the demarcation point when Hong Kong chief executive changed the response level of COVID-19 to emergency. Thus, 1 February 2020 to 30 July 2020 is classified as the sample period during the outbreak of COVID-19. Meanwhile, the CSAD and return from 2 August 2019 to 31 January 2020 are observed to reflect the situation before COVID-19.

3.2 Calculation of CSAD

Then, we compute the return of these stocks:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1\#(7.)$$

$$R_{m,t} = \frac{P_{m,t}}{P_{m,t-1}} - 1\#(8.)$$

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|, N = 249, 305, 327\#(9.)$$

where $R_{i,t}$ is the return of stock of i at time t, and $R_{m,t}$ is market return calculated based on Hang Seng Index. Additionally, Hong Kong's one-week bonds return is used as risk-free interest rate.

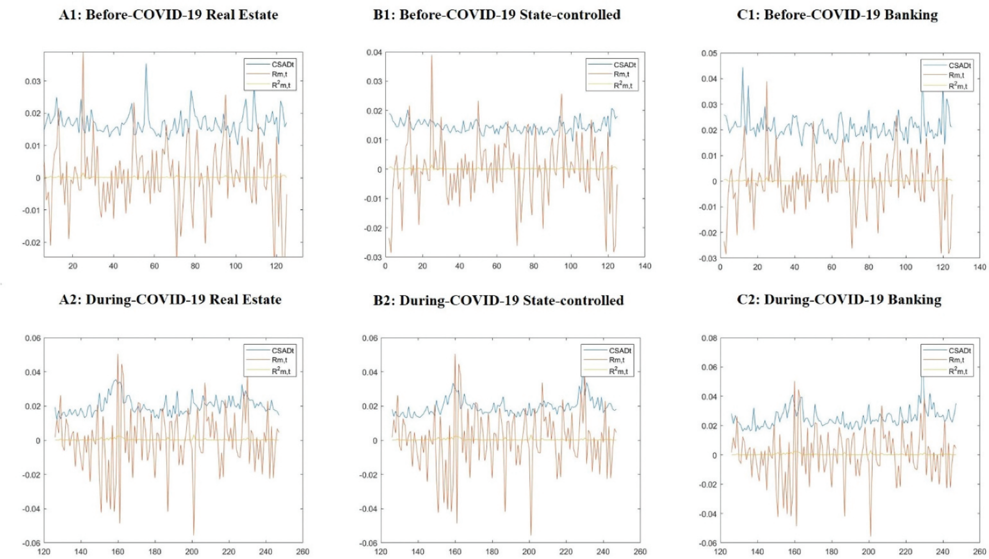

Figure 1. Movement of $CSAD_t$, $R_{m,t}$ and $R^2_{m,t}$.

Table 1. ADF test results $CSAD_t$, $R_{m,t}$ and $R^2_{m,t}$.

Before COVID-19	Variable	ADF	P value	During COVID-19	Variable	ADF	P value
Real Estate	$CSAD_t$	−1.9997	0.0439	Real Estate	$CSAD_t$	−2.0153	0.0424
State-controlled	$CSAD_t$	−2.0433	0.0396	State-controlled	$CSAD_t$	−2.2752	0.0225
Banking	$CSAD_t$	−2.0223	0.0417	Banking	$CSAD_t$	−2.0878	0.0357
Market Return	$R_{m,t}$	−10.2858	0.0000	Market Return	$R_{m,t}$	−12.4427	0.0000
	$R^2_{m,t}$	−11.1729	0.0000		$R^2_{m,t}$	−4.9182	0.0000

3.3 Stationary test

The stationary property is an essential precondition for modeling time series. Figure 1 shows the variation of variables of CCK model, including $CSAD_t$, $R_{m,t}$ and $R^2_{m,t}$. Plotting movement of variables helps to provide an intuitive judgment of the stationary of variables. The movement of $CSAD_t$, $R_{m,t}$ and $R^2_{m,t}$ in all subplots do not show significantly visible upward or downward trend, which preliminary reflect the stationary of variables. Furthermore, Table 1 shows that the P values of ADF tests are all close to 0 for all parameters in the real estate, state-controlled and banking sectors in both periods before or during COVID-19. The variables are stationary at a significant level of 0.05 and satisfy the premise for the further regression analysis.

The figure shows the movement of $CSAD_t$, $R_{m,t}$ and $R^2_{m,t}$ in the two periods before and during COVID-19, no significant visible trend is observed.

The table tests the stability of the values in regression $CSAD_t = \alpha + \beta_1 R_{m,t} + \beta_2 R^2_{m,t} + \mu_t$. All test results are significant under 0.05 level and prove the stationary of all-time series.

4 Empirical analysis

4.1 Herding detection

We use the ordinary least squares (OLS) method to estimate coefficients in Equation 4 and adopt the Newey-West approach for the adjustment of possible heteroscedasticity. Table 2 reveals the regression results for stocks in the real estate, banking, and state-controlled sectors. It is observable that during the period before COVID-19, the β_1 of real estate, state-controlled company stocks, and banking stocks are −0.0522, −0.01 and −0.0016, respectively, under 0.05 confident level, indicating the emergence of herding, while the herding is not detected among real estate stocks. However, in the period during the outbreak of COVID-19, the herding seems to disappear.

The OLS regression results based on CCK model are shown in the table. We adopt the T test to examine the significance of coefficients. Terms in boldface are significant negative coefficients revealing the presence of herding among the real estate, state-controlled, and banking stocks before COVID-19.

To make sure that the regression results are reliable and the heteroscedasticity issue does not exist in the model fitting, we furtherly execute the residual analysis. Figure 2 shows the temporal residuals plot of the regressions mentioned above. The Y-axis of the subplots reflects the confident level of residuals in OLS regressions, and the residuals, which are confident in 0.05 level, are shown in green. If a large proportion of residuals locate out of 0.05 confident level and are marked in red, the heteroscedasticity of the regressions is detected. However, shown in Figure 2, each subplot has no more than seven red bars out of 124 cases, and the residuals mostly fluctuate around 0, which means the heteroscedasticity does not exist in all regressions. Generally, the results of OLS regression reveals that the herding is detected in the period before COVID-19, while the market information reflected by the OLS regression is limited, and further analysis is required for herding detection.

The residuals are plotted in the period before COVID-19 at the top row and during COVID-19 plot at the bottom row. The Y-axis reflects the confident level of residuals, and the residuals located in confident level are shown in green. If there is no large proportion of residuals located out of confident level (shown in red), indicating no sign of the heteroscedasticity of the regressions.

Table 2. Result of OLS regression based on CCK model.

Real Estate Before COVID-19	Coefficient	Estimated value	P value	During COVID-19	Coefficient	Estimated value	P value
	α	0.0169	0.000		α	0.0192	0.000
	β_1	**−0.0522**	**0.036**		β_1	0.0068	0.778
	β_2	−0.1273	0.904		β_2	3.1918	0.005
State-controlled							
	α	0.0143	0.000		α	0.0189	0.000
	β_1	**−0.0100**	**0.020**		β_1	0.0208	0.353
	β_2	1.8946	0.817		β_2	2.0346	0.048
Banking							
	α	0.0211	0.001		α	0.0247	0.000
	β_1	**−0.0016**	**0.041**		β_1	0.0412	0.216
	β_2	0.2102	1.547		β_2	2.217	0.016

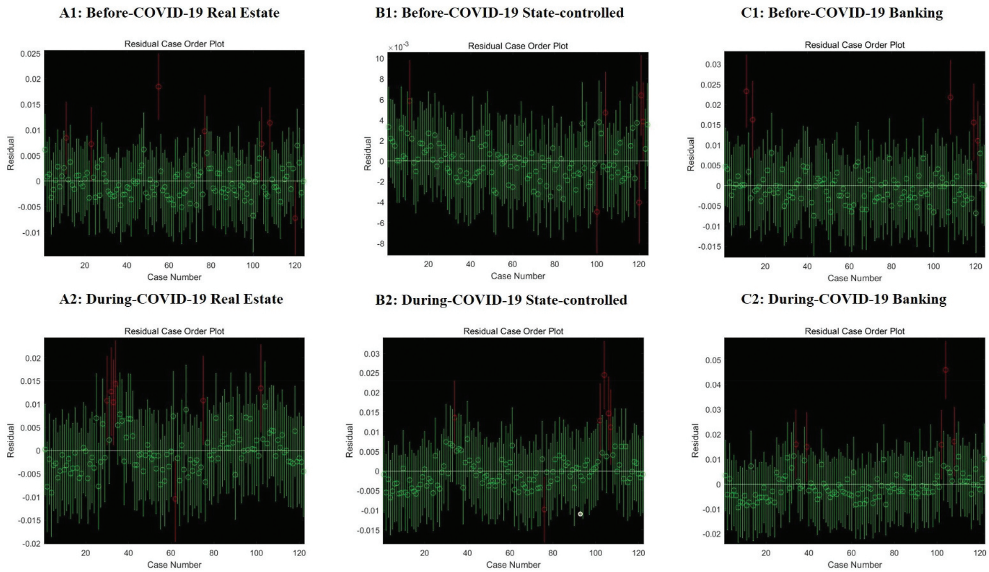

Figure 2. Residual time series of OLS regression.

Unlike OLS regression, quantile regression detects herding under different quantile levels and provides a more convincing measurement of herding. Therefore, a quantile regression is performed on the original data below and the results are shown in Table 3, and the analysis can also minimize the influence of extreme values on the coefficients of independent variables. We set the quantile from 10% to 90% and observe whether the negativity exists among the coefficients β_1 or β_2. Before the outbreak of COVID-19, the β_1 of real estate stocks are –0.0645 and –0.1328, under 0.5 and 0.9 quantile level, and the β_1 of state-controlled companies' stocks are –0.0376 and –0.0410 under 0.5 and 0.7 quantile levels, revealing some signs of herding, but these coefficients merely under 0.1 significant level. However, based on the quantile regressions, the herding effect in these samples appears to have diminished during COVID-19, with no negative β_1 significant at the 10%–90% quantile for three group of stocks during COVID-19. Overall, quantile analysis indicates that only real estate and state-controlled stocks reveal mild herding during the observation period prior to COVID-19. In the second period, negative β_1 appears in all three sample groups, but the coefficients are not significant, indicating that the herding effect is generally weak or non-existent. However, herding is not invariable in the market while it can change with time. CCK model can measure the herding condition in the whole period, but fails to reflect the change of herding in the observed period. Therefore, we adopt HS model to reveal the variation of herding's magnitude.

The table is a quantile regression of CCK model in order to avoid the effect of extreme values, and five quantile points are set for each group of stocks. Terms in boldface are significant negative coefficients revealing the presence of herding.

Table 3. Results of quantile regression based on CCK model.

Before COVID-19	Quantile	α	β_1	β_2	During COVID-19	Quantile	α	β_1	β_2
Real Estate									
	0.1	0.0131	−0.0044	0.5343		0.1	0.0144	0.0238	1.9401
		(0.0000)	(0.8955)	(0.7211)			(0.0000)	(0.3409)	(0.0038)
	0.3	0.0147	−0.0308	1.1145		0.3	0.0166	0.0293	2.2549
		(0.0000)	(0.3257)	(0.4481)			(0.0000)	(0.2427)	(0.0084)
	0.5	0.0162	**−0.0645**	1.0481		0.5	0.0183	0.0173	2.9784
		(0.0000)	**(0.0565)**	(0.533)			(0.0000)	(0.5561)	(0.0019)
	0.7	0.0181	−0.0623	−0.2504		0.7	0.0201	−0.0133	5.3607
		(0.0000)	(0.1092)	(0.8841)			(0.0000)	(0.7132)	(0.0)
	0.9	0.0212	**−0.1328**	−0.4575		0.9	0.0263	−0.0413	3.8906
		(0.0000)	**(0.0862)**	(0.9329)			(0.0000)	(0.5666)	(0.1059)
State-controlled									
	0.1	0.0122	0.0032	−0.4807		0.1	0.0142	0.0498	0.9144
		(0.0000)	(0.8758)	(0.4712)			(0.0000)	(0.0411)	(0.3547)
	0.3	0.0132	0.0062	1.8578		0.3	0.0164	0.0100	1.1287
		(0.0000)	(0.7628)	(0.0408)			(0.0000)	(0.6865)	(0.1745)
	0.5	0.0141	**−0.0376**	2.3757		0.5	0.0179	−0.0042	2.9850
		(0.0000)	**(0.0764)**	(0.0257)			(0.0000)	(0.8793)	(0.0009)
	0.7	0.0149	**−0.0410**	2.9700		0.7	0.0198	0.0121	3.8567
		(0.0000)	**(0.0761)**	(0.0089)			(0.0000)	(0.6817)	(0.0001)
	0.9	0.0168	−0.0154	3.3379		0.9	0.0251	0.0080	1.8669
		(0.0000)	(0.6274)	(0.0345)			(0.0000)	(0.9092)	(0.4307)
Banking									
	0.1	0.0158	−0.0152	2.4451		0.1	0.0178	0.0712	2.3363
		(0.0000)	(0.7046)	(0.0817)			(0.0000)	(0.0332)	(0.1012)
	0.3	0.0185	−0.0140	0.9984		0.3	0.0209	0.0256	2.8225
		(0.0000)	(0.7134)	(0.5493)			(0.0000)	(0.3939)	(0.0066)
	0.5	0.0205	−0.0261	−0.0395		0.5	0.0227	0.0046	3.6460
		(0.0000)	(0.5203)	(0.9845)			(0.0000)	(0.8963)	(0.0014)
	0.7	0.0221	−0.0635	−0.1267		0.7	0.0266	0.0306	2.0967
		(0.0000)	(0.1396)	(0.9513)			(0.0000)	(0.5583)	(0.2112)
	0.9	0.0255	0.0325	2.2094		0.9	0.0341	−0.0193	1.8603
		(0.0000)	(0.682)	(0.5795)			(0.0000)	(0.8575)	(0.5515)

4.2 Measurement of herding magnitude

Meanwhile, the HS model is applied to measure the magnitude of herding by calculating the H_t in Equation 6. As it is mentioned, a smaller H_t refers to a stronger herding effect. Figure 3 demonstrates the variation of Ht for the chosen samples. The Ht of all six samples generally range from 1 to 1.5, except for several outliers, but the fluctuation of H_t in the period before COVID-19 is generally smaller than the fluctuation during COVID-19. As for the real estate stocks, merely two points are greater than 1.2 while the number is about 10 during COVID-19. As for the group of banking stocks, three points of H_t are larger than 1.1 but the number in the period during COVID-19 is more than 10. The situation of state-controlled companies is also similar, indicating a larger magnitude of herding in the period before COVID-19 than during COVID-19 in general. The results of the HS model are consistent with the findings based on CCK model. Furthermore, the higher average H_t from February to July 2020 in Hong Kong helps to explain why the herding detection in the second observed period of CCK model is not significant.

In this figure, we exhibit H_t values against the time line. A larger H_t value indicates a less significant herding effect.

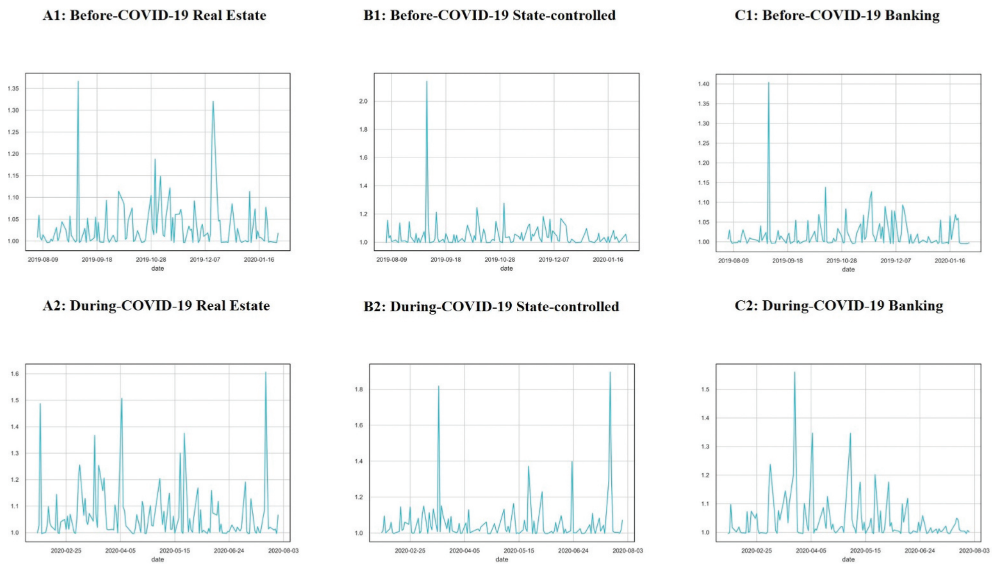

Figure 3. The magnitude of herding measured by HS model.

5 Conclusion

In this paper, we systematically detect the existence of herding and measure its magnitude among Heng Sang Index Components in the two periods: before and during COVID-19. We take 1 February 2020 as the turning point with the time window for each period as 6 months and collect stocks from three market sectors, including the real estate, state-controlled and banking stocks for analysis. OLS regression and quantile regression based on CCK model are executed to determine the existence of herding effect in the market, and the HS model is adopted to describe the variation of the magnitude of herding with time. The comparison results imply that the quantile analysis based on CCK model gives more reliable detection of herding than the traditional OLS regression of CCK model. The conclusion drawn from HS model explains and supports the results from the quantile analysis of CCK model. HS model provides more detailed information about the herding and effectively reveals the herding magnitudes in each time spots.

The empirical results reveal the presence of herding effect among the selected market sectors merely from August 2019 to January 2020. Mild herding is detected in the period before COVID-19, which is quite likely caused by the Hong Kong social chaos occurred in the second half of 2019. Meanwhile, the release of new land and housing policy that aims to balance the demand and supply of housing has a huge impact on the real estate and banking industry in Hong Kong. On the other hand, no significant visible herding is observed mainly from February to July 2020 during COVID-19. The significantly visible fluctuation of market returns in the first half of 2020 proves the huge impact of herding during COVID-19, while its effect on investors' behavior is multi-faceted. Future study can move forward to more specific situations, which can contribute to the deeper understanding of herding in financial markets. For example, taking the market's upward and downward trends under consideration is likely to reveal some difference of herding along with these two market trends. Accurate detection of herding contributes to the understanding and monitoring of investors' irrational behavior in financial markets, especially useful when the markets have huge uncertainty. The herding detection system (based on CCK model adopting quantile and OLS regression, and HS model) combined with market volatility indicators such as VIX in U.S. can contribute to the real-time informing of investors' sentiment and irrational behaviors and ultimately be helpful to conduct a financial crisis early warning system that will be furtherly explored subsequently.

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References

Avery, C., and P. Zemsky. 1998. "Multidimensional Uncertainty and Herding Behavior in Financial Markets." *American Economic Review* 88: 724–748. https://www.jstor.org/stable/117003

Cha, B., and S. Oh. 2000. "The Relationship between Developed Equity Markets and the Pacific Basins Emerging Equity Markets." *International Review of Economics & Finance* 9 (4): 299–322. doi:10.1016/S1059-0560(00)00057-5.

Chang, E. C., W. J. Cheng, and A. Khorana. 2000. "An Examination of Herding Behavior in Equity Markets: An International Perspective." *Journal of Banking and Finance* 24 (10): 1651–1679. doi:10.1016/S0378-4266(99)00096-5.

Cheng, A., N. Chow, D. Chui, and W. Wong. 2019. "The Three Musketeers Relationships between Hong Kong, Shanghai and Shenzhen before and after Shanghai-Hong Kong Stock Connect." *Sustainability* 11 (14): 3845. doi:10.3390/su11143845.

Cho, Y., and R. F. Engle. 1999. "Time-Varying Betas and Asymmetric Effect of News: Empirical Analysis of Blue Chip Stocks." *NBER Working Paper Series* 7330: 1–42. doi:10.3386/w7330.

Choi, N., and R. W. Sias. 2009. "Institutional Industry Herding." *Journal of Financial Economics* 94 (3): 469491. doi:10.1016/j.jfineco.2008.12.009.

Chong, O., A. N. Bany-Ariffin, B. T. Matemilola, and C. B. Mcgowan. 2020. "Can China's Cross-sectional Dispersion of Stock Returns Influence the Herding Behaviour of Traders in Other Local Markets and China's Trading Partners?" *Journal of International Financial Markets, Institutions and Money* 65: 101–168. doi:10.1016/j.intfin.2019.101168.

Christie, G. W., and D. R. Huang. 1995. "Following the Pied Piper: Do Individual Returns Herd around the Market?" *Financial Analysts Journal* 51 (3): 31–37. doi:10.2469/faj.v51.n4.1918.

Devenow, A., and I. Welch. 2006. "Rational Herding in Financial Economics." *European Economic Review* 40 (3–5): 603–615. doi:10.1016/0014-2921(95)00073-9.

Fei, T., X. Liu, and C. Wen. 2019. "Cross-sectional Return Dispersion and Volatility Prediction." *Pacific Basin Finance Journal* 58: 101218. doi:10.1016/j.pacfin.2019.101218.

Hwang, S., and M. Salmon. 2001. "A New Measure of Herding and Empirical Evidence." *Working papers (Warwick Business School. Financial Econometrics Research Centre*) 1: 1–35.

Jegadeesh, N., and W. Kim. 2009. "Do Analysts Herd? An Analysis of Recommendations and Market Reactions." *Review of Financial Studies* 23: 901–937. https://doi-org.cmsdie.top/10.1093/rfs/hhp093

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1992. "The Impact of Institutional Trading on Stock Prices." *Journal of Financial Economics* 32 (1): 23–44. doi:10.1016/0304-405X(92)90023-Q.

Lee, C., M. Chen, and K. Hsieh. 2013. "Industry Herding and Market States: Evidence from Chinese Stock Markets." *Quantitative Finance* 13 (7): 1091–1113. doi:10.1080/14697688.2012.740571.

Luo, Y. 2019. "The Herding Behavior and Financial Crisis: Evidence from Chinese ADRs." *International Journal of Financial Management* 9 (4): 11–15.

Markowitz, H. 1959. *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons.

Pretcher, R. R. 2001. "Unconscious Herding Behaviour as the Psychological Basis of Financial Market Trends and Patterns." *The Journal of Psychology and Financial* 2 (3): 120–125. https://doi-org.cmsdie.top/10.1207/S15327760JPFM0203_1

Shiller, J. R. 1989. "Investor Behavior in the October 1987 Stock Market Crash: Survey Evidence." *National Bureau of Economic Research Working Paper* 2446: 1–41. https://ssrn.com/abstract=227115

Song, J., and C. Wu. 2001. "A Study of Herd Behavior in Financial Markets Based on Dispersion." *Economic Research* 11: 21–27.

Summers, L. H. 1986. "Does the Stock Market Rationally Reflect Fundamental Values?" *The Journal of Finance* 41 (3): 591–601. doi:10.1111/j.1540-6261.1986.tb04519.x.

Wind Information Co., Ltd, 2020. "Hong Kong Stocks." Wind. Accessed 5 May 2021. https://www.wind.com.cn/en/mobi.html

Xiong, X., C. Wang, and D. Shen. 2020. "Market Participation Willingness and Investors Herding Behavior: Evidence from an Emerging Market." *Asia-Pacific Financial Markets* 27 (3): 439452. doi:10.1007/s10690-020-09302-8.