ERF Working Papers Series

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ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

Working Paper No. 1570
August 2022

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First published in 2022 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Abstract

With the global spread of the COVID-19 pandemic, financial markets have experienced instability and high volatility due to increased uncertainty, which, in turn, has led investors to become pessimistic about decisions to buy/sell stocks in the market. Therefore, these pessimistic investors – who are generally the less informed in the market – decide to follow others due to their belief that they are more informed, especially during down market periods. Consequently, a natural question arises: can we confirm that herding behavior during the COVID-19 pandemic occurred due to investor pessimism? In this paper, we investigate the impact of COVID-19 on herding behavior in the MENA region. A comparison before and during the COVID-19 pandemic will be conducted due the increased global uncertainty it has caused. As developed in the financial literature devoted to behavioral finance, events and news can change the behavior and beliefs of investors, which can cause price changes and fluctuations in stock markets. This work studies the effect of investor sentiment on herding behavior in the MENA region in the last decade considering the COVID-19 effect. In fact, it was highlighted in many works (such as Mishra et al., 2021) that during periods of crisis, the sentiment of investors is unstable and they aren't able to make the right decisions when buying and selling stocks. Therefore, they decide to follow others in the market without relying on their own information. New information can have a big effect on investor sentiment, which, in turn, can have a huge impact on their judgments about future decisions. Good news can make investors optimistic about their future decisions, while bad news can make them pessimistic. Based on the methodology used in Chiang et al. (2010) and by employing a quantile regression analysis for data covering the period 3 January 2011 to 15 July 2021, results show some differences in herding behavior in the Egyptian, Jordanian, Moroccan, and Tunisian stock markets. These different findings on countries and investors' sentiment have important empirical implications since the results suggest different situations of herding, especially between North African and Middle Eastern countries. There is a concordance in the sentiment of investors in both these regions toward herding behavior. Therefore, there is a link between herding behavior and investors' sentiment.

Keywords: COVID-19, financial markets, uncertainty, herding behavior
JEL Classifications: G1

ملخص

مع تفشي جائحة فيروس كورونا (كوفيد-19) حول العالم، شهدت الأسواق المالية عدم استقرار وتقلبات مرتفعة بسبب زيادة حالة عدم اليقين التي تؤدي بدورها إلى تشاؤم المستثمرين فيما يتعلق بقرارات شراء/ بيع الأسهم في الأسواق. لذلك، يقرر هؤلاء المستثمرون المتشائمون الذين عادة ما يكونون غير ملمين بالسوق اتباع الآخرين معتقدين أنهم أكثر إلمامًا خاصة خلال فترات هبوط أسعار السوق. وبالتالي، السؤال الذي يطرح نفسه هنا: هل يمكن حصل سلوك القطيع على الدعم خلال جائحة فيروس كورونا (كوفيد-19) بسبب تشاؤم المستثمرين أثناء هذه الفترة؟ في هذه الدراسة، يتم بحث تأثير فيروس كورونا (كوفيد-19) على سلوك القطيع في منطقة الشرق الأوسط وشمال إفريقيا. سيتم إجراء مقارنة للفترة قبل جائحة فيروس كورونا (كوفيد-19) وخلالها في هذا التحليل لأن جائحة فيروس كورونا (كوفيد-19) أسفرت عن زيادة عدم اليقين في جميع بلدان العالم. إن الأحداث والأخبار، كما ورد في الأدبيات المالية المخصصة للتمويل السلوكي، يمكنها تغيير سلوك المستثمرين واعتقاداتهم والتي يمكن أن تسبب تغيرات وتقلبات في أسعار أسواق الأسهم. تدرس هذه الورقة تأثير شعور المستثمرين على سلوك القطيع في منطقة الشرق الأوسط وشمال إفريقيا في العقد الماضي بالنظر إلى تأثير فيروس كورونا (كوفيد-19). وفي الواقع، تم تسليط الضوء في العديد من الأبحاث) مثل ميشرا وآخرون(Mishra and al.) ، 2021 (على أن شعور المستثمرين خلال فترات الأزمة سيكون غير مستقر، ولن

يتمكن المستثمرون من اتخاذ القرار الصحيح عند شراء الأسهم وبيعها في الأسواق، وبالتالي، يقررون السير على خطى غيرهم في الأسواق. لا يعتمد المستثمرون على معلوماتهم الخاصة ويقرروا اتباع خطى الآخرين. يمكن أن تؤثر المعلومات الجديدة تأثيرًا ملحوظًا على شعور المستثمرين، والذي بدوره يمكن أن يكون له تأثيرًا كبيرًا على أحكامهم المتعلقة بقراراتهم المستقبلية. سيتحلى المستثمرون بالتفاؤل عند اتخاذ قراراتهم المستقبلية في صدد أخبار سارة، بينما قد تؤدي الأخبار السيئة إلى تشاؤم المستثمرين. بناءً على المنهجية المستخدمة في شيانج وآخرون (2010) (Chiang et al.) وباستخدام تحليل الانحدار الكمي لبيانات الفترة من 3 يناير 2011 إلى 15 يوليو 2021، تُظهر النتائج بعض الاختلافات المتعلقة بسلوك القطيع في البورصات المصرية، والأردنية، والمغربية، والتونسية. ولهذه النتائج المختلفة بين البلدان وحالات شعور المستثمرين بآثار تجريبية مهمة، حيث تشير النتائج إلى وجود مختلف حالات سلوك القطيع، خاصة بين بلدان شمال إفريقيا والشرق الأوسط. ويوجد توافق في شعور المستثمرين في هاتين المنطقتين تجاه سلوك القطيع. فيوجد ارتباط بين سلوك القطيع وحالة شعور المستثمرين.

1. Introduction

Many studies on investment decisions accept the assumption that individuals display rational behavior in their decision-making. This presumes that people are profit maximizers in their decisions and choices. The classical theory of market efficiency built upon this strand of assumptions, before being challenged by works in behavioral economics and finance, particularly prospect theory. To better understand the logic of investor behavior, researchers attempted to explain the reasoning patterns of investors, with the emotional processes involved and the degree to which investors focus on the decision-making process. Kahneman and Tversky (1979) show that normal decision-making behavior in humans is not consistent with profit maximization motives. The person's emotions and psychology play a large role (Dang and Lin, 2016).

The irrational behavior of investors implies that they sometimes ignore their private information in decision-making, which changes some payoffs from investment. Several studies have shown that behavioral elements play a significant role in determining market prices. This view contradicts traditional finance theories (Scharfstein and Stein, 1990; Chen et al., 2003; Demirer and Kutan, 2006). The development of behavioral finance theories gives rise to the development of different biases from which we cite the herding bias. The herding behavior theory refers to mimicking other investors' actions in the stock market, and studies have examined herding behavior to explain investors' decision-making. The motivation of investors to follow or mimic other investors' actions has a significant implication for financial markets. According to the herding behavior theory, investors who tend to herd avoid their own private information and, in the process, place the prices far from the intrinsic values. This could cause markets to become more volatile (Balcilar et al., 2013).

Financial markets fluctuate over time. Bullish markets refer to when the market offers a high rate of return. Bearish markets, on the other hand, are linked with low rates of return. In this regard, the behavior of investors during different market situations may not be the same and therefore requires further investigation. Moreover, investors' herding behavior changes during up and down market periods, and the relationship between herding behavior and market (portfolio) return does not remain linear (Chang et al., 2000).

Two streams of theories are recognized in the literature exploring the herding behavior; one is heading toward a particular stock, and the other is market-wide herding. In the former, individuals (or a group of investors) focus only on a subset of securities at the same time by surrendering other securities with identical characteristics. The earliest methodological developments rely on Christie and Huang (1995), who developed a model during periods of market stress by employing a cross-sectional standard deviation of return (CSSD) to detect herd behavior in the market. Chang et al. (2000) investigate herding behavior by modifying the study of Christie and Huang (1995) to employ a cross-sectional absolute deviation of returns (CSAD) instead of a CSSD. In a related approach concentrating on the utility of advanced analytical tools vis-à-vis herding in markets, Chiang and Zheng (2010) find that sophisticated

investors with access to high-quality microeconomic information were the least likely to engage in herding. Their findings rely on a study of 18 countries from 1988 to 2009. Javaira and Hassan (2016) focus their research on market-wide herding, where investors follow market trends and tend to move with the actions of the market.

According to the efficient market hypothesis (EMH), market participants exhibit rational risk aversion. Moreover, the information efficiency of the market does not allow participants to outperform the market (Fama, 1965). This theory fails to explain the systematic mispricing in capital markets that results from sentimental factors. Behavioral finance theories claim that the irrational behavior of noise traders and arbitrators causes a disparity in asset prices from their intrinsic values. Theoretical developments in behavioral finance and empirical evidence have both rejected the hypotheses of classical financial theory because of their assumption of the rationality of agents in capital markets. Baker and Wurgler (2007) believe that rational participants do not seem to play a leading role in bringing the value of assets up to the current value of anticipated cash flows. Behavioral finance offers an alternative model that claims that economic phenomena can be better understood if investors accept that they are not entirely rational. In this context, asset pricing not only includes the risk-related anticipated rates, but also the impact of investor expectations on the returns. Behavioral finance explains the relationship between investment and investors' psychology. Investor behavior is reflected in the stock prices, and market fluctuations, which ultimately shape the market, are themselves shaped by the psychology of the investors. Baker and Wurgler (2006) argue that market sentiment creates a tendency for investors to be optimistic or pessimistic while speculating prices instead of deciding on fundamental factors.

Previous studies sought to detect the predictability of sentiments as a systematic risk factor valued in accordance with certain conditions in the market. Studies from developed economies like the US are far ahead in understanding sentiment-related market dynamics (Barberis et al., 1998; Lee et al., 2002; Neal and Wheatley, 1998). Academic studies on investor sentiment in developing economies with rapidly growing capital markets are still in their infancy. Previous research has mainly focused on the influence of investors' sentiment on investment returns, whereas the effect of sentiment on the conditional volatility structure of the market is less explored. During periods of high and low sentiment, noise traders act differently to keep their positions secure. During the high sentiment episodes, their participation and trading are more aggressive compared to low sentiment episodes. This is caused by naive and unaware noise traders' misjudgment of potential risks. Past academic studies about emerging economies have not explored such factors in depth for the MENA region. Scholars have recently been paying more attention to emerging and frontier markets, as global portfolio traffic finds palatable the developing economies' markets due to – inter alia – deteriorating yields in traditional financial asset classes. Moreover, the herding phenomena in emerging markets merit closer scrutiny since they differ from established financial centers by virtue of being in the budding stages of financial development, lower liquidity and capitalization, imperfect and non-smooth information flow, and idiosyncratic institutional features. These factors motivate us to examine herding behavior in some emerging markets in the MENA region. In addition, the study of a

panel of 60 countries by Nasarudin et al. (2017) using the CSAD method classifies Egypt, Morocco, and Tunisia among the group of countries where herding behavior exists.

In this paper, we contribute to the existing literature by investigating the impact of COVID-19 on herding behavior in the MENA region. A comparison before and during the pandemic will be conducted in this analysis as the pandemic has increased uncertainties on a global scale. As developed in the financial literature devoted to behavioral finance, events and news can change the behavior and beliefs of investors, which can cause changes and fluctuations in stock market prices. This work studies the effect of investor sentiment on herding behavior in the MENA region in the last decade considering the COVID-19 effect. In fact, it was highlighted in many works (such as Mishra et al., 2021) that during periods of crisis, the sentiment of investors is unstable and they aren't able to make the right decision when buying and selling stocks in the market. Therefore, they decide to follow others in the market. For this analysis, data were collected over the period 3 January 2011 to 15 July 2021 to the series of stock prices. This study is devoted to four MENA countries, so we consider 20 listed companies for Egypt, 17 for Jordan, 14 for Morocco, and 21 for Tunisia. The remainder of the paper proceeds as follows. Section 2 presents the herding behavior and investor sentiment. Section 3 discusses the empirical results, and section 4 concludes.

2. Herding behavior and investor sentiment

2.1 Herding and market rationality

The evolution of behavioral finance models has contributed to the investigation of herding behavior, which, by definition, is an anomaly induced by investors' decision-making processes. Though tested extensively using various approaches and in different empirical settings, the findings in this field are largely inconclusive. The propensity to herd is demonstrated not merely among market participants, but also among professional forecasters (Rülke, 2013). As Devenow and Welch (1996) note, three important themes (models) emerge from studies discussing rational herding behavior in financial markets. The payoff externalities models of herding, principal-agent models of herding, and Cascade models of herding can occur when agents make decisions based on the actions of other agents and decide to ignore their own information (Devenow and Welch, 1996). Moreover, correlated predicted errors also influence the rational herding behavior of managers. On the other hand, irrational herding behavior may be the result of irrational investors or investor psychology. As an illustration, social gatherings may affect investors and encourage them to ignore their information and mimic other investors' actions during market uncertainties.

With the growing evidence of herding in the finance literature, it is becoming clear that herding in financial markets is a global phenomenon. The presence of herding behavior among investors causes market imbalances by maneuvering securities' prices away from their innate values. Hence, in this case, securities' prices would reflect both the rational and irrational expectations of investors (Kataria and Choudhary, 2015). Christie and Huang (1995) investigate the herding behavior of investors in the US market using the cross-sectional

standard deviation of returns, and their findings reveal the inconsistency of herding behavior of investors during large price movements. They also reveal the inconsistency of herding behavior for low- and high-frequency datasets. Chang et al. (2000) study the herding behavior of investors in various international markets such as the US, Hong Kong, Japan, South Korea, and Taiwan. They find that, for all five markets, herding behavior, which was measured by the dispersion, had a high coefficient during the up market with respect to the down market. Moreover, they also investigate the herding behavior of investors across various developed and emerging markets. In this regard, they state that the existence of herding behavior among emerging markets is partially related to the disclosure of information in emerging markets. These are the market efficiency implications of investors' herding behavior toward markets.

Some key recent developments in herding behavior are worth mentioning. Duasa and Kassim (2008) examine foreign portfolio flows to/from Malaysia using error correction techniques, and they confirm the existence of herding behavior among foreign investors in Bursa Malaysia. Omay and Iren (2019) investigate the behavior of foreign investors in Malaysia during the crisis period. They use a smooth-transition autoregressive as well as generalized impulse response functions and find evidence of herding behavior among foreign investors in Malaysia during periods of crisis. Moreover, Kumar et al. (2020) discriminate the herding behavior of investors with respect to different market conditions and find herding behavior among the investors of the Asia-Pacific region.

For the MENA region, we can find studies for different markets, but no study has been carried out to identify the comparative results between markets in the region for the same period. Charilaos Mertzanis and Noha Allam (2018) provide evidence of adverse herding behavior in bullish markets for both phases, but only during the post-revolution phase in bearish markets. These findings are due to the special nature of Egypt's stock market, which is dominated by large domestic owners and features the prevalence of strict microstructure conditions in the stock market. El Mehdi Ferrouhi (2020), using data for the period 2007-2017 for the Moroccan Stock Exchange, concludes that herding behavior is detected for the overall market and in all size-based portfolios. The results also show a positive impact of liquidity and volatility on investors' herding behavior for the four portfolios and the overall market. In the Tunisian market, Hanafi and Abaoub (2016) use the relationship between stock price and trading volume to detect herding. The empirical results indicate the presence of herding behavior during crisis periods regardless of prices and trading volume movements. However, during the pre-crisis period, herding is detected only when the market is up.

2.2 Investor sentiment

Investor sentiment refers to market participants' expectations about future cash flows (returns) and investment risk (De Long et al., 1990). Because traditional stock market theories comprehended market dynamics under the theoretical framework of the EMH and random walk theory, they did not consider investor sentiment as an important aspect. However, they failed to explain the heterogeneous behavior of investors in the capital market. Investor sentiment is

a vital aspect of the capital market, as it contributes to frequent fluctuations in stock prices and thus creates uncertainty about future returns on investments.

Market sentiment refers to the general prevailing attitude of investors to anticipate price developments in a market. It is the accumulation of a variety of fundamental and technical factors, including price history, economic reports, seasonal factors, and national and global events. Investor sentiment is a very broad concept that incorporates several ideas, such as investor mood, investor confidence, investor satisfaction, and investor uncertainty and panic. Some research finds that there is a significant relationship between investor sentiment and stock returns in both developed and developing countries. As a psychological factor, it is not easy to estimate investor sentiment because of its subjective and qualitative nature. However, different proxies have been used to measure sentiment. These indicators of the sentiment index are classified as indirect and direct measures. In direct measures, researchers measure individual investor sentiment via surveys and polling techniques. They are highly sample-dependent, and the chances of sampling errors are high. Moreover, they may not be able to give a broad picture of the prevailing sentiment. Indirect measures use market-determined sentiment proxies, such as trading volume, turnover volatility ratio, put-call ratio, advance-decline ratio, market turnover, and share turnover for measuring the same. They posit that investors' sentiments are reflected in the structure and breadth of the market, and understanding these dynamics helps capture the irrational aspects of the market. The consistent and theoretically comprehensible nature of the sentiment index has led to its wide adoption in previous studies (Baker and Wurgler, 2006; Brown and Cliff, 2004; Chen et al., 1993; Clarke and Statman, 1998; DeBondt and Thaler, 1985; Elton et al., 1998; Fisher and Statman, 2000; Lee et al., 2002; Neal and Wheatley, 1998; Sias et al., 2001).

According to Zhou (2018), investor sentiment indicates the distance of the asset's value from its economic bases. This can be measured from different sources, such as official documents, media reports, and market surveys. Mushinada and Veluri (2018) use trading volume and return volatility to understand the relationship between sentiments and returns. Their findings show that post-investment analysis is essential to correct errors in previous behavioral estimations.

Since the sentiment measures the emotional state of the capital market, we might expect it to influence herd behavior. Baek and Bandopadhyaya (2005) conclude that changes in sentiment can explain short-term movements in asset prices better than any other set of fundamental factors. The results obtained by Lee et al. (2002), based on the Investors' Intelligence Sentiment index, indicate that changes in sentiment are negatively correlated with market volatility. Volatility increases (decreases) when investors become more optimistic (pessimistic). Brown and Cliff (2005) find evidence that sentiment affects asset valuation. As a group, investors tend to overvalue (undervalue) assets during times of extreme optimism (pessimism) or high (low) sentiment. When investors are optimistic (pessimistic), the market valuation is higher (lower) than the intrinsic value. Consequently, the authors suggest that asset pricing models should consider the role of investor sentiment. There is empirical evidence suggesting both that investor sentiment has a significant influence on stock market returns (e.g., Baker and Wurgler,

2006 and 2007) and that the capital market is positively related to investor sentiment. Despite the growing interest in this issue and the large number of studies that focus on analyzing the relationship between investor sentiment and market returns, there are very few studies analyzing the impact of sentiment on herd behavior in the MENA region. Consequently, further work needs to be done on the relationship between herding intensity and investor sentiment. Elisabete et al. (2015) conclude that sentiment negatively influences herding behavior and, using a Granger causality test, suggest that the direction of causality is from sentiment to herding. Brown and Cliff (2005) find evidence that sentiment affects asset valuation; investors tend to overestimate assets during times of utmost optimism or high sentiment. Once investors are optimistic, the market valuation is higher than the intrinsic value. Also, investors tend to undervalue assets during times of extreme pessimism or low sentiment. Once investors are pessimistic, the market valuation is under the intrinsic value.

Some research finds evidence of a significant relationship between investor sentiment and stock returns in both developed and developing countries. Bhaskaran (1996) examines the relationship between closed-end fund discounts and small firm returns. He discovers that discounts forecast future small firm returns, which also provide independent information about the conditional expected returns of small firms. According to Zhou (2018), investor sentiment indicates the distance of the asset's value from its economic bases. This can be measured from different sources, such as official documents, media reports, and market surveys. Mushinada and Veluri (2018) use trading volume and return volatility to understand the relationship between sentiments and returns. Their findings show that post-investment analysis is essential to correct errors in previous behavioral estimations.

Kumari (2019) analyzes the Indian market using unit root statistics and a nonlinear GARCH model and concludes that the stock market is highly liquid when sentiment is bullish, and vice versa. Using a Granger-causality test, Debata, Dash, and Mahakud (2020) conclude that there is a significant flow of causality from investor sentiment to stock market liquidity. The results of time series estimates suggest that the market is more liquid when local investor sentiment is higher. Moreover, the results of Dunham and Garcia (2020) indicate that improvements (deterioration) in investor sentiment derived solely from Twitter content lead to a decrease (increase) in the average firm's share liquidity. Although not as strong, the results for investor sentiment derived solely from news articles show the opposite; improvements (deterioration) in news sentiment lead to an increase (decrease) in the average firm's share liquidity. Choi and Yoon (2020) conclude that the relationship between investor sentiment and herding behavior shows that investor sentiment has a positive effect in the KOSDAQ stock market but is not significant in the KOSPI stock market using a regression analysis. Galariotis, Krokida, and Spyrou (2016) conclude that herding behavior is more prevalent in high sentiment stocks irrespective of the period, and that there may be a two-way relationship between sentiment and herding in major equity markets.

3. Empirical results

3.1 Methodology

Herding modeling and investors' sentiment (bullish and bearish sentiment)

Most of the studies analyzing herding behavior use dispersion measures of returns, such as the CSSD and CSAD, as a dependent variable. In general, the explanatory variables in the model are stock market return, absolute stock market return, and squared market return. According to the models developed by Christie Huang (1995), Chang et al. (2000), Chang and Zheng (2010), and many others, there is evidence of a herding effect when the estimated coefficient relative to the variable squared market return is statistically negative and significant. According to Chang et al. (2000), the dependent CSAD variable is defined as follows:

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

Where, $R_{i,t}$ is the return of the stock price of company i at date t and $R_{m,t}$ is the stock market return at date t.[3]

Nonlinearity is the main characteristic of the herding factor in the regression, which can be reflected by a significant negative relationship between dispersion and square returns. In fact, the basic equation to analyze herding, as developed by Chang et al. (2010), is expressed as follows:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t \qquad (3)$$

We confirm evidence of herding behavior when the estimated coefficient β_2 is negative and significant.

Many authors have declared that the behavior of investors differs among situations, so they consider the asymmetries characterizing stock markets. Authors highlighted that the results about herding bias during down and up market periods are different for many markets. They also concluded that for periods of crisis, upper and lower tails, and during extremely high and low returns, dispersions are, in general, unstable. In fact, herding behavior is more evidenced during these extreme periods. For these reasons, we focus our analysis on extremely low and high returns for the full sample, before and during the COVID-19 pandemic. We consider the following regressions:

$$CSAD_t^{UP} = \beta_0^{UP} + \beta_1^{UP}\left|R_{m,t}^{UP}\right| + \beta_2^{UP} R_{m,t}^{Up2} + \varepsilon_t^2 \qquad \text{When } R_{m,t} > 0 \quad (4)$$

[3] CSSD and CSAD are considered proxy variables to the equity market herding that explain the rise and fall that characterize market returns during stress and boom periods from which herding can be grabbed. Many other works use the CSSD as a dependent variable, which is defined as follows: $CSSD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}$.

$$CSAD_t^{DOWN} = \beta_0^{DOWN} + \beta_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \beta_2^{DOWN}R_{m,t}^{DOWN2} + \varepsilon_t^2 \qquad \text{When } R_{m,t} < 0 \quad (5)$$

On the other hand, herding behavior can be affected by the sentiment of investors. When the economic situation is unstable, or when economic and financial indicators such as inflation, interest rates, and exchange rates are extremely high or low, investors feel incompetent to make the right decision and decide to follow others in the market. As investors are very sensible to the exchange rate currency, we choose daily variations of exchange rate currency as a proxy variable to investor sentiment. We consider three possible situations: (1) a stable situation when the exchange rate is stable and in the range of the mean variation minus/plus standard deviation; (2) a bullish situation when the variation is above the mean variation plus standard deviation; and (3) a bearish situation when the variation is below the mean variation minus standard deviation. We consider the following equations:

$$CSAD_t^{bearish} = \beta_0^{bearish} + \beta_1^{bearish}\left|R_{m,t}^{bearish}\right| + \beta_2^{bearish}R_{m,t}^{bearish2} + \varepsilon_t^2 \quad \text{For } situation1 \quad (6)$$

$$CSAD_t^{stable} = \beta_0^{stable} + \beta_1^{stable}\left|R_{m,t}^{stable}\right| + \beta_2^{stable}R_{m,t}^{stable2} + \varepsilon_t^2 \qquad \text{For } situation2 \quad (7)$$

$$CSAD_t^{bullish} = \beta_0^{bullish} + \beta_1^{bullish}\left|R_{m,t}^{bullish}\right| + \beta_2^{bullish}R_{m,t}^{bullish2} + \varepsilon_t^2 \qquad \text{For } situation3 \quad (8)$$

Equations 3-8 are estimated for the four countries using OLS and quantile regressions methods. Our analysis will be based on examining the herding behavior before COVID-19, during COVID-19, and for the whole period under different scenarios.

3.2 Data and descriptive statistics

For this analysis, data were collected for the period 3 January 2011 to 15 July 2021 to the series of stock prices. Since this study is devoted to four MENA countries, we consider 20 listed companies for Egypt, 17 for Jordan, 14 for Morocco, and 21 for Tunisia. Table 1 presents the main descriptive statistics of stock market returns $R_{m,t}$, and their respective dispersions of CSAD variables.[4]

In Table 1, we show the difference between periods and among countries for both stock market return and absolute cross-section dispersion statistics. Standard deviations are more important during the COVID-19 period than in the pre-COVID-19 period, especially for Moroccan stock market return, where the standard deviation increased from .272 percent to .511 percent. On average, stock market returns are still positive even after the COVID-19 pandemic, except for

[4] It is worth noting that all series are stationary according to the ADF test. We accept the hypothesis of stationarity at the one percent significance level for CSAD and $R_{m,t}$ series for all countries.

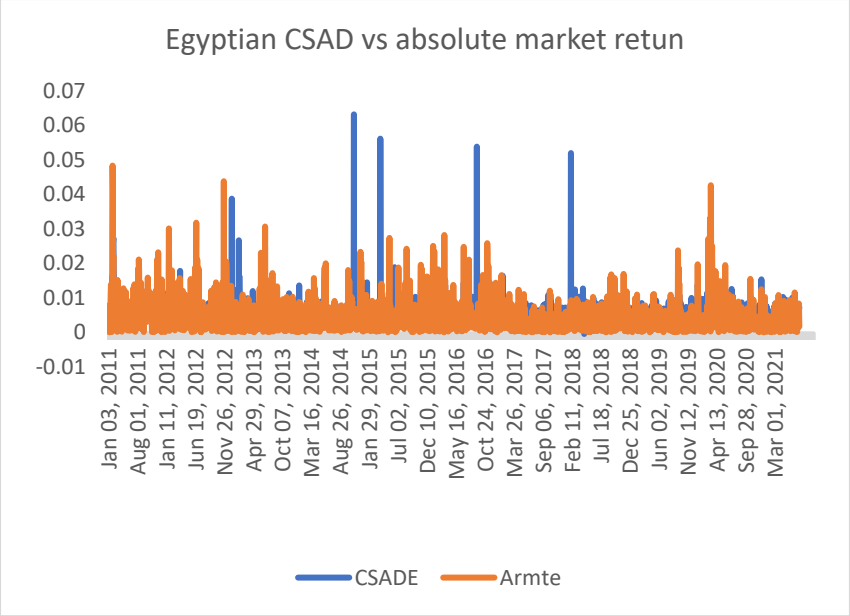
the Egyptian stock market, for which the mean of stock return becomes negative for the period March 2020 to July 2021. For this, market fluctuations are the more important in the region. In fact, the standard deviations in Egypt for all periods considered in this analysis are the higher overall periods compared to the other markets.

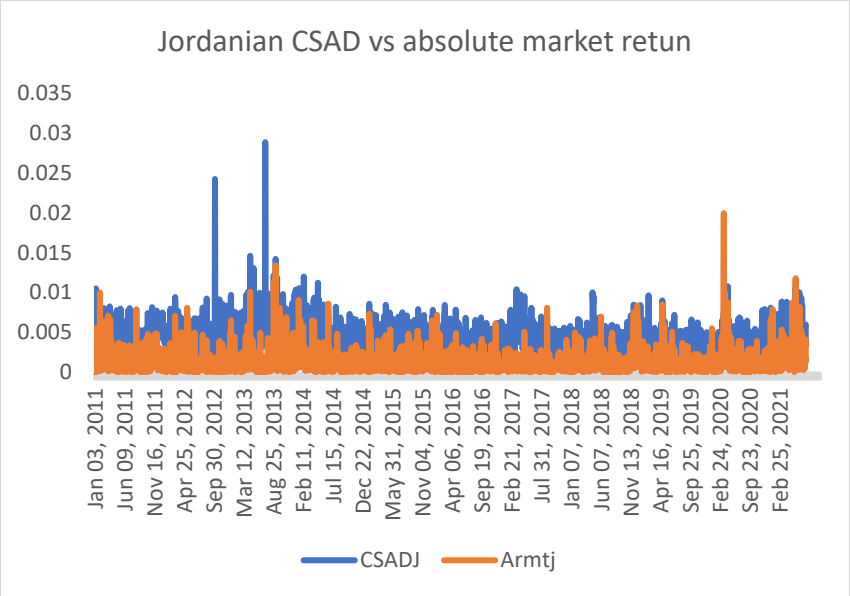
Statistics by Kurtosis and Skewness confirm the rejection of the null hypothesis, suggesting the non-normality of all series for all periods in all countries.

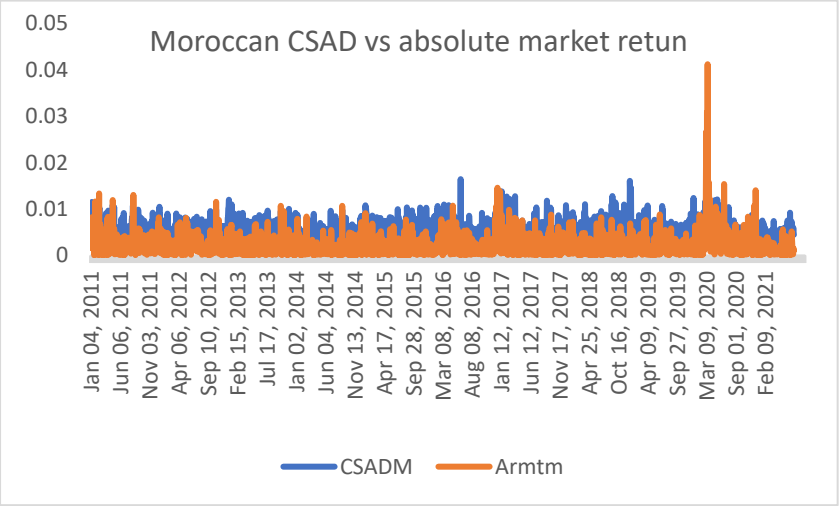
Table 1. Descriptive statistics

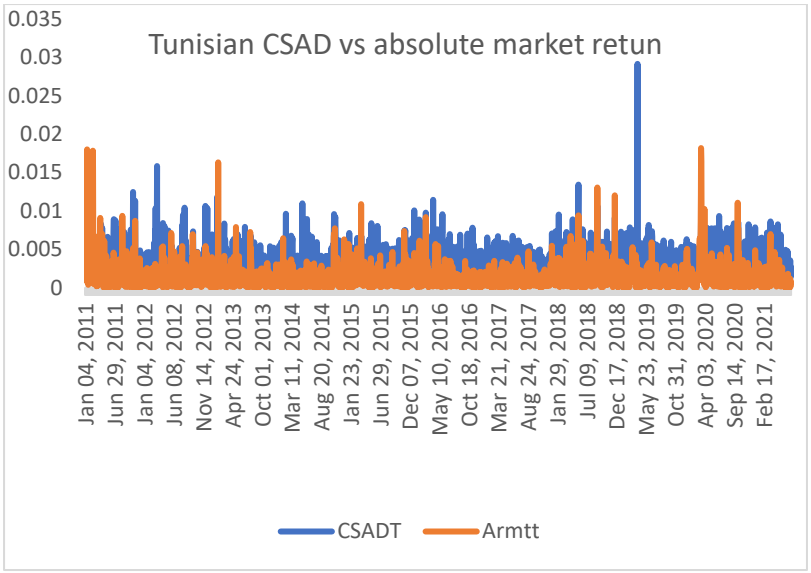
			Mean	**Std**	**Min**	**Max**	**Median**	**Skewness**	**Kurtosis**
Whole period	EGY	CSAD	.00583	.0031	.0005	.0631	.00531	7.995	24.85
		Rmt	6.9E-5	**.00632**	-.0483	.0317	.00031	-.691	6.301
	JOR	CSAD	.00047	.00183	.00076	.0287	.00445	2.131	17.444
		Rmt	-2.01E-5	.00211	-.0199	.0134	-4E-5	-.192	7.059
	MOR	CSAD	.00501	.00208	.00074	.0164	.00472	.958	20.044
		Rmt	-6.91E-6	**.00312**	-.0411	.0236	2.23E-5	-1.155	12.936
	TUN	CSAD	.00391	.00174	.00074	.0291	.00364	2.401	20.044
		Rmt	5.91E-5	.00228	-.0181	.0178	4.93E-5	-.896	12.936
Pre-covid-19	EGY	CSAD	.00575	.00324	.0005	.0631	.0053	8.315	38.5
		Rmt	**.00012**	**.00627**	-.0483	.0317	.0003	-.566	5.709
	JOR	CSAD	.00467	.00184	.00076	.0289	.00441	2.323	19.68
		Rmt	-5E-5	.00196	-.0113	.0134	-3.67E-5	-.0109	4.049
	MOR	CSAD	.00502	.00208	.00074	.0164	.00472	.918	1.396
		Rmt	-5.24E-6	**.00272**	-.0133	.0145	5.56E-6	.231	2.766
	TUN	CSAD	.00338	.00172	.00075	.0291	.00355	2.742	24.338
		Rmt	6.65E-5	.00222	-.0179	.0178	3.43E-5	-.556	12.602
During-covid-19	EGY	CSAD	.006	.0021	.003	.024	.006	2.215	9.272
		Rmt	**-.0001**	**.007**	-.04	.025	1.01E-4	-1.4	9.466
	JOR	CSAD	.005	.002	.002	.011	.005	.671	.398
		Rmt	.00021	.00296	-.0199	.0117	.000126	-.685	8.887
	MOR	CSAD	.00496	.00209	.0013	.0143	.00467	1.243	2.474
		Rmt	-1.84E-5	**.00511**	-.0412	.0236	.000175	-2.343	20.541
	TUN	CSAD	.0045	.00174	.00074	.0104	.00426	.591	.249
		Rmt	9.89E-6	.00264	-.0182	.00824	.000175	-2.224	13.013

The following figures indicate the fluctuations of $R_{m,t}$ and $CSAD_t$ over the period January 2011 to July 2021


Egyptian CSAD vs absolute market retun
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-0.01
Jan 03, 2011
Aug 01, 2011
Jan 11, 2012
Jun 19, 2012
Nov 26, 2012
Apr 29, 2013
Oct 07, 2013
Mar 16, 2014
Aug 26, 2014
Jan 29, 2015
Jul 02, 2015
Dec 10, 2015
May 16, 2016
Oct 24, 2016
Mar 26, 2017
Sep 06, 2017
Feb 11, 2018
Jul 18, 2018
Dec 25, 2018
Jun 02, 2019
Nov 12, 2019
Apr 13, 2020
Sep 28, 2020
Mar 01, 2021
CSADE
Armte


Jordanian CSAD vs absolute market retun
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Jan 03, 2011
Jun 09, 2011
Nov 16, 2011
Apr 25, 2012
Sep 30, 2012
Mar 12, 2013
Aug 25, 2013
Feb 11, 2014
Jul 15, 2014
Dec 22, 2014
May 31, 2015
Nov 04, 2015
Apr 06, 2016
Sep 19, 2016
Feb 21, 2017
Jul 31, 2017
Jan 07, 2018
Jun 07, 2018
Nov 13, 2018
Apr 16, 2019
Sep 25, 2019
Feb 24, 2020
Sep 23, 2020
Feb 25, 2021
CSADJ
Armtj


Moroccan CSAD vs absolute market retun
0.05
0.04
0.03
0.02
0.01
0
Jan 04, 2011
Jun 06, 2011
Nov 03, 2011
Apr 06, 2012
Sep 10, 2012
Feb 15, 2013
Jul 17, 2013
Jan 02, 2014
Jun 04, 2014
Nov 13, 2014
Apr 17, 2015
Sep 28, 2015
Mar 08, 2016
Aug 08, 2016
Jan 12, 2017
Jun 12, 2017
Nov 17, 2017
Apr 25, 2018
Oct 16, 2018
Apr 09, 2019
Sep 27, 2019
Mar 09, 2020
Sep 01, 2020
Feb 09, 2021
CSADM
Armtm



3.3 Empirical results

In this section, we present the empirical estimations according to the basic model of Chiang and Zheng (2010) for the full sample, during down and up market periods. These scenarios were also applied according to the properties of the herding bias focusing on the impact of investor sentiment. As mentioned in the methodology, we employ least squares and quantile regressions according to different scenarios. For the results, we focus on the sign and statistical significance of the estimated coefficients β_2. Tables 2a, 2b, 2c, and 2d present the results of estimates according to the basic approach of Chiang and Zheng (2010). It is worth noting that different estimations were applied for the whole period, the down market period, and the up market period. To distinguish between the up and down market periods, we consider the following: the down market period is determined when $R_{mt} < 0$, while the up market period corresponds to the case of $R_{mt} > 0$.

By using the least squares method, we notice first that, for the whole period, there is evidence of herding behavior for all countries. In fact, we obtain a negative significant coefficient β_2 for these cases. For a better understanding of herding behavior in different moments of stock market fluctuations, we propose a detailed analysis of herding behavior by decomposing the whole period into two sub-samples: down and up market periods. When considering the asymmetric properties characterizing the stock markets, we find some differences in herding behavior between down and up market periods. There is evidence of herding behavior during down market periods for the whole period for all series, whereas herding is absent during up market periods for the Egyptian and Jordanian stock markets. Before the pandemic, we don't identify evidence of herding behavior for all markets except for the Tunisian stock market, where a herding effect is identified for all sub-samples. For the COVID-19 period, the estimated coefficient β_2 is negative and statistically significant for the full sample, indicating a herding effect in this critical period where investors' decisions become irrational.

Table 2a. Estimates of herding behavior from Chiang and Zheng (2010) method for Egypt

		Full sample		Down market		Up market	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00488[a]	*.00283[a]*	.00481[a]	*.00276[a]*	.00499[a]	.00692[a]
	Rmt	.240[a]	*.185[a]*	.244[a]	*.204[a]*	.183[a]	.208[c]
	Rmt^2	**-3.076[a]**	***-2.006[a]***	**-2.203[a]**	***-2.416[b]***	1.141	11.463
Pre-covid-19	Constant	.00487[a]	.00692[a]	.00477[a]	*.00270[a]*	.00494[a]	*.00285[a]*
	Rmt	.205[a]	.292[a]	.222[a]	*.211[a]*	.181[a]	*.149[a]*
	Rmt^2	-.894	-.693	-1.192	***-3.463[a]***	1.204	*-.331*
During-covid-19	Constant	.00521[a]	.00692[a]	.00492[a]	*.00368[a]*	.00532[a]	.00697[a]
	Rmt	.312[a]	.481[b]	.404[a]	*.124*	.223[b]	.311[c]
	Rmt^2	**-6.583[a]**	-8.493	**-7.819[a]**	*-1.041*	-1.936	2.337

For all tables, significance levels a, b and c represent one percent, five percent and 10 percent, respectively. Values in bold indicate the presence of herding behavior in the market.

Table 2b. Estimates of herding behavior from Chiang and Zheng (2010) method for Jordan

		Full sample		Down market		Up market	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00396[a]	*.00207[a]*	.00376[a]	*.00209[a]*	.00408[a]	.00586[a]
	Rmt	.545[a]	*.660[a]*	.586[a]	*.593[a]*	.541[a]	.684[a]
	Rmt^2	**-12.062[a]**	***-19.160[a]***	**-16.484[a]**	***-15.845[a]***	-1.729	-4.701
Pre-covid-19	Constant	.00401[a]	*.00214[a]*	.00385[a]	*.00203[a]*	.00408[a]	*.00219[a]*
	Rmt	.445[a]	*.584[a]*	.462[a]	*.682[a]*	.504[a]	*.590[a]*
	Rmt^2	8.639	***-3.927[a]***	8.511	***-28.214[b]***	7.121	*-6.005*
During-covid-19	Constant	.00414[a]	.00565[a]	.00374[a]	*.00174[a]*	.00423[a]	.00182[a]
	Rmt	.506[a]	.783[a]	.555[a]	*1.075[a]*	.596[a]	.946[a]
	Rmt^2	**-18.476[a]**	**-24.380[a]**	**-18.718[a]**	*-9.018*	**-18.867[c]**	**-32.639[b]**

Table 2c. Estimates of herding behavior from Chiang and Zheng (2010) method for Morocco

		Full sample		Down market		Up market	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00401[a]	*.00185[a]*	.00395[a]	*.00197[a]*	.00391[a]	.00620[a]
	Rmt	.526[a]	*.626[a]*	.574[a]	*.543[a]*	.584[a]	.607[a]
	Rmt^2	**-9.246[a]**	***-21.867[c]***	**-9.956[a]**	***-7.99[a]***	**-15.075[a]**	**-16.426[a]**
Pre-covid-19	Constant	.00409[a]	.00613[a]	.00409[a]	*.00190[a]*	.00400[a]	.00646[a]
	Rmt	.472[a]	.627[a]	.423[a]	*.563[a]*	.544[a]	.467[b]
	Rmt^2	.607	**-11.911[a]**	15.102	***.936***	-7.346	**-2.033**
During-covid-19	Constant	.00387[a]	.00511[a]	.00399[a]	.00513[a]	.00331[a]	.00494[a]
	Rmt	.459[a]	.894[a]	.495[a]	.919[a]	.771[a]	1.012[a]
	Rmt^2	**-7.862[a]**	**-18.371[a]**	**-9.006[a]**	**-7.862[a]**	**-40.497[a]**	**-31.289[a]**

Table 2d. Estimates of herding behavior from Chiang and Zheng (2010) method for Tunisia

		Full sample		Down market		Up market	
		OLS	**Quantile** [5]	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00312[a]	*.00152[a]*	.00310[a]	*.00155[a]*	.00309[a]	*.00148[a]*
	Rmt	.623[a]	*.617[a]*	.476[a]	*.504[a]*	.772[a]	*.791[a]*
	Rmt^2	**-23.304[c]**	***-26.313[a]***	**-12.193[a]**	***-17.717[a]***	**-30.744[a]**	***-37.163[a]***
Pre-covid-19	Constant	.00303[a]	.00466[a]	.00299[a]	*.00156[a]*	.00304[a]	*.00146[a]*
	Rmt	.634[a]	.746[a]	.504[a]	*.472[a]*	.758[a]	*.773[a]*
	Rmt^2	**-24.477[a]**	**-17.817**	**-14.701[a]**	***-18.367[a]***	**-29.092[a]**	***-36.110[a]***
During-covid-19	Constant	.00365[a]	.00590[a]	.00387[a]	.00184[a]	.00332[a]	*.00175[a]*
	Rmt	.591[a]	.545[a]	.345[a]	.435[a]	.973[a]	*.878[a]*
	Rmt^2	**-20.286[a]**	**-16.638[c]**	-4.573	-1.624	-36.178	***-37.389[a]***

Since research has emphasized the importance of extreme values in studying herding effects, we employ quantile regression analysis to estimate equations 3-8, address problems of non-normality, and take asymmetries and extreme values in the data into account to better analyze herding for these markets. According to the results presented in Tables 2a-2d, quantile estimations show some differences among markets and periods on both extreme tails of return distribution (low 10 percent and high 90 percent). For the whole period, there is evidence of a herding effect for all markets. Herding behavior was confirmed in the COVID-19 period during down market periods for the Moroccan stock market only, whereas this effect was confirmed for all countries during up market periods. Investors in the Moroccan stock market were more pessimistic during the crisis period because of COVID-19 compared to other investors and for that reason, they decided to herd.

We next examine the evidence of herding behavior using variations of exchange rates as proxies for the sentiment of investors in these countries. Tables 3a-3d present the results of the estimation of equations 7, 8, and 9.

Table 3a. Herding behavior toward investors' sentiment for Egypt

		Bearish situation		***Normal situation***		***Bullish situation***	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00496[a]	.00303[a]	.00103[a]	.00633[a]	.00509[a]	.00292[a]
	Rmt	.213[a]	.118	-.0175	.269[a]	.201[a]	.0173[a]
	Rmt^2	1.908	2.506	**-.176[a]**	2.113	-1.416	**-2.715[a]**
Pre-covid-19	Constant	.00488[a]	.00299[a]	.00103[a]	.00610[a]	.00521[a]	*.00282[a]*
	Rmt	.212[a]	.117[a]	-.00612[a]	.302[a]	.153[a]	*.184[a]*
	Rmt^2	2.163	4.346[b]	**-.143[a]**	1.155	-.236	***-2.912[b]***
During-covid-19	Constant	.00524[a]	.00495[a]	.00861[a]	.00712[a]	.00508[a]	*.00692[a]*
	Rmt	.267	.534	.112	.394[b]	.294[b]	*.486[a]*
	Rmt^2	.160	3.841	-.167	2.633	**-4.906[c]**	***-11.322[a]***

[5] For the quantile regressions, we present the best method of estimation. Results presented in italic correspond to the lower tail $\tau = 10$ percent while normal character corresponds to the results of greater tail $\tau = 90$ percent.

Table 3b. Herding behavior toward investors' sentiment for Jordan

		Bearish situation		***Normal situation***		***Bullish situation***	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00404[a]	*.00214[a]*	.00374[a]	*.00191[a]*	.00404[a]	*.00233[a]*
	Rmt	.489[a]	*.614[a]*	.587[a]	*.684[a]*	.561[a]	*.555[a]*
	Rmt^2	14.256	***-1.827***	**-15.205[c]**	***-17.933[b]***	**-14.923[a]**	***-14.539[a]***
Pre-covid-19	Constant	.00402[a]	*.00214[a]*	.00367[a]	*.00189[a]*	.00403[a]	.00573[a]
	Rmt	.501[a]	*.602[a]*	.605[a]	*.651[a]*	.491[a]	.772[a]
	Rmt^2	14.82	*.306*	-13.836	*-8.426*	9.112	-10.296
During -covid-19	Constant	.00433[a]	*.00230[a]*	.00402[a]	.00541[a]	.00431[a]	*.00498[a]*
	Rmt	.429	*.683[a]*	.483[a]	.846[a]	.599[b]	*1.327[c]*
	Rmt^2	11.027	*6.551*	-8.403	-6.534	**-21.464[c]**	***-19.987[c]***

Table 3c. Herding behavior toward investors' sentiment for Morocco

		Bearish situation		***Normal situation***		***Bullish situation***	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00395[a]	*.00203[a]*	.00396[a]	*.00165[a]*	.00387[a]	.00630[a]
	Rmt	.574[a]	*.504[a]*	.564[a]	*.771[a]*	.642[a]	.593[a]
	Rmt^2	**-9.474[a]**	***-7.076[a]***	**-10.612[a]**	***-26.289[a]***	**-23.429[a]**	**-12.154[a]**
Pre-covid-19	Constant	.00398[a]	*.00189[a]*	.00407[a]	.00189[a]	.00402[a]	.00193[a]
	Rmt	.569[a]	*.593[a]*	.428[a]	.651[a]	.537[a]	.449[a]
	Rmt^2	-11.168	*-16.563*	16.079	-8.426	-6.883	12.717
During -covid-19	Constant	.00362[a]	.00496[a]	.00423[a]	.00486[a]	.00328[a]	.00274[a]
	Rmt	.694[a]	1.099[a]	.279[a]	1.033[a]	.844[a]	.173[a]
	Rmt^2	**-12.420[a]**	**-16.271[a]**	-.296	**-19.594[a]**	**-25.841[a]**	3.397

Whole period: Bearish, stable, 90 percent, also herding effect.
During COVID-19 period: stable, 10 percent, also herding effect.

Table 3d. Herding behavior toward investors' sentiment for Tunisia

		Bearish situation		***Normal situation***		***Bullish situation***	
		OLS	**Quantile**	**OLS**	**Quantile**	**OLS**	**Quantile**
Whole period	Constant	.00289[a]	*.00147[a]*	.00311[a]	*.00159[a]*	.00308[a]	.00465[a]
	Rmt	.691[a]	*.678[a]*	.597[a]	*.495[a]*	.671[a]	.699[a]
	Rmt^2	**-18.657[c]**	***-30.843[a]***	**-14.171[a]**	***-14.195[a]***	**-19.061[a]**	-9.897
Pre-covid-19	Constant	.00279[a]	*.00149[a]*	.00306[a]	*.00163[a]*	.00299[a]	*.00142[a]*
	Rmt	.625[a]	*.654[a]*	.588[a]	*.476[a]*	.682[a]	*.751[a]*
	Rmt^2	-10.031	***-29.573[a]***	**-16.022[a]**	***-13.009[a]***	**-17.155[b]**	*-9.640*
During -covid-19	Constant	.00358[a]	*.00171[a]*	.00349[a]	*.00164[a]*	.00384[a]	*.00462[a]*
	Rmt	.831[a]	*.842[b]*	.625[a]	*.681[a]*	.513[a]	*.778[a]*
	Rmt^2	**-15.554[b]**	***-5.649***	**-17.088[b]**	***-14.475[c]***	-15.196	*-17.954*

Whole period, during COVID-19: stable, 90 percent, also herding effect.

As a common result for all countries, we notice evidence of a herding effect for the normal situation related to investors' sentiment when we consider the whole period. Results are different among countries during bearish and bullish situations for both before and during the pandemic. During the COVID-19 period, herding behavior is only evident in the Tunisian stock market during the bearish situation. There is no herding effect during this turbulent period in the Egyptian and Tunisian stock markets, while this effect is present for this scenario in the Jordanian and Moroccan stock markets.

For the quantile regression results, we examine the effect of herding in extreme tails of market return distribution. Results suggest some differences between periods, extremely low and high returns, and sentiment state. Looking for herding behavior during the period preceding the COVID-19 pandemic, there is no evidence of herding behavior in all markets for the three situations with respect to the sentiment of investors for the whole period, except for the case of Egypt for the bullish situation, where we find evidence of herding effects for extremely high returns. For the case of the Jordanian, Moroccan, and Tunisian stock markets, we find a herding effect during bearish and stable situations for the extremely low returns for the whole period. Evidence of herding behavior was also confirmed in the Tunisian and Moroccan markets even during the COVID-19 period in both bearish and stable situations. During bullish periods, there is no evidence of herding behavior in these markets, while herding was confirmed for this period in the Egyptian and Jordanian markets for the extremely low returns.

In overall estimations, we can notice some differences in herding behavior in the four MENA countries before and during the COVID-19 pandemic periods according to the variations of exchange rates as a proxy for investors' sentiment. Investors may change their beliefs about the trading of stocks when there is a change in the variations of exchange rates. Herding behavior was more evident during the COVID-19 period than in the pre-COVID-19 period. We highlight a significant impact of the sentiment of Moroccan and Tunisian investors after COVID-19 for the herding behavior. Herding behavior is evident in the Egyptian and Jordanian stock markets during bullish situations after the COVID-19 pandemic. These different results reflecting the sentiment of investors toward the herding effect can be explained by the economic instability since the 2011 revolution, which affected investors and, in turn, is reflected in their sentiments.

4. Conclusion

In this analysis, we examine the impact of investors' sentiment on herding behavior among investors in the Egyptian, Jordanian, Moroccan, and Tunisian stock markets from 3 January 2011 to 15 July 2021. We consider a comparison between the behaviors of investors according to their sentiment and link exchange rates before and during the COVID-19 period. Based on the methodology used in Chiang et al. (2010), we find evidence of herd behavior in the Moroccan and Tunisian stock markets during the COVID-19 period when investors have a bearish or stable sentiment. There is no evidence of herd behavior for these markets during this period when the sentiment is bullish, suggesting evidence for the stock market efficiency hypothesis in Morocco and Tunisia. There is evidence of herding behavior during the COVID-19 period in bullish investors' sentiment for the Egyptian and Jordanian stock markets for extremely low returns. These different findings among countries and investors' sentiment have important empirical implications since the results suggest different situations of herding, especially between MENA countries. There is a concordance in the sentiment of investors in both regions toward herding behavior, for which there is a change in herding behavior according to the state of investors' sentiment.

Future research to better understand the effect of sentiment on herding behavior calls for constructing a sentiment indicator for each country that reflects country-specific realities. This would allow for constructing an index to study different situations of herding behavior through alternative scenarios.

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