Is there a change in the investor sentiment and herding behavior in the MENA region after COVID-19?

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Extended Abstract

With the spread of the COVID-19 pandemic around the world, financial markets have known instability and high volatility due to the increase of uncertainty which in turn lead investors to be pessimist on their decisions about buying/selling stocks in the market. Therefore, these pessimist investors who are in general the less informed in the market decide to follow the others believing that they are the more informed especially during down market periods. Consequently, a natural question arises: can the herding behavior be confirmed during the corona virus pandemic due to investor pessimism during this period.

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 in this analysis as the corona virus pandemic have risen uncertainties in all countries of the world. As developed in the financial literature devoted to behavioral finance, events and news can change the behavior and the beliefs of investors which can cause changes and fluctuations of prices 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 and al. 2021) that during periods of crisis sentiment of investors will be unstable and investors do not be able to take the right decision when buying and selling stocks in the market, therefore, they decide to follow the others in the market. Investors do not rely on their own information and decide to follow others. New information can have a big effect on investor sentiment, which can in turn have a huge impact on their judgments about future decisions. According to good news, investors will be optimistic in their future decisions while bad news can make investors pessimistic.

Based on the methodology used in Chiang et al. (2010) and by employing quantile regression analysis for the data ranging from January 3, 2011, to July 15, 2021, results show some differences about herding behavior in the Egyptian, Jordanian, Moroccan, and Tunisian stock markets. These different findings among countries and investors' sentiment states have important empirical implications since the results suggest different situations of herding especially between North African and Middle East countries. There is a concordance in the

sentiment of investors in these both regions towards herding behavior. There is a link between herding behavior and the situation of investors' sentiment.

1- Introduction

Many studies on investment decisions pursue the rationality of investors and accept the assumption that individuals have rational behavior in their decision makings. These approaches presuppose that people are profit maximizers in their decision of choices. The classical theory of market efficiency builds upon this strand of assumptions, before being challenged by works in behavioral economics and finance in general and prospect theory in particular. 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) showed that normal decision-making behavior in humans is not consistent with profit maximization motives. Emotion and psychology of the person play a large role (Dang and Lin, 2016).

The irrational behavior of investors implies that investors sometimes ignore their private information in decision makings which changes some payoffs from investment. Series of studies have shown that behavioral elements play a significant role in determining market prices. This view is contradicting the traditional finance theories (Scharfstein and Stein, 1990; Chen et al., 2003; Demirer and Kutan, 2006). Development of behavioral finance theories, give rise to the development of different biases from which we cite the herding bias. Herding behavior theory refers to mimicking other investors' actions in the stock market. Studies have examined herding behavior to explain investment decision-making of investors. Motivation of investors to follow other investors' actions or mimic those of others investors' actions has a significant implication for financial markets. As herding behavior theory says, the investors who tend to herd would avoid their own private information and, in the process, cause to place the prices in a position away from the intrinsic values. This could cause the markets to be more volatile (Balcilar et al., 2013).

Financial markets are fluctuating over time. Bullish market refers to the position that the market offers a high rate of return. On the other hand, bearish markets are linked with low rates of return. In this regard, the behavior of investors during different market situations may not be the same and it requires further investigations. Moreover, during up and down-market periods, investor's herding behavior is also changing and the relationship of herding behavior and market (portfolio) return does not remain linear (Chang et al, 2000).

Two streams of theories are recognized in literature exploring the herding behavior; one is heading toward a particular stock, and the other is market-wide herding. Based on herding

toward specific stock, 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 the market stress by employing the cross-sectional standard deviation of return (CSSD) to detect herd behavior in the market. Chang et al. (2000) investigate the herding behavior by modifying the study of Christie and Huang by employing Cross-sectional Absolute Deviation of returns (CSAD) instead of CSSD. In a related approach concentrating on the utility of advanced analytical tools vis-à-vis herding in markets, Chiang and Zheng (2010) found 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), have focused their research on market-wide herding where investors follow market trends and tend to move with the actions of the market.

According to the 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 presence of systematic mispricing in the capital markets resulting from sentimental factors. Behavioral financial theories claim that irrational behavior of noise traders and arbitrators causes a disparity in asset prices from their intrinsic values. Theoretical advances in behavioral finance and empirical evidence have both rejected the hypotheses of classical financial theory because of its assumption of rationality of agents in capital markets. Baker and Wurgler (2007) considered that rational participants did not seem to have played a leading role in bringing the value of assets up to the current value of anticipated cash flows. Behavioral finance offers an alternative model which claims that economic phenomena can be better understood if the investors accept to not be entirely rational. In this context, the 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 the investor's 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) argued 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 as per certain conditions in the market. Studies from developed economies like the USA are far ahead in understanding the sentiment-related market dynamics (Barberis et al. 1998; Lee et al. 2002; Neal and Wheatley 1998). Academic studies of investor sentiment in developing economies with rapidly growing capital markets are still in 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 the 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 that during a low sentiment episode. This is caused by naive and unaware noise traders' misjudgment of potential risk. Past academic studies about emerging economies have not explored such factors in-depth for the MENA region. In particular, scholars are paying more attention to emerging and frontier markets recently 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 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.'s (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 Covid-19 will be conducted in this analysis as the corona virus pandemic has risen uncertainties in all countries of the world. As developed on the financial literature devoted to behavioral finance, events and news can change the behavior and the beliefs of investors which can cause changes and fluctuations of prices 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 and al. 2021) that during periods of crisis sentiment of investors will be unstable and investors do not be able to take the right decision when buying and selling stocks in the market, therefore, they decide to follow the others in the market. For this analysis data were collected over the period January 3, 2011, to July 15, 2021, to the series of stock prices. In this study, devoted to some MENA countries, we have considered 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. Concluding remarks are provided in Section 4.

2- Herding Behavior and Investor Sentiment

2.1 Herding and Market Rationality

The evolution of behavioral finance models contributed to the investigation of herding behavior, which, by definition, is an anomaly induced by investors' decision-making process. 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 noted, three important themes (models) emerge from studies discussed on rational herding behavior in financial markets. Payoff externalities models of herding, Principal–agent models of herding and Cascade models of herding that can occur when agents make conclusion from the action of other agents and decide to ignore their own information and follow other's actions (Devenow and Welch, 1996). Moreover, correlated predicted errors are also influencing the rational herding behavior of managers. On the other hand, irrational herding behavior may be the result of irrational investor or investor psychology. As an illustration, social gathering may affect the investors and encourage them to ignore their information and mimic other investors' actions during market uncertainties.

As evidence of herding in finance literature mounts, it is becoming clear that herding in financial markets is a global phenomenon. The presence of herding behavior among investors would cause market imbalances by maneuvering the securities' prices away from their innate values. Hence, in this case the securities' prices would reflect both the rational and irrational expectations from investors (Kataria and Choudhary, 2015). The study of Christie and Huang (1995) investigated the herding behavior of investors in the US market. To capture the herding behavior, they used the cross-sectional standard deviation of returns and their findings stated the inconsistency of herding behavior of investors during large price movements. They have also stated the inconsistency of herding behavior for low and high frequency data sets. Chang et al. (2000) studied herding behavior of investors for various international markets such as the USA, Hong Kong, Japan, South Korea and Taiwan. They found for all five markets, herding behavior which was measured by the dispersion was having a high coefficient during the up market in respect to the down market. Moreover, they have also investigated herding behavior of investors across various developed and emerging markets. In this regard, they stated 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 herding behavior of investors toward the markets.

Several key recent developments on 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. The authors investigated the herding behavior by using

smooth-transition autoregressive as well as generalized impulse response functions, and they concluded the evidence of herding behavior among foreign investors in Malaysia during crises period. Moreover, the study of Kumar et al. (2020) explores the herding behavior by discrimination of herding behavior of investors with respect to different market conditions and found the existence of herding behavior among the investors of Asia-Pacific region.

For the MENA region, we can find studies for different markets but no study have been carried out to identify 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 post-revolution phase in bearish markets. These findings are due to the special nature of Egypt's stock market dominated by large domestic owners as well as 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 conclude that the herding behavior is detected for the overall market and in all size-based portfolios. Also, the results show a positive impact of liquidity and volatility on investors' herding behavior for the four portfolios and for the overall market. In the Tunisian market, the study of Hanafi and Abaoub (2016) use the relationship between the stock price and trading volume to detect herding. The empirical results indicate the presence of herding behavior during crisis period regardless to prices and trading volume movements. However, during the pre-crisis period herding is detected only when the market is up.

2.2 The investor's sentiment

Investor sentiment is the expectation of market participants about the 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 efficient market hypothesis (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. Investors' sentiment is a vital aspect of the capital market, as it contributes to frequent fluctuations in the stock price and thus creates uncertainty about future returns on investments.

Market sentiment is the general prevailing attitude of investors as to anticipate price development 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 world events. Investor sentiment is a very broad concept which incorporates several ideas such as investor mood, investor confidence, investor satisfaction and investor uncertainty and panic. It was found by certain research 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 investors' sentiment because of their 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 the individual investor sentiment via surveys and polling techniques. They are highly sampling-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 to capture the irrational aspects of the market. The consistent and theoretically comprehensible nature of the sentiment index has led to its wide adoption (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) used trading volume and return volatility for understanding the relationship between sentiments and returns. Their findings showed that post-investment analysis was 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) concluded 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, indicated that changes in sentiment are negatively correlated with market volatility. Volatility increases (decreases) when investors become more optimistic (pessimistic). Brown and Cliff (2005) found evidence that sentiment affects asset valuation. As a group, investors tend to over value (under value) 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 in the stocks market returns (e.g., Baker & Wurgler, 2006, 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 the analysis of 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) found evidence that sentiment affects asset valuation, investors tend to overestimate assets throughout 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 throughout times of extreme pessimism or low sentiment. Once investors are pessimistic, the market valuation is under the intrinsic value.

It was found by certain research that there is a significant relationship between investor sentiment and stock returns in both developed and developing countries. Bhaskaran (1996) examines the relation 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) used trading volume and return volatility for understanding the relationship between sentiments and returns. Their findings showed that post-investment analysis was essential to correct errors in previous behavioral estimations.

Kumari (2019), analyse the Indian market using unit root statistics and non linear GARCH model and he conclude 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 it's there a significant flow of causality from investor sentiment to stock market liquidity. The results of time series estimates suggest that 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 leads to a decrease (increase) in the average firm's share liquidity. Result although not as strong, are opposite for investor sentiment derived solely from news articles: improvements (deterioration) in news sentiment leads to an increase (decrease) in the average firm's share liquidity. Choi and Yoon (2020) concude that the relationship between investor sentiment and herding behavior showed that investor sentiment has a positive effect in the KOSDAQ stock market but is not significant in the KOSPI stock market using regression analysis. Galariotis, Krokida, and Spyrou (2016) conclude that Herding behavior is more prevalent in high sentiment stocks irrespective of the period and there may be two ways 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 studies interested to the analysis of herding behavior used dispersion measures of returns, such as Cross-sectional squared deviation of returns (CSSD) and cross-sectional absolute deviation of returns (CSAD), as dependent variable. The explanatory variables in the model are in general 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 herding effect when the estimated coefficient relative to the variable squared market return is statistically negative and significative. According to Chang et al. (2000) the dependent variable cross-sectional absolute deviation of returns (CSAD) 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.[1]

Nonlinearity is the main characteristic of 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.

As many authors declared that behavior of investors differs among situations, they considered asymmetries characterizing stock markets. Authors highlighted that results about herding bias during down and up market periods are different for many markets. Also, authors concluded that for the periods of crisis, upper and lower tails and during extremely high and low returns, dispersions are in general instable. 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 Amid COVID-19 pandemic. In other way we consider the following regressions:

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

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

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

On the other hand, herding behavior can be affected by the sentiment of investors. When economic situation is instable or economic and financial indicators such as inflation, interest rates, exchange rates, etc. are extremely high or low, investors feel incompetent to take the right decision and decide to follow the others in the market. As investors are very sensible to the exchange rate currency, we choose daily variations of exchange rate currency as poxy variable to the investors' sentiment. We consider three possible situations: stable situation when exchange rate is stable and it is in the range of the mean variation minus/plus standard deviation, bullish situation when the variation is above the mean variation plus standard deviation and the bear situation when the variation is below the mean variation minus standard deviation. In fact, we consider the following equations:

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

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

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

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

3.2 Data and descriptive statistics

For this analysis data were collected over the period January 3, 2011, to July 15, 2021, to the series of stock prices. In this study, devoted to some MENA countries, we have considered 20 listed companies for Egypt, 17 for Jordan, 14 for Morocco and 21 for Tunisia. Table1 presents the main descriptive statistics of stock market returns $R_{m,t}$, and their respective dispersions CSAD variables[2].

According to table1 we can show a difference between periods and among countries for both stock market return and absolute cross section dispersion statistics. Standard deviations are more important during covid-19 period than pre-covid-19 period, especially for Moroccan stock market return where standard deviation increased from .272% to .511%. In average stock market returns still positive even after the covid-19 pandemic, except the Egyptian

[2] It is worth noting that all series are stationary, for what, according to the test ADF we accept the hypothesis of stationarity at significance level 1% for CSAD and $R_{m,t}$ series for all countries.

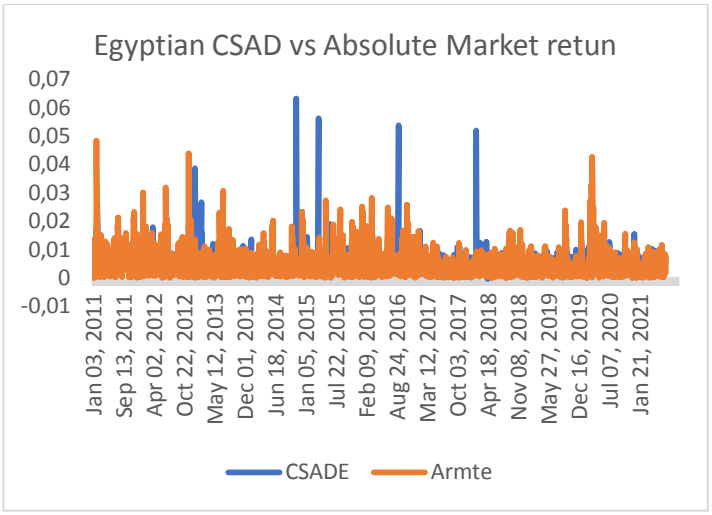
stock market for which the mean of stock return became negative for the period March 2020 – July 2021. For this market fluctuations are the more important in the region. In fact, the Egyptian standard deviations for all periods considered in this analysis are the higher overall periods compared to the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

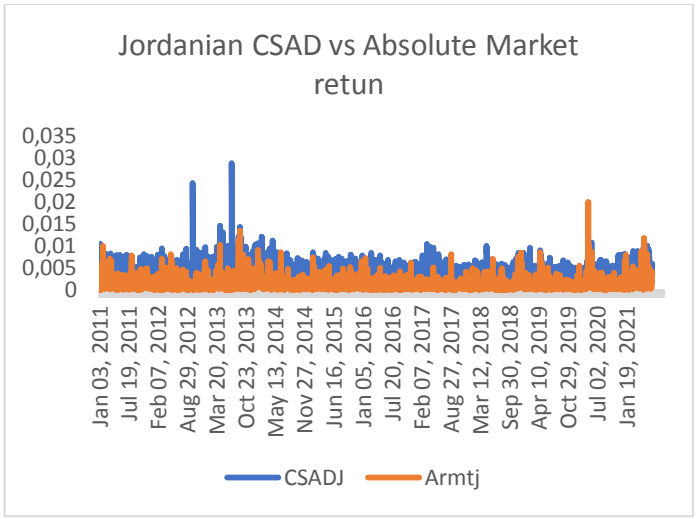
Kurtosis and Skewness statistics confirm the rejection of the null hypothesis suggesting the non-normality of all series for all periods to all countries.

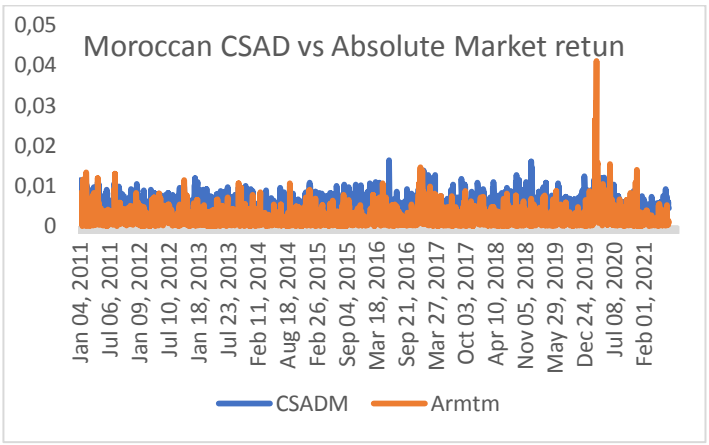
Table1. Descriptive statistics

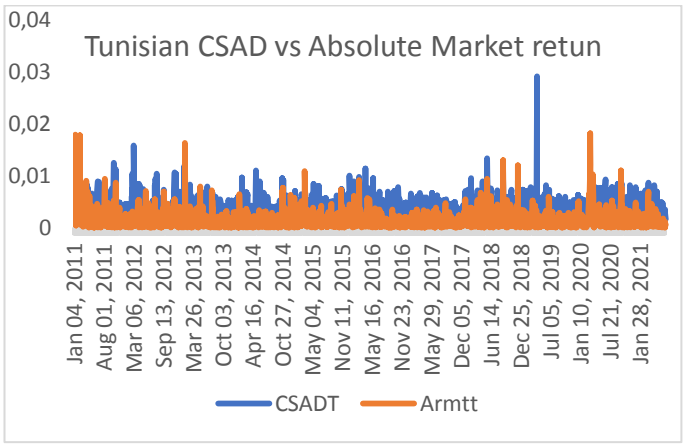
			Mean	**Std**	**Min**	**Max**	**Median**	**Skewness**	**Kurtosis**
Whole period	EGY	CSAD	.00583	.0031	.0005	.0631	.00531	7.995	24.85
		Rmt	6.9E-5	**.00632**	-.0483	.0317	.00031	-.691	6.301
	JOR	CSAD	.00047	.00183	.00076	.0287	.00445	2.131	17.444
		Rmt	-2.01E-5	.00211	-.0199	.0134	-4E-5	-.192	7.059
	MOR	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
Amid-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-July2021









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 we said in the methodology, least squares and quantile regressions according to different scenarios are employed. For the results we focus our attention on the sign and statistical significance of the estimated coefficientsβ_2. Tables 2-a, 2-b, 2-c and 2-d 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 up-market period. To distinguish between up market and down-market periods we are considering the following: down-market period is determined when $R_{mt} < 0$, while up-market period corresponds to the case of $R_{mt} > 0$.

By using least squares method, we can 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 the herding behavior in different moments of the

stock market fluctuations, we propose a detailed analysis of herding behavior by decomposing the whole period in two sub-samples down and up market periods. When considering the asymmetric properties characterizing the stock markets, we find some differences between down and up-market periods about herding behavior. 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 COVID-19, we don't identify evidence of herding behavior for all markets except the Tunisian stock market where herding effect is identified for all sub-samples. For the Amid covid-19 period, we obtain an estimated coefficient β_2 negative and statistically significant for the full sample which indicate then a herding effect in this critical period where investors' decisions became irrational.

Table2.a 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*
Amid-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 respectively represent 1%, 5% and 10%. Values in bold indicate the presence of herding behavior in the market.

Table2.b 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*
Amid-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]**

Table2.c 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**
Amid-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]**

Table2.d Estimates of herding behavior from Chiang and Zheng (2010) method for Tunisia

		Full sample		Down market		Up market	
		OLS	**Quantile [3]**	**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]***
Amid-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]***

As many researchers insisted in the importance of extreme values in studying herding effect and to better analyze herding for these markets, we are considering the quantile regression analysis to estimate equations 3 – 8 and to solve problems of non-normality and take into account asymmetries and extreme values existing in data. According to the results presented in tables 2, quantile estimations show some differences among markets and periods on both extreme tails of return distribution (low 10% and high 90%). For the whole period there is evidence of herding effect for all markets. Herding behavior was confirmed in the Amid covid-19 period during down market period 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 pessimists during crisis period because of covid-19 than the other investors for that reason they decided to herd.

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

In a second way we examine the evidence of herding behavior according to the variations of exchange rates as proxies to the sentiment of investors in these countries. Tables 3-a, 3-b, 3-c and 3-d present the estimations of the equations 7, 8 and 9.

Table3.a Herding behavior towards 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]***
Amid-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]***

Table3.b Herding behavior towards 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
Amid-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]***

Table3.c Herding behavior towards 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
Amid-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% also herding effect
Amid-covid-19 period: stable: 10% also herding effect

Table3.d Herding behavior towards 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*
Amid-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, Amid covid-19: Stable: 90% also herding effect

As a common result for all countries, we can notice evidence of herding effect for the normal situation related to the sentiment of investors when we consider the whole period. Results are different among countries during bearish and bullish situations for both pre and amid covid-19 pandemic. While in the period Amid COVID-19 herding behavior is only evident in the Tunisian stock market during bearish. There is no herding effect for 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 that it precedes covid-19 pandemic, we can notice that for the whole period there is no evidence of herding behavior for all markets for the three situations with respect to the sentiment of investors, except the case of Egypt for the bullish situation where we found an evidence of herding effect for the extremely high returns. For the case of Jordanian, Moroccan and Tunisian stock markets, we accept the effect of herding during bearish and stable situations for the extremely low returns for the whole period. Evidence of herding behavior was also confirmed in Tunisian and Moroccan markets even in the Amid covid-19 period in both bearish and stable situations. During bullish period, there is no evidence of herding behavior in these previous 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 about 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 to the investors' sentiment. In fact, investors may change their beliefs about the trading of stocks when there is a change in the variations of exchange rate. Also, herding behavior was more evident during amid-19 period than in the pre-covid-19 period. We suggest 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 pandemic covid-19. These different results reflecting the sentiment of investors towards herding effect can be explained by the economic instability since the revolution 2011 for which investors have touched well, which in turn has been reflected in their feelings.

4- Conclusion

In this analysis, we have examined the impact of investors' sentiment on herding behavior among investors in Egyptian, Jordanian, Moroccan, and Tunisian stock markets for the period ranging from January 3, 2011, to July 15, 2021. A comparison between behaviors of investors according to their sentiment linked exchange rates before and amid covid-19 periods was considered. Based on the methodology used in Chiang et al. (2010) we find evidence of herd behavior for Moroccan and Tunisian stock markets during Amid 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 sentiment is bullish suggesting then the evidence for the stock market efficiency hypothesis in Morocco and Tunisia. There is evidence Based on the methodology used in Chiang et al. (2010) of herding behavior during the amid covid-19 period in bullish investors' sentiment for Egyptian and Jordanian stock markets for extremely low returns. These different findings among countries and investors' sentiment states have important empirical implications since the results suggest different situations of herding especially between North African and Middle East countries. There is a concordance in the sentiment of investors in these both regions towards herding behavior for which according to the situation of investors' sentiment there is a change in the behavior to herd.

In future research, and to better explain the effect of the sentiment on herding behavior, we attempt to construct a sentiment indicator for each country able to significantly reflect the reality. With this constructed index we can study the different situations of herding behavior according to the different possible scenarios.

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