Anales del Instituto de Actuarios Españoles

4ª Época, Número 30, Año 2024/83-106
DL M-3160-1961 – ISSN 0534-3232 – eISSN 2531-2308

AN UPDATE ABOUT HERDING BEHAVIOR DURING THE 2008 AND COVID-19 CRISES

ACTUALIZACIÓN SOBRE EL COMPORTAMIENTO DE MANADA DURANTE LAS CRISIS DE 2008 Y COVID-19

M. Mercè Claramunt Bielsa
Department of Economic, Financial and Actuarial Mathematics. Universitat de Barcelona. Barcelona, Spain.
ORCID: https://orcid.org/0000-0002-5184-9106

Laura González-Vila Puchades
Department of Economic, Financial and Actuarial Mathematics. Universitat de Barcelona. Barcelona, Spain.
ORCID: https://orcid.org/0000-0003-4824-5894
(Corresponding author)

Mohamed Mehdi Hijazi
Business School. Universitat de Barcelona. Barcelona, Spain.
ORCID: https://orcid.org/0000-0001-6426-2809

Fecha de recepción / Date of reception: September 15th 2024
Fecha de aceptación / Date of acceptance: October 24th 2024

ABSTRACT

The purpose of this article is to analyze the effect of the Covid-19 crisis on herding behavior after it ended, comparing it to the 2008 crisis across a large number of countries. Although the existence of herding behavior in financial markets over crisis periods has already been evaluated by some authors, this evaluation has been limited to only a few markets, and many others remain unevaluated. However, this article explores herding behavior during financial crises, focusing on the 2008 global financial crisis and the Covid-19 pandemic, offering a comparative analysis of both events. Using the CSAD of returns method, a sample composed of 31 stock markets and 195.174 observation days (from 02 January 2000 till 05 May 2023) is analyzed. Herding behavior is found during the entire period, during the different periods of crises, during both high and low volatility periods, and during both high and low trading volume periods.

Keywords: Herding behavior, 2008 crisis, Covid-19 crisis, Volatility, Trading volume

RESUMEN

El propósito de este artículo es analizar el efecto de la crisis de la Covid-19 en el comportamiento de manada una vez finalizada, comparándolo con la crisis de 2008 en un gran número de países. Aunque la existencia del comportamiento de manada en los mercados financieros durante períodos de crisis ya ha sido evaluada por algunos autores, esta evaluación se ha limitado a unos pocos mercados, y muchos otros aún no han sido evaluados. Sin embargo, este artículo explora el comportamiento de manada durante las crisis financieras, centrándose en la crisis financiera global de 2008 y la pandemia de la Covid-19, ofreciendo un análisis comparativo de ambos eventos. Utilizando el método del CSAD de rentabilidades, se analiza una muestra compuesta por 31 mercados bursátiles y 195.174 días

DOI 10.26360/2024_05

de observación (desde el 2 de enero de 2000 hasta el 5 de mayo de 2023). Los resultados muestran comportamiento de manada durante todo el período, en los diferentes períodos de crisis, tanto en períodos de alta como de baja volatilidad, y tanto en períodos de alto como de bajo volumen de negociación.

Palabras clave: Comportamiento de manada; crisis de 2008; crisis de la Covid-19; volatilidad; volumen de negociación

1. INTRODUCTION

Currently, financial markets are being analyzed from the perspective of Behavioral Finance, a subfield of Behavioral Economics that considers aspects of the Psychology and Sociology of Finance, which emerged from several authors' criticism of Classical Finance, including Kahneman and Tversky (1979). Research shows that investors do not necessarily think rationally, but are also guided by emotions, subjective thoughts, and sometimes the so-called herding mentality (Christie and Huang, 1995; Shah and Oppenheimer, 2008). Herding behavior is considered one of the most interesting concepts in Behavioral Finance. This concept is not recent, as it was already mentioned in Vega (1688).

Herding in financial markets is defined as an imitation, a convergence of action (Daniel et al. 2002) and can be explained as a psychological tendency to follow in the footsteps of others while ignoring one's own skills (Litimi et al., 2016).

In the realm of financial markets, understanding herding behavior among investors is crucial for comprehending market dynamics and predicting systemic risks. Initially recognized for its potential to amplify market movements, herding behavior has been studied extensively to uncover patterns of collective decision-making among investors. Researchers have developed various methodologies to measure and analyze herding, ranging from early metrics focusing on dispersion relative to market returns (Christie and Huang, 1995; Chang et al., 2000) to sophisticated models exploring the interplay of social learning and economic indicators (Hwang and Salmon, 2004; Sias, 2004).

Financial markets fluctuate over time. Market anomalies and major deviations from stock market efficiency are likely to be facilitated or even generated during crisis situations, with significant consequences for optimal asset allocation, portfolio diversification, and financial stability in general (Economou, 2017). Thus, searches for the correlation between crises, and the evolution of financial markets have become frequent. Likewise, studies targeting investors, specifically in relation to the rationality of capital allocation and its behavior, have increased dramatically.

According to Chang et al. (2000), herding behavior is more common during financial crises, and it can cause prices to deviate from fundamentals. Investors panic when the market is strained during a financial crisis, and they tend to have a free ride on the market information.

The existence of herding behavior in financial markets during crises has been extensively studied by various authors. For instance, regarding the 2008 crisis, Chiang and Zheng (2010) analyze investors' herding activity across 18 countries, categorizing them into three groups: advanced stock markets, Latin American markets, and Asian markets. Similarly, Lao and Singh (2011) examine herding behavior in the Chinese and Indian stock markets, finding evidence of such behavior in both.

More recently, in the context of the Covid-19 crisis, several studies have emerged. Among others, Luu and Luong (2020) use the Cross-Sectional Standard Deviation (CSSD) of returns and a State Space model to identify herding behavior in the Vietnamese and Taiwanese stock markets. Kizys et al. (2021) conduct an empirical analysis using daily stock market data from 72 countries, including both developed and emerging economies, for the first quarter of 2020. Their results indicate evidence of investor herding in these markets. Jiang et al. (2022) also investigate herding behavior triggered by the Covid-19 outbreak in 2020, focusing on 6 Asian stock markets. They employ CSSD and Cross-Sectional Absolute Deviation (CSAD) as key indicators, finding a clear presence of herding from February 2020 to January 2021, with a sharp increase during the market crash in March 2020. Likewise, Nguyen et al. (2023) study herding behavior in the Vietnamese stock market, using the CSAD method and quantile regression, and detect such behavior.

Additionally, several papers have examined both the 2008 and Covid-19 crises, including, e.g.[1], Rubesam and Junior (2022), Yang and Chuang (2022), Metawa et al. (2024), Xing et al. (2024), and Zhang et al. (2024). However, our study distinguishes itself by covering more countries and a longer time period with regard to the Covid-19 crisis. For instance, Rubesam and Junior (2022) focus on a sample of 10 countries, Yang and Chuang (2022) examine only 3 countries, and Metawa et al. (2024) focus solely on Egypt. Zhang et al. (2024) restrict their analysis to Brazil, Russia, India, China, and South Africa, while Xing et al. (2024) limit their study to China and the United States of America.

Therefore, to the best of our knowledge, there are no works that analyze the effect of the Covid-19 crisis on herding behavior once this crisis finished for a big number of countries with a comparison of this crisis with the 2008 one. Therefore, this article delves into herding behavior amidst financial crises, focusing on the global financial crisis of 2008, the Covid-19 pandemic and comparing both.

An evaluation of this scale can be useful to obtain a general representation of the main global markets as well as to facilitate the ability to compare and contrast market behavior between countries. Therefore, this study aims to verify the existence of herding behavior during the 2008 and Covid-19 crises and analyze the impact of volatility and trading volume in markets that have not yet been thoroughly investigated over an extended period. Additionally, it incorporates recent data. We apply a model to detect herding in 31 main markets, and differentiate between high volatility and low volatility, and high and low trading volume on a large scale. The primary contribution of this article is to provide additional empirical evidence from the world's major financial markets. By analyzing data across different regions and periods, we aim to deepen the understanding of herding behavior. This comprehensive approach not only broadens the scope of existing research but also offers valuable insights that can inform both academic theory and practical policy-making in the context of global finance amid crises like the global financial crisis in 2008 and the Covid-19 crisis in 2020.

The paper is structured as follows. After this Introduction, Section 2 presents a brief literature review, particularly focusing on herding behavior during the 2008 and Covid-19 crises and states the hypotheses our work tests. Section 3 describes the data sample and the research methodology used in the study. Section 4 summarizes and discusses the results, while Section 5 explores the conclusions and provides suggestions for further research.

2. LITERATURE REVIEW AND HYPOTHESES FORMULATION

Herding behavior is the result of an intention or action by one group of investors to imitate or copy the behavior of another group (Daniel et al., 2002). Bikhchandani and Sharma (2000) defined it as the correlated movement of investors, which present investment decisions similar to a particular group. The herding effect on the financial market is also marked by a homogenization of the activities of its members, who act in the same way at a given time. In other words, it occurs when a market agent attempts to follow the herd despite having a different viewpoint (Toscani, 2006; Delitala and Lorenzi, 2014). It can also occur when investors prefer to follow the market consensus above their own personal information and ideas (Christie and Huang, 1995). According to During et al. (2017), this conduct is driven by emotions, and it frequently occurs because of societal pressure to comply. Another reason given is the notion that a vast number of people cannot all be wrong.

This movement has been studied extensively in a variety of international contexts (stock market, bond market, derivatives market, commodities market, exchange rates, mutual funds, hedge funds), referring to institutional investors, analysts, individual investors, and

[1] For a brief description of the content of these articles, see Section 2.

financial markets in both developed and developing/emerging markets (Tan et al., 2008; Chiang and Zheng, 2010; Mobarek et al., 2014; Economou, 2017; Chen, 2021).

Herding can occur in the event of markets' uncertainty (Lao and Singh, 2011) and this uncertainty increases during times of crisis, when most investors panic and strive to protect the value of their investments. As a result of this scenario, investors reduce their confidence when allocating investments and this may lead to greater volatility in the market and high trading volume.

As for volatility, some studies verified that herding behavior is more pronounced under high volatility markets (Tan et al., 2008; Demirer et al., 2019; Arjoon et al., 2020). When using a herding model, Bikhchandani et al. (1992) found a positive link between transaction volume and excessive volatility. Meanwhile, Economou (2017) found that herding is more present during volatility market conditions.

Regarding trading volume, Economou et al. (2015) examined its impact and reported that herding is present during high trading volume periods. Jlassi and BenSaïda (2014) also found a positive and significant correlation between market trading volume and herding. Babalos et al. (2015) used trading volume as an investment sentiment gauge, arguing that when investors are more optimistic, they bet on rising stocks and contribute liquidity to the market, resulting in increased trading volume. During periods of pessimism or crisis, on the other hand, investors were found to avoid trade altogether.

The global financial crisis of 2008 and the Covid-19 pandemic are two prominent instances of times when herding behavior became very noticeable. Because investors were so fearful and uneasy during these crises, they followed the herd, which increased market volatility as well as trading volume. These two crises can be compared to get important insights into how herding behavior appears and affects market dynamics under high stress. This provides a rare opportunity to assess the influence of an unanticipated and dreaded disease on the behavior of investors in increasingly interconnected stock markets (Maquieira and Espinosa-Mendéz, 2022; Yang and Chuang, 2022).

Several studies have focused on herding behavior during the 2008 and Covid-19 crises. It is beyond the scope of this article to give an extensive description of all those studies. However, it is worth highlighting some of them to better identify the research gap that our work aims to fill.

Thus, Rubesam and Junior (2022) investigate herding in 10 equity markets from January 2001 to August 2021 using a methodology that considers movements in assets due to changes in fundamentals. They find heterogeneous patterns in herding across the 10 countries during the pandemic, with limited evidence of herding overall. However, Italy, Sweden, and the United States of America displayed signs of herding. The authors note that fear, uncertainty, and rapid information dissemination during crises could lead to significant deviations from rational market behavior.

On the other hand, for the period January 2001 - June 2021, and using a modified herding model with the Kalman filter and GARCH methodology, Yang and Chuang (2022) investigate the presence of herding in the United States of America, China, and Taiwan and find that investors exhibited herding behavior during the 2008 crisis, but not during the Covid-19 crisis.

In the case of Egypt, Metawa et al. (2024) check for the existence of herding for the whole period from January 2003 to December 2022. They employ the CSSD and the CSAD models and, additionally, use the quantile regression approach. For the whole period, they find evidence of herding behavior only in down-market conditions using the CSAD model. Conversely, when the market was up, herding behavior was absent. Therefore, when the market was down, investors were afraid of the condition of uncertainty, neglecting their own private information, avoiding acting independently and consequently, following other investors; and when the market was up, investors became rational and acted fully independent. Moreover, when the whole period is split into subperiods and, among others, the 2008 and Covid-19 crises are considered, the authors find evidence of herding before, after and during the five significant crises examined in the study, except for 2008 crisis where no herding behavior was observed.

Likewise, based on data starting from January 2005 to May 2020 for the 2008 crisis, and from January 2019 to December 2021 for the Covid-19 crisis, Xing et al. (2024) investigate the impact of these two global crises on herding behavior in the stock markets of China and the United States of America. They find no evidence of herding in the United States of America during these crises but significant herding in the Chinese stock market during the Covid-19 crisis. Their results highlighted the differences in the effects of financial and public health crises on herding behavior and the variations between emerging and developed stock markets.

Finally, the paper by Zhang et al. (2024) explores herding behavior towards several systematic risk factors derived from the Capital Asset Pricing Model (CAPM) and its extensions. They use the dispersion of risk factor loadings and a State Space model to study herding dynamics in the stock markets of Brazil, Russia, India, China, and South Africa from January 2006 to December 2022. Their results show significant increases in herding linkages during market stress, particularly during the 2008 global financial crisis and the Covid-19 pandemic, questioning the effectiveness of asset allocation for diversification in these markets.

Based on the ideas described in the previous paragraphs, and bearing in mind the objective of this article, which is to verify the existence of herding behavior during the 2008 and Covid-19 crises across a large number of stock markets, including some that are less studied, over an extended period and analyze the impact of volatility and trading volume on this behavior, we analyze 31 stock markets from 02 January 2000 to 05 May 2023. Specifically, our study tests the following hypotheses:

H1. There is significant presence of herding behavior in the analyzed period.
H2. Herding behavior is more prominent in times of crisis.
H3. Market volatility has a significant effect on herding behavior.
H4. Trading volume has a significant effect on herding behavior.

3. DATA AND METHODOLOGY

Regarding the data collecting, sample selection, and evaluation processes for the objective of this article, the data used for the study has been obtained from Refinitiv Datastream. The sample consists of daily adjusted closing prices of stocks listed in the most capitalized markets (current US$), as included in the World Bank (2021). To avoid compromising the results due to lack of data in the observations and to have reliable regression results, the following criteria has been adopted:

1) Only countries with data from January 2000 onwards have been included in the study.
2) Following recommendations by Hair et al. (2005) and Enders (2010), indexes and companies whose stocks lack available data for 10 consecutive years have been excluded from the sample.
3) Single-stock trading days have not been incorporated in the sample.

To ensure the accuracy and reliability of our analysis, we have taken into consideration the dynamic nature of the index compositions over the sample period. Specifically, we have accounted for additions and deletions of constituents within the indices. By incorporating these changes, we mitigate the risk of survivorship bias, which could otherwise skew the results. This comprehensive approach ensures that our findings reflect the true performance and behavior of the indices over time. As a result, the following countries or markets have been selected: Argentina, Australia, Brazil, Canada, Chile, China, Denmark, Egypt, Finland, France, Germany, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Mexico, Norway, Portugal, Qatar, Russia, Saudi Arabia, South Africa, Spain, Sweden, Turkey, the United Arab Emirates, the United Kingdom, and the United States of America for the period from 02 January 2000 to 05 May 2023.

The selected countries, based on their high market capitalization (World Bank, 2021) and the criteria outlined in points 1) to 3), represent a significant portion of global stock markets. This diverse selection ensures that the findings are comprehensive and applicable across a wide range of financial contexts.

Data has been adopted on a daily basis due to the sensitivity of the information to reflect any movement in the financial market, and because this reflects change more efficiently than utilizing weekly or monthly data, as adopted in several studies (Tan et al., 2008; Chiang and Zheng, 2010; Lao and Singh, 2011; Mobarek et al., 2014; Galariotis et al., 2016; Chang et al., 2020).

The final sample is composed of 31 markets and 195.174 observation days, as per Table 1.

In order to examine our sample and test the hypotheses described in Section 2, we split the sample into 4 periods:

- Period 1, from 02 January 2000 till 01 August 2007. This last date is considered the beginning of the 2008 crisis (Galariotis et al., 2016; Messaoud and Ben Amar, 2024).
- Period 2, from 02 August 2007 till 30 March 2009, which is the 2008 crisis as stated by Messaoud and Ben Amar (2024).
- Period 3, from 31 March 2009 till 29 January 2020, considered the period preceding the Covid-19 crisis.
- Period 4, the Covid-19 crisis. As considered by Chang et al. (2020) and Dhall and Singh (2020), it began on 30 January 2020 when the World Health Organization declared the Covid-19 outbreak as a Public Health Emergency of International Concern till 05 May 2023 when that organization declared the end of Covid-19 as the end of the health emergency.

Country	**Acronym**	**Index**	**Observation days**
Argentina	ARG	MERVAL25 (24/25)	5971
Australia	AUS	AXJO (147/200)	6071
Brazil	BRA	B3 (71/89)	6390
Canada	CAN	S&P/TSX 60 (60/60)	7320
Chile	CHL	S&P CLX IPSA (26/29)	6450
China	CHI	TSE CHINA A50 (41/50)	4970
Denmark	DEN	OMXC20 (19/20)	6142
Egypt	EGY	EGX30 (22/30)	5981
Finland	FIN	OMX25 (22/25)	6151
France	FRA	CAC 40 (36/40)	6262
Germany	GER	DAX30 (28/30)	6506
Hong Kong	HOK	HK50 (48/50)	6036
India	IND	BSESN30 (30/30)	6092
Indonesia	INA	FTSE (27/35)	5951
Ireland	IRE	ISEQ (21/32)	6208
Israel	ISR	TA35 (24/35)	6169
Italy	ITA	IT40 (27/40)	6221
Japan	JAP	JP225 (212/225)	7152
Mexico	MEX	MXX (29/34)	6862
Norway	NOR	OSEAX20 (15/20)	6147

Portugal	POR	PSI20 (13/20)	6246
Qatar	QAT	QSE (16/20)	5840
Russia	RUS	MOEX (27/45)	6313
Saudi Arabia	SAU	TASI (127/214)	5805
South Africa	SAF	JTOPI40 (36/40)	6484
Spain	SPA	IBEX35 (30/35)	6229
Sweden	SWE	OMXS30 (25/30)	6104
Turkey	TUR	BIST50 (39/50)	6453
United Arab Emirates	UAE	DFMGI (32/32)	4766
United Kingdom	UKI	UK100 (88/100)	6209
United States of America	USA	NASDAQ100 (94/100)	6798

Table 1: Sample composition
Note: Data between parenthesis refer to the number of selected stocks that make up the sample/the total number of stocks in the index.
Source: Own elaboration.

Several methods have been proposed in the literature to measure herding behavior. Initially, Lakonishok et al. (1992) introduce the LSV (Lakonishok, Shleifer, and Vishny) indicator, but its inability to capture intertemporal herding behavior was noted by some authors, e.g., Merli and Roger (2012). Subsequently, using measures of dispersion in relation to market returns during periods of significant market changes or times of crisis, Christie and Huang (1995) introduce the CSSD measure. Inspired by the CSSD measure, a widely used method proposed by Chang et al. (2000) examines herding behavior based on the degree of return dispersion, which is measured by the CSAD of returns. According to the CAPM, Chang et al. (2000) demonstrate a positive linear correlation between CSAD and stock market return in a rational market. However, this linear relation is disrupted by herding behavior, leading to a nonlinear relationship. Therefore, the relationship between market return dispersion and market return rate serves as an indicator for identifying the presence of herding behavior:

$$CSAD_t = \alpha + y1 \cdot |R_{m,t}| + y2 \cdot R_{m,t}^2 + \varepsilon_t \quad (1)$$

being $CSAD_t$ the CSAD at time t defined as:

$$CSAD_t = \frac{1}{N}\sum_{X=1}^{N}|R_{X,t} - R_{m,t}| \quad (2)$$

N the number of assets; $R_{X,t}$ the return of stock X at time t calculated as a continuous rate:

$$R_{X,t} = \ln\left(\frac{P_{X,t}}{P_{X,t-1}}\right) \quad (3)$$

with $P_{X,t}$ the adjusted closing value of stock X on day t, $P_{X,t-1}$ the prior day adjusted closing value; $R_{m,t}$ the average return of the market at time t, i.e., $R_{m,t} = \frac{1}{N}\sum_{X=1}^{N} R_{X,t}$; and ε_t the term of the error at time t.

According to Chang et al. (2000), a market is in equilibrium when CAPM holds, and $CSAD_t$, as the measure of return dispersion, should be linearly related to average market return $R_{m,t}$. This is represented in equation (1) by $y2 = 0$. Nevertheless, when herding behavior exists, CAPM is invalid and $CSAD_t$ does not show a linear relationship with $R_{m,t}$. In this case, the quadratic term $y2 \cdot R_{m,t}^2$ is indicative of such behavior: when herding exists, $CSAD_t$ decreases and $y2$ is significantly negative.

Unlike CSSD, CSAD's emphasis on the proximity of individual returns to market averages improves its sensitivity to market movements (Litimi et al., 2016; Espinosa-Méndez and Arias, 2021). Therefore, in this paper, we use the CSAD of returns method. Table 2 includes the main descriptive statistics for $CSAD_t$ and $R_{m,t}$ in the different markets in our sample.

Country		μ	σ	**Min.**	**Max.**
ARG	$CSAD_t$	0.017	0.009	0.001	0.169
	$R_{m,t}$	0.014	0.020	-0.385	0.778
AUS	$CSAD_t$	0.0139	0.007	0.003	0.104
	$R_{m,t}$	0.007	0.009	0.003	0.114
BRA	$CSAD_t$	0.023	0.053	0.002	3.674
	$R_{m,t}$	0.016	0.030	0.013	1.786
CAN	$CSAD_t$	0.015	0.006	0.003	0.224
	$R_{m,t}$	0.008	0.012	0.004	0.133
CHL	$CSAD_t$	0.012	0.006	0.002	0.174
	$R_{m,t}$	0.009	0.010	0.002	0.226
CHN	$CSAD_t$	0.031	0.048	0.007	0.849
	$R_{m,t}$	0.009	0.006	0.001	0.096
DEN	$CSAD_t$	0.014	0.007	0.003	0.149
	$R_{m,t}$	0.009	0.009	0.001	0.126
EGY	$CSAD_t$	0.016	0.016	0.003	0.323
	$R_{m,t}$	0.001	0.007	0.002	0.469
FIN	$CSAD_t$	0.013	0.006	0.003	0.050
	$R_{m,t}$	0.010	0.010	0.002	0.122
FRA	$CSAD_t$	0.011	0.005	0.002	0.085
	$R_{m,t}$	0.010	0.010	0.001	0.146
GER	$CSAD_t$	0.007	0.004	0.001	0.052
	$R_{m,t}$	0.006	0.006	0.001	0.086
HOK	$CSAD_t$	0.042	0.079	0.003	0.987
	$R_{m,t}$	0.020	0.032	0.001	0.314
IND	$CSAD_t$	0.014	0.009	0.002	0.415
	$R_{m,t}$	0.010	0.011	0.001	0.246
INA	$CSAD_t$	0.019	0.010	0.001	0.156
	$R_{m,t}$	0.012	0.013	0.001	0.175
IRE	$CSAD_t$	0.022	0.014	0.001	0.519
	$R_{m,t}$	0.010	0.010	0.001	0.149
ISR	$CSAD_t$	0.009	0.009	0.001	0.064
	$R_{m,t}$	0.001	0.013	0.001	0.132
ITA	$CSAD_t$	0.011	0.005	0.002	0.070
	$R_{m,t}$	0.009	0.010	0.001	0.185
JAP	$CSAD_t$	0.010	0.008	0.001	0.439
	$R_{m,t}$	0.008	0.010	0.001	0.266
MEX	$CSAD_t$	0.013	0.006	0.002	0.077
	$R_{m,t}$	0.010	0.010	0.001	0.161
NOR	$CSAD_t$	0.016	0.009	0.001	0.197
	$R_{m,t}$	0.014	0.0140	0.001	0.179
POR	$CSAD_t$	0.011	0.005	0.001	0.073
	$R_{m,t}$	0.009	0.009	0.001	0.127
QAT	$CSAD_t$	0.013	0.064	0.002	1.321
	$R_{m,t}$	0.004	0.015	0.001	0.876
RUS	$CSAD_t$	0.021	0.054	0.002	0.264
	$R_{m,t}$	0.005	0.019	0.001	0.214
SAF	$CSAD_t$	0.016	0.007	0.002	0.174
	$R_{m,t}$	0.013	0.013	0.001	0.224

SAU	$CSAD_t$	0.018	0.016	0.005	1.168
	$R_{m,t}$	0.001	0.010	0.002	0.265
SPA	$CSAD_t$	0.012	0.005	0.003	0.069
	$R_{m,t}$	0.010	0.010	0.001	0.167
SWE	$CSAD_t$	0.010	0.008	0.002	0.054
	$R_{m,t}$	0.001	0.016	0.001	0.158
TUR	$CSAD_t$	0.020	0.010	0.002	0.160
	$R_{m,t}$	0.001	0.015	0.001	0.359
UAE	$CSAD_t$	0.017	0.017	0.001	0.184
	$R_{m,t}$	0.010	0.019	0.001	0.217
UKI	$CSAD_t$	0.011	0.005	0.001	0.077
	$R_{m,t}$	0.008	0.009	0.001	0.146
USA	$CSAD_t$	0.018	0.009	0.001	0.154
	$R_{m,t}$	0.004	0.010	0.001	0.101

Table 2: Descriptive statistics of the sample
Note: μ is mean; σ is standard deviation; Min. is minimum value; Max. is maximum value.
Source: Own elaboration.

Based on equation (1), H1 is tested by considering the whole period analyzed. In order to test H2, the same equation is estimated but, in this case, using the data related to the 4 periods the whole period has been split into.

As far as the hypothesis H3 is concerned, we examine the role of volatility on herding by splitting the sample into high and low volatility days. According to Tan et al. (2008), high volatility is defined as a day's volatility above the last 30-day moving average, and vice versa. In accordance with that definition, we first calculate the average of the market returns for the last 30 days, and then its standard deviation, according to the following formulas:

$$\bar{R}_{m,t} = \frac{1}{30} \sum_{s=t-29}^{t} R_{m,s} \tag{4}$$

$$\sigma_t^2 = \frac{1}{30} \sum_{s=t-29}^{t} (R_{m,s} - \bar{R}_{m,t})^2 \tag{5}$$

being $\sigma_t = \sqrt{\sigma_t^2}$ the volatility of day t. In order to verify if the volatility of day t is higher or lower/equal than the previous 30 days, we calculate the average of the volatilities of the last 30 days and compare it with the volatility of the respective day. The average of the volatilities of the last 30 days is given as:

$$\bar{\sigma}_t = \frac{1}{30} \sum_{s=t-29}^{t} \sigma_s \tag{6}$$

If $\sigma_t > \bar{\sigma}_t$ the day t is considered of high volatility, otherwise it is low/equal.
Then, equation (7) and equation (8) allow us to replicate equation (1) but with respect to high and low volatility days, respectively:

$$CSAD_t^{\sigma 2,H} = \alpha + y1^{\sigma 2,H} \cdot \left|R_{m,t}^{\sigma 2,H}\right| + y2^{\sigma 2,H} \cdot (R_{m,t}^{\sigma 2,H})^2 + \varepsilon_t \tag{7}$$

$$CSAD_t^{\sigma 2,L} = \alpha + y1^{\sigma 2,L} \cdot \left|R_{m,t}^{\sigma 2,L}\right| + y2^{\sigma 2,L} \cdot (R_{m,t}^{\sigma 2,L})^2 + \varepsilon_t \tag{8}$$

where ${R_{m,t}}^{\sigma 2,H}$ (${R_{m,t}}^{\sigma 2,L}$) is the market return during day t when the volatility is high (low/equal).

Instead of estimating equations (7) and (8) for all markets and all subperiods, we first perform a Wald test. The objective of this test is to examine the equality of the herding coefficients $y2^{\sigma 2,H}$ and $y2^{\sigma 2,L}$ in equations (7) and (8). Specifically, the null hypothesis to be tested is $H_0: y2^{\sigma 2,H} = y2^{\sigma 2,L}$. This hypothesis can be assessed by determining whether the coefficients

$\beta3$ and $\beta4$ in regression (9) are equal. Conducting the Wald test prior to analyzing the impact of volatility ensures the statistical validity of our subsequent findings.

$$CSAD_t = \alpha + \beta1 \cdot D_t^{\sigma2,H} \cdot |R_{m,t}| + \beta2 \cdot (1 - D_t^{\sigma2,H}) \cdot |R_{m,t}|$$
$$+\beta3 \cdot D_t^{\sigma2,H} \cdot R_{m,t}^2 + \beta4 \cdot (1 - D_t^{\sigma2,H}) \cdot R_{m,t}^2 + \varepsilon_t \quad (9)$$

where $D_t^{\sigma2,H}$ is a dummy variable equal to 1 when volatility is high and 0 otherwise.

According to Mobarek et al. (2014), when the Wald test is statistically significant, the null hypothesis of equality of herding coefficients $y2^{\sigma2,H}$ and $y2^{\sigma2,L}$ is rejected. This indicates that the herding coefficients for high and low volatility are different. Conversely, if the Wald test is not statistically significant, the null hypothesis is not rejected, indicating that $y2^{\sigma2,H} = y2^{\sigma2,L}$. Therefore, we only verify herding behavior under high and low volatility by using equations (7) and (8) for those markets where the Wald test shows statistical significance.

Similarly, to test hypothesis H4, trading volume is characterized as high if on day t it is greater than the previous 30-day moving average and low/equal if it is less/equal than the previous 30-day moving average. Then, we estimate equation (10) and equation (11) hence:

$$CSAD_t^{V,H} = \alpha + y1^{V,H} \cdot |R_{m,t}^{V,H}| + y2^{V,H} \cdot (R_{m,t}^{V,H})^2 + \varepsilon_t \quad (10)$$

$$CSAD_t^{V,L} = \alpha + y1^{V,L} \cdot |R_{m,t}^{V,L}| + y2^{V,L} \cdot (R_{m,t}^{V,L})^2 + \varepsilon_t \quad (11)$$

where V,H and V,L refer to high and low/equal trading volume in the day t.

Again, instead of estimating equations (10) and (11) for all markets and subperiods, a Wald test is first carried out to examine the equality of herding coefficients $y2^{V,H}$ and $y2^{V,L}$ in equations (10) and (11). The null hypothesis to check is $H_0\colon y2^{V,H} = y2^{V,L}$. This hypothesis can be tested if coefficients $\delta3$ and $\delta4$ in regression (12) are equal:

$$CSAD_t = \alpha + \delta1 \cdot D_t^{V,H} \cdot |R_{m,t}| + \delta2 \cdot (1 - D_t^{V,H}) \cdot |R_{m,t}|$$
$$+ \delta3 \cdot D_t^{V,H} \cdot R_{m,t}^2 + \delta4 \cdot (1 - D_t^{V,H}) \cdot R_{m,t}^2 + \varepsilon_t \quad (12)$$

where $D_t^{V,H} = 1$ when trading volume is high and 0 otherwise.

We only estimate equations (10) and (11) to check the influence of herding behavior under high/low trading volume for those markets where the Wald test shows statistical significance and, therefore, in markets where the Wald test is not statistically significant, indicating equal herding coefficients, we do not proceed with that estimation.

To perform the data analysis and draw the corresponding conclusions, we use EViews. Moreover, all equations related to regressions have been estimated by using Ordinary Least Squares (OLS) regression technique.

4. RESULTS AND DISCUSSION

Tables 3 and 4 report the results of the estimations of equation (1) when considering the whole sample from 02 January 2000 till 05 May 2023 and the four periods into which it has been divided, respectively.

Table 3 depicts the values of the coefficient y2 in equation (1), where a significantly negative value (grey highlighted) is consistent with herding. The results showed that y2 is significantly negative for Argentina, Canada, Chile, China, Egypt, Finland, India, Indonesia, Mexico, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, Turkey, and the United Arab Emirates, suggesting that herding behavior exists considering the whole period analyzed from 2000 till 2023, not rejecting hypothesis H1 as there is significant impact of herding behavior. Australia, Brazil, Denmark, Germany, Hong Kong, Ireland, Israel, Japan, Sweden, the United Kingdom, and the United States of America have a positive and significant y2 indicating that there is no herding behavior during that period. For France, Italy, and Norway the coefficient y2 is not statistically significant.

Country	$y2$
ARG	-0.287***
AUS	0.140***
BRA	0.862***
CAN	-1.371***
CHL	-0.532***
CHN	-0.010**
DEN	1.764***
EGY	-0.563***
FIN	-0.445**
FRA	0.011
GER	2.467***
HOK	5.653***
IND	-4.075***
INA	-0.227*
IRE	2.207***
ISR	1.214***
ITA	-0.138
JAP	3.942***
MEX	-0.216***
NOR	0.141
POR	-1.283***
QAT	-6.412***
RUS	-3.421***
SAF	-0.042***
SAU	-5.489***
SPA	-0.667***
SWE	2.300***
TUR	-0.126***
UAE	-0.480***
UKI	0.688***
USA	2.304***

Table 3: Results of $y2$ in equation (1) for the whole period
Note: Grey highlighted countries for which $y2$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Own elaboration.

Results of herding behavior in the four periods considered as per equation (1) are presented in Table 4. Considering the periods of crisis, China, Finland, Indonesia, Italy, Japan, Mexico, Qatar, South Africa, Saudi Arabia, and the United Arab Emirates presented a significant negative result in the 2008 crisis. Regarding the Covid-19 crisis, Argentina, Canada, China, Egypt, Finland, India, Indonesia, Italy, Mexico, Portugal, Qatar, South Africa, Saudi Arabia, Spain, and the United Arab Emirates, presented significant negative result exhibiting evidence of herding behavior in these markets. It is worth highlighting that Table 4 allows us not to reject H2, i.e., the hypothesis that herding behavior is more present in times of crises. The results show that more countries exhibited herding behavior during periods of financial turmoil compared to stable periods, with herding being more widespread during the Covid-19 crisis than during the 2008 crisis.

Country	Before 2008 crisis	2008 Crisis	Before 2019 Covid crisis	Covid 19 Crisis
ARG	-0.214**	0.039***	-0.126***	-0.341**
AUS	1.886***	0.010***	0.313***	0.006***
BRA	-1.552***	0.221***	0.021***	0.134***
CAN	2.121***	1.673***	0.216**	-0.982***
CHL	1.296***	0.005***	0.563***	0.234***
CHN	-4.336***	-3.915***	1.783***	-0.012***
DEN	4.867***	0.010***	1.211***	0.043***
EGY	4.314***	0.988***	-0.443***	-1.241***
FIN	0.134***	-0.459**	0.122*	-0.012**
FRA	1.544***	0.010***	1.538***	0.012***
GER	1.495***	0.015***	1.312***	1.742***
HOK	1.541***	0.110***	6.312***	0.021***
IND	1.843***	0.065***	1.312***	-0.998**
INA	0.198	-0.413**	0.377**	-0.174*
IRE	8.759***	1.567***	1.298***	0.011***
ISR	0.563	1.388***	0.208	0.076***
ITA	-0.431	-0.431**	1.275***	-0.308***
JAP	6.662***	-1.351***	2.379***	1.284***
MEX	-9.874***	-1.335***	-3.785***	-0.014***
NOR	-0.350	0.004***	0.131**	0.010***
POR	4.331***	0.012***	0.065	-1.138***
QAT	0.964***	-1.664***	-2.873***	-2.531***
RUS	1.438***	0.732***	0.387***	1.883***
SAF	-3.778***	-3.043***	-3.987***	-0.366**
SAU	1.379***	-2.312***	-2.102***	-1.564***
SPA	7.785***	0.037***	1.045 ***	-0.883***
SWE	1.941***	0.012***	0.558**	0.005***
TUR	0.022	0.004***	0.425***	1.746***
UAE	-0.549*	-1.115***	0.310**	-1.437**
UKI	4.769***	0.007***	0.546***	1.009**
USA	2.664***	0.012***	0.239*	0.015***

Table 4: Results of y2 in equation (1) by periods

Note: Grey highlighted countries and periods for which $y2$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Source: Own elaboration

Country	Before 2008 crisis		2008 crisis		Before Covid-19 crisis		Covid-19 crisis	
	$y2^{\sigma 2,H}-y2^{\sigma 2,L}$	$t-stat$	$y2^{\sigma 2,H}-y2^{\sigma 2,L}$	$t-stat$	$y2^{\sigma 2,H}-y2^{\sigma 2,L}$	$t-stat$	$y2^{\sigma 2,H}-y2^{\sigma 2,L}$	$t-stat$
ARG	1.501***	4.034***	-2.152*	-0.643*	-1.221*	-1.129*	-0.521	-0.443*
AUS	-1.440***	-4.642***	-0.583***	-0.433***	-0.254***	-0.211***	-0.867***	0.544***
BRA	-1.554	-0.998	-0.420	-0.843*	-0.021	-0.387	0.118***	2.889***
CAN	-4.886***	-1.647***	-0.214	-1.780	-1.541*	-1.008***	0.431	0.687*
CHL	-0.118	-0.663	-2.388	-1.409	-0.381	-1.487	-2.546*	-1.461*
CHN	-1.998	0.387	-1.643	-0.443*	-1.123	-1.098	-5.433*	-4.398*
DEN	-5.438**	-2.209**	-2.311*	-1.212	-3.874***	-2.341***	-5.009*	-0.820**
EGY	1.873**	8.831**	2.092	-1.004	-0.338*	-0.738*	-0.885	-2.576**
FIN	-2.026***	-3.360***	0.401	0.488*	-0.288**	-0.380**	-4.458**	-0.298
FRA	-0.732	-0.440	0.221	0.366	-0.503	-1.253	-0.354	-1.313*
GER	1.213	0.312	-1.541	-0.662**	-1.115**	-1.731**	-1.554*	-2.353***
HOK	-5.438	-1.958	-0.531	-0.439**	-6.531***	-8.475***	-10.869***	-0.776**
IND	-10.785***	-11.110***	-2.709***	-3.218***	-2.011*	-1.307*	-3.341	-1.909*
INA	-7.658***	-3.332***	-1.248*	-1.346*	0.124	0.158	-3.553*	-0.109*
IRE	-3.221**	-1.887**	1.041	0.746	-2.253***	-1.784***	-0.641	-0.743
ISR	-14.451***	-10.131***	-2.144***	-2.093**	-1.783**	-1.443**	-1.313	-1.776***
ITA	-1.094	-0.335	-3.338	-1.774**	-5.789***	-1.101***	-7.448***	-3.317**
JAP	11.321***	7.554***	6.658***	6.221***	15.583***	9.958***	-2.553***	2.311**
MEX	4.368***	9.764***	5.483***	5.473***	3.778***	4.322***	2.009**	-4.093***
NOR	-4.531***	-3.471**	-0.334***	-0.641*	-1.312**	-1.099**	-3.312**	-2.013***
POR	-4.331**	-1.177*	-4.086***	-2.127***	-5.313***	-3.306***	-11.781**	-2.154**
QAT	11.384***	3.039***	-1.413**	-1.337**	-0.109*	-0.433*	1.537*	0.431*
RUS	-8.864***	-4.431***	0.663*	1.554*	6.416***	4.873***	8.648***	3.281***
SAF	11.875***	5.478***	2.208**	1.459*	-2.088*	-1.124*	7.574***	10.845***
SAU	7.523***	4.313***	0.830**	0.135**	1.012*	0.882*	0.312*	-0.431*
SPA	-2.115*	-1.085*	-2.116***	-2.463***	-6.874***	-7.568***	-1.323*	0.694*
SWE	-2.641***	-2.753***	-2.004***	-3.464***	-2.235*	-1.531*	-0.654	-1.241***
TUR	-0.222*	-1.471*	-0.794*	-1.114*	-1.095***	-2.295***	-3.811***	-0.105**
UAE	-0.985	-0.743	-0.115**	-0.605**	-3.475***	-1.584***	-0.284***	-0.141*
UKI	0.436	0.250	0.296***	0.641***	3.124***	3.271***	-0.196*	0.236*
USA	-1.312***	-4.853***	-1.009***	-2.115***	-7.531***	-10.784***	-5.541***	-2.295***

Table 5: Volatility - Wald Test
Note: Grey highlighted countries and periods for which $y2^{\sigma 2,H}=y2^{\sigma 2,L}$; ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively, of t-statistics.
Source: Own elaboration.

Regarding the volatility, results of the Wald test described in Section 3 are shown in Table 5 (grey highlighted those countries and periods for which the Wald test is not statistically significant, i.e., the null hypothesis is not rejected and so $y2^{\sigma2,H} = y2^{\sigma2,L}$). Overall, considering all periods, we witness that most countries present different herding coefficients related to volatility during the analyzed periods. When we compare the two periods of crises, we notice that the number of markets that rejected the null hypothesis (Wald test statistically significant) in the 2008 crisis is lower compared to the Covid-19 crisis considering the impact of volatility on herding behavior.

Analyzing the periods of crises individually, we find that during the 2008 crisis the results for Argentina, Australia, Brazil, China, Finland, Germany, Hong Kong, India, Indonesia, Israel, Italy, Japan, Mexico, Norway, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, Sweden, Turkey, the United Arab Emirates, the United Kingdom, and the United States of America suggest the presence of asymmetric herding behavior because the null hypothesis is rejected. Meanwhile during the Covid-19 crisis, all markets rejected the null hypothesis, except Finland and Ireland.

Table 6 and 7 present the results of equations (7) and (8), regarding the volatility and the presence of herding, only for those countries for which $y2^{\sigma2,H} \neq y2^{\sigma2,L}$. Before analyzing the periods of high and low volatility individually, it is possible to identify that there are more cases with the presence of herding behavior during periods of high volatility than low volatility, as can be seen by comparing Tables 6 and 7, being more present in the period of the Covid-19 crisis.

Country	Before 2008 crisis	2008 crisis	Before Covid-19 crisis	Covid-19 crisis
ARG	0.001***	-0.238**	-0.133***	-0.413***
AUS	1.586**	0.004	0.839*	0.005***
BRA	N/A	-0.330**	N/A	-0.122***
CAN	21.942***	N/A	0.001***	0.753*
CHL	N/A	N/A	N/A	0.001***
CHN	N/A	-5.638**	N/A	-16.033***
DEN	5.461***	N/A	5.121***	0.003***
EGY	3.415***	N/A	0.543*	-0.112**
FIN	0.454***	-0.443***	0.123***	N/A
FRA	N/A	N/A	N/A	0.683**
GER	N/A	1.185**	1.913***	0.006***
HOK	N/A	0.483***	8.967***	0.003***
IND	2.461***	0.006***	1.225**	-0.105**
INA	0.249	-1.255**	N/A	-0.425*
IRE	13.246***	N/A	4.599**	N/A
ISR	1.144*	1.904***	0.001*	0.455
ITA	N/A	-0.337**	1.293***	-0.604*
JAP	3.872***	-0.002	2.984	2.339**
MEX	-10.919***	-0.005***	-4.078***	1.658**
NOR	0.012	0.009	0.005**	0.007***
POR	7.506***	0.007***	0.002***	-2.286***
QAT	1.397***	-5.926***	-3.757***	-5.144***

RUS	11.255***	4.371*	0.766*	-0.857**
SAF	-7.468***	-4.790***	-4.912***	-0.520***
SAU	6.901***	-1.413***	-3.101***	-2.785***
SPA	8.742***	0.003***	0.973***	-0.319**
SWE	1.260*	0.003***	0.001***	0.856**
TUR	-1.031**	-1.475**	0.418***	-1.367***
UAE	N/A	-0.483*	0.689***	-0.774**
UKI	N/A	0.978	2.034***	-0.415*
USA	2.122**	0.005***	0.835*	1.135**

Table 6: Results of $y2^{\sigma 2,H}$ in equation (7) by periods
Note: Grey highlighted countries and periods for which $y2^{\sigma 2,H}$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Own elaboration.

During high volatility periods, herding behavior was reported (Table 6) during the crisis of 2008 in Argentina, Brazil, China, Finland, Indonesia, Italy, Mexico, Qatar, South Africa, Saudi Arabia, Turkey, and the United Arab Emirates. Table 6 also shows that during the Covid-19 crisis, herding was evidenced in Argentina, Brazil, China, Egypt, India, Indonesia, Italy, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, Turkey, the United Arab Emirates, and the United Kingdom suggesting that volatility is a driving factor of this behavior in these markets. A characteristic that can be evidenced from these results is that most of the markets are developing or emerging markets. The results show that herd behavior was more noticeable during the Covid-19 crisis.

Country	Before 2008 crisis	2008 crisis	Before Covid-19 crisis	Covid-19 crisis
ARG	-2.125***	0.243**	0.003***	0.021
AUS	8.168***	0.002***	1.844***	0.001***
BRA	N/A	0.143**	N/A	-1.453***
CAN	8.754***	N/A	0.009***	0.205***
CHL	N/A	N/A	N/A	0.034**
CHN	N/A	-0.214**	N/A	-12.641***
DEN	2.341***	N/A	3.586***	0.005***
EGY	-8.425***	N/A	0.685*	0.351
FIN	-5.655	0.648**	-0.759**	N/A
FRA	N/A	N/A	N/A	0.326**
GER	N/A	0.985***	1.120***	0.006***
HOK	N/A	0.431**	3.759**	0.001
IND	3.475***	-2.658***	2.543**	-0.538*
INA	3.535***	0.006**	N/A	0.030***
IRE	11.965***	N/A	6.531***	N/A
ISR	1.353*	3.125***	1.002*	0.439
ITA	N/A	0.953**	1.435***	0.464*
JAP	-0.596***	5.896***	4.573	4.316***
MEX	-5.993***	-3.431***	-4.679***	0.005***
NOR	2.875	0.998*	0.004***	0.057***
POR	3.759***	1.198*	0.001***	1.850**
QAT	-13.749***	0.374**	0.996*	4.375

RUS	9.976***	-1.274**	0.094***	0.841**
SAF	-15.964**	-6.552***	-7.471***	-5.217***
SAU	-6.384***	-4.371**	0.005***	-1.198
SPA	8.210***	0.123***	0.032***	0.094***
SWE	1.569**	2.487*	0.002***	0.764***
TUR	0.510	1.658*	0.864	0.048
UAE	N/A	0.573**	2.475***	0.005**
UKI	N/A	0.547**	-1.475***	0.413***
USA	1.778**	0.095***	0.104***	0.005***

Table 7: Results of $y2^{\sigma 2,L}$ in equation (8) by periods
Note: Grey highlighted countries and periods for which $y2^{\sigma 2,L}$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Own elaboration.

Table 7 includes results during low volatility days. During the period of the 2008 crisis, China, India, Mexico, Russia, South Africa, and Saudi Arabia presented a significant negative result for the herding coefficient. In the Covid-19 crisis, Brazil, China, India, and South Africa showed presence of herding.

Based on the results described in the previous paragraphs concerning volatility, we do not reject hypothesis H3. Our findings indicate that market volatility has a significant effect on herding behavior, being more prevalent during periods of financial crisis than in non-crisis periods.

In relation to the analysis of trading volume and the presence of herding behavior, Table 8 shows the results of the Wald. It can be seen that most countries have different herding coefficients in the analyzed periods (grey highlighted those countries and periods for which the Wald test is not statistically significant, i.e., the null hypothesis is not rejected and so $y2^{V,H} = y2^{V,L}$). When the two periods of crises are compared, we notice that the number of markets that rejected the null hypothesis are very similar in both crises.

Moreover, considering the crisis of 2008, we find that for Argentina, Australia, Brazil, China, Egypt, Finland, Germany, Hong Kong, India, Indonesia, Israel, Italy, Mexico, Norway, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, Sweden, Turkey, the United Arab Emirates, the United Kingdom, and the United States of America the null hypothesis of symmetric herding behavior is rejected. However, Canada, Chile, Denmark, France, Ireland, and Japan evidenced a symmetry of herding behavior. During the Covid-19 pandemic crisis, all markets rejected the null hypothesis, except Australia, Canada, Ireland, Israel, and Sweden, indicating symmetric in herding coefficients during high and low trading volume periods.

Country	Before 2008 crisis		2008 crisis		Before Covid-19 crisis		Covid-19 crisis	
	$y2^{V,H}-y2^{V,L}$	$t-stat$	$y2^{V,H}-y2^{V,L}$	$t-stat$	$y2^{V,H}-y2^{V,L}$	$t-stat$	$y2^{V,H}-y2^{V,L}$	$t-stat$
ARG	1.341***	3.714***	-1.473*	-0.553*	-1.004*	-1.241*	-0.663**	-0.743**
AUS	-1.531	-2.221	-0.887***	-0.251***	-0.288***	-0.104***	1.313	0.776
BRA	-2.458	-0.114	-0.664*	-0.337*	-0.059	-0.124	0.156***	0.005***
CAN	-2.341***	-0.458***	-0.199	-0.051	-1.314**	-1.864***	0.118	0.493
CHL	-0.115**	-0.070**	-1.593	-0.514	-0.259	-1.563	-1.846*	-1.998*
CHN	-2.459**	0.661**	-1.006**	-0.877**	-1.583	-1.531	-4.332**	-4.047**
DEN	-1.475**	-2.491**	-1.413	-1.004	-2.538***	-2.064**	-3.414*	-0.553*
EGY	1.639**	2.331**	0.499**	-1.049**	-0.344*	-0.249*	-0.774**	-1.495**
FIN	-1.573***	-2.583***	0.330*	0.441*	-0.593**	-0.250**	-1.771**	-0.353**
FRA	-0.435	-0.849	0.115	0.745	-0.312	-1.475	-0.214*	-1.531*
GER	1.008	0.055	-1.195	-0.453**	-1.339**	-1.149**	-1.356*	-2.435***
HOK	-5.400	-1.253	-0.275	-0.284**	-4.353***	-2.414***	-8.573***	-0.385**
IND	-7.475***	-9.481***	-1.284***	-3.241***	-1.485**	-1.105**	-2.756**	-2.004**
INA	-3.475***	-2.475***	-0.051*	-1.495*	0.133	0.070	-3.249*	-0.593*
IRE	-2.485**	-1.513**	1.134	0.531	-1.482***	-1.438***	-0.453	-0.556
ISR	-7.573***	-6.005***	-1.535***	-1.584**	-1.385**	-1.115**	-1.313	-1.459
ITA	-1.459	-0.250	-3.115*	-1.553**	-2.583***	-1.059***	-7.448***	-3.317**
JAP	9.957	6.414	3.584	2.483	10.583***	3.358***	-2.110***	2.009**
MEX	2.458***	1.586***	2.485***	4.384***	2.485***	3.485***	1.493**	-2.773***
NOR	-3.485***	-2.485**	-0.204***	-0.483*	-1.694**	-1.294**	-2.483**	-1.485***
POR	-2.483**	-1.059**	-4.385***	-2.492***	-2.495***	-1.495***	-7.583**	-1.437**
QAT	3.475***	1.495***	-1.778**	-1.097**	-0.148*	-0.285*	1.105*	0.228*
RUS	-5.683***	-2.474***	0.850*	1.257*	2.372***	2.174***	1.382***	0.489***
SAF	7.371***	2.485***	2.105**	1.095*	-1.471*	-1.494*	6.463***	8.846***
SAU	2.475***	2.354***	0.830**	0.147**	1.114*	0.440*	0.377*	-0.104*
SPA	-2.115*	-1.085*	-2.385***	-0.491***	-6.220***	-4.573***	-1.109*	0.605*
SWE	-1.48***	-2.094***	-1.485***	-2.573***	-2.109*	-1.374*	-0.394	-1.104
TUR	-0.104*	-1.254*	-0.857*	-1.094*	-0.948***	-1.049***	-2.485***	-0.094**
UAE	-0.274	-0.140	-0.374**	-0.583**	-1.385***	-1.106***	-0.718***	-0.091*
UKI	0.259	0.150	0.185***	0.358***	2.184***	2.499***	-0.149*	0.200*
USA	-1.093	-4.491	-1.394***	-1.493***	-4.314***	-3.583***	-2.493***	-0.310***

Table 8: Trading volume - Wald Test

Note: Grey highlighted countries and periods for which $y2^{V,H}=y2^{V,L}$; ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively, of t-statistics.

Source: Own elaboration.

Table 9 reports the results of high trading volume periods. During the crisis of 2008, Argentina, Brazil, China, Egypt, Portugal, Qatar, South Africa, Saudi Arabia, and the United Arab Emirates have a significant negative result, suggesting presence of herding in these markets. During the pandemic crisis of Covid-19, Argentina, Brazil, China, Egypt, Finland, India, Italy, Mexico, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, and the United Arab Emirates show presence of herding behavior, being more present in this period than in the 2008 crisis.

Country	**Before 2008 crisis**	**2008 crisis**	**Before Covid-19 crisis**	**Covid-19 crisis**
ARG	-0.294	-0.079***	-0.239**	-2.394***
AUS	N/A	0.348***	0.344***	N/A
BRA	N/A	-1.483**	N/A	-1.495***
CAN	4.584***	N/A	-0.394***	N/A
CHL	-3.347**	N/A	N/A	0.010***
CHN	-3.613***	-4.383***	N/A	-2.485***
DEN	1.495**	N/A	3.483***	0.010***
EGY	-8.493***	-4.384**	-0.583***	-4.789***
FIN	0.497***	0.734**	0.482	-0.009***
FRA	N/A	N/A	N/A	0.023***
GER	N/A	1.249**	2.843***	1.385***
HOK	N/A	0.485***	13.485***	4.585***
IND	-1.589***	0.596**	0.571***	-1.998***
INA	0.055	-1.405	N/A	0.053***
IRE	5.381***	N/A	3.584***	N/A
ISR	1.334	1.195***	0.039***	N/A
ITA	N/A	0.005***	1.277***	-0.459**
JAP	N/A	N/A	1.009***	2.774**
MEX	-4.384***	0.903***	0.931	-0.304*
NOR	3.843***	-0.431	1.493**	3.588***
POR	3.598*	-0.010***	0.058***	-1.485***
QAT	-4.856***	-6.573***	-3.221***	-4.785***
RUS	4.588***	0.961*	0.588	-2.471*
SAF	-3.495***	-0.488**	-3.475***	-0.095***
SAU	2.385***	-2.401***	-1.304***	-1.725***
SPA	4.348***	0.013***	1.391***	-1.255***
SWE	1.394***	0.049***	0.403*	N/A
TUR	2.495***	0.319***	0.229***	0.010***
UAE	N/A	-1.493***	1.220***	-1.384***
UKI	N/A	0.984***	1.403***	1.914***
USA	N/A	0.014***	0.994*	0.039***

Table 9: Results of $y2^{V,H}$ in equation (10) by periods

Note: Grey highlighted countries and periods for which $y2^{V,H}$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Source: Own elaboration.

Considering periods of low trading volume in Table 10, Argentina, Egypt, Italy, Portugal, Qatar, South Africa, Saudi Arabia, and the United Arab Emirates present a significant negative result of the coefficient γ2 on the 2008 crisis. Meanwhile Argentina, Brazil, Egypt, India, Italy, Mexico, Portugal, Qatar, South Africa, Saudi Arabia, Spain, and the United Arab Emirates have the same result during the Covid-19 crisis. Herding behavior had a greater presence over the Covid-19 crisis than in the crisis of 2008.

Comparing Tables 9 and 10, we identify that where herding behavior prevails in both crises (Argentina, Egypt, Portugal, Qatar, South Africa, Saudi Arabia and the United Arab Emirates), it is almost always more pronounced in periods of high trading volume than in periods of low trading volume. Moreover, herding behavior is more present in the period of the Covid-19 crisis, during both low trading and high trading volume days, than in the 2008-crisis.

To conclude the findings of the previous paragraphs, we do not reject H4. It has been observed that trading volume plays a significant role on various markets affecting herding behavior across all periods, particularly during crises.

Country	Before 2008 crisis	2008 crisis	Before Covid-19 crisis	Covid-19 crisis
ARG	-0.114**	-0.055***	-0.200**	-1.384***
AUS	N/A	0.249***	0.104***	N/A
BRA	N/A	0.998**	N/A	-1.774***
CAN	3.594***	N/A	-0.224***	N/A
CHL	2.495**	N/A	N/A	0.009***
CHN	0.789	0.448	N/A	-0.593
DEN	1.394**	N/A	2.485***	0.025***
EGY	-2.840***	-3.485**	-0.443***	-4.789***
FIN	0.559***	0.284**	-0.482	0.010***
FRA	N/A	N/A	N/A	0.014***
GER	N/A	0.887**	1.948***	1.221***
HOK	N/A	0.348***	7.473***	2.484***
IND	-1.129***	0.294**	0.449***	-2.485***
INA	0.045	-0.958	N/A	0.024***
IRE	2.483***	N/A	1.856***	N/A
ISR	0.085***	1.285***	0.054***	N/A
ITA	N/A	-0.008***	1.494***	-0.320**
JAP	N/A	N/A	1.283***	3.474**
MEX	-2.385***	0.910***	0.658	-0.277*
NOR	1.284***	-0.454	1.499**	2.476***
POR	2.375*	-0.009***	0.020***	-1.174***
QAT	-2.585***	-4.378***	-1.857***	-2.857***
RUS	2.475***	0.875*	0.493	-1.574
SAF	-4.869***	-0.367**	-2.574***	-0.057***
SAU	1.465***	-2.486***	-1.355***	-1.098***
SPA	2.375***	0.056***	1.209***	-1.579***
SWE	0.988	0.105***	0.207**	N/A

TUR	1.109***	0.299***	0.333***	0.012***
UAE	N/A	-1.223***	1.621***	-1.009***
UKI	N/A	0.764***	1.554***	1.421***
USA	N/A	0.039***	0.847*	0.009***

Table 10: Results of $y2^{V,L}$ in equation (11) by periods
Note: Grey highlighted countries and periods for which $y2^{V,L}$ is negative and statistically significant; ***,** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Own elaboration.

5. CONCLUSION

This article aims to verify the existence of herding behavior during the 2008 and Covid-19 crises, particularly in the aftermath of the latter, and to analyze the impact of volatility and trading volume on markets that have not been thoroughly investigated over an extended period. By examining the Covid-19 crisis up to the point it ended, we provide a detailed assessment of how herding behavior evolved throughout the crisis. This approach enhances our understanding of market dynamics during critical periods and offers new perspectives for future research.

Using a sample from the main indexes of 31 financial markets over the period from January 2000 to May 2023, we find evidence of herding during the whole period, during the different periods of crises, during both high and low volatility periods, and during both high and low trading volume periods.

Throughout the entire period analyzed, Argentina, Canada, Chile, China, Egypt, Finland, India, Indonesia, Mexico, Portugal, Qatar, Russia, South Africa, Saudi Arabia, Spain, Turkey, and the United Arab Emirates exhibited evidence of herding in their markets. These results partially align with the findings of Rubesam and Junior (2022), Yang and Chuang (2022), and Zhang et al. (2024). Rubesam and Junior (2022) examine herding behavior from 2001 to 2021 across 10 countries, including all those analyzed in our study, and also find that herding persisted throughout the period. Yang and Chuang (2022) identify significant evidence of herding in China, Taiwan, and the United States of America, although their study covers only the period from 2001 to 2021, without the analysis of the complete Covid-19 pandemic. Zhang et al. (2024), considering a shorter period (from 2006 to 2022) and using monthly data, observe presence of herding in Brazil, China, India, Russia, and South Africa.

Our study shows that herding behavior was more prevalent during crises, particularly throughout the Covid-19 crisis, across all observed markets. Similar findings are reported by Xing et al. (2024), who analyze two time periods (2005-2010 and 2019-2021), and observe the greatest presence of herding during Covid-19 in China, while the United States of America showed no evidence of herding in any crisis, which aligns with our results despite their smaller sample. Rubesam and Junior (2022), however, find herding to be more pronounced before crises rather than during them, contrasting with our findings of increased herding during crises, which is based on a larger sample and broader set of markets. Specifically, during the Covid-19 period, they report no evidence of herding in Australia, Belgium, Japan, and the United Kingdom, while Italy, Sweden, and the United States of America exhibited herding, and Brazil and France only showed herding for shorter periods. In contrast, our study finds evidence of herding in Argentina, Canada, China, Egypt, Finland, India, Indonesia, Italy, Mexico, Portugal, Qatar, South Africa, Saudi Arabia, Spain, and the United Arab Emirates, with no herding detected in the other countries during the Covid-19 crisis. Yang and Chuang (2022) report the presence of herding only in China and Taiwan during the Covid-19 pandemic and not in the United States of America, converging with our study.

When considering volatility, we find that herding was more prevalent during high volatility periods compared to low volatility periods, which is consistent with Arjoon et al. (2020). When examining the crises individually, herding was more frequent during high volatility periods of the Covid-19 pandemic and during low volatility periods of the 2008 crisis.

Regarding trading volume, herding was slightly more common during high trading volume periods than during low trading volume periods. Additionally, herding was more frequent in both crises during high trading volume days compared to low trading volume days, which is consistent with Jlassi and BenSaïda (2014) and Economou et al. (2015).

Considering the analysis of both crises in their entirety, including up to the point when they were officially declared over, our article provides substantial empirical evidence on the effects of herding behavior in markets. This comprehensive approach enhances the existing literature by offering new insights into how herding behavior evolves across different crises and its persistence until their conclusion. This contribution deepens our understanding of market dynamics and informs future research in this area.

Moreover, the increased occurrence of herding during crises such as the 2008 global financial crisis and the Covid-19 pandemic underscores the dominance of emotional responses over rational decision-making in turbulent market conditions. This study highlights the need for greater awareness and measures to mitigate market disruptions in future crises.

Future research should explore the impact of macroeconomic policies and government interventions on herding behavior during crises. Given that herding was more pronounced during periods of high volatility and trading volume, it would be valuable to examine how different policy responses influence this behavior. Additionally, investigating the role of technological advancements and digital trading platforms in shaping herding behavior could provide deeper insights into contemporary financial market dynamics. On the other hand, our study could be complemented by using alternative models or techniques to measure herding behavior, such as the CSAD quartile (Indārs et al., 2019; Arjoon et al., 2020) or window regression (Economou et al., 2015; Kumar et al., 2020).

6. REFERENCES

Arjoon, V., Bhatnagar, C. S., & Ramlakhan, P. (2020). Herding in the Singapore stock Exchange. *Journal of Economics and Business, 109*, 105889. https://doi.org/10.1016/j.jeconbus.2019.105889

Babalos, V., Stavroyiannis, S., & Gupta, R. (2015). Do commodity investors herd? Evidence from a time-varying stochastic volatility model. *Resources Policy, 46*, 281–287. https://doi.org/10.1016/j.resourpol.2015.10.011

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy, 100 (5)*, 992–1026. https://doi.org/10.1086/261849

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Paper*. Retrieved on January 16, 2024. http://www.imf.org/External/Pubs/FT/staffp/2001/01/pdf/bikhchan.pdf

Chang, E., Cheng, J., & Khorona, A. (2000). An examination of Herding behavior in equity markets: an international perspective. *Journal of Banking & Finance, 24 (10)*, 1651-1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Chang, C. L., McAleer, M., & Wang, Y. A. (2020). Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. *Renewable and Sustainable Energy Reviews*, *134*, 110349. https://doi.org/10.1016/j.rser.2020.110349

Chen, T. (2021). Does Country Matter to Investor Herding? Evidence from an Intraday Analysis. *Journal of Behavioral Finance, 22 (1)*, 56–64. https://doi.org/10.1080/15427560.2020.1716760

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance*, *34 (8)*, 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, *51 (4)*, 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Daniel, K., Hirshleifer, D., & Teoh, S. H. (2002). Investor psychology in capital markets: evidence and policy implications. *Journal of Monetary Economics*, *49 (1)*, 139-209. https://doi.org/10.1016/S0304-3932(01)00091-5

Delitala, M., & Lorenzi, T. (2014). A mathematical model for value estimation with public information and herding. *Kinetic and Related Models*, *7*, 29-44. https://doi.org/10.3934/krm.2014.7.29

Demirer, R., Leggio, K. B., & Lien, D. (2019). Herding and flash events: Evidence from the 2010 Flash Crash. *Finance Research Letters*, 1–4. https://doi.org/10.1016/j.frl.2018.12.018

Dhall, R., & Singh, B. (2020). The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market. *Millennial Asia*, *11 (3),* 366-390. https://doi:10.1177/0976399620964635

During, B., Juengel, A., & Trussardi, L. (2017). A Kinetic Equation for Economic Value Estimation with Irrationality dnd Herding. *Kinetic and Related Models*, *10 (1)*, 239-261. https://doi.org/10.3934/krm.2017010

Economou, F. (2017). Herding in the Athens stock exchange during different crisis periods. In *Handbook of Investors' Behavior during Financial Crises*, edited by F. Economou, K. Gavriilidis, G.N. Gregoriou and V. Kallinterakis (Academic Press). https://doi.org/10.1016/B978-0-12-811252-6.00017-7

Economou, F., Gavriilidis, K., & Goyal, A. (2015). Herding dynamics in exchange groups: Evidence from Euronext. *Journal of International Financial Markets, Institutions & Money*, *34*, 228–244. https://doi.org/10.1016/j.intfin.2014.11.013

Enders, C. K. (2010). *Applied missing data analysis.* Guilford Press.

Espinosa-Méndez, C., & Arias, J. (2021). COVID-19 effect on herding behaviour in European capital markets. *Finance Research Letters*, *38*, 101787. https://doi.org/10.1016/j.frl.2020.101787

Galariotis, E. C., Krokida, S. I., & Spyrou, S. I. (2016). Herd behavior and equity market liquidity: Evidence from major markets. *International Review of Financial Analysis*, *48*, 140–149. https://doi.org/10.1016/j.irfa.2016.09.013

Hair, J. F., Tatham, R. L., Anderson, R. E., & Black, W. C. (2005). *Multivariate Data Analysis*. Bookman.

Hwang, S., & Salmon, M. (2004). Market Stress and Herding. *Journal of Empirical Finance*, *11 (4)*, 585-616. https://doi.org/10.1016/j.jempfin.2004.04.003

Indārs, E. R., Savin, A., & Lublóy, Á. (2019). Herding behaviour in an emerging market: Evidence from the Moscow Exchange. *Emerging Markets Review*, *38*, 468–487. https://doi.org/10.1016/j.ememar.2018.12.002

Jiang, R., Wen, C., Zhang, R., & Gui, Y. (2022). Investor's herding behavior in Asian equity markets during COVID-19 period. *Pacific-Basin Finance Journal, 73,* 101494. https://doi.org/10.1016/j.pacfin.2022.101771

Jlassi, M., & BenSaïda, A. (2014). Herding Behavior and Trading Volume: Evidence from the American Indexes. *International Review of Management & Business Research*, *3 (2)*, 705–722.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263–292. https://doi.org/10.2307/1914185

Kizys, R., Tzouvanas, P., & Donadelli, M. (2021). From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. *International Review of Financial Analysis*, *74*, 101663. https://doi.org/10.1016/j.irfa.2021.101663

Kumar, A., Badhani, K. N., Bouri, E., & Saeed, T. (2020). Herding behavior in the commodity markets of the Asia-Pacific region. *Finance Research Letters*, *41*, 101813. https://doi.org/10.1016/j.frl.2020.101813

Lakonishok, J., Shleifer, A., & Vishny, W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32 (1)*, 23–44. https://doi.org/10.1016/0304-405X(92)90023-Q

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics*, *22 (6)*, 495–506. https://doi.org/10.1016/j.asieco.2011.08.001

Litimi, H., BenSaïda, A., & Bouraoui, O. (2016). Herding and excessive risk in the American stock market: A sectoral analysis. *Research in International Business and Finance*, *38*, 6–21. https://doi.org/10.1016/j.ribaf.2016.03.008

Luu, Q. T., & Luong, H. T. T. (2020). Herding behavior in emerging and frontier stock markets during pandemic influenza panics. *Journal of Asian Finance, Economics and Business*, *7 (9)*, 147–158. https://doi.org/10.13106/jafeb.2020.vol7.no9.147

Maquieira, C., & Espinosa-Méndez, C. (2022). Herding behavior in the Chinese stock market and the impact of COVID-19. *Estudios de Economia, 49,* 199-229. Retrieved on February 20, 2024. https://estudiosdeeconomia.uchile.cl/index.php/EDE/article/view/69083

Merli, M., & Roger, T. (2012). What Drives the Herding Behavior of Individual Investors? *Finance*, *34 (3)*, 67-104. https://doi.org/10.3917/fina.343.0067

Messaoud, D., & Ben Amar, A. (2024). Herding behaviour and sentiment: evidence from emerging markets. *EuroMed Journal of Business.* https://doi.org/10.1108/EMJB-08-2023-0209

Metawa, N., Metawa, S., Metawea, M., & El-Gayar, A. (2024). Asymmetry risk and herding behavior: a quantile regression study of the Egyptian mutual funds. *Journal of Risk Finance, 25*, 366-381. https://doi.org/10.1108/JRF-10-2023-0252

Mobarek, A., Mollah, S., & Keasey, K. (2014). A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, *32*, 107–127. https://doi.org/10.1016/j.intfin.2014.05.008

Nguyen, H. M., Bakry, W., & Vuong, T. H. G. (2023). COVID-19 pandemic and herd behavior: Evidence from a frontier market. *Journal of Behavioral and Experimental Finance 38*. https://doi.org/10.1016/j.jbef.2023.100807

Rubesam, A., & Junior, G. S. R. (2022). Covid-19 and herding in global equity markets. *Journal of Behavioral and Experimental Finance, 35*. https://doi.org/10.1016/j.jbef.2022.100672

Shah, A. K., & Oppenheimer, D. M. (2008). Heuristics Made Easy: An Effort-Reduction Framework. *Psychological Bulletin, 134 (2)*, 207–222. https://doi.org/10.1037/0033-2909.134.2.207

Sias, W. R. (2004). Institutional Herding. *The Review of Financial Studies, 17 (1),* 165-206. https://doi.org/10.1093/rfs/hhg035

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific Basin Finance Journal, 16 (1-2)*, 61–77. https://doi.org/10.1016/j.pacfin.2007.04.004

Toscani, G. (2006) Kinetic models of opinion formation. *Communications in Mathematical Sciences, 4 (3)*, 481-496. https://doi.org/10.4310/CMS.2006.v4.n3.a1

Vega, J. D. L. (1688). *Confusion de Confusiones*. Amsterdam, Baker Library, Harvard Graduate School of Business Administration, Boston, MA.

World Bank. (2021). *Market capitalization of listed domestic companies* (current US$). Retrieved on December 15, 2023. https://data.worldbank.org/

Yang, W., & Chuang, M. (2022). Do investors herd in a volatile market? Evidence of dynamic herding in Taiwan, China, and US stock markets. *Finance Research Letters,* 103364. https://doi.org/10.1016/j.frl.2022.103364

Xing, S., Cheng, T., & Sun, S. (2024). Do investors herd under global crises? A comparative study between Chinese and the United States stock markets. *Finance Research Letters, 62*. https://doi.org/10.1016/j.frl.2024.105120

Zhang, Y., Zhou, L., Liu, Z., & Wu, B. (2024). Herding behaviour towards high order systematic risks and the contagion Effect—Evidence from BRICS stock markets. *The North American Journal of Economics and Finance, 74*. https://doi.org/10.1016/j.najef.2024.102219