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Herding behaviour towards high order systematic risks and the contagion Effect—Evidence from BRICS stock markets

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ABSTRACT

This paper investigates the existence of herding movements towards several systematic risk factors derived from the Capital Asset Pricing Model (CAPM) and its extensions. The measure of herding is estimated using the dispersion of the risk factor loadings. The state space model is employed to extract time series of herding dynamics. We empirically survey the herding behaviors in the BRICS stock markets (i.e., Brazil, Russia, India, China, and South Africa) using monthly stock index data from 2006 to 2022, and identify various herding patterns towards specific factors. We also examine the impact of unanticipated shocks in crucial macroeconomic variables on the degree of herding measure in these countries. Lastly, we test the contagion hypothesis of herding across markets using correlation analysis. The results show that the level of herding linkages increases significantly in periods of market stress, casting doubt on the effectiveness of asset allocation in these markets for the sake of diversity.

1. Introduction

The study of investor herding behavior has always been a subject of keen interest in the behavioral finance realm. Herding behavior refers to the tendency of investors to follow the investment decisions of others, leading to similar investment behaviors within the group. This herding behavior can exacerbate the volatility of financial markets, as the synchronized buying and selling activities of a large number of investors can lead to rapid increases or decreases in asset prices. This can result in asset prices deviating from their intrinsic values, causing the formation of market bubbles and crashes. More seriously, herding behavior can also occur from a country perspective, and become an important channel for the transmission of systemic risk across markets. In this regard, studying and analyzing herding behavior and its contagion effect is important for understanding the mechanisms of financial market operations and developing appropriate policies.

Herd behavior is particularly significant in emerging markets. Emerging market investors generally lack independent judgment. They often rely too heavily on the opinions of the media, institutions, or others, and find it difficult to form their own rational analysis. This blind following mentality makes herd effects more likely to occur in emerging markets. Additionally, the regulatory system and information disclosure standards in emerging markets are often not robust enough. This can lead to frequent incidents of market manipulation, insider trading, and other illegal activities, exacerbating investors' anxiety and the emergence of herd behavior.

In the literature, researchers have developed various econometric models to investigate the presence of herding in financial

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markets, among which the most broadly used methods are the Cross-Sectional Standard Deviation (CSSD) model proposed by Christie and Huang (1995), and the Cross-Sectional Absolute Deviation (CSAD) model proposed by Chang Cheng & Khorana (2000). These two methods share the core idea of capturing evidence of herding by measuring the cross-sectional dispersion of stock returns, with the difference being that the former uses the standard deviation of returns, while the latter uses the absolute deviation of returns.

However, the dispersion-based models of herding measurement are sometimes criticized, as they are unable to distinguish whether investor moves should be attributed to adjustments toward market fundamentals or to herding. To address this problem, Hwang and Salmon (2004) propose a methodology to measure herding based on the state space model, which aims to control for shifts in fundamentals. The authors advocate that a time-variation effect in the cross-sectional changing of factor sensitivities is unlikely to be induced by fundamental shifts but more likely to be due to behavioral anomalies such as herding. In this sense, the specific risk measure "beta" in the Capital Asset Pricing Model (CAPM) provides a perfect indicator for observing the cross-sectional movement of factor sensitivities with respect to each of the individual securities.

In parallel, the CAPM model, proposed by Sharpe, Lintner, and Mossin (1960), lies at the central pillar of modern financial theory. The standard CAPM model suggests a particular linear risk-adjustment relationship between excess return and the risks associated with it, and has been extensively used in the field of financial theory and practice, such as portfolio construction, capital cost estimation, and project evaluations (Banz, 1981; Basu and Chawla, 2010; Liu et al., 2022; Zhang, Zhou, and Lee, 2021; Zhang et al., 2022). However, the CAPM framework has also come under scrutiny, as it is based on the assumption of normality and investors are risk-averse, which often contradicts empirical evidence using naturally generated data. Vast evidence shows that asset returns constantly deviate from the normal distribution, and investors' required excess returns include not only compensation for regular market risk, but also compensation for higher-order moment risks such as volatility, skewness, and kurtosis (Atanasov and Nitschka, 2017; Gerlach, Obaydin, and Zurbruegg, 2015; Dias, 2013; Shu, Song, and Zhu, 2021). Among these studies, Vendrame, Guermat and Tucker (2023) extend the basic CAPM model to a four-moment CAPM, which incorporates coskewness and cokurtosis. Although debatable, these pricing anomalies all demonstrate that the basic CAPM is incomplete in describing market equilibrium.

Theoretically, the higher moments of asset returns represent additional systemic risk factors beyond the mean (or variance) risk factors in the process of price formation. For example, skewness represents a form of direction risk: Positive skewness indicates a higher likelihood of generating positive returns, thus favored by investors. While negative skewness implies that there is more downside risk in the investment. Kurtosis measures the probability of extreme return occurrences, thus reflecting the risks of asset price bubbles or crashes. In this regard, it is meaningful to study herd behavior in relation to these higher moment risk factors. This not only helps to better understand and predict the collective behavioral dynamics of the investor group, but also helps to understand the composition of price fluctuation risks and how to mitigate them. Moreover, it is also very important to investigate herding contagion from a cross-country perspective to assess the cross-market spillovers of systemic risk through the channel of investor activity. However, existing research on this aspect is still very scarce.

This study contributes to the herding literature in three ways. First, we follow Messis & Zapranis (2014) by extending the standard CAPM into a high order framework and investigate whether herding behavior towards higher moment systematic risks (i.e., skewness and kurtosis) exist in five BRICS markets (Brazil, Russia, India, China, and South Africa). To the best of our knowledge, the present study is among the first to study the herding activity within the high order moment framework relying on the most fresh database. Second, numerous studies have demonstrated that market performance is significantly affected by unexpected macroeconomic shocks or news events (Kim et al., 2022; Flaschel et al., 2018). Motivated by these facts, this study investigates how and to what extent the herding measure is affected by shocks to a group of selected macroeconomic variables. Lastly, we extend our study to test the hypothesis of herding spillover across the BRICS markets using the conditional correlation analysis framework. This issue is of great interest for global investors who allocate their assets across international financial markets, since the increasing market linkages may reduce the benefits of investment diversification.

We detect various patterns of herding behavior toward higher moment risk factors through empirical analysis. Furthermore, the unexpected shocks on a variety of macroeconomic variables induce heightened herding activity. Finally, we find evidence of herding spillover across the country perspective during market turbulent periods, and poor market conditions undermine the benefits of risk diversification within these selected markets.

The remainder of the paper is organized as follows. Section 2 provides a high moment asset pricing model and derives the herding measures toward the selected systematic risk factors. Section 3 describes the data used and shows the summary statistics. Section 4 provides the main insights from the empirical studies, and we conclude the paper in Section 5.

2. Methodology

2.1. CAPM and its high order exploration

As the most popular asset pricing model based on the risk-return theory, the CAPM specifies the nature of risk and the extent to which it should be priced as:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + e_{it} \tag{1}$$

where $R_{it} - R_{ft}$ is the excess return of asset i, $R_{mt} - R_{ft}$ is the expected market excess return associated with market risk premium, β_i is the sensitive risk factor, which measures the systematic, nondiversifiable risk, and α_i and e_{it} are the intercept and error terms, respectively: both are assumed to be zero in this model.

The basic CAPM in Eq. (1) assumes normally distributed returns, which are often inconsistent with real-world data sources. Investors are also interested in the higher moment characteristics of returns, such as skewness and kurtosis, when pricing an asset. In this respect, we apply the approach proposed by Messis and Zapranis (2014) by expanding the basic CAPM model to include higher moment specifications as:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \gamma_i(R_{mt} - R_{ft})^2 + e_{it} \quad (2)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \gamma_i(R_{mt} - R_{ft})^2 + \delta_i(R_{mt} - R_{ft})^3 + e_{it} \quad (3)$$

where β_i, γ_i and δ_i are the loading of variance, skewness and cokurtosis risk factors, respectively.

2.2. A state-space model of herding measure

Under the rationality assumption, the CAPM in equilibrium relates the expected excess returns and the expected excess returns on a market portfolio as:

$$E_t(r_{it}) = \beta_{it} E_t(r_{mt}) \quad (4)$$

where r_{it} and r_{mt} are the excess return of security i and market return at time t respectively, and $E(\cdot)$ denotes the conditional expectation at time t. The occurrence of herding will bias the relationship between return and risk delineated in Eq. (4). Hwang and Salmon (2004) redefine relationship (4) in the presence of herding time t as:

$$\frac{E_t^b(r_{it})}{E_t^b(r_{mt})} = \beta_{it}^b = \beta_{it} - h_{mt}(\beta_{it} - 1) \quad (5)$$

where $E_t^b(r_{it})$ is the adjusted expected return for security i and β_{it}^b is its corresponding beta coefficient. h_{mt} is the measure of herding variation over time. When $h_{mt} = 0$, the CAPM holds in equilibrium as Eq. (4) and no herding exists. When $h_{mt} = 1$, perfect herding occurs toward the market and all individual assets move synchronously with the market portfolio. Generally, $0 < h_{mt} < 1$ means that there is herding to some extent in the market, measured by the magnitude of h_{mt}. h_{mt} can also be negative, indicating that adverse herding occurs.

In a rational market environment, the CAPM indicates that the dispersion in loading of risk factors is not related to the changes in market return but only depends on the beta coefficient for each individual security at time t. As retail investors trade on the basis of their private information, individual security holds its long-term return-risk equilibrium in the CAPM, and this corresponds to a relatively constant level of market dispersion. When the market turns to an extreme state, investors turn more towards overall market sentiment than private information in decision-making, and their trading behaviour tends to be consistent with that of the surrounding traders. This results in a deviation from long-term equilibrium for most of the securities in terms of beta loading. When the individual returns converge to the market aggregate returns, they will produce a decrease in returns dispersion from overall market returns. Therefore, the excessive low level of cross-sectional standard deviation in individual returns will suggest the occurrence of herding. The cross-sectional standard deviation method proposed by Hwang and Salmon (2004) is given as:

$$std_c(\beta_{it}^b) = \sqrt{E_c\left(\left(\beta_{it}^b - E(\beta_{it}^b)\right)^2\right)} = \sqrt{E_c\left((\beta_{it} - h_{mt}(\beta_{it} - 1) - 1)^2\right)} = std_c(\beta_{it})(1 - h_{mt}) \quad (6)$$

where h_{mt} is the measure of herding, $E_c(\cdot)$ is the cross-sectional expectation, and $std_c(\cdot)$ is the standard deviation of the cross-section.

As both $std_c(\cdot)$ and h_{mt} are latent in the market, Hwang and Salmon (2004) propose a state space model and use the Kalman filter technique for estimating h_{mt}. Logarithmicising Eq. (6) and allowing $std_c(\beta_{it})$ to be stochastic, we have:

$$\log std_c(\beta_{it}^b) = \log[std_c(\beta_{it})] + \log(1 - h_{mt}) \quad (7)$$

defining $H_{mt} = \log(1 - h_{mt})$, where H_{mt} follows a mean zero AR(1) process, $\log[std_c(\beta_{it})] = \mu_m + \nu_{mt}$ where $E(\log[std_c(\beta_{it})]) = \mu_m$, $\nu_{mt} \sim iid(0, \sigma_{m\nu}^2)$. We can obtain the following state space model:

$$\log[std_c(\beta_{it})] = \mu_m + H_{mt} + \nu_{mt} \quad (8)$$

$$H_{mt} = \varphi H_{mt-1} + \eta_{mt} \quad (9)$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$. Eq. (9) can be estimated using the Kalman filter method. When $\sigma_{m\eta}^2 = 0$, H_{mt} and h_{mt} are also zero, indicating that no herding exists. Instead, a significant value of $\sigma_{m\eta}^2$ suggests the existence of some degree of herding depending on the absolute value of $\sigma_{m\eta}^2$. A significant value of φ supports the AR(1) structure specified in the model.

In the same spirit, we can build a herding measure in the same way to detect the herding towards high order risk factors at time t within the high moment CAPM framework. Herding toward coskewness is captured by:

$$\gamma_{it}^b = \gamma_{it} - h_{cskt}(\gamma_{it} - E_c[\gamma_{it}]) \quad (10)$$

and herding toward cokurtosis is delineated by:

$$\delta_{it}^{b} = \delta_{it} - h_{ckurt}(\delta_{it} - E_c[\delta_{it}]) \quad (11)$$

where $E_c[\gamma_{it}]$ and $E_c[\delta_{it}]$ are the cross-sectional expected loading for the related risk factors, while h_{cskt} and h_{ckurt} represent the degree of herding. When $E_c[\gamma_{it}]$ ($E_c[\delta_{it}]$) is equal to 1, there exist a perfect herding movement in the market, indicating that all the securities will react universally in the presence of changes in the factor. All the presentations discussed previously regarding h_{mt} also hold here for h_{cskt} and h_{ckurt}.

3. Data description

We use the herding detection approach discussed in Section 2.1 to examine the herding activity by relying on constituents of BRICS equity markets, which are the Bovespa index for Brazil, the RTS index for Russia, the SENSEX index for India, the CSI 300 index for China, and the JSE index for South Africa. The observing period spans from January 3, 2006 to December 31, 2022, covering several of the most prominent phases of market turmoil in the past fifteen years, namely the 2008 global financial crisis, the 2011 European debt crisis, and the Covid-19 pandemic. We employ the yield of one-year treasury bonds of each country as a proxy for the market risk-free rate, and use the monthly continuous compounding adjusted returns to calculate the excess returns for each individual market. As for the estimation of betas, we follow Hwang and Salmon’s (2004) suggestion and consider herding as a relatively slow process of market movement rather than a short-lived appearance that grows rapidly. So we use the rolling estimation of 24-monthly data points to avoid any mispricing caused by market short-term noise. Moreover, this selection also takes into account the trade-off between the lower amount of empirical data associated with lower frequency sampling and the reliability of outcomes in the state space model (Ng et al., 2013). To examine the effect of macroeconomic shocks on the dynamics of the herding measure, we choose several economic fundamental variables, including the Economic Growth (GDP), Inflation (CPI), Industrial Production (IP), and the Money supply (M2) of each market. The choice of macroeconomic variables is linked to Messis and Zapranis (2014). The authors suggest that these particular variables are crucial to financial markets, and they affect the securities in the same function, thus providing the same operating environment for all the securities available in the market. The above data are collected from Datastream, Bloomberg, and the National Central Bank websites of the considered markets.

Table 1
Estimated results of state space models for herding on market systematic risk factors.

	Standard CAPM	Three-moment CAPM		Four-moment CAPM		
	Beta coefficient	Beta coefficient	Skewness coefficient	Beta coefficient	Skewness coefficient	Kurtosis coefficient
Bovespa (Brazil)						
μ_m	−0.127(0.391)	−0.109(0.312)	0.821(0.282)*	0.013(0.082)	0.989(0.321)*	2.312(0.0395)*
φ_m	0.936(0.212)*	0.969(0.266)*	0.985(0.056)*	0.977(0.032)*	0.971(0.075)*	0.976(0.053)*
σ_{mv}	0.059(0.023)*	0.071(0.022)*	0.111(0.049)*	0.159(0.051)*	0.097(0.039)*	0.112(0.039)*
$\sigma_{m\eta}$	0.003(0.001)*	0.002(0.001)*	0.023(0.010)*	0.002(0.001)*	0.013(0.005)*	0.039 (0.011)*
SIC	−0.201	−0.214	0.113	−0.069	0.015	0.303
RTS (Russia)						
μ_m	−0.232(0.222)	−0.251(0.223)	1.511(0.479)*	−0.076(0.223)	1.769(0.458)*	4.012(0.583)*
φ_m	0.971(0.131)*	0.963(0.221)*	0.962(0.104)*	0.951(0.107)*	0.963(0.073)*	0.969(0.022)*
σ_{mv}	0.079(0.029)*	0.089(0.041)*	0.222(0.079)*	0.121(0.049)*	0.248(0.111)*	0.166(0.065)*
$\sigma_{m\eta}$	0.014(0.003)*	0.004(0.002)*	0.051(0.013)*	0.016(0.005)*	0.039(0.012)*	0.151(0.058)
SIC	−0.041	−0.139	1.487	0.061	1.587	1.131
SENSEX (India)						
μ_m	−0.254(0.119)	−0.241(0.561)	2.187(0.587)*	0.121(0.223)	2.397(0.414)*	5.329(0.586)*
φ_m	0.985(0.084)*	0.974(0.078)*	0.981(0.049)*	0.971(0.244)*	0.978(0.032)*	0.981(0.034)*
σ_{mv}	0.097(0.039)*	0.072(0.021)*	0.111(0.039)*	0.069(0.021)*	0.133(0.064)*	0.119(0.048)*
$\sigma_{m\eta}$	0.007(0.004)*	0.007(0.001)*	0.061(0.022)*	0.006(0.001)*	0.058(0.029)	0.087(0.039)*
SIC	−0.075	−0.154	0.364	−0.139	0.604	0.684
CSI 300 (China)						
μ_m	−0.422(0.495)	−0.411(0.384)	1.311(0.687)*	−0.089(0.541)	1.487(0.778)*	4.121(0.684)*
φ_m	0.979(0.051)*	0.972(0.069)*	0.975(0.039)*	0.972(0.053)*	0.971(0.046)*	0.970(0.032)*
σ_{mv}	0.112(0.041)*	0.079(0.029)*	0.121(0.078)*	0.121(0.039)*	0.154(0.059)*	0.129(0.059)*
$\sigma_{m\eta}$	0.021(0.007)*	0.013(0.004)*	0.033(0.019)*	0.019(0.006)*	0.054(0.022)*	0.112(0.053)
SIC	0.055	−0.004	0.254	0.112	0.487	0.804
JSE (South Africa)						
μ_m	0.174(0.223)	0.211(0.119)	2.301(2.111)*	0.221(0.158)*	2.412(2.397)	5.214(2.341)*
φ_m	0.977(0.470)*	0.989(0.033)*	0.979(0.087)*	0.989(0.031)*	0.987 (0.093)*	0.966(0.053)*
σ_{mv}	0.058(0.019)*	0.022(0.011)*	0.121(0.038)*	0.011(0.004)*	0.154(0.121)*	0.182(0.068)*
$\sigma_{m\eta}$	0.003(0.001)*	0.002(0.001)*	0.047(0.054)*	0.004(0.002)*	0.038(0.121)*	0.103(0.036)*
SIC	−0.241	−2.541	1.587	−3.879	1.547	1.795

The cross-sectional standard deviations are yielded using the least squares technique. φ_m is the coefficient of the AR(1) process. σ_{mv} and $\sigma_{m\eta}$ denote the deviations of v_{mt} and η_{mt}, respectively. Columns 1, 2, and 4 denote beta loadings coming from the three established models. Columns 3 and 5 refer to the coskewness loadings, while Column 6 describes the cokurtosis systematic. SIC stands for the Schwarz Information Criterion. “*” indicates normality according to the J-B test result at 5% significance level.

4. Empirical findings

4.1. Herding towards the considered risk factors

We first estimate the sensitivity coefficients of the three aforementioned models using the least squares method (OLS) technique, and then compute the *cssd* of the factor loadings used to estimate the state space model. Table 1 reports the estimated results of the state space model in Eq. (8) and (9). We can see that H_{mt} is highly persistent for all five markets, as the coefficients $\widehat{\varphi}_m$ in the AR(1) process are statistically significant at the level of 5 % in the three CAPM-type models, and they are all less than and close to one. The estimated results of $\sigma_{m\eta}$ further confirm the existence of herding, as the same levels of significance are produced in accordance with $\widehat{\varphi}_m$. When we turn to the higher moment risk factors, namely coskewness and cokurtosis, we observe similar features. Herding appearances are detected for all the cases except for CSI 300 towards cokurtosis, supporting the hypothesis that investors do consider higher order risk factors when trading securities in these markets.

Fig. 1 illustrates the time-varying of herding measures over the sample period for each considered market. Beginning with the herding measure towards the first moment factor (h_{mt}), we observe several periodic patterns of herding movement in each of the markets. What they have in common is that herding behaviour in all of the five markets experienced a number of high levels of persistence within the whole sample period, observed to be the periods from August 2008 to March 2009, September 2010 to February 2011, and January 2021 to May 2021. These periods respectively correspond to market convulsions caused by the 2008 global financial crisis, the 2011 European debt crisis, and the 2020 Covid-19 pandemic. This finding is partially consistent with that in Ferreruela and Mallor (2021). For the rest of the sample period, each of the markets has its own herding style. In the Brazil market, the herding measure fluctuates irregularly around the value of zero most of the time. The South African market has a similar pattern of fluctuation to the Brazil market in terms of the herding measure, although the magnitude is apparently greater. In the case of India, it is negative, with a small absolute value most of the time before every occasion of market stresses, indicating the presence of a slightly adverse herding movement. However, the value of the herding measure increases rapidly and surpasses zero in periods prior to the onset of financial turmoil. This appearance is particularly obvious with respect to the 2008 global financial crisis and the 2020 financial problems caused by the Covid-19 pandemic. In relation to the Russian market, we observe that market stress does enhance the degree of herding; however, its effect is relatively small and transient. A notable pattern for the Chinese market's herding is that, besides the several high levels of herding persistence associated with global financial crises, it also experienced unique extreme values of herding referring to the period from September 2014 to July 2015. During this period, China's stock market experienced an unprecedented sharp rise and crash in just nine months, which the Shanghai Composite Index climbed from its lowest value of 1849 points to a peak of 5178.19 points. This extreme market mood and herding behaviour evolved through mutual excitation, accelerating the unilateral movement of the market.

When we turn to the higher moment risk factors, we find clear patterns of herding towards coskewness and cokurtosis. The estimated coefficients η_{skt} and η_{curt} are statistically significant for the majority of the cases except for η_{skt} in SENSEX, and η_{curt} in CSI 300. Moreover, the time-varying dynamics of the herding measures towards these factors present periodic shifts, implying the existence of

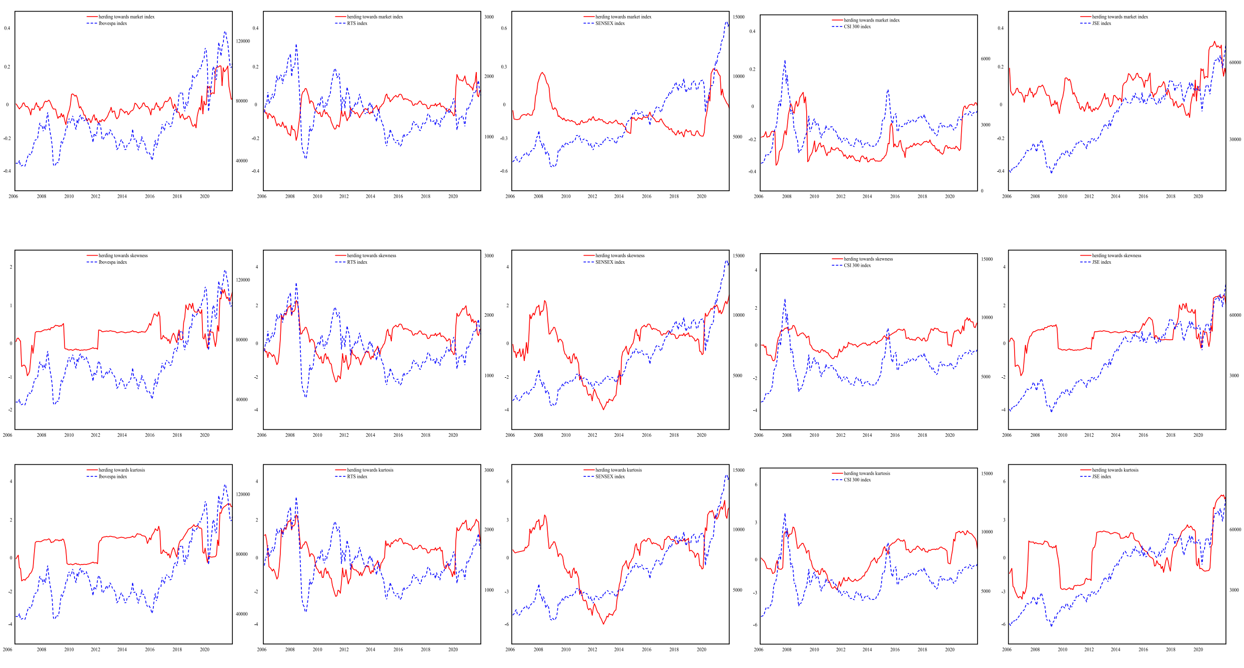

Fig. 1. Evolution of herding measure towards different risk factors.

regime-dependent risk preferences. These herding patterns can particularly explain some features of the market indices movement as observed. For example, we observe that high level of cokurtosis in Brazil and South African markets usually corresponds to sharp variations of the market indices, suggesting that participants of these two markets prefer securities with higher kurtosis betas in pursuing excess gains during extreme market periods.

4.2. Herding towards macroeconomic shocks

In this section, we explore our work in relation to a meaningful issue: that is, we examine the effect of macroeconomic shocks on herding movement. As mentioned earlier, the macroeconomic variables selected in this work involve Economic Growth (GDP), Inflation (CPI), Industrial Production (IP), and Money Supply (M2). We follow the way of Wasserfallen (1989) and use the Box-Jenkins methodology to capture the unanticipated components of the considered macroeconomic variables in an ARIMA (p, d, q) framework.

To begin with, the standard form of an ARIMA (p, d, q) model can be expressed as:

$$A(L)(1-L)^d Y_t = \delta + \Theta(L)\varepsilon_t \tag{12}$$

where L denotes the lag operator, $A(L) = 1 - \alpha_1 L - \cdots - \alpha_p L^p$ and $\Theta(L) = 1 - \theta_1 L - \cdots - \theta_q L^q$ are polynomials in L, and parameter d is the fractional order of differencing for producing the variable Y to be stationary. $\delta < \infty$ is a constant intercept term, and ε_t is a white noise process with fixed variance σ^2. We estimate Eq. (8) by incorporating the residuals derived from the ARIMA models as explanatory variables and report the results in Table 2. From Table 2, we can see some cases of macroeconomic shocks affecting herding movement. Herding movement in the Brazilian market is highly correlated to the positive shocks on GDP and CPI, while Industrial Production is a key factor affecting investors in the Russian stock market, evidenced by a positive and significant estimated result of coefficients. It also suggests that the level of herding declines in the case of the China index when negative shocks on M2 happen. This reflects the fact that China's stock market is more a money liquidity driven market, and investors will treat negative shocks on M2 as good news in rising market circumstances.

4.3. Contagion of herding

In this section, we test the herding contagion hypothesis across the BRICS markets when a negative market condition prevails in a specific market. This is particularly meaningful for international investors because herding comovement might undermine the benefit of investment diversification when these markets are targeted. For this purpose, we calculate conditional correlations of the estimated herding measures based on the bivariate GARCH (1, 1) model as:

$$Y_t = M + E_t E_t(0, H_t) \tag{13}$$

in which $Y_t = \begin{bmatrix} y_{i,y} \\ y_{k,t} \end{bmatrix}$ is a 2 × 1 vector, and $y_{k,t}$ and $y_{i,t}$ are the estimated herding measures of the sourced markets and the infected market, respectively. $M = \begin{bmatrix} \mu_{y_i} \\ \mu_{y_k} \end{bmatrix}$ is the conditional mean vector, and H_t is the 2 × 2 conditional covariance matrix. According to Engle and Kroner (1995), the following relation holds:

$$VECH(H_t) = C + AVECH(E_{t-1}E'_{t-1}) + BVECH(H_{t-1}H'_{t-1}) \tag{14}$$

where C is 3 × 1 vector of intercepts, and A and B are 3 × 3 parameter matrices. To make the estimation more illustrative, we can impose various restrictions on the parameters of the loading matrices and achieve a simplified version of Eq. (14) as:

$$h_{11,t} = c_{01} + \alpha_{11} e^2_{1,t-1} + b_{11} h_{11,t-1} \tag{15}$$

$$h_{12,t} = c_{02} + \alpha_{22} e_{1,t-1} e_{2,t-1} + b_{22} h_{12,t-1} \tag{16}$$

Table 2
The influences of macroeconomic shocks on herding behaviour.

	Bovespa (Brazil)	RTS (Russia)	SENSEX (India)	CSI 300 (China)	JSE (South Africa)
μ	−0.211(0.211)	−0.313(0.211)*	−0.221(0.214)**	0.209(0.088)**	−0.239(0.015)
φ	0.881(0.037)*	0.886(0.039)*	0.889(0.022)*	0.914(0.019)*	0.886(0.059)**
σ_v	0.019(0.006)*	0.011(0.002)*	0.002(0.001)*	0.001(0.002)**	0.003(0.001)
σ_η	0.088(0.005)*	0.101(0.031)**	0.071(0.038)**	0.031(0.007)*	0.071(0.007)*
IP	0.115(0.534)	0.449(0.297)*	−0.394(0.815)	−0.108(0.183)	0.131(0.002)
GDP	0.409(1.384)**	0.202(0.595)	0.118(1.054)	0.311(1.256)	0.334(1.287)
CPI	0.334(2.015)**	0.413(1.311)	−0.219(1.568)	−0.018(0.392)	0.021(0.401)
M2	0.038(0.553)	0.316(0.203)	−0.023(0.134)*	0.211(0.009)**	0.015(0.017)

The table presents the estimated results of the Kalman state space model, as described in Eq. (8), for all the five markets by incorporating macroeconomic shock components as explanatory variables. "*" and "**" indicate statistical significance at 5% and 10% levels, respectively.

$$h_{22,t} = c_{03} + \alpha_{33}e^2_{2,t-1} + b_{33}h_{22,t-1} \tag{17}$$

where $h_{11,t}$ and $h_{22,t}$ are the estimated conditional variance of the affected market and the sourced market, respectively. $h_{12,t}$ is the estimated conditional covariance between the affected market and the sourced market. Consequently, the conditional correlation is given as:

$$\hat{\rho}^{ki}_t = \frac{\hat{\sigma}_{ki,t}}{\hat{\sigma}_{ki,t}\hat{\sigma}_{i,t}} \tag{18}$$

As mentioned earlier, we investigate the contagion effect of herding across markets incurred by economic shocks occurring in a specified market. The unanticipated component contained in the macroeconomic condition is estimated by the residuals from the ARIMA model. Furthermore, we particularly take into account the influence of extreme macroeconomic conditions on herding linkage by introducing the dummy variable into the model. Extreme macroeconomic shocks are defined as the top 10 % of the sample with extreme values of residuals derived from the ARIMA model. The choice of considering the top 10 % as extreme values of macroeconomic variables is a common practice in statistical analysis to identify outliers or extreme events that may have a significant impact on the data. By focusing on the top 10 % of values, we can capture the most extreme scenarios or shocks in the data that deviate substantially from the norm.

The results are reported in Table 3. We find that extreme macroeconomic shocks in each individual market are scattered irregularly over the sample period. A notable outcome is that, besides the periods of turmoil in 2008 and 2011, caused by shocks from the financial market, extreme economic events have also occurred frequently since mid-2020 for all of the five markets under consideration, as the impact of the pandemic on the economy has become visible. In respect of the five markets under investigation, the Chinese market accommodates some specific features, such as its significant contribution to world economic growth and distinctive economic structure. Moreover, the Chinese market is not a fully liberalized market, and hence might be less affected by external market conditions (Yamamoto, 2014). Thus, we take China's market as a candidate country and particularly examine contagion effects of herding from the other four countries to China in the context of economic shocks. Fig. 2 illustrates the time-varying average correlation between the Chinese market and the remaining markets. We observe that the correlation has been changing narrowly around 0 for most of the time from the beginning of the sample to January 2020. However, extreme values of herding linkage become more frequent in periods of several specific market pressures. This is a preliminary confirmation of the existence of contagion between the herding measures in this particular context.

We further employ the panel regression analysis to quantitatively test the hypothesis of herding contagion across markets in the context of extreme economic conditions. The explained variable is herding correlation between the selected market and China, while the explanatory variables include the lagged value of the correlation and the extreme values of the four macroeconomic variables captured by the ARIMA model. The model also incorporates the dummy variable as a proxy crisis indicator.

$$\rho^{ki}_t = c^{ki} + a^k\rho^{ki}_{t-1} + d1^kD_{IPt} + d2^kD_{GDPt} + d3^kD_{CPIt} + d4^kD_{M2t} + b^kD_{Ct} + u^{ki}_t \tag{19}$$

in Eq. (19), D_{IPt}, D_{GDPt}, D_{CPIt}, and D_{M2t} denote the extreme components of the four selected macroeconomic variables, while D_{Ct} is the indicative dummy variable of crisis. k denotes the Brazilian, Russian, Indian, and South African market indices, and i denotes the Chinese market index. We estimate model (19) using the OLS method and report the results in Table 4. According to the first column of Table 4, the coefficients on ρ_{t-1}, D_{IPt}, M_{M2t}, and D_{Ct} are positive and statistically significant at the level of 10 %, suggesting that herding linkage is significantly correlated to the events of extreme shocks on IP and M2 that occurred in the observed markets. We further regress the conditional correlation on the crisis dummies only (column 2), and the macroeconomic shocks dummies only (column 3), and find no signs of additional correlation patterns. The last column of the table presents the regressed results of the model when only significant variables are present. Overall, the findings from various regression analyses indicate that the unique character of China's market cannot prevent it from being infected by herding in the other four emerging countries in the context of turbulence and

Table 3
Regressions of the estimated correlations between China and the other four markets on their lagged values and a number of dummy variables.

Coefficients	Dummies	Crisis dummies	Macroeconomic dummies	Only significant dummies
Constant term	0.004(0.021)	0.011(0.015)	0.021(0.009)	0.001(0.013)
Lagged variable	0.499(0.021)*	0.603(0.012)*	0.494(0.021)*	0.445(0.021)*
Crisis dummy	0.033(0.021)*	0.022(0.017)*		0.086(0.021)*
IP extreme component	0.069(0.011)*		0.079(0.013)*	0.031(0.154)*
GDP extreme component	0.028(0.019)		0.041(0.018)	
CPI extreme component	−0.022(0.019)		−0.025(0.019)	
M2 extreme component	−0.025(0.021)*		−0.023(0.019)**	−0.025(0.019)*
R^2 value	0.716	0.654	0.693	0.713

The table reports the estimated results of the panel data regression model in Eq. (19) using the least squares method. The explanatory variables include the lagged value of the correlation and the extreme values of the four macroeconomic variables, which are Economic Growth (GDP), Inflation (CPI), Industrial Production (IP), and Money Supply (M2). The extreme components of macroeconomic shocks are characterized as the top 10% of the sample with extreme values of residuals derived from the ARIMA model. "*" and "**" indicate statistical significance at 5% and 10% levels, respectively.

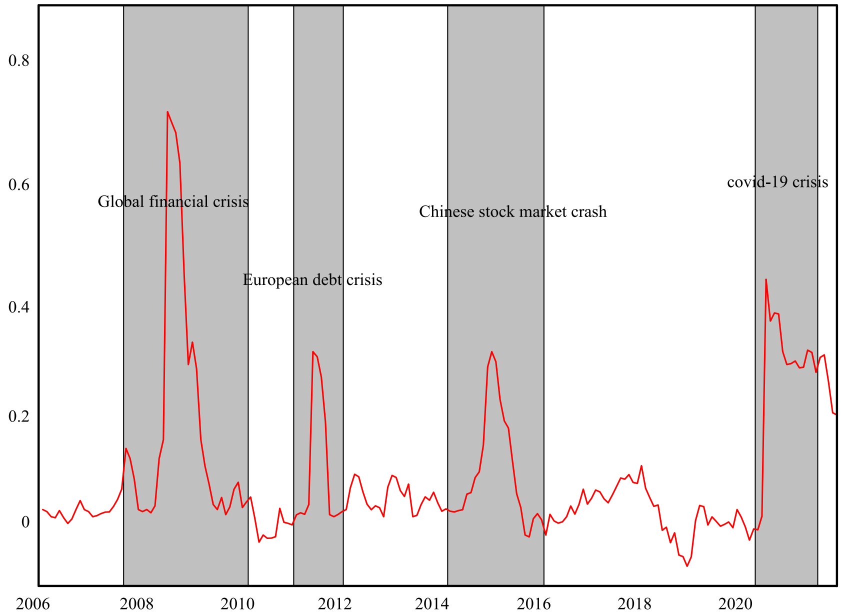

Fig. 2. Average correlation between the China market with the remaining BRICS countries.

economic shocks.

In the last part of this section, we implement a comprehensive OLS regression analysis to survey the extent to which macroeconomic shocks in one of the BRICS markets affect pairwise market correlations. As some related studies point out that public information on one market may be regarded as information with respect to the other economies with similar characteristics, resulting from investor sentiment contagion (Shi, Tang and Long, 2019; Niţoi et al., 2020; Dash and Maitra, 2019), we may expect that the more similar the economic endowments of the two countries are, the more obvious the contagion effect of herd behaviour will be. We only remark on the statistically significant results and report the results in Table 4. From the table, we can see some interesting patterns of herding coupling between the five considered markets. This shows that the herding correlation changes between the Russian and Brazilian markets when unanticipated macroeconomic shocks occur in Russia, while the Indian and South African markets seem to be broadly influenced by some different macroeconomic shocks occurring in China. These finding are in line with some of the literature related to financial contagion, such as the works of Messis and Zapranis (2014) and Racicot and Théoret (2016). The patterns of herding linkage might be related to countries' economic characteristics. Brazil and Russia are endowed with plentiful natural resources: hence, the economic performance of these two countries is excessively dependent on commodity price cycles, while the economic performances of China, India and South Africa are strongly dependent on exports of manufactured products. According to the "wake-up call hypothesis" in behavioural economics, economic shock events that occur in one country will induce the investors in other fundamentally similar countries to reassess local fundamentals, resulting in a convergent attitude towards market prospects. It suggests that the Chinese and Russian markets' herding movements are closely linked, as evidenced by the highly and extensively significant estimated coefficients on macroeconomic shocks occurring in either of the two countries. It also shows that the herding linkage between China and Brazil is significantly affected by shocks to a variety of China's fundamental economic variables. This may be attributed to, in addition to the huge bilateral trade volume between the two countries, the similarity of development modes and stages of the two countries (both actively encourage foreign investment inflow and both are experiencing rapid economic growth).

5. Robustness test

In this section, we check the robustness of our findings by taking into account a variety of alternative settings. We summarize the results of the robustness test as follows.

We first demonstrate that β^b_{it} estimated with different estimation window lengths will not affect the dynamics of herd behaviour as displayed in our main findings. In the baseline scenario, we use the monthly data with a window length of 24 months, and we vary the length further to 36 and 48 months in the robustness test to estimate β^b_{it}. We find that the outputs of the herding model are not significantly influenced by variation of estimation window lengths.

Then, we test if the herding measure derived from the state space model is unaffected when an alternative factor model for estimating β^b_{it} is employed. Specifically, we apply the Fama-French 3 model and Fama-French 5 model through the value-weighting procedure to re-estimate β^b_{it} in the robustness test. Overall, the results generated from the herding model are very consistent with those reported in Table 1, suggesting that the herding measure estimates are robust to model specifications for the β^b_{it} coefficient. However, we note that the significance level of estimated coefficient decreases with the Fama-French 5 model specification.

Table 4
Correlations between herding movements of a specific market and other markets when this specific market is in extreme market conditions.

From Brazil to	Russia	India	China	South Africa
Constant term	0.004(0.021)*	0.002(0.015)	0.012(0.027)	0.023(0.031)
Lagged variable	0.499(0.021)*	0.215(0.278)	0.494(0.021)*	0.305(0.019)*
Crisis dummy	0.191(0.313)	0.103(0.115)	0.128(0.045)	0.135(0.224)
IP extreme component	0.205(0.425)	0.212(0.062)	0.134(0.185)	0.102(0.296)
GDP extreme component	0.158(0.514)	0.305(0.254)	0.122(0.254)	0.215(0.314)
CPI extreme component	0.264(0.124)	0.385(0.313)	0.214(0.078)	0.118(0.228)
M2 extreme component	0.052(0.319)	0.405(0.541)	0.056(0.218)	0.006(0.414)
R^2 value	0.406	0.297	0.493	0.313(0.312)
From Russia to	**Brazil**	**India**	**China**	**South Africa**
Constant term	0.132(0.254)	0.112(0.321)	0.161(0.109)	0.123(0.329)
Lagged variable	0.539(0.111)*	0.203(0.198)	0.504(0.231)*	0.103(0.321)
Crisis dummy	0.123(0.034)*	0.012(0.208)	0.225(0.054)	0.232(0.504)
IP extreme component	0.079(0.211)*	0.187(0.048)	0.029(0.643)*	0.139(0.473)
GDP extreme component	0.146(0.321)	0.014(0.248)	0.101(0.228)	0.121(0.269)
CPI extreme component	−0.412(0.219)*	0.013(0.314)	−0.115(0.219)*	−0.106(0.233)
M2 extreme component	−0.135(0.361)*	0.068(0.315)	−0.153(0.219)*	−0.113(0.239)
R^2 value	0.836	0.541	0.893	0.509
From China to	**Brazil**	**Russia**	**India**	**South Africa**
Constant term	0.305(0.212)	0.485(0.032)*	0.013	0.001(0.013)*
Lagged variable	0.128(0.352)	0.593(0.202)*	0.514(0.131)*	0.631(0.221)*
Crisis dummy	0.205(0.284)	0.111(0.217)*	0.103(0.212)	0.049(0.105)*
IP extreme component	0.168(0.157)	0.603(0.312)*	0.109(0.213)*	0.078(0.109)*
GDP extreme component	0.213(0.205)	0.151(0.247)*	0.115(0.412)	0.096(0.011)
CPI extreme component	0.138(0.158)	0.009(0.373)	0.118(0.549)	0.084(0.009)
M2 extreme component	0.221(0.217)	0.633(0.242)*	−0.133(0.058)**	−0.074(0.035)*
R^2 value	0.584	0.811	0.793	0.713
From South Africa to	**Brazil**	**Russia**	**India**	**China**
Constant term	0.254(0.451)*	0.121(0.231)	0.132(0.241)	0.232(0.241)
Lagged variable	0.384(0.521)*	0.193(0.208)	0.243(0.392)	0.193(0.208)
Crisis dummy	0.112(0.368)	0.142(0.328)	0.132(0.318)	0.112(0.318)
IP extreme component	0.217(0.238)	0.127(0.148)	0.217(0.448)	0.133(0.248)
GDP extreme component	0.104(0.428)	0.124(0.312)	0.024(0.354)	0.224(0.318)
CPI extreme component	0.031(0.134)	0.133(0.234)	0.133(0.344)	0.023(0.424)
M2 extreme component	0.086(0.513)	0.128(0.245)	0.128(0.339)	0.121(0.336)
R^2 value	0.404	0.354	0.298	0.303

The explanatory variables include the lagged value of the correlation and the extreme values of the four macroeconomic variables, which are Economic Growth (GDP), Inflation (CPI), Industrial Production (IP), and Money Supply (M2). The extreme components of macroeconomic shocks are characterized as the top 10% of the sample with extreme value of residuals derived from the ARIMA model. "*" and "**" indicate statistical significance at 5% and 10% levels, respectively.

Next, we employ alternative methods of herding estimation instead of the state space model to show that our main results are independent to these different herding measures. Specifically, we apply two other broadly used herding models, namely the Cross-Sectional Absolute Deviation (CSAD) of returns, proposed by Chang et al. (2000), and the Cross-Sectional Standard Deviation (CSSD) of returns, proposed by Christie and Huang (1995) to re-estimate the herding measures for the five markets. We observe that the CSAD model generates more significant herding activity towards skewness and kurtosis factors for most of the markets. This finding is not beyond our expectation as herding estimation based on cross-section dispersion usually overestimates the level of herd behaviour compared with the state space model (Babalos, Balcilar and Gupta, 2015). Besides, the herding dynamics in relation to various systematic factors under investigation is not significantly affected by other alternative herding measure estimations.

Lastly, we test if the results are sensitive to the selection of sample periods. For this purpose, we separate the whole sample into two subsamples which correspond to before and after the onset of the Covid event, respectively. We uncover the herding patterns based on the subsamples and find that the results generally corroborate the main findings that regardless of market status, there exists a significant herding activity towards higher moment factors for all the studied markets.

6. Conclusion

This paper focuses on the existence of herding behaviour in BRICS stock markets, which are the Brazilian, Russian, Indian, Chinese, and South African markets. Specifically, we use the state space model proposed by Hwang and Salmon (2004) to examine herding movement toward three particular systematic risk factors coming from the CAPM and its higher order extensions. These risk factors, in the asset pricing literature, have been suggested to be prominent in explaining price dynamics. The results show various patterns of herding toward the selected risk measures of coskewness and cokurtosis, and these herding movements are closely linked to the behaviours of market indices in these markets. We further extend the study of herding to survey the extent to which unexpected macroeconomic shocks affect the degree of herding movement in these selected markets. We use the residuals estimated from ARIMA models to capture the unanticipated components in some critical macroeconomic variables and add them into the state space as exogenous explanatory variables. Finally, we test the contagion hypothesis of herding across markets in the context of market pressures by using the panel regression framework. The results show that the levels of herding linkages between markets remarkably increase in periods prior to financial turbulence, and this high level of herding linkage lasts for some time, related to the persistence of financial crises.

The above empirical findings have important implications for market investors. Investors should be aware of the potential for herding behavior towards higher moment CAPM factors, not just market indices, when making investment decisions. Moreover, investors should be cautious about the limited benefits of international portfolio diversification during crisis periods, especially in markets prone to contagion effects. These implications can help investors navigate the complexities of financial markets and make more informed decisions in response to changing market conditions.

CRediT authorship contribution statement

Yi Zhang: Formal analysis, Conceptualization. **Long Zhou:** Software. **Zhidong Liu:** Methodology. **Baoxiu Wu:** Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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