Pacific-Basin Finance Journal 90 (2025) 102664

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

The evolution of herding behavior in stock markets: Evidence from a smooth time-varying analysis[☆]

Shuo Xing[a,b], Tingting Cheng[c], Liping Qiu[c,*], Xiaoyang Li[d]

[a] Hua Xia Bank Co., Ltd, PR China
[b] PBC School of Finance, Tsinghua University, PR China
[c] School of Finance, Nankai University, PR China
[d] Deakin Business School, Deakin University, Australia

ARTICLE INFO

JEL classification:
C10
G10
G23

Keywords:
Herding behavior
Stock markets
Time-varying coefficient model
Simulation

ABSTRACT

We apply a new, nonparametric approach to study time-varying herding behavior. Using this approach to compare herding behavior between the A-share, Hong Kong, and the U.S. stock markets over the past two decades, we present several new findings. First, before the Global Financial Crisis, the A-share stock market exhibited a pro-longed yet weakening herding behavior, which was mainly driven by non-fundamental factors. Second, periods with no herding and periods with adverse herding alternated between 2008 and 2021. Adverse herding, mainly driven by fundamental factors, intensified during market turbulence. Third, both the Hong Kong and the U.S. stock markets displayed adverse herding behavior persistently. In sum, our approach provides some new evidence on time-varying herding in both emerging and developed markets.

1. Introduction

The human instinct to herd is common in life. In financial markets, herding behavior is often said to occur when investors follow what they perceive other investors are doing, rather than relying on their own analysis (Hwang and Salmon, 2004). Prior literature has studied herding behavior extensively but often considered this behavior to be a time-invariant trait.[1] However, stock markets evolve and so do market participants' behavior. Neglecting the time-varying nature of herding may lead to conflicting inferences about investor behavior (Bohl et al., 2016; Fu and Wu, 2021; Cheng et al., 2022; Yang and Chuang, 2023). In this paper, we use a new, nonparametric approach to study herding behavior in mainland China, Hong Kong, and the United States.

Our approach is based on a widely-used method proposed by Chang et al. (2000) (hereafter CCK model). The CCK model studies the relationship between market return dispersion and market return levels to detect herding behavior. In the presence of severe (moderate) herding, the return dispersion will decrease (increase at a decreasing rate) with an increase in the market return. We estimate the evolution of coefficients in the CCK model using a local linear estimation method following the recent literature on time-varying coefficient models (Cai, 2007; Cheng, 2019; Cai et al., 2018). Our approach differs from the recent papers which either attempt to test herding behavior over different periods to examine the effects of certain events, such as financial crises and

☆ We are grateful to the financial support from the National Natural Science Foundation of China (72173068, 71803091), the Social Science Development Fund of Nankai University (ZB22BZ0321), and the Fundamental Research Funds for the Central Universities, China (998-63243050).

* Corresponding author.
E-mail address: qlplibby@163.com (L. Qiu).

[1] Evidence of herding behavior has been found in different markets, including equity, bond, peer to peer lending, etc. Hung et al. (2010), Zheng et al. (2021), Hong et al. (2000), Chiang and Zheng (2010), Cui et al. (2019), Caglayan et al. (2021a), Blake et al. (2017), Cai et al. (2016), Caglayan et al. (2021b).

https://doi.org/10.1016/j.pacfin.2025.102664
Received 23 May 2024; Received in revised form 14 November 2024; Accepted 1 January 2025
Available online 7 January 2025
0927-538X/

pandemics (Sharma et al., 2015; Wu et al., 2020) or rely on a regime switching approach to explore whether the herding effects vary across different periods (Babalos et al., 2015; Balcilar et al., 2013; Kabir and Shakur, 2018; He, 2020; Chiang et al., 2013; Yang and Chuang, 2023). The advantage of our approach is to 'let data speak' without needing to make any assumptions about the linear or nonlinear relationships. Therefore, this nonparametric method can estimate the time-varying coefficients in the CCK model flexibly and detect possible changes in herding behavior at any point in time.

We apply this new, nonparametric method to study the evolution of herding behavior in the Chinese mainland stock markets (A-share market), in comparison to the markets in Hong Kong and the United States. China offers a great setting to test herding behavior. China's stock market, previously a side experiment in a financial system dominated by banks, has grown to become one of the world's largest.[2] Despite its size, the A-share market has been often dubbed as a casino, as it is mainly dominated by retail investors with speculative motives (Han and Li, 2017; Han et al., 2020). As a result, investors in the A-share market are more likely to herd than investors in other markets (Demirer and Kutan, 2006; Yao et al., 2014; Wang et al., 2021; Chen and Zheng, 2022). Recently, Carpenter et al. (2021) find that the A-share market has been gradually successful in aggregating information about future corporate profits and improving the efficiency of capital allocation. Considering the significant developments, only a time-varying method can characterize the evolving herding behavior.

Based on daily data over a 25-year period from 1996 to 2021, when we use a static model estimation, we conclude that the A-share market exhibits strong herding patterns. In contrast, using the nonparametric approach, we find that herding waxed and waned before transitioning from herding to adverse herding. In particular, herding behavior was pervasive until October 2007, but the degree of herding gradually declined toward the end of this period. We find a transition from no herding to adverse herding from 2008 to 2016 and a reversal back to no herding from 2017 to 2021. Overall, several new conclusions emerge from our analysis. First, herding behavior was present at the early stage development of the A-share stock market. However, with fast growth in market capitalization and greater investor participation, herding behavior gradually disappeared. Second, investors in turbulent periods were more likely to display a tendency of adverse herding rather than herding in the A-share stock market. Notably during the Global Financial Crisis (GFC) period when the A-share market plummeted from its peak in October 2007, herding behavior became minimal and insignificant. Adverse herding strengthened, especially during the 2015–2016 market crash. The degree of adverse herding declined after 2017 but resurfaced again in 2020 Covid-19 pandemic. In general, investors tend to follow others (herd) during booming markets, to act rather independently (not to herd) during weak markets, but are skeptical of others (adversely herd) during turbulent markets.

In comparison, both the static and the nonparametric estimation yield a consistent finding for both H.K. and New York Stock Exchange (NYSE) markets, which exhibited adverse herding behavior during the sample period. The H.K. stock market changed from no herding to persistent adverse herding behavior, the intensity of which increased substantially after the Shanghai–Hong Kong Stock Connect in 2015. The NYSE stock market exhibited strong adverse herding during the entire sample period, which is consistent with the findings in Chang et al. (2000), Chiang and Zheng (2010) and Klein (2013). The existence of herding behavior challenges the validity of the Efficient Market Hypothesis (EMH), which implies that investors are rational information processors. Despite the rapid development of the Chinese mainland stock markets, it is safe to say that investor behavior is still substantially different from that in Hong Kong and the United States. It is worth noting that the NASDAQ market exhibited a heavy herding behavior before the early 2000s. This result is contrary to the NYSE market. On average, NASDAQ-listed companies are smaller, operate in technology-savvy industries, and enjoy volatile earning prospects, compared with NYSE. Therefore, investor sentiment plays a larger role in the NASDAQ market, especially during the dotcom bubble period.

We proceed to investigate the driving factors of herding in the A-share market by augmenting the model proposed by Galariotis et al. (2015) with our nonparametric approach. We divide the factors into non-fundamental factors including investor sentiment and speculative motives, and fundamental factors including macroeconomic forces (Balcilar et al., 2012; Galariotis et al., 2015; Cui et al., 2019; Wang et al., 2021; Cheng et al., 2022; Bikhchandani and Sharma, 2000; Galariotis et al., 2015; Hudson et al., 2020). The evidence from a time-varying analysis indicates that herding in the early stage of the A-share market was mainly driven by non-fundamental factors, while adverse herding behavior toward the end of our sample period was mainly driven by fundamental factors.

We further explore the existence of time-varying cross-herding across the Chinese mainland, H.K. and U.S. stock markets. As financial globalization deepens, the A-share market is increasingly integrated with the global markets. The cross-herding hypothesis of investor behavior has received some attention recently (Economou et al., 2011; He, 2020). Testing the time-varying cross-herding effects across markets, we find no evidence of cross-herding between the A-share and H.K. stock markets. Moreover, cross-herding behaviors between A-share and the U.S. stock market have been weakening and finally disappeared in our sample period.

This paper contributes to the literature on herding in several fronts. First, our time-varying, nonparametric approach overcomes several limitations from the static approach in analyzing herding behavior. For instance, one has sometimes to use arbitrary time cutoffs or a regime switching approach to differentiate periods with respect to herding behavior. It is worth noting that investor behavior does not change discretely but rather fluidly. Therefore, our approach can depict the long-term trend of herding behavior and help analyze the relations between herding and stock market evolution. Second, we extend the driving factor testing model and cross-market herding model to the dynamic level. Third, we compare the herding behavior in the Chinese mainland markets

[2] The number of A-share listed companies grew from 530 (293 on the Shanghai Stock Exchange and 237 on the Shenzhen Stock Exchange) by the end of 1996 to 4,615 (2037 on the Shanghai Stock Exchange and 2578 on the Shenzhen Stock Exchange) at the end of 2021. The market value grew from 287 billion RMB in 1996 to 7,5156 billion in 2021.

with that in the H.K. and U.S. stock markets, to illustrate the differences in investor behavior between an emerging market and two developed markets.

The remainder of our paper proceeds as follows. Section 2 describes the methodology. Section 3 presents a simulation study. Section 4 introduces our data and empirical results. Section 5 concludes.

2. Methodology

In this section, we first present a widely-used measure of herding in the literature, referred to as the static herding model. We then describe our time-varying coefficient model which is able to capture the time-varying herding behavior.

2.1. Static herding model

A common approach to detect herding behavior is to examine the relationship between return dispersion and the market return (Christie and Huang, 1995; Chang et al., 2000). When there is no herding, the equity return dispersions are linearly increasing with the market return according to the rational asset pricing model. Conversely, herding behavior will distort this linear and positive relationship, which will become nonlinearly increasing or even decreasing with respect to market returns.

We use the following quadratic regression specification proposed by Chang et al. (2000) to examine herding behavior and measure return dispersion using the cross-sectional absolute deviation of returns (CSAD):

$$CSAD_t = \alpha + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t, \tag{1}$$

where $R_{m,t}$ is the return of the equally-weighted market portfolio in period t, $t = 1, \dots, T$, where T denotes the time length for our sample, and $CSAD_t$ stands for the cross-sectional absolute deviation of returns, defined as

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|, \tag{2}$$

$R_{i,t}$ is the return of asset i, and N is the number of traded assets.

The parameters α, β_1, and β_2 in model (1) are constants, hence we refer to it as the static herding model. In the absence of herding, the equity return dispersion ($CSAD_t$) increases linearly with the market return which implies that β_1 is significantly positive and β_2 is insignificant in model (1). Conversely, when there exists herding behavior, $CSAD_t$ decreases (or increases at a decreasing rate) as the market return increases and β_1 or β_2 will be significantly negative.

2.2. Time-varying herding model

We augment Eq. (1) by introducing a nonparametric time-varying coefficient time series model with a time trend to capture the time-varying herding behavior. The model is formulated as follows:

$$CSAD_t = \alpha(\tau_t) + \beta_1(\tau_t)\left|R_{m,t}\right| + \beta_2(\tau_t) R_{m,t}^2 + e_t, \tag{3}$$

where $\tau_t = t/T$[3], $R_{m,t}$ and $CSAD_t$ are the market return and the cross-sectional absolute deviation of returns at time t, $t = 1, \dots, T$. The coefficients $\alpha(\tau_t)$, $\beta_1(\tau_t)$, and $\beta_2(\tau_t)$ are unknown time-varying functions, therefore we refer to it as the time-varying herding model. We assume that errors and factor returns are orthogonal, but do not impose any ex-ante parametric constraints on the dynamics of alphas/betas and any potential relationship between alphas/betas and the variables. Note that model (3) nests model (1) as a special case when $\alpha(\tau_t)$, $\beta_1(\tau_t)$, and $\beta_2(\tau_t)$ reduce to constants.

We use local linear estimation method to estimate the unknown coefficient function following (Cai, 2007) and Cai et al. (2018). We briefly describe the estimation procedure of Eq. (3) as follows. Eq. (3) can be written as a more compact form

$$y_t = \gamma(\tau_t)' x_t + e_t, \tag{4}$$

where $x_t = (1, |R_{m,t}|, R_{m,t}^2)'$, $\gamma(\tau_t) = (\alpha(\tau_t), \beta_1(\tau_t), \beta_2(\tau_t))'$. Assuming that $\gamma(\cdot)$ has a continuous second order derivative, we approximate $\gamma(\tau_t)$ by a linear function given as

$$\gamma(\tau_t) \approx \gamma(\tau) + \gamma^{(1)}(\tau)(\tau_t - \tau), \tag{5}$$

where $\gamma^{(1)}(\tau_t)$ is the first order derivative of $\gamma(\tau_t)$, $\tau \in [0,1]$. Let z_t denote a column vector with elements x_t and $x_t(\tau_t - \tau)$, $\theta(\tau)$ denote $(\gamma(\tau)', \gamma^{(1)}(\tau)')'$, we rewrite Eq. (4) as $y_t \approx z_t'\theta(\tau) + e_t$. The locally weighted sum of squares is as below:

$$\sum_{t=1}^{T}(y_t - z_t'\theta(\tau)^2)K_h(\tau_t - \tau), \tag{6}$$

where $K_h(\mu) = K(\mu/h)/h$, $K(\cdot)$ is a kernel function, and h is a bandwidth parameter satisfying that $h \to 0$ and $Th \to \infty$ as $T \to \infty$.

By minimizing the locally weighted sum of squares, we can estimate the parameter vector $\theta(\tau)$ by

[3] Here the specification that each of the time-varying coefficients is a function of t/T rather than time t is commonly used in the literature. This is necessary for the consistent estimation of the above time-varying coefficient functions. For more discussion, see Robinson (1989, 1991).

$$\hat{\theta}(\tau;h)=\left[\begin{array}{cc} S_{T,0}(\tau) & S_{T,1}'(\tau)\\ S_{T,1}(\tau) & S_{T,2}(\tau)\end{array}\right]^{-1}\left[\begin{array}{c} R_{T,0}(\tau)\\ R_{T,1}(\tau)\end{array}\right],$$

where $S_{T,j}(\tau)=\frac{1}{T}\sum_{t=1}^{T}x_t x_t'(\tau_t-\tau)^j$, for $j=0,1,2$, and $R_{T,j}(\tau)=\frac{1}{T}\sum_{t=1}^{T}x_t(\tau_t-\tau)^j K_h(\tau_t-\tau)y_t$, for $j=0,1$. It is easy to see that the first three components of $\hat{\theta}(\tau;h)$ are the estimators of $\gamma(\tau_t)=(\alpha(\tau_t),\beta_1(\tau_t),\beta_2(\tau_t))'$, and the rest components of $\hat{\theta}(\tau;h)$ are the estimators of $\gamma^{(1)}(\tau_t)$. For practical implementation, we choose the Epanechnikov kernel function. As for the bandwidth selection, we use the normal reference rule that $h=1.06\omega T^{-1/5}$, where ω is the standard deviation of the smoothing variable.

We construct the 95% confidence interval for the local linear estimators as follows.

(1) Compute the residuals based on the local linear estimator by

$$\hat{e}_t=CSAD_t-\hat{\alpha}(\tau_t)-\hat{\beta}_1(\tau_t)\left|R_{m,t}\right|-\hat{\beta}_2(\tau_t)R_{m,t}^2. \tag{7}$$

(2) Sample $\hat{e}_t^*$ from $\{\hat{e}_t\}_{t=1}^T$ and then generate a bootstrap sample by

$$CSAD_t=\hat{\alpha}(\tau_t)+\hat{\beta}_1(\tau_t)\left|R_{m,t}\right|+\hat{\beta}_2(\tau_t)R_{m,t}^2+\hat{e}_t^*. \tag{8}$$

(3) Estimate the unknown coefficient functions in Eq. (3) using the bootstrap sample and save the estimated coefficient function as $\hat{\alpha}^{(1)*}(\tau_t)$, $\hat{\beta}_1^{(1)*}(\tau_t)$, and $\hat{\beta}_2^{(1)*}(\tau_t)$.

(4) Repeat steps (2) and (3) from B times and obtain $\hat{\alpha}^{(b)*}(\tau_t)$, $\hat{\beta}_1^{(b)*}(\tau_t)$, and $\hat{\beta}_2^{(b)*}(\tau_t)$ for $b=1,2,\ldots,B$.

(5) Save the standard error of the series $\{\hat{\alpha}^{(b)*}(\tau_t)\}_{b=1}^B$, $\{\hat{\beta}_1^{(b)*}(\tau_t)\}_{b=1}^B$, and $\{\hat{\beta}_2^{(b)*}(\tau_t)\}_{b=1}^B$ as $\sigma_\alpha(t)$, $\sigma_{\beta_1}(t)$, and $\sigma_{\beta_2}(t)$, and obtain the confidence interval at 95% significance level: $[\hat{\alpha}(\tau_t)-1.96\sigma_\alpha(t),\hat{\alpha}(\tau_t)+1.96\sigma_\alpha(t)]$, $[\hat{\beta}_1(\tau_t)-1.96\sigma_{\beta_1}(t),\hat{\beta}_1(\tau_t)+1.96\sigma_{\beta_1}(t)]$, and $[\hat{\beta}_2(\tau_t)-1.96\sigma_{\beta_2}(t),\hat{\beta}_2(\tau_t)+1.96\sigma_{\beta_2}(t)]$.

2.3. Time-varying driving factor testing model

A significant challenge from herding behavior is to distinguish between the fundamental driving factors and non-fundamental driving factors. We follow Galariotis et al. (2015) and decompose the CSAD into a fundamental driven part and a non-fundamental driven part.

In the first step, we use the regression of $CSAD_t$ on Fama–French three factors given by

$$CSAD_t=\gamma_0+\gamma_1 MKT_t+\gamma_2 HML_t+\gamma_3 SMB_t+\epsilon_t, \tag{9}$$

where MKT denotes the market excess return factor, SMB denotes the small-minus-big size factor, and HML denotes the high-minus-low value factor. The error term ϵ_t represents the variation of CSAD due to non-fundamental factors. We define

$$CSAD_{NONFUND,t}=\epsilon_t,\qquad \text{and}\qquad CSAD_{FUND,t}=CSAD_t-CSAD_{NONFUND,t}.$$

$CSAD_{NONFUND,t}$ and $CSAD_{FUND,t}$ are the variation in $CSAD_t$ driven by non-fundamental and fundamental factors, respectively.

In the second step, we can investigate the driving factors of herding behavior using model (3) with $CSAD_t$ replaced by each of these two components as follows:

$$CSAD_{NONFUND,t}=\alpha(\tau_t)^{(n)}+\beta_1(\tau_t)^{(n)}\left|R_{m,t}\right|+\beta_2(\tau_t)^{(n)}R_{m,t}^2+e_t, \tag{10}$$

$$CSAD_{FUND,t}=\alpha(\tau_t)^{(f)}+\beta_1(\tau_t)^{(f)}\left|R_{m,t}\right|+\beta_2(\tau_t)^{(f)}R_{m,t}^2+e_t. \tag{11}$$

Negative value of $\beta_2(\tau_t)$ in Eq. (10) (Eq. (11)) suggests the existence of herding due to non-fundamentals (fundamentals) at time t.

3. Simulation study

In this section, we perform simulations based on the parameters informed by real data from the Chinese stock market to examine the finite sample performance of our time-varying coefficient time series model. We generate CSAD using the following data generating process (DGP):

$$CSAD_t=\alpha(\tau_t)+\beta_1(\tau_t)|R_{m,t}|+\beta_2(\tau_t)R_{m,t}^2+e_t, \tag{12}$$

where $R_{m,t}$ and e_t are generated from the normal distributions $N(0.00028,0.00797^2)$ and $N(0,0.00218^2)$, respectively. The parameters of these two normal distributions are set equal to their sample counterparts obtained from real data in the A-share stock market. $\alpha(\tau_t)$, $\beta_1(\tau_t)$, and $\beta_2(\tau_t)$ are generated from the following DGPs:

$$\text{DGP1}: \alpha(\tau_t)=0.005+0.1\sin(\pi\tau_t),\ \beta_1(\tau_t)=1+100\sin(2\pi\tau_t)/T,\ \beta_2(\tau_t)=0.5\tau_t+\tau_t^2.$$
$$\text{DGP2}: \alpha(\tau_t)=0.005+0.0125(\tau_t-0.4)^2,\ \beta_1(\tau_t)=-0.4\tau_t^2+0.4,\ \beta_2(\tau_t)=-24(\tau_t-0.7)^2+4.$$

Table 1
Mean Squared Errors (MSE) of the nonparametric estimates.

DGP	T	$MSE(\hat{\alpha}(\tau_t))$	$MSE(\hat{\beta}_1(\tau_t))$	$MSE(\hat{\beta}_2(\tau_t))$
DGP1	1000	0.000077	0.002635	0.218088
	3000	0.000018	0.000391	0.099920
	5000	0.000004	0.000212	0.048006
DGP2	1000	0.000001	0.000540	0.452874
	3000	0.000000	0.000212	0.214814
	5000	0.000000	0.000127	0.137402

This table reports MSE of nonparametric estimates of the $\hat{\alpha}_i(\tau_t)$, $\hat{\beta}_{1i}(\tau_t)$, and $\hat{\beta}_{2i}(\tau_t)$ for $T = 1000, 3000, 5000$ from DGP1 and DGP2. T is the time length.

In DGP1, we randomly set time-varying functions for $\alpha(\tau_t)$, $\beta_1(\tau_t)$, and $\beta_2(\tau_t)$, respectively. To further convince the readers, we generate the time-varying coefficients in DGP2 based on their sample estimates obtained from real data in the A-share stock market. We have also considered other smooth linear and nonlinear functional forms for those three coefficients, the results are qualitatively unchanged. For each DGP, we set the time length T to be 1000, 3000, and 5000, respectively. The number of replications N is 200. We measure the accuracy of local linear estimation method by computing mean squared errors (MSE) for $\hat{\alpha}(\tau_t)$, $\hat{\beta}_1(\tau_t)$ and $\hat{\beta}_2(\tau_t)$ separately as follows:

$$MSE(\hat{\alpha}(\tau_t)) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{\alpha}_i(\tau_t) - \alpha(\tau_t))^2,$$

$$MSE(\hat{\beta}_1(\tau_t)) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{\beta}_{1i}(\tau_t) - \beta_1(\tau_t))^2,$$

$$MSE(\hat{\beta}_2(\tau_t)) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{\beta}_{2i}(\tau_t) - \beta_2(\tau_t))^2,$$

where $i = 1, 2, \dots, N$ and $N = 200$. We plot the median[4] of estimated coefficient functions $\hat{\alpha}(\tau_t)$, $\hat{\beta}_1(\tau_t)$, and $\hat{\beta}_2(\tau_t)$ under DGP1 (DGP2) in Fig. 1 (Fig. 2). We can clearly see that the estimated curve becomes closer to the true curve as the length of time series increases. Accordingly, Table 1 shows that MSE of the nonparametric estimates of $\alpha(\tau_t)$, $\beta_1(\tau_t)$, and $\beta_2(\tau_t)$ becomes smaller when T gets larger[5]. Especially, when the time series is 5000, the values of MSE are quite small, which indicates that the local linear estimation for our time-varying coefficient time series model performs quite well.

4. Empirical results

This section examines the herding behavior of the A-share markets and two developed markets including the H.K. and U.S. stock markets using the time-varying herding model. We then investigate the driving factor models and cross-herding effects from the time-varying perspective. We first introduce our data and descriptive statistics.

4.1. Data and descriptive statistics

We collect stock daily prices for all firms listed on Shanghai Stock Exchange (SHSE), Shenzhen Stock Exchange (SZSE), Hong Kong Stock Exchange (HKSE), New York Stock Exchange (NYSE), and the National Association of Securities Dealers Automated Quotations (NASDAQ).[6] The sample period is from January 1996 to February 2021. We calculate stock return $R_{i,t}$ for stock i on day t by $R_{i,t} = \ln P_t - \ln P_{t-1}$, where P_t and P_{t-1} denote the stock price of stock i on day t and $t-1$, respectively. The market return $R_{m,t}$ is obtained by taking the arithmetic mean of all stock returns on day t,

$$R_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t} R_{i,t}, \tag{13}$$

where N_t is the number of stocks on day t.

Table 2 provides the descriptive statistics for the market returns $R_{m,t}$ (Panel A) and return dispersion $CSAD_t$ (Panel B) for stocks in different markets. Firstly, the average stock returns and the standard deviation of A-share are relatively higher than H.K. and U.S. markets. Secondly, Panel B of Table 2 shows that the average values of $CSAD_t$ in H.K. and U.S. stock markets are generally

[4] We also plot the mean of estimated coefficient functions and obtain quantitatively similar results, which are reported in Fig. 13 and Fig. 14 in Appendix A.

[5] Given the scale of β_2 we set is larger than α and β_1, $MSE(\hat{\beta}_2(\tau_t))$ is relatively larger than $MSE(\hat{\alpha}(\tau_t))$ and $MSE(\hat{\beta}_1(\tau_t))$.

[6] We include all the firms in the American Stock Exchange (AMEX) market in the group of the NYSE following (Chang et al., 2000).

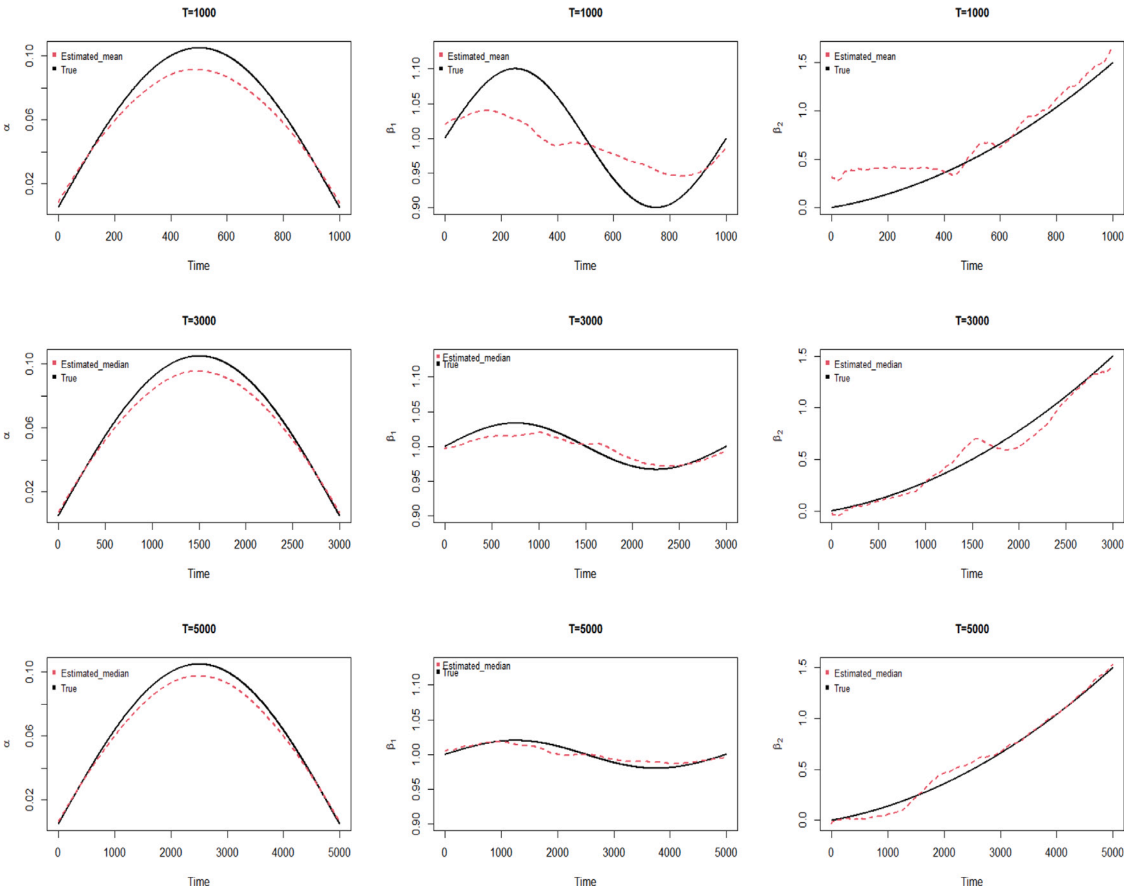

Fig. 1. The nonparametric estimates from simulated data of DGP1. This figure plots the median of estimated $\alpha(\tau_t)$, $\beta_1(\tau_t)$ and $\beta_2(\tau_t)$ from the simulated data of DGP1 in each row with $T = 1000, 3000$, and 5000, respectively.

Table 2
Summary statistics.

Market	Mean (%)	Min.	Max.	S.D.	Skew.	Kurt.	JB test	ADF test
Panel A: Descriptive statistics of $R_{m,t}$								
A-share	0.0304	−0.0457	0.0403	0.0081	−0.7120	3.8744	4460.7***	−54.295***
SHA	0.0277	−0.0453	0.0420	0.0080	−0.6923	4.4607	5711.2***	−54.722***
SZA	0.0337	−0.0461	0.0450	0.0084	−0.6362	3.5797	3778.3***	−53.620***
HKSE	−0.0181	−0.0542	0.0752	0.0054	−0.7449	24.4048	151584***	−46.141***
NYSE	0.0118	−0.0616	0.0468	0.0055	−1.0218	14.9109	61586***	−54.708***
Panel B: Descriptive statistics of $CSAD_t$								
A-share	0.7238	0.0009	0.0246	0.0026	1.5719	4.4007	7660.3***	−20.312***
SHA	0.6943	0.0007	0.0250	0.0025	1.5389	4.1728	7041.3***	−21.829***
SZA	0.7394	0.0014	0.0384	0.0028	2.0289	9.3865	27385***	−21.504***
HKSE	1.1555	0.0007	0.1068	0.0050	4.6092	46.2397	563740***	−20.247***
NYSE	0.6763	0.0026	0.0474	0.0029	2.9318	17.7296	4824***	−17.141***

This table reports the descriptive statistics of stock market return $R_{m,t}$ (Panel A) and the cross-sectional absolute deviation $CSAD_t$ (Panel B) for different markets. For each group, we present the mean, minimum, maximum, and standard deviation of $R_{m,t}$ and $CSAD_t$. We also report skewness, kurtosis, as well as the test statistics of the Jarque–Bera (JB) test and Augmented Dickey–Fuller (ADF) test. ***,**,* represents significance at 1%, 5% and 10% levels, respectively.

larger than those of the Chinese mainland stock markets. Thirdly, the test statistics of the Jarque–Bera (JB) test and the Augmented Dickey–Fuller (ADF) test in the last two columns of Table 2 are all significant at 1% level of significance. Therefore, $R_{m,t}$ and $CSAD_t$ are stationary but not normally distributed.

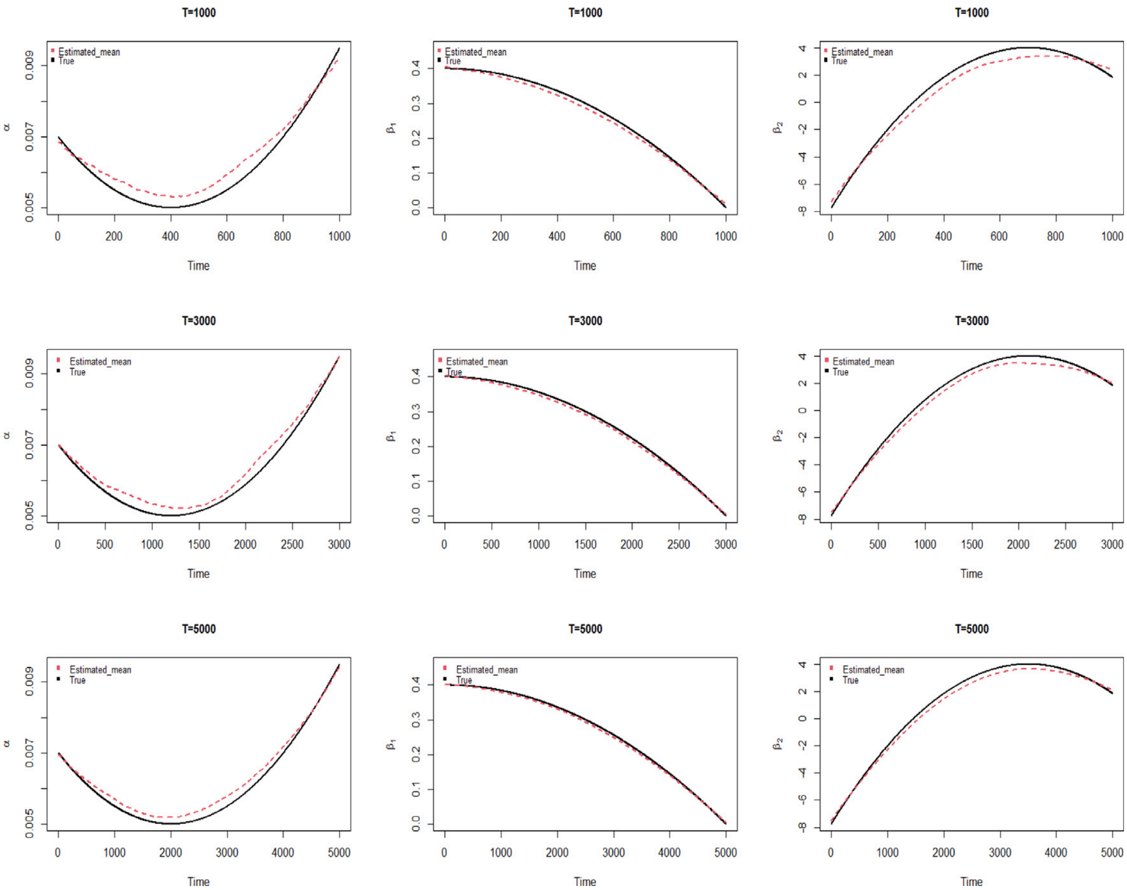

Fig. 2. The nonparametric estimates from simulated data of DGP2. This figure plots the median of estimated $\alpha(\tau_t)$, $\beta_1(\tau_t)$ and $\beta_2(\tau_t)$ from the simulated data of DGP2 in each row with $T = 1000, 3000$, and 5000, respectively.

4.2. Herding detection from the static model

We first apply the static model (1) to examine herding behavior in each stock market. Note that the significantly positive value of β_2 corresponds to adverse herding behavior, which is first proposed by Hwang and Salmon (2004). Adverse herding behavior reflects stronger self-confidence of investors and their mistrust against each other (Christie and Huang, 1995; Klein, 2013).

We show the estimation results in Table 3. Firstly, consistent with Chang et al. (2000), we show that CSAD is positively related to the market return as the value of β_1 is significantly positive for each stock market. Secondly, $\widehat{\beta}_2$ is negative and statistically significant for the A-share market, which suggests a persistent herding behavior from 1996 to 2021. In contrast, there is no pronounced herding behavior identified in the H.K. or the U.S. stock market during the sample period.

The static results imply that investors in the Chinese stock markets tend to use a "passive" investing strategy by copying their peers (Economou et al., 2015). On the contrary, the investors in the H.K. market and the U.S. market are more independent and exhibit no tendencies to herd. However, the static results cannot capture the time-varying characteristics of herding behavior for each market. Thus, we further extend the static model to a time-varying model to examine time-varying herding behavior in mainland China, Hong Kong, and the United States.

4.3. Time-varying herding of the Chinese mainland stock market

In this subsection, we use model (3) to detect the herding behavior of the Chinese mainland stock market by estimating the time-varying coefficients at every time point instead of period-specific constants in Section 4.2. We estimate the time-varying coefficients with nonparametric methodology and compute the 95% confidence interval of estimated coefficients using the bootstrap procedure in Section 2.2. We also show the traditional OLS estimation results for comparison.

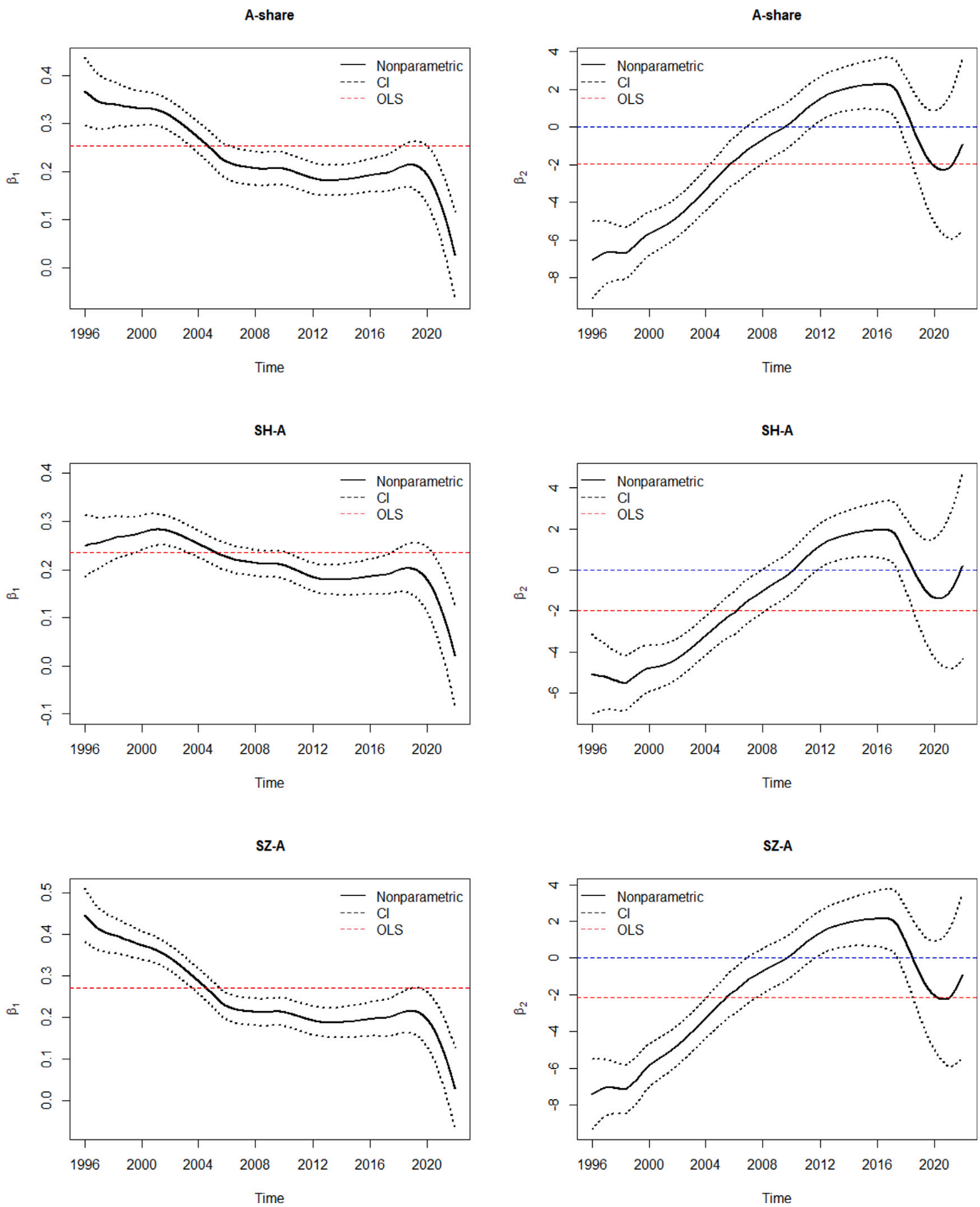

Fig. 3. The nonparametric estimates of betas for the Chinese stock market. This figure plots the nonparametric estimates of betas for the A-share stock market, including the Shanghai A-share and Shenzhen A-share stock markets. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of β.

Table 3
Estimation results based on the static herding model for each stock market.

Market	α	β_1	β_2	R^2
A-share	0.0059***	0.2535***	−1.9840***	0.2066
SHA	0.0058***	0.2357***	−1.9800***	0.1891
SZA	0.0059***	0.2708***	−2.1610***	0.2123
HKSE	0.0091***	0.7362***	1.3090***	0.4310
NYSE	0.0055***	0.3373***	3.2880***	0.3674

This table presents the time-invariant OLS estimates from Eq. (1) for the A-share, SHA, SZA, HKSE, and NYSE stock markets, respectively. R^2 is the adjusted R-square. The sample period is from 02/01/1996 to 15/12/2021. ***,**,* represents significance at 1%, 5% and 10% levels, respectively.

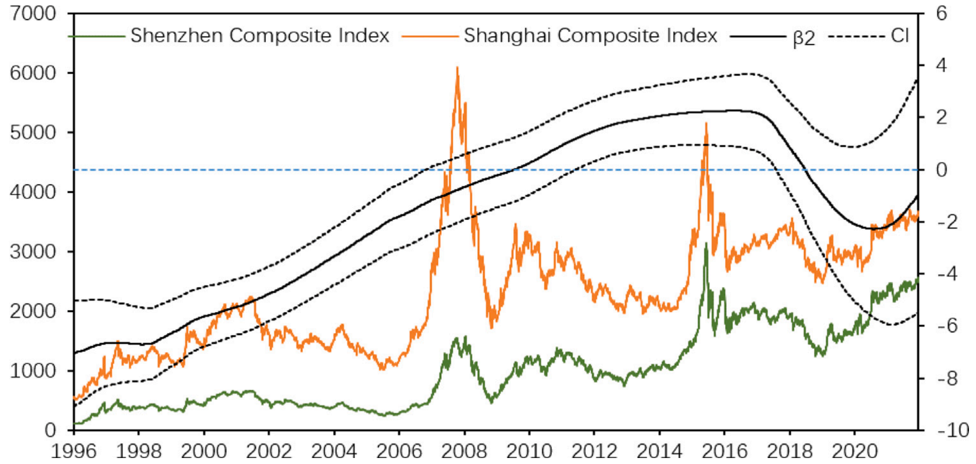

Fig. 4. The trend of the Shanghai Composite Index and Shenzhen Composite Index. This figure plots the trend line of the Shanghai Composite Index, Shenzhen Composite Index and the estimated coefficient of $\beta_2(\tau_t)$ from 1996 to 2021.

4.3.1. Herding in the A-share markets

We show the results of the A-share stock market in Fig. 3, which includes A-share, Shanghai A-share, and Shenzhen A-share stock market.[7] Consistent with the static herding result in Section 4.2, the nonparametric estimates of $\beta_1(\tau_t)$ in each stock market are all positive in general, which confirms that the value of CSAD is positively related to the market return. The nonparametric estimates of $\beta_2(\tau_t)$ in each figure indicate when the herding behavior exists for each market. We find that $\widehat{\beta}_2(\tau_t)$ rose from significantly negative before 2007 to indistinguishable from zero, and then kept increasing to significantly positive in June 2011 as in Fig. 3. The upward trend of $\widehat{\beta}_2(\tau_t)$ continued into May 2016 and turned into a downward trend to become insignificant in August 2017, and then bounced back in the second half year of 2020. In addition, the trend of $\widehat{\beta}_2(\tau_t)$ for the Shanghai A-share and Shenzhen A-share stock markets are similar to that for A-share stock market.

Our results yield some new insights about the Chinese mainland stock market. First of all, $\widehat{\beta}_2(\tau_t)$ stays significantly negative with the absolute value declining until 2007. The relatively long-term herding behavior was mostly present in the early stage of the A-share market. The strong herding behavior reveals a tendency of participants to imitate in their trading decisions. As an emerging stock market established in 1990, the A-share market features some deficiencies such as irrational valuation, excessive volatility, and imperfect regulations (He, 2020). The immaturity of the investors in the early stage of the stock market led to the prevalence of herding behavior, which is considered undesirable because it can damage the market efficiency (Goodhart et al., 2013).

As the A-share stock market is maturing, the herding behavior is declining. The investors become more mature as the scale of institutional investors expands. The experience of a developed stock market, like the U.S. stock market, highlights the important role of institutional investors (He, 2020). Recently, the Chinese mutual fund industry has experienced rapid growth, growing from the negligible Asset Under Management (AUM) of 10.7 billion in 1998 to 25.03 trillion yuan in 2021.[8] In addition, a more effective regulatory system and policy support can improve the market efficiency. For example, Chen and Zheng (2022) demonstrate that joining WTO accelerates the process of integrating China into the world financial market and improves the development of the Chinese financial markets. They find that the severity of herding in the Chinese market declined after China joined the WTO.

Second, periods with no herding and adverse herding were alternating between 2008 and 2021, during which the market was quite turbulent. Moreover, we find that the turning points of herding behavior corresponded to important events in the capital market (see Fig. 4): (i) Herding behavior disappeared during the 2008 global financial crisis (GFC) as the $\widehat{\beta}_2(\tau_t)$ was insignificant,

7 We only present the results of $\widehat{\beta}_1(\tau_t)$ and $\widehat{\beta}_2(\tau_t)$ for brevity, and the estimates of $\alpha(\tau_t)$ for each herding test are available upon request.
8 The data of AUM of mutual funds is from Asset Management Association of China (AMAC).

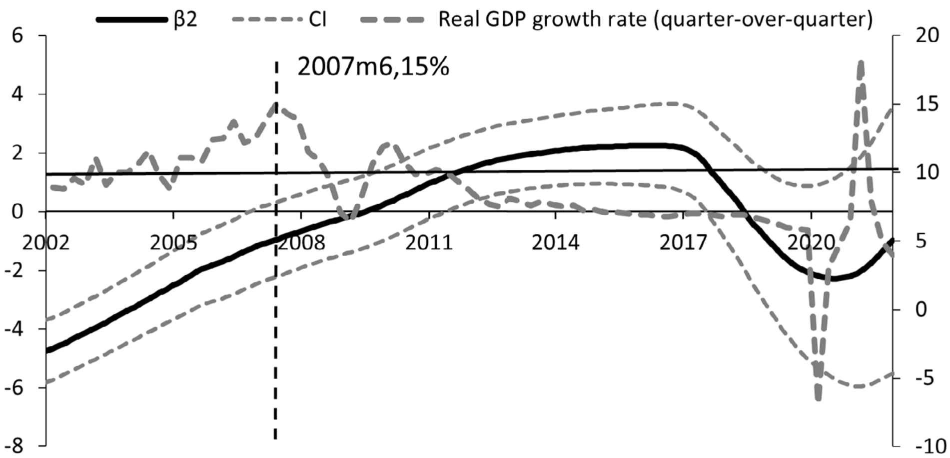

Fig. 5. The trend of the quarterly GDP growth rate of China. This figure plots the trend line of the real GDP growth rate quarter-over-quarter of China and the estimated coefficient of $\beta_2(\tau_t)$ from 2002 to 2021.

and reversed to adverse herding behavior during the post-GFC period as $\hat{\beta}_2(\tau_t)$ keeps rising. (ii) Adverse herding behavior continued to strengthen during another significant turbulent period featuring a short-lived bull market and a short-lived bear market from March 2014 to mid-2016. The turbulence ended in August 2017 when the stock market stabilized ($\hat{\beta}_2(\tau_t)$ keeps declining after August 2017). (iii) The tendency of adverse herding resurfaced in the turbulent market during the 2020 Covid-19 pandemic as can be seen from the brief bounce of $\hat{\beta}_2(\tau_t)$. Our result adds to the recent studies. For example, Yang and Chuang (2023) find that in recent years anti-herding is prevalent and herding is minimal even in turbulent markets, such as the 2020 Covid-19 pandemic. In addition, the conclusion that financial shocks do not contribute to herding behavior is also supported by some prior papers (Cheng et al., 2022; Sharma et al., 2015; Babalos and Stavroyiannis, 2015; Philippas et al., 2013).[9] In this paper, we not only find the absence of herding behavior during the 2008 GFC period, but also capture the adverse herding tendency ($\hat{\beta}_2(\tau_t)$ increases). Overall, adverse herding rather than herding is more likely to occur during market turbulent periods in the A-share market.

Third, herding behavior is closely related to the macroeconomic environment. Firstly, the inflection points of herding behavior correspond to the important inflection points of the economy. Herding behavior roughly coincides with the stage of rapid economic growth while adverse heading behavior manifests during economic recession. Fig. 5 plots China's real GDP growth rate between 2002 to 2021. In particular, the annual growth rate peaked in 2007 at 14.23% and dropped steadily since 2007, and the herding behavior of the A-share stock market also disappeared in 2007. In June 2011, the adverse herding behavior surfaced, when the economy entered a volatile era since 2011. The tendency of adverse herding behavior resurfaced in 2020, amid an economic recession triggered by the Covid-19 pandemic.

Secondly, adverse herding behavior tends to intensify during periods with high level of economic policy uncertainty (EPU). Economic entities are often unable to predict whether, when, and how the government will change the current economic policies during highly uncertain periods (Guan et al., 2021; Antonakakis et al., 2013; Colombo, 2013). Existing literature has considered EPU as an influential risk factor on stock returns since (Baker et al., 2016) introduced this news-based measure (Babaei et al., 2023). We examine the relationship between herding behavior and EPU by regressing $\hat{\beta}_2$ obtained above on the EPU Index and find a positive and significant correlation, with the estimated coefficient being 0.33%.[10]

In sum, investors are more likely to herd during economic expansion. A rapidly-expanding economy injects confidence and optimism to investors. Therefore, investors in this period are more afraid of missing out the opportunities, and more likely to imitate each other. Conversely, under highly uncertain economic conditions with pessimistic forecasts, mistrust against each other can easily lead to adverse herding behavior (Hwang and Salmon, 2004; Christie and Huang, 1995; Klein, 2013).

[9] Cheng et al. (2022) show that GFC does not contribute to the emergence of herding behavior in the Chinese mutual fund market. Sharma et al. (2015) find that herding behavior in the Chinese A-share stock market ends after the onset of the financial crisis. Babalos and Stavroyiannis (2015) find the absence of herding or anti-herding behavior during the crisis for the U.S. metal commodities futures. Philippas et al. (2013) believe that the GFC did not seem to contribute to herding behavior.

[10] The data is downloaded from 'http://www.policyuncertainty.com/index.html'. Given the data of EPU Index is monthly, we convert $\hat{\beta}_2$ to monthly data by calculating the monthly arithmetic average.

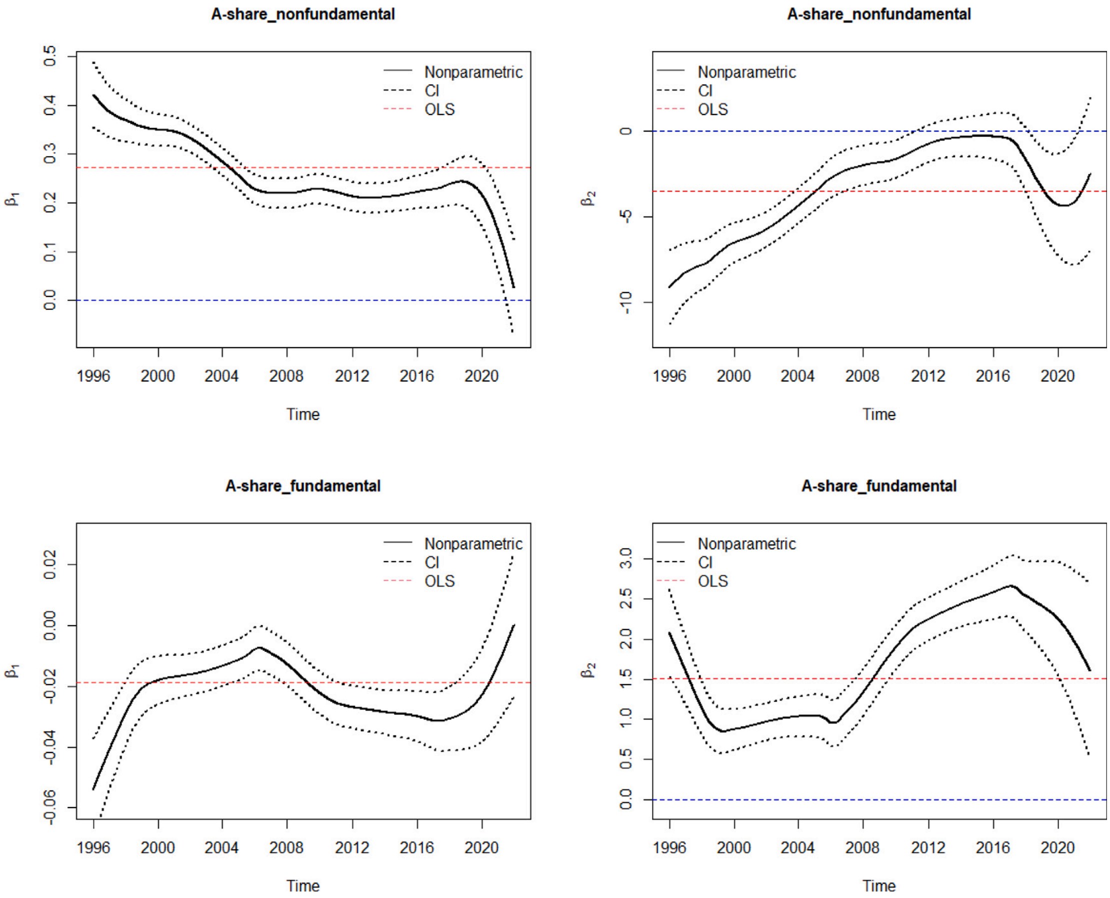

Fig. 6. Time-varying driving factor tests for A-share stock market. This figure plots the nonparametric estimates of betas driven by both non-fundamental factors and fundamental factors for the A-share stock market. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of α or β.

4.3.2. Time-varying driving factor tests

Herding behaviors are often driven by fundamental factors and non-fundamental factors (Galariotis et al., 2015; Cui et al., 2019; Wang et al., 2021; Cheng et al., 2022). The fundamental factor refers to the similar decision problems and information sets such as major economic announcements, which may lead to an efficient outcome (Bikhchandani and Sharma, 2000; Galariotis et al., 2015). Conversely, herding driven by non-fundamental factors (also known as noise/sentiment factor) including social, psychological, emotional factors, and fad and fashion is inefficient (Hudson et al., 2020).

The drivers of herding behavior are also time-varying (Galariotis et al., 2015). Cheng et al. (2022) find that fundamental factors impact weakly and intermittently, which implies that the driving factors are period-specific. Therefore, we need to investigate the time varying driving factors of herding. We follow Galariotis et al. (2015) by decomposing CSAD into a fundamental driven part and a non-fundamental driven part as shown in model (10) and model (11), respectively. We plot the nonparametric estimates of model (10) and model (11) for A-share market in Fig. 6.

Our result shows that the noise factor dominates the herding behavior in the A-share market. Fundamental factors drive adverse herding, which only exhibits when the noise factor is insignificant. Firstly, the trend line of non-fundamental time-varying β_2 is similar to the result of A-share in Section 4.3.1. Secondly, $\widehat{\beta}_2(\tau_t)^{(f)}$ keeps significantly positive in our sample period. Thirdly, there was no apparent herding driven by non-fundamental factors in the period from April 2011 to January 2018, which also overlapped with the period of adverse herding behavior in Section 4.3.1.

In conclusion, herding in the early-stage A-share stock market was mainly driven by non-fundamental factors, but weakened as market efficiency improved. The late-stage A-share market exhibited adverse herding behavior, which was driven by fundamental factors from market and macroeconomic conditions.

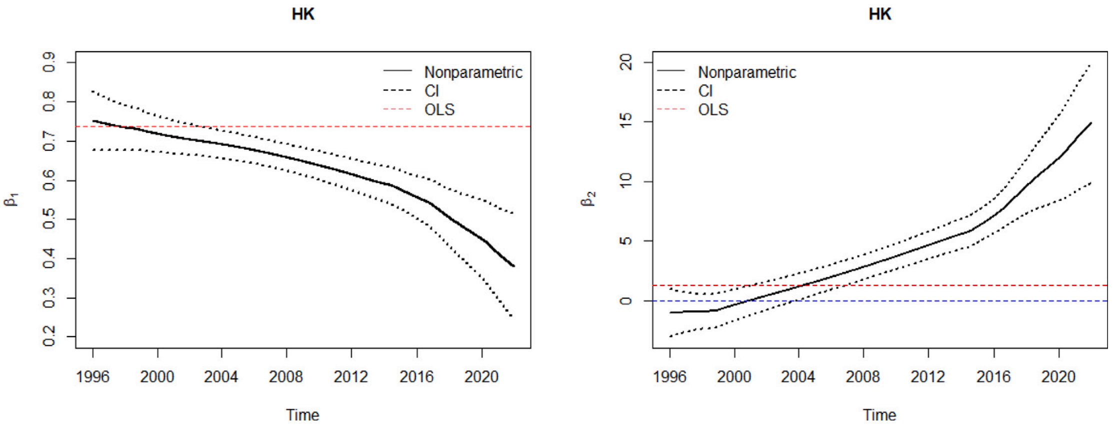

Fig. 7. The nonparametric estimates of betas for the H.K. stock market. This figure plots the nonparametric estimates of alpha and betas for H.K. stock markets. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates.

4.4. Time-varying herding of the H.K. and U.S. stock market

Compared with the developed markets, the Chinese mainland stock market is an emerging market dominated by retail investors. In this section, we examine the herding behavior in the U.S. and H.K. stock markets as a comparison.

4.4.1. Herding in the H.K. stock market

As the world's third largest financial center after New York and London, Hong Kong boasts a more developed financial market relative to the mainland market, and attracts more sophisticated investors, who are more rational and less inclined to follow others' trading behavior. We plot the nonparametric estimates of coefficients of H.K. stock market in Fig. 7.

Similar to the A-share stock market, $\widehat{\beta}_2(\tau_t)$ of the H.K. stock market also rose, changing from insignificantly negative to significantly positive in October 2003, which indicated a change from no herding to adverse herding. Adverse herding rose substantially after 2015. We conjecture that this may be due to the Shanghai–Hong Kong Stock Connect, which was officially launched on November 17, 2014. Its establishment removed some barriers for mainland investors to access eligible shares in the H.K. stock market (He, 2020).

4.4.2. Herding in the U.S. stock market

We proceed to investigate the herding behavior in the U.S. markets. Fig. 8 shows the results for the NYSE stock market and NASDAQ stock market. For the NYSE stock market, We find a strong and persistent adverse herding behavior during the sample period. In addition, we find an apparent change in herding behavior after the outbreak of GFC. This echoes the finding in Jlassi and Naoui (2015) who document a significant change in herding tendency across sub-periods of GFC. Our findings indicate that the growing trend of adverse herding behavior in the NYSE stock market stopped in 2005. The NYSE market exhibited a weakened adverse herding in the subsequent years. Our result is consistent with Babalos and Stavroyiannis (2015) who also find a rapid decline in adverse herding behavior around 2005. The fact that β_2 occurred around 2005, earlier than the 2008 GFC, is mainly due to two factors. First, to prevent the further expansion of asset bubbles and to curb crude oil inflation, the Federal Reserve of the United States implemented continued rate hikes from June 2004 to July 2006 and the federal funds rate was elevated from 1% to 5.25%. The rise in interest rates led to the decline of herding behavior (Hwang and Salmon, 2004). Second, the growth of passive and index-based investing after 2005 also contributed to the decline of adverse herding behavior. The increase in passive investing strategies, especially through exchange-traded funds (ETFs) and index funds, has reduced adverse herding behavior.

Although the time-varying trends of adverse herding behavior in the NYSE and H.K. stock markets are different, both markets show persistent and strong adverse herding behavior during our sample period. The evidence further supports that the special characteristics of the Chinese mainland stock market induce a strong herding behavior compared with other developed markets. An important difference between the A-share, Hong Kong, and U.S. stock markets is their market structure. In particular, the A-share market operates under a "T+1" trading system, which allows investors to purchase stocks on a given trading day but requires them to wait at least until the following trading day to sell those stocks. In addition, the short-selling mechanisms in the A-share market are rather limited. While short-selling tools have recently become available with index futures, their usage is limited by high costs and regulatory burdens, constraining investors' trading flexibility. Moreover, short-selling individual stocks is extremely rare. In contrast, the U.S. and Hong Kong markets impose no such restrictions and allow investors to execute buy-and-sell transactions within the same day. These markets also offer a variety of short-selling instruments, such as options, futures, and other derivatives, providing investors with greater flexibility and effective means to hedge. Furthermore, the A-share market imposes daily price limits, capping price fluctuations at (+/−)10% for the Main and SME boards and (+/−)20% for the ChiNext and Science and Technology

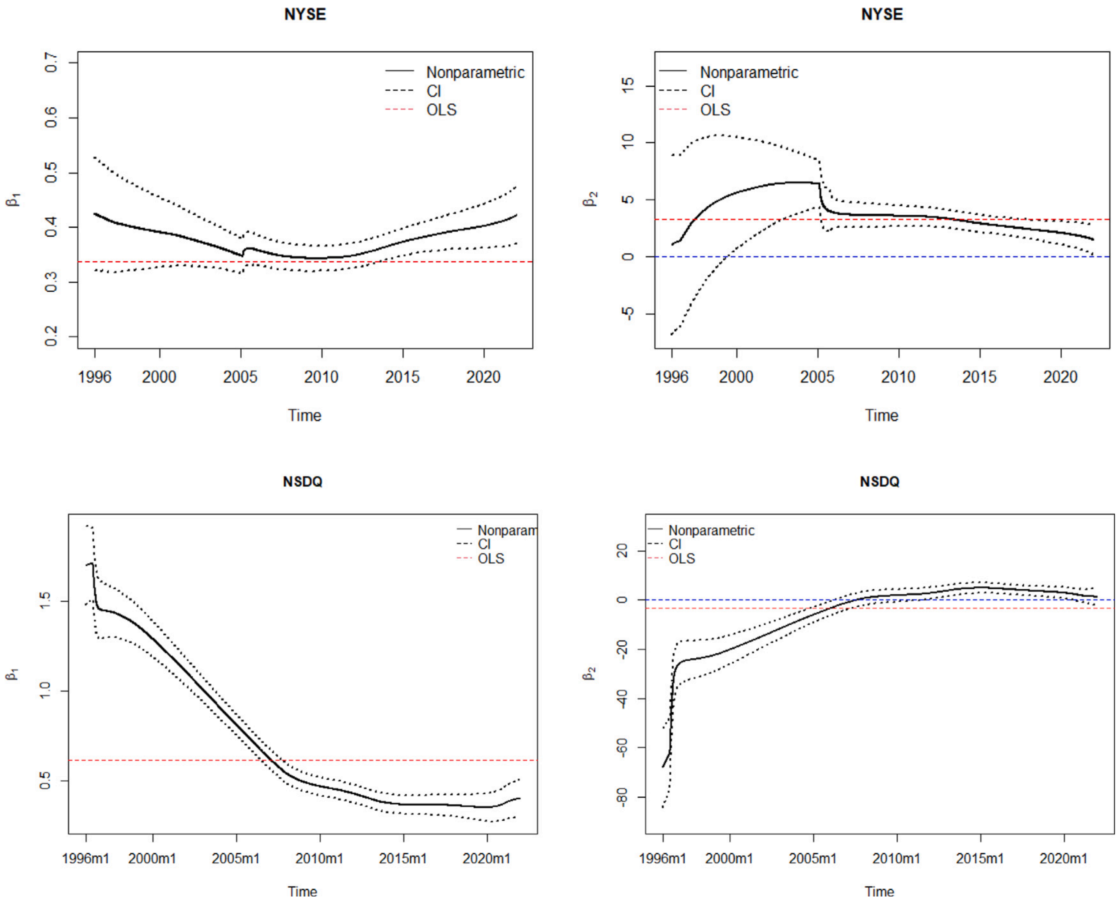

Fig. 8. The nonparametric estimates of betas for the U.S. stock market. This figure plots the nonparametric estimates of alpha and betas for the U.S. stock market. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates.

Innovation Board. As a result, investors in the A-share market often focus on short-term profits, leading them to exhibit herding behavior (Froot et al., 1992; Ma et al., 2021).

Moreover, the unique composition of investors in the A-share market significantly contributes to the prevalence of herding behavior. The high proportion of individual investors exacerbates irrational investment behaviors (He, 2020). By 2021, institutional investors held only 20.33% of the A-share market's market value (data source: WIND). In contrast, institutional investors held a substantially larger share of the market value in other markets, with 60% in the U.S. stock market by 2021 (data source: SIFMA) and 84.6% in the Hong Kong stock market by 2020 (data source: Hong Kong Exchanges and Clearing Limited). Individual investors, who have relatively limited access and ability to process information, are more prone to being influenced by market sentiment, leading to herding behavior (Tan et al., 2008). Conversely, institutional investors possess strong information-gathering capabilities, enabling them to have greater confidence in their own information sets and investment decisions.

It is worth noting that the herding behavior of the NASDAQ market is quite different from the NYSE market. The NASDAQ market exhibited a heavy herding behavior before the early 2000s. This result can be explained by the following two factors. Firstly, the NASDAQ market is one in which sentiment plays a particularly large role, especially during the dotcom bubble period from the late 1990s to the early 2000s.[11] The dotcom bubble fueled herding behavior in the stock market, as investors, driven by optimism and fear of missing out, blindly followed one another in purchasing overvalued internet stocks. This collective action further inflated prices, contributing to the eventual collapse of the bubble. Secondly, the NASDAQ market uses Electronic Communication Networks (ECNs) to achieve high transparency and liquidity in the market, which facilitates the contagion of market sentiment.

[11] The NASDAQ stock market experienced the dotcom bubble during the late 1990s and early 2000s, a period marked by extreme speculation in internet-related stocks. This bubble ballooned as investors poured money into companies with little earnings, driven by enthusiasm about the future of the Internet economy. However, the bubble burst in 2000, leading to significant declines in the NASDAQ Composite Index and wiping out trillions of dollars in market value.

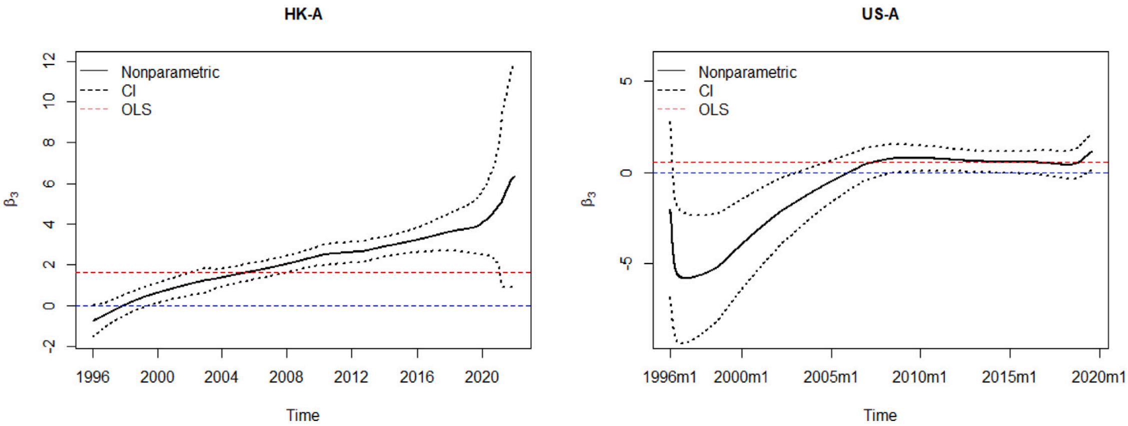

Fig. 9. The nonparametric estimates of $\beta_{3,t}$ from the time-varying cross-herding tests between A-share and H.K. stock market. This figure plots the nonparametric estimates of $\beta_{3,t}$ from the time-varying cross-herding tests between A-share and H.K. stock market. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_{3,t}$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of β_3.

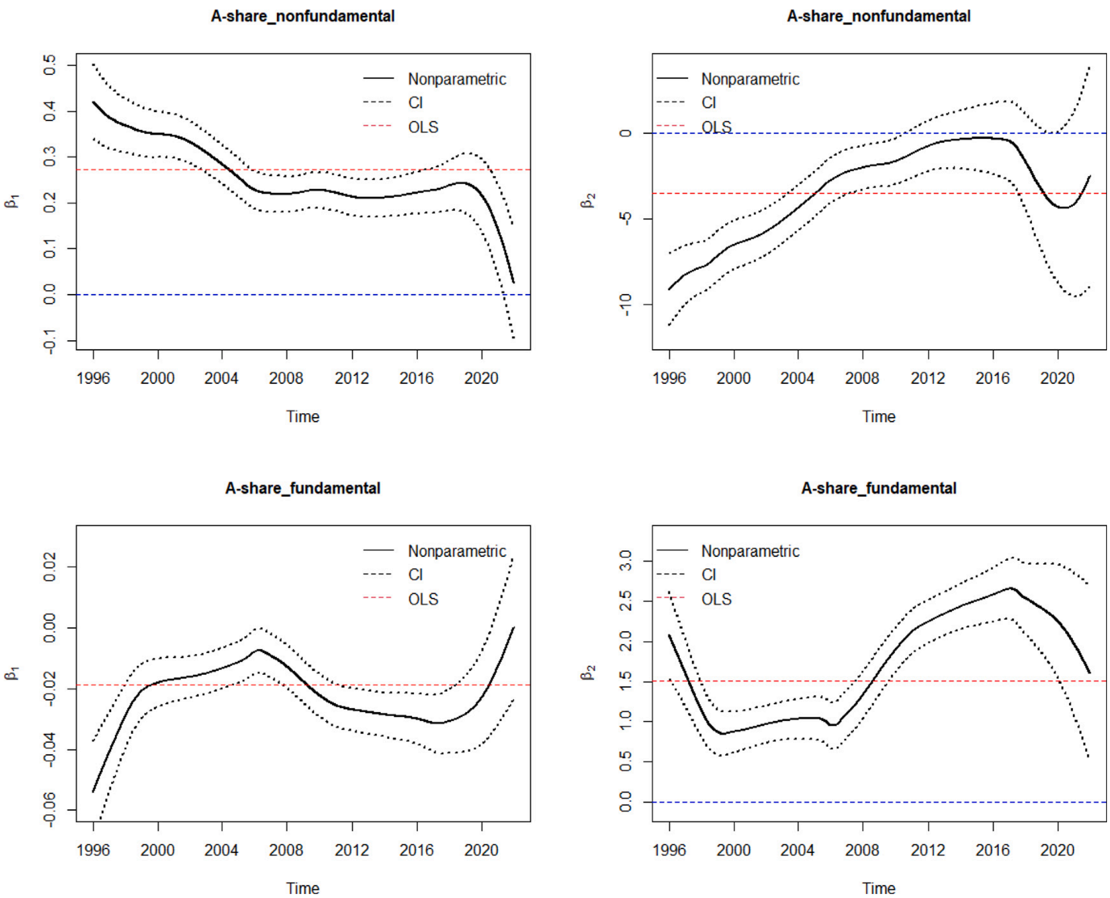

Fig. 10. The robustness check of using the Fama–French–Carhart four factors. This figure plots the nonparametric estimates of betas driven by both non-fundamental factors and fundamental factors for the A-share stock market by using Fama–French–Carhart four factors. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of α or β.

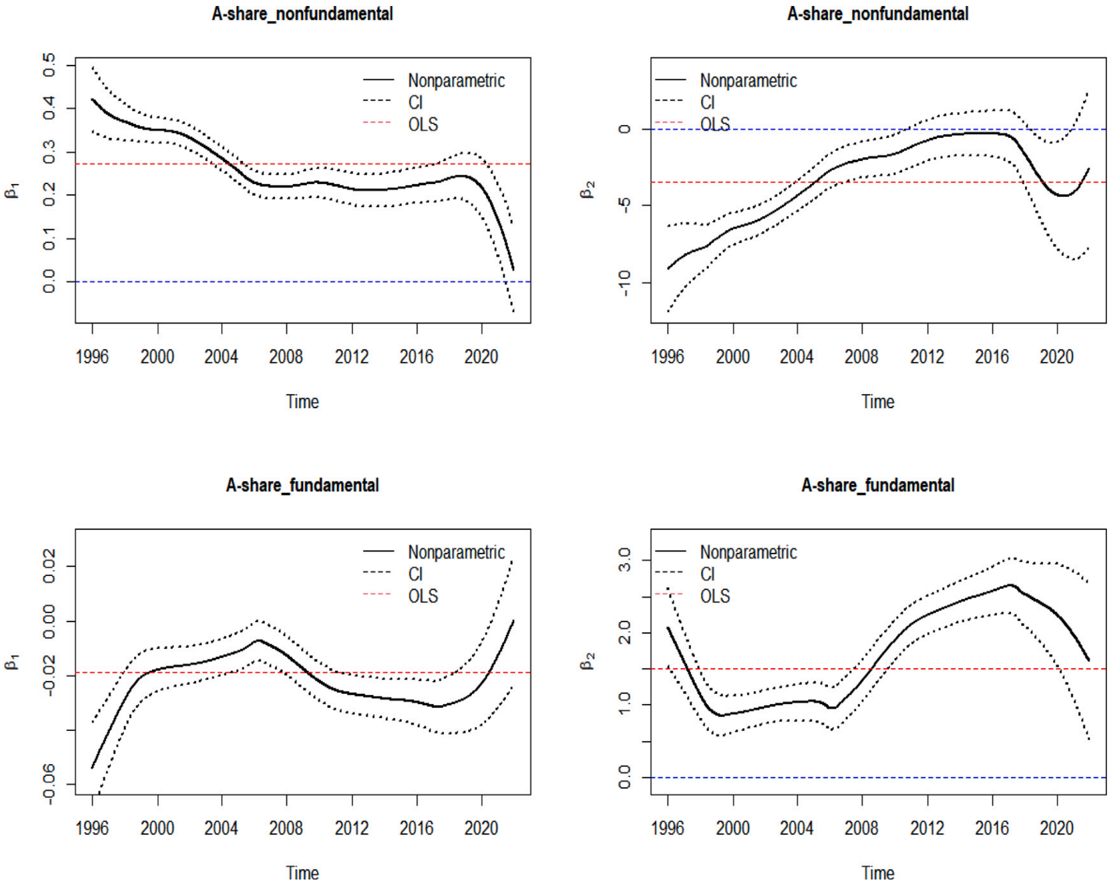

Fig. 11. The robustness check of using the Fama–French five factors. This figure plots the nonparametric estimates of betas driven by both non-fundamental factors and fundamental factors for the A-share stock market by using Fama–French five factors. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of α or β.

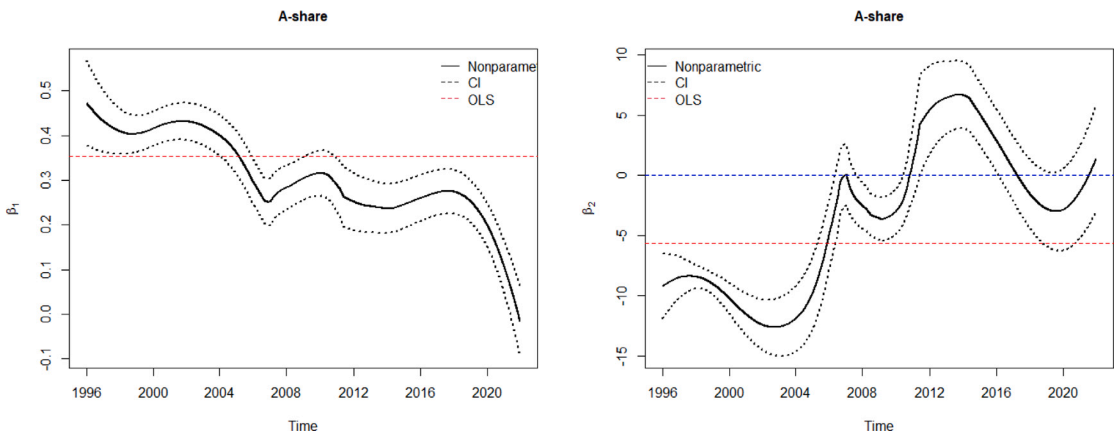

Fig. 12. The robustness check of using the market return constructed based on the equal-weighted portfolio. This figure plots the nonparametric estimates of betas driven by both non-fundamental factors and fundamental factors for the A-share stock market by using the market return constructed based on the value-weighted portfolio. In each graph, the black solid line denotes the corresponding nonparametric estimates of $\beta_1(\tau_t)$ or $\beta_2(\tau_t)$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates of α or β.

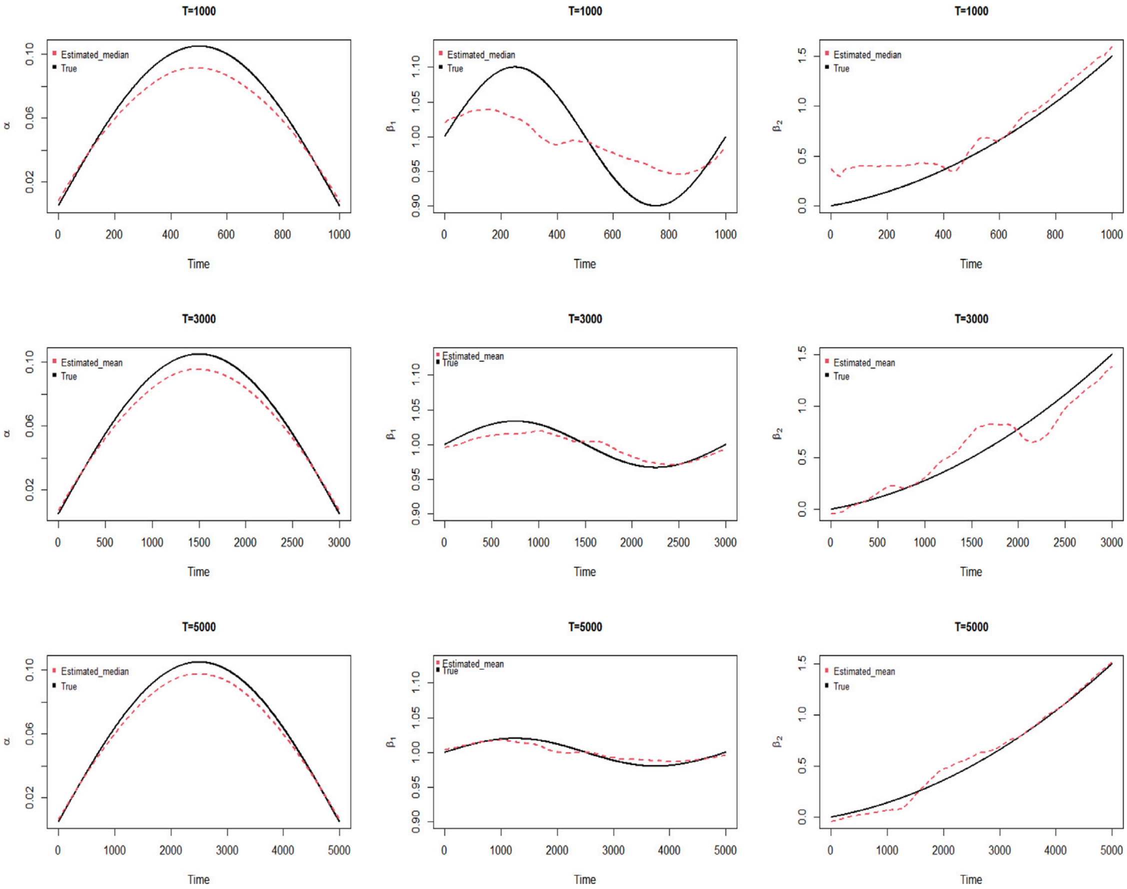

Fig. 13. The nonparametric estimates from simulated data of DGP1. This figure plots the mean of estimated α, β_1 and β_2 from the simulated data of DGP1 in each row with T = 1000, 2000, and 3000.

4.4.3. *Time-varying cross-herding effects*

In the backdrop of financial globalization, there is an increasingly stronger linkage among different markets. Information flows across markets, and thus the herding spillover effects have received much attention recently. For example, Balcilar et al. (2012) find that A-share markets herd around the H.K. stock market during the crash volatility regime. (Economou et al., 2011) examine whether the cross-sectional dispersion of returns in one market is related by the cross-sectional dispersion of returns in the other markets among four Southern European markets.

The relationship between the Chinese mainland and H.K. stock markets in macroeconomic characteristics is strengthening as more interconnection policies are released. In addition, the U.S. stock market is arguably the most important capital market in the world, with strong impacts on other financial markets. Therefore, two questions arise: (i) Is there a cross-herding effect of the H.K. and the U.S. market on A-share? (ii) If so, what are the cross-herding characteristics in the past 20 years?

To answer these questions, we examine the time-varying cross-herding behavior by extending the static cross-market herding model, which has been widely used (for example, Masih and Masih, 2001; Balcilar et al., 2013, 2012; Cheng et al., 2022). The extended time-varying cross-market herding model is specified as:

$$CSAD_{k,t} = \beta_{0,t} + \beta_{1,t}\left|R_{k,m,t}\right| + \beta_{2,t}R^2_{k,m,t} + \beta_{3,t}R^2_{f,m,t} + e_t, \tag{14}$$

where $CSAD_{k,t}$ and $R_{k,m,t}$ respectively denote the cross-sectional absolute deviation of returns and the market return in market k, the influenced market, and $R_{f,m,t}$ denotes the market return in market f, the influencing market. The estimated value of $\beta_{3,t}$ identifies the time-varying cross-herding effect of stocks in f market on the stocks in k market. The significant and negative $\beta_{3,t}$ indicates that market k herd around market f at time t.

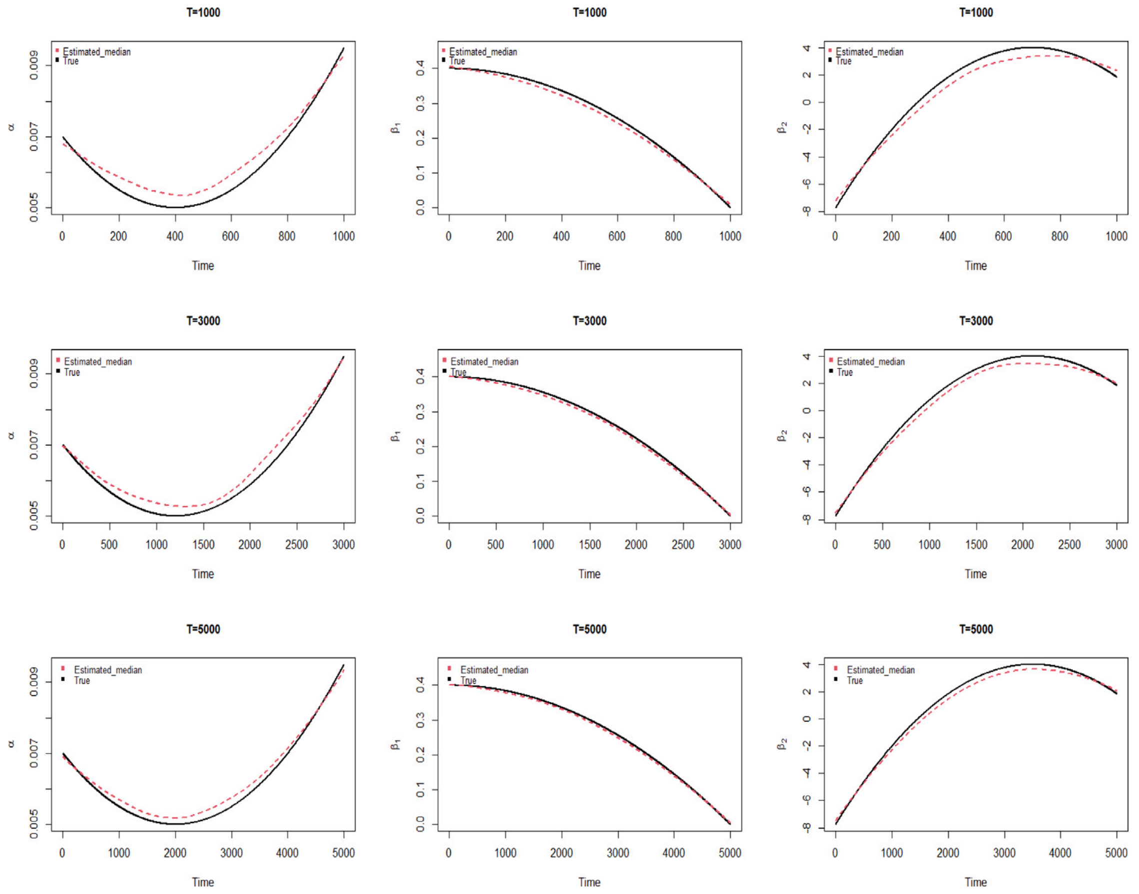

Fig. 14. The nonparametric estimates from simulated data of DGP2. This figure plots the mean of estimated α, β_1 and β_2 from the simulated data of DGP2 in each row with $T = 1000$, 2000, and 3000.

We plot the nonparametric estimate of $\beta_{3,t}$ of each cross-herding test in Fig. 9, respectively.[12] The result shows that there is no pronounced cross-herding behavior of the A-share market from the H.K. stock market, as indicated by the non-negative estimated coefficients of $\beta_{3,t}$. Our result is consistent with (Chiang and Zheng, 2010) who also find no significant effect of Hong Kong on the herding behavior of A-share market. In contrast, we find a strong herding spillover from the U.S. stock market to A-share market. However, the cross-herding behavior of A-share from the U.S. stock market has been weakening and finally disappears.

4.5. Robustness checks

4.5.1. Alternative number of factors

In Section 4.3.2, we use the regression of $CSAD_t$ on Fama–French three factors to examine the driving factor of herding behavior. In this section, we perform robustness checks to assess whether our result is sensitive to changes in benchmark models such as the Fama–French–Carhart four factors and Fama–French five-factors. In general, we demonstrate that our main findings are robust to these variations. We use the regression of $CSAD_t$ on Fama–French–Carhart four factors, which is given by:

$$CSAD_t = \gamma_{10} + \gamma_{11}\text{MKT}_t + \gamma_{12}\text{HML}_t + \gamma_{13}\text{SMB}_t + \gamma_{14}\text{MOM}_t + \epsilon_{1t}, \tag{15}$$

where MKT, HML, SMB, and MOM denote the market, value, size, and momentum factors. The Fama–French five factor model is given by:

$$CSAD_t = \gamma_{20} + \gamma_{21}\text{MKT}_t + \gamma_{22}\text{HML}_t + \gamma_{23}\text{SMB}_t + \gamma_{24}\text{RMW}_t + \gamma_{25}CMA_t + \epsilon_{2t}, \tag{16}$$

where RMW and CMA denote the robust-minus-weak probability factor and conservative-minus-aggressive investment factor. Fig. 10 plots the nonparametric estimates of Eqs. (10) and (11) for non-fundamental and fundamental time-varying driving factor by

[12] We only present the estimates of $\beta_{3,t}$ for brevity, and the other estimates for each cross-herding test are presented in Appendix B.

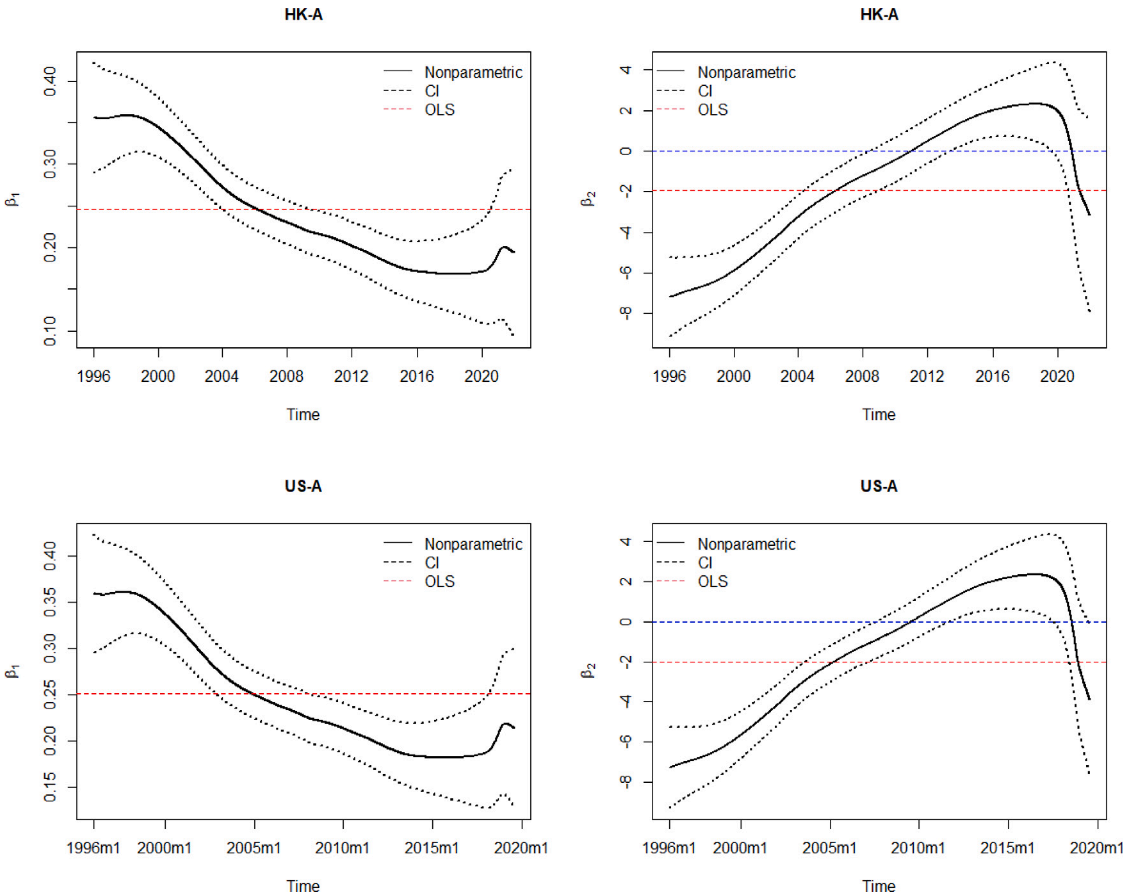

Fig. 15. The nonparametric estimates of $\beta_{1,t}$ and $\beta_{2,t}$ from the time-varying cross-herding tests. This figure plots the nonparametric estimates of $\beta_{1,t}$ and $\beta_{2,t}$ from the cross-herding test between the Chinese mainland and H.K. (U.S.) stock market. The black solid line denotes the corresponding nonparametric estimates of $\beta_{1,t}$ and $\beta_{2,t}$ and the black dotted line denotes their corresponding 95% confidence interval. The red dashed line denotes the corresponding time-invariant OLS estimates.

using Fama–French–Carhart four factors. Fig. 11 plots the nonparametric estimates of Eqs. (10) and (11) for non-fundamental and fundamental time-varying driving factor by using Fama–French five factors. The results of the Fama–French–Carhart four factor and the Fama–French five factor model are qualitatively unchanged from the results of the Fama–French three factor model.

4.5.2. Using the market return obtained by the value-weighted portfolio

In Section 4.3, we construct market return $R_{m,t}$ using the equal-weighted portfolio of all stocks. In this section, we construct the market return based on the value-weighted portfolio of all stocks in line with the real market to check the robustness. Fig. 12 shows that $\widehat{\beta}_2(\tau_t)$ turned significantly positive in June 2011. Then $\widehat{\beta}_2(\tau_t)$ became insignificant in February 2016 and bounced back in the second half year of 2020. The findings are similar with those presented in Fig. 3.

5. Conclusion

Our understanding of herding behavior is still limited given the inconclusive evidence of herding behavior in stock markets (Komalasari et al., 2021). This paper investigates the evolution of herding behavior in stock markets from a time-varying perspective by applying a nonparametric approach. To investigate whether the Chinese mainland stock market exhibits a different degree of herding behavior relative to other developed markets, we examine the time-varying herding behavior in the Chinese mainland, H.K., and U.S. stock markets using this new approach.

Applying our new approach, we find that the A-share stock market exhibited a persistent yet weakening herding behavior between 1990 and 2007, and such herding behavior was mainly driven by non-fundamental factors. Between 2008 and 2021, we find that periods with no herding and periods with adverse herding periods alternating, and the adverse herding behavior was mainly driven by fundamental factors. Moreover, we find that adverse herding was more likely to take place during turbulent periods, especially when the economic policy is highly uncertain.

In comparison, both the NYSE and H.K. stock markets display persistent and strong adverse herding behavior during the sample period. We also find that the intensity of adverse herding in the H.K. stock market increases after the Shanghai–Hong Kong Stock Connect begins. Overall, the evidence supports the conjecture that the early stage of the Chinese market induces a stronger herding behavior compared with the developed markets, but the degree of herding weakens significantly and eventually disappears as the market matures.

CRediT authorship contribution statement

Shuo Xing: Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Tingting Cheng:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition. **Liping Qiu:** Writing – original draft, Software, Methodology, Conceptualization. **Xiaoyang Li:** Writing – review & editing, Validation, Investigation, Formal analysis, Conceptualization.

Appendix A

In this Appendix, we provide the mean of estimated coefficient functions, which are reported in Fig. 13 and Fig. 14. We obtain quantitatively similar results with the median of estimated coefficient functions in Fig. 1 and Fig. 2.

Appendix B

See Fig. 15.

References

Antonakakis, N., Chatziantoniou, I., Filis, G., 2013. Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Econ. Lett. 120 (1), 87–92.
Babaei, H., Hübner, G., Muller, A., 2023. The effects of uncertainty on the dynamics of stock market interdependence: Evidence from the time-varying cointegration of the G7 stock markets. J. Int. Money Finance 139, 102961.
Babalos, V., Balcilar, M., Gupta, R., 2015. Herding behavior in real estate markets: Novel evidence from a Markov-switching model. J. Behav. Exp. Finance 8, 40–43.
Babalos, V., Stavroyiannis, S., 2015. Herding, anti-herding behaviour in metal commodities futures: A novel portfolio-based approach. Appl. Econ. 47 (46), 4952–4966.
Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.
Balcilar, M., Demirer, R., Hammoudeh, S.M., 2012. Market regimes and herding behavior in Chinese A and B shares. Available At SSRN 2150300.
Balcilar, M., Demirer, R., Hammoudeh, S., 2013. Investor herds and regime-swiching: Evidence from gulf arab stock markets. J. Int. Financial Mark., Institutions and Money 23, 295–321.
Bikhchandani, S., Sharma, S., 2000. Herd behavior in financial markets. IMF Staff. Pap. 47 (3), 279–310.
Blake, D., Sarno, L., Zinna, G., 2017. The market for lemmings: The herding behavior of pension funds. J. Financial Mark. 36, 17–39.
Bohl, M.T., Klein, A.C., Siklos, P.L., et al., 2016. A Markov switching approach to herding. Credit. Cap. Mark. 49 (2), 193–220.
Caglayan, M.O., Hu, Y., Xue, W., 2021a. Mutual fund herding and return comovement in Chinese equities. Pac.-Basin Finance J. 68, 101599.
Caglayan, M., Talavera, O., Zhang, W., 2021b. Herding behaviour in P2P lending markets. J. Empir. Finance 63, 27–41.
Cai, Z., 2007. Trending time-varying coefficient time series models with serially correlated errors. J. Econ. 136 (1), 163–188.
Cai, B., Cheng, T., Yan, C., 2018. Time-varying skills (versus luck) in U.S. active mutual funds and hedge funds. J. Empir. Finance 49, 81–106.
Cai, F., Han, S., Li, D., Li, Y., 2016. Institutional herding and its price impact: Evidence from the corporate bond market. Soc. Sci. Electron. Publ..
Carpenter, J.N., Lu, F., Whitelaw, R.F., 2021. The real value of China's stock market. J. Financial Econ. 139 (3), 679–696.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. & Finance 24 (10), 1651–1679.
Chen, Z., Zheng, H., 2022. Herding in the Chinese and US stock markets: Evidence from a micro-founded approach. Int. Rev. Econ. & Finance 78, 597–604.
Cheng, T., 2019. Functional coefficient time series models with trending regressors. Econ. Rev. 38 (6), 636–659.
Cheng, T., Xing, S., Yao, W., 2022. An examination of herding behaviour of the Chinese mutual funds: A time-varying perspective. Pacific-Basin Finance J. 74, 101820.
Chiang, T., Li, J., Tan, L., Nelling, E., 2013. Dynamic herding behavior in Pacific-basin markets: Evidence and implications. Cap. Mark. Mark. Effic. EJ..
Chiang, T.C., Zheng, R., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. & Finance 34 (8), 1911–1921.
Christie, W.G., Huang, R.D., 1995. Following the pied piper: Do individual returns herd around the market? Financial Anal. J. 51 (4), 31–37.
Colombo, V., 2013. Economic policy uncertainty in the US: Does it matter for the euro area? Econ. Lett. 121 (1), 39–42.
Cui, Y., Gebka, B., Kallinterakis, V., 2019. Do closed-end fund investors herd? J. Bank. & Finance 105, 194–206.
Demirer, R., Kutan, A.M., 2006. Does herding behavior exist in Chinese stock markets? J. Int. Financial Mark., Inst. Money 16 (2), 123–142.
Economou, F., Gavriilidis, K., Kallinterakis, V., Yordanov, N., 2015. Do fund managers herd in frontier markets — and why? Int. Rev. of Financial Anal. 40, 76–87.
Economou, F., Kostakis, A., Philippas, N., 2011. Cross-country effects in herding behaviour: Evidence from four south European markets. J. Int. Financial Mark., Institutions and Money 21 (3), 443–460.
Froot, K.A., Scharfstein, D.S., Stein, J.C., 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. J. Finance 47 (4), 1461–1484.
Fu, J., Wu, L., 2021. Regime-switching herd behavior: Novel evidence from the Chinese A-share market. Finance Res. Lett. 39, 101652.
Galariotis, E.C., Rong, W., Spyrou, S.I., 2015. Herding on fundamental information: A comparative study. J. Bank. Finance 50, 589–598.
Goodhart, C., Hartmann, P., Llewellyn, D.T., Rojas-Suarez, L., Weisbrod, S., 2013. Financial regulation: Why, how and where now?. Routledge.
Guan, J., Xu, H., Huo, D., Hua, Y., Wang, Y., 2021. Economic policy uncertainty and corporate innovation: Evidence from China. Pacific-Basin Finance J. 67, 101542.
Han, X., Li, Y., 2017. Can investor sentiment be a momentum time-series predictor? Evidence from China. J. Empir. Finance 42, 212–239.
Han, X., Li, K., Li, Y., 2020. Investor overconfidence and the security market line: New evidence from China. J. Econ. Dyn. Control. 117, 103961.

He, L., 2020. Herding behavior between Chinese and Hong Kong stock market—Based on shanghai-Hong Kong stock connect policy. Mod. Econ. 11 (4), 829–847.
Hong, H., Kubik, J.D., Solomon, A., 2000. Security analysts' career concerns and herding of earnings forecasts. the Rand J. Econ. 31 (1), 121–144.
Hudson, Y., Yan, M., Zhang, D., 2020. Herd behaviour & investor sentiment: Evidence from UK mutual funds. Int. Rev. of Financial Anal. 71, 101494.
Hung, W., Lu, C.C., Cheng, F.L., 2010. Mutual fund herding its impact on stock returns: Evidence from the Taiwan stock market. Pacific-Basin Finance J. 18 (5), 477–493.
Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Finance 11 (4), 585–616.
Jlassi, M., Naoui, K., 2015. Herding behaviour and market dynamic volatility: Evidence from the US stock markets. Am. J. Finance Account. 4 (1), 70–91.
Kabir, M.H., Shakur, S., 2018. Regime-dependent herding behavior in Asian and latin American stock markets. Pacific-Basin Finance J. 47, 60–78.
Klein, A.C., 2013. Time-variations in herding behavior: Evidence from a Markov switching SUR model. J. Int. Financial Mark., Institutions and Money 26, 291–304.
Komalasari, P.T., Asri, M., Purwanto, B.M., Setiyono, B., 2021. Herding behaviour in the capital market: What do we know and what is next? Manag. Rev.Q. 1–43.
Ma, Y., Qian, W., Luan, Z., 2021. Could increasing price limits reduce up limit herding? Evidence from China's capital market reform. Finance Res. Lett. 42, 101909.
Masih, R., Masih, A.M., 2001. Long and short term dynamic causal transmission amongst international stock markets. J. Int. Money Finance 20 (4), 563–587.
Philippas, N., Economou, F., Babalos, V., Kostakis, A., 2013. Herding behavior in REITs: Novel tests and the role of financial crisis. Int. Rev. Financial Anal. 29, 166–174.
Robinson, P.M., 1989. Nonparametric estimation of time-varying parameters. In: Hackl, P. (Ed.), Statistical Analysis and Forecasting of Economic Structural Change. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 253–264.
Robinson, P.M., 1991. Time-varying nonlinear regression. In: Hackl, P. (Ed.), Economic Structural Change Analysis and Forecasting. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 179–190.
Sharma, S.S., Narayan, P., Thuraisamy, K., 2015. Time-varying herding behavior, global financial crisis, and the Chinese stock market. Rev. Pac. Basin Financial Mark. Policies 18 (02), 1550009.
Tan, L., Chiang, T.C., Mason, J.R., Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of a and b shares. Pacific-Basin Finance J. 16 (1), 61–77.
Wang, H., Li, S., Ma, Y., 2021. Herding in open-end funds: Evidence from China. North Am. J. Econ. Finance 57, 101417.
Wu, G., Yang, B., Zhao, N., 2020. Herding behavior in Chinese stock markets during COVID-19. Emerg. Mark. Finance Trade 56 (15), 3578–3587.
Yang, W.-R., Chuang, M.-C., 2023. Do investors herd in a volatile market? Evidence of dynamic herding in Taiwan, China, and US stock markets. Finance Res. Lett. 52, 103364.
Yao, J., Ma, C., He, W., 2014. Investor herding behaviour of Chinese stock market. Int. Rev. Econ. Finance 29, 12–29.
Zheng, Z., Tang, K., Liu, Y., Guo, J.M., 2021. Gender and herding. J. Empir. Finance 64, 379–400.