

Impact of Investor Sentiments in Response to Local and Global Mega Events on Herding Behavior

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Abstract

This paper investigates herding behavior derived from investor sentiments based on local and global mega-events. Four countries are considered to have different backgrounds, e.g., developed, emerging, and developing economies, including the USA, Russia, China, and Pakistan. We used daily stock return data from 2006 to 2021. We also used an intense set of investor sentiment through Twitter. The study uses the CSAD approach to measure herding and reveals no evidence of herding found in selected countries except China. The study further explores the impact of investor sentiment on herding behavior during local and global mega-events, such as the USA election in 2016, the Russian-Ukraine War in 2014, the Hong Kong protest in 2014, and the Lahore blast in 2016. All events affect investor sentiment, leading to herding in all selected countries. The results found significant evidence from the USA to China and Pakistan for cross-country herding effect in the presence of investor sentiments. Furthermore, two-way herding spillover exists among Russia and China in the presence of mega events. The findings have implications for individual investors and institutions, as irrational herding behavior may lead to financial crises. Different policies and regulations could design a monitoring system to predict investor sentiment in response to local and global events that may cause herding, preventing volatility caused by irrational behavior.

Keywords: *Behavioral Finance, Herding Behavior, Investor Sentiment, Cross-Sectional Absolute Deviation.*

Jel classification: *G01, G11, G12, G40.*

1. INTRODUCTION

Investors behave rationally in the efficient market hypothesis (EMH) to maintain an optimal portfolio and maximise profits at a given level of risk (Fama, 1970). The market is considered efficient when all available information is reflected in the form of prices. Traditional finance deals with the rational working of markets. On the contrary, in behavioural finance, several scholars found that psychological biases play a significant role in investors' decision-making (Barberis & Thaler, 2003; Rehan et al., 2021; Ritter, 2003; Shiller, 2003). Most of the literature in the past two decades highlights the influence of unexpected results or anomalies in the financial market, which leads to inefficiency. One of those anomalies is herding, and many researchers have shown considerable interest in investigating how investor herds (Christie & Huang, 1995; Metwally, 2016; Yousaf et al., 2018)

Herding behaviour is a widespread financial aspect characterised by investor decisions being affected by a group of investors for a while (Yousaf & Alokla, 2022). Investors engage in herding when they ignore their personal beliefs in favour of their peers, which ultimately causes them to trade in the same pattern as their peers do (Nofsinger & Sias, 1999). Investors imitate each other after receiving new information in the market, and this behaviour usually expands throughout the market. A herding phenomenon impedes the market's ability to bring assets to their true valuations, resulting in market inefficiency. Investors typically prevent themselves from market inefficiency by diversifying their holdings (Blasco et al., 2012).

Herding in the market is a threat to financial stability (Yasir & Önder, 2022). When investors explore different markets to diversify their portfolios, there is a great chance that other markets will also show herding and the investor cannot foresee this risk. The same pattern emerged, particularly during the economic crises of the USA housing market in 2007 and 2008, leading to the collapse of Lehman Brothers in 2008 (Bekiros et al., 2017), the European debt crisis in 2010 (Hui & Chung, 2011), the Chinese stock market crash in 2015 (Wang et al., 2019). These crises, though different in nature but, highlight the global financial system's vulnerability to external shocks and the consistent impact of investor sentiment on market dynamics. These trends persisted during the unprecedented COVID-19 pandemic in 2020 (Ghorbel et al., 2022). Most countries took the pandemic seriously, and global financial markets stopped their operations. As a result, investors in the financial markets were worried about a global credit crunch because of a long-term pandemic. This situation leads to a volatile USA currency market, where investors sell their stock and create a vicious spiral. During this vicious spiral, most investors behave irrationally, which leads to herding and face losses in the long run because the stock regained its market value after a few months (C. L. Chang et al., 2020).

Herding behaviour is not only limited to one country or region; its effect is evident worldwide. Researchers have explored herding in different countries and time periods. For instance, Tauseef (2022) analyses firm-level daily data of the Pakistan Stock Exchange from 2001 to 2020 by examining calendar events and stock portfolios. The result showed that herding existed during the financial crisis. Mallek et al. (2022) found the impact of economic and political risks on herding in the Gulf Cooperation Council (GCC) from 2004 to 2020. Bougatef and Nejeh (2022) also found herding among Shariah-compliant stocks during COVID-19 using the Titans 25 Index from 2017 to 2021. Loang and Ahmad (2022) reported herding in the Malaysian stock market from 2016 to 2020 under market stress (bullish and bearish markets).

As discussed earlier, many researchers have investigated herding behaviour in several countries. Still, there exists a gap to study countries with different backgrounds, such as developed, emerging, and developing countries. This research addresses the above-mentioned research gap by studying herding behaviour in three sets of markets, i.e., the USA as developed markets, Russia and China as emerging markets, and Pakistan as a developing market. The recent literature has contributed a lot toward the exploration of herding anomalies in stock markets. However, this area is still underexplored. The existing literature lacks to explore the impact of social media sentiment on herding behavior in stock markets during multiple events. The literature also lacks an exploration of the spillover effect during megaevents. In this study, we calculated investor sentiment using an intensive set of social media tweets in response to local and global mega-events such as the USA election, Russia's invasion of Ukraine, the Hong Kong protest, and the Lahore blast.

The data for this research is taken from January 2006 to December 2021, which includes the 2007 financial crisis, the 2014 economic crisis when Russia invaded Ukraine, the 2018 economic crisis where most of the stock markets in the USA and Europe got affected and the COVID-19 period from 2019 to 2021.

The remainder of the paper is arranged as follows: literature review, methodology, estimation of results, and conclusion of the study.

2. LITERATURE REVIEW

Investors are believed to make rational investment decisions by collecting, analysing, and interpreting public information (Kashif et al., 2021). The widely recognised efficient market hypothesis fails to explain technical and calendar anomalies. These anomalies make people believe that traditional financial theories do not explain everything. This situation leads people toward behavioural finance, which believes that investors engage emotionally in critical situations. Investors' emotional decision-making implies that they do not act rationally. Herding is one of the behavioural finance concepts that economists and academics need to understand. Herding behaviour occurs when investors follow other investors' decisions rather than their own (Yousaf & Alokla, 2022).

Most of the literature on herding behaviour is published in the context of developed markets, such as the United States (BenSaïda, 2017), Japan (E. C. Chang et al., 2000), the United Kingdom (Hudson et al., 2020) and Australia (Espinosa-Méndez & Arias, 2021). The research on emerging and developing markets is very limited, as discussed below. This literature also discusses the methodology used to understand the research gap better.

2.1 Herding behaviour

Wermers (1999) evaluated mutual fund trading activity from 1975 to 1994 in USA market to assess herding. He finds herding in mutual funds' average stock at a very small scale but more in small equities and growth-oriented funds. Sias (2004) discovered that institutional investors tend to follow each other when trading the same equities, and they also follow their past trading patterns. According to Sais, institutional investors are *momentum* traders and only account for a small portion of their herding. Both present and previous institutional demand have a stronger relationship with previous returns. Hwang and Salmon (2004) propose a new method for measuring herding based on cross-sectional dispersion, which allows for evaluating herding toward particular sectors or styles in the market. They analysed the USA and South Korean stock markets and found significant herding regardless of market circumstances and macro-factors. They also discover signs of herding in both bullish and bearish markets.

Kim and Nofsinger (2005) investigated institutional herding in Japanese firms owned by financial institutions and other corporations. Herding in Japan is less than in the USA, but it significantly impacts prices. In addition, they discover that the consequences and behaviour of institutional herding depend on the regulatory environment and the economic condition. Walter and Weber (2006) found herding of German managers from 1998 to 2002. A large percentage of German herding is spurious due to changes in benchmark index composition. N. Choi and Sias (2009) reported herding among institutional investors while working in the same industry. They discovered a cross-sectional association between the proportion of institutional traders who purchased industrial stocks in the same and previous quarters. The findings provide clear evidence of industrial herding.

Klein (2013) examined the time-varying nature of herding during turbulent and calm markets. Behavioural factors significantly influence stock prices in the USA and Eurozone during crises. BenSaïda (2017) modified the cross-sectional absolute deviation model during turbulent times to study the effect of herding behaviour on sectoral market volatility in the USA. As expected, herding is found in every USA stock market sector. Stock markets are frequently used to gauge economic expansion, improved regulation, growth, and stability (Hussain et al., 2022). Hussain and colleagues used a structural equation model to study herding in Pakistan. The results reveal that herding significantly impacts investors' rational decision-making processes. It is more common among young people with non-business occupations and higher incomes.

Herding is found in most of the literature that is discussed above, but contrary to these studies, a few researchers have not found herding. For instance, Christie and Huang (1995) used cross-sectional dispersion to investigate herding. Both daily and monthly returns did not support herding during market volatility. Gleason et al. (2004) found no evidence of herding during extreme market fluctuations by using extreme up and down markets. E. C. Chang et al. (2000) also found no evidence of herding among market participants in the USA and Hong Kong. Still, they reported indications of herding in Japan and strong evidence of herding in South Korea and Taiwan. Yasir and Önder (2021) investigated dynamic herding under various market regimes. Their research made a breakthrough contribution to the literature on non-linear modelling and concluded that non-linear modelling is superior to linear modelling. They also claim that no evidence of herding is found based on the linear modelling results. Hence, the literature demands more empirical research in this context. Thus, our study compared these two approaches with different data sets and suggested one best approach for future research.

As discussed earlier, the researchers have investigated herding behaviour in several countries. Still, a gap exists in studying countries with different backgrounds, such as developed, emerging and developing economies. This research addresses the above-mentioned research gap by studying the USA as a developed country, Russia and China as emerging countries and Pakistan as a developing country. The study also covers different approaches, which are not very common in the literature. This study addressed this gap using the Linear and Bai and Perron Structural Change model.

Hypothesis 1:

H₀: There is no herding behaviour in the USA, Russia, China, and Pakistan

H₁: There is herding behaviour in the USA, Russia, China, and Pakistan

Hypothesis 2:

H₀: There is no herding behaviour in the USA, Russia, China, and Pakistan across different regimes.

H₁: There is herding behaviour in the USA, Russia, China, and Pakistan across different regimes.

2.2 Herding behaviour and investor sentiment

Investor sentiment is an opinion regarding future cash flows or investments that is not supported by the facts (Baker & Wurgler, 2007). Therefore, investor sentiment is not influenced by fundamental changes in stock markets but rather by emotional responses to various information. By influencing predicted future cash flows, sentiment can influence

investment decisions and stock returns. A positive attitude encourages investors to be more confident about taking risks. Negative emotions frequently have a negative effect on stock returns and investor confidence (Kuhnen & Knutson, 2011).

Many studies used investors' happiness as a proxy to study investor sentiment. These studies tried to find herding based on these sentiments and found diverse results. It is worth noting that feedback-based investors tend to follow the direction of previous price patterns (e.g., Blasco et al., 2018; Bonato et al., 2020; Gavrilidis et al., 2016). Vieira and Pereira (2015) mentioned the lack of studies on herding behaviour and investor sentiment.

Bekiros et al. (2017) modified the herding model by including implied volatility as a risk agent and found that herding tends to be intense in extreme market conditions. A positive and significant association was found between investor sentiments and herding. K. H. Choi and Yoon (2020) used cross-sectional absolute deviation (CSAD) and quantile regression techniques to identify herding in Korea. They also found that investor sentiment is one of the key elements that can lead to herding. Hudson et al. (2020) reported herding by the managers and concluded that managers are likely to herd due to the market's portfolio size and value.

The extant literature collected data on investor sentiment through indexing. Very few studies collected data from social media platforms (McGurk et al., 2020). Also, these studies have not addressed investor sentiment in response to various events. We use investor sentiment to fill this research gap, calculated using intensive social media tweets in response to local and global mega-events such as the USA election, the Russian War, the Hong Kong protest, and the Lahore blast. These research directions remain unexplored.

Hypothesis 3:

H_0 : There is no herding behaviour in the presence of social media sentiment in the USA, Russia, China, and Pakistan

H_1 : There is herding behaviour in the presence of social media sentiment in the USA, Russia, China, and Pakistan

2.3 Herding Behaviour and its Spillover

Financial crises have always been difficult for policymakers to avoid and control. Several crises between the 1980s and 2010s spread to other nations (Kuusk & Paas, 2013; Rigobon, 2019). Corsetti et al. (2005) provide detailed information on financial crises affecting regional markets, including the 1987 Black Monday, the 1994 Mexican peso crisis, the 1997 Hong Kong crisis that extended to the French stock market, and the late 1990s Asian crisis. Contagion is the term used to describe the spreading phenomenon from one country to another. It is often classified into two groups and is detected through co-movement (Masson, 1998). The initial kind highlights the effects of standard market economy interdependence, which can be local and worldwide. The other type occurs when financial actors, such as investors, cause a financial crisis without any fundamental shifts in the macroeconomy (Claessens et al., 2001).

Wahyudi et al. (2018) use CSRD (cross-sectional returns dispersion) and OLS with static correlation to study the USA, China, and ASEAN-5 stock market spillover effects. The global finance crisis witnessed directional herding transmission from the top stock market to other related markets. Herding in integrated foreign markets affected domestic markets. In contrast to 2017-2018, market contagion only occurs during crises. Thus, during crises, actors should predict integrated market occurrences more conservatively.

Many research have examined the effects of herding between countries. Galariotis et al. (2015) found that herding in the USA only occurs when macroeconomic factors are revealed. The study also found herding from the USA to the UK during financial crises. During crises, USA investors herd because of fundamental and non-fundamental concerns. Messis and Zapranis (2014) used Hwang and Salmon (2004) state space model to explore herding behaviour in five developed markets. They discovered herding contagion in the UK, Germany, France, the USA, and China. Balcilar et al. (2013) used Markov regime-switching to study Gulf herd behaviour. Many researchers have employed dynamic models to show herding behaviour in markets where static tests failed (Akinsomi et al., 2018). Bukhari et al. (2021) studied Chinese and Pakistani stock market herding. Global Industry Classification Standard was used to divide daily stock returns. By using CSAD, the study found no herding spillover in these markets. Yasir and Önder (2022) suggest Russia and China engage in cross-country herding amid crises and unstable regimes. Brazilians and Indians herd during crisis regimes. Turkish herding spread to BRIC countries during the global financial and post-European debt crises. The extant literature only worked on herding spillover as a whole data set. None of the studies tries to find herding spillover in response to mega-events. To fill this research gap, this research uses investor sentiment, which is calculated using an intensive set of social media tweets in response to local and global mega-events.

Hypothesis 4:

H_0 : *There is no herding contagion across borders in the presence of social media sentiment*

H_1 : *There is herding contagion across borders in the presence of social media sentiment*

3. METHODOLOGY

The data for this research is collected from developed, emerging, and developing countries. For instance, the USA is a developed market, Russia and China are emerging markets, and Pakistan is a developing market. There are two main reasons for collecting data from these countries: 1) a lack of research comparing different developed, emerging and developing countries; 2) the investor sentiment data is estimated using Twitter-based data for specific events related to these countries, such as the USA election 2016, Russian War 2014, Hong Kong protest 2014, and the Lahore blast 2016. The latest events cannot be studied because of the change in Twitter's data privacy policy. We obtained the daily data on stock indices and individual stocks using the Thomson Reuters DataStream. The data ranged from January 2006 to December 2021. This period includes the 2007–2008 global financial crisis and the recent COVID-19 pandemic.

3.1 CSAD approach

Cross-section standard deviation (CSSD) of asset returns is used to test herding behaviour in different markets (Christie & Huang, 1995). However, the existence of outliers significantly impacts this approach (CSSD). E. C. Chang et al. (2000) used a more robust measure known as CSAD to overcome this issue. This measure can be used as eq. 1:

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

Where N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of the industry i at time t , and $R_{m,t}$ is the cross-sectional average return at time t .

3.2 General model

Price movements are large during extreme market conditions, which reduces the proportional increase in CSAD. As a result, the relationship between CSAD and market return would be non-linear (E. C. Chang et al., 2000). In order to derive this relationship, the following equation 2 is used (Economou et al., 2011):

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t \quad (2)$$

In herding behaviour, the relationship between CSAD and market return is non-linear and negative. $R_{m,t}^2$ is used to capture the non-linearity of market returns (E. C. Chang et al., 2000; Henker et al., 2006). The coefficient γ_2 is used to capture the non-linearity between CSAD and market return. A negative γ_2 indicates that herding behaviour exists in the market (Economou et al., 2011).

3.3 Investor sentiment

Hwang and Salmon (2004) suggest that investor sentiment is important in fuelling herding. Chiang and Zheng (2010) state that herding behaviour becomes more pronounced during stress (Litimi et al., 2016). Thus, investor sentiment measured based on social media tweets was introduced. We adopt the Maqsood et al. (2020) approach to measure sentiment. First, they use Davies' word list to determine whether a simple approach could compare market movement. They classified approximately 5,000 words for this purpose and divided them into three categories: neutral, positive, and negative. They tokenised the tweet into a word list and sorted it using a parsing algorithm. They used more accurate negative, neutral, and positive dictionary words and replaced that word collection with one created with SentiWordNet, which has over 4000 words. This word list considers multiword expressions and word relationships to enhance results. This method employs neutral, positive, and negative percentages of tweets to provide a more comprehensive explanation of daily Tweets. This measure can be used through eq. 3:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 InS_t + \varepsilon_t, \quad (3)$$

Here, InS_t is investor sentiments and $CSAD_t$ is cross-sectional absolute deviation at time t .

$$CSAD_{k,t} = \gamma_0 + \gamma_1 |R_{m,k,t}| + \gamma_2 R_{m,k,t}^2 + \gamma_3 CSAD_{j,t} + \gamma_4 R_{m,j,t}^2 + \gamma_5 InS_t + \varepsilon_t \quad (4)$$

Here, InS_t investor sentiments are measured based on social media tweets during mega-events. $CSAD$ is cross-sectional absolute deviation and $\gamma_2 R_{m,k,t}^2$ is the squared average market return. Where a significant and negative estimate for γ_2 is used to support the presence of herding. $\gamma_3 CSAD_{j,t}$ describes the volatility spillover in the equation when the value is positive and significant. $\gamma_4 R_{m,j,t}^2$ support the presence of herding contagion when the value is significant and negative.

3.4 Graphical representation of the data

The graphical representation of the whole data set is given in Figures 1, 2, 3 and 4.

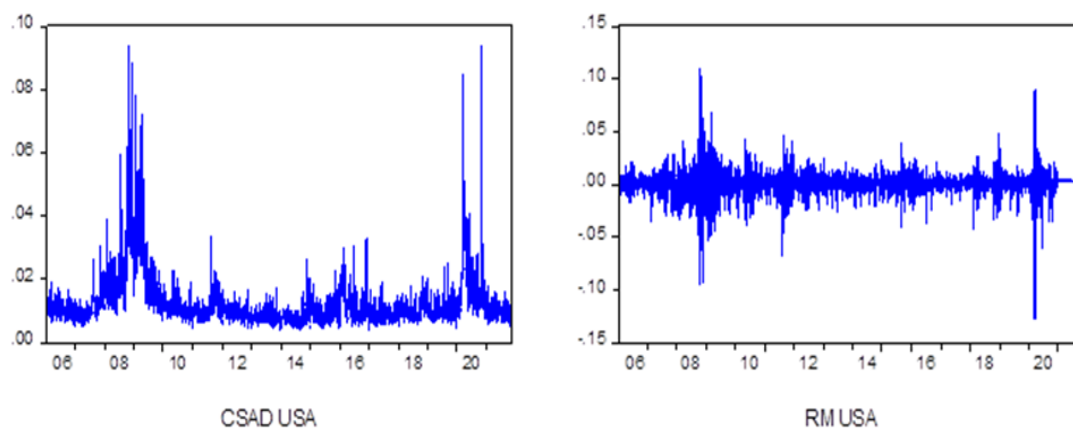


Figure 1: Graph of CSAD and RM USA

Source: authors' research

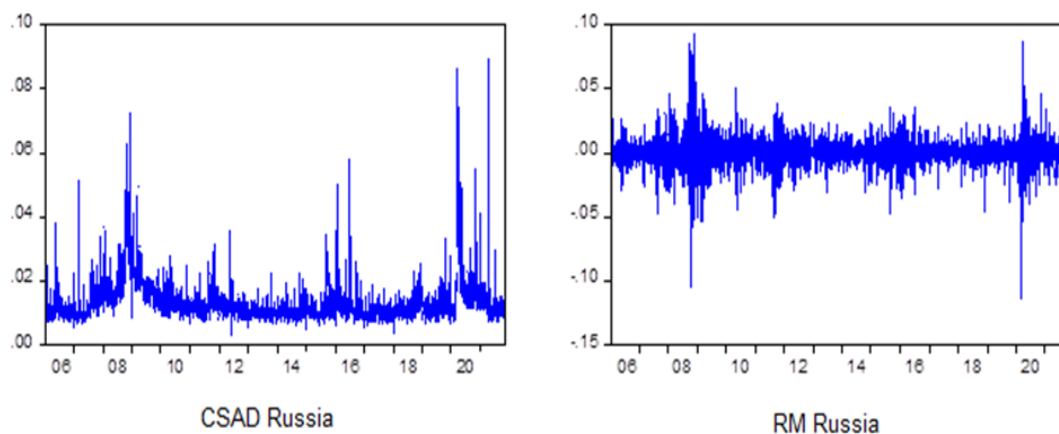


Figure 2: Graph of CSAD and RM Russia

Source: authors' research

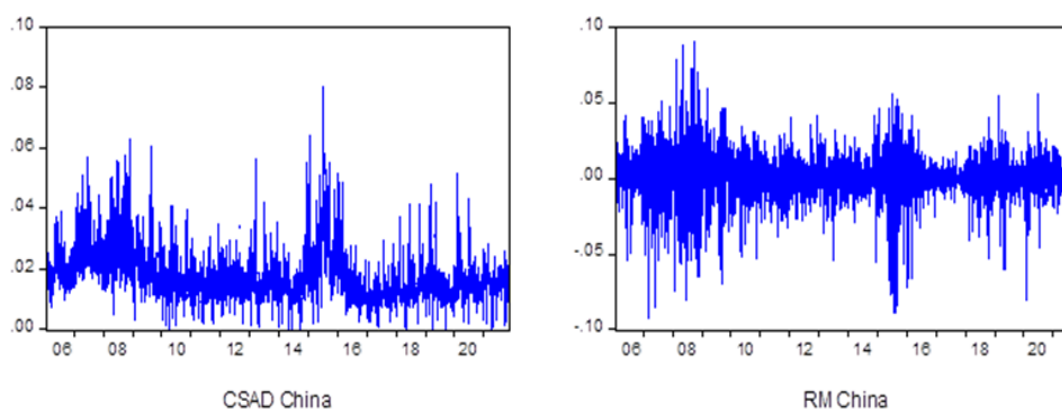


Figure 3: Graph of CSAD and RM China

Source: authors' research

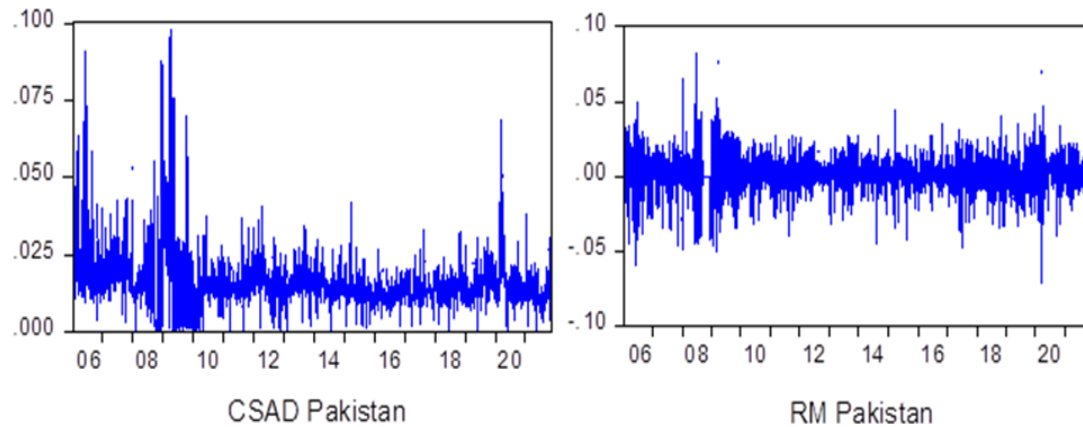


Figure 4: Graph of Pakistan CSAD and RM

Source: authors' research

4. RESULTS AND DISCUSSION

In this section, the study will present and discuss the results of different models employed in the research.

4.1 Descriptive statistics

In this section, the study discussed the descriptive analysis of the selected set of countries.

Table 1: Descriptive statistics

Country	Variables	Mean	Median	Standard Deviation	Jarque-Bera
USA	CSAD	0.012	0.010	0.008	73710.17***
	$ R_{m,t} $	0.008	0.005	0.010	120716.4***
Russia	CSAD	0.014	0.013	0.006	109533.3***
	$ R_{m,t} $	0.009	0.007	0.009	78533.69***
China	CSAD	0.018	0.016	0.009	5226.006***
	$ R_{m,t} $	0.011	0.007	0.012	16430.94***
Pakistan	CSAD	0.016	0.015	0.008	56455.99***
	$ R_{m,t} $	0.009	0.006	0.009	12037.89***

Note(s): *** represents the significance at 1% level

Source: authors' research

The descriptive statistics of the selected set of countries are shown in Table 1. China has the highest mean and median value of CSAD, while the USA has the lowest values. China has the highest value of mean and median of $|R_{m,t}|$ and Russia has the lowest values. China has the highest value of the standard deviation of CSAD, and Russia has the lowest value of CSAD. The $|R_{m,t}|$ China has the highest value and $|R_{m,t}|$, and Russia has the lowest value. All values of the Jarque-Bera test are significant at the 1% level, which supports the existence of non-normal distributions in the data.

4.2 Regression analysis

In this section, the study discusses herding behaviour by using a linear model. By using equation 2, we find the following result.

Table 2: Linear Model

Countries	Exchange	Linear Model			
		γ_0	γ_1	γ_2	Herding
USA	S&P	0.009	0.436*** (21.371)	1.606*** (5.066)	No
Russia	MOEX	0.017	0.323*** (20.323)	0.372 (1.104)	No
China	SSE	0.014	0.386*** (17.666)	-1.663*** (-4.497)	Yes
Pakistan	PSX	0.011	0.521*** (18.039)	-0.907 (-1.331)	No

Note(s): *, **, *** represents the significance at 10, 5 and 1% level. t-statistics are reported in parenthesis.

Source: authors' research

Equation (2) determines herding behaviour in the selected countries (see Table 2). The herding only exists when the coefficient (γ_2) of squared market return ($R_{m,t}^2$) has a negative and significant value (Chang et al., 2000). It is found that the coefficient of absolute $R_{m,t}$ is positive and significant for all countries, which means that $R_{m,t}$ has a positive and significant effect on CSAD. The coefficient γ_2 of $R_{m,t}^2$ is positive and significant for the USA., whereas the coefficient γ_2 of $R_{m,t}^2$ in Russia and Pakistan is insignificant. Therefore, the results reveal no herding in the USA, Russia, and Pakistan. Similar results were reported by (Benkraiem et al., 2019; Javaira & Hassan, 2015; Yasir & Önder, 2021, 2022). In China, the coefficient γ_2 of $R_{m,t}^2$ is negative and significant, demonstrating that herding is present in the Chinese stock market. It is also in line with the literature (Ahmed et al., 2022; Chong et al., 2017). The findings show that herding behaviour was not present in the selected set of countries like the USA, Russia, and Pakistan, except China. This means the results support the hypothesis (H_0) that these countries have no herding behaviour. However, there was evidence of herding behaviour in China, so we reject the hypothesis (H_0) that no herding behaviour exists in China and accept (H_1). This highlights that investor behaviour can vary across different countries. The results indicate that the EMH may not hold uniformly across the markets. The absence of herding behavior in the USA, Russia, and Pakistan supports EMH, and the presence of herding in China suggests market inefficiencies. This shows that there is variation in market efficiency and highlights the potential for distinct investor behaviors across the countries.

4.3 Herding Behavior using Investor sentiment of Mega Events

In this section, the study discusses herding behaviour in the presence of investor sentiment. By using equation 3, the study finds the following results.

Table 3: Investor sentiment

Investor Sentiment							
Countries	Event	Date	γ_0	γ_1	γ_2	γ_3	Herding
USA	USA election	11/8/2016	0.012	0.260 (1.158)	-6.660* (-1.841)	0.005*** (4.623)	Yes
Russia	Ukraine War	2/20/2014	0.009	0.870*** (5.107)	-1.988* (-1.793)	0.004 (0.862)	Yes
China	Hong Kong Protest	9/26/2014	0.013	0.665*** (5.908)	-1.996*** (-2.544)	0.013*** (3.953)	Yes
Pakistan	Lahore Blast	3/29/2016	0.010	0.453*** (2.971)	-14.986** (-2.112)	0.0001 (0.153)	Yes
Note(s): * ** *** represents the significance at 10, 5 and 1% level. t-statistics are reported in parenthesis							

Source: authors' research

The results of investor sentiment are given in Table 4. Elections in the USA (2016) were selected because they are among the most interesting elections. Hillary Clinton was the first woman to win the party nomination from 200 candidates, and Donald Trump, who was 70 years old, was the oldest person to win the party nomination. The results show that herding was present after elections with a coefficient of -6.660 and significant at a 10 % level. The coefficient of sentiment is positive and highly significant as the result of this election is against pre-election surveys. The Pre-election surveys predicted Hillary Clinton's chance of winning was 71 to 99 percent (Katz, 2016). The 2016 presidential election result shocked experts, reporters, and even Trump's campaign team (Jacobs & House, 2016).

Russia War 2014 is selected for Russia. The result shows strong evidence of herding during this time as the coefficient of squared market return is -1.988 and significant at 10%. During this War, the MOEX Index experienced a significant decline. The index fell by more than 10% in March 2014, around the time that Crimea was annexed. Geo-political tensions and the implementation of economic sanctions exacerbated the unfavourable attitude among investors. According to Gisse & Nivorozhkin, (2016), the co-movement of the Russian equities market fell between 30% and 50% when compared to global equity returns and the BRIC markets.

The Hong Kong Protest, often called the Umbrella Revolution, was selected for China. The result shows strong evidence of herding during this time frame as the squared market return coefficient value is -1.996 and significant at 1%. The coefficient γ_3 represents the sentiment measured based on Twitter data. The value of γ_3 is positive and significant at 1% level. This is evident that social media sentiment became the major reason for herding during the Hong Kong protest in 2014. Lahore blast is the event considered for Pakistan. As expected, herding exists during this period with a coefficient value of -14.986 and is significant at 5% level. The coefficient γ_3 is insignificant. The reason for insignificance is that many other events happened in 2016. For instance, the Quetta blast, Charsadda University blast, Peshawar blast, polio team attack and Pervaiz Musharraf acquitted in Akbar Bugti murder case happened in Pakistan.

4.4 Herding Spillover in the Presence of Investor Sentiment

In this section, the study discusses herding spillover in the presence of investor sentiment in response to megaevents, i.e., the USA election, the Russian War, the Hong Kong protest and the Lahore blast. By using equation 4, the study finds the following results.

Table 4 Herding Spillover in the Presence of Sentiments

Herding Spillover in the presence of investor sentiment from USA (USA Election 2016)						
Coefficients	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
Russia MOEX	0.005	-0.040 (-0.33)	18.124* (1.78)	0.312*** (2.14)	-0.142 (-0.17)	0.003 (1.19)
China SSE	0.010	-0.405 (-1.38)	32.658** (2.38)	0.205** (2.11)	-1.564*** (-4.57)	0.0002 (0.17)
Pakistan PSX	0.010	0.444* (1.86)	-5.041 (-0.40)	-0.157** (-2.24)	0.365** (-2.17)	0.001 (0.71)
Herding Spillover in the presence of investor sentiment from Russia (Russian War 2014)						
Coefficients	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
USA S&P	0.009	0.229 (1.41)	2.700 (0.51)	0.003 (0.08)	-0.498 (-0.79)	0.002 (0.71)
China SSE	0.014	0.059 (0.20)	5.110 (0.33)	0.312*** (3.51)	-0.271*** (-2.59)	0.004** (2.13)
Pakistan	0.011	-0.199	11.722	0.070	-0.029	-0.004***

PSX		(-1.13)	(1.09)	(1.56)	(-0.19)	(-3.45)
Herding Spillover in the presence of investor sentiment from China (Hong Kong Protest 2014)						
Coefficients	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
USA S&P	0.008	-0.029 (-0.11)	9.880 (0.72)	0.046 (0.96)	0.666** (2.11)	-0.001 (-0.85)
Russia MOEX	0.020	0.072 (0.42)	7.450 (1.40)	-0.079* (-1.81)	0.310*** (-2.89)	-0.002 (-0.50)
Pakistan PSX	0.014	0.210 (0.82)	-1.259 (-0.11)	0.027 (0.58)	-0.063*** (-3.21)	-0.001 (-0.77)
Herding Spillover in the presence of investor sentiment from Pakistan (Lahore Blast 2016)						
Coefficients	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
USA S&P	0.011	-0.197 (-1.03)	21.294*** (3.28)	0.008 (0.05)	-2.135 (-0.50)	0.000 (-0.33)
Russia MOEX	0.015	-0.411 (-1.59)	20.633*** (3.99)	0.075 (0.51)	3.621 (0.51)	0.003 (0.50)
China SSE	0.010	-0.100 (-0.38)	9.710 (1.07)	0.211 (0.86)	-5.563 (-0.98)	0.002 (1.05)

Note(s): *, **, *** represents the significance at 10%, 5%, and 1% level. t-statistics are reported in parenthesis. Source: authors' research.

The Table 4 shows the results of herding contagion across borders in the presence of social media sentiment of multiple events. We used the mega events of the USA Election 2016, the Russian War 2014, the Hong Kong Protest 2014, and the Lahore Blast 2016. We estimated equation 4 to investigate the herding contagion among the stock markets in the presence of events. The results are very interesting when the herding spillover was measured from the USA to China during the period of the 2016 USA election. When we incorporated the social media sentiment of the USA election, the herding spillover coefficient became highly significant at 1%. Thus, there is a herding spillover from the USA to China in the presence of Twitter sentiments, which shows a sensitive connection among these markets during mega-events. The findings are against the result of (Chen et al., 2017), and the Possible reason of the 2016 USA presidential election affected the Chinese stock market is that the market was influenced by fears over U.S.-China trade hostilities, notably.

The major focus of the campaign was on USA-China trade imbalances, unfair tactics and South-China geopolitical tensions. The presidential candidate also criticised China's currency policies, which increased market concern during the election campaign. (Shen et al., 2017) found the impact of the presidential election on stock prices. (Guo et al., 2021) investigate the impact of Trump's China-related tweets on the Chinese stock market and found that the president's tweets with a positive sentiment significantly increased abnormal returns for the manufacturing industry in the Chinese stock market. According to (Shaikh, 2017), the USA presidential election has shown a mixed effect on different stock returns Nifty50 and S&P have negative effects, while FTSE, DJIA, EuroStoxx50, and Nikkei225 have reported positive returns. The study also found herding spillover from the USA to the Pakistan Stock market as coefficient is 0.365 with t value of -2.17. These results are similar to the study of (Bibi et al., 2020; Gajurel & Chawla, 2022).

When we incorporate the sentiment of the Russian War to measure herding spillover from Russia to China, the study found herding spillover from Russia to China. Interestingly, when we incorporate the sentiment of the Hong Kong Protest, the spillover from China to Russia is also found, so there is a two-way spillover between Russia and China. So, both markets are sensitive to each other during mega-events. This is because both countries have close ties in

defence and geo-political issues. The result of this study is also in line with the result of (Yasir & Önder, 2022), who found two-way herding during highly volatile and crisis regimes. There is no herding spillover from the Pakistan Stock Market to any selected set of countries.

The results of this research conclusively find the existence of herding spillover in the selected countries. In the context of the 2016 USA election, the 2014 Russian War, the 2014 Hong Kong protests, and the 2016 Lahore blast, a consistent pattern of herding behaviour emerges. These empirical findings provide substantial support for this study's hypotheses except for Pakistan, as no herding contagion was found from Pakistan to any set of countries. The correlation between investor sentiment and herding tendencies is bolstered due to the consistency of herding behaviour across these diverse and consequential events. This study thus highlights the pivotal role played by investor sentiment in triggering herding behaviour during significant mega-events, contributing valuable insights into the complex dynamics of governing global financial markets.

5. CONCLUSION

This research paper investigates the presence of herding behaviour in countries with different backgrounds, such as developed, emerging, and developing economies. The USA is a developed country; Russia and China are emerging countries; and Pakistan is a developing economy. The data set was collected based on the daily closing prices, and individual stock returns were calculated. The academic literature on herding shows diverse results in previous studies. CSAD approach is used to measure herding. The study found no evidence of herding in the USA, Russia, and Pakistan using least squares regression. Contrary to this, we found strong evidence of herding in China. Another important contribution of this study is to explore the effect of investor sentiment in reaction to local and global mega events on herding in selected countries. In the literature, investor sentiment is studied through sentiment indexes during the regular market, but we used the data during specific mega-events. It is evident from the research that mega-events affected the investors' sentiments, which leads to herding. The stock markets of all countries herd after the USA election, the Russian War, the China Hong Kong protest, and the Pakistan Lahore blast. Overall, investor sentiment plays a significant role in developed, emerging and developing countries.

Cross-country herding behaviour can have an impact on financial stability. When herding behaviour occurs across multiple markets, it can increase volatility and contagion, which occurs when problems in one market spread to others. Herding behaviour across markets increases the difficulty as investors find it harder to diversify and reduce risk. Therefore, knowing the extent of cross-country herding behaviour can help investors make better investment decisions. The study uses the linear model to measure herding contagion in the presence of social media sentiment response to mega-events. From the USA, herding contagion is found in all the countries except Russia. For Russia and China, a two-way herding contagion is found. No herding contagion was found from Pakistan to any selected set of countries. It is worth noting that the social media sentiment in response to the mega events of emerging and developing countries shows no herding contagion effect toward developed countries.

The findings of this research have some implications for individual investors and institutions. Investors' irrational herding behaviour can enhance market volatility, creating bubbles and leading to a financial crisis. To protect themselves from financial crises, investors can evaluate the intrinsic value of financial assets, which can protect them from the effects of economic downturns. If strict laws and severe penalties were in place, regulators could design

and implement a monitoring system that helps them predict investor sentiment in response to local and global events that may cause herding in the market. This monitoring system allows the regulator to stabilise the market and prevent volatility caused by investors' irrational behaviour. This research has contributions but also has limitations as well. For instance, we found herding behaviour in the presence of investor sentiment in response to a local and global event calculated based on social media Tweets. Due to new rules and regulations, it is quite difficult to collect updated data from Twitter. So, no recent event data has been obtained from Twitter.

Reference

- 1) Ahmed, K., Shafi, K., & Nawab, S. (2022). Dynamics of Herding Behaviour During Extreme Market Movements in China and Pakistan. *Pakistan Journal of Social Research*, 4(04), 664–682. <https://doi.org/10.52567/PJSR.V4I04.881>
- 2) Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129–151. <https://doi.org/10.1257/jep.21.2.129>
- 3) Barberis, N., & Thaler, R. (2003). Chapter 18 A survey of behavioral finance. In *Handbook of the Economics of Finance* (Vol. 1, Issue SUPPL. PART B, pp. 1053–1128). Elsevier. [https://doi.org/10.1016/S1574-0102\(03\)01027-6](https://doi.org/10.1016/S1574-0102(03)01027-6)
- 4) Bekiros, S., Jlassi, M., Lucey, B., Naoui, K., & Uddin, G. S. (2017). Herding behavior, market sentiment and volatility: Will the bubble resume? *The North American Journal of Economics and Finance*, 42, 107–131. <https://doi.org/10.1016/J.NAJEF.2017.07.005>
- 5) Benkraiem, R., Bouattour, M., Galariotis, E., & Miloudi, A. (2019). Do investors in SMEs herd? Evidence from French and UK equity markets. *Small Business Economics*, 56(4), 1619–1637. <https://doi.org/10.1007/s11187-019-00284-0>
- 6) BenSaïda, A. (2017). Herding effect on idiosyncratic volatility in U.S. industries. *Finance Research Letters*, 23, 121–132. <https://doi.org/10.1016/j.frl.2017.03.001>
- 7) Bibi, R., Arslan, S. A., & Javid, A. Y. (2020). Article Herding Behaviour: Empirical Analysis of Pakistan, China, USA Stock Market. *Journal of Finance and Accounting Research*, 2(2), 1–1. <https://doi.org/10.32350/jfar/2020/0202/480>
- 8) Blasco, N., Corredor, P., & Ferrer, E. (2018). Analysts herding: when does sentiment matter? *Applied Economics*, 50(51), 5495–5509.
- 9) <https://doi.org/10.1080/00036846.2018.1486999>
- 10) Blasco, N., Corredor, P., & Ferreruela, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, 12(2), 311–327. <https://doi.org/10.1080/14697688.2010.516766>
- 11) Bonato, M., Gkillas, K., Gupta, R., & Pierdzioch, C. (2020). Investor happiness and predictability of the realized volatility of oil price. *Sustainability (Switzerland)*, 12(10), 4309. <https://doi.org/10.3390/su12104309>
- 12) Bougatef, K., & Nejeh, I. (2022). The COVID-19 pandemic and herding behaviour among investors in Shariah-compliant stocks. *Journal of Islamic Accounting and Business Research*, 13(5), 832–844. <https://doi.org/10.1108/JIABR-08-2021-0237>

- 13) Castagneto-Gissey, G., & Nivorozhkin, E. (2016). No contagion from Russia toward global equity markets after the 2014 international sanctions. *Economic Analysis and Policy*, 52, 79–98. <https://doi.org/10.1016/J.EAP.2016.08.006>
- 14) 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>
- 15) Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance*, 24(10), 1651–1679. [https://doi.org/10.1016/S0378-4266\(99\)00096-5](https://doi.org/10.1016/S0378-4266(99)00096-5)
- 16) Chen, Y.-C., Wu, H.-C., & Huang, J.-J. (2017). Herd Behavior and Rational Expectations: A Test of China's Market Using Quantile Regression. *International Journal of Economics and Financial Issues*, 7(2), 649–663. <http://www.econjournals.com>
- 17) Choi, K. H., & Yoon, S. M. (2020). Investor sentiment and herding behavior in the Korean stock market. *International Journal of Financial Studies*, 8(2), 1–14. <https://doi.org/10.3390/ijfs8020034>
- 18) Choi, N., & Sias, R. W. (2009). Institutional industry herding. *Journal of Financial Economics*, 94(3), 469–491. <https://doi.org/10.1016/j.jfineco.2008.12.009>
- 19) Chong, T. T. L., Liu, X., & Zhu, C. (2017). What Explains Herd Behavior in the Chinese Stock Market? *Journal of Behavioral Finance*, 18(4), 448–456. <https://doi.org/10.1080/15427560.2017.1365365>
- 20) 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>
- 21) Economou, F., Kostakis, A., & Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, 21(3), 443–460. <https://doi.org/10.1016/j.intfin.2011.01.005>
- 22) Espinosa-Méndez, C., & Arias, J. (2021). Herding Behaviour in Australian stock market: Evidence on COVID-19 effect. *Applied Economics Letters*, 28(21), 1898–1901. <https://doi.org/10.1080/13504851.2020.1854659>
- 23) Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383. <https://doi.org/10.2307/2325486>
- 24) Gajurel, D., & Chawla, A. (2022). International Information Spillovers and Asymmetric Volatility in South Asian Stock Markets. *Journal of Risk and Financial Management*, 15(10), 471. <https://doi.org/10.3390/jrfm15100471>
- 25) Gavriilidis, K., Kallinterakis, V., & Tsalavoutas, I. (2016). Investor mood, herding and the Ramadan effect. *Journal of Economic Behavior and Organization*, 132, 23–38. <https://doi.org/10.1016/j.jebo.2015.09.018>

- 26) Ghorbel, A., Snene, Y., & Frikha, W. (2022). Does herding behavior explain the contagion of the COVID-19 crisis? *Review of Behavioral Finance, ahead-of-p*(ahead-of-print). <https://doi.org/10.1108/RBF-12-2021-0263>
- 27) Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance*, 11(5), 681–694. <https://doi.org/10.1016/j.jempfin.2003.06.003>
- 28) Guo, S., Jiao, Y., & Xu, Z. (2021). Trump's Effect on the Chinese Stock Market. *Journal of Asian Economics*, 72, 101267. <https://doi.org/10.1016/J.ASIECO.2020.101267>
- 29) Henker, J., Henker, T., & Mitsios, A. (2006). Do investors herd intraday in Australian equities? *International Journal of Managerial Finance*, 2(3), 196–219. <https://doi.org/10.1108/17439130610676475>
- 30) Hudson, Y., Yan, M., & Zhang, D. (2020). Herd behaviour & investor sentiment: Evidence from UK mutual funds. *International Review of Financial Analysis*, 71, 101494. <https://doi.org/10.1016/j.irfa.2020.101494>
- 31) Hui, C.-H., & Chung, T.-K. (2011). Crash risk of the euro in the sovereign debt crisis of 2009–2010. *Journal of Banking & Finance*, 35(11), 2945–2955. <https://doi.org/10.1016/j.jbankfin.2011.03.020>
- 32) Hussain, M., Sadiq, S., Rasheed, M. H., & Amin, K. (2022). Exploring the Dynamics of Investors' Decision Making in Pakistan Stock Market: A Study of Herding Behavior. *Journal of Economic Impact*, 4(1), 165–173. <https://doi.org/10.52223/jei4012220>
- 33) 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>
- 34) Jacobs, J., & House, B. (2016). *Trump Says He Expected to Lose Election Because of Poll Results (13st December 2016 on Bloomberg.com)*. Bloomberg.Com. <https://www.bloomberg.com/news/articles/2016-12-14/trump-says-he-expected-to-lose-election-because-of-poll-results?leadSource=uverify wall>
- 35) Javaira, Z., & Hassan, A. (2015). An examination of herding behavior in Pakistani stock market. *International Journal of Emerging Markets*, 10(3), 474–490. <https://doi.org/10.1108/IJoEM-07-2011-0064>
- 36) Kashif, M., Palwishah, R., Ahmed, R. R., Vveinhardt, J., & Streimikiene, D. (2021). Do investors herd? An examination of Pakistan stock exchange. *International Journal of Finance & Economics*, 26(2), 2090–2105. <https://doi.org/10.1002/ijfe.1895>
- 37) Katz, J. (2016). Who Will Be President? *New York Times*. <https://www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html>
- 38) Kim, K. A., & Nofsinger, J. R. (2005). Institutional herding, business groups, and economic regimes: Evidence from Japan. *Journal of Business*, 78(1), 213–242. <https://doi.org/10.1086/426524>
- 39) Klein, A. C. (2013). Time-variations in herding behavior: Evidence from a Markov switching SUR model. *Journal of International Financial Markets, Institutions and Money*, 26(1), 291–304. <https://doi.org/10.1016/j.intfin.2013.06.006>

- 40) Kuhnen, C. M., & Knutson, B. (2011). The Influence of Affect on Beliefs, Preferences, and Financial Decisions. *The Journal of Financial and Quantitative Analysis*, 46(3), 605–626. <https://doi.org/10.1017/S0022109011000123>
- 41) 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>
- 42) Loang, O. K., & Ahmad, Z. (2022). Does Volatility Cause Herding in Malaysian Stock Market? Evidence from Quantile Regression Analysis. *Millennial Asia*. <https://doi.org/10.1177/09763996221101217>
- 43) Maqsood, H., Mehmood, I., Maqsood, M., Yasir, M., Afzal, S., Aadil, F., Selim, M. M., & Muhammad, K. (2020). A local and global event sentiment based efficient stock exchange forecasting using deep learning. *International Journal of Information Management*, 50, 432–451. <https://doi.org/10.1016/J.IJINFOMGT.2019.07.011>
- 44) McGurk, Z., Nowak, A., & Hall, J. C. (2020). Stock returns and investor sentiment: textual analysis and social media. *Journal of Economics and Finance*, 44(3), 458–485. <https://doi.org/10.1007/S12197-019-09494-4/TABLES/9>
- 45) Metwally, A. (2016). Does Herding Behaviour Vary in Bull and Bear Markets? Perspectives from Egypt. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2788485>
- 46) Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *Journal of Finance*, 54(6), 2263–2295. <https://doi.org/10.1111/0022-1082.00188>
- 47) Rehan, M., Alvi, J., Javed, L., & Saleem, B. (2021). Impact of Behavioral Factors in Making Investment Decisions and Performance: Evidence from Pakistan Stock Exchange. *Market Forces*, 16(1), 22. <https://doi.org/10.51153/mf.v16i1.435>
- 48) Ritter, J. R. (2003). Behavioral finance. *Pacific Basin Finance Journal*, 11(4), 429–437. [https://doi.org/10.1016/S0927-538X\(03\)00048-9](https://doi.org/10.1016/S0927-538X(03)00048-9)
- 49) Saadaoui Mallek, R., Albaity, M., & Molyneux, P. (2022). Herding behaviour heterogeneity under economic and political risks: Evidence from GCC. *Economic Analysis and Policy*, 75, 345–361. <https://doi.org/10.1016/J.EAP.2022.05.015>
- 50) Shaikh, I. (2017). The 2016 U.S. presidential election and the Stock, FX and VIX markets. *The North American Journal of Economics and Finance*, 42, 546–563. <https://doi.org/10.1016/j.najef.2017.08.014>
- 51) Shen, C. H., Bui, D. G., & Lin, C. Y. (2017). Do political factors affect stock returns during presidential elections? *Journal of International Money and Finance*, 77, 180–198. <https://doi.org/10.1016/J.JIMONFIN.2017.07.019>
- 52) Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, 17(1), 83–104. <https://doi.org/10.1257/089533003321164967>
- 53) Sias, R. W. (2004). Institutional Herding. In *Review of Financial Studies* (Vol. 17, Issue 1, pp. 165–206). Oxford University Press. <https://doi.org/10.1093/rfs/hhg035>

- 54) Simões Vieira, E. F., & Valente Pereira, M. S. (2015). Herding behaviour and sentiment: Evidence in a small European market. *Revista de Contabilidad-Spanish Accounting Review*, 18(1), 78–86. <https://doi.org/10.1016/j.rcsar.2014.06.003>
- 55) Tauseef, S. (2022). Herd behaviour in an emerging market: an evidence of calendar and size effects. *Journal of Asia Business Studies*, ahead-of-p(ahead-of-print). <https://doi.org/10.1108/JABS-10-2021-0430>
- 56) Walter, A., & Weber, F. M. (2006). Herding in the German mutual fund industry. *European Financial Management*, 12(3), 375–406. <https://doi.org/10.1111/j.1354-7798.2006.00325.x>
- 57) Wang, Y., Tsai, J., & Li, X. (2019). What Drives China's 2015 Stock Market Surges and Turmoil? *Asia-Pacific Journal of Financial Studies*, 48(3), 410–436. <https://doi.org/10.1111/ajfs.12261>
- 58) Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54(2), 581–622. <https://doi.org/10.1111/0022-1082.00118>
- 59) Yasir, M., & Önder, A. Ö. (2021). Dynamic herding behaviour in the US stock market. *Prague Economic Papers*, 30(1), 115–130. <https://doi.org/10.18267/j.pep.760>
- 60) Yasir, M., & Önder, A. Ö. (2022). Time-varying herding spillover for emerging countries: evidence from BRIC countries and Turkey. *Review of Behavioral Finance*. <https://doi.org/10.1108/RBF-10-2021-0218>
- 61) Yousaf, I., Ali, S., & Shah, S. Z. A. (2018). Herding behavior in Ramadan and financial crises: the case of the Pakistani stock market. *Financial Innovation*, 4(1), 16. <https://doi.org/10.1186/s40854-018-0098-9>
- 62) Yousaf, I., & Alokla, J. (2022). Herding behaviour in the Islamic bank market: evidence from the Gulf region. *Review of Behavioral Finance*, ahead-of-p(ahead-of-print). <https://doi.org/10.1108/RBF-02-2021-0018>