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IMPACT OF MARKET LIQUIDITY AND INFORMATION DEMAND ON HERDING BEHAVIOR PRE AND POST COVID PERIOD:EVIDENCE FROM PAKISTAN STOCK MARKET

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ABSTRACT
The main objective is to study herding behavior changes throughout different times in the COVID-19 pandemic. In addition, this research seeks to examine how investors' herding actions depend on market liquidity and the amount of information being searched for. For this study, we utilize daily stock closing prices of 30 firms from the Pakistan Stock Exchange between 2018 and 2024 to examine herding behavior. We found that changing our investment strategy from herding had negative results, even though the theory predicts high returns. The failure of the study uncovered a more detailed truth than anticipated. There are moments when the crowd's enthusiasm causes prices to rise without being supported by important reasons. Because people can change their actions rapidly, a crowd's behavior may turn negative, resulting in lower returns. Don't only count on the hot stocks, since choosing them hastily can be dangerous. To invest wisely, you need to know the market well and what affects it, rather than being caught up in what others do. The findings suggest ways that help investors, policymakers, and researchers during the COVID-19 crisis. The frequent failures seen in the market are due to a mix of poor market sentiment, overwhelming news, illiquid markets, the state of the economy, and risky trading. As a result of these activities, market activity decreases, and outcomes become negative.

Keywords: COVID-19, Herding behavior, Liquidity, Information demand, Pakistan

INTRODUCTION
As a result of COVID-19, people worried about their future, economies around the world were shaken, and an emergency was declared on a worldwide scale (Carlsson-Szlezak et al., 2020). In China, scientists first discovered COVID-19 in December 2019, after which it rapidly impacted the aviation industry and endangered people and society. People weren't sure how long the pandemic would continue, what steps the government would take, or how much shoppers would spend. These changes may cause companies' profits to fall (Altig et al., 2020; Moran et al., 2022). Financial markets around the globe showed the true qualities of a black swan incident as the pandemic triggered frequent, large changes in stock prices (Pochea, 2021). As a result, people started to feel uneasy about investing. A number of studies show that COVID-19 led to investors having fewer positive feelings and becoming more fearful about their investments (Dash & Maitra, 2022). Under these conditions, many investors acted on the suggestions of their social group and reduced their attention to the actual findings, which is called herding (Bikhchandani & Sharma, 2000).
Traders in all advanced and growing economies make their choices influenced by common practices in the economic industry, a concept used widely by researchers for many years. The tendency of investors to behave like a group and ignore their thoughts in favor of others' actions is called herding (Chang et al., 2000). This may result in inventory values being further apart from their true value, which could have a major but poor effect on the inventory markets, Hsieh explains (2013). The recent advancements in behavioral finance and extreme ups and downs during the COVID-19 period sparked research leading to proven evidence of herding behavior in various inventory markets throughout the global pandemic (Aldeki, 2022), (Aslam et al., 2022), (Espinosa-Mendez and Arias, 2021), (Wu et al., 2020).

Herding among traders is described by Chang et al. (2000) as changing in both up and down markets, and the relationship between herding and market (portfolio) return is not always straightforward. Research on this takes a look at points out how traders copy each other in non-moving waves.

This study look at the herding phenomenon in a frontier market during multiple COVID-19 intervals. A range of factors in the inventory market caused investors to behave similarly at times, resulting in the economic crisis seen in 2007–2008 (Chang et al., 2000; Galariotis et al., 2016). Investors in developing countries often lack experience and much information, which can result in copying others' actions (Chen, 2013; Vo, 2019). According to Vieira and Pereira (2015), buyers can behave differently in minuscule and drop-down markets than in larger ones. Results from empirical research suggest that agribusinesses in industrialized nations generally managed herds more effectively during the COVID-19 epidemic. The authors investigate how the impact of COVID-19 on stock market behaviors has endured through time. Previous scholarly work on the 2007-2008 events (Galariotis et al. and VO & Phan, 2019) identified important changes in the way farmers handled herding at different intervals. All of them argue that due to the added risk that human beings face when their portfolios drop, they are more prone to join a panic of investors during and after the collapse. It was clear from the studies by Aslamet et. al. (2022), Dhall and Singh (2020), and Wu et al. (2020) that the pandemic occurred in two distinct phases: before and after it started. They reveal how the influence of herding was modified both before and during the COVID-19 pandemic.

Even though the Pakistan stock market is becoming more important and appealing, there are important obstacles to its growth. A major barrier called records float and openness has been discovered to play a key role in why herding occurs (Bikhchandani et al., 1992). Between the years 2017 and the beginning of the COVID-19 outbreak, researchers had already recorded many deals as herding patterns in the Pakistani inventory market (Vo & Phan, 2017). Moreover, outside shocks have demonstrated that they can induce herding behaviors in buyers (Chiang & Zheng, 2010; Vo & Phan, 2017), and the COVID-19 epidemic should be regarded as just such an event. As a result, it is likely that at some point, buyers will share the same strategies, which means everyone pays the cost. Publication of what is almost always private information can result in market efficacy being lowered, remarks Bikhchandani et al. (1992) and Banerjee (1992). The reason is that the marketplace does not always present all important details. Because of herding, the pricing of assets may go wrong, and in time, this can lead to both asset price rises and falls along with fears about the facts.

This study is interested in whether herding was more common in some COVID-19 sub-periods than others. The results indicate that herding was present before, during, and after COVID-19, but not always during the pre-pandemic era. The same types of results appear in every financial market phase. We observe that herding stands out at average order sizes, with the effect of herding depending on other external factors. In addition, both medium and infrequent traders run a higher risk of following the popular trend.

RESEARCH OBJECTIVES

The findings reveal that people exhibit herding behavior during or even after the COVID era. In the theory, the goal assertion explores herding behavior, where individuals tend to act alike even if they are making buying decisions.

For even greater detail, we can analyze records and marketplace liquidity to study herding trends in Pakistan both before and after COVID-19, so as to prove its impact during the pandemic. When we study the factors controlling herding behavior, we try to understand how they influence Pakistan's share market in particular.

Significance of the study

Looking at investor habits during the pandemic is necessary to judge the COVID-19 results before and after action that leads to herding in the market. This study will give clear results about the connection between herding conduct and media variables, as well as how liquid the market is at various stages of the COVID-19 situation. Since the outbreak of COVID-19 increases uncertainty and fear and damages both international economies and societies, one way to look at traders is by their herding propensity, which means watching and following the behavior of informed group members. Also, researchers believe that marketplace liquidity can determine how investors view the market and act similarly to others. Even if immoderate liquidity signals that there could be one exact moment for irrational buyers to act at once, during the pandemic, herding behavior tells us to focus on factors such as rising data, asymmetry, strong emotions, and the influence of presidential moves and stimulus measures. They might also explain why investors become more likely to copy each other's behavior and actions during periods of strong performance.

Assessing how the pandemic impacted investors allows researchers to judge market changes due to COVID-19 before and after herding behavior. This work can provide a clear connection between herding activities and the impact of news reports, along with trends in market depth during the COVID-19 pandemic. COVID-19 creates doubt and fear and damages both societies and economies worldwide, leading ordinary traders with less information to follow the actions of knowledgeable ones. But the idea is that liquidity in markets shapes the way investors react and can lead to simple herding. While immoderate liquidity may lead the market to think there is a specific moment for uninformed buyers to correct themselves each time, it is helpful to think about elevated metrics, asymmetry, quick emotions, and what happens when politicians and banking systems act. All these things could have changed how investors feel and act, which may have led to more examples of herding when the market was up.

Theoretical background

At times, similar activity among investors in the stock market is described in behavioral finance as "herding." It makes sense that many retail traders want to replicate hot traders, as using their knowledge usually becomes too costly. The behavior described by Nofsinger and Sias (1999) often leads to the same group of traders trading in the same direction for a period. Based on studies, this may lead to the discovery of common behavioral styles and many errors in group decisions by society as a whole (Bikhchandani et al., 1992). For this reason, buying a wider range of securities reduces their connection to help buyers build the same amount of diversification. Not following the usual charges for assets can make participants prefer to agree with the majority; actions by investors in the market might also make asset prices drift from their real values. Another possibility is due to buyers who buy on a lark if the market indexes move together.

Evidence has proven that retail investors in America rely on industry returns from the past to decide where to place their funds (Barberis and Shleifer, 2003). Using information from buy and sell transactions inside the NASDAQ, the United States made use of enterprise herding for investors. The study found that there is industry herding in the US market (Jame and Tong, 2014). The researchers checked that buyers of weak equities were likely to have made those trades last time and traded away from them the next time. It is found that industry-exhensive herding actions are common across different industries during all periods in the Romanian stock market, both positive and negative (Peace, 2014). From 2007 to 2012, the only concern in researching enterprise herding among traders was the Turkish banking sector, and enough facts were found to show it exists (Cakan and Balagyozan, 2014). To analyze market behavior and company herding, herding conduct within the Chinese equity markets turned into studied during the time the Shanghai and Shenzhen stock exchanges were bullish and bearish between

January 1999 and December 2002. Data from the research concluded that investors in information technology do not engage in herding (Demirer and Kutan, 2006). Evidence of enterprise herding was found in all Shanghai inventory exchanges in another study, whereas extra of such actions have been seen in Shenzhen, in keeping with She (Lee et al., 2013). Compared to before, more investors began participating in Malaysian employer shares, but results from the examination showed that public corporation industry herding only existed in the facts-era period and only tended to occur when the market was experiencing weakness (Dehghani and Sapian, 2014). Both the product and statistics era divisions of any company address key aspects of retail herding, and it can occur in either a booming or sluggish market. Tests to find market-wide and industry-huge herding behavior in the Australian equity market did not detect them on an intraday basis (Henker et al., 2006).
Research published recently suggests that social media can be applied during disasters and also helps forecast changes in the stock market and financial indices (Castillo, 2016; Bollen et al., 2011; Mittal and Goel, 2013; Duz and Tan, 2020). Based on research, how people use social media influences observations in the inventory marketplace (Ge et al., 2020). That's also why emotionally interesting details (mainly the bad ones) lead to more tweets (Berger and Milkman, 2012), helping show the strong relationship between stock returns and risky events (Li et al., 2014).

Theme of literature evaluation

Years of research have clearly shown that herding is a common behaviour in stocks. Most of the research suggests that herding is more widespread in new fairness markets than in markets that are well developed (Borensztein and Gelos, 2003; Chang et al., 2000). It has been pointed out by research that investors tend to join the crowd in a fearful market rather than in a growing market (Dhall and Singh, 2020; Philippa et al., 2013; Tan et al., 2008; VO and Phan, 2017). Still, the herd phenomenon is affected by different external issues, mainly how other investors feel about the market. In high-liquidity inventory markets, herding is a visible phenomenon (Galariotis et al., 2016; VO and Phan, 2019). Vieira and Pereira (2015) demonstrate that the European Economic Sentiment Indicator is linked to herding. To add more uniqueness, Tsionas et al. (2022) have decided to identify early warning signs of the way asset prices move by using a multivariate stochastic volatility version of the model. Not all big issues in herd behaviour studies come from the inventory marketplace alone. In 2020, Bernales et al. introduced evidence of herd occasions in the alternative market.
Due to COVID-19 hurting the stock market so seriously, several governments introduced new rules and legislation (like banning fast-profit schemes) to help minimise the chance of a collapse, reduce ups and downs, and secure the stability of the markets (Anh and Gan, 2020). Besides new lockdowns, different rules and prohibitions have introduced a feeling of worry and unease to share markets, which has made investing more challenging and led to bigger losses. Amid the COVID-19 epidemic, traders are likely to change decisions fast and move along with the consensual view due to their fear. Dhall and Singh (2020) indicated that information broadcasts in the market are volatile and attract high levels of attention.

2.2.1 Market liquidity on herding conduct pre-COVID-19

Authors Rosch and Kaserer (2013) say that risk in the inventory marketplace is strongly linked to liquidity, and liquidity is a main principle in financial markets (Ma et al., 2018). They find that when the fairness marketplace falls, both market liquidity and the degree of the correlation between fairness and liquidity do as well. According to recent findings by Nagel (2012), Rosch and Kaserer (2013), and Ma et al. (2018), the key reasons for the 2008 global financial crisis were a drop in market liquidity. Market players, regulators, and teachers pay close attention to liquidity when looking at the emerging markets in fashion and the Pakistan stock market.

Rising markets also face a challenge because that type of market tends to be less liquid than the advanced markets (Fong et al., 2017).

Exchanging with informed investors means that marketplace sellers often deal with a selection problem, proving that capital markets display an asymmetry of statistics. Frequently, it is difficult to spot asymmetry in the inventory market because of liquidity. There are a number of techniques for telling if a market is liquid. A high level of liquidity is when doing a transaction doesn't require costly fees. Liquidity is largely created by Kyle's (1985) strong tightness, high intensity, and strong resilience. If inventory charges are higher or lower than their efficient fee, it is called a tight inventory market. Sellers use regular bidding to set both bid and ask prices slightly above and below the equilibrium price. When a broker can trade at the same cost and also promote, the market is completely liquid with no distinction between the prices of stocks bought and sold. The name commonly used in industry for the tightness component is the bid-ask unfold.

2.2.2 Market liquidity on herding conduct post-COVID-19 period

The big impact liquidity has on herding means there is another strong reason to follow the crowd. Increasing numbers of academic studies are revealing that liquidity may help foresee inventory returns for both commercial and market stages. Measuring liquidity can provide insight into the mental state of the market, which Amihud (2002) explains can predict how stock combinations behave. If a market is liquid to an unusual degree, it probably means that unreasonable traders contribute most of its fees. As an example, if the market is liquid, it often indicates that those irrational customers are feeling hopeful, which could help cause more customers to herd. It has also been proposed that individuals imitating known members of the market are boosting the trading of precise stocks, causing the market to become especially liquid.

Vo et al. (2016) analysed the relationship between herding and liquidity in the Pakistani stock market. This result implies that during the testing period, group behaviour was present in the Vietnamese stock market. Moreover, based on stock volume in the common market, some evidence for asymmetric herding behaviour is seen in highly and medium liquidity stocks. In addition, real data shows that market liquidity and herding both affect the stock market in both directions. Even when I split the facts into three distinct periods—before, during, and after the crisis—the results were strong.

Lan & Lai (2011) centred on a quantity factor in their research and located strong evidence of herding from records starting from each day that can be used to study the Hong Kong stock market. When people try to do more alternative volume, it often drives increased herding. Even though it has continued for many years, herding does not lead to valuable results in the marketplace. However, herding is conducted when investment returns in the market are strong. Furthermore, evidence shows that the Chinese and Hong Kong inventory markets are no longer connected via pass-marketplace herding. Even so, the behaviour of herding on one exchange can be impacted by what takes place in other markets. They added to the literature on herd behaviour by examining how the quantity of trades drives the CSAD. That's why marketplace liquidity likely helps explain why herding is more common in the equities market. Therefore, we decided to include liquidity in our herding version of the model to analyse their relationship (VO, Phan, Dang, & Vietnam, 2016).

2.2.3 Information demand for on-herding behavior pre-COVID-19 duration

According to Lakonishok et al. (1992), herding means that many individuals trade in the same name, emphasizing it to others, until they form their independent views, but their trading in the end usually starts to differ. In other words, an investor could not buy a certain stock, but then begin to think about it differently when he notices others purchasing that stock.

People who look to others for their actions often invest in the wrong things. They report that these examples indicate that herding behavior happens due to the differences in the information that participants in the market have. As economists suggest, sometimes called "monkey-see-monkey-do for investors. When investors decide to ignore their data and keep pace with others, the results could be a steady chain reaction (Easley and Kleinberg 2010).

Trades are considered assuming that three tiers of goals belong to the facts asymmetry version (e.g., Copeland and Galai 1983): uninformed investors, informed buyers, and chance-impartial specialists. Buyers who go beyond normal limits are called speculative since they rely on personal non-public statistics that the trade doesn't use in price estimates. Buyers labelled LLe, also referred to as liquidity traders, focus on trading to adjust their portfolio so the weight of their coins is better, whereas surplus inputs on the market are by traders who know future asset values that haven't been disclosed. Experts may serve as agents or dealers in the marketplace. A dealer can manage his giving and taking of shares, though the main purpose of using a brokerage in a transaction is to aid clients' investment decisions. As a result, dealers must deal with customers who ruin the value of different deals, which increases the risk of financial loss. The provider helps moderate how losses are split between liquid and knowledgeable investors.

2.2.4 Information demands on herding conduct post-COVID-19 duration

In addition to examining herding, this research provides clear evidence of the role played by media and liquidity in the markets over different COVID-19 changes. There may be proof from the discipline of monetary behavior that social media news can impact the way funds are chosen, says Phillippas et al. (2020). The stress caused by COVID-19 has more traders ignoring their intuition to follow select behaviors passed on from individuals who have more knowledge, according to Aslam et al. (2022). Similarly, market liquidity is said to shape investors' opinions and may cause them to act similarly (Galariotis et al., 2016). Galariotis et al. (2016) state that lots of trading and sales in high liquidity may improve the mood of irrational traders to exchange, but those same situations in low liquidity can cause buyers to turn pessimistic. With today's surplus of liquidity in the markets, it's important to look further into those ideas in Vietnam. The amount of data supporting the role of media and liquidity in shaping herding during the COVID-19 period is still meager and limited.

Because there is little investor education in Pakistan, news coverage will play an important role in what Investors learn. BILAL and NASIR (2023) mention that social media platforms affect behavior through herding. They wanted to explore how Political interventions could shape the actions of government investors and the Regulatory body in Pakistan in Bilal and Nasir (2023). To help avoid misleading investors in uncertain situations, regulators must be clear about what they require. Especially, the research they perform. It appears that group platforms offer a platform where investors come together as a team and make decisions, with everyone's thoughts counted rather than their own analysis. In their work, Bilal and Nasir (2023) examined the link between Political interventions and how government investors and the Regulatory body respond in Pakistan. To help avoid misleading investors in uncertain situations, regulators must be clear about what they require.

Population and sampling techniques of the study

Using a sample of the daily closing prices of 30 companies' stocks from 2018 to 2024, this study examines herding behavior on the Pakistan stock exchange.

First, for the months of February 25, 2018, to February 25, 2020, pre-COVID from February 26, 2020 to April 1, 2022 During the COVID period and April 02, 2022 to April 02, 2024, the Pakistani stock market gives us the daily closing price and trading volume of all stocks. Next, after filtering the full dataset, this study decided to use stock trading as the main source of data for our study period.

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Every period's unconditional herding is examined, and data is extracted for every sub-sample and the sample as a whole.

Measures

Two commonly used methods for measuring liquidity are the price impact (Galariotis et al., 2016; Vo and Phan, 2019) and the bid-ask spread (Aldeki, 2022; Galariotis et al., 2016). In the first approach, our analysis measures market liquidity as:

$$liq_{i,t} = -\log\left(1 + \left(\frac{|R_{i,t}|}{P_{i,t} * V_{i,t}}\right)\right)$$

$$liq_{m,t} = \frac{1}{N} * \sum_{i=1}^{N} liq_{i,t}$$

Liquidity of a stock (Liqi,t) is defined as the ease of purchasing or selling that stock in the market without causing too much in terms of price changes. You can think of it as the ease of finding a buyer or seller for that stock.

Liquidity in the global market (Liqm,t) refers to the overall market level of how freely all stocks can be bought or sold, as it relates to the market's liquidity (availability of buyers and sellers) at that moment in time.

Next is Ri,t, Which represents the performance of one stock at a specific point. The return on stocks is found by multiplying 100 by log(Pt|Pt-1). A stock's return compares its adjusted closing price on two different days. The way to calculate the stock return is to multiply 100 by the natural logarithm of the ratio between the adjusted closing price (Pt) at time t and the adjusted closing price (Pt-1) at one period prior. It shows us the amount a stock's price has gone up or down in a given period.

Last, trading volume (Vi,t) is how many shares of a stock are bought or sold at a specific time (t), which shows how actively the stock is traded at that point.

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$$

Cross-sectional absolute deviation at time t (CSADt) is what CSADt represents. It shows how much investors feel pressured to adjust their behaviour with the crowd. The way to get CSADt is with the following equation:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |Ri,t - Rm,t|$$

Let's explain what every part of a query means:

1. Ri,t is the return on one stock at time t.
2. Rm,t shows the market's return at a time, which is the simple average of all the individual stock returns at that time.

We will find the difference between each stock return and the market return, and then add all these differences together, divide by N, and find their average.

It helps us see if investors are copying their peers and working together within the market trend. Cross-sectional absolute deviation at time t is named CSADt. It indicates pack behaviour among investors in the market. The model made by Chang et al. (2000) focuses on two theories. It is understood in the first theory that the greater the market return, the more likely individual stocks are to experience larger variance. If we get a strong and positive γ1, it fits with this theory.

The next theory focuses on herding behaviour. It advises that, when stock returns differ greatly from market returns, the crowd tends to act alike. Doing this can shrink the divide between how individual stocks perform and how the market performs. We model this relationship in the equation by the quadratic part of the market return. When γ2 is negative and strongly so, we know there is an indication of herding behaviour. We will also look at how herding changes in up and down markets to better see how herding influences the market during different COVID-

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19 periods. Both sides have been seen among previous studies, as some say herding is higher in decreasing markets, while others find the opposite.

4.2 Descriptive statistics

Table 4.2.1 Behavioral Characteristics of Market Variables before COVID-19

PRE COVID			
DESCRIPTIVE STATISTICS			
Variables	$info_d$	$csad_t$	liq_{mt}
Mean	1.260196	2.016556	-2.130671
Median	1.0141	1.985651	-2.21467
Maximum	2.999861	4.996507	-0.05061
Minimum	-3.09691	0.307496	-4.73E+00
Std. Dev.	1.153123	0.731325	1.310129
Skewness	-0.109529	0.47021	-0.078066
Kurtosis	2.194371	3.459283	1.895983
Jarque-Bera	411.2734	646.2911	733.5573
Probability	0.00000	0.00000	0.00000
Sum	17845.63	28556.45	-30172.43
Sum Sq. Dev.	18828.46	7573.288	24304.77
Observations	14161	14161	14161

TABLE 4.2.1

Table 4.2.2 Behavioral Characteristics of Market Variables during COVID-19

DURING COVID			
DESCRIPTIVE STATISTICS			
Variables	$info_d$	$csad_t$	liq_{mt}
Mean	1.167878	2.080911	-2.19747
Median	0.97635	1.996337	-2.23054
Maximum	2.999983	3.954194	-0.05061
Minimum	-2	0.217484	-4.72584
Std. Dev.	1.185901	0.730965	1.286802
Skewness	-0.08208	0.211074	-0.02665
Kurtosis	2.110921	3.297432	1.94883
Jarque-Bera	497.8008	162.4049	674.6499
Probability	0.00000	0.00000	0.00000
Sum	17069.71	30414.6	-32118.2
Sum Sq. Dev.	20553.96	7808.929	24200.4
Observations	14616	14616	14616

TABLE 4.2.2

Table 4.2.3 Behavioral Characteristics of Market Variables after COVID-19

AFTER COVID			
DESCRIPTIVE STATISTICS			
Variables	$info_d$	$csad_t$	liq_{mt}
Mean	1.278116	1.986827	-2.132459
Median	1.125318	1.977564	-2.21467

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Maximum	2.999996	3.949341	-0.05061
Minimum	-2	-0.236572	-4.725842
Std. Dev.	1.156221	0.76636	1.309196
Skewness	-0.182243	-0.039397	-0.074313
Kurtosis	2.062067	3.328662	1.896834
Jarque-Bera	606.3593	68.40322	741.9928
Probability	0.00000	0.00000	0.00000
Sum	18369.08	28554.68	-30647.7
Sum Sq. Dev.	19211.81	8440.208	24631.83
Observations	14372	14372	14372

TABLE 4.2.3

4.3 Correlation analysis

Table 4.3.1 Relationships among Market Variables in the Pre-COVID Period

PRE COVID			
	$info_d$	$csad_t$	liq_{mt}
$info_d$	1		
$csad_t$	-0.1946	1	
liq_{mt}	-0.0053	-0.4788	1

TABLE 4.3.1

Table 4.3.2 Relationships among Market Variables in the during-COVID Period

DURING COVID			
	$info_d$	$csad_t$	liq_{mt}
$info_d$	1		
$csad_t$	-0.2494	1	
liq_{mt}	0.0057	-0.4065	1

TABLE 4.3.2

Table 4.3.3 Relationships among Market Variables in the after-COVID Period

AFTER COVID			
	$info_d$	$csad_t$	liq_{mt}
$info_d$	1		
$csad_t$	-0.3784	1	
liq_{mt}	0.0362	-0.1663	1

TABLE 4.3.3

4.4 Regression analysis

Table 4.4.1 Impact of Information demand and Market Liquidity on Herding Behavior across COVID-19 Periods

BEFORE COVID				
Dependent Variable: $csad_t$				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.

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C	1.603413	0.011544	138.8918	0.0000
Info-d	-0.125041	0.00456	-27.42166	0.0000
Liq-m	-0.267859	0.004013	-66.74009	0.0000
R-squared	0.268129	**Adjusted R-squared**	0.268026	
Prob(F-statistic)	0.0000	**Durbin-Watson stat**	0.08714	
DURING COVID				
Dependent Variable: $csad_t$				
Method: Least Squares				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.753128	0.01178	148.8258	0.0000
Info-d	-0.152325	0.004485	-33.96294	0.0000
Liq-m	-0.230119	0.004133	-55.67372	0.0000
R-squared	0.226318	**Adjusted R-squared**	0.226212	
Prob(F-statistic)	0.0000	**Durbin-Watson stat**	0.067166	
AFTER COVID				
Dependent Variable: $csad_t$				
Method: Least Squares				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.626603	0.01256	129.5039	0.0000
Info-d	-0.134832	0.004856	-27.7648	0.0000
Liq-m	-0.249738	0.004289	-58.23028	0.0000
R-squared	0.22968	**Adjusted R-squared**	0.229573	
Prob(F-statistic)	0.0000	**Durbin-Watson stat**	0.048583	

TABLE 4.4.1

Discussion on results

It is possible to explain negative outcomes by a number of interrelated factors. To start with, market psychology has a significant effect- every time the investors are exposed to bad news they lose their confidence hence, reducing the market activity. The positive effect of information can be mitigated by this disruption. Secondly, when there is information overload, it may create some confusion in the traders because of contradicting signals, and this creates uncertainty and withdrawal. Third, this type of confusion can trigger liquidity problems, as cautious investors withdraw out of the market. Economic circumstances also play a major role; in times of decline when liquidity is relatively strong, in the end pervasive pessimism will be doing its job of straining the trading volumes. Also, liquidity induced speculative activity triggers erratic price movements. Investors tend to base their decisions on short term trends instead of basing them on fundamentals and thus destabilize marke ts, contributing to the worsening of adverse outcomes. Finally, a combination of these factors creates an unfavorable environment to achieve optimal market performance.

Persisting differences in the information demand and market liquidity, according to this research, suggest that there is a link between herding behavior and both factors in the Pakistan Stock Exchange at all times. In addition, an alternative view was presented by the research using the alternative hypothesis.

Changes in info_d and liq_mt over time can be used to identify how they affect herding on the market (csad), as revealed in the descriptive statistics.

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Before the COVID-19 pandemic, the variables info_d and liq_mt had symmetry, which implied that there was little market stress on them, but, on the other hand, the skewness of the variable of csad_t is small, negative, which implies that there is a slight amount of herding. The variable info_d went down during the pandemic suggesting that the information-seeking behavior decreased and that there was more uncertainty in the market.Liq_mt, at the same time, declined, indicating an increased challenging trading situation, which could possibly have contributed to an increased herding effect. After the outbreak of COVID-19, info_d went up to 1.28, which means that there was a high demand of information that could be used to reduce the crowds. However, csad_t remained unchanged at 1.99, whereas liq_mt has decreased by -2.13 indicating continuing reliance on the market and herding.

The effect of infodemics on herding behavior is multidimensional: even though the pressure of information availability can mitigate the effects of herding behavior, its absence can still be helpful to support it. The level of information demand (Info-d) and liquidity in the market (Liq-m) are the decisive factors of herding as well as liquidity has the amplifying effect on herding even in the context, which is defined by high information demand. However, in contrast to preliminary assumptions, the results showed continuously negative relationships among the metric of csadt and market liquidity in all periods under analysis, and thus indicated contrary directional trends.

Before the outbreak of COVID-19, the correlation coefficient of the correlation between herding and liquidity was found to be equal to -0.4788, meaning that increased herding behavior was associated with the decrease of liquidity. In the case of the pandemic, the correlation remained at -0.4065, which indicated continued stress in the working of the market. Correlation in the post-pandemic period was also negative at -0.1663 which shows a continued lack of connection between herding behavior and liquidity provision. Regression analyses supported a strong and statistically significance negative correlation between csad-t and information demand, as well as liquidity in the market during all the periods studied. The structural relationship (SRB) models show that the historical interrelationship was changed due to an impact of COVID19 pandemic thus reflecting the changing investor behaviour and the changing market environment. The high information demand levels and market liquidity seem to alleviate herding effects, as there is an assumption that the more these people are given access to information and better facilitation of transactions, the more they can be allowed to control investor behavior. Taken together, these findings highlight the ability of the significant disruption like the COVID-19 to transform the market dynamics, affect investor confidence, and change behavior patterns.

5.3 Implications of the Study

This study is highly important for advancing our understanding of how a major external shock, such as a pandemic, changes both market activity and the choices of investors. Experts studying financial behavior usually look at whether people behave sensibly or impulsively within a stable economic environment. The researchers build on that point, adding that high-impact, low-probability events such as COVID-19 impact the usual narrative in this area. Changes in liquidity and the need for information in the market are thought to be important in influencing herding, requiring clearer explanations of market behavior at crucial times. These findings help us see how liquidity and easy access to data lead to less herding behavior and a steadier market performance. As a result, the research's main applications are extensive and play a key role for top decision-makers in the financial world. Knowing about how liquidity and information change at each step of the crisis can help investors decide what action to take. Thinking this way, investors may be encouraged to make their own decisions instead of imitating others. Furthermore, credit scoring allows us to stop bubble and panic selling behavior if the market falls.

Such findings help financial analysts improve their ideas and advice on market performance and insights during and after economic crises. With a focus on liquidity and information, analysts can provide more useful advice that fits the conditions in each business environment. The findings suggest to policymakers that when markets are either transparent or liquid, they can handle fluctuations more smoothly. Rules that improve transparency in markets and information sharing can play a big role in tempering the stark investor reactions we see during a crisis. Enforcing the presence of good market data for everyone in the market could lower the amount of speculation occurring.

5.4 Limitations of the Study

This research contributes much to our understanding of market behavior during the COVID-19 pandemic; however, its limitations may reduce how widely the findings can be used. However, there are a few important limitations: the study's results are only useful for the current pandemic because its effect on world markets is exceptional. Because every crisis is different, its impact on investor decisions cannot simply be copied to situations caused by other economic shocks. This study mainly uses a quantitative approach which is strong, but does not always capture specific psychological and herding factors.

Data-based research may show us what influences investors as they react to major disasters. Although most research is carried out on specific markets or regions, this may introduce inconsistency or weaken the findings' role in different international financial systems. Hence, the response to changes in liquidity and the flow of information changes depending on a market's cultural, regulatory and economic conditions. Because of these limitations, the current study starts the analysis of the research questions, but the results should be considered only as a foundation for more research rather than firm knowledge on the subject. It is recommended that future work in the field should help fill in these gaps by expanding the measures and using various research methods, both quantitative and qualitative.

5.5 Recommendations for Future Research

This study examining in other cases of financial distress and throughout different markets. Additional research can test if the connection established between market liquidity, information demand and herding behavior during COVID-19 is also present during the 2008 financial crisis, the Dotcom bubble or a local economic crisis. The findings of such studies could be more widely applied or show if such behaviors occur in similar ways across cultures or need special contexts for them to take place. Looking at more financial markets may give a better picture. Anions can show researchers whether other types of regulatory systems and cultures are affected by the same correlation under global economic conditions. And expand the range of factors that can affect the observed correlation by including markets that are in their development stage or less active, compared to the benchmark world stock markets. This expansion would assist researchers in establishing whether identical patterns that apply to other regulation systems and complementary environments are prevalent, which has severe global economic policy and investment consequences. Herding excluded qualitative methods: interviews or focus groups, the investors, and finance patterns, could complement quantitative results. This is because while quantitative analysis may give part information about herding, it is likely that qualitative data could discover the reasons, even the conscious thought patterns, why herding occurs, depending on the state of the market.

A potential future research topic is to see if important new factors, especially those related to social media platforms, might affect herding behavior. Quickly sharing information and the impact of digital influencers can help expand how this study examine the necessity of information and how investors respond. More research might process herding data and information using machine learning and artificial intelligence to foresee herding patterns. With these new technologies, data is processed that other tools cannot handle and offers a modern

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set of tools for examining financial behavior. These suggestions provide opportunities for future studies to expand upon the findings here and deliver a better understanding of the main processes driving financial markets and how investors act.

REFERENCES

Ah Mand, A., et al. (2023). "Herding behavior and stock market conditions." PSU research review **7**(2): 105-116.

Ahmed, K., et al. (2022). "Dynamics of herding behaviour during extreme market movements in China and Pakistan." Pakistan Journal of Social Research **4**(04): 664-682.

Ahmed, S. (2020). "Impact of COVID-19 on performance of Pakistan stock exchange." Available at SSRN 3643316.

Al-Awadhi, A. M., et al. (2020). "Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns." Journal of Behavioral and Experimental Finance **27**: 100326.

Aldeki, R. G. (2022). "Herding behavior and financial market price behavior under the COVID-19 pandemic: implications for the Amman Stock Exchange." Journal of Enterprise and Development (JED) **4**(1): 137-155.

Aldeki, R. G. (2024). "Journal of Enterprise and Development (JED)." Journal of Enterprise and Development (JED) **6**(2).

Alhaj-Yaseen, Y. S. and X. Rao (2019). "Does asymmetric information drive herding? An empirical analysis." Journal of Behavioral Finance **20**(4): 451-470.

Alhaj-Yaseen, Y. S. and X. Rao (2019). "Does asymmetric information drive herding? An empirical analysis." Journal of Behavioral Finance **20**(4): 451-470.

Ali, M., et al. (2020). "Coronavirus (COVID-19)—An epidemic or pandemic for financial markets." Journal of Behavioral and Experimental Finance **27**: 100341.

Allam, S., et al. (2020). "Determinants of herding behavior in the time of COVID-19: The case of Egyptian stock market sectors." Available at SSRN 3717995.

Apuke, O. D. and B. Omar (2021). "Fake news and COVID-19: modelling the predictors of fake news sharing among social media users." Telematics and informatics **56**: 101475.

Arsi, S., et al. (2022). "Herding behavior and liquidity in the cryptocurrency market." Asia-Pacific Journal of Operational Research **39**(04): 2140021.

Aslam, F., et al. (2022). "Herding behavior during the COVID-19 pandemic: A comparison between Asian and European stock markets based on intraday multifractality." Eurasian Economic Review **12**(2): 333-359.

Baker, M. and J. C. Stein (2004). "Market liquidity as a sentiment indicator." Journal of financial Markets **7**(3): 271-299.

Bernales Silva, A., et al. (2020). "Do Investors Follow the Herd in Option Markets."

Bernales, A., et al. (2020). "Do investors follow the herd in option markets?" Journal of Banking & Finance **119**: 104899.

Blasco, N., et al. (2012). "Does herding affect volatility? Implications for the Spanish stock market." Quantitative Finance **12**(2): 311-327.

Borensztein, E. and R. G. Gelos (2003). "A panic-prone pack? The behavior of emerging market mutual funds." IMF Staff papers **50**(1): 43-63.

Braun, B., et al. (2018). "Governing through financial markets: Towards a critical political economy of Capital Markets Union." Competition & change **22**(2): 101-116.

Chang, E. C., et al. (2000). "An examination of herd behavior in equity markets: An international perspective." Journal of Banking & Finance **24**(10): 1651-1679.

Chang, E. C., et al. (2000). "An examination of herd behavior in equity markets: An international perspective." Journal of Banking & Finance **24**(10): 1651-1679.
Chen, T. (2013). "Do investors herd in global stock markets?" Journal of Behavioral Finance **14**(3): 230-239.
Chiang, T. C. and D. Zheng (2010). "An empirical analysis of herd behavior in global stock markets." Journal of Banking & Finance **34**(8): 1911-1921.
Dhall, R. and B. Singh (2020). "The COVID-19 pandemic and herding behaviour: Evidence from India's stock market." Millennial Asia **11**(3): 366-390.
Espinosa-Méndez, C. and J. Arias (2021). "Herding Behaviour in Asutralian stock market: Evidence on COVID-19 effect." Applied Economics Letters **28**(21): 1898-1901.
Galariotis, E. C., et al. (2016). "Herd behavior and equity market liquidity: Evidence from major markets." International Review of Financial Analysis **48**: 140-149.
Ganesh, R., et al. (2016). "Industry herding behaviour in Indian stock market." American Journal of Finance and Accounting **4**(3-4): 284-308.
Ganesh, R., et al. (2016). "Industry herding behaviour in Indian stock market." American Journal of Finance and Accounting **4**(3-4): 284-308.
Ghorbel, A., et al. (2023). "Does herding behavior explain the contagion of the COVID-19 crisis?" Review of Behavioral Finance **15**(6): 889-915.
He, Q., et al. (2020). "The impact of COVID-19 on stock markets." Economic and political studies **8**(3): 275-288.
Hsieh, S.-F. (2013). "Individual and institutional herding and the impact on stock returns: Evidence from Taiwan stock market." International Review of Financial Analysis **29**: 175-188.
Javaira, Z. and A. Hassan (2015). "An examination of herding behavior in Pakistani stock market." International journal of emerging markets **10**(3): 474-490.
Javed, T., et al. (2015). "Herding behavior in Karachi stock exchange." International Journal of Management Sciences and Business Research **2**(2).
Kashif, M., et al. (2021). "Do investors herd? An examination of Pakistan stock exchange." International Journal of Finance & Economics **26**(2): 2090-2105.
Khan, K., et al. (2020). "The impact of COVID-19 pandemic on stock markets: An empirical analysis of world major stock indices." The Journal of Asian Finance, Economics and Business **7**(7): 463-474.
Khan, K., et al. (2020). "The impact of COVID-19 pandemic on stock markets: An empirical analysis of world major stock indices." The Journal of Asian Finance, Economics and Business **7**(7): 463-474.
Khoa, B. T. and T. T. Huynh (2021). "Is it possible to earn abnormal return in an inefficient market? An approach based on machine learning in stock trading." Computational Intelligence and Neuroscience **2021**(1): 2917577.
Komalasari, P. T. (2016). "Information asymmetry and herding behavior." Jurnal Akuntansi dan Keuangan Indonesia **13**(1): 4.
Lazzini, A., et al. (2022). "Emotions, moods and hyperreality: social media and the stock market during the first phase of COVID-19 pandemic." Accounting, Auditing & Accountability Journal **35**(1): 199-215.
Phan, H. M., et al. (2023). "Herd behavior in Vietnam's stock market: Impacts of COVID-19." Cogent Economics & Finance **11**(2): 2266616.
Philippas, D., et al. (2020). "Signal-herding in cryptocurrencies." Journal of International Financial Markets, Institutions and Money **65**: 101191.
Philippas, N., et al. (2013). "Herding behavior in REITs: Novel tests and the role of financial crisis." International Review of Financial Analysis **29**: 166-174.

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CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

Salisu, A. A. and A. A. Sikiru (2020). "Pandemics and the Asia-Pacific islamic stocks." Asian Economics Letters **1**(1).

Shah, F., et al. (2024). "Herding Behavior and Its Impact on Market Volatility: Empirical Evidence from the Pakistan Stock Market." Dialogue Social Science Review (DSSR) **2**(4): 218-232.

Tan, L., et al. (2008). "Herding behavior in Chinese stock markets: An examination of A and B shares." Pacific-Basin finance journal **16**(1-2): 61-77.

Tsionas, M. G., et al. (2022). "Multivariate stochastic volatility for herding detection: Evidence from the energy sector." Energy Economics **109**: 105964.

Vo, X. V. and D. B. A. Phan (2019). "Herding and equity market liquidity in emerging market. Evidence from Vietnam." Journal of Behavioral and Experimental Finance **24**: 100189.

Vo, X. V. and D. B. A. Phan (2019). "Herding and equity market liquidity in emerging market. Evidence from Vietnam." Journal of Behavioral and Experimental Finance **24**: 100189.

Wu, G., et al. (2020). "Herding behavior in Chinese stock markets during COVID-19." Emerging Markets Finance and Trade **56**(15): 3578-3587.

Wu, G., et al. (2020). "Herding behavior in Chinese stock markets during COVID-19." Emerging Markets Finance and Trade **56**(15): 3578-3587.