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Herding during different types of crises: The COVID-19 health crisis and Russia–Ukraine political crisis

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ABSTRACT

We analysed herding behaviour in the recent pandemic and conflict. We employed the cross-sectional dispersion of daily stock returns to estimate herding's intensity in the Saudi stock market. We conducted all analyses for the entire sample and four sub-samples. Additionally, we investigate the existence of the asymmetry in the investors' responses; whether there are differences between up and down markets and between high-volatility and low-volatility days. We found that herding did not occur in the pre-COVID-19, occurred in the during-COVID-19, disappeared in the post-COVID-19 and did not occur during the Russia–Ukraine conflict. Robustness checks confirm our finding that herding manifested in the during-COVID-19 period. Additionally, no difference exists between bearish and bullish or high-and low-volatility days, pushing aside the asymmetry in the investors' responses. This study may raise investors' awareness of their cognitive bias's influence on their decisions, improving market efficiency by increasing the rationality of investors' decisions.

1. Introduction

Although the data change dramatically daily basis, at the time of writing (March 7, 2022), over 447 million individuals were infected and more than 6 million were killed by COVID-19 worldwide, with almost 747,715 cases and more than 9009 deaths in Saudi Arabia (Worldwide, Worldometer, https://www.worldometers. info/coronavirus/). COVID-19 creates fear of death and infection among stock market investors because of its effect on health and economic activities at the global level [1]. Aslam, Ferreira [2] provide evidence that investors in Asia and Europe have feelings of fear and anxiety due to COVID-19, leading them to display herding behaviour.

While many economies began healing from COVID-19's effects, the Russia–Ukraine war began on February 24, 2022, when Russia invaded Ukraine, starting the most crucial military conflict in Central Europe in 1945. According to Yousaf, Patel [3], the fastest-growing refugee crisis in Europe started due to the conflict since the Second World War, which caused numerous civilians to be killed and injured. This conflict has significantly affected the food, health, and financial markets globally [4]. Military conflicts may elevate investors' uncertainty about firms' future profitability, possibly increasing stock price variations [3,5,6]. Moreover, wars increase government spending on military and defence, which may negatively affect other sectors of the economy. Military conflicts may also affect import and export relationships between countries involved in wars and non-wars [7], negatively affecting firm prices and profitability.

In the academic literature, black swan events, including health crises and wars, are among the most significant events that affect

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investors' behaviour by triggering their fear, leading to panic selling [8,9], and affecting stock markets globally [3]. We believe that the COVID-19 health pandemic and the Russia–Ukraine crisis can be characterised as black swan events for stock markets because both large-scale disasters caused excess mortality and were difficult to predict because they surprised most people, had a huge economic impact, and affected the global order. Some researchers have referred to the COVID-19 health crisis as a black swan event [e.g. 9], while others have referred to the Russia–Ukraine war as a black swan event [e.g. 3].

There are many reasons to examine the COVID-19 health crisis and the Russian–Ukraine war from the perspective of the global stock market and investor behaviour. First, periods of high uncertainty, such as pandemics and conflicts, are likely to affect regional and international markets because of spillover effects and the globalisation of stock markets. Umar, Polat [10] argue that financial markets' connectedness increases during periods of high uncertainty. For example, COVID-19 substantially affects investors' lives, emotions, daily routines, and their behaviour in the stock market. Similarly, although the conflict seems bilateral, the consequences of the Russia–Ukraine conflict may increase uncertainty in financial markets worldwide and threaten the global economy. The literature suggests that herding intensifies in periods of heightened uncertainty and market stress [11,12]. Less informed investors facing uncertain information may imitate informed investors' behaviours, leading to herding behaviour [2,13].

Moreover, the COVID-19 pandemic and conflicts may stimulate the psychological emotions of anxiety and fear among investors, which may affect their behaviour. For example, the COVID-19 epidemic has produced an environment of uncertainty worldwide and panic and fear among investors. Chen, Liu [14] confirm that investor fear during the COVID-19 pandemic is positively correlated with uncertainty in financial markets. Similarly, the Russia–Ukraine conflict triggered fear and anxiety globally, especially because of the threat of nuclear war. This threat was widely reported at the start of the war, and the Putin administration affirmed its right to use nuclear weapons in Ukraine. Furthermore, social media works as a stress multiplier and spreader [15] because the news and anxieties stemming from the coronavirus and the war spread on social media, and no one is isolated from the realities of the pandemic and the war, creating fear and stress stemming from these crises globally. Therefore, these events may have implications for stock markets and investor behaviour worldwide.

Additionally, although the conflict seems bilateral, the contagion effect from Russia may affect stock markets globally because Russia has a strong economy well connected to the world through the export of goods and services. Russia and Ukraine are two major agricultural powers and are among the largest producers and exporters of food items worldwide [16]. Further, Russia's role in global energy markets is significant. Many European countries rely heavily on Russia for their energy supplies, such as oil, gas and coal [17]. Therefore, the conflict has increased worldwide inflation, food hikes, and energy prices [18].

Herding behaviour is a common behavioural bias regularly found in financial markets and usually occurs during turmoil and crises [19]. In financial markets, herding behaviour occurs when investors with uncertain information tend to follow a market consensus rather than their information [20]. Welch [21] states that herding behaviour is pervasive in financial markets. Herding behaviour in stock markets has drawn considerable attention from researchers [20,22–24]. According to Christie and Huang [20], it is crucial to consider that investors tend to copy others' actions to understand empirical realities.

Herding behaviour violates the efficient market hypothesis (EMH), and market prices gradually deviate away from their fundamentals [25]. Investor behaviour may impact asset valuation and stock market efficiency, which might explain EMH violations, such as financial crises, speculative bubbles and stock market meltdowns [26,27]. Moreover, some economists suggest that investor herding behaviour may destabilise markets, exacerbate volatility, increase the financial system's fragility, limit the possibility of diversification, jeopardise market efficiency, and lead to bubbles and crashes in financial markets through panic buying and selling [9,28,29], making investor herding worth detecting. Furthermore, price instability in financial markets caused by herding may create additional risks, making them unsuitable for investors with low risk tolerance. Individual and institutional investors may prefer safer and less volatile stock markets.

Empirical studies show that herding occurs because of the presence of irrational and psychological restraints that affect investor behaviour [30–34]. In the real world, markets are not perfectly efficient, and the price of an asset does not reflect all available information; therefore, obtaining new information incurs costs, which may explain why investors herd. It may also make it difficult for investors to acquire the reliable and credible information necessary to make rational decisions because it may not be available to the public. According to Zhou and Lai [35], less informed investors may follow better informed investors who obtain more reliable information. One reason could be that in periods of market distress, investors may not have sufficient time to collect all the information needed and make the best possible decisions based on rational thinking and market analysis; hence, they may tend to mimic successful investors' activities. Moreover, investors may be overwhelmed by other investors' decisions and the excessive information in stock markets. Teraji [36] argues that individuals naturally tend to trust the majority consensus, leading investors to mimic others' actions. According to Devenow and Welch [37], investors may herd to increase their confidence in investment returns and reduce uncertainty. They offer an argument regarding the emergence of herd behaviour among investors: investors under uncertainty feel more secure following a crowd.

Our study of the Saudi Arabia's stock market is motivated by the following aspects. First, herding behaviour is proven to be relatively stronger in emerging stock markets, such as Saudi Arabia's stock market, than in developed markets because these markets suffer from lower transparency, regulatory weaknesses, information inefficiency, and lack of financial analysts and quality information [38–40]. Therefore, this issue should be investigated in the Saudi stock market. Additionally, unlike stock markets in the US and Europe, many investors in the Saudi stock market are individuals rather than institutions [41,42], mostly inexperienced young males [42]. Individual investors may have higher herding intensity levels than institutional investors because they tend to be inexperienced, lack access to information, and have a short-term investment strategy. Thus, herding may characterise trading transactions as having a significant effect on the stock market. It also provides a suitable environment for testing individual investors' herding behaviour using easily accessible stock market data. It is easier to attribute market-wide herding to individual investors' activities rather than institutions, which may present a relatively clearer picture of individual investors' herding behaviour.

One investment strategy could mimic the actions of the market consensus, and the consequences of such a strategy may be reflected in aggregated asset returns [43]. The cross-section of the return dispersions was used to measure herding behaviour. To capture market-wide herding, many researchers use the cross-sectional dispersion of market returns because information at the investor level is scarce. The pioneering measures of Christie and Huang [20] and Chang, Cheng [22] suggest that if the herding phenomenon occurs, it would be stronger under extreme market conditions, during extreme rises and falls because, in such conditions, investors are prone to imitate the market consensus and suppress their own beliefs. Christie and Huang's [20] cross-sectional standard deviation (CSSD) model and Chang et al.'s [22] cross-sectional absolute deviation (CSAD) model are the most commonly used herd behaviour measures that use aggregate market data. The main idea behind their model is that the cross-sectional dispersion of stock market returns can measure herding. They argue that when herding behaviour occurs in a market, each individual stock's returns listed on the market cluster around the return of the market; hence, we expect to find lower dispersion in the mean returns. However, the nonlinear CSAD model is a more accurate measurement of dispersions and improves the linear CSSD model because it has been criticised for its empirical sensitivity to outliers, which makes it difficult to find evidence of investor herding under normal conditions [23,44]. Many studies have used aggregate market data to examine herding behaviour using the CSAD approach [35,45–47]. We also examine whether asymmetric herding behaviour occurs on high- and low-volatility days, using Parkinson's [48] and Garman and Klass's [49] volatility measures.

The situations created by the COVID-19 health crisis and the Russia–Ukraine political crisis differ from the financial crisis—COVID-19 and the conflict are exogenous events for the stock markets, whereas the COVID-19 and the Russia–Ukraine conflict are exogenous shocks to stock markets that may create extreme market conditions. Each of these events may create dissimilar emotional reactions. Therefore, investor behaviour during the COVID-19 disease period and the Russia–Ukraine conflict may show different features from the situation of financial crises. Although COVID-19 and the conflict may have different characteristics and implications for financial crises, they may have a similar influence on financial crises because investors are emotionally unstable.

The Saudi stock market index, shown in Fig. 1, suggests a pattern of bubbles and crashes that might have occurred because of herding behaviour among investors during the COVID-19 period, when they initially overpriced assets, eventually leading to market crashes. Theis study contributes to the literature in the following ways. First, we contribute to the limited literature on whether Back Swan events affect stock markets. Second, we contribute to the growing literature on the crucial effects of the COVID-19 pandemic on herding behaviour in emerging stock markets. We extend the examination of COVID-19's effect on investor herding to an emerging stock market in which evidence of herd behaviour is limited. Third, to the best of our knowledge, this is the first quantitative analysis of the impact of the Russia–Ukraine conflict on investors' herding behaviour in stock markets, including Saudi Arabia. Further, to our knowledge, this is the first analysis of herding behaviour in the Saudi stock market during the COVID-19 and Russia–Ukraine War on high-volatility days compared to calm days.

Additionally, to our knowledge, this is the first quantitative analysis of COVID-19's impact on investors' herding behaviour in the Saudi stock market. A few previous studies on herding in the Saudi stock market show significant herding in the Saudi stock market [40,50]. Researchers found that herding occurs during crash times [51] and periods of market losses [52] and concluded that individual investors are more likely to be noise traders [40]. However, unlike the financial crisis, COVID-19 is a health crisis, and the Russia–Ukraine conflict is a political crisis. As they are crises of different origins, studying their impact on the Saudi stock market is worthwhile. Finally, the Saudi stock market is an emerging market and a part of the MENA and Gulf Cooperation Council (GCC) stock

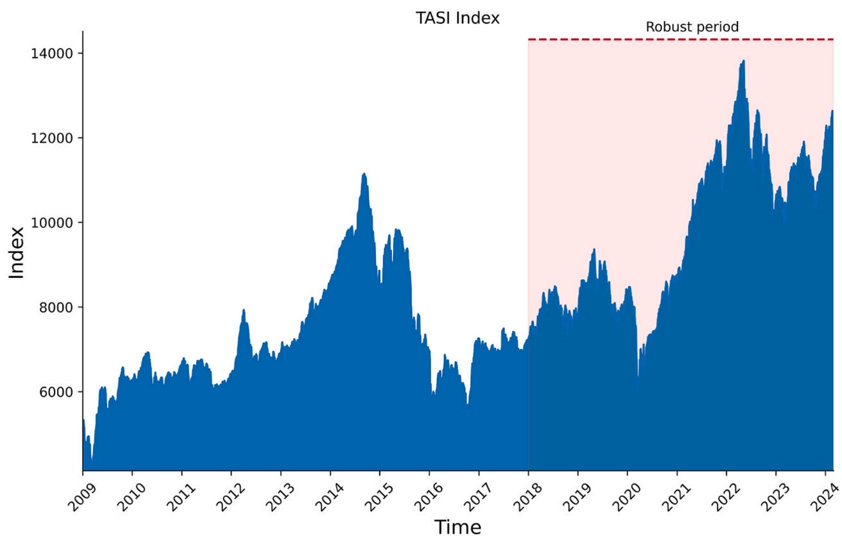


Fig. 1. The Saudi Stock Market Index (TASI). The sample covers the period from January 2009 to February 2024. The robust period (highlighted in red) covers the period from January 2018 to February 2024. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

markets [53]. Therefore, this study adds to our understanding of the impact of black swan events (COVID-19 and Russia–Ukraine outbreaks) on herding behaviour in emerging markets, specifically the MENA and GCC stock markets, on which a few studies have been conducted.

The explosion of the COVID-19 crisis and the Russia–Ukraine war and the absence of research on the effect of these black swan events on investors' herding in the Saudi stock market motivated us to conduct our study. This study is based on the following research questions. First, are any changes observed in investor herding behaviour during black swan events (COVID-19 and Russia–Ukraine outbreaks) in the Saudi stock market? Second, do the increasing and decreasing days of return differ? Third, are there any differences between high-volatility and normal-volatility days? We investigate whether COVID-19 and the Russia–Ukraine War affected investors' herding behaviour because these critical events have recently depressed financial markets globally [54]. Our objective is to investigate investor herding during the COVID-19 crisis in comparison with the periods before and after the COVID-19 pandemic in the emerging stock market of Saudi Arabia. Moreover, we examine the impact of the ongoing Russia–Ukraine conflict on investors' herding behaviour in stock markets, specifically the Saudi stock market.

For this purpose, we checked for the occurrence of herding behaviour by comparing four successive periods partitioned by the COVID-19 coronavirus outbreak and the Russian–Ukrainian conflict. We assess the effect of COVID-19 and the Russia–Ukraine war by testing whether herding differs significantly in the periods included in this study (before, during, and after the COVID-19 crisis and during the Russia–Ukraine conflict). We use Christie and Huang's [20] and Chang et al. 's [22] measures on the Saudi stock market. Our study uses the daily returns on the Tadawul All Shares Index (TASI) for the Saudi stock market from January 2009 to February 2024. We conducted robustness checks for the pre-COVID-19 period because it was considerably longer than the other periods. The robustness checks cover the period from January 2018 to February 2024. The periods chosen for our study were sufficiently long to include the pre-COVID-19 period, during-COVID-19 period, post-COVID-19 period, and the Russia–Ukraine conflict, allowing us to examine the variation in herding behaviour in various situations.

When investors exhibit a bias in herding behaviour, they ignore their beliefs and information and follow different investors' beliefs, leading securities prices away from their fundamental values because they may not reflect important information. They also move in or out of the same securities, leading to market bubbles [55]. This study has several important implications. First, it provides clear insights into effect of black swan events (COVID-19 and the Russia–Ukraine outbreak) on stock markets. Moreover, it helps Saudi financial authorities understand the impact of black swan events, establish effective guidelines to cope with such events, and create suitable investment strategies. Furthermore, it helps investors in the Saudi stock market to better understand the situation of the Saudi stock market during outbreaks and crises. Additionally, it helps investors understand the effects of black swan events on their behaviour.

We report the following important results. Herding did not occur in the pre-COVID-19 period for the full period (since 2009) or the robust period (since 2018). It appeared during the COVID-19 period and disappeared again in the post-COVID-19 period and did not occur during the Russia–Ukraine conflict, confirming that investor herding manifested during the COVID-19 period. Robustness checks confirmed our finding that the COVID-19 pandemic has increased herding behaviour. Therefore, the results provide insights into the significance of herding during the COVID-19 crisis—investors in the Saudi stock market traded following market consensus at the time of COVID-19. Moreover, the results indicated the occurrence of herding during the COVID-19 period on high- and low-volatility days, in which the greatest herding intensities were observed. Additionally, the results of the Wald test confirm that no difference exists in herding behaviour between bearish and bullish days or high- and low-volatility days in the Saudi stock market, pushing aside the asymmetry in investors' responses in periods when the market declines and rises and during days of high and low volatility for the entire sample and all sub-samples.

The remainder of this paper proceeds as follows. Section 2, reviews the literature, and Section 3 presents the data for the Saudi stock market. Subsequently, Section 4 describes the methodology used in the study, and Section 5 discusses the empirical findings. Finally, Section 6 concludes the paper.

2. Literature review

Financial crises, the COVID-19 pandemic, and the Russia–Ukraine conflict can create extreme market conditions that might increase the incentives to herd because, during times of heightened uncertainty, it is costlier and more time-consuming to process the amount of information. Thus, investors may imitate the actions of other investors under these conditions.

2.1. Financial crisis

Herding evidence is mixed in the literature; some studies show no herding during the financial crisis, whereas others support the presence of herding. Many studies have documented significant herding behaviour during crises. For example, Chiang and Zheng [46] examine 18 markets from 1988 to 2009. They find significant herding behaviour in developed Asian, US, and Latin American markets. Another study conducted by Ouarda, El Bouri [56] found evidence of herding behaviour during the Asian crisis. Mobarek, Mollah [57] find significant herding behaviour during crises. They find that herding was pronounced in most continental countries during the global financial crisis and in Nordic countries during the Eurozone crisis. Further, Portugal, Italy, Ireland, Greece, and Spain were victims of both crises. Moreover, herding has been frequently observed during global financial crises and bubble periods [58–60]. Many other authors have documented significant herding behaviour under extreme market conditions [46,61–63]. conversely, Ferruela and Mallor [9] found that herding behaviour disappeared during the financial crisis.

2.2. COVID-19 pandemic

Regarding the COVID-19 pandemic and herding, evidence is mixed. For example, Ferreruela and Mallor [9] analysed herding behaviour during the COVID-19 pandemic in Spanish and Portuguese stock markets. However, they did not detect herding in the Spanish stock market. Nevertheless, in the Portuguese market, herding behaviour was observed during the pandemic period, highlighting the differences between the two markets. Wu, Yang [64] found that herding behaviour was significantly lower than usual in Chinese stock markets during the COVID-19 pandemic. Similarly, Yarovaya, Matkovskyy [65] analyse this behaviour in cryptocurrency markets during the COVID-19 pandemic and found that COVID-19 did not increase. Other studies have documented significant herding behaviour during the COVID-19 pandemic. Among them, Chang, McAleer [23] examined herding in renewable energy stock markets in the USA, Europe, and Asia using the CSSD and CSAD approaches. Their results suggest that investors became more sensitive to asset losses after the global financial crisis; therefore, during SARS and COVID-19, investors' panic pushed them to sell their assets unwisely. More recently, Espinosa-Méndez and Arias [66] investigated whether the COVID-19 pandemic affected herding behaviour in the Australian stock market. Using a sample of all firms listed from 2008 to 2020, they found evidence that the COVID-19 pandemic has increased herding behaviour. They concluded that herding behaviour manifested during the crises and extreme periods. In the same year, Espinosa-Méndez and Arias [67] conducted another study to investigate whether the COVID-19 pandemic affected herding behaviour in Europe. They found that the COVID-19 pandemic increased herding behaviour in European capital markets. Similarly, Fang, Chung [68] found that the COVID-19 pandemic increased herding behaviour in the Eastern European stock markets of Russia, Poland, the Czech Republic, Hungary, Croatia, and Slovenia from 2010 to 2021. More recently, Ampofo, Aidoo [69] investigated the effects of the COVID-19 pandemic on herding behaviour among investors in the US and UK stock markets. They found that herding occurred during the COVID-19 period in the bullish US and UK markets; however, herding behaviour occurred only during the COVID-19 period in the bearish US markets. The cited studies were conducted in developed and emerging stock markets; nonetheless, no study has focused on GCC countries, including the emerging stock market of Saudi Arabia. Moreover, the existing literature on how the COVID -19 pandemic has affects herding behaviour is limited.

2.3. Russia–Ukraine conflict

Choudhry [70] finds that most wartime events resulted in structural breaks in price movements and stock return volatility (risk) in the US stock market. Hudson and Urquhart [5] studied the effects of World War II on the UK stock market and found weak linkages between war events and stock market returns. In a more recent work, Hudson and Urquhart [71] studied the effects of naval disasters on the UK stock market and found that the market was significantly affected by only a few naval disasters, which have clear strategic and political importance. Tosun and Eshraghi [72] compared the effect of the Russia–Ukraine conflict on two types of firms: 'leaver firms'—firms that chose to exit the Russian market due to its invasion, and 'remaining firms'—firms that chose to keep their businesses operating in Russia. They find that a portfolio of the remaining firms in Russia underperforms leaver firms and market benchmarks. Umar, Riaz [73] found an increase in the abnormal returns of renewable energy markets caused by the Russia–Ukraine War. Pandey and Kumar [74] examined the effects of the Russia–Ukraine conflict on global-tourism sector stocks. They find that the abnormal returns of firms in Europe, the Middle East, Africa, and the Pacific are significantly negative on event days. Yousaf, Patel [3] examine the effect of the Russia–Ukraine conflict on the G20 and other selected stock markets using the event study approach. The analysis of the abnormal returns revealed a strong negative impact of this conflict on the event day and post-event days on most stock markets, especially in the Russian market. Moreover, regional analysis indicates that this event adversely affected the European and Asian regions.

2.4. Asymmetric herding behaviour: market volatility

One strand of the literature concern the relationship between volatility and herding behaviour among investors [see 9, 75, 76, 77]. High market volatility may affect investors' decision-making because investors tend to overestimate losses and underestimate profits in times of high uncertainty [75]. Moreover, it is worth examining herding behaviour in the market during the pandemic and the conflict of high volatility in comparison with calm days because these extreme events may increase uncertainty about firms' future profitability, leading to greater stock price variations [3,5,70]. Some studies do not show any differences between days with high volatility and the rest of the days [e.g. 79]. However, these results differ from those of other studies [e.g. 9, 80, 81], which found evidence of asymmetric herding behaviour in periods of high and low volatility and concluded that the level of herding is significantly high during high-volatility days. Other authors [e.g. 24, 82] found that herding occurs on low-volatility days.

2.5. The Saudi stock market

Relatively few studies have been conducted in the context of herding in the Saudi stock market, all of which show significant herding in the Saudi stock market. Balcilar, Demirer [51] examine herding behaviour under three market regimes (low, high, extreme, or crash volatility), concentrating on the Gulf Arab stock markets of Abu Dhabi, Dubai, Kuwait, Qatar, and Saudi Arabia. They found evidence of herding behaviour under the crash regime for all markets except Qatar, which underwent herding under the high-volatility regime. Balcilar, Demirer [76] examine the effect of market volatility on herding behaviour in GCC stock markets. Using weekly data from 2001 to 2012, they report strong and persistent herding behaviour in all GCC markets during the high-volatility regime. Nevertheless, there is no evidence of herding behaviour during the low-volatility regime. Rahman, Chowdhury [40] investigate herding in the Saudi stock market from 2002 to 2012 and find evidence of pervasive herding among market participants. They conclude that individual investors are more likely to be noise traders. Ulussever and Demirer [52] examine whether investor herds exist in the GCC stock markets. They found significant evidence of herd behaviour in all GCC equity markets except Oman and Qatar, more consistently during market losses. They also found significant oil price effects on herding behaviour in the GCC markets. Youssef and Mokni [50] tested whether herding behaviour affect the dependence structure between stock markets in GCC countries by considering different market conditions. They found that herding behaviour occurred in all GCC markets, except for Bahraini and Kuwaiti, and this behaviour's effect on the dependence structure was statistically significant and positive. More recently, Gabbori [77] examine herding behaviour in the Saudi equity market between 2006 and 2016 using the method of Chang, Cheng [22]. The results showed significant herding behaviour in most of the sub-periods. Furthermore, the results show pronounced herding in all GCC equity markets affected by significant herding spillover from the Saudi market and insignificant spillover from the US, indicating regional integration of markets, with the Saudi market pre-eminent.

The following points need to be clarified by reviewing the relevant literature. Herding behaviour has not been widely studied in the context of the Saudi stock market; only a few studies have been conducted on herding in the Saudi stock market. Owing to this lack of research, it is necessary to explore herding behaviour in emerging markets, such as the Saudi stock market. The limited research on the Saudi stock market in this area is surprising, especially because the Saudi stock market is by far the largest, most liquid, and most actively traded stock market in the GCC countries and the entire Arab world [40,78,79]. Moreover, the herding behaviour literature has documented the presence of herding behaviour in the Saudi stock market and provided conclusive results showing that individual investors tend to be noise traders who are prone to herding, providing a suitable environment to test the effect of black swan events (COVID-19 and Russia–Ukraine conflict) on investor herding behaviour.

Herding is more pronounced in emerging stock markets [80], such as Saudi Arabia. This occurs mainly in emerging markets rather than developed stock markets [52]. Emerging stock markets have an ambiguous informational environment and low transparency; therefore, investors may resort to herding to resolve this ambiguity [39]. Herding behaviour may be more pronounced in the Saudi stock market because of the lack of transparency and difficulty in information acquisition. According to Lerner, Leamon [81], the Saudi stock market must move away from reliance on retail investors and increase transparency and disclosure.

Regarding the COVID -19 pandemic and investor herding behaviour, researchers have conducted several empirical studies in developed [23] and emerging stock markets [64] but not in GCC countries, including the Saudi stock market. The lack of literature on COVID-19's effect on herding behaviour in the Saudi stock market motivated us to examine this issue more deeply. Moreover, herding evidence is mixed in the literature because some studies have shown evidence that the COVID-19 pandemic increased herding behaviour and that herding behaviour manifests during crises and extreme periods [9,64], while others have suggested that herding behaviour disappears and is not generally detected in COVID-19 times [23,66,68]. Investors in other stock markets may react differently to the COVID-19 crisis. Therefore, it is necessary to explore its effects on other markets, such as the Saudi stock market.

Little research has been conducted on herding behaviour in the Saudi stock market [40,50,76]. However, in Saudi Arabia, there is no literature that examines the effect of the COVID-19 pandemic and the Russia–Ukraine conflict on herding behaviour. Most of the existing literature has concentrated on herding behaviour during financial crisis periods, but not during the COVID-19 pandemic or the Russia–Ukraine conflict. The situations created by the COVID-19 health crisis and the Russia–Ukraine conflict differ from the financial crisis in that the financial crisis is an endogenous event for stock markets, whereas the COVID-19 and the Russia–Ukraine crises are exogenous shocks to stock markets that may create extreme market conditions. Each situation had different psychological implications. Furthermore, the literature has focused on the effect of other disease periods, such as the SARS period, on herding behaviour [11]. Nevertheless, the effect of COVID-19 is different from that of SARS because COVID-19 is a global health crisis that requires further investigation. To our knowledge, this is the first study to investigate investor herding behaviour in Saudi Arabia's emerging stock markets during the COVID-19 global pandemic period in comparison with the periods before and after the COVID-19 crisis. Moreover, to the best of our knowledge, this is the first study to investigate investor herding behaviour in stock markets during the Russia–Ukraine conflict. Given the psychological behaviour of stock market investors, this study comprehensively explores investor herding behaviour. In particular, we analyse the impact of the COVID-19 pandemic and Russia–Ukraine conflict on herding behaviour in the Saudi stock market.

3. Data

We collect data from the Saudi Stock Exchange (SSE).[1] The SSE provides financial data and is the official source of financial information for Saudi Arabia. We used the closing prices of daily data for all firms listed on the SSE from January 4, 2009 to February 29, 2024 as well as the TASI, which is the main market index of the SSE and tracks the performance of all firms listed on the SSE. Our sample comprises 135 companies and 3430 daily observations for each firm. The sample includes firms listed on the SSE after January 4, 2009 (the starting date) because a larger sample is more informative. Specifically, we base our analysis on the average data of all firms and not on individual firms. We conducted all analyses for the entire sample and split our sample into four additional subsamples, classified as pre-COVID-19, during-COVID-19, post-COVID-19, and Russia–Ukraine conflict. The three major events are the COVID-19 global health crisis, the Interior Ministry of Saudi Arabia's announcement to lift coronavirus restrictions and the Russia–Ukraine political conflict. First, the COVID-19 global crisis corresponds to the first confirmed COVID-19 case in the Kingdom of

[1] Saudi Stock Exchange https://ereference.tadawul.com.sa/ir/user/refDataLogin.xhtml?lang=en.

Saudi Arabia (KSA), which was observed on March 2, 2020 [82]. Second, although the coronavirus is ongoing, we believe that the worst of COVID-19's impact on the stock market and economic activities ended on June 21, 2020 coinciding with the Interior Ministry of Saudi Arabia's announcement to lift curfews and lockdown restrictions across the country in an effort by the Kingdom to return to normalcy, allowing all economic and commercial activities to resume.[2]

Third, Russian troops entered Ukraine after President Putin asked his nation to conduct a special military operation against Ukraine on February 24, 2022 [3]. Therefore, we selected February 24, 2022 as the event date to analyse the impact of the Russia–Ukraine military crisis on the Saudi stock market. We carefully chose each period's start and end dates as follows: the pre-COVID-19 sub-period extends from January 4, 2009 to March 1, 2020; the during-COVID-19 sub-period from March 2, 2020 to June 20, 2020; the post-COVID-19 sub-period from June 21, 2020 to February 23, 2022; and the Russia–Ukraine war sub-period from February 24, 2022 to February 29, 2024 which is the end of our sample.

We performed robustness checks on the length of the pre-COVID-19 sub-period. Thus, the start and end dates of the entire sample and the pre-COVID-19 sub-period are affected. However, the other periods (during- and post-COVID-19 and the Russia–Ukraine war) have the same start and end dates. We chose these dates for the robustness checks as follows: the entire sample spans from January 1, 2018 to February 29, 2024 and the pre-COVID-19 sub-period spans from January 1, 2018 to March 1, 2020.

4. Methodology and empirical analysis

4.1. Descriptive statistics

We use two major empirical measures based on the stock return dispersion to examine the intensity of herding behaviour: CSSD and CSAD. CSSD is empirically sensitive to outliers, making it difficult to find evidence of investor herding under normal conditions. Therefore, we also used the CSAD, which is claimed to be a more accurate measurement of dispersions. These methods show that in the presence of herding behavioural bias, individual stock returns converge towards the main stock market index return; hence, the dispersion of stock returns from market returns decreases. Lower cross-sectional dispersions of returns and increased similarity of movement in stock prices in times of market stress indicate the presence of herding behaviour. The idea behind these models is that if investors do not herd but think individually, stocks would have different performances, and their returns may deviate from the main stock market index return. Nonetheless, if investors herd and follow the market's performance during periods of market stress, the return on individual stocks will not differ significantly from the market return. Daily market returns ($\boldsymbol{R_{m,t}}$) are the daily returns of the TASI because it is the main index tracking the performance of all companies listed on the SSE [79]. Table 1 reports the descriptive statistics of the market returns of the daily data for the TASI (R_m), CSSD, and CSAD for the KSA stock market from January 4, 2009 to February 29, 2024. We can see some similarities with the Portuguese stock market: the mean returns for the Saudi and Portuguese markets are relatively larger than that of Spain [9], and the median is higher in the Saudi stock market. The spread between the maximum and minimum values is not considerably high; however, the standard deviation is large. The asymmetry coefficient is negative, and the market shows a leptokurtic distribution of returns, but it is not considerably large compared to previous studies [9]. The descriptive statistical results for the CSSD and CSAD are similar, with lower mean, median, maximum, and standard deviation values for the CSAD than for the CSSD. Nevertheless, the CSAD had higher asymmetry and kurtosis coefficient values, but the difference is not large.

4.2. Measuring herding with the CSSD approach

The first herding behaviour measure is based on Christie and Huang's [20] work, which calculated the CSSD to measure the dispersion of stock returns listed in the stock market, as the following Equation (1) shows:

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

where $R_{i,t}$ is the return of stock i at time t, $R_{m,t}$ is the main stock market index return at time t, and the number of stocks listed on the stock market at time t is represented by N.

According to Christie and Huang [20], dispersion should be lower than anticipated in the presence of herding behaviour, unlike when herding does not occur. The authors propose Equation (2) to investigate whether market investors copy the market consensus's actions during extreme return periods in the markets—if the return dispersion is significantly lower in extreme return periods in the US market.

$$CSSD_t = \alpha + \beta^{low} D_t^{low} + \beta^{up} D_t^{up} + \varepsilon_t, \tag{2}$$

where D_t^{low} and D_t^{up} are dummy variables: $D_t^{low} = 1$ if the main stock market index return $R_{m,t}$ is located in the (5 %) lower tail of the

[2] Ministry of Interior Saudi Arabia (2020). https://www.my.gov.sa/wps/portal/snp/agencies/AC169/!ut/p/z0/04_Sj9CPykssy0xPLMnMz0vMAfIjo8zi_QxdDTwMTQz9DUyM3AwCXVwc_UxDDL38TYz0g1Pz9AuyHRUBWBYSxQ!!/and Saudi Press Agency (2020). https://www.spa.gov.sa/aboutwas.en.php.

Table 1
Descriptive statistics.

	TASI	CSSD	CSAD
Mean	0.024361	1.817917	1.235980
Median	0.074681	1.692189	1.128643
Maximum	8.547474	85.62765	28.96159
Minimum	−8.684583	0.677549	0.508570
Std. deviation	1.095735	1.475615	0.630018
Skewness	−0.869482	48.50681	23.27001
Kurtosis	13.01041	2750.889	994.0414

This table reports the descriptive statistics of the market return and the two herding measures, CSSD and CSAD, for the period between January 4, 2009 and February 29, 2024.

return distribution, and $D_t^{low} = 0$ otherwise, and where $D_t^{up} = 1$ if the main stock market index return $R_{m,t}$ is located in the (5 %) upper tail of the return distribution and $D_t^{up} = 0$ otherwise.

This table reports the results of the model in Eq. (2), as proposed by Christie and Huang [20]. Panel A: the entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period is from January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to the presence of heteroskedasticity, we estimated Eq. (2) using OLS with White's variance and the covariance matrix. Numbers in parentheses represent t-statistics. We denote the statistical significance at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

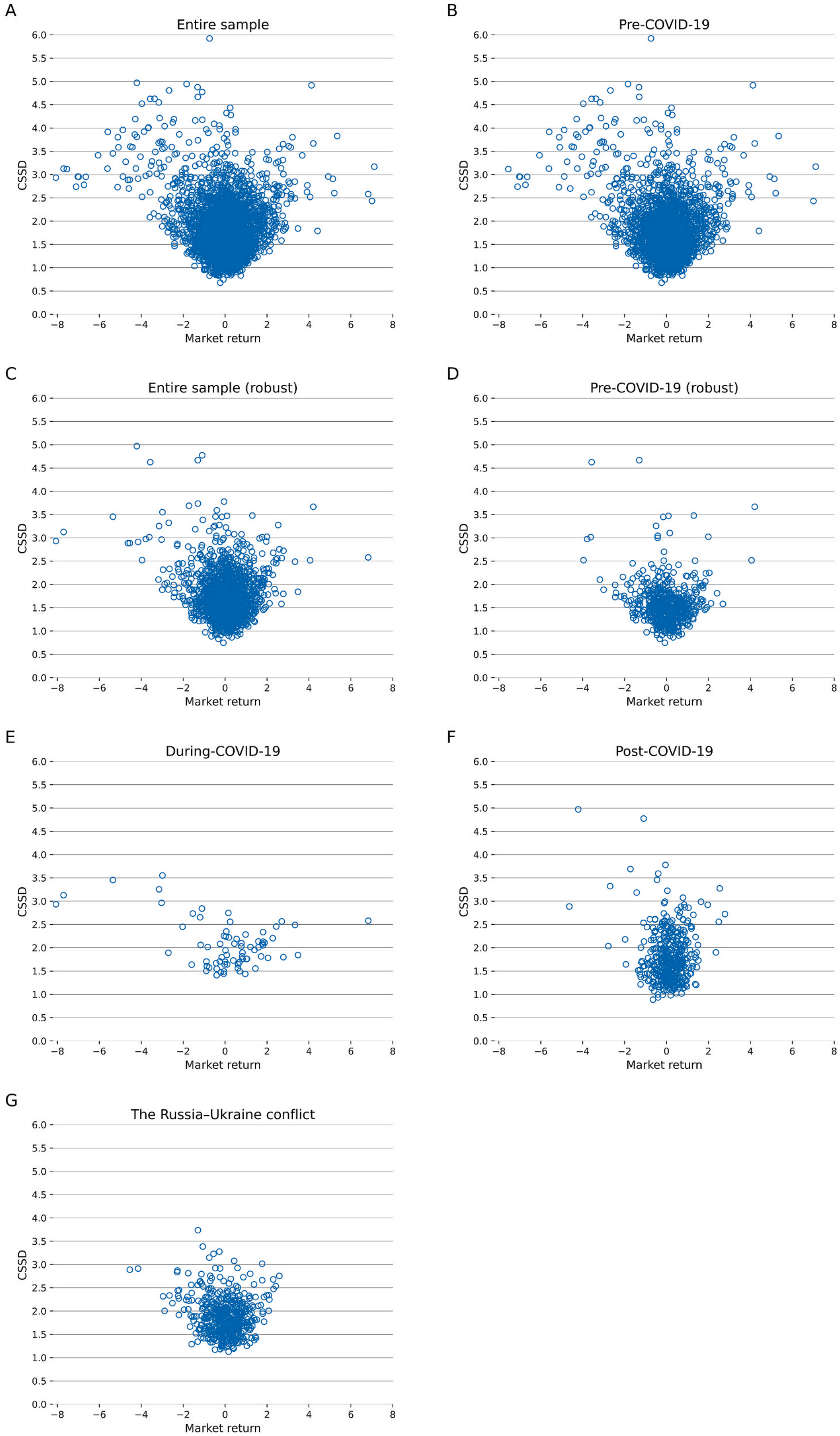
We estimated Equation (2) for the KSA stock market using the least squares method and accounted for heteroskedasticity using White's variance-covariance matrix. For herding to occur, the beta coefficients (β^{low} and β^{up}) must be negative and significant. Table 2 presents the findings regarding herding in the Saudi stock market for the entire sample, as well as the pre-, during-, and post-COVID-19 periods and the ongoing Russia–Ukraine sub-period. The difference between Panels A and B is that the lengths of the entire sample and the pre-COVID-19 sub-period are different. In Panel B, we conduct robustness checks for the length of the pre-COVID-19 sub-period. The other periods (during- and post-COVID-19 and the Russia–Ukraine war periods) have the same length and produce the same results; hence, they are not reported in Panel B. The beta coefficients in Panel A are positive either significant or non-significant for the subsamples included in this study (complete sample, as well as the pre-, during-, and post-COVID-19 and Russia–Ukraine conflict periods). Therefore, we find evidence of the absence of herding when using Christie and Huang's [20] CSSD herding measure. Table 2, Panel B, presents the results of the robustness checks for the pre-COVID-19 sub-period because it has a considerably different length from those of all other periods under study. The robustness results reported in Panel B confirm the results in Panel A, showing the absence of herding when using the CSSD herding measure. The CSSD increases in the left and right tails, suggesting that investors do not herd or follow key influencers' market signals or opinions. However, not detecting herding in the KSA stock market by the CSSD measure should not stop us from further investigation using another measure because the literature [9,83] proves that this measure is extremely restrictive on many occasions and fails to detect herding when other measures could detect herding and reveal its existence. For the CSSD to detect herding, herding must occur, particularly during extreme market periods. This condition implies that it would not be possible to detect herding with this measure if herding occurred in other periods.

4.3. *Measuring herding following the CSAD approach*

Chang, Cheng [22] propose a second herding measure based on the CSAD of returns, inspired by Black's [84] capital asset pricing

Table 2
Estimates of herding behaviour using cross sectional standard deviation measure.

Panel A		α	βlow 5 %	βup 5 %	α	βlow 1 %	βup 1 %
Entire sample	Coef.	1.747990***	0.951837***	0.557415***	1.795227***	1.544143***	0.981793***
	t-stat	(67.64611)	(14.12317)	(11.02586)	(74.10687)	(15.61927)	(8.300973)
Pre-COVID-19	Coef.	1.691687***	1.029288***	0.610652***	1.746561***	1.618050***	1.115085***
	t-stat	(167.9954)	(13.98233)	(11.36201)	(163.4226)	(15.89400)	(8.825887)
During-COVID-19	Coef.	1.894143***	1.051948***	0.254900***	2.009066***	1.092337***	0.168074
	t-stat	(35.03076)	(6.063597)	(2.956956)	(35.72420)	(8.648256)	(0.876177)
Post-COVID-19	Coef.	1.763173***	1.196834***	0.963785***	1.784350***	2.142772***	0.938036***
	t-stat	(70.35352)	(2.962677)	(5.393430)	(69.07986)	(2.895435)	(36.31538)
The Russia–Ukraine conflict	Coef.	2.022555***	0.328405*	0.307569	2.030734***	0.868690***	Not defined because of singularities
	t-stat	(11.17233)	(1.667374)	(1.546574)	54.315	22.651	
Panel B: robustness checks		α	βlow 5 %	βup 5 %	α	βlow 1 %	βup 1 %
Entire sample	Coef.	1.770397***	0.684943***	0.418141***	1.799853***	1.375676***	0.716787***
	t-stat	(29.44378)	(6.036778)	(4.903835)	(31.90904)	(5.924429)	(3.170577)
Pre-COVID-19	Coef.	1.529650***	0.617174***	0.437798***	1.561636***	0.959419***	1.531132***
	t-stat	(84.4136)	(3.7692)	(3.8740)	(83.1899)	(51.1092)	(3.7644)



(caption on next page)

Fig. 2. Market return and CSSD measures for the periods under this study. (A) The entire sample from January 4, 2009 to February 29, 2024, (B) the pre-COVID-19 sub-period from January 4, 2009 to March 1, 2020, (C) the entire sample (robust) from January 1, 2018 to February 29, 2024, (D) the pre-COVID-19 sub-period (robust) from January 1, 2018 to March 1, 2020, (E) the during-COVID-19 sub-period from March 2, 2020 to June 20, 2020, (F) the post-COVID-19 sub-period from June 21, 2020 to February 23, 2022, and (G) the Russia–Ukraine conflict sub-period from February 24, 2022 to February 29, 2024.

model:

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

where $R_{i,t}$ is the observed return of each stock i at time t, $R_{m,t}$ is the main stock market index return at time t, and the number of stocks listed on the stock market at time t is represented by N.

Chang, Cheng [22] argue that if investors herd in times of sharp movements in stock prices, the linear and positive relationship between CSAD and the main stock market index return will no longer hold, and it might become a nonlinear and even negative relationship. Therefore, they estimated the relationship between CSAD and market returns using a nonlinear specification captured by the non-linear coefficient as follows:

$$CSAD_t = \alpha + \boldsymbol{\gamma_1}\left|\boldsymbol{R_{m,t}}\right| + \boldsymbol{\gamma_2}\boldsymbol{R^2_{m,t}} + \varepsilon_t, \tag{4}$$

If herding occurs, we expect a significantly decreasing non-linear relationship between CSAD and the main stock market index return represented by the $\boldsymbol{\gamma_2}$ coefficient [85].

Fig. 2 displays the relationship between the main stock market index return and CSSD in Saudi Arabia for the entire period and the four sub-periods. If herding behaviour exists, the ends of the figure will indicate a declining line, indicating less cross-sectional dispersion in extreme movement periods of the stock market. The figures show a clear difference between the during-COVID-19 period (Fig. 2E) and the other periods. Fig. 2E looks flatter than the other figures—it shows the lowest level of dispersion for the same level of market return compared to all other periods, allowing us to draw the conclusion that herding occurred during the COVID-19 pandemic. However, Fig. 2B, D, 2F, and 2G for the other sub-periods (pre- and post-COVID-19, as well as the Russia–Ukraine conflict) seem to provide higher levels of dispersion at the same return levels than that observed in during-COVID-19 period. The dispersion increases on extreme days of market returns, anticipating that herding does not occur in the pre- and post-COVID-19 and Russia–Ukraine conflict sub-periods in the Saudi stock market.

Table 3 reports the results for the Saudi stock market of Equation (4) using the CSAD measure calculated by Equation (3). It provides the results for the entire period in addition to the four sub-periods (pre-, during- and post-COVID-19, as well as the Russia–Ukraine conflict). The difference between Panels A and B is that the lengths of the entire sample and the pre-COVID-19 sub-period are different. In Panel B, we conduct robustness checks on the length of the pre-COVID-19 sub-period. The other periods have the same length and produce the same results (during- and post-COVID-19 and the Russia–Ukraine war periods); hence, they are not reported in Panel B. According to the results of Equation (4) presented in Table 3, Panel A, using the CSAD measure, we found that herding occurs in the Saudi stock market for the entire sample from 2009 to 2024 and the during-COVID-19 sub-period because the γ_2 terms relative to the non-linear negative coefficient that are significant at the 1 % and 5 % levels, respectively. Thus, the empirical results show evidence that investors in the Saudi stock market follow the market consensus while trading during the COVID-19 crisis. Nevertheless, the results confirm that herding is not detected in the pre- or post-COVID-19 or the Russia–Ukraine conflict periods, given the non-significant coefficients of the non-linear term γ_2. Therefore, investors in the Saudi stock market are trading following their own information in the pre- or post-COVID-19 or the Russia–Ukraine conflict periods. The results indicate the absence of herding in the pre-

Table 3
Estimates of herding behaviour using cross-sectional absolute deviation in up and down markets.

Panel A		α	γ1	γ2
Entire sample	Coef.	0.983328***	0.383642***	−0.018177***
	t-stat	86.32552	12.55648	−2.969845
Pre-COVID-19	Coef.	0.946653***	0.370656***	−0.012227
	t-stat	71.23888	12.99688	−1.594054
During-COVID-19	Coef.	1.157872***	0.276025***	−0.015766**
	t-stat	18.37413	4.014862	−2.019898
Post-COVID-19	Coef.	1.126389***	0.106928	0.093960
	t-stat	29.74556	0.924908	1.613962
The Russia–Ukraine conflict	Coef.	1.112163***	0.463482*	−0.043138
	t-stat	14.65676	1.729122	−0.670262
Panel B: robustness checks		α	γ1	γ2
Entire sample	Coef.	1.026374***	0.358118***	−0.019563**
	t-stat	49.76213	5.469066	−1.966872
Pre-COVID-19	Coef.	0.958144***	0.123301*	0.064236**
	t-stat	1.800808	1.800808	2.140398

COVID-19 sub-period. Nonetheless, it appears in the during-COVID-19 sub-period and disappears again in the post-COVID-19 and Russia–Ukraine conflict periods, confirming that investor herding behaviour manifested during COVID-19. These findings show that during COVID-19, the Saudi stock market exhibited patterns consistent with herding behaviour and that investors in this market traded following the market consensus during the pandemic. The highest herding intensity occurs in the during-COVID-19 sub-period compared to all other sub-periods included in this study.

Panel B of Table 3 shows the results of robustness checks on the length of the pre-COVID-19 sub-period because it has a considerably different length from those of all other periods under study. The robustness results reported in Panel B confirm our results in Panel A that herding is detected for the entire sample and is not detected for the pre-COVID-19 sub-period. In Panel B, the γ_2 term in Equation (4) becomes significantly positive for the pre-COVID-19 sub-period, whereas, as Panel A shows, it was negative but not significant for the same period. Robustness checks confirm that the market behaves rationally for the pre-COVID-19 sub-period because the non-linear coefficient is positive and significant. We need to say here that the robustness results in Panel B seem more robust and tell us that herding does not occur in the pre-COVID-19 sub-period, and investors trade rationally in normal, more relaxed periods where no crisis of any type occurs. This is reasonable because the length of the pre-COVID-19 sub-period is not considerably different from that of the other periods under study.

This table reports the estimated coefficients of Eq. (4). Panel A: the entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from March 2, 2020 to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period is from January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to the presence of heteroskedasticity, we estimated that Eq. (4), using OLS with White's variance and a covariance matrix. Numbers in parentheses represent t-statistics. We denote the statistical significance at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

4.4. Herding in bullish versus bearish markets

Chang, Cheng [22] also investigate whether investors' reactions are asymmetric and suggest that more herding might occur in bearish periods than in bullish periods. This result is based on the various emotional implications of times of declining stock prices compared to times of increasing prices. Therefore, we follow Chiang and Zheng [46], who propose a model that examines asymmetry and differentiates between trends to determine whether herding occurs in up and down markets:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2(1 - D^{up})\left|R_{m,t}\right| + \gamma_3 D^{up}\left(R^2_{m,t}\right) + \gamma_4(1 - D^{up})\left(R^2_{m,t}\right) + \varepsilon_t, \tag{5}$$

where D^{up} is a dummy variable such that $D^{up} = 1$ if the main stock market index return, $R_{m,t}$, at time t is non-negative and zero otherwise.

Table 4 provides the results of Equation (5) for the entire period, in addition to four sub-periods (pre-, during-, and post-COVID-19 and the Russia–Ukraine War). The difference between Panels A and B is the length of the entire sample and the pre-COVID-19 sub-period. Panel B shows the results of the robustness checks for the length of the pre-COVID-19 sub-period. The other periods (during- and post-COVID-19 and the Russia–Ukraine War) have the same length and results; therefore, they are not reported in Panel B. In Panel An of Table 4, the results align with those obtained from the analysis conducted without distinguishing between bearish and bullish markets; herding was detected for the during-COVID-19 subsample in both markets (albeit with a significance level of 0.10 on bullish days compared to a significance level of 0.01 on bearish days). Similarly, the results align with those in Table 3, showing that herding did not occur on bullish or bearish days in the post-COVID-19 and Russia–Ukraine war sub-periods. However, the analysis results for the pre-COVID-19 sub-period are inconsistent with those in Table 3, which did not show herding behaviour. Herding is observed only in bullish periods for the pre-COVID-19 subsample, with a significance level of 0.05.

Table 4
Estimates of herding behaviour using cross-sectional absolute deviation in up and down markets.

Panel A		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	0.982741***	0.377332***	0.402477***	−0.025976***	−0.017385***
	t-stat	85.21762	8.374769	15.64465	−2.809015	−3.174419
Pre-COVID-19	Coef.	0.948180***	0.351991***	0.393043***	−0.019912**	−0.009794
	t-stat	79.22372	13.20363	13.10019	−2.245762	−1.398020
During-COVID-19	Coef.	1.154874***	0.223435***	0.409610***	−0.015787*	−0.031299***
	t-stat	18.53568	3.518277	5.030585	−1.938278	−3.250183
Post-COVID-19	Coef.	1.140390***	0.009195	0.106753	0.159879***	0.087847
	t-stat	31.97463	0.088406	0.767975	2.574558	1.417053
The Russia–Ukraine conflict	Coef.	1.135693***	0.395563	0.325086***	0.054246	−0.018075
	t-stat	15.54776	1.065775	2.844013	0.678273	−0.642115
Panel B: robustness checks		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	1.024478***	0.378168***	0.344725***	−0.024769	−0.017285***
	t-stat	43.01495	3.298356	8.724575	−1.095565	−2.812654
Pre-COVID-19	Coef.	0.957841***	0.111868*	0.135517	0.072095**	0.057376
	t-stat	34.80401	1.654465	1.530626	2.276578	1.352677

This table reports the estimated coefficients of the Chiang and Zheng's [46] model in Eq. (5). Panel A: the entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period from January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to the presence of heteroskedasticity, Eq. (5) was estimated using OLS with White's variance and a covariance matrix. Numbers in parentheses represent t-statistics. Statistical significance was denoted at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

In Panel B of Table 4, we perform robustness checks on the length of the pre-COVID-19 period because it is considerably different from all other periods under study. Herding is detected for the entire sample only on bearish days at a significance level of 0.01. However, herding did not occur on either bullish or bearish days in the pre-COVID-19 sub-period. The results in Panel B differ from those in Panel A. Regarding the entire sample, in Panel A, herding is detected in both markets, whereas in Panel B, herding is observed only on bearish days. Regarding the pre-COVID-19 sub-period, in Panel A, herding is detected on bullish days, whereas in Panel B, herding is not detected on bullish or bearish days. The findings in Panel B of Table 4 are more consistent with those in Panels A and B of Table 3 when we conduct the analysis without distinguishing between bearish and bullish markets. Overall, the coefficient for bullish days is close in absolute value to that for bearish days. The robustness results in Panel B, seem robust and more consistent with the previous results reported in Table 3, confirming that herding does not occur in the pre-COVID-19 sub-period, and investors trade rationally in more relaxed periods where no crisis of any type occurs. This is reasonable because the length of the pre-COVID-19 sub-period is not considerably different from that of the other periods under study.

Additionally, we conducted the Wald test. The Wald test's null hypothesis is that the coefficients of herding are equal ($\gamma_3 = \gamma_4$) on periods of increasing and declining market prices. If the null hypothesis is rejected, it indicates that investors' responses are significantly asymmetric and that investors act differently when the market fall. Table 5 provides the Wald test results, showing that no difference exists between bearish and bullish days or between rising and declining markets for the periods under study; hence, the null hypothesis cannot be rejected. Thus, that the coefficients of herding are equal, pushing aside the asymmetry in investors' responses in periods when the market declines and rises for the entire sample and all sub-periods. Our main novelty is that when we distinguish between bullish and bearish days, we find that herding behaviour occurred only on bearish days in the robust entire sample period; nonetheless, herding was not detected on bullish days. Therefore, it is important to consider the differences between bull and bear markets when analysing herding behaviour.

This table reports the Wald test results for the null hypotheses. $\boldsymbol{\gamma_3 - \gamma_4}$ in Eq. (5) and the corresponding chi-square ($\boldsymbol{x^2}$). Panel A: the entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period is from January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to the presence of heteroskedasticity, Eq. (5) is estimated using OLS with White's variance and a covariance matrix. Numbers in parentheses represent t-statistics. Statistical significance is denoted at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

4.5. *Herding during high versus normal volatility days*

Empirical studies [e.g. 55] have confirmed that periods of high volatility affect investors' decision-making processes. They state that investors' tendency to herd increases with volatility because high volatility and oscillations may create a situation in which investors sense safety when acting similarly to the crowd and market consensus to ensure at least average market returns.

We investigate the relationship between investor herding behavioural bias and Saudi stock market volatility and determine whether black swan events (COVID-19 and the Russia–Ukraine war) affected this relationship. Based on the results obtained above using the two measures of herding behaviour and the literature, which indicate that the CSSD measure is extremely restrictive and fails to detect herding, we decided to employ only the CSAD measure for the analysis in this section.

Table 5
Wald tests results.

Panel A: $H_0 : \gamma_3 = \gamma_4$		
Entire sample	$\gamma_3 - \gamma_4$	−0.008591
	Chi-Square (x^2)	(0.3684)
Pre-COVID-19	$\gamma_3 - \gamma_4$	−0.010117
	Chi-Square (x^2)	(0.976899)
During-COVID-19	$\gamma_3 - \gamma_4$	0.015512
	Chi-Square (x^2)	(2.487162)
Post-COVID-19	$\gamma_3 - \gamma_4$	0.072032
	Chi-Square (x^2)	(0.893130)
The Russia–Ukraine conflict	$\gamma_3 - \gamma_4$	0.072321
	Chi-Square (x^2)	(0.2409)
Panel B: $H_0 : \gamma_3 = \gamma_4$		
Entire sample	$\gamma_3 - \gamma_4$	0.007484
	Chi-Square (x^2)	0.7173
Pre-COVID-19	$\gamma_3 - \gamma_4$	0.014719
	Chi-Square (x^2)	(0.100036)

We use two volatility measures, following Parkinson [48] and Garman and Klass [49]. Parkinson incorporated maximum and minimum daily prices when calculating his volatility measure, allowing him to detect extreme intraday changes in prices that are not presented in closing prices. Garman and Klass incorporated market opening and closing prices, in addition to maximum and minimum prices, when calculating their volatility measures. For Parkinson's and Garman and Klass's measures, the volatilities are calculated using the following expressions:

$$\sigma_P^2 = \frac{1}{4\,ln\,2}(ln\,H_t - ln\,L_t)^2, \tag{6}$$

$$\sigma_{GK}^2 = \left[\frac{1}{2}\left(ln\frac{H_t}{L_t}\right)^2 - (2\,ln\,2-1)\left(ln\frac{c_2}{O_2}\right)^2\right], \tag{7}$$

where the maximum and minimum stock prices of the TASI at time t are represented by H_t and L_t, respectively, and the closing and opening stock prices of the TASI at time t are represented by C_t and O_t, respectively.

Equations (6) and (7) calculate Parkinson's and Garman and Klass's volatility measures, respectively. Table 6 presents the descriptive statistics of Parkinson's and Garman and Klass's volatility methods in the Saudi stock market. The two measures show similar values, with Garman and Klass's measure showing slightly higher volatility (mean, median, and maximum) than Parkinson's. The distribution shows many days with volatility values close to the mean, and the values form a non-normal distribution because they are highly skewed with heavy tails. The impact of volatility on herding behaviour may differ from one market to another, depending on the investors who trade in the market and the information they receive. To investigate asymmetry in investors' behaviour and the effect of market volatility on investor herding in the Saudi stock market, we estimate the following regression using both volatility measures:

$$CSAD_t = \alpha + \gamma_1 D^{vol}|R_{m,t}| + \gamma_2(1-D^{vol})|R_{m,t}| + \gamma_3 D^{vol}\left(R_{m,t}^2\right) + \gamma_4(1-D^{vol})\left(R_{m,t}^2\right) + \varepsilon_t, \tag{8}$$

where D^{vol} is a dummy variable such that $D^{vol} = 1$ on high-volatility days and zero otherwise. Following Tan, Chiang [86], we assume that the market exhibits high volatility on day t when that day's volatility exceeds the moving average of the previous 30 days.

Tables 7–9 report the two volatility measures and Wald test results for the Saudi stock market, respectively. We estimated Equation (8) for the KSA stock market using the least squares method and account for heteroskedasticity using White's variance–covariance matrix. To obtain evidence of herding, the coefficients γ_3 and γ_4 must be significantly negative. When we examined the complete sample, we found that the coefficients of herding γ_3 and γ_4 are negative and significant for high- and low-volatility days; however, this asymmetry is rejected by the Wald test when using the two volatility measures. When we conduct a robustness check (as shown in Panel B), we find that herding appears only at times of low volatility. Regarding the pre-COVID-19 period, we found that only the coefficient γ_3 is negative and significant on high-volatility days, according to both volatility measures. Nevertheless, when we conducted the robustness check, we found that the coefficients of herding γ_3 and γ_4 were no longer significant, meaning we cannot reject the null hypothesis that the herding coefficients are equal.

Regarding the during-COVID-19 period, we found evidence similar to that presented in Table 4. The herding coefficients appear to be significantly negative during COVID-19, indicating the existence of herding in high- and low-volatility periods, in which the greatest herding intensities are observed, without differences between high- and low-volatility periods. In line with Table 4, herding disappears in the post-COVID-19 sub-period, and the same occurs in the Russia–Ukraine war period when γ_3 and γ_4 are no longer negative and significant. Additionally, the asymmetry is rejected by the Wald test when using the two volatility measures, showing no difference in investor herding on high- and low-volatility days in the Saudi stock market.

This table reports the estimated coefficients of Eq. (8) using the volatility measure Parkinson [48] proposed. Panel A: The entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period is of Eq. (8) using the volatility measure Parkinson [48] proposed. Panel A: The entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2020. Owing to the presence of heteroskedasticity, Eq. (8) was estimated using OLS with White's variance and a covariance matrix. Numbers in parentheses represent t-statistics. Statistical significance was denoted at the 1 %, 5 %,

Table 6
Descriptive statistics of Parkinson's and Garman & Klass's volatility measures.

	Parkinson volatility estimator	Garman and Klass volatility estimator
Mean	0.007851	0.010907
Median	0.006500	0.008900
Maximum	0.026400	0.037000
Minimum	0.003100	0.003900
Std. deviation	0.004020	0.005792
Skewness	1.836295	1.856447
Kurtosis	6.799256	6.843810

This table provides the descriptive statistics of the volatility methods for the period between January 4, 2009 and February 29, 2024.

Table 7
Estimates of herding behaviour using Parkinson's volatility estimation on high- and low-volatility days.

Panel A		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	0.980032***	0.373508***	0.395050***	−0.025712***	−0.016753***
	t-stat	86.26568	8.285642	15.61670	−2.789887	−3.136098
Pre-COVID-19	Coef.	0.943990***	0.346766***	0.384165***	−0.019479**	−0.009049
	t-stat	81.49800	13.29268	13.16187	−2.199139	−1.335926
During-COVID-19	Coef.	1.154818***	0.223486***	0.409646***	−0.015794**	−0.031303***
	t-stat	18.53514	3.519947	5.030013	−1.939731	−3.249969
Post-COVID-19	Coef.	1.140395***	0.009105	0.106816	0.159929**	0.087828
	t-stat	31.97450	0.087545	0.768407	2.575430	1.416755
The Russia–Ukraine conflict	Coef.	1.135693***	0.395563	0.325086***	0.054246	−0.018075
	t-stat	15.54776	1.065775	2.844013	0.678273	−0.642115
Panel B: robustness checks		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	1.024480***	0.378151***	0.344734***	−0.024764	−0.017287***
	t-stat	43.01772	3.298286	8.724928	−1.095330	−2.813067
Pre-COVID-19	Coef.	0.957840***	0.111870*	0.135520	0.072095**	0.057375
	t-stat	34.80377	1.654477	1.530624	2.276566	1.352629

Table 8
Estimates of herding behaviour using GK's volatility estimation on high- and low-volatility days.

Panel A		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	0.980032***	0.373495***	0.395062***	−0.025710***	−0.016756***
	t-stat	86.27072	8.285705	15.61717	−2.789547	−3.136676
Pre-COVID-19	Coef.	0.943988***	0.346763***	0.384173***	−0.019478**	−0.009051
	t-stat	81.49773	13.29286	13.16168	−2.199026	−1.336141
During-COVID-19	Coef.	1.154818***	0.223486***	0.409646***	−0.015794**	−0.031303***
	t-stat	18.53512	3.519937	5.030009	−1.939717	−3.249967
Post-COVID-19	Coef.	1.140414***	0.008846	0.106989	0.160072**	0.087777
	t-stat	31.97336	0.085042	0.769686	2.577558	1.416013
The Russia–Ukraine conflict	Coef.	1.135693***	0.395563	0.325086***	0.054246	−0.018075
	t-stat	15.54776	1.065775	2.844013	0.678273	−0.642115
Panel B: robustness checks		∝	γ_1	γ_2	γ_3	γ_4
Entire sample	Coef.	1.024486***	0.378107***	0.344758***	−0.024752	−0.017291***
	t-stat	43.02061	3.297970	8.725901	1.094694	−2.814170
Pre-COVID-19	Coef.	0.957840***	0.111869*	0.135520	0.072095**	0.057375
	t-stat	34.80375	1.654467	1.530623	2.276572	1.352630

Table 9
Wald test.

Panel A: $H_0 : \gamma_3 = \gamma_4$		Parkinson	Garman and Klass
Entire sample	$\gamma_3 - \gamma_4$	−0.008959	−0.008954
	Chi-Square (x^2)	(0.3444)	(0.3447)
Pre-COVID-19	$\gamma_3 - \gamma_4$	−0.010430	−0.010428
	Chi-Square (x^2)	(1.058266)	(1.057780)
During-COVID-19	$\gamma_3 - \gamma_4$	0.015509	0.015509
	Chi-Square (x^2)	(2.486934)	(2.486961)
Post-COVID-19	$\gamma_3 - \gamma_4$	0.072101	0.072295
	Chi-Square (x^2)	(0.894870)	(0.899685)
The Russia–Ukraine conflict	$\gamma_3 - \gamma_4$	0.072321	0.072321
	Chi-Square (x^2)	(0.2409)	(0.2409)
Panel B: $H_0 : \gamma_3 = \gamma_4$		**Parkinson**	**Garman and Klass**
Entire sample	$\gamma_3 - \gamma_4$	0.007477	−0.007461
	Chi-Square (x^2)	(0.7175)	(0.7181)
Pre-COVID-19	$\gamma_3 - \gamma_4$	0.014720	0.014720
	Chi-Square (x^2)	(0.100049)	(0.100051)

and 10 % levels with ***, **, and *, respectively.

This table provides the estimated coefficients of Eq. (8) using the volatility measure Parkinson [48] proposed. Panel A: The entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: the entire sample period is from

January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to the presence of heteroskedasticity, Eq. (8) was estimated using OLS with White's variance–covariance matrix. Numbers in parentheses represent t-statistics. Statistical significance was denoted at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

This table provides Wald test results for the null hypotheses. $\gamma_3 - \gamma_4$ in Eq. (8), and the corresponding chi-square (x^2). Panel A: the entire sample period is from January 4, 2009 to February 29, 2024, from January 4, 2009 to March 1, 2020, from 2 March to June 20, 2020, from June 21, 2020 to February 23, 2022, and from February 24, 2022 to February 29, 2024. Panel B: The entire sample period is from January 1, 2018 to February 29, 2024, and the pre-COVID-19 sample is from January 1, 2018 to March 1, 2020. Owing to heteroskedasticity, Eq. (8) was estimated using OLS with White's variance–covariance matrix. Numbers in parentheses represent t-statistics. Statistical significance was denoted at the 1 %, 5 %, and 10 % levels with ***, **, and *, respectively.

5. Discussion

Investor herding behaviour may destabilise markets, exacerbate volatility, increase financial system fragility, limit the possibility of diversification, jeopardise market efficiency, and lead to bubbles and crashes in financial markets. This study reveals the importance of crises and black swan events. In particular, it shows how different types of crises impact investor behaviour by creating uncertainty and triggering fear and anxiety among investors, leading less informed investors to copy more informed investors and market consensus during times of turmoil. Therefore, this study may provide market investors with knowledge and raise their awareness of the influence of cognitive bias on their investment decisions, improving market efficiency by investor rationality. This study also enhances investors' understanding of the effects of black swan events and encourages investors to develop trading strategies to mitigate downside risks during outbreaks and crises.

We investigate whether different types of crises (COVID-19 and Russia–Ukraine War) affect investors' herding behaviour because they are critical events that have recently depressed financial markets globally. We investigate investor herding during the COVID-19 crisis in comparison with the periods before and after the COVID-19 pandemic in the emerging stock market of Saudi Arabia. Moreover, we examine the impact of the ongoing Russia–Ukraine conflict on investors' herding behaviour in stock markets, specifically the Saudi stock market. We also investigate the asymmetry in investor responses on bullish versus bearish days and high versus low volatility days due to differences in the psychological implications of times of decreasing prices versus times of increasing prices and times of high volatility days versus times of low volatility days.

We analyse investor herding behaviour in different types of crises (the COVID-19 health crisis and Russia–Ukraine conflict). Most of the existing literature in the context of the Saudi stock market has concentrated on herding behaviour during financial crisis periods but not during the COVID-19 pandemic or the Russia–Ukraine conflict. Unlike the financial crisis, COVID-19 is a health crisis, and the Russia–Ukraine conflict is a political crisis. Therefore, they are crises of different origins, and studying their impact on the Saudi stock market is worthwhile. The situations created by the COVID-19 health crisis and the Russia–Ukraine conflict differ from the financial crisis—the financial crisis is an endogenous event for stock markets, whereas the COVID-19 and Russia–Russia–Ukraine conflicts are exogenous shocks to stock markets that may create extreme market conditions. Each situation had different psychological implications. These results highlight the differences in investor responses to turmoil resulting from various types of crises (i.e. the global COVID-19 crisis and the Russia–Ukraine political crisis), confirming the notion that crises of various origins have dissimilar characteristics and psychological effects on investors.

We used Christie and Huang's [20] cross-sectional standard deviation (CSSD) model and Chang et al.'s [22] CSAD model, which are the most commonly used herd behaviour measures. The CSSD and CSAD models are based on studies by Christie and Huang [20] and Chang et al. [22], respectively. Researchers have used aggregate market data to examine the occurrence of herding behaviour by applying CSSD and CSAD approaches in their studies [87–91]. However, the non-linear CSAD model is a more accurate measurement of dispersions and improves the linear CSSD model because it has been criticised for its empirical sensitivity to outliers, which makes it difficult to find evidence of investor herding under normal conditions [23,44]. Therefore, in many studies, researchers have used aggregate market data to examine the presence of herding behaviour by applying the CSAD approach [35,45–47].

We did not detect herding in the Saudi stock market using the CSSD measure. Nevertheless, this should not stop us from further investigation using another measure because the literature [9,83] proves that this measure is extremely restrictive on many occasions and fails to detect herding when other measures were able to detect herding and reveal its existence. For the CSSD to detect herding, herding must occur, particularly during extreme market periods. This condition implies that it would not be possible to detect herding with this measure if herding occurred in other periods.

The first point of discussion is the relationship between the market return and cross-sectional dispersion graphically represented in Fig. 2. This shows that the figure during COVID-19 period looks flatter than the other figures because it has the lowest level of dispersion for the same level of market return compared with all other periods. This allowed us to draw a conclusion that herding occurs during the COVID-19 pandemic.

Subsequently, we measured herding behaviour using the CSAD measure for the entire period, in addition to the four sub-periods (pre-, during- and post-COVID-19, as well as the Russia–Ukraine conflict). We conducted robustness checks on the length of the pre-COVID-19 sub-period. We find that herding occurs in the Saudi stock market for the entire sample from 2009 to 2024 and during the COVID-19 sub-period because the coefficients are significant at the 1 % and 5 % levels, respectively. Therefore, the empirical results show that investors in the Saudi stock market followed the market consensus during the COVID-19 crisis. However, the results confirm that herding is not detected in the pre- or post-COVID-19 or Russia–Ukraine conflict periods. Robustness checks confirm that the market behaves rationally for the pre-COVID-19 sub-period because the nonlinear coefficient is positive and significant. The robustness results in Panel B seem more robust and indicate that herding does not occur in the pre-COVID-19 sub-period, and investors trade rationally in normal, more relaxed periods where no crisis of any type occurs. This is reasonable because the length of the pre-COVID-19 sub-period is not considerably different from that of the other periods under study. Our findings show that herding behavioural bias increased during the COVID-19 global pandemic. Therefore, market authorities must be aware of herding behaviour's possible effects on market efficiency, price fluctuations, bubbles and crashes in financial markets and should monitor investor sentiment to mitigate any unpleasant consequences. It helps the Saudi financial authorities understand the effects of black swan events and establish effective guidelines to cope with such events and create suitable investment strategies.

Regarding the COVID-19 findings, we expected herding behaviour to occur during the COVID-19 period in the Saudi stock market because, according to Christie and Huang [20] and Nath and Brooks [92], herding should occur during extreme crises. The results of this study are consistent with those of several earlier investigations, including those by Dhall and Singh [93], who found evidence of herding in the post-COVID-19 sub-period at the industry level on the national stock exchange in the Indian stock market. Susana, Kavisanmathi [94] found that herding behaviour occurred in cryptocurrencies during COVID-19. Espinosa-Méndez and Arias conducted two studies in 2021 to investigate COVID-19's effect on herding behavioural biases [66,67]. They concluded that herding increased during the COVID-19 pandemic in the Australian stock and European capital markets. In line with these results, Fang, Chung [68] present the same findings for Eastern European stock markets. Ferreruela and Mallor [9] confirm the existence of a herding behavioural bias during the COVID-19 pandemic in the Portuguese stock market. However, herding was not detected during the COVID-19 pandemic in the Spanish stock market. Similarly, Wu, Yang [64] found that herding was less common than during normal times in Chinese stock markets during COVID-19.

The COVID-19 crisis has significantly affected investors' herding behaviour in the Saudi stock market for several reasons. First, it significantly affected the Hajj and Umrah, which are important sources of revenue for Saudi Arabia. The Ministry of Hajj and Umrah limited Hajj pilgrimages to domestic pilgrims in 2020 and 2021 to prevent the spread of COVID-19. The 2020 Hajj was limited to only a few selected domestic pilgrims and no international pilgrims [95]. Umrah stopped completely in 2020, and most countries worldwide, including Saudi Arabia, closed their airports because of the COVID-19 pandemic, affecting Umrah companies and agencies because their work stopped completely during the COVID-19 period. Undoubtedly, the Saudi government had to make decisions to stop the spread of COVID-19 and keep pilgrims safe; consequently, the Hajj and Umrah sectors incurred significant losses, causing sharp price changes. Investors tend to suppress their own beliefs and imitate the market consensus during sharp falls, which explains why herding increased during the COVID-19 pandemic.

Moreover, the COVID-19 pandemic has shut down markets and borders worldwide. Trading floors require vaccinations for access, and some physical trading floors and offices closed permanently because of the COVID-19 pandemic, such as the New York Stock Exchange. Furthermore, herding is found to be relatively stronger in emerging markets, such as the Saudi stock market, than in developed markets because emerging markets suffer from a combination of lower transparency, regulatory weaknesses, information inefficiency, and lack of financial analysts and quality information [38–40]. Therefore, in uncertain periods caused by a crisis such as the COVID-19 crisis, less-informed investors who face uncertain information in a stock market environment with insufficient available information may imitate the behaviour of more informed investors, leading to herding behaviour [2,13]. Additionally, according to Aljifri [53], investors in the Saudi stock market are inexperienced males aged 30–39. More than 90 % of the total trading in the Saudi stock market is initiated by retail traders, who are extremely aggressive traders and by far the most active market investors [40]. Individual investors may have a greater tendency to herd than institutional investors because they tend to be inexperienced, have limited access to information, and have short-term investment strategies. Saudi stock market investors who are young, inexperienced retail traders and have limited access to information may have a greater tendency to herd when facing uncertainty and sharp price changes caused by the COVID-19 pandemic than investors in other stock markets who might be more experienced and institutional investors.

Regarding the Russia–Ukraine conflict findings, this is the first study to analyse the impact of the Russia–Ukraine conflict on investors' herding behavioural bias in stock markets. There are many reasons for the conflict not affecting investors' herding behaviour in the Saudi stock market or not being considered a crisis affecting the Saudi economy and investors in the Saudi stock market. First, several countries imposed sanctions in reaction on Russia, such as reducing energy imports. According to Zheng, Zhou [96], oil prices increased because of reduced Russian energy imports, and the additional gains for crude exporters amounted to billions. Oil-exporting countries, such as the KSA, will benefit from energy exports because they are rich in fossil energy and have close trade links with European countries. Another effect of inflating oil prices in net oil-exporting countries such as Saudi Arabia is that government revenue, government expenditure, and aggregate demand in the Saudi economy may increase, enhancing corporate output, earnings, and stock prices because, in net oil-exporting countries, the price of a stock is positively related to oil prices [97]. There is consensus in the literature that TASI is significantly and positively related to oil prices, which is expected to indicate that the KSA is a net oil-exporting country [98]. Therefore, the Russia–Ukraine conflict is not considered a crisis that caused sharp falls in stock prices; consequently, it did not result in panic selling among investors in the Saudi stock market. Moreover, social media platforms keep everyone informed about the consequences of the war; thus, investors are well informed, doubt and uncertainty sentiment in the stock market may decrease, and investors tend to follow their own beliefs and do not herd.

However, the Russia–Ukraine crisis could dampen investor sentiment and significantly affect investors' herding behaviour in Russia, Belarus, Ukraine, and EU countries, as well as in countries closer to the conflict and those that condemned it. First, an invasion's economic costs include the consequences of economic sanctions. Moreover, this war has imposed severe stress on the Ukrainian population in many ways, including citizens who continually live under the threat of bombing, hear air raids, and suffer sudden negative wealth shocks, as well as refugees abroad who face uncertain futures and the possibility of losing their homes, jobs and families [15]. Social media also works as a stress multiplier and spreader [15] because war is a common theme in social media, and no one is isolated from its realities, especially inside Ukraine. According to Ciuriak [99], this is the first social media war. Therefore, investors in other stock markets, such as Russia and Ukraine, might have exhibited increased herding during the Russia–Ukraine conflict and, consequently, have different results than those obtained in our study.

European countries might also be significantly affected. According to Cliffe [100], trade and investment between Russia and the EU are affected. According to Liadze, Macchiarelli [101], European countries rely on Ukraine and Russia for their energy and food supplies. According to Jagtap, Trollman [102], the Russia–Ukraine conflict's most severe impact on global food supply chains is felt in Europe and Africa; nonetheless, some regions of Asia, such as the Middle East, are less affected by the conflict. Moreover, fears of war, including nuclear war, have emerged owing to the constant news cycle regarding the war. Russia's nuclear threats are instilling fear and anxiety, particularly in European countries, because of their geographical proximity to the war. Therefore, investors in European countries may face fear, anxiety, and uncertainty over the Russia–Ukraine conflict, leading less-informed investors to abandon their own beliefs and follow more informed investors and market consensus. Furthermore, according to Ari, Arregui [103], war affects the older and poorer segments of the population, who are the most vulnerable, because it triggers concerns about recession, higher food and energy bills, and inflation. According to Ciuriak [15], approximately 20 % of the European population is at risk of poverty, and approximately 20 % of the European population is over 65 years old; thus, European countries might be the most affected. Additionally, Boungou and Yatié [104] found a considerably stronger and more significant effect of war on the value of equities in countries closer to the conflict and those that condemned it. Thus, Russia, Belarus, Ukraine, the EU, countries near the conflict, and those that condemned it may be the countries most affected by the Russia–Ukraine conflict. Consequently, investors in other stock markets, such as European stock markets, might have exhibited increased herding during the Russia–Ukraine conflict.

Wald's test results show that no difference exists between bearish and bullish days or between rising and declining markets for the periods under our study, pushing aside the asymmetry in investors' responses in periods when the market declines and rises for the entire sample and all sub-periods. These results are similar to those obtained by Refs. [9,85], who found evidence of asymmetry. Previous literature [e.g. 22] finds an asymmetry in investors' reactions; investors exhibit greater herding in down markets than in up markets because of the various emotional implications of periods of declining prices compared with rising prices. Consequently, herding tends to be greater in a down market than in an up market. Investors in the Saudi stock market may exhibit less loss aversion bias than those in some European markets [85] and in Spanish and Portuguese markets [9] because they are less concerned about the risk of falling market prices; hence, they do not behave differently when prices decline.

Saudi investors may be less loss averse than those in other countries for the following reasons. First, Saudi Arabia is a collectivist society in which individuals have strong relationships and are expected to look after each other and their immediate and extended family members, providing Saudi citizens with protection in the case of financial losses. Nevertheless, individualistic societies, such as the US, are more loss-averse than collectivist societies, such as China [105], because people are less likely to receive financial help from their families if they are in need. According to Cherono [106], people from collectivistic societies such as Africa are less loss-averse than those from individualistic societies such as the US and Europe. According to the cushion hypothesis, people from collectivistic societies are more inclined to take risks than people from individualistic societies because they receive more social help if needed [105]. Consequently, they are less risk-averse than those in individualistic societies. Moreover, people from collectivistic cultures are more receptive to gains and losses [107], with male investors between 25 and 40 years old being less loss averse than female investors between 41 and 55 years old [108]. Most investors in the Saudi stock market are young males investors [53]. Therefore, Saudi investors may be less loss averse than investors in other stock markets. Furthermore, Saudi literature suggests that loss aversion does not have a significant impact on investors' behaviour in the KSA stock market [42]. Thus, we expect investors in the Saudi stock market to be less loss-averse than those in other stock markets.

Additionally, the Wald test rejects the asymmetry when using the two volatility measures, showing no difference in investor herding on high- and low-volatility days in the Saudi stock market. These findings align with those of Economou, Kostakis [85], who conclude that there is no difference between high- and low-volatility days in four European markets. However, Tan, Chiang [86] report the opposite findings in the Chinese stock markets, finding that herding occurs only on high-volatility days. Ferreruela and Mallor [9] also find evidence supporting asymmetry, confirming that imitation appears only on days of high volatility. Our findings show no difference in investor herding behaviour on high- and low-volatility days in the Saudi stock market. We draw the same conclusion that the highest herding intensity occurs during the COVID-19 sub-period compared with all other sub-periods included in this study.

Our results provide insights into herding in the MENA, GCC, and emerging stock markets because The stock market of Saudi Arabia is an emerging stock market which is part of the MENA and GCC stock markets. Moreover, early studies mainly focused on the US and Europe [9]. Therefore, further research is needed on the effect of black swan events (COVID-19 and the Russia–Ukraine War) on investor herding behaviour in other regions of the world, such as Saudi Arabia. Second, Saudi Arabia's market is the most liquid and active stock market in the Arab world, including the GCC countries [53,78]. The largest oil producers in the world are the GCC countries, with Saudi Arabia being the largest global oil producer [109]. The Kingdom of Saudi Arabia (KSA) is the largest oil exporter and the fifth largest natural gas reserves globally [110]. It also plays a political role, which makes it an important global actor [111]. It is also the most influential member of the OPEC + group [111] and the Group of Twenty (G20) Forum, one of the world's 20 largest economies. Moreover, the KSA is one of the world's largest economies. As of 2022, the contribution of Saudi Arabia's GDP to the global GDP is 1.4 %, which places this nation in the same category as other developed nations around the globe, such as Canada and Spain [112]. Saudi Arabia is expected to be one of the world's fastest growing economies. Its gross domestic product (GDP) is anticipated to expand by 7.6 %, the fastest growth in almost a decade [113]. Furthermore, the pandemic's effect on stock markets has been heterogeneous across financial markets [114,115]. Therefore, the Saudi stock market may respond differently to black swan events because it has different characteristics from the stock markets in the US and Europe.

Although the results of this study highlight the differences in investor responses to the turmoil resulting from various types of crises (i.e. the global COVID-19 crisis and the Russia–Ukraine political crisis), there are some limitations. For example, we only considers the

Saudi stock market. The stock market of Saudi Arabia is an emerging stock market which is a part of the Middle East and North Africa (MENA) and GCC stock markets; therefore, it provides insights into herding in all the above mentioned stock markets [53]. However, potential future studies may investigate whether the other GCC countries that are rich in oil will have similar findings. Moreover, potential future studies may investigate whether other countries; developed, emerging and developing countries have different. Furthermore, potential future studies may investigate whether collectivist societies have different findings from individualistic societies. Additionally, other types of crises maybe considered, such as, the "Arab spring" due to its geographical proximity Saudi Arabia. Potential future studies may include a comparative study between various emerging and developed markets to explore the differences in herd behaviour in times of turmoil resulting from various types of crises in various markets in more depth. In addition, we only focus on black swan events' (i.e. the global COVID-19 crisis and the Russia–Ukraine war) impact on the stock market; therefore, for future studies, we suggest studying these events' effects on the cryptocurrency, fiat currency, bonds, metal and energy markets. Moreover, investors in various markets might have different characteristics and psychological responses to different types of crises; therefore, we emphasise the importance of investigating herding in various markets and situations. Another limitation might be lack of available data at the investor level. We used the market return's cross-sectional dispersion to capture and measure market-wide herding behaviour.

6. Conclusion

This study provides novel empirical results of herding behavioural bias in Saudi Arabia's emerging stock market during black swan events (the global COVID-19 crisis and the Russia–Ukraine war) and offers an explanation for investors' herding behavioural bias in the KSA Stock market during various types of crises, none of which have been examined. We investigate investor herding behavioural bias in the Saudi stock market during the recent extreme events of the global COVID-19 crisis and the Russia–Ukraine war. We also investigate herding in rising versus declining markets and high-versus low-volatility days (under different market conditions). Regarding the subsamples, herding did not occur in the pre-COVID-19 sub-period, appeared in the during-COVID-19 sub-period, disappeared in the post-COVID-19 sub-period, or occurred during the Russia–Ukraine war, confirming that investor herding manifested during the COVID-19 pandemic. Furthermore, our findings show that different market conditions have no effect on investors' behaviour. The results of the Wald test confirm that there is no difference in investor herding during positive and negative markets or on high- and low-volatility days in the Saudi stock market, pushing aside asymmetry in investors' responses. Our findings point to the occurrence of herding in the during-COVID-19 sub-period on positive and negative days and on high- and low-volatility days, in which the greatest herding intensities are observed. The robustness checks confirm our finding that investors in the Saudi stock market traded following market consensus in the during-COVID-19 sub-period. Overall, the robustness results in Panel B seem more robust and consistent, confirming that herding does not occur in the pre-COVID-19 sub-period and investors trade rationally in normal and more relaxed periods where no crisis of any type occurs. This is reasonable because the length of the pre-COVID-19 sub-period is not considerably different from that of the other periods under study.

The results show that herding behaviour increased during the COVID-19 pandemic because it did not occur before the COVID-19 period; it only occurred during the COVID-19 period and disappeared again after COVID-19 and during the conflict periods, perhaps because of Saudi Arabia's ability to control the COVID-19 crisis in its initial stages. Moreover, whereas the COVID-19 global health crisis increased herding behaviour in the Saudi stock market, the Russia–Ukraine conflict did not, perhaps because COVID-19 is a global health crisis that affects all countries, regardless of geographical location. However, the Russia–Ukraine conflict might have primarily affected Russia, Ukraine, and European countries because of their geographical proximity to war.

We report that the COVID-19 pandemic has significantly amplified herding in the Saudi stock market, supporting the belief that herding is stronger during times of heightened uncertainty. pandemic has the general expectations of the Saudi stock market. The global COVID-19 crisis affected countries worldwide, with disastrous economic consequences. Nevertheless, the most severe impact of the Russia–Ukraine political war on food supply chains occurred in Europe and Africa [102]. Unlike some regions of Asia, such as the Middle East, which was less affected by the conflict, the Russia–Ukraine conflict could affect investors' herding behaviour in Russia, Ukraine, and the EU countries as well as countries closer to the conflict and those that condemned it. Ukrainian citizens live under the threat of bombing and face an uncertain future as refugees. European countries rely on Ukraine and Russia for their energy and food supply; therefore, they are expected to be affected by this conflict. Investors in European countries may also face fear of war, including nuclear war, anxiety, and uncertainty over the Russia–Ukraine conflict, leading them to herd themselves. Conversely, the COVID-19 pandemic affected important sectors in Saudi Arabia, such as the Hajj and Umrah sectors, which are important sources of revenue. For example, companies and agencies in Umrah completely stopped working during the COVID-19 pandemic, which led to significant losses in these sectors. The COVID-19 pandemic also has closed borders worldwide, including Saudi Arabia, which has closed its airports due to the pandemic.

These results highlight the differences in investor responses to turmoil resulting from various types of crises (i.e. the global COVID-19 crisis and the Russia–Ukraine political crisis), confirming the notion that crises of various origins have dissimilar characteristics and psychological effects on investors. These results indicate fear and uncertainty over the effects of COVID-19, which drives less-informed investors to imitate more-informed investors and may exhibit a collective co-movement. However, during the Russia–Ukraine conflict, investors followed their beliefs and did not follow the market consensus. We performed robustness checks on the length of the pre-COVID-19 sub-period, and the results confirmed our main findings, showing that the COVID-19 crisis and its related uncertainty amplified herding in the Saudi stock market.

This study has several implications. First, they may provide market investors with knowledge and raise their awareness of the influence of cognitive bias on their investment decisions, improving market efficiency by increasing the rationality of investors' decisions. Raising investors' awareness of their behavioural biases is important because it educates them on how to use information sources more effectively to make the best decisions. This study also enhances investors' understanding the effects of the black swan events and encourages them to form their trading strategies to mitigate downside risks during outbreaks and crises. Moreover, our findings show that herding behavioural bias increased during the COVID-19 pandemic. Therefore, market authorities must be aware of the possible effects of herding behaviour on market efficiency, price fluctuations, bubbles, and crashes in financial markets, and should monitor investor sentiment to mitigate any unpleasant consequences. It helps Saudi financial authorities understand the impact of black swan events, establish effective guidelines to cope with such events, and create suitable investment strategies.

This study provides a better understanding of Saudi Arabia's emerging stock market, which may be an attractive investment choice for investors seeking to diversify their equity portfolios, because it is deep, broad, and liquid. Future studies may include a comparative study between various emerging and developed markets to explore the differences in herd behaviour in times of turmoil resulting from various types of crises in various markets. Moreover, we only focus on the impact of black swan events (i.e. the global COVID-19 crisis and the Russia–Ukraine war) on the stock market; thus, for future studies, we suggest studying the effects of these events on the cryptocurrency, fiat currency, bonds, metal, and energy markets. Additionally, investors in various markets may have different characteristics and psychological responses to different types of crises; therefore, we emphasise the importance of investigating herding in various markets and situations.

Ethics declarations

Review and/or approval by an ethics committee was not needed for this study because the work reported in this study is based on secondary data that is publicly available. Informed consent was not required for this study because the work reported in this study is based on secondary data that is publicly available.

Data availability statement

The raw data required to reproduce the above findings are available to download from https://ereference.tadawul.com.sa/ir/user/refDataLogin.xhtml?lang=en.

CRediT authorship contribution statement

Ruqayya Aljifri: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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