Journal of Enterprise and Development (JED)
Vol. 6, No. 2, 2024
ISSN (PRINT): 2715-3118, ISSN (ONLINE): 2685-8258

Impact of stock market liquidity and external factors on herding behavior in the Amman Stock Exchange

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ABSTRACT

Purpose — *The research investigation was centered on the potential for herding behavior in the Amman Stock Exchange. The major goal of the current investigation is to identify any herding behavior that may occur, including behavior caused by liquidity and global factor drivers (such as oil prices and Fed fund rates).*

Method — *The study employed the quantitative research method. The sample consists of 50 observations from 171 companies, and the data were collected from monthly records spanning January 2019 to March 2023. The Generalized Method of Moments (GMM) and a deductive approach were utilized in the quantitative methodology of this study.*

Result — *At this stage, employing a CSSD regression analysis makes it possible to observe evidence of herding behavior in the left tail. The study also found no evidence suggesting that stock market liquidity affects herding behavior in the right tail during periods of both high and low liquidity. However, it did find evidence indicating that liquidity affects herding behavior in the left tail. The Amman capital market has demonstrated that herding behavior is not significantly influenced by global factors.*

Practical implications — *This study suggests that the Amman Stock Exchange should make information accessible to all investors to encourage them to take an active role in making their own investment decisions.*

Keywords: *irrational investor, herding behavior, stock market liquidity, fed fund rate, oil price*

INTRODUCTION

The phrase "herding behavior" is commonly used in literature to refer to a group of individuals moving together haphazardly. Herding behavior can be caused by both global and local factors (Balcilar et al., 2014; Rahman & Abstrak, 2019; Youssef, 2022). Demand and supply on the stock market frequently fluctuate. According to Datar (2000), market liquidity is the ability of the market to endure momentary fluctuations in supply and demand without significantly disrupting prices. He proposed that the turnover ratio, which measures overall turnover relative to market capitalization, may be used to gauge the liquidity of the stock market. Market efficiency and stock market liquidity, as stated by Kumar & Misra (2015), are incompatible because as market liquidity rises, market efficiency declines. They underlined that when new information is introduced into a liquid market, noise and significant price changes are minimized. However, as soon as fresh information becomes accessible, prices in healthy markets immediately adjust. In light of a market that is inefficient and where information is difficult to come by, it may lead to investors acting in a herd. How does the availability of market liquidity affect this behavior? Determining whether market liquidity will have an impact on herding behavior is significant. Market efficiency and stock market liquidity, according to Kumar & Misra (2015), cannot coexist because as market liquidity rises, market efficiency drops. They assert that a liquid market reduces noise and quick price changes in reaction to fresh information. However, as soon as fresh information becomes available, prices in healthy markets immediately adjust. Given that a market that is inefficient and where information is difficult to come by may lead to investors acting in a herd, how does the availability of market liquidity affect this behavior? This issue has not been considered in many studies. Ouarda et al. (2013) note that determining whether market liquidity will have an impact on herding behavior on the Amman stock exchange is significant.

Although there has been little research on the reasons for herding behavior, two global factors—world oil prices and the US Fed funds rate—are regularly investigated. While they are not equally dispersed throughout all nations or industries examined, the association between oil prices and the Fed funds rate with herding behavior has been demonstrated (Balcilar et al., 2014; Rahman & Abstrak, 2019; Youssef, 2022). According to Balcilar et al. (2014), it has been proven that the Fed Fund Rate and the price of oil influence capital market activity in the GCC. Ulussever & Demirer (2017) found that herding behavior is associated with oil prices in the GCC region, especially when oil prices move sharply. When oil prices drop as opposed to rising, herding behavior is more pronounced (BenMabrouk & Litimi, 2018). Indars et al. (2019) claim that herding behavior and oil price volatility are closely related.

Although there has been less research, the US Fed funds rate is a global issue that is regularly looked at as a reason for herding behavior. While they are not equally dispersed throughout all nations or investigated sectors, a correlation between the Fed funds rate and herding behavior has been demonstrated. The FFR strengthens herding behavior in the capital markets of Indonesia, the Philippines, Thailand, and Singapore, according to Rahman & Abstrak (2019). Arisanti (2020) discovered that the FFR induces herding behavior in the capital markets of Indonesia, Malaysia, Thailand, Vietnam, and the Philippines. The novelty of the study lies in identifying the emergence of herding behavior on the Amman stock exchange, as well as the influence of both local (asymmetrical liquidity) and international (oil prices and Fed funds rates) factors.

The purpose of this study is to identify any herding behavior that may occur, including herding behavior caused by liquidity and global factor drivers (oil prices and Fed funds rates).

METHOD

Sampling and data collection

The study employed the quantitative research method. The sample comprises 50 observations from 171 companies, and the data include both firm-specific data and market data, including monthly stock prices and trading volume of all firms traded on the Amman Stock Exchange (ASE).

Data analysis

The Generalized Method of Moments (GMM) was employed in this study to comprehensively define the model thought to be estimated, which is necessary for typical classical approaches such as the Maximum Likelihood (ML) method. The probability distribution of the variable is also incorporated in this method. In contrast to the ML approach, the Generalized Method of Moments (GMM) only requires a certain set of moment conditions suggested by the underlying econometric model's assumptions.

Measurement items

The weighted index is utilized as the proxy for market indicators to estimate market returns with a monthly frequency from January 2019 to March 2023. The monthly stock returns are determined by applying the formula:

$$R_{i,t} = \frac{P_{i,t} * P_{0,t}}{P_{0,t}} \qquad (1)$$

Information:
Pi,t represents the monthly closing prices of stock i at time t while P0,t represents the monthly opening prices of stock 0 at time t.

The interest rate at which depository institutions transact overnight with one another in federal funds (balances kept at Federal Reserve Banks) is known as the federal funds rate. When a depository institution has surplus balances in its reserve account, it lends to other banks in need of greater balances. Simply put, a bank with extra cash, often referred to as liquidity, will lend to another bank that urgently needs to raise liquidity. The weighted average rate for all such agreements is known as the effective federal funds rate, which is the rate that the borrowing institution pays to the lending institution.

To achieve the federal funds rate goal, the Federal Reserve uses open market operations to influence the market, thereby determining the effective federal funds rate. Data for the Federal Funds Effective Rate (FEDFUNDS) is sourced from FRED Economic DATA of St.

The Brent Spot price, serving as a proxy for the global oil price and representing over 30% of global oil market demand, is closely monitored by most policymakers and market experts to gauge changes in the price of crude oil. Other crude oil prices are often derived by comparing them to Brent. Specifically, for other crude oils in Europe, the Middle East, and Africa, Brent Blend crude oil remains the primary benchmark. Consequently, their prices closely follow the trends in the global oil price. Information on the Brent Spot price FOB (dollars per barrel) is provided by the US Energy Information Administration (EIA).

Herding behavior

Christie and Huang (1995) proposed the CSSD as a proxy for herding. The CSSD is expressed as follows:

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

In order to account for all market conditions and avoid limiting the model to stressful circumstances, Chang et al. (1999) proposed the CSSDt. As the CSSDt is sensitive to outliers, they computed the dispersion of results by:

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

Stock market liquidity

We modify the measure according to Karolyi et al. (2012) in order to measure liquidity instead of illiquidity. Specifically, we construct the following variable:

$$\mathrm{Liq_{i,t}} = -\log\left(1 + \left(\frac{|R_{i,t}|}{P_{i,t}VO_{i,t}}\right)\right) \quad (4)$$

In equation (4) $R_{i,t}$, $P_{i,t}$ and $VO_{i,t}$ is the return, price and trading volume of stock i at time t. The average liquidity across stocks is obtained as:

$$\mathrm{Liq}_{m,t} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{Liq}_{i,t} \qquad (5)$$

The model for analyzing herding behavior during periods of stock market liquidity was expanded from the work of Ouarda et al. (2013), which is in line with the study conducted by Chiang and Zheng (2010).

According to Christie and Huang (1995), the CSSD model is illustrative of:

$$\mathrm{CSSD}_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \qquad (6)$$

Where D_t^U = 1 if the market return at time t lies in the extreme upper tail of the return distribution, and D_t^U = 0 otherwise; D_t^L = 1 if the market return at time t lies in the extreme lower tail of the return distribution, and D_t^L = 0 otherwise. The coefficient measures the average dispersion of the sample that lies outside the two extreme tails of the return's distribution. The dummy variables D_t^U and D_t^L are supposed to capture the degree of variation in an investor's behavior during high volatile periods (extreme tails). The existence of herding is captured by the negatively significant β_1 and β_2 coefficients (Christie & Huang, 1995). However, if these coefficients are positive, this will indicate the absence of herd behavior and the presence of rational asset pricing.

Given that it is based on the dispersion between stock returns and market returns, Chang et al. (1999) assessment of CSAD is a potent approach. The CSAD model can be represented as:

$$\mathrm{CSAD}_t = \beta_1 + \beta_2 |R_{m,t}| + \beta_3 R_{m,t}^2 + \varepsilon_t \qquad (7)$$

β_1 represents the market return, $\beta_2|R_{m,t}|$ represents absolute market return and $\beta_3 R_{m,t}^2$ is the square of market return. The relationship between market return and CSAD is no longer linearly increasing, rather becomes non-linearly decreasing or increasing at a decreasing rate. Negative and significant coefficient value $\beta_3 R_{m,t}^2$ (non-linear term) implies herding in the above equations.

This study expanded on the work of Ouarda et al. (2013) and Rahman & Abstrak (2019) to determine herding behavior during periods of high and low stock market liquidity. The potential effects of herding behavior in relation to asymmetric liquidity and global factors are measured by:

$$\mathrm{CSSD}_{i,t} = \gamma_0 + \gamma_1 D^{\mathrm{Hliquidity}} D_t^U + \gamma_2 (1 - D^{\mathrm{Hliquidity}}) D_t^U + \gamma_3 D^{\mathrm{Hliquidity}} D_t^L + \gamma_4 (1 - D^{\mathrm{Hliquidity}}) D_t^L + \gamma_5 \text{fed fund rates} + \gamma_6 \text{Oil price} + \varepsilon \qquad (8)$$

OR

$$\mathrm{CSAD}_{i,t} = \gamma_0 + \gamma_1 D^{\mathrm{Hliquidity}} |R_{m,t}| + \gamma_2 (1 - D^{\mathrm{Hliquidity}}) |R_{m,t}| + \gamma_3 D^{\mathrm{Hliquidity}} R_{m,t}^2 + \gamma_4 (1 - D^{\mathrm{Hliquidity}}) R_{m,t}^2 + \gamma_5 \text{fed fund rates} + \gamma_6 \text{Oil price} + \varepsilon \qquad (9)$$

Where $D^{\mathrm{Hliquidity}}$ is a dummy variable which takes the value 1 during the month of high liquidity and 0 otherwise.

Market liquidity is assumed to be high if it exceeds the weighted average of the liquidities of the six months preceding the study period, and vice versa.

Hypotheses development

The existence of herding behavior

Avoiding expensive information acquisition is another rationale that might support focusing on the majority's belief. When the market is perceived as the safest investment option, herding is expected to become more intense during times of extreme stress. A significant quantity of literature focuses on herding and rational asset pricing is utilized as a benchmark in assessing price data to spot rationality anomalies. The foundation of this literature lies in the closeness of single stock returns to the market return during both calm and chaotic periods (Chang et al., 1999). According to this technique, herding can be identified using a measure of cross-sectional equity return dispersion (Christie & Huang, 1995; Chang et al., 1999). Representative research is required to develop a herding measure that concentrates on the cross-sectional dispersion of betas (Hwang & Salmon, 2004). In contrast, the effectiveness of this measure in the US and South Korean markets found that herding behavior occurred independent of the state of the market and macroeconomic indicators (Chang et al., 1999). Based on the explanation above, we posit the following hypothesis:

H1: There is herding behavior in the Amman Stock Exchange

Stock market liquidity and herding behavior

The effect of trade volume on herding builds a model to examine the connection between herding and stock prices using the level of ownership by money managers of 769 tax-exempt funds in the US to conclude that herding does exist for smaller businesses, albeit with a faint signal, but that it is very uncommon for bigger shares, which make up the majority of institutional holdings and trading (Lakonishok et al., 1992). In the case of the US equity market, focus on identifying the expression of herding and the link between it and trade volume to show that herding happens on both days with high and low trade volume in the US financial market by including the dummy variables (10th percentile top and bottom, respectively), which indicate unusually high and low trading days. However, the herding asymmetry has not been well captured, showing how little changes in market liquidity have an impact on the market return dispersion by using the Granger Causality test demonstrate a significant bilateral connection between herding and trade volume. Trading speed is aided by herding, which is especially sparked by transaction volume (BenSaïda et al., 2015). To analyze how trading volume may impact herding in certain US businesses by concentrating on the larger stock market only three out of the 12 analyzed sectors—according to the CSSD model—produce herding through trade volume and when alter the CSAD model by using trade volume as an independent variable to identify herding across diverse sectors the trade volume influences herding behavior on the US stock market and in five particular industries (Litimi et al., 2016). In line with the above understanding, the following hypothesis, H2, was formulated:

H2: Stock market liquidity drives herding behavior in the Amman Stock Exchange

Federal Funds Effective Rate (FEDFUNDS) and herding behavior

Interest rates and the stock market are believed to be indirectly related; however, one of these macroeconomic factors tends to move in the opposite direction of the stock market. Almost all investors worldwide utilize the US Federal Reserve Fund Rate, also known as the Fed Fund Rate (FFR), as a basic guideline, and it is commonly used as an indicator influencing the dynamics of international financial markets. The relationship between FFR and herding behavior has been observed in five ASEAN nations, where the FFR has a significant impact on the capital markets of Indonesia, the Philippines, Thailand, and Singapore (Rahman & Abstrak, 2019). US investors tend to herd on days when important macroeconomic data are released, and there have been herding spillover effects from the US to the UK during previous financial crises (Galariotis et al., 2015). The Fed Fund Rate considerably promotes herding behavior and has an impact on capital markets in oil-producing nations, particularly the GCC (Balcilar et al., 2014). Additionally, the Fed Fund Rate causes herding behavior among 130 financial sector companies in five ASEAN nations (Indonesia, Malaysia, Thailand, Vietnam, and the Philippines) (Arisanti, 2020), and it significantly encourages herd behavior in the Indonesian capital market (Silitonga et al., 2021). Therefore, based on the above line of argumentation, we propose the following hypothesis:

H3: Federal Funds Effective Rate (FEDFUNDS) drives herding behavior in the Amman Stock Exchange

Oil price and herding behavior

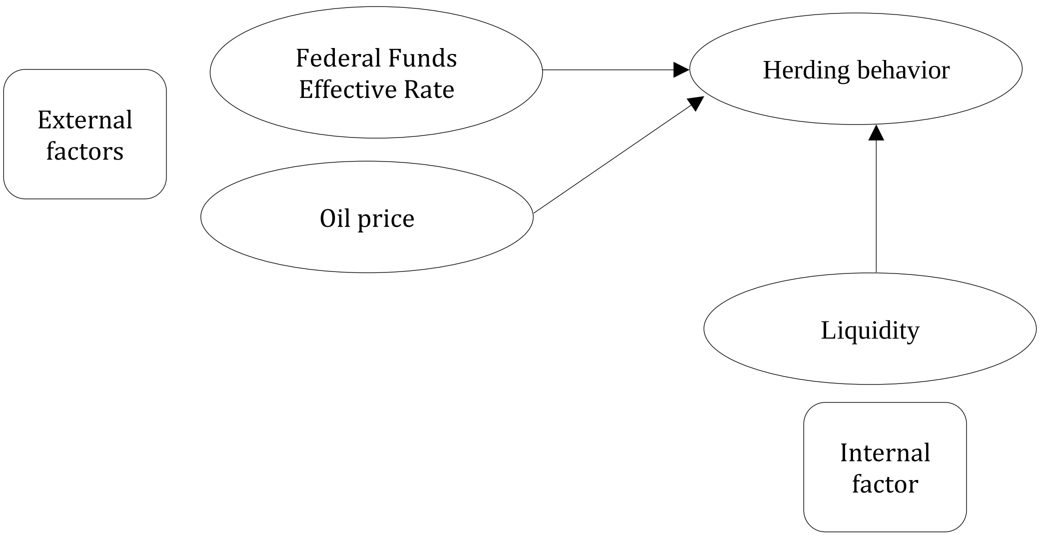
Oil's importance to the economy means that changes in oil prices will affect stock prices. Due to behavioral contagion between the capital market and the crude oil market, it is highly likely that the global crisis will be the primary driver of herd behavior in the capital market. Investors seek speculative signals from the oil market as positive expectations and attempt to make higher returns by going against the crowd in their market (Balcilar et al., 2014). There are significant changes in oil prices which are influenced by both fundamental and non-basic information that can lead to herding behavior. Even though there is not much research, some have discovered a connection between oil prices and herding behavior (Indars et al., 2019).

The US stock market was examined to show that herding behavior is more obvious when oil prices decline than when they increase. Additionally, it was found that the US capital market's herd behavior decreased by sector in response to changes in the oil market, suggesting a connection between the oil markets and herd behavior (BenMabrouk & Litimi, 2018). In the commodities market, the price of oil mostly encouraged herd behavior in the energy sector, but not in other industries (Youssef, 2022).

In the ASEAN capital market, there has been relatively little investigation into the connection between oil prices and herding behavior. Some studies suggest there is no connection between oil prices and herding behavior in the capital markets of the United States, Indonesia, Malaysia, Thailand, Singapore, and the Philippines (Rahman & Abstrak, 2019).

H4: Oil prices drive herding behavior in the Amman Stock Exchange

Figure 1. Research framework



Source: Developed by the author (2024)

RESULT AND DISCUSSION

Descriptive statistics

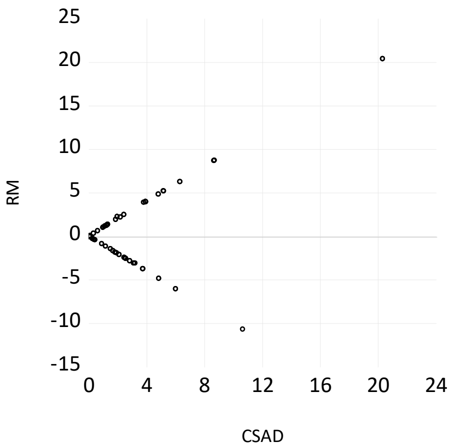
Table 1 enumerates the descriptive statistics of the variables. The average market return, RM, is positive at 0.638800. The CSAD and CSSD exhibited positive returns during the period, indicating bearish sentiments in the markets (Bharti & Kumar, 2022). The volatility of index RM is also very high, reported at 4.538999. The skewness of market return RM indicates that the daily return during the period of COVID is positively skewed, and CSAD, CSSD, Federal Funds Effective Rate, and Brent Spot Price Fob are positively skewed, except for Liquidity, which is negatively skewed. All the kurtosis values exhibit leptokurtic distributions except for global factors (Federal Funds Effective Rate-Brent Spot Price Fob), reflecting platykurtosis distributions.

Table 1. Descriptive statistics

	RM	CSSD	CSAD	Liquidity	Federal Funds Effective Rate	Brent Spot Price Fob
Mean	0.638800	2.975706	2.960371	-2.22E-05	1.209400	69.91920
Median	0.015000	1.950603	1.946614	-1.11E-05	0.490000	66.72500
Maximum	20.40000	20.33934	20.33900	1.33E-05	4.570000	122.7100
Minimum	-10.71000	0.078548	0.056153	-0.000128	0.050000	18.38000
Std. Dev.	4.538999	3.449152	3.456119	2.49E-05	1.330525	23.04346
Skewness	1.520050	2.960999	2.951973	-1.993591	0.862136	0.226115
Kurtosis	9.063264	14.33896	14.27911	8.009927	2.709093	2.882047
Jarque-Bera	95.84453	340.9209	337.6560	85.41039	6.370291	0.455054
Probability	0.000000	0.000000	0.000000	0.000000	0.041372	0.796501
Sum	31.94000	148.7853	148.0185	-0.001109	60.47000	3495.960
Sum Sq. Dev.	1009.523	582.9357	585.2930	3.03E-08	86.74448	26019.06
Observations	50	50	50	50	50	50

Source: Processed data (2024)

Figure 2. Cross Sectional Average Deviation and market return

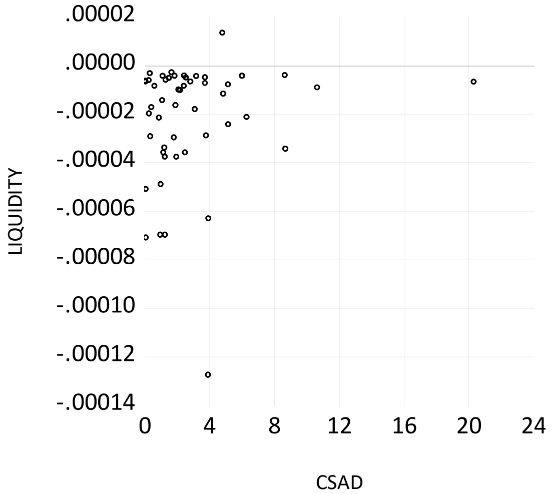


Source: Processed data (2024)

Figure 2 depicts the relationship between CSAD and market return with the help of a scatter plot. It can be observed from the chart above that there does not exist any linear relationship between

CSAD and market return. The dots representing CSAD are clustered mainly where the market return is zero (Ng et al., 2022). The clustering of CSAD cannot be seen beyond a market return of 0.05. This observation is further substantiated with the empirical analysis performed in the section below.

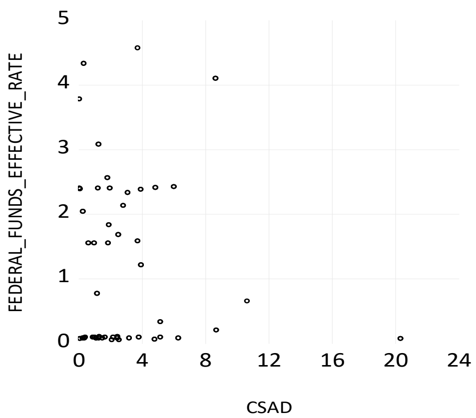
Figure 3. Cross Sectional Average Deviation and liquidity



Source: Processed data (2024)

Figure 3 depicts the relationship between CSAD and liquidity with the help of a scatter plot. The plots confirm the results presented above: monthly equity return deviations are negatively related to average liquidity; that is, when liquidity is high, return clustering is less intense, and when liquidity is low, return clustering is more intense.

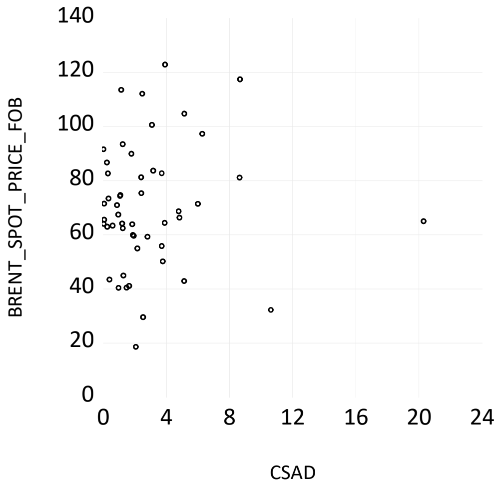
Figure 4. Cross Sectional Average Deviation and Federal Funds Effective Rate



Source: Processed data (2024)

Figure 4 depicts the relationship between CSAD and the Federal Funds Effective Rate with the help of a scatter plot. The plots confirm the results presented above: monthly equity return deviations are positively related to the Federal Funds Effective Rate; that is, when the Federal Funds Effective Rate is low, return clustering is less intense, and when the Federal Funds Effective Rate is high, return clustering is more intense.

Figure 5. Cross Sectional Average Deviation and Brent spot price fob



Source: Processed data (2024)

Figure 5 depicts the relationship between CSAD and Brent spot price fob with the help of a scatter plot. The plots confirm the results presented above: monthly equity return deviations are negatively related to Brent spot price fob; that is, when Brent spot price fob is high, return clustering is less intense, and when Brent spot price fob is low, return clustering is more intense.

Preliminary analysis

Stationarity testing is required before modeling any data in a time series dataset. Since this is a time series analysis, the variables must be stationary in nature. The stationarity of CSAD, CSSD, Market Return, Liquidity, Federal Funds Effective Rate, and Brent Spot Price FOB has been tested using an Augmented Dickey Fuller test (ADF), where the null hypothesis is "Variable has a unit root indicating that the variable is not stationary." Table 2 exhibits the results of the ADF test of stationarity, signifying the absence of a unit root in all the variables, as the value of ADF is significant at 5%, rejecting the null hypothesis.

Table 2. ADF unit root test results

	ADF-Stat	5% Critical	P-Value	Order of Station.
CSAD	-6.900099	-2.922449	0.0000*	l(0)
CSSD	-6.907835	-2.922449	0.0000*	l(0)
RM	-5.045389	-2.922449	0.0001*	1(0)
Liquidity	-5.908570	-2.922449	0.0000*	1(0)
Federal funds effective rate	-2.927462	-2.923780	0.0496*	1(1)
Brent spot price fob	-5.342959	-2.923780	0.0000*	1(1)

*Symbol denote statistical significance at the 5% level.

Source: Processed data (2024)

Hypotheses testing

Herding behavior has gained popularity and prominence as a result of a series of global crises, prompting scholars from numerous countries to become interested in studying the phenomenon, both in developed and emerging capital markets. The purpose of this study is to detect herding behavior, including herding within the up-market and down-market, as well as local factors (such as asymmetric liquidity) and global factors (such as oil prices and fed funds rates) that drive herding behavior in Amman, an emerging capital market. This study will contribute to the financial literature by detecting the presence of herding behavior in addition to local and global factors that drive it. To achieve the research goal, monthly stock price data for all shares listed on the Amman capital markets from January 2019 to March 2023 were employed.

Regression analysis by CSSD & CSAD approach

Table 3 below exhibits the results of the regression analysis of CSSD. The positive and statistically significant values of the coefficient at the upper and lower tails (right and left tails) indicate an absence of herding. The negative and significant coefficient value (-0.995561) of D_t^L indicates markets to be more irrational and herding behavior appears in the left tail during this period of COVID. Thus, the first hypothesis (H1) in this study was accepted.

Table 3. Herding behaviour CSSD approach

	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C	0.018214	0.013372	1.362024	0.1797
D_t^U RIGHT_TAIL (Upper)	0.995110	0.002962	335.9504	0.0000*
D_t^L LEFT_TAIL (Lower)	-0.995561	0.005114	-194.6899	0.0000*

*Symbol denote statistical significance at the 5% level

Source: Processed data (2024)

In order to analyze the herding behavior in the Amman Stock Exchange, the present research employs the CSAD approach suggested by Chang et al. (1999). Herd behavior in the market exists if the coefficient $R_{m,t}^2$ is negative and significant. As enumerated in the below Table 4, the $R_{m,t}^2$ is insignificant, which depicts the absence of herding behavior during the period of COVID.

Table 4. Herding behaviour CSAD approach

	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C	0.003116	0.006210	0.501855	0.6181
$\lvert R_{m,t} \rvert$	0.996851	0.002556	390.0644	0.0000*
$R_{m,t}^2$	8.66E-06	0.000145	0.059862	0.9525

*Symbol denotes statistical significance at the 5% level

Source: Processed data (2024)

The results show that herding behavior is absent according to the CSAD approach, while it is evident by the CSSD approach in the left tail during this period of COVID. Therefore, the CSSD approach was applied to study the impact of local and global factors on herding behavior in the Amman Stock Exchange.

Regression analysis by Generalized Method of Moments (GMM)

The analysis thus far has assumed that both liquidity and the Federal Funds Effective Rate (FEDFUNDS) and Brent Spot price free on board (FOB) are strictly exogenous. This inevitably leads to a significant increase in the number of instruments available in the estimation of the Generalized Method of Moments (GMM) model.

Table 5 shows how local and global factors drive herding behavior. The results of the effects of stock market liquidity on herding behavior during high and low liquidity, with coefficient values of -0.997218 and -0.992819, showed evidence of herding behavior in the left tail during high and low liquidity. While there is no impact of stock market liquidity on herding behavior in the right tail during high and low liquidity, so the second hypothesis (H2) in this study was accepted.

Meanwhile, it has not been demonstrated that the Fed Fund Rate can encourage herd behavior in the Amman capital market, so the third hypothesis (H3) in this study was rejected. In addition, it has not been demonstrated that the Brent Spot Price FOB can encourage herd behavior in the Amman capital market, so the fourth hypothesis (H4) in this study was rejected.

In general, investors in Amman are constantly monitoring the evolution of the Fed Funds Rate announcements and oil prices, but not to the extent that they make investment decisions that blindly follow other investors without having clear information. The Amman capital market does not overreact to interest rate increases and oil price increases, which can trigger herd behavior.

The results of this study can aid investors in the Amman capital markets in avoiding overreacting and imitating market movements when making investment decisions based on changes in liquidity, particularly during times of low market activity, which can lead to herding behavior negatively impacting investors. Investors should thus continue basing their selections on their studies and personal experience.

Table 5. Estimation results of herding behavior CSSD approach with asymmetric liquidity & global factors

	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
$D^{Hliquidity}D_t^L$	-0.997218	0.005152	-193.5743	0.0000*
$D^{Hliquidity}D_t^U$	0.995552	0.000957	1039.954	0.0000*
$(1 - D^{Hliquidity})D_t^L$	-0.992819	0.002900	-342.3085	0.0000*
$(1 - D^{Hliquidity})D_t^U$	0.993575	0.003406	291.7517	0.0000*
DBRENT_SPOT_PRICE_FOB	0.001548	0.001053	1.470291	0.1489
DFEDERAL_FUNDS_EFFECTIVE_RATE	0.012285	0.014818	0.829067	0.4118
γ_0	0.022359	0.010481	2.133279	0.0388
Instrument rank	7			

* Denote significance at the 5% level.

Source: Processed data (2024)

Discussion

The existence of herding behavior

The result shows that herding behavior appears in the left tail when using the CSSD approach. Consequently, this result is consistent with Christie and Huang (1995), who suggested that the CSSD approach is suitable for extreme market periods. This study applies to the Amman stock exchange during the COVID-19 pandemic, which qualifies as an extreme market period.

Stock market liquidity and herding behavior

There is an impact of stock market liquidity on herding behavior in the left tail during both high and low liquidity periods. However, there is no impact of stock market liquidity on herding behavior in the right tail during high and low liquidity periods. This phenomenon occurs because, during extreme market periods such as the COVID-19 pandemic, investors tend to exhibit herding behavior when they experience fear, which is reflected in the trading volume in financial markets. The result shows that herding occurs on both days with high and low trade volume, which is consistent with the findings of BenSaïda et al. (2015).

Federal Funds Effective Rate (FEDFUNDS) and herding behavior

It has not been demonstrated that the Fed Fund Rate influences herding behavior in the Amman capital market, which contradicts findings from Rahman & Abstrak (2019), Galariotis et al. (2015), Arisanti (2020), and Silitonga et al. (2021). This is because investors in Amman are constantly monitoring the evolution of the Fed Fund Rate, but they do not make investment decisions that blindly follow other investors without having clear information. The Amman capital market does not overreact to Fed Fund Rate increases, which could potentially trigger herd behavior.

Oil price and herding behavior

It has not been demonstrated that oil prices influence herding behavior in the Amman capital market. This is because investors in Amman are constantly monitoring the evolution of oil prices, but they do not make investment decisions that blindly follow other investors without having clear information. This finding is consistent with Rahman & Abstrak (2019).

CONCLUSION

This study aimed to analyze the potential of herding behavior in the Amman Stock Exchange. The major goal of the current investigation is to identify any herding behavior that may occur, including herding behavior caused by liquidity and global factor drivers (such as oil prices and Fed fund rates).

Using a CSSD regression analysis at this stage, the study found evidence of herding behavior in the left tail. Additionally, it found no evidence indicating that stock market liquidity affects herding behavior in the right tail during periods of high and low liquidity, but it did find evidence that liquidity affects herding behavior in the left tail. The Amman capital market has demonstrated that herding behavior is not considerably influenced by global influences.

Several practical implications can be drawn from this study. The Amman Stock Exchange should make information accessible to all investors to encourage them to take a role in making their own choices. The study is highly beneficial for both local and foreign investors interested in investing in the Amman capital market, as it will help them develop the best investment plans and choices, particularly in situations of great uncertainty that commonly cause herding behavior. Given that herding behavior results in high amounts of volatility and uncertainty, the empirical results provided can offer information that policymakers can employ to ensure capital market stability in Amman, particularly under challenging market conditions.

However, if the market becomes unstable, it can be challenging for investors to diversify their holdings and allocate their assets appropriately. By using more powerful models on the dataset of the Amman stock exchange, such as Wavelet Coherence (WC) analysis (Ghorbel et al., 2023) and Quantile Regression (Bharti & Kumar, 2022), the study can be further expanded to identify herding behavior in the market. Further study in this area will lead to more developed and efficient markets, which will have significant implications for investors and policymakers.

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