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Herding behavior and financial market price behavior under the COVID-19 pandemic: implications for the Amman Stock Exchange

Raneem Ghazi Aldeki
Al Sham Private University, Syria
Corresponding e-mail: r.d.foas@aspu.edu.sy

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ABSTRACT

Purpose — *This study investigates herding behavior and the link between herding behavior with the liquidity and volatility of financial markets amid the COVID-19 pandemic.*

Research method — *This study employed the Cross-Sectional Absolute Deviation (CSAD) approach technique for each of the previous and COVID-19 phases, as well as for the complete sample period. The sample includes 172 securities that have been traded in the Amman Stock Exchange from January 2006 to February 2022. The full sample data was separated into three subsamples: 1) the whole period from January 1, 2006, to February 28, 2022; 2) prior the COVID-19 outbreak from January 1, 2006 to February 28, 2020; and 3) during the COVID-19 outbreak from March 1, 2020, to February 28, 2022.*

Result — *The results for the whole sample period show that herding behavior may be detected in the Amman Stock Exchange during down-market intervals, and the result does not change before or during the COVID-19. Furthermore, both down liquidity and down volatility periods exhibit contrary herding behavior. The study found that financial market price behavior is an important factor that may contribute to herding behavior, which occurs when volatility increases and liquidity decreases in the Amman Stock Exchange, and the result does not change prior to the COVID-19 period. While liquidity has a negative and large influence throughout the COVID-19 period, herding tendency does not increase when volatility changes.*

Recommendation — *This study suggested traders to plan their purchasing and selling strategies of financial market instruments in various scenarios amid the COVID-19 pandemic.*

Keywords: *behavioral finance, herding behavior, liquidity, volatility, COVID-19*

BACKGROUND

The COVID-19 pandemic has weakly the financial markets' performance and has induced a scare among financial market investors. In general, it proposes that a few economic phenomena can normally be properly understood using models within which a few players are not definitely rational. That has been driven by the belief that behavioral finance theory has more constructible blocks. In fact, it investigates whether one or either of the concepts that constitute characteristic rationalism.

Herding, a type of related behavior, can be defined as a strategy in which traders purchase and sell in the same direction, imitate one other, and make judgments based on prior traders' actions, or as a behavioral response to the common market (Hirshleifer & Teoh, 2003).

Traders are more likely to follow the mobilize decision with repressing their personal information at times of market agony, such as the COVID-19. The purpose of this study is to explore the herding behavior on the Amman Stock Exchange during down-market periods and to investigate herding behavior and financial market price behavior at each of the previous and COVID-19 phases, as well as for the whole sample interval. The current COVID-19 outbreak, on the other hand, has produced a panic and fear environment in financial markets, resulting in extreme volatility, high market attention, low returns, and a disproportionately high inability to mobilize additional investment. As a result, the aim of this investigation is to see if there is any proof of herding behavior in the Amman Stock Exchange. Second, this research investigates whether herding tendency exists in a variety of market situations (changes in liquidity and volatility). Third, the connection between herding behavior and financial market price behavior will be checked in this study.

This study gives a detailed account of herding behavior in the Amman Stock Exchange under extreme conditions, as well as the role of liquidity and volatility in the herding behavior model's affect and feature. Because after the spread of the COVID-19, a state of uncertainty appeared among investors which was reflected in the stock market's volatility around the world through stock price declines and a negative impact on investor sentiment, as global stock market volatility exceeded previous crises in 2008, 1930, and 1987. As a result, it was essential to examine and discover how the financial market, such as the Amman Stock Exchange, reacted to the pandemic spread. The results are beneficial to investors and who are interested in the investment field.

LITERATURE REVIEW

According to traditional finance theory, stock values normally advance toward fair values, and any market instabilities are corrected by an automatic mechanism, meaning that fundamental values prevail in the long run. As a consequence, only intrinsic variables impact asset prices, cross-sectional returns, and liquidity. The assumption of rationality has recently faced criticism for explaining various empirical deviations from efficient markets satisfactorily.

As a reaction to the constraints of the traditional paradigm, behavioral finance appeared as a new approach to finance. In prospect theory describes how cognitive heuristics and biases express investor preferences and are used to make decisions under ambiguity.

In the financial market, there may be an expanding disagreement in the literature on whether herding is largely information setup or non-information setup. By modeling prior transactions in the financial market, (Hirshleifer et al., 1994) presented proof in support of non-information-based totally behavior of traders. By contradicting the truth of the efficient market hypothesis theory, (Caparrelli et al., 2004) discovered significant purposeful or irrational herding in large corporations in the Italian financial market. (Lin et al., 2013) used the efficient market hypothesis notion to see if herding is entirely herding and non-facts-mainly setup herding is information primarily setup. (Galariotis et al., 2016) found no herding behavior in the evolved financial market, however the advanced financial market shows herding when the liquidity of shares is limited. However, the emerging financial market is typically characterized as illiquid with a significant level of herding.

Given the importance of behavioral factors, past research on liquidity that was only focused on a neoclassical paradigm is inadequate. As a result, it is critical to figure out if a behavioral component like emotion has an impact on liquidity.

Market liquidity and investor attitude are connected, according to academic frameworks in behavioral finance. The theoretical framework intuitively emphasizes how liquidity is influenced by investor mood via financial market actors. It is critical to comprehend how investors can indirectly impact liquidity, as emotion impacts liquidity via investors. (Kyle, 1985) explained the link between emotion and liquidity via the channel of market investors. Insider traders, noisy traders, and rational market makers are the three sorts of market participants in Kyle's (1985) paradigm. First, insider trader's trading methods and investment patterns are mostly derived from private information. Market liquidity is inextricably affected by price effect. Second, behavioral theories suggest that some reasonable characteristics of stocks might be understood as departures from faire values caused by noisy investors. This type of trading raises mood and pulls prices away from their underlying values. As a result of this variation, liquidity rises (de Long et al., 1990). As a result of the lesser price adjustment by market makers, the price effect of such order flow is reduced, and this lower price impact enhances liquidity. (Baker & Stein, 2004) present a unified theoretical model that shows a clear link between liquidity and irrational investor mood. As a result, increased market liquidity is an indication of good mood in a market driven by irrational investors.

(Liu, 2015) empirically examines back with theoretical assumption that increased investor mood in the US market boosts market liquidity. However, they used a static technique, despite the fact that the relationship between these two variables should be dynamic. The data from the ideal free market, such as the United States, does not provide any insight into how EMs function.

(Debata et al., 2018) also studied trader mood and liquidity in a few emerging markets. The study finds that mood is one of the most important elements influencing stock market liquidity in emerging markets. In addition, the study shows that these exchanges have a contagious emotion impact.

(Choi & Yoon, 2020) studied herding behavior and the relationship between it and investor mood. First, they found that herding behavior occurs in the KOSPI and KOSDAQ stock markets during down-market periods. However, that herding behavior occurs during periods of low trade volume and low volatility. Second, herding behavior may be detected in the low and high quantiles of the KOSPI and KOSDAQ stock markets, according to the results of the quantile regression. However, there is evidence of an unfavorable herding tendency, which indicates that investors herd in severe market situations. Finally, using regression and quantile regression, the link between investor sentiment and herding behavior is examined, and investor sentiment is verified to be one of the significant components that might induce herding behavior in the Korean stock market.

(Friedman, 1953) explained the relationship between trader behavior and volatility, finding that irrational traders purchasing when shares were increase and offering when they were decrease, whereas rational traders follow the direction of fair values by purchasing down and offering up. (Wang, 1993) suggested that volatility is affected by misinformed or liquidity buying and selling, based on Friedman's theory of Noisy Rational Expectations, since value changes increasing from uninformed buying and selling toward to reverse, purchasing when shares increase and offering when shares decrease; a behavior that we would consider herding.

Many research has theorized that liquidity and volatility are significant influences that might cause to herding behavior, but only a few studies investigations have definitively demonstrated by evidence this claim. As a result, this research is useful since it studies the connection between herding behavior and financial market price behavior on the Amman stock exchange during severe occurrences over the whole sample, prior and during the COVID-19 pandemic.

RESEARCH METHOD

Data

This research looks at financial markets to see if there has been any evidence of herding behavior in the Amman Stock Exchange. The Amman Stock Exchange uses a market capitalization weighted price index for banking and finance, insurance, services, and industry. We also look at how liquidity and volatility affect the link between herding behavior and financial market price behavior. The data includes 172 securities that have been traded in the Amman Stock Exchange from January 2006 to February 2022. There are 194 observations in total.

The first COVID-19 infection in Jordan happened on March 2, 2020. To study more about herding behavior before and during the COVID-19, the full sample data was separated into three subsamples from January 1, 2006 to February 28, 2022:

1. The whole period: from January 1, 2006, to February 28, 2022
2. Prior COVID-19 outbreak: January 1, 2006 to February 28, 2020
3. During COVID-19 outbreak: March 1, 2020, to February 28, 2022

Many previous studies have used other liquidity measures; however, this study selected spread measure because the trader is more pessimistic when the spread is lower, and the trader is more optimistic when the spread is higher. Garman and Klass σ_{GK} are the volatility representatives. When the volatility index decreases, the trader believes positive things will happen, and when the volatility index increases, the trader believes negative things will happen.

Methodologies

Liquidity variable measurement

Liquidity has proven to be significantly more complex to measure (Heshmat, 2009). According to (Aitken et al., 1997), there are 68 existent measures in the literature, indicating that there is little consensus on the appropriate measure to utilize. Many of these measurements have little or no association, implying that using the wrong measures might lead to incorrect conclusions about market structure changes.

Liquidity measurement is complicated as there is no one agreement technique. Therefore, we choose Bid – Ask Spread because it is often used as an indicator of liquidity. There is inverse relationship, the higher liquidity the narrower spread. The bid-ask spread for the Amman Stock Exchange index measures the spread close and open monthly prices index.

1. Turnover Rate (TR)

   The Turnover rate represented by:

$$\mathrm{TR_{imd}} = \frac{\sum_{d=1}^{\mathrm{Dimd}} \mathrm{VO_{imd}}}{\mathrm{NSO_{imd}}}$$

   $\sum_{d=1}^{Dimd} VO_{imd}$ is sum of stocks traded in the Amman Stock Exchange, and NSO_{imd} is the number of stocks in issue. According to (Datar et al., 1998) this strategy is simple and intuitive.

2. Trading Volume (TV)

$$\mathrm{TV_{imd}} = \ln\left(\sum_{d=1}^{D=imd} (\mathrm{VO_{imd}P_{imd}})\right)$$

$\sum_{d=1}^{Dimd} VO_{imd}$ is sum of stocks traded in ASE, and $\mathrm{P_{imd}}$ is market price. According to (Brennan et al., 1998), a rise in Trading Volume (TV) indicates increased liquidity.

Many liquidity studies include trading volume per time interval (Qt) (Campbell et al., 1993; Lee & Swaminathan, 2000; Lo & Wang, 2006a; Chordia & Swaminathan, 2000; Wang, 2002; Sun, 2003; Nagel, 2005; Hearn et al., 2010; Hearn, 2010; Chandrapala, 2011). The average number of shares traded every day during year t-1 is known as trading volume (Chordia & Swaminathan, 2000). Trading volume is an essential feature of the economic interactions between various participants in financial markets. Trading volume is influenced by underlying economic causes, and so provides crucial information on market liquidity (Lo & Wang, 2006b). It can be determined on a daily, weekly, annual, or any other time period deemed suitable for study (Wyss, 2004).

3. Market capitalization

The value of a company is represented by its market capitalization in relation to the current market price:

$$\text{Market Capitalization}_t = \sum_{i=1}^{n} \mathrm{p_i} * \mathrm{q_i}$$

Where qi is the number of outstanding shares and pi is the stock price which has been used as a proxy for liquidity in several previous studies (Hobijn & Jovanovic, 2001; Lukács, 2002; Beaupain et al., 2011; Odularu, 2009; Hearn, 2009; Khrawish et al., 2010). Both volume and prices are influenced by underlying economic forces and thus provide valuable insight into how the market works (Lo & Wang, 2006c).

4. Amihud's (2002) illiquidity ratio

$$\mathrm{LIQ} = \frac{1}{\mathrm{D_t^i}} \sum_{d=1}^{\mathrm{D_t^i}} \frac{|\mathrm{R_{td}^i}|}{\mathrm{VOL_{td}^i}}$$

$|\mathrm{R_{td}^i}|$ is total returns stocks and $\mathrm{VOL_{td}^i}$ stocks traded in the Amman Stock Exchange. (Hasbrouck, 2009) and (Goyenko & Ukhov, 2009) both demonstrate the usefulness of the illiquidity ratio as a price effect indicator that is indicating how price reacts to order flows. Many research has utilized this approach (Næs, 2004).

5. The Bid-Ask spread

   This measure is the range between purchasing and selling price for each security. It is frequently used as a liquidity indicator. The higher liquidity, the narrower spread. The amount of willing buyers or sellers for a certain security determines the spread for that asset. This range is determined by a number of additional variables. The spread on securities with a higher trading volume is less than the spread on assets that are traded rarely. Volatility is another crucial aspect. The gap is significantly wider during volatile periods because market players demand a bigger return for the additional risk, they are ready to incur. The price of a stock is another aspect that affects this measure. Because most low-priced assets are new or tiny in size, they have a broader spread because they have fewer trades. Finally, the risk that investors face, such as stock risk and asymmetric information risk posed by informed traders, influences the bid-ask spread. The bid-ask spread for the Amman Stock Exchange index is calculated using the methods of this study as the difference between the index's monthly closing and open prices.

$$\mathrm{Hi-Low} = \frac{2(\mathrm{e}^{\mathrm{a}-1})}{1+\mathrm{e}^{\mathrm{a}}}$$

$$a = \frac{\left(\sqrt{2\beta - \sqrt{\beta}}\right)}{(3-2\sqrt{2})} - \sqrt{\frac{\gamma}{3} - 2\sqrt{2}}$$

$$\beta = (\ln(\frac{H_t}{L_t}))^2 + (\ln(\frac{H_{t+1}}{L_{t+1}}))^2$$

$$\gamma = (ln(\frac{H_{t,t+1}}{L_{t,t+1}}))^2$$

   Hi–Low spread applying high and low prices (Corwin & Schultz, 2012). This technique is a more complete measure of liquidity than the Hi–Low spread alone since it includes both cross-sectional and time series fluctuations in liquidity spreads.

Volatility variable measurement

1. Historic volatility: Parkinson and Garman-Klass

   It takes a lot more time to get the values than it does to obtain the opening and closing values. because it requires market surveillance in the creation of other historical volatility indicators; however, because the additional work might add value to the studies since extreme value is much insightful than opening and closing value. The cause for this is that whenever volatility hits extreme values, it reverts to the mean, making this estimator useful for tracking extreme volatility and predicting. The reason when volatility reaches peak values, it refers back to the mean, making this beneficial for following and forecasting volatility. The following equation is used to construct volatility:

$$\sigma_P = \frac{1}{2\sqrt{\ln 2}}\sqrt{\frac{1}{n}\sum_{t=1}^{n} P_t^2}$$

H_t and L_t are the up and down values on month t, and n is the number of priors monthly prices. The goal is establishing substantial relationships between monthly herding and monthly volatility therefore n=1. Garman and Klass provide a method for calculating volatility that takes into account both starting and ending values, in addition peak values. To calculate historical volatilities, use the formula below:

$$\sigma_{GK} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\frac{1}{2}P_t^2 - (2\ln 2 - 1)Q_t^2\right]}$$

C_t is closing prices and O_t is opening prices. As previously, we will use n=1.

2. Implied volatility

All of the volatility indicators have been based on spot market data. Nonetheless, numerous analyses of the S&P index agree that this measure is a more accurate estimator than other measures. Among others, (Corredor & Santamaría, 2004) indicated that this measure is a more useful predictor of volatility than other indicators. Many studies have also appeared this measure which are now being developed in different nations throughout the world have great forecast potential in predicting volatility (Fleming et al., 1995; Simon, 2003; Giot, 2005).

According to several articles, this measure also expresses investor emotion. As a result, we wondered if this indicator influenced the existence of herding behavior. We assumed this variable as an additional volatility indicator in our study will assist us to better understand to get a far more thorough and comprehensive view of the influence of herding on volatility. (Black & Scholes, 1973) applied their model to calculate implied volatility indicators. The main reason for this is the tools are widely use. (Fleming, 1998) showed that the BS model produces estimates that are equal among the given by other stochastic volatility in short term.

Herding behavior measures

The research method was discovered via significant market herding. This brief method has the benefit of being very clear. The method's disadvantage is that it depends on subjective judgments or information to guide trader selections in response to the market's overall performance.

Dispersion is a good indicator of the market effect of trader herding. It is bounded from under 0 since it gauges the frequency of individual shares returns to the market return. The number of distributions will increase as each share's individual return varies from the market return. As a result, extensive herding may mean a low in distribution.

Because various traders have distinct return ranges, their returns can differ from the average market return. However, after the traders' herd has crowded the market, share returns will no longer have as much variance. Consequently, each share will be connected to the market's average return. According (Chang et al., 2000), CAPM assumes straight-line connection between distribution in individual shares returns and the market return. The researchers employed the CAPM and used CSAD as a dimension of dispersion. They suggest that herding may cause straight-line connection to turn into nonlinear diminishing the range of dispersions. As a consequence, this method may be used to examine herding behavior in both normal and extreme situations.

Traders' personal beliefs and information are repressed by (Christie & Huang, 1995) in the quest of market admission in a variety of market scenarios. CSSD has been used as a criterion of herding and it has been used measured according to below:

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

Where:
$\boldsymbol{R_{i,t}}$ is individual shares return
$\boldsymbol{R_{m,t}}$ is market return
$\boldsymbol{N}$ is number of individual shares

Outliers can make the $CSSD_t$ vulnerable. (Chang et al., 2000) employed the CSAD as a criterion of herding according to below:

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

Where:
$\boldsymbol{R_{i,t}}$ is individual shares return
$\boldsymbol{R_{m,t}}$ is market return
$\boldsymbol{N}$ is number of individual shares

$$CSAD_t = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t$$

The CSAD is regression relationship between $\left|R_{m,t}\right|$ the absolute market return and $R_{m,t}^2$ the squared market return.
The CSAD is a measure of the relation between the mean value of $\left|R_{m,t}\right|$ and corresponding values of $R_{m,t}^2$.
β_1 is the coefficient of average market return's absolute value, and β_2 is the coefficient of average market return's squared value.

It demonstrates how to use a nonlinear model to examine herding behavior in extreme settings by:

$$CSAD_t = \alpha + \beta_1^{bull}\left|R_{m,t}^{bull}\right| + \beta_2^{bull}R\left(_{m,t}^{bull}\right)^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \beta_1^{bear}\left|R_{m,t}^{bear}\right| + \beta_2^{bear}R\left(_{m,t}^{bear}\right)^2 + \varepsilon_t$$

To study the impact of herding behavior in the Amman Stock Exchange market we use the average market return, $r_{m,t}$>0 to indicate the trend is up and $r_{m,t}$<0 to indicate the trend is down. If (β2) has a substantial negative value, it indicates that herding occurs while the market is decreasing (when the market goes up).

Furthermore, traders' reactions to changes in liquidity and volatility might differ. As a result, variations in liquidity and volatility can be connected to herding behavior.

We split into low and high intervals to explain the influence of liquidity and volatility on herding behavior. If they are less (more) at time t than the prior period, they are low (high). As a result, the intervals are categorized as having low liquidity and volatility. We investigate the influence of liquidity and volatility changes on herding behavior by:

$$CSAD_t = \alpha + \beta_1^{bull(liq)}\left|R_{m,t}^{bull(liq)}\right| + \beta_2^{bull(liq)}R\left(_{m,t}^{bull(liq)}\right)^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \beta_1^{bear(liq)}\left|R_{m,t}^{bear(liq)}\right| + \beta_2^{bear(liq)}R\left(_{m,t}^{bear(liq)}\right)^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \beta_1^{bull(v)}\left|R_{m,t}^{bull(v)}\right| + \beta_2^{bull(v)}R\left(_{m,t}^{bull(v)}\right)^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \beta_1^{bear(v)}\left|R_{m,t}^{bear(v)}\right| + \beta_2^{bear(v)}R\left(_{m,t}^{bear(v)}\right)^2 + \varepsilon_t$$

Where liq and v denote the monthly low value of liquidity and volatility in the Amman Stock Exchange market respectively.

Herding behavior and financial market price behavior

The effects of financial market pricing behavior, as indicated by liquidity and volatility, on herding behavior are investigated by:

$$CSAD_{i,t} = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2R_{m,t}^2 + \beta_3LIQ_t + \varepsilon_t$$

$$CSAD_{i,t} = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2R_{m,t}^2 + \beta_3VASE_t + \varepsilon_t$$

LIQ refers to liquidity while VASE refers to volatility. A negative value β3 indicates when volatility increases and liquidity decreases, traders are probably to imitate one another. This indicates that when traders switch from a pessimistic perspective in the upcoming days, the traders display herding behavior.

As a result, when volatility is low, traders do not feel compelled to follow other traders' decisions. A positive value β3 means that when volatility diminishes and liquidity rises. As a result, the Amman Stock Exchange market shows move backward in herding behavior.

RESULT AND DISCUSSION

Descriptive statistics and unit root test

The descriptive statistics and unit root test for CSAD, spread, and volatility are shown in Table 1. The average value of CSAD in the Amman Stock Exchange market is low, indicating that the market is volatile. The average value of CSAD at the spread is negative indicating that the trader is more pessimistic. The Augmented Dickey–Fuller (ADF) test and the Philips–Perron test were employed as unit root tests (PP). CSAD, spread, and volatility are all detected as stationary time series in the results. The CSAD was extremely high during the financial crisis as shown in Figure 1.

Table 1. Descriptive statistics and unit root test

Descriptive statistics

	Mean	Max	Min	Std. D.	Ske.	Kur.	J-B	N
CSAD	3.566726	24.81073	0.841558	3.139991	3.174252	17.06992	1925.985*	194
Spread	-11.76876	408.4600	-901.6700	126.0942	-2.388316	18.77165	2183.805*	194
Volatility	0.146769	0.205882	0.069438	0.018510	-1.248143	7.201342	192.0569*	194

Unit root test

	ADF(1)	ADF(2)	PP(1)	PP(2)
CSAD	-10.11687*	-10.93648*	-10.60041*	-11.18416*
Spread	-10.35467*	-10.35063*	-10.34738*	-10.34583*
Volatility	-6.617488*	-7.010832*	-10.04427*	-10.54661*

Note: *represent significance level at 5%
source: author (2022)

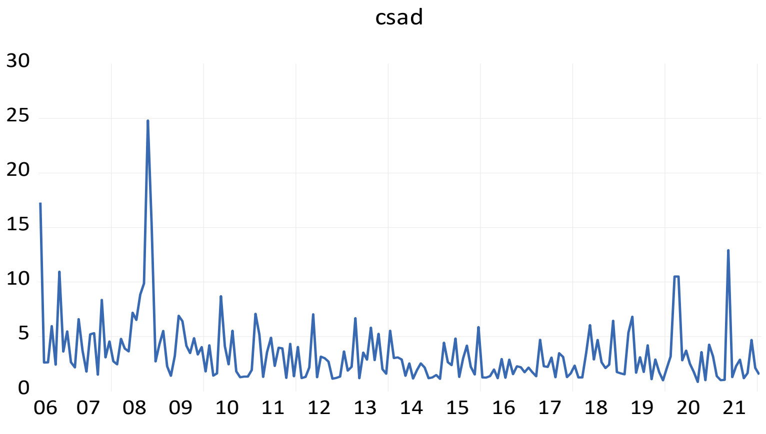

Figure 1. CSAD
source: author (2022)

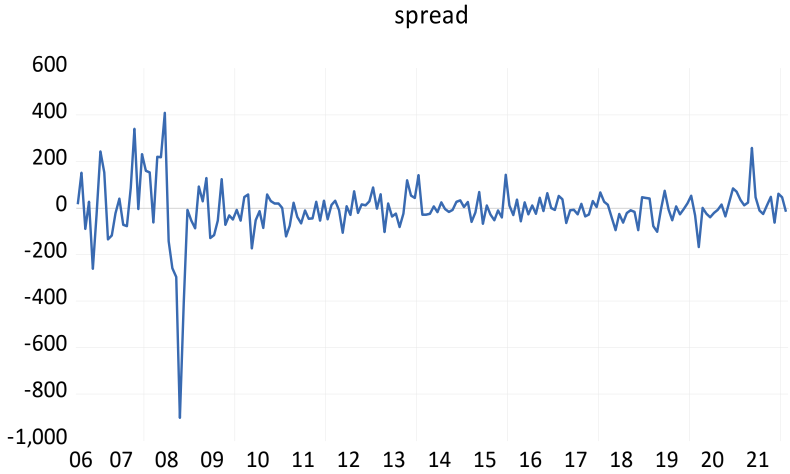

Figure 2. Liquidity (spread)
source: author (2022)

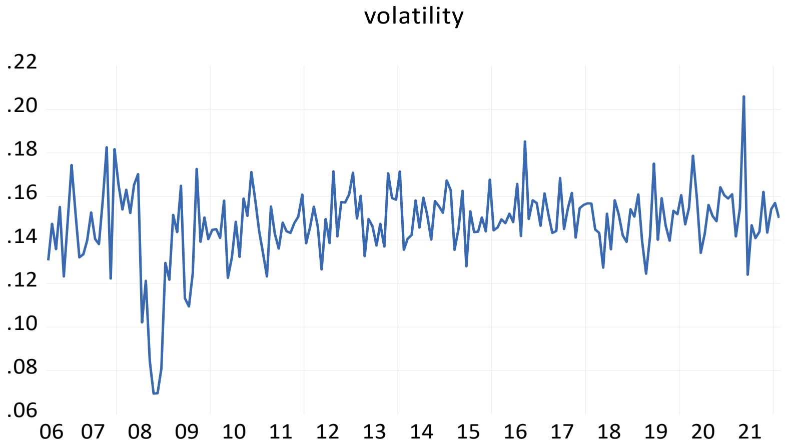

Figure 3. Volatility
source: author (2022)

Empirical results of herding behavior

The findings of herding behavior in the Amman Stock Exchange are shown in Table 2. The regression findings for the whole period show that β2 is positive and significant, indicating that the Amman Stock Exchange market shows reverse herding behavior.

The Amman Stock Exchange market displayed the reverse herding behavior previous to the COVID-19 period. Herding behavior in the Amman Stock Exchange market disappears during the COVID-19 period.

Table 2. Test of herding behavior

	Whole interval	Prior COVID-19	During COVID-19
α	1.391040	1.411625	1.402262
	(0.0000)*	(0.0000)*	(0.0728)**
β_1	0.688488	0.693795	0.301336
	(0.0000)*	(0.0000)*	(0.5130)
β_2	0.019170	0.019882	0.035092
	(0.0002)*	(0.0001)*	(0.2519)
R^2	0.805190	0.802697	0.918394

Note: *represent significance level at 5%
source: author (2022)

The results of evaluating herding behavior in up and down-market intervals summarizes the results in Table 3. The regression results for the whole sample period show that traders react during bull and bear-market periods. Because coefficient β3 shows a significant result, there is proof of herding behavior during bear market intervals which is consistent with the results. This shows that when market returns are down and traders' anxiety increases, traders participate in herding behavior. While the β4 coefficient has a positive significant result, this suggests that during the up-market interval, contrary herding behavior appears in the Amman Stock Exchange market. Prior to the COVID-19 period, the result stays consistent; however, during the bull market interval exhibits the reverse herding behavior in the Amman Stock Exchange market. Traders' anxiety increases during the COVID-19 period, causing to herding behavior in the Amman Stock Exchange market during the down-market interval and the reverse herding behavior in the Amman Stock Exchange market during the up-market interval.

Table 3. Herding behavior in up and down-market intervals

	Whole Interval	Prior COVID-19	During COVID-19
α	1.388859	1.441564	0.970554
	(0.0000)*	(0.0000)*	(0.0016)*
β_1	1.174226	1.156400	2.069183
	(0.0000)*	(0.0000)*	(0.0008)*
β_2	0.107662	0.043476	0.153713
	(0.0539)**	(0.5469)	(0.2400)
β_3	-0.004668	-0.003834	-0.278642
	(0.0704)**	(0.1504)	(0.0436)*
β_4	0.051836	0.062753	0.047436
	(0.0000)*	(0.0000)*	(0.0004)*
R^2	0.955693	0.954041	0.997024

Note: ** and * represent significance level at 10% and 5%
source: author (2022)

The outcomes of the liquidity and volatility analyses illustrates the summary in Tables 4 and 5. Table 4 examines if herding behavior occurs when liquidity changes. Table 4 shows that the parameters are estimated (β3, β4) for total time of increase and decrease liquidity periods are significant. However, β3 is not significant, indicating that herding behavior does not exist during up liquidity periods. Since β4 is positive, there is opposite herding behavior during down liquidity periods. The parameters are estimated (β3, β4) in Table 5 are significant and positive. This indicates that throughout the duration of the up and down volatility periods, there is reverse herding behavior.

Table 4. Herding behavior in up and down Liquidity intervals

	Whole Interval
α	2.135096 (0.0000)*
β_1	0.977342 (0.0000)*
β_2	-0.204362 (0.0369)*
β_3	0.004303 (0.3699)
β_4	0.077438 (0.0000)*
R^2	0.848956

Note: * represent significance level at 5% level
source: author (2022)

Table 5. Herding behavior in up and down volatility intervals

	Whole Interval
α	2.238934 (0.0000)*
β_1	0.684808 (0.0000)*
β_2	-0.062919 (0.6048)
β_3	0.017617 (0.0040)*
β_4	0.074723 (0.0000)*
R^2	0.755862

Note: * represent significance level at 5%
source: Author (2022)

Empirical results of liquidity and volatility with herding behavior

The regression results show that coefficient (β3) is negative and significant for liquidity and volatility for the whole sample period, indicating that herding behavior occurs when volatility increases and liquidity decreases in the Amman Stock Exchange due to traders' pessimism about the future.

Table 6. Herding behavior incorporating Liquidity and Volatility

	Liquidity			Volatility		
	Whole Interval	**Prior COVID-19**	**during COVID-19**	**Whole Interval**	**Prior COVID-19**	**during COVID-19**
α	1.102325	1.178977	1.136734	9.004531	10.23257	5.431511
	(0.0000)*	(0.0000)*	(0.0003)*	(0.0000)*	(0.0000)*	(0.1294)
β_1	0.911413	0.906052	0.569573	0.755099	0.711549	0.865919
	(0.0000)*	(0.0000)*	(0.0006)*	(0.0000)*	(0.0000)*	(0.0014)*
β_2	-0.007897	-0.011096	0.035869	0.009310	0.008278	0.012297
	(0.0226)*	(0.0018)*	(0.0035)*	(0.0156)*	(0.0292)*	(0.5165)
β_3	-0.010309	-0.011084	-0.014629	-51.98622	-59.42086	-31.88531
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.1765)
R^2	0.926256	0.931648	0.969345	0.891514	0.901037	0.903682

Note: * represent significance level at 5%
source: author (2022)

Discussion

After spread of the COVID-19, a state of uncertainty appeared among investors. It should have to insert liquidity and volatility in the herding behavior model in the Amman Stock Exchange because it caused stock price declines and had a negative impact on investor behavior.

The study both down liquidity and down volatility periods exhibit contrary herding behavior. The study found that financial market price behavior is an important factor that may contribute to herding behavior which occurs when volatility increases and liquidity decreases in the Amman Stock Exchange, and the result does not change prior to the COVID-19 period. While liquidity has a negative and large influence throughout the COVID-19 period, the herding behavior does not increase when volatility changes.

(Choi & Yoon, 2020) found that herding behavior occurs during down-market periods. Herding behavior occurs during periods of low trade volume and low volatility. There is evidence of an unfavorable herding tendency which indicates investors herd in severe market situations. The link between investor sentiment and herding behavior is examined, and investor sentiment is verified to be one of the significant components that might induce herding behavior

CONCLUSION

This study investigates herding behavior and determines if it exists using the liquidity and volatility in the Amman Stock Exchange at some point throughout the whole sample, before, and during the COVID-19 period.

During bear market interval, herding behavior appears. Traders ignore their personal information and replicate other traders as a reaction of their anxiety and fear. However, during the bull market interval, there is contrary herding behavior in the financial market, and the result does not change before or during the COVID-19 outbreak period.

There is no herding behavior during increase liquidity periods according to estimates of herding behavior in up and down liquidity intervals, and herding behavior in the presence of decreasing liquidity intervals. When it comes to herding behavior in up and down volatility periods, that is inverse herding behavior. We also found that financial market pricing behavior is a significant factor that might lead to herding which occurs when volatility rises and liquidity decreases in the Amman Stock Exchange, indicating traders are pessimistic about the future. The result does not change before the COVID-19. When volatility changes throughout the COVID-19 period, liquidity has a negative and significant impact and herding behavior does not happen.

This study adds to previous literatures by conducting a comprehensive examination of herding in the Amman stock exchange under various market conditions, including the financial market pricing behavior represented by liquidity and volatility into the herding behavior model. Furthermore, the research helps traders in planning their buying and selling strategies throughout various COVID-19 scenarios.

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