The Impact of Investor Sentiment on Stock Market Liquidity: The Mediating Role of Investor Herding Behavior "An Empirical Study on the Egyptian Stock Exchange"

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Abstract

Behavioural finance is a recent approach in financial markets that has appeared because of the complexities long faced by the traditional or neoclassical finance theory. This paper investigates the influence of investor sentiment and herding behaviour on stock market liquidity using an empirical study on the Egyptian Stock Market. We examine the direct impact of the Egyptian investor sentiment on the Egyptian Stock Market liquidity. As well as the indirect impact of the Egyptian investor sentiment on the Egyptian Stock Market liquidity through the Egyptian investor herding behaviour. Therefore, the major contribution is filling the gap of indirect sentiment-liquidity impact conflict. We use the monthly data of the EGX30 index from January 2004 up to December 2018 for building up investor sentiment index, investor herding behaviour, and stock market liquidity measures. Moreover, we are using two additional types of data (closed-end mutual fund discounts and the equity open-end mutual fund flows) that represent major measures which are used to build up investor sentiment index ranging through the same time-series of the previously mentioned period of this paper. Additionally, we use four control variables for stock market liquidity, namely market volatility, excess market return, term spread, and lag of the dependent variable, considering that the fourth variable is also used for investor herding behaviour. Our result shows that the investor sentiment index has both a direct and indirect impact on stock market liquidity. In addition, regarding event study analysis' results, there are different signs of the direct and indirect impacts and different correlations between the research variables throughout the four different events that differ completely from the usual signs and correlations of the theoretical background.

Keywords: Behavioral Finance; Investor Sentiment; Investor Herding Behaviour; Stock Market Liquidity; Egypt; Structural Equation Modelling (SEM); Event Study; EGX30

1. Introduction

Behavioral finance is considered a recent approach in financial markets that has appeared because of the complications long faced by the traditional or neoclassical finance theory. Generally, it suggests that some financial phenomena can typically be deciphered using models within which some players do not seem to be totally rational, that has been rose from the concept that behavioural finance theory has two building blocks. The primary one is that the irrational investor and the second is that the limits of arbitrage. More specifically, it investigates the conditions that one or both principles that underlie individual rationality are relaxed [1]. These financial phenomena, which might be more interpreted by other alternatives than efficient market hypothesis, will be short-listed as short-term momentum, long-run reversals, additionally to expectation patterns based on valuation parameters and firm characteristics such as dividend yields, Price/Earnings multiples, size effect and value/growth stocks [2]. A set of studies, like [3] and [4], have stated that aggregate liquidity within the stock market changes over time. The necessity of this variation has been shown in several recent studies on asset pricing. As an example, [5] reports that

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stock market liquidity predicts market returns, and [6] shows that the variation in market liquidity is an underlying risk factor about the stock market.

This paper analyses the impact of investor sentiment and his/her herding behaviour on stock market liquidity, a case that has been little explored. Investor sentiment, as suggested by [7], is defined as investor optimism or pessimism about the long run stock market. Higher investor sentiment indicates that investors are additional bullish about the long run performance of the stock exchange. Lower investor sentiment illustrates that investors are additional bearish about the longer-term performance of the stock exchange. Herding, a shape of correlated behavior, could even be outlined as the way wherever investors are trading within the same direction, imitating one another, and build their choices upon the actions of previous investors, or as a behavior grouping to the common [8]. In sum, this paper investigates whether the time-series variation in stock market liquidity is expounded directly and indirectly to investor sentiment. Hence, the indirect influence from investor sentiment to exchange liquidity is via investor herding behavior. Liquidity, as framed in [9] study, is that the inverse of the price sensitivity to order flows. Stocks are less liquid if the value impact brought by order flows is larger. The principal aim of this paper is to explore the potential impact of the Egyptian investor sentiment and his/her herding behavior on the Egyptian Stock Market liquidity.

In essence, this paper adds to the literature by focusing on two important factors that are related to liquidity variation-investor sentiment and his/her herding behavior-that influence the aggregate liquidity fluctuation which offers a relates the two main pillars of research, liquidity, and investor behavior, especially in an emerging market: the Egyptian market. As previously mentioned, this paper seeks results that may prove that the Egyptian investor sentiment combines helpful direct information for estimating the current and future conditions of the Egyptian Stock Market liquidity, and that the Egyptian investor sentiment combines useful indirect information for evaluating the current and future conditions of the Egyptian Stock Market liquidity through the Egyptian investor herding behavior. This paper intends to fill the gap of indirect sentiment-liquidity impact conflict. The researchers use the deductive approach taking into consideration two types of statistical techniques, namely Structural Equation Modeling (SEM) and event study. The event study considers four suitable events which are the September 2008 Global Financial Crisis, 25 January 2011 Revolution, 30 June 2013 Revolution, and November 2016 Egyptian Pound Floatation. The major result of this research is that the investor sentiment index has both a direct impact on stock market liquidity and an indirect one through the mediator variable, namely investor herding behavior. Concerning event study analysis' results, there are different signs of the direct and indirect impacts and different correlations between the research variables throughout the four different events that differ completely from the usual signs and correlations of the theoretical background.

This paper consists of six major sections. Section one demonstrates literature review. This section begins with the concepts of investor sentiment, his/her herding behavior, and the determinants of stock market liquidity and anomalies. Then, the researchers present the literature review of direct and indirect sentiment-liquidity relations. Finally, they write their general comment and criticism on that literature. Section two is about hypotheses development. Section three is research methodology. It starts with sample selection. Then, sources of data collection. Finally, the variables are demonstrated. Section four includes results and discussion. Section five presents the implications of the study. Finally, section six provides a conclusion about this paper.

2. Literature review

The history of the stock market is full of major events, such as the 1929 crash, the ironic boom in the early 1960s, the beautiful fifties bubble in the early 1970s, the Black Monday crash in October 1987, the Internet or Dot.com bubble of the 1990s, and the financial crisis of 2008. Behavioral finance researchers have been working to improve the standard model using alternative models based on two basic assumptions [10]. [11] put forward the first hypothesis that investors will be affected by sentiments, which is related to their confidence in future cash flows. Investor sentiment in a broad sense may be a belief about future cash flow and investment risk, and these beliefs do not seem to be justified by relevant facts [10]. [12] mention that playing with sentimental investors is costly and risky. Thus, rational investors, or arbitrageurs in general, do not appear to be pushing prices as aggressively towards fundamentals as the standard model implies. [13] based on the results obtained by the investor intelligence sentiment index show that changes in sentiment are negatively correlated with market fluctuations. Once investors become more optimistic, volatility will decrease. Also, once investors become more pessimistic, volatility will increase. [14] suggest that asset pricing models should consider the role of investor sentiment.

Different researchers use different agents for sentiments. The most common are those proposed by [7], who construct a sentimental index based on many factors. [15] used these proxies. Recently, [16] applied two tools to measure investor sentiment in mutual fund flows. The first is based on the Consumer Confidence Index surveyed by the University of Michigan Survey Center, which was also used by [17]. The second is the [7] measurement index, which is based on six indirect measures of investor sentiment: trading volume measured by the turnover of the New

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York Stock Exchange, final closing fund discount, dividend premium, initial public offering (IPO) number and first day, the profitability of the IPO, and finally the newly issued equity. Although there is growing interest in this topic, and there are a lot of studies on the relationship between investor sentiment and market profitability, there are few studies analyzing the impact of sentiment on stock market liquidity. Therefore, more research on this relationship is needed. The current literature lacks empirical evidence on the direct and indirect relationship between stock market liquidity and investor sentiment. The liquidity literature focuses on how changes in liquidity affect stock performance. Few articles have studied the sources of changes in total liquidity in the stock market.

In what follows, the paper first discusses the concepts of investor sentiment, investor herding behavior and the determinants of stock market liquidity and anomalies. The literature review of direct and indirect sentiment-liquidity relations is then presented. The indirect sentiment-liquidity relation literature is divided into two main categories, namely sentiment-herding and herding-liquidity relations. Finally, it ends with a general comment and criticism on that literature.

2.1 THE CONCEPT OF INVESTOR SENTIMENT

Various terms have been used to describe investors whose preferences and beliefs conform to psychological evidence rather than normative economic models. The definitions mentioned in the literature range from obscure statements about overreacting investor errors to precise model-specific psychological biases [18]. However, the definition of is derived from [19]'s noise trading concept. The noise trader theory has led to the emergence of various behavior-based models developed by different researchers, namely: [11] and [20] to clarify the effects of noise. The trader decides the stock price. Although some researchers refer to investor sentiment as trading noise rather than information propensity ([19]; [11]; [12]). Other refers to it as excessively pessimistic (bearish) or optimistic (bullish) investors in the stock market current and future prices [10].

2.2 THE CONCEPT OF INVESTOR HERDING BEHAVIOR

Behavioral finance researchers believe that herd behavior in the financial market is behavior that may have an impact on financial asset prices and future returns. Therefore, articles were written to understand whether herding exists in different stock markets, and if so, whether it will affect the market in terms of volatility and future returns. The empirical study of herd behavior in financial markets is divided into two main research directions [21]. Front-line research examines the behavior of linkages based on the measurement of the dynamic correlation between asset prices. The second line research focuses on the horizontal dispersion of stock returns, which is an indicator of herd behavior. This can also be observed in the herding of the entire market [15]. The method of [22] is widely accepted as a herding measure. Some studies have applied their methods or changed its version [23]. [24] found evidence of gregarious behavior in the Japanese stock market during the bearish period, as investors undoubtedly herded, as evidenced by the literature. [25] found that China's A-share market has a herd effect during ups and downs, but no evidence of a herd effect was found in these two B-share market states. [26] found that, first, during the rise and fall of the two markets, the herd retreated, but was more prominent in the B-share market (this contradicts the findings of [27], that is, the herd effect in the stock market A is stronger). Second, the herd effect is the strongest among the smallest and largest populations, but the medium-sized commercial firm does not show a significant herd effect. Finally, they provide evidence that herding can be a transitory phenomenon, depending on the level of the industry.

2.3 DETERMINANTS OF STOCK MARKET LIQUIDITY AND ANOMALIES

Understanding the liquidity of financial markets requires understanding its determinants. Research on the field of liquidity determinants can be divided into two types, namely, company-specific factors and macroeconomic factors. For the first category, namely firm-specific factors, [26] found that further diversification of property will increase market liquidity. It is also found that there is a positive correlation between the ownership of large holders and the listing margin, the effective margin, and the adverse selection part of the effective margin, which indicates that once market liquidity decreases, saturation trading strategies will have an adverse effect on returns. Market abnormalities, such as excess momentum and value investment returns, when checked through these arbitrage framework limits, you can see the possibility of abnormal return levels over time. In this case, arbitrageurs have to worry about the net income after transaction costs when making investment decisions. This will clearly establish a theoretical link between arbitrage returns and transaction convenience, namely market liquidity. Changes in market liquidity should change the net profitability of arbitrage activities, thereby limiting the amount of mispricing that can be eliminated by arbitrage, as shown by [12]. This has prompted researchers to shift from the traditional financial determinants of stock market liquidity to the other side of behavioral financial liquidity determinants.

2.4 LITERATURE ON DIRECT SENTIMENT-LIQUIDITY RELATION

Many studies report that sentiments affect liquidity (eg, [27]; [28]; [29]; [30]; [31]; [32]; [33]; [34]; [35]; and [36]). [27] investigated the reasons for common liquidity in the Korean stock market from 2003 to 2004. They take information asymmetry, volatility, utilitarian trading interest, style-based trading, inventory costs and investor

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sentiment as potential candidates. [31] show that during periods of deterioration in investor confidence, the increase in SEO price discounts for illiquid corporations is greater than for companies with liquid stocks. This shows that investors dislike illiquidity even more when sentiment weakens, and when they subscribe to illiquid company SEO, they need higher compensation and deeper price discounts. [32] found empirical evidence that investor sentiment has a positive impact on stock market liquidity. [33] shows that investor sentiment and stock market liquidity are important ratios of stock market growth and development. However, the road map that investor sentiment may have an impact on economic growth is also provided through a one-way movement from sentiment to liquidity and growth.

[34] obtain the following results: the sentiments of the investors are actively affecting the liquidity of the market. The development of margin transactions touched the fluidity of the market of investor sentiments. The cognitive capacity of information negatively affects market liquidity. The explosive amount of information increases the liquidity of the bull market and has a great impact as it is surprised to weaken the fluidity of the bear market. [35] examines the sentiments of investors and the fluidity of the stock market using evidence of emerging economies, that is, evidence of the indexes. [36] examine using an empirical analysis of Bloomberg's firm-level, daily investor sentiment scores derived from firm-level news and Twitter content in United States (US), the impact of firm-level investor sentiment on a firm's share liquidity in a regression model to explain the variability in a firm's share liquidity. The sample period covers four years ranging from 2015 to 2018. This is determined by the availability of Bloomberg printing data. The proxy for shared fluidity is the bid-ask spread, which may be a fluid incomplete measure. The measurement of the [5] which represents illiquidity was used as an alternative indicator and similar results were obtained. The results have an important meaning for investors when evaluating the determinants of shared liquidity. They rely on the pooled regression analysis as statistical technologies. The results show that the improvement (degradation) of the sentiment of investors only using Twitter content leads to a decrease (increase) of the average fluidity of the average company. The result is not so strong, but it is opposed to the sentiments of investors who take only in news articles. [37] indicate that when local investor confidence is high, the market is more liquid.

3. Hypotheses Development

Considering the literature review, and in an attempt to reach the research objectives, hypotheses can be formulated as follows:

- **H1:** There is a statistically significant direct impact of the Egyptian investor sentiment on the Egyptian Stock Market Liquidity.
- **H2:** There is a statistically significant indirect impact of the Egyptian investor sentiment on the Egyptian Stock Market Liquidity through the Egyptian investor herding behavior.

4. Methodology

This study uses the monthly data of the EGX30 index from January 2004 up to December 2018 for building up investor sentiment index, investor herding behavior, and stock market liquidity measures. Moreover, there are two additional types of data that represent major measures which is used to build up investor sentiment index ranging through the same time-series of the previously mentioned period of this research. These two measures are the closed-end mutual fund discounts and the equity open-end mutual fund flows. As for investor herd behavior variables, the researchers used the monthly returns of the EGX30 index as a proxy for the market index and the monthly returns of 69 individual companies listed on the index to calculate the measurement of investor herd behavior variables. The choice of these companies depends on the availability of monthly closing prices and opening prices of individual EGX30 listed companies during the empirical study period from January 2004 to December 2018. As suggested by , herding is not a short-term phenomenon, and it may take time to influence the market. The choice of 2004 as the starting year is because of the notion that the chairman of EGX established the EGX Index Committee on April 7, 2004. During the investigation of the research period, 2011 was considered a glorious year in the history of Egyptian capital markets. This year seems to be completely different. The Egyptian Stock Exchange is facing internal tensions. The year began with the revolution on January 25. According to the 2011 annual report of the Egyptian Stock Exchange, the market value lost approximately £194 billion. The transitional phase began to rebuild state institutions. This was a turbulent phase full of political tensions and clear categorical demands, causing the economy to regress to one of the worst levels in history [38].

The type of data which will be collected to serve this research is secondary data. Secondary data are going to be gathered whether from its internal sources {those found within the Egyptian Stock Market for whom the research is being done}, or external sources like books, references, scientific periodicals, previous studies, records,

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publications, reports……etc. which dealt with topics of investor sentiment, investor herding behavior, and stock market liquidity, and that's for determining the research problem, importance and objectives, constructing the theoretical framework of the study, writing literature review, phrasing hypotheses, and conducting the empirical study. The study uses information acquired from many completely various sources. The sample period spans from January 2004 up to December 2018, for one hundred eighty monthly observations. This range of observations could also be somewhat tiny compared with different studies in developed stock markets. However, for Egypt, aggregating the frequency or extending the length of the data does not appear doable because it isn't out there. Data availability is the key constraint that enforces somewhat shorter periods.

Data employed in the study could also be classified into four groups: stock market liquidity data, investor sentiment data, investor herding behavior data, and stock market liquidity control variables' data, all are publicly available data (secondary data). The variables accustomed to proxy investor sentiment and herding behavior are developed within the lightweight of previous studies. Secondary data (the data that already exist prior to the current needs of the researcher) has been collected for the purpose of this study. For stock market liquidity data and investor sentiment data, they are collected from EGX30 Monthly Bulletin. Additionally, Closed-End Mutual Fund Discounts (CEFDs) Index's data and that of Equity Open-End Mutual Fund (EOEF) data are collected from the Egyptian Investment Management Association (EIMA) with considering that CEFDs Index's Data that are disclosed by EIMA are not complete for the empirical study's historical period. More definitely, the available disclosed CEFDs' data are from January 2004 till March 2013. For investor herding behavior data, the researcher uses monthly return of Egx30 and the individual monthly return of 69 sample companies listed within the Egx30 with complete monthly close and open prices data during the empirical study period to account for the probability that herding is not a short-lived phenomenon, and that it might take time to affect the market, as suggested by . Data was gathered from EGX30 Monthly Bulletin. For stock market liquidity control variables' data, the yield on a 10-year Treasury bond benchmark and the yield on the 3-month T-bill are collected from the monthly statistical bulletin of the central bank of Egypt.

4.1 Investor Sentiment Variable Measurement

In this part, the researcher presents the individual sentiment indicators and describes the variables accustomed to construct the sentiment index employed in the study. The challenge scholars are facing is, however, to evaluate investor sentiment and quantify its effects [10]. Investor sentiment is not straightforward to measure. Although the finance literature provides some investor sentiment measures, the researcher still does not have any definitive investor sentiment measures that scholar agree on. The effectiveness of each proxy continues to be not definitive and subject to debates. Previous research used many methods to quantify investor sentiment. One aspect of research concerns the direct sentiment measures, like survey-based measures developed to attract the outlook of market participants. An alternative stream of research uses many indirect sentiment accesses for investor sentiment.

To measure *direct sentiments*, US-oriented research [39] has centered on the American Association of Individual Investors (AAII) sentiment index survey and the Investors Intelligence (II) service to differentiate between different classes of investors. Regarding the direct sentiment indicators, most of the literature revolves around *indirect sentiment indicators* (such as discounts on closed mutual funds, equity funds, retail trade, and risk appetite indices). Indirect sentiment indicators are determined by observing objective variables that implicitly indicate investor sentiment. Although the theoretical connection with investor sentiment is weak, they avoid the problems of direct measurement of the lack of sample size and statistical representativeness (participants and number of people participating in the survey). Also, indirect measures of sentiment can generally be obtained at a higher frequency (e.g. monthly) . Advantages of using indirect measures are [40]:

1. They are based on simple market data.
2. They are easy to be established.
3. Indirect measures are observed in real time and reflect both the power of market participant and the strength of their feeling either optimism or pessimism. [7] and [10] general approach is taken to show that there is no perfect index of investor sentiment. Instead, there are a variety of accessible, imperfect sentiment proxies that are doubtless to contain some element of investor sentiment. Taking these factors into consideration, the best decision is to incorporate as several obtainable proxies as potential and form a composite index primarily based on a standard element of the underlying factors similar among them. Subject to data availableness, this study considers a variety of proxies and forms them into a composite sentiment index primarily based on their principal component. It is primarily based on the common variation in four underlying proxies for sentiment. The variables used to investor sentiment are developed according to the previous studies as sentiment proxies: closed-end mutual fund discounts, equity open-end fund, retail trades; and risk appetite indices. The sentiment proxies are measured monthly from 2004 to 2018. The researcher can initially introduce all of them in this section and then discuss how they're fashioned into overall sentiment index within the part of statistical analysis. These proxies are examined in bigger details below:

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4.1.1 CLOSED-END MUTUAL FUND DISCOUNT INDEX

Closed-End Fund Discount (CEFD) Averages The difference between the net asset value of the shares of fixed capital funds and their market price. Previous work suggested that CEFD is related to sentiments. [41] used it to predict the reversal of the Dow Jones stock, [42] believe that sentiments are behind the different characteristics of closed fund discounts.

[42] developed a weighted discount index based mainly on closed funds. Therefore, like several studies in the literature on investor sentiment, this study uses this technique. The evolution of the weighted discount index is as follows:

$VWD_t = \sum_{t=1}^{n_t} W_i \, Disc_{it}$ (1)

Where,
* VWD_t is the value-weighted index of month t discounts.
* Disc is the closed-end fund discount, and

$w_i = \frac{NAV_{it}}{\sum_{t=1}^{n_t} NAV_{it}}$ (2)

* NAV_{it} is the net asset value of fund i at end of month t.

$Disc_{it} = \frac{NAV_{it} - SP_{it}}{NAV_{it}} X\ 100,$ (3)

* SP_{it} is Market Price of fund i at the end of month t.
* n_t = the number of funds with available $Disc_{it}$ and NAV_{it} data at the end of period t.

In addition, changes within the value-weighted index of monthly discounts are computed. For this measure, the researcher computes VWD in a similar fashion, except he needs that every fund enclosed within the index should have the DISC and NAV data available for months t and t-1, so that monthly changes within the index are computed over the identical asset base. The researcher then defines $\Delta\, VWD_t$ to be:

$$\boldsymbol{\Delta} VWD_t = VWD_t - VWD_{t-1} \quad (4)$$

4.1.2 EQUITY OPEN-END MUTUAL FUND FLOWS INDEX

Data on how mutual fund investors allocate between fund categories is readily available [10]. [43] found that mutual fund flows can represent investor sentiment. [43] investigated the existence of investor sentiment in the United States and Japan using an investor sentiment index based on daily mutual fund flow data. The index was found to be important for both markets. [44] found some positive evidence when using the flow of capital to represent the sentiment of individual stocks. They found that when funds owning a particular stock experienced a strong inflow of funds, the stock's subsequent performance was relatively poor. Previous research defined mutual fund flow as positively correlated with sentiment. According to the literature, researchers have calculated mutual fund flows, such as [45]:

$$FLOW_{it} = \frac{TNA_{i,t} - TNA_{i,t-1}\,(1 + R_{i,t})}{TNA_{i,t-1}} \quad (5)$$

Where, $FLOW_{it}$ is the flow of fund *i* at the end of month *t*, and $TNA_{i,t}$ is the total net assets of fund *i* at the end of month *t*;

$$R_{i,t} = \frac{P_{i.t}}{P_{i,t-1}} - 1, \quad (6)$$

Where, $P_{i.t}$ and $P_{i,t-1}$ are the share prices of fund *i* at the end of months *t* and *t – 1*, respectively.

The average flow of all A-type mutual funds is computed as below:

$$AFLOW_t = \frac{1}{n}\sum_{i-1}^{n} FLOW_{i,t}. \quad (7)$$

4.1.3 RETAIL TRADES (BUY-SELL IMBALANCE) INDEX

The inexperienced retail investor is additional subject to investor sentiment than the professional institutional investors. There is growing empirical evidence that co-movement of security returns is expounded to the trading patterns of groups of investors. This was illustrated typically by, [46] who analyzed trading volume and found that

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retail investors consistently buy stocks with robust recent performance and with high trading volume. The results are consistent with systematic sentiment. Thus, the trading of retail investors is affected by shared psychological biases. Those biases then have an accumulative impact on stock prices.

[41] found in micro-trade data that retail investors buy and sell shares together, which is consistent with the sentiment of the system, which is a necessary condition for people's activities to affect prices. They show that the related transactions of retail investors are related to the patterns of co-movement within the returns of the shares. They found direct evidence of transactions related to individual investors and provided evidence that capturing the elements of the imbalance between the buying and selling of individual traders helps clarify the linkages of the returns of stocks (including small stocks) with a high concentration of investors. retailers.

According to [47] using BSI (buy-sell imbalance) in a specific time period of t, total trading activities of investors can be measured. For a given period, the BSI indicates that, at the overall level, retail investors are net buyers (stock BSI> zero, that is, their positive correction of total stock sentiment) or net sellers (stock BSI is less than zero, that is, a negative amendment in their aggregate stock sentiment). In other words, this measure may be an over-determining directional indicator of net retail demand during the period. To calculate monthly BSI:

$$BSI_{it} = \frac{\sum_{j=1}^{D_t}(VB_{ijt} - VS_{ijt})}{\sum_{j=1}^{D_t}(VB_{ijt} + VS_{ijt})} \qquad (8)$$

Where, D_t is the number of days in month t; VB_{ijt} (VS_{ijt}) is the dollar- denominated buy (sell) volume for stock *i* on day *j* of month *t*.

4.1.4 RISK APPETITE INDEX

Researchers constructed the risk appetite index based on the technique developed by [42]. RAI is constructed using daily market price data from 2004 to 2018. The average monthly return of is calculated by EGX 30. Then the average standard deviation of return of the previous 30 days ("historical volatility") is calculated for every month of the sample period. Then rank monthly returns and historical volatility; calculate the Spearman rank correlation coefficient between the monthly income rank of each company and the monthly income rank of historical volatility. Therefore,

$$\text{RAI} = \frac{\sum(R_r - \bar{R}_r)(R_v - \bar{R}_v)}{[\sum(R_r - \bar{R}_r)^2 \sum(R_v - \bar{R}_v)^2]^{1\backslash 2}} * 100; \quad -100 \leq EMSI \leq +100 \qquad (9)$$

Where, R_r, and R_v, are the rank of the monthly return and the historical volatility, respectively. And $\bar{R}_r$ and $\bar{R}_v$ are the population mean return and historical volatility rankings, respectively.

4.2 Investor Herding Behavior Variable Measurement

The focus of the researcher is to discover the herding of the entire market. Once investors in the market ignore the individual characteristics of assets and follow the behavior of the market, the latter will appear. The advantage of this explicit method is very simple [23]. However, the downside is that this strategy is based on subjective beliefs or information and guides individual investors to make choices based on the performance of the entire market.

suggest that an acceptable measure of the market impact of investor herding is dispersion. Since it measures the mutual proximity of individual returns to market returns, the dispersion is finite from under zero. Once investor's personal return and market return are inconsistent, the degree of dispersion will increase. Therefore, market-wide herding will indicate a decrease in dispersal [23]. Other investors believe that individual stocks tend to behave differently and have different sensitivity to market reactions, so their returns will deviate from overall market returns. However, once investors herd in, stock returns will not show such a big deviation; individual stock returns will accumulate around the overall market performance. Christie and Huang use the standard deviation of the cross-section, namely Cross-Sectional Standard Deviation (CSSD) as a measure of dispersion. They also plan that under stressful market conditions (a period of severe market volatility), people are likely to pay attention to market performance. Therefore, investor's personal return will not be much different from market return. Therefore, the degree of dispersion, CSSD, is in the traditional market conditions. This is different from the rational asset pricing model, which assumes that dispersions will continue during periods of high market volatility.

More specifically, wherever they measure dispersion by:

$$CSSD_t = \sqrt{\frac{\sum_{t=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \qquad (10)$$

Where:

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- $CSSD_t$ is the Cross Section Standard Deviation of individual stocks' returns around the market,
- $R_{i,t}$ is stock i's return at time t,
- $R_{m,t}$ is the average return of the sample at time t, and
- N is the number of companies included in the sample

The researcher follows [22] in order to account for all market states and not restrict the model to stressful conditions and this is the reason for using the $CSAD_t$ as a measure of investor herding behavior. Because the $CSSD_t$ can be sensitive to outliers, they measured returns' dispersion by:

$$CSAD_t = \frac{\sum_{t=1}^{N} |R_{i,t} - R_{m,t}|}{N} \qquad (11)$$

Where:

- $CSAD_t$ is the Cross Section Absolute Deviation of individual stocks' returns around the market,
- $R_{i,t}$ is stock i's return at time t,
- $R_{m,t}$ is the average return of the sample at time t, and
- N is the number of companies included in the sample.

The previous two measures of investor herding behavior are employed in two recent studies in Egypt (e.g. [48]; [49]).

4.3 Liquidity Variable Measurement

Although easy to define, it turns out that measuring liquidity is much more difficult [50]. [51] report that around 68 existing measures are used in the literature, indicating that there is little agreement on the best measures to use. [51] also reported that many of these indicators have little or no correlation between them, indicating that inappropriate measures can lead to erroneous conclusions about changes in the market structure. To serve the purpose of this research, the researcher uses three intuitive liquidity measures, namely the trading volume, the market capitalization, and the bid-ask spread. These three measures are commonly used in the literature as previously illustrated in literature review. These three measures are examined in bigger details below:

4.3.1 Trading Volume

Trading volume per time interval (Qt) is integrated in a lot of liquidity studies (e.g., [52]). Trading volume can be defined as the average number of shares traded per day during year t-1 [3]. The volume of transactions is an important aspect of the economic interaction of the financial market between different investors. The volume of operations is driven by potential economic forces, which provide important information on the operation of market liquidity. It can be calculated daily, weekly, annually or at any other time interval deemed suitable for analysis.

4.3.2 Market Capitalization

Market capitalization represents the value of the firm with respect to current market price:

$$\text{Market Capitalization}_t = \sum_{i=1}^{N_t} P_i * q_i \qquad (12)$$

Among them, q_i is the number of outstanding shares and P_i is the price of stock i. In addition, the total number of issued shares used to calculate the market value is equal to the actual number of shares available for trading and has been used in several previous studies (e.g., [52] and [53]) as a proxy for liquidity. Both volume and prices are driven by underlying economic forces, and thus convey important information about the workings of the market liquidity.

4.3.3 The Bid-Ask Spread

The bid to ask spread is the difference between buying and selling price of a particular security. It is often used as an indicator of liquidity. The narrower the spread, the greater the liquidity of a stock. Different stock has different spreads based on number of willing buyers or sellers for this particular security. There are several other factors that determine the difference between the bid and ask prices. The volume of a security traded on a daily basis is the first factor. The stock that has larger trading volume have a narrower spread than the stock that are traded infrequently. Another important factor is volatility. In volatile period, the spread is much larger because market participants require a higher return for an extra amount of risk that they are willing to take. Another factor that affects bid to ask spread is a stock's price. Most of low-priced stock have a wider spread as they have limited trades because most of them are new or small. Finally, the risk facing investors, such as inventory risk and asymmetric information risk arising from informed traders, is another determiner of bid to ask spread [54]. Using the methodology of this

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research, the researcher calculates the bid-ask spread for the Egx30 index as the difference between the monthly close and open prices of the index.

4.4 Control Variables Affecting Investor Herding Behavior and Stock Market Liquidity, and their Measurement

The researcher follows the notion of [55] by considering the lagged investor herding variable to control for the influence of previous period herding on the herding behavior in the subsequent period. Control variables commonly used in previous literature as control variables for stock market liquidity include market volatility, excess market return, term spread, and lag of the dependent variable (e.g. [56]). These four measures are examined in bigger details below:

4.4.1 Market Volatility

Market volatility is measured as the cross-sectional average volatility of the sample stocks, where volatility is calculated as the standard deviation of the daily returns for the month [56].

4.4.2 Excess Market Return

Excess market return is calculated as the weighted return by the value in excess of the 3-month T-bill rate [56]. There is a negative correlation between liquidity and excess market return. Excess stock returns, commonly known as "risk premiums," are in part a premium for reverse of equity liquidity. Compared to Treasury securities, excess returns on stocks not only reflect higher risks, but also lower liquidity [5].

4.4.3 Term Spread

The term spread is calculated as the difference between the yield on a 10-year Treasury bond benchmark and the yield on the 3-month T-bill [56]. The term spread is an important predictor variable and a model that contains this control variable in addition to liquidity has a higher prediction compared to the model just containing liquidity and the lag of the dependent variables. [56]. Fluctuations of portfolio future profitability affect the ability to cover for any liquidity shortage and hence influence the premium that is required to carry maturity risk. In another words, there is negative relationship between term spread and liquidity.

4.4.4 Lag of the Dependent Variable

In time series applications, reasonable functional forms with no autoregressive terms often produce theoretically meaningful coefficients in a modestly successful fit. However, when one or more lagged dependent variables are added as explanatory factors, the autoregressive terms take on strongly significant coefficients which improve the fit but squash the effects of the other variables. The traditional conclusion is that the original variables make no real difference. In practice, the anomaly is often due to the combination of high serial correlation and heavy trending in the exogenous variables, which can jointly produce dominating autoregressive terms even when they have little or no real explanatory power. The use of lag of the dependent variable is to minimize the autocorrelation problem between the error terms of the original dependent variable and its future lag. That is means that the original dependent variable and its future lag are treated as separate dependent variables to isolate the autocorrelation effects. This phenomenon is well-known in the case of variables that are affected by political conditions as the variables of this research [57].

5. Results & Discussion

This research will be conducted in the Egyptian Stock Market which is considered as an emerging market. The Egyptian Stock Market is considered as the biggest and oldest stock market in the Arabic area (forexpeoples.com). The following are the statistical techniques that utilized for analyzing the research data:

5.1 The Sentiment Index (SI):-

5.1.1 Constructing Index:-

Because most researchers cannot even agree on a direct definition of sentiment, because of the notion that the word sentiment has multiple meanings and will be understood in other ways when looking at its context. And regardless of whether at least one researcher has a transparent concept of sentiments, another researcher may not agree at all. For example, some people may think that sentiment is like investor optimism, while others may generalize it based on general risk appetite. As for the method of measuring it, scholars obviously even have many differences. Investor sentiment is not easy to measure. Dozens of sentiment measures have been proposed, ranging from direct measures such as surveys conducted by professional market analysts to indirect measures of financial data or stock prices and types of stocks. [7] and [10] adopted a similar strategy in the mood of the New York Stock Exchange. The first

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principal component of a set of time series variables is simply a linear combination of variables and constants selected to capture the maximum joint variation of the entire series as much as possible. Principal component analysis is a variable reduction process. Once you have data on multiple variables, and there is some redundancy in these variables, it can be very useful. In this case, redundancy means that many variables are related to each other, possibly because they measure the same structure. Because of this redundancy, it should be possible to reduce the discovered variables to smaller principal elements (artificial variables) that can explain most of the variance in the observed variables. The principal components can be used as predictors or standard variables in the analysis of results. Principal component analysis is just a variable reduction process, which (usually) leads to relatively few components to explain most of the variance in a set of observed variables.

5.1.2 Assessment of the Suitability of the Data for Factor Analysis:-

Principal component analysis is a large sample process. In order to obtain reliable results, the minimum number of subjects who provide usable data for the analysis should be 100 subjects or 5 times the number of variables analyzed, whichever is greater. The factors obtained from a small data set are different from those obtained from a large sample. However, some authors suggest that the focus is not on the total sample size. Two statistical measures further facilitate the evaluation of tire data decomposition: the Bartlett sphericity test and the KaiserMeyer-Olkin (KMO) sampling adequacy measurement. Bartlett's sphericity test must be significant (p less than 0.10) to be considered an appropriate factor analysis. The KMO index ranges from 0 to 1. It is recommended to use 0.5 as the minimum value for a good principal component analysis. For this research, both Bartlett test and KMO are valid, as shown in the table 4.3 below:

Table 4.3: KMO and Bartlett's Test to Assess the Factorability of the Data

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.512
Bartlett's Test of Sphericity	**Approx. Chi-Square**	12.542
	df	6
	Sig.	0.051

Here, the table reveals that the Bartlett's test of sphericity is significant with a value of .051 which is less than the 10% significance level. Additionally, the first principal component explains 51.2% of the sample variance of the orthogonalized variables. Additionally, the following table 4.4 shows the resulted first principal component matrix of the four used investor sentiment proxies:

Table 4.4: First Principal Component Matrix

ΔVWDt	0.471
Mutual Funds Flows	0.684
Retail Trades (Buy-Sell Imbalance) Index	-0.206
Risk Appetite Index	-0.734

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Thus, investor sentiment index can be built depending upon first principal component matrix in the above table 4.4 using the following equation:

$$\textit{Investor Sentiment Index} = 0.471\ \Delta VWD_t + 0.684\ \textit{Mutual Funds Flows} - 0.206\ \textit{Retail Trades (Buy-Sell Imbalance) Index} - 0.734\ \textit{Risk Appetite Index}$$

5.2 Time-Series Adjustment: -

The sample period used by the researchers is 15 years. During this long period of time, changes in the market structure, competition, technology and activities in the financial market can produce a non-stationarity in the liquidity sequence. Therefore, the researchers performed a KPSS unit root test on each series to see if the series should become a stationary series. The KPSS test is a test proposed by [58], in which the null hypothesis is that the series used by the EViews statistical program is stationary. Many time series demonstrate trends and non-stationary

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behavior. These characteristics are especially clear in financial series, such as stock prices. If the series is not stable and that it is not combined with other non-stationary series to form a stationary alignment, the regression, including the series, can cause spurious regression. The researcher built his sample period using seven years. Changes in market structures, competition, technology, and activity in financial markets for more than this period can produce any frequency in the data series. Therefore, researchers can perform some unitary route tests for each series to determine if the series needs to become a stationary series.

The standard KPSS test is oversized for highly autoregressive processes because it employs a semi-parametric heteroskedasticity and autocorrelation consistent covariance estimator (HAC) of the long run variance of the process with an important positive finite sample bias. However, in the case of an HAC estimator, another bandwidth as proposed by KPSS can be selected. In finite samples, the bandwidth selection means the following exchange: Selecting too large bandwidth means that the long run variance is overestimated. The test statistics are too small, and tests will have little or no power in finite sample if it has common nominal significance levels. On the other hand, if the process is highly autoregressive, the process is undervalued, and the test statistics are too large, and the test is oversized. The introduction of more convenient estimators of the long-term variance under the null hypotheses do not automatically repair the KPSS type in tests. A long-term variance estimator that works well in null will lead to the inconsistencies of the KPSS type of test instead of a random walk alternative, i.e., the power of the test for some relevant alternatives does not approach 1 as the sample size increases. In this study, researchers suggest an automatic KPSS test format that reduces the size distortion which leads not to suffer from inconsistency.

Based on the results illustrated in Table 5.1, the null hypothesis of stationarity is not rejected for all series. It is, however, rejected for the series of CSAD, and log trading volume. The test statistic for investor sentiment index, for example, is 0.064170, which is less than the critical value at the 1% significance level, which is 0.216000. Similarly, this rule is applicable to the remaining stationary variables. The test statistic for non-stationary variables, which are CSAD and log trading volume, are 0.312316 and 0.281085, which are greater than the critical value at the 1% significance level, which is 0.216000. The two non-stationary variables are treated using the first difference. Based on the findings shown in Table 5.1, the null of stationarity is not rejected for these two series after taking the first difference. The test statistic for the first differences for CSAD and log trading volume are 0.016120 and 0.119702, which are less than the critical value at the 1% significance level, which is 0.216000. This means that the two variables are transformed to be stationary variables.

Table 1: Unit Root (KPSS) Test

Series to be Tested	**1% Critical Value**	**Exogenous Regressors Assumptions**	
		Constant, Linear Trend	
		KPSS Statistic	**Band Width (Newey-West automatic) using Bartlett kernel**
Before Differencing			
Investor Sentiment Index	0.216000	0.064170	5
Investor Herding Behavior Measure (CSAD)	0.216000	0.312316	9
Stock Market Liquidity Measures:			
1. Log Trading Volume	0.216000	0.281085	9
2. Log Market Capitalization	0.216000	0.169353	10
3. The Bid-Ask Spread	0.216000	0.065862	7
Stock Market Liquidity Control Variables Measures:			
1. Market Volatility	0.216000	0.031846	7
2. The Excess Market Return	0.216000	0.074018	6
3. Term Spread	0.216000	0.095998	10
After Differencing (First Difference)			
Investor Herding Behavior Measure (CSAD)	0.216000	0.016120	4
Stock Market Liquidity Measure (Log Trading Volume)	0.216000	0.119702	47

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5.3 STATISTICAL DESCRIPTION OF RESEARCH VARIABLES AND CORRELATION MATRIX

The sample covers the period from 2004 through 2018. The independent variable examined is investor sentiment measured by an index built by using four sentiment measures by using first principal component analysis. These four measures are closed-end mutual fund discount index, equity open-end mutual fund flows index, retail trades index, and risk appetite index. The dependent variable is stock market liquidity, which is measured by trading volume, market capitalization, and the bid-ask spread. The mediator variable is investor herding behavior evaluated by CSAD. The control variables examined are market volatility, the excess market return, and term spread, and the lag of dependent variable. All measures are calculated each month. In Table 5.2, the researcher presents describing the research variables of interest.

Delving into the descriptive statistics in Panel A of Table 5.2, for investor sentiment index as a measure of the independent variable, the mean is -15.86, its median is -73.04987, its standard deviation is 71.84088, its minimum is -80.34314, and finally its maximum is 82.59585. For stock market liquidity variable's measures, the mean of 1st. difference log trading volume is 0.00951, its median is 0.00602, its standard deviation is 1.03664, its minimum is -9.86012, and finally its maximum is 9.46533. Additionally, the mean of log market capitalization is 11.66017 Egyptian pounds, its median is 11.65605 Egyptian pounds, its standard deviation is 0.16351 Egyptian pounds, its minimum is 11.22361 Egyptian pounds, and finally its maximum is 12.00270 Egyptian pounds. Also, for the bid-ask spread, the mean is -64.54151 Egyptian pounds, its median is -102.05 Egyptian pounds, its standard deviation is 660.94759 Egyptian pounds, its minimum is -3055.13 Egyptian pounds, and finally its maximum is 2342.91 Egyptian pounds. For the mediator variable is investor herding behavior measured by 1st. difference CSAD, the mean of 1st. difference CSAD is 0.00001%, its median is 0.00006%, its standard deviation is 0.0016%, its minimum is -0.00537%, and finally its maximum is 0.00896%. For control variables' measures, the market volatility ranges between 0.0005% and 0.03523%, its mean is 0.01004%, its median is 0.00896%, and finally its standard deviation is 0.00464%. The maximum of the excess market return is 0.2957%, its minimum is -0.35443%, its mean is -0.09718%, its median is -0.09683%, and finally its standard deviation is 0.10745%. The maximum of term spread is 0.11893%, its minimum is -0.0972%, its mean is 0.00385%, its median is 0.0086%, and finally its standard deviation is 0.046%.

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Table 4: Describing Research Variables
Panel A: Descriptive Statistics

		Investor Sentiment Index	1st. Diff. CSAD	Lag 1st. Diff. CSAD	1st. Diff. Log Trading Volume	Log Market Capitalization	The Bid-Ask Spread	Market Volatility	The Excess Market Return	Term Spread	Lag 1st. Diff Log Trading Volume	Lag Log Market Capitalization	Lag the Bid-Ask Spread
N	**Valid**	180	179	178	179	180	179	179	179	179	178	179	178
	Missing	1	2	3	2	1	2	2	2	2	3	2	3
Mean		-15.86000	0.00001	0.00001	0.00951	11.66017	-64.54000	0.01004	-0.09718	0.00385	0.01037	11.65897	-66.42000
Median		-73.05000	0.00006	0.00006	0.00602	11.65605	-102.05000	0.00896	-0.09683	0.00860	0.00662	11.65588	-102.65000
Std. Deviation		71.84000	0.00160	0.00161	1.03664	0.16351	660.95000	0.00464	0.10745	0.04600	1.03950	0.16317	662.33000
Minimum		-80.34000	-0.00537	-0.00537	-9.86012	11.22361	-3055.13000	0.00050	-0.35443	-0.09720	-9.86012	11.22361	-3055.13000
Maximum		82.60000	0.00896	0.00896	9.46533	12.00270	2342.91000	0.03523	0.29570	0.11893	9.46533	12.00270	2342.91000

Panel A shows descriptive statistics of research variables. The independent variable examined is investor sentiment measured by an index built by using four sentiment measures by using first principal component analysis. These four measures are closed-end mutual fund discount index, equity open-end mutual fund flows index, retail trades index, and risk appetite index. The dependent variable is stock market liquidity which is measured by 1st. diff. log trading volume, log market capitalization, and the bid-ask spread. The mediator variable is investor herding behavior measured by 1st. diff. CSAD. The control variables examined are market volatility, the excess market return, and term spread, and the lag of dependent variable.

Panel B shows correlation matrix of research variables. The independent variable examined is investor sentiment measured by an index built by using four sentiment measures by using first principal component analysis. These four measures are closed-end mutual fund discount index, equity open-end mutual fund flows index, retail trades index, and risk appetite index. The dependent variable is stock market liquidity which is measured by 1st. diff. log trading volume, log market capitalization, and the bid-ask spread. The mediator variable is investor herding behavior measured by 1st. diff. CSAD. The control variables examined are market volatility, the excess market return, and term spread, and the lag of dependent variable.

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Table 4: Describing Research Variables (Continued)
Panel B: The Contemporaneous Bivariate Correlation Matrix

	Investor Sentiment Index	***1st. Diff. CSAD***	***Lag 1st. Diff. CSAD***	***1st. Diff. Log Trading Volume***	***Log Market Capitalization***	***The Bid-Ask Spread***	***Market Volatility***	***The Excess Market Return***	***Term Spread***	***Lag 1st. Diff Log Trading Volume***	***Lag Log Market Capitalization***	***Lag the Bid-Ask Spread***
Investor Sentiment Index	1											
1st. Diff. CSAD	-0.12266	1										
Lag 1st. Diff. CSAD	-0.00564	0.4838	1									
1st. Diff. Log Trading Volume	0.052847	-0.197738	-0.13764	1								
Log Market Capitalization	0.00293	-0.01422	-0.00651	0.00423	1							
The Bid-Ask Spread	0.07738	-0.12547	-0.03259	0.09432	0.01023	1						
Market Volatility	0.002749	-0.074075	0.01186	0.20015	0.22006	0.30105	1					
The Excess Market Return	-0.39066	0.02066	0.053152	-0.04282	-0.09773	-0.023041	-0.013447	1				
Term Spread	-0.081581	0.000962	0.033321	-0.000331	-0.20234	-0.037272	-0.111583	0.42382	1			
Lag 1st. Diff Log Trading Volume	-0.000003	0.10422	-0.19759	0.48748	0.00636	0.043603	0.13869	-0.01258	-0.01090	1		
Lag Log Market Capitalization	-0.03172	0.03458	-0.01264	0.01321	0.78156	0.147542	0.13999	-0.0696	-0.1843	-0.00314	1	
Lag the Bid-Ask Spread	-0.081712	0.047819	-0.12492	0.17734	0.04525	0.143217	0.21230	-0.06118	-0.05668	-0.09359	-0.01404	1

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Panel B of Table 4.2 illustrates the contemporary bivariate correlations between each two variables employed in the analysis. First, the correlations between research variables are less than 0.80 which means that that there are no multicollinearities between variables. There is a positive relationship between investor sentiment index and stock market liquidity measures ([9] and [11]). There is a negative relationship between investor sentiment index and investor herding behavior measure, namely 1st difference CSAD [55]. There is a negative relationship between investor herding behavior measures, namely 1st difference CSAD, and stock market liquidity..

For control variables, there is a positive relationship between stock market liquidity measures and market volatility [56]. There is a negative correlation between stock market liquidity measures and the excess return on the market [5]. There is negative relationship between term spread and stock market liquidity measures [88].

5.4 The Impact of Investor Sentiment and Investor Herding Behavior on Stock Market Liquidity: -

The researcher uses the "Structural Equation Modeling (SEM)" statistical technique to test the two hypotheses of this research. The independent variable examined in this empirical study is investor sentiment measured by an index built by using four sentiment measures by using first principal component analysis. These four measures are closed-end mutual fund discount index, equity open-end mutual fund flows index, retail trades index, and risk appetite index. The dependent variable is stock market liquidity, which is measured by three measures, namely the trading volume, market capitalization, and the bid-ask spread. The mediator variable is investor herding behavior measured by CSAD. The control variables examined are market volatility, the excess market return, and term spread, and the lag of dependent variable.

The results on the predictive content of investor sentiment index for stock market liquidity variable's measure which is the bid-ask spread, with the consideration of CSAD as investor herding behavior variable's measure can be visualized using an "event study." Considering that the suitable events are the September 2008 global financial crisis, 25 January 2011 Revolution, 30 June 2013 Revolution, and November 2016 Egyptian Pound Floatation.

5.4.1 STRUCTURAL EQUATION MODELING (SEM)

Depending on the previous illustration through the first four chapters of the research, the empirical model exploited in it has two main characteristics. First, there are three outcome measures in the model. These measures are for the dependent stock market liquidity variable. They are the 1st. difference log trading volume, log market capitalization, and the bid-ask spread. Second, there are observed and unobserved variables simultaneously in the model. This research investigates the direct impact of investor sentiment on stock market liquidity. The independent investor sentiment variable is measured by an index built by using four sentiment indicators by using first principal component analysis. These four indicators are closed-end mutual fund discount index, equity open-end mutual fund flows index, retail trades index, and risk appetite index. Additionally, this impact can be examined indirectly through a mediator variable which is investor herding behavior measured by 1st. difference CSAD. The control variables examined are market volatility, the excess market return, and term spread, and the lag of dependent variable.

Structural Equation Modeling (SEM) is the second generation of data analysis techniques, which can be thought of as the generalization, integration, and expansion of familiar techniques such as analysis of variance (ANOVA), multiple regression analysis, and factor analysis. SEM enables researchers to answer a set of interrelated research questions in a single, systematic, and comprehensive analysis by simultaneously modeling the relationships between multiple independent and dependent structures. It allows researchers to simultaneously estimate the relationship between observed and unobserved variables and the relationship between unobserved variables. In addition, it allows researchers to include continuous and categorical observational variables and latent variables. Taking into account the main characteristics of the conceptual model, SEM is selected as the main statistical method to test the empirical model.

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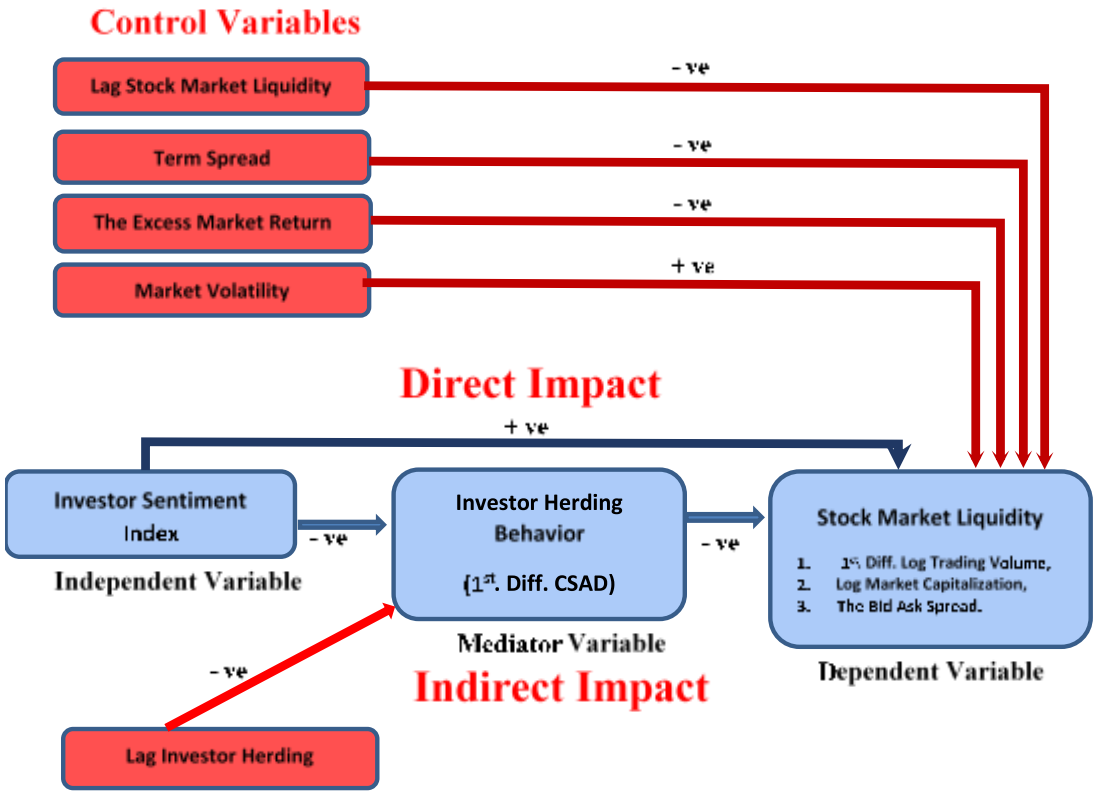
Figure 5.1 shows the main empirical SEM model used to test the two hypotheses of this research, as shown below:



(**Figure 1**: The General Empirical SEM Model)

Depending upon the previous Figure 1 and the statistical outputs in tables 1 and 2, the researcher accepts the two hypotheses of the direct impact of investor sentiment on stock market liquidity and the indirect one through investor herding behavior. The direct impact can be demonstrated using the first model built up using 1st. Diff. Log Trading Volume as the stock market liquidity dependent variable. Looking at this model, the p-value from the investor sentiment index independent variable to stock market liquidity variable is significant. On the other side, the indirect impact can be demonstrated using the three models. Looking at these models, the p-value from the investor sentiment index independent variable to the investor herding behavior mediating variable or from the investor herding behavior mediating variable to stock market liquidity dependent variable are significant. These two results are built upon using 1%, 5%, and 10% significance levels, respectively considering the signs of betas as previously illustrated in Panel B of correlation matrix in table 5.2.

Thus, the researcher accepts the two hypotheses of the direct and the indirect impacts. The type of mediation here is called a "partial mediation" since the direct impact is still significant after the mediator entered the model [59]. Thus, investor sentiment index has a direct impact on stock market liquidity and an indirect one through the mediator variable investor herding behavior.

Table 1: SEM Results

Variables	**Dependent Variable**	**Direct Effect**	**Indirect Effect**	**Total Effect**
Investor Sentiment Index		-.126	.014	-0.112
1st. Diff.		.115	0	.115

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CSAD	**1st. Diff. Log Trading Volume**			
Market Volatility		.053	0	.053
The Excess Market Return		-.396	0	-.396
Term Spread		.291	0	.291
Lag 1st. diff. Log Trading Volume		-.455	0	-.455
Lag 1st. Diff. CSAD		0	-.056	-.056
Investor Sentiment Index	**Log Market Capitalization**	.016	.003	.019
1st. Diff. CSAD		.022	0	.022
Market Volatility		-.070	0	-.070
The Excess Market Return		.006	0	.006
Term Spread		-.010	0	-.010
Lag Log Market Capitalization		.981	0	.981
Lag 1st. Diff. CSAD		0	-.011	-.011
Investor Sentiment Index	**The Bid-Ask Spread**	-.081	-.018	-.099
1st. Diff. CSAD		-.145	0	-.145
Market Volatility		.290	0	.290
The Excess Market Return		-.029	0	-.029
Term Spread		.018	0	.018
Lag the Bid-Ask Spread		.102	0	.102
Lag 1st. Diff. CSAD		0	.071	.071

Table 2: Regression Weights

Variable	Dependent Variable	P	Standardized Beta
Panel A: 1st. Diff. Log Trading Volume			
Investor Sentiment Index	**1st. Diff. CSAD**	0.060	-0.122
Lag 1st. Diff. CSAD		***	-0.487
Investor Sentiment		0.021	0.126

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Index	**1st. Diff. Log Trading Volume**		
1st. Diff. CSAD		0.036	-0.115
Market Volatility		0.332	0.053
The Excess Market Return		***	-0.396
Term Spread		***	-0.291
Lag 1st. diff. Log Trading Volume		***	-0.455
Panel B: Log Market Capitalization			
Investor Sentiment Index	**1st. Diff. CSAD**	.060	-.122
Lag 1st. Diff. CSAD		***	-.487
Investor Sentiment Index	**Log Market Capitalization**	.197	.017
1st. Diff. CSAD		.092	-.022
Market Volatility		***	.068
The Excess Market Return		.641	-.006
Term Spread		.426	-.011
Lag Log Market Capitalization		***	-.982
Panel C: The Bid-Ask Spread			
Investor Sentiment Index	**1st. Diff. CSAD**	.061	-.122
Lag 1st. Diff. CSAD		***	-.487
Investor Sentiment Index	**The Bid-Ask Spread**	.252	.081
1st. Diff. CSAD		.041	-.145
Market Volatility		***	.290
The Excess Market Return		.676	-.029
Term Spread		.792	-.018
Lag the Bid-Ask Spread		.146	-.102

Given that there are too many fitting indices, it becomes tempting to decide which fit indices represent the best fit (see Table 3 for a summary of some of the key indexes shown here). This should be avoided at all costs, as it is basically all about removing the necessary information under the carpet. In the over examination, it was found that the most important fitting indices frequently reported were CFI, GFI, NFI and NNFI. When deciding which indeics to report, it is inherently not a wise good practice to stick to frequently used metrics, as some of these statistics (such as the GFI mentioned above) are usually used strictly for

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historical reasons rather than complexity. Although there are no empirical rules to assess the fit of the model, it is important to report various indicators. This is because different indices reflect different aspects of model fitting. Although the Chi Square model has several related problems, the statistics and their degrees of freedom and related p values are still important and can be reported at any time. Researchers recently evaluated the threshold level, and they recommended a double exponential representation format. This always includes SRMR with NNFI (TLI), RMSEA or CFI. The various combinations are summarized in Table 4 below.

Table 5 below shows the fit indicators of the SEM model. The results of the chi square test show the bivariate correlation between the predictor variables and the liquidity of the stock market. It was found that the correlation between all predictors and stock market liquidity was negligible ($p<0.05$). The chi square test results shown in Table 5 do not confirm that the model is consistent with the observed data. The level of discovery probability is negligible ($p<0.05$). In order to verify these results and recognize the weakness of the chi square test statistic established above, an additional and more robust test was applied using an additional goodness of fit indicators. All other indicators in Table 5 below confirm that all the sample data fit the model significantly. Only the Root Mean Squared Error Approximation (RMSEA) showed a poor fit of the model. However, since most of the indices confirmed a good fit of the model, the results of the RMSEA index were discarded. The bottom line is that the model is adequate for the data being tested.

Table 3: Fit Indices and their Acceptable Thresholds

Fit Index	Acceptable Threshold Levels	Description
Absolute Fit Indices		
Chi-Square $\chi 2$	Low $\chi 2$ relative to degrees of freedom with an insignificant p value ($p > 0.05$)	
Relative $\chi 2$ ($\chi 2$/df)	2:1 3:1 5:2	Adjusts for sample size.
RMSEA	Values less than 0.07	Has a known distribution. Favors parsimony. Values less than 0.03 represent excellent fit.
GFI	Values greater than 0.95	Scaled between 0 and 1, with higher values indicating better model fit. This statistic should be used with caution.
AGFI	Values greater than 0.95	Adjusts the GFI based on the number of parameters in the model. Values can fall outside the 0-1.0 range.
RMR	Good models have small RMR	Residual based. The average squared differences between the residuals of the sample covariances and the residuals of the estimated covariances. Unstandardized.
SRMR	SRMR less than 0.08	Standardized version of the RMR. Easier to interpret due to its standardized nature.
Incremental Fit Indices		
NFI	Values greater than 0.95	Assesses fit relative to a baseline model which assumes no covariances between the observed variables. Has a tendency to overestimate fit in small samples.
NNFI (TLI)	Values greater than 0.95	Non-normed, values can fall outside the 0-1 range. Favors parsimony. Performs well in simulation studies.
CFI	Values greater than 0.95	Normed, 0-1 range.

Source: [60]

Table 4: [60]'sTwo-Index Presentation Strategy (1999)

Fit Index Combination	Combinational Rules
NNFI (TLI) and SRMR	NNFI of 0.96 or higher and an SRMR of .09 or lower

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RMSEA and SRMR	RMSEA of 0.06 or lower and a SRMR of 0.09 or lower
CFI and SRMR	CFI of .96 or higher and a SRMR of 0.09 or lower

Source: [60]

Table 5: SEM Model Fit Indices

Fit Index ***Absolute Fit Indices***	**Output**	**Remark**	**Output**	**Remark**	**Output**	**Remark**
	1st. Diff. Log Trading Volume		**Log Market Capitalization**		**The Bid-Ask Spread**	
Absolute Fit Indices						
Chi-Square $\chi 2$ p > 0.05	95.239 P=0.000	Reject	82.94 P=0.000	Reject	82.34 P=0.000	Reject
Relative $\chi 2$ ($\chi 2$/df)	4.762	Accept	4.147	Accept	4.117	Accept
RMSEA	.145	Reject	.152	Reject	.151	Reject
GFI	No report with missing value	-----	No report with missing value	-----	No report with missing value	-----
AGFI	No report with missing value	-----	No report with missing value	-----	No report with missing value	-----
RMR	No report with missing value	-----	No report with missing value	-----	No report with missing value	-----
SRMR	No report with missing value	-----	No report with missing value	-----	No report with missing value	-----
Incremental Fit Indices						
NFI	.965	Accept	.955	Accept	.982	Accept
NNFI (TLI)	.992	Accept	.995	Accept	.951	Accept
CFI	.953	Accept	.986	Accept	.976	Accept
Parsimony Fit Indices						
PNFI	.525	Accept	.681	Accept	.534	Accept

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5.5 EVENT STUDY

The first most and vital goal of the event study analysis is determining the research event. In addition, the time of changes, which may emerge because of the event, should be decided. Using global, economic, and political events such as crisis, revolutions, and nation's currency floatation. as examples, firstly, the suitable event should be selected, Then, the research time period of the event study before and after the event should be fixed, e.g. 12 months. The results on the predictive content of investor sentiment index for stock market liquidity variable's measure which is trading volume in direct impact, considering CSAD as investor herding behavior variable's measure in indirect impact, can be visualized using an "event study." The suitable events are the September 2008 global financial crisis, 25 January 2011 Revolution, 30 June 2013 Revolution, November 2016 Egyptian Pound Floatation. The reason for choosing trading volume as stock market liquidity indicator in the event study, excluding market capitalization and the bid-ask spread liquidity measures, is because that this is the only measure which confirmed the acceptance of the two hypotheses of the study; e.g. direct and indirect impacts in path analysis.

Figure 2: Event Study Plots

Panel A: The September 2008 Global Financial Crisis Event

Panel B: 25 January 2011 Revolution Event

Panel C: 30 June 2013 Revolution Event

Panel D: November 2016 Egyptian Pound Floatation Event

The event study time period could be chosen as illustrated in table 6. The researcher takes each event individually to be the "event date," and plots the development of many significant series of concern around this date. In Figure 5.3 panels, he plots changes in the sentiment index, CSAD, as an investor herding behavior measure, and trading volume, as a liquidity measure, to the onset of each event. He first calculates the sentiment index starting twelve months before (t = -12M) the event and ending twelve months after the end of the event (t = 12M). Next, he averages the sentiment index for each month across the event, and he accumulates the average sentiment index over the event windows. He then does the same for CSAD, as an investor herding behavior measure, and trading volume, as an indicator for stock market liquidity. Thus, figure 5.3 shows the average patterns in investor sentiment, CSAD, as an investor herding behavior indicator, and trading volume stock market liquidity measure before, during, and after the event period.

Table 6: Event Study Time-Series Data

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Panel A: The September 2008 Global Financial Crisis Event

Year	Month	Investor Sentiment Index	CSAD	Trading Volume
	2007-09	-73.25960763	0.270364	9.362400015
	2007-10	-73.01478694	0.283536	9.364064741
	2007-11	-72.82150456	0.216157	9.868105444
	2007-12	73.53507109	0.246427	9.673488303
2008	2008-01	73.73467867	0.314044	9.615944729
	2008-02	-71.71008017	0.41056	9.620294594
	2008-03	-74.23204365	0.345153	9.774685784
	2008-04	73.40257843	0.290101	9.726147133
	2008-05	-73.77411066	0.337285	9.775053016
	2008-06	-72.61275641	0.378341	9.616870886
	2008-07	69.81121183	0.4812	9.504509136
	2008-08	-74.85978966	0.289065	9.490859673
	2008-09	73.52791222	0.344138	9.75834088
	2008-10	-74.47063725	0.53636	9.468657599
	2008-11	74.29310316	0.296856	9.670649653
	2008-12	74.50940098	0.240835	9.604375715
2009	2009-01	77.95241651	0.258134	9.542559165
	2009-02	72.96379563	0.219892	9.600302978
	2009-03	73.56919975	0.454516	9.842098537
	2009-04	72.06794019	0.555512	9.963227073
	2009-05	-74.66221365	0.327039	9.966436326
	2009-06	73.67021139	0.35878	10.00972058
	2009-07	-72.29577835	0.235895	9.725164313
	2009-08	-72.59928469	0.313034	9.782141662
	2009-09	72.84316625	0.239947	9.821597842

Panel B: 25 January 2011 Revolution Event

Year	Month	Investor Sentiment Index	CSAD	Trading Volume
2010	2010-01	-76.71206786	0.320324	9.71691736
	2010-02	74.4440613	0.443189	9.688833881
	2010-03	-74.04180289	0.223269	9.740294827
	2010-04	-73.16138289	0.251765	10.00641725
	2010-05	74.34336251	0.237277	9.88121057
	2010-06	-72.88389561	0.228033	10.05108436
	2010-07	73.26818776	0.39544	9.793919777
	2010-08	-73.34022421	0.186125	9.793866891
	2010-09	73.99469494	0.363889	9.913027499
	2010-10	-72.84754462	0.208597	9.941613492
	2010-11	73.76703865	0.18964	9.908198108
	2010-12	73.62538456	0.281849	9.837707945
2011	2011-01	-72.74884124	0.390351	9.86012268
	2011-02	0	0	0
	2011-03	73.40085779	0.310669	9.465329837
	2011-04	74.75950086	0.233575	9.625794652
	2011-05	-74.88386677	0.247811	9.829511291
	2011-06	-73.68061631	0.2007	9.969006831
	2011-07	-73.10945678	0.30951	9.74181714
	2011-08	-73.9447918	0.251126	9.667509902
	2011-09	-73.51621857	0.605675	9.659036022
	2011-10	73.1759957	0.192679	9.627438181
	2011-11	-74.04225204	0.177158	9.522415551
	2011-12	73.38613905	0.313439	9.531073569
2012	2012-01	73.31980225	0.264986	9.714276435

Panel C: 30 June 2013 Revolution Event

Year	Month	Investor Sentiment Index	CSAD	Trading Volume
	2012-06	-73.6340755	0.228595	9.711085781
	2012-07	-73.23005273	0.288318	10.00175246
	2012-08	-73.40213577	0.299465	10.00897592
	2012-09	-78.96063502	0.450748	10.1826382
	2012-10	-67.14814607	0.331531	9.997266003
	2012-11	-79.66804414	0.361336	9.896207458
	2012-12	-67.80624084	0.285128	9.917217439
2013	2013-01	-73.17851798	0.187149	9.856322799
	2013-02	73.45538903	0.245626	9.840314062
	2013-03	-79.25297365	0.3092	9.847723693
	2013-04	-73.39998761	0.185249	9.742899828
	2013-05	73.40489053	0.205887	9.577585299
	2013-06	-73.40063068	0.463904	9.690381548
	2013-07	-73.39978966	0.442556	9.845053408
	2013-08	-73.39193563	0.224836	9.722975963
	2013-09	73.40015936	0.441901	9.959337693
	2013-10	73.40120278	0.219082	9.921522244
	2013-11	-73.40003897	0.193362	10.08564164
	2013-12	73.40038317	0.204695	10.01552682
2014	2014-01	-73.40776663	0.319658	10.24073597
	2014-02	-73.39967663	0.270155	10.23735245
	2014-03	73.29001437	0.26531	10.32393502
	2014-04	-73.43844581	0.295729	10.16013655
	2014-05	73.39991826	0.357446	10.2122019
	2014-06	-73.39193622	0.20297	10.22853557

Panel D: November 2016 Egyptian Pound

Year	Month	Investor Sentiment Index	CSAD	Trading Volume
	2015-11	73.39927014	0.409528	10.3747066
	2015-12	-73.37520247	0.324564	10.37751239
2016	2016-01	-73.4010525	0.407845	10.29062709
	2016-02	73.40006923	0.257034	10.19981067
	2016-03	73.40159901	0.363811	10.55513781
	2016-04	-73.39983273	0.29377	10.33239349
	2016-05	73.39980317	0.250432	10.1997769
	2016-06	73.40767212	0.268807	10.09435256
	2016-07	73.40049681	0.284784	10.18768507
	2016-08	-73.39995117	0.252141	10.36115213
	2016-09	-73.3837003	0.244171	9.913902659
	2016-10	73.40025538	0.279971	10.21641566
	2016-11	73.40037488	1.176427	10.71429262
	2016-12	73.40917553	0.639033	10.58609089
2017	2017-01	-73.39995034	0.553668	10.60080372
	2017-02	74.28923664	0.447195	10.36010366
	2017-03	73.40610346	0.800353	10.37589297
	2017-04	-72.62632626	0.488341	10.19727274
	2017-05	-73.39967575	0.494301	10.46985005
	2017-06	73.40975316	0.638303	10.27767333
	2017-07	-73.40000362	0.797035	10.40992201
	2017-08	-73.40634958	0.482987	10.28823666
	2017-09	-73.4013742	0.567943	10.49714069
	2017-10	-73.40235314	0.592743	10.57996539
	2017-11	-73.38335292	0.628547	10.45263876

Table 6 indicates event study time-series data. For Panel A, which demonstrates the September 2008 Global Financial Crisis event, through pre-event period, a fall in investor sentiment (-74.85978966) is followed by a fall in stock market liquidity measure, namely trading volume (9.490859673) for the direct impact. Also, a fall in sentiment index can be viewed to decrease investor herding behavior measure, namely CSAD (0.28906468) as a result of investor fear from herding because of the indicator of crisis which is the fall in sentiment. This is

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followed by a decrease within stock market liquidity measure, namely trading volume for the indirect impact. During the event period, the increase in investor sentiment index (73.52791222) is followed by a rise in liquidity measure, namely trading volume (9.75834088) for the direct impact. Also, this fall in sentiment index can be viewed to increase investor herding behavior measure, namely CSAD (0.344138081) that is followed by a rise in liquidity. The unusual rise in liquidity is a result of a phenomenon which is called flight-to-quality, or simply flight-to-liquidity. This basically states that investors aim to change their portfolio towards less risky and more liquid assets in stressed market scenarios [124]. Thus, high liquidity moves the event to the normal post-event period with a fall in investor sentiment index (-74.47063725), a rise in CSAD (0.536359535), and a fall in liquidity (9.468657599).

For Panel B, which demonstrates 25 January 2011 Revolution event, through pre-event period, a fall in investor sentiment (73.62538456) is followed by a fall in stock market liquidity measure, namely trading volume (9.837707945) for the direct impact. Also, a fall in sentiment index can be viewed to increase investor herding behavior measure, namely CSAD (0.281849481) that is followed by a decrease within stock market liquidity measure, namely trading volume for the indirect impact. During the event period, the fall in investor sentiment index (-72.74884124) is followed by a rise in liquidity measure, namely trading volume (9.86012268) for the direct impact. Also, this fall in sentiment index can be viewed to increase investor herding behavior measure, namely CSAD (0.390350662) that is followed by a rise in liquidity. The rise in liquidity is a result of a phenomenon which is called flight-to-quality, or simply flight-to-liquidity. This basically states that investors tend to shift their portfolio towards less risky and more liquid assets in stressed market scenarios [124]. Thus, high liquidity moves the event to the normal post-event period taking into consideration that the Egyptian Stock Market was closed in the first month (February 2011) after the revolution. After that, the three measures rise; the rise of herding is a result of the investors' well to compensate their losses in the previous two months.

According to Panel C, which demonstrates 30 June 2013 Revolution event, through pre-event period, a rise in investor sentiment (73.40489053) is followed by an unusual fall in stock market liquidity measure, namely trading volume (9.577585299) for the direct impact. Also, a rise in sentiment index can be viewed to show unusual increase investor herding behavior measure, namely CSAD (0.205886834), which is followed by an unusual fall in stock market liquidity measure, namely trading volume for the indirect impact. These two unusual signs which show an increase in herding and a decrease in liquidity may be attributed to the political conditions in this period, the revolution to free from the Islamic Brotherhood administration phase. During the event period, the fall in investor sentiment index (-73.40063068) is followed by a rise in liquidity measure, namely trading volume (9.690381548) for the direct impact. Also, this fall in sentiment index can be viewed to increase investor herding behavior measure, namely CSAD (0.463903538) which is followed by a rise in liquidity. The rise in liquidity is a result of a phenomenon which is called flight-to-quality, or simply flight-to-liquidity. This basically states that investors tend to shift their portfolio towards less risky and more liquid assets in stressed market scenarios. Thus, high liquidity moves the event to the normal post-event period where an increase in sentiment (-73.39978966) is followed by a decrease in herding (0.442556085) and a rise in liquidity (9.845053408).

For Panel D, which demonstrates November 2016 Egyptian Pound Floatation event, through pre-event period, a rise in investor sentiment (73.40025538) is followed by a rise in stock market liquidity measure, namely trading volume (10.21641566) for the direct impact. Also, a rise in sentiment index can be viewed to increase investor herding behavior measure in usual manner, namely CSAD (0.279970503), which is followed by a rise within stock market liquidity measure, namely trading volume for the indirect impact. This unusual increase in herding is because of fear from floatation decision application's consequences. The investors tend to herd to achieve the maximum possible gains before floatation. During the event period, the rise in investor sentiment index (73.40037488) is followed by a rise in liquidity measure, namely trading volume (10.71429262) for the direct impact. Also, this rise in sentiment index can be viewed to cause an unusual massive increase in investor herding behavior measure, namely CSAD (1.176427261), which is followed by a rise in liquidity. This is because this is the first time that the Central Bank of Egypt (CBE) has allowed banks to determine the purchase and sale price of Egyptian pounds based on the relationship between supply and demand without the intervention of CBE, thus eliminating the black market. In addition, the Egyptian government began to implement the value added tax and increase fuel prices, with the aim of restructuring the general public budget and reducing energy subsidies. High liquidity moves the event to the post-event period with an increase in

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sentiment which is followed by a normal fall in herding (0.63903256) and an unusual decrease in liquidity (10.58609089) as a result of the Egyptian Pound Floatation and the noticeable change in exchange rates.

Table 7 shows the contemporaneous bivariate correlations between pre and post investor sentiment index, CSAD, and trading volume, as follows:

Table 7: The Contemporaneous Bivariate Correlations between Pre and Post Investor Sentiment index, CSAD, and Trading Volume

Panel A: The September 2008 Global Financial Crisis Event

A.1 Pre

	Pre Investor Sentiment Index	*Pre CSAD*	*Pre Trading Volume*
Pre Investor Sentiment Index	1		
Pre CSAD	0.103534659	1	
Pre Trading Volume	0.067821704	-0.1436246	1

A.2 Post

	Post Investor Sentiment Index	*Post CSAD*	*Post Trading Volume*
Post Investor Sentiment Index	1		
Post CSAD	-0.114513751	1	
Post Trading Volume	0.049200994	0.22008054	1

Panel B: 25 January 2011 Revolution Event

B.1 Pre

	Pre Investor Sentiment Index	*Pre CSAD*	*Pre Trading Volume*
Pre Investor Sentiment Index	1		
Pre CSAD	0.502144549	1	
Pre Trading Volume	-0.16577189	-0.4618209	1

B.2 Post

	Post Investor Sentiment Index	*Post CSAD*	*Post Trading Volume*
Post Investor Sentiment Index	1		
Post CSAD	-0.142450729	1	
Post Trading Volume	-0.051527329	0.58343767	1

Panel C: 30 June 2013 Revolution Event

C.1 Pre

	Pre Investor Sentiment Index	*Pre CSAD*	*Pre Trading Volume*
Pre Investor Sentiment Index	1		
Pre CSAD	-0.35849498	1	
Pre Trading Volume	-0.507962335	0.800536257	1

C.2 Post

	Post Investor Sentiment Index	*Post CSAD*	*Post Trading Volume*
Post Investor Sentiment Index	1		
Post CSAD	0.111868989	1	
Post Trading Volume	0.033357498	-	1

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		0.1248686	

Panel D: November 2016 Egyptian Pound Floatation Event

D.1 Pre

	Pre Investor Sentiment Index	*Pre CSAD*	*Pre Trading Volume*
Pre Investor Sentiment Index	1		
Pre CSAD	-0.021023394	1	
Pre Trading Volume	0.018963322	0.599052478	1

D.2 Post

	Post Investor Sentiment Index	*Post CSAD*	*Post Trading Volume*
Post Investor Sentiment Index	1		
Post CSAD	0.234583049	1	
Post Trading Volume	-0.141617367	0.142463886	1

Moreover, table 8 shows a Summary of the Contemporaneous Bivariate Correlations' Signs between Pre and Post Investor Sentiment index, CSAD, and Trading Volume:

Table 8: Summary of the Contemporaneous Bivariate Correlations' Signs between Pre and Post Investor Sentiment index, CSAD, and Trading Volume

Pre			**Post**		
Direct Impact	**Indirect Impact**		**Direct Impact**	**Indirect Impact**	
Sentiment-Liquidity	**Sentiment-Herding**	**Herding-Liquidity**	**Sentiment-Liquidity**	**Sentiment-Herding**	**Herding-Liquidity**
Panel A: The September 2008 Global Financial Crisis Event					
+ve	+ve	-ve	+ve	-ve	+ve
Panel B: 25 January 2011 Revolution Event					
-ve	+ve	-ve	-ve	-ve	+ve
Panel C: 30 June 2013 Revolution Event					
-ve	-ve	+ve	+ve	+ve	-ve
Panel D: November 2016 Egyptian Pound Floatation Event					
+ve	-ve	+ve	-ve	+ve	+ve

From Table 7 and 8, According to Panel A, regarding the direct impact, there is a normal positive correlation (0.067821704) between pre investor sentiment index and pre liquidity. Regarding the indirect impact, there is an unusual positive correlation (0.103534659) between pre investor sentiment index and pre CSAD. Moreover, there is a normal negative correlation (-0.143624659) between pre CSAD and pre liquidity. On the other hand, regarding the direct impact, there is a normal positive correlation (0.049200994) between post investor sentiment index and post liquidity. Regarding the indirect impact, there is a normal negative correlation (-0.114513751) between post investor sentiment index and post CSAD. Moreover, there is an unusual positive correlation (0.22008054) between post CSAD and post liquidity. For the pre time-series unusual correlations result, exactly for the indirect impact, it can be attributed to the various economic conditions that led to the financial crisis. High sentiment leads to high herding which consequently decrease liquidity and vice versa. This is logical because optimistic investors push the rest investors to herd, but liquidity on the other side decrease causing the financial crisis. For post time-series unusual correlation result, regarding the indirect impact,

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pessimistic investors herd more and imitate other successful investors in the market which increases CSAD which forces liquidity to increase and be stable because of its positive correlation with herding. According to Panel B, for the direct impact, there is unusual negative correlation (-0.16577189) between pre investor sentiment index and pre liquidity. For the indirect impact, there is an unusual positive correlation (0.502144549) between pre investor sentiment index and pre CSAD. Moreover, there is a normal negative correlation (-0.461820905) between pre CSAD and pre liquidity. On the other hand, for the direct impact, there is an unusual negative correlation (-0.051527329) between post investor sentiment index and post liquidity. For the indirect impact, there is a normal negative correlation (-0.142450729) between post investor sentiment index and post CSAD. Moreover, there is an unusual positive correlation (0.58343767) between post CSAD and post liquidity. Regarding the pre time-series unusual correlations results, for the direct impact, it can be attributed to the various political conditions that led to the revolution. Optimistic investors are not satisfied about their performance and profits which leads to decrease liquidity. For the indirect impact, high sentiment leads to high herding and low liquidity and vice versa. This is logical because optimistic investors push the rest investors to herd, but liquidity, on the other hand decreases leading to the revolution. Regarding post time-series unusual correlation result, for the direct impact, pessimistic investors tend to buy and sell more which increases liquidity and moves it to be stable. For the indirect impact, pessimistic investors tend to herd more because of fear from individual losses which depends on their own decisions. High herding leads to high liquidity which force liquidity to be stable.

According to Panel C, for the direct impact, there is an unusual negative correlation (-0.507962335) between pre investor sentiment index and pre liquidity. For the indirect impact, there is a normal negative correlation (-0.35849498) between pre investor sentiment index and pre CSAD. Moreover, there is unusual positive correlation (0.800536257) between pre CSAD and pre liquidity. On the other hand, for the direct impact, there is a normal positive correlation (0.033357498) between post investor sentiment index and post liquidity. For the indirect impact, there is unusual positive (0.111868989) between post investor sentiment index and post CSAD. Moreover, there is a normal negative correlation (-0.124868686) between post CSAD and post liquidity. Regarding the pre time-series unusual correlations results, for the direct impact, it can be attributed to the various political conditions that led to the revolution, especially the Islamic Brotherhood performance that represented a big fear to the investors. Optimistic investors stop buy and sell transactions in the market causing low liquidity which leads to revolution. For the indirect impact, high sentiment leads to low herding and low liquidity and vice versa. This is logical because optimistic investors push the rest investors to herd, but liquidity on the other hand, decreases causing the revolution. For post time-series unusual correlation result, especially for the indirect impact, less pessimism because of revolution leads to less herding and more liquidity which forces liquidity to be stable and moves to a new phase of loss compensation after the revolution period.

Regarding Panel D, for the direct impact, there is a normal positive correlation (0.018963322) between pre investor sentiment index and pre liquidity. For the indirect impact, there is a normal negative correlation (-0.021023394) between pre investor sentiment index and pre CSAD. Moreover, there is unusual positive correlation (0.599052478) between pre CSAD and pre liquidity. On the other hand, for the direct impact, there is unusual negative correlation (-0.141617367) between post investor sentiment index and post liquidity. Also, there is an unusual positive (0.234583049) between post investor sentiment index and post CSAD. Moreover, there is an unusual positive correlation (0.234583049) between post CSAD and post liquidity. For the pre time-series unusual correlations results, especially the indirect impact, it can be attributed to the various economic conditions that led to the floatation, especially the unstable Egyptian pound value and exchange rates. Low sentiment leads to high herding and high liquidity. This is logical because pessimistic investors tend to herd more because of fear of loss because of invalid individual decisions, and liquidity increases as unusual because of inflation effects. Regarding the abnormally related results of the post-time series, for the direct impact, the high sentiment leads to a reduction in liquidity, forcing liquidity to stabilize after the effect of inflation is corrected. Whereas for the first time, the Central Bank of Egypt (CBE) allowed banks to determine the purchase and sale of Egyptian pounds based on the forces of supply and demand. CBE does not interfere with the price to eliminate the black market. In addition, the Egyptian government began to implement the value added tax and increase fuel prices, with the aim of restructuring the public budget and reducing energy subsidies. For the

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indirect impact, taking into consideration the previous reasons, high sentiment unusually increases herding, which in turn normally decreases liquidity.

5.The Implications

The main findings of this study are expected to benefit five types of people in the Egyptian Stock Market, namely individual and institutional investors, stockbrokers, portfolio managers as well as policy makers. They are expected to benefit individual and institutional investors, as well as stockbrokers in predicting the period of heavy or light trading and the volume flow of orders. Moreover, they are expected to benefit portfolio managers in portfolios selection and the timing of buying and selling decisions. Finally, they are expected to benefit policy makers in the selection of market surveillance policy. All of these benefits are attained through proving that the Egyptian investor sentiment contains helpful direct information for evaluating the current and future conditions of the Egyptian Stock Market liquidity. Also, all of these benefits are achieved by proving that the Egyptian investor sentiment contains useful indirect information for estimating the current and future conditions of the Egyptian Stock Market liquidity through the Egyptian investor herding behavior.

6.Conclusion

The main goal of this research is to investigate the potential impact of the Egyptian investor sentiment and his/her herding behavior on the Egyptian Stock Market liquidity. This general objective can be divided into the following two specific objectives: to investigate the potential direct impact of the Egyptian investor sentiment on the Egyptian Stock Market liquidity and to investigate the potential indirect impact of the Egyptian investor sentiment on the Egyptian Stock Market liquidity through the Egyptian investor herding behavior. The major result of this paper is that the investor sentiment index has both a direct impact on stock market liquidity and an indirect one through the mediator variable investor herding behavior. Concerning event study analysis' results, there are different signs of the direct and indirect impacts and different correlation between the research variables throughout the four different events that differ completely from the usual signs and correlations of the theoretical background. This study provides a major suggestion for future research, which considers the impact of other behavioral factors, such as regret, overconfidence, and risk perception whether directly or indirectly using mediators on stock market liquidity. Additionally, this study provides several suggestions for future research not only for investor sentiment index components, but also for investor herding behavior and stock market liquidity. Firstly, the overall study can be expanded to include not only individual investors, but also the institutional investors. Secondly, investor sentiment index can be built using other variables, such as direct measures as surveys, or even other indirect measures as IPO volume (Average annual first day returns on IPOs), put-call ratio (Puts outstanding/Calls outstanding), and Price % (Gross annual equities issued/Gross annual debt & equity issued). Thirdly, investor herding behavior can be measured using CSSD as an additional measure besides CSAD, Fourthly, liquidity variables can include other additional measures for stock market liquidity, such as trading value measure (the value of the firm which equals the number of outstanding shares minus treasury shares with respect to current market price), the illiquidity ratio measure (the absolute daily return divided by daily trading volume), turnover ratio of market capitalization, or simply turnover ratio measure (the ratio of the total value traded divided by market capitalization), the Lesmond, Ogden, and Trczika (1999) measure (the difference between the percent buying cost and the percent selling cost) and The Roll (1984) implicit spread estimator (the serial covariance of successive price movements). Fifthly, the empirical study can be examined using EGX100, EGX70, or even listed firms instead of EGX30. Sixthly, the events can be expanded with the consideration of a longer time-series period to include the Coronavirus disease (COVID-19) pandemic crisis in 2020. Finally, the bidirectional effects between each two variables of research can be examined using the Granger causality test.

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