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The Power of Bad to Cause Herding Behaviour in the Market: An Empirical Analysis from Istanbul Stock Exchange

Ali Mohammed ADEM

Istanbul University, School of Business, Department of Finance, Istanbul, Turkey

ABSTRACT: The traditional Financial Economics theories argue that information plays a significant role for price formation in the market. Empirical studies in the field of Psychology and Neuroscience proved that information can be divided in to bad, good and neutral information and bad information has a strong as well as a dominant effect than positive and neutral information. Whereas, empirical studies in the field of Behavioural Finance shows that investors' psychology has a significant impact in the process of price formation. In line with these findings, the objective of this study is to examine herding behaviour of investors in Istanbul stock exchange using intraday data. The study period covers from the beginning of 2006 to the end of 2018, and the data is collected from Finnet. The empirical finding indicates that herding is more prevalent when the market return falls and it is also dominant in the first half (first session) of a trading day or in the morning than afternoon. This empirical finding shows that whether the cause of negative market return is information or non-information sources, investors herd the market consensus when the market return falls. And this finding shows the existence of an asymmetrical investors' behaviour in Istanbul stock exchange. To explain the implication of the findings I use the negativity effect theory in that negative information or event has a stronger effect than positive information or event.

KEYWORDS: herd behaviour, intraday, negativity effect, negative information, negative event

I. INTRODUCTION

The field of classical financial economics assumes that investors or decision makers are rational (Markowitz, 1952), (Friedman, 1953), (Sharpe, 1964) and (Fama, 1970). According to this field of study rational investors have unlimited processing power to any available information and holds a consistent preferences (Bloomfield, 2010). This means that they know how to interpret new information correctly and they are able to correctly estimate the probability of future events on that basis. Thus, rational decision makers evaluate different choices based on all the axioms (completeness, transitivity, continuity and independence) of expected utility theory. This approach assumes that the rational investors are so strong, dominant and influential as a group and they are able to quickly and efficiently eliminate any sign of irrationality on the part of other investor's action. Furthermore, any investor who makes irrational decisions would be punished through poor performance and/or they would learn to either make better decisions or leave the market place (Friedman, 1953). In addition, any error that market participants make are independent (not correlated) with each other and the errors do not have the power to affect market prices (Fama, 1965). Accordingly, the market will act as if all participants acted rationally (Szyszka, 2013). However, the empirical work of (Kahneman & Tversky, 1979) shows that people/investors actually deviate systematically from rationality while making decisions. And they are not perfectly rational as they are expected to be. Starting from 1980s, researchers have identified ways in which people systematically depart from optimal judgement and decision making.

For the following reasons, it is so difficult to sustain investors are fully rational: many investors react to irrelevant information as well as trade with noise as an information (Black, 1986), investors are overconfident and they buy and sell securities actively (De Bondt & Thaler, 1994), (Barber & Odean, 1999), (Odean, 1999) and (Barber & Odean, 2000), (French, 2008), (Barber & Odean, 2011), investors fail to diversify (Huberman, 2001), (Campbell, 2006), (Barber & Odean, 2011) and (Cornil, Hardisty, & Bart, 2019), investors define prospects as a gain or a loss and they are loss averter than risk averse (Kahneman & Tversky, 1979), they sell winning stock earlier and hold a losing stock for a long period (Shefrin & Statman, 1985) and (Odean, 1998), investors decision is affected by the way choices are presented (Kahneman & Tversky, 1979), investors show herding behavior and follow the market consensus (Christie & Huang, 1995), (Hirshleifer & Teoh, 2003), (Hwanga & Salmon, 2004), (Gleason, Mathurb, & Peterson, 2004), (Demirer & Kutan, 2006), (Song, Kim, & Won, 2009), (Sun & Shyu, 2010), (Holmes, Kallinterakis, & Ferreira, 2011), (Richards, 2014), (Adem, 2020) and (Adem & Sarioğlu, 2020), follow a stock price patterns (De Bondt & Thaler, 1985) and (Jegadeesh & Titman, 1993), and investors give more emphasis to negative event or information than positive information and events

(Zuckerman, 1979), (Suls & Mullen, 1981), (Peeters & Czapinski, 1990), (Taylor, 1991), (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001), (Hanson, 2013), (Tierney & Baumeister, 2019). Individuals are not the only one who are far from rationality but institutional investors' also shows irrationality (Shleifer, 2000).

Individuals thinking process does not work like a computer. Instead, the human brain often processes information using shortcuts and emotional filters. These processes influence financial decision makers such that people often act in a seemingly irrational manner, routinely violate traditional concepts of risk aversion, and make predictable errors in their forecasts (Baker & Nofsinger, 2010). One of the criticism for the classical financial economics theories is to their assumption that a decision maker would consider all relevant information and come up with the best choice. However, here we need to ask one question. How does investors make rational decisions with limited time and with huge amount of available information in a world of uncertainty and full of competition? Since too much information is difficult to deal with, people have developed shortcuts or heuristics in order to come up with reasonable decisions (Ackert & Deaves, 2010). Herding is one of the shortcut investors use to simplify complex decision making process (Adem & Sarioğlu, 2020). However, heuristics may lead to biases (Ackert & Deaves, 2010).

Thus, the main focus of this paper is to investigate, one of the irrational behaviour of investors, herding behaviour of investor in Istanbul stock exchange. To the best of my knowledge some researches were done to investigate the existence of herding behaviour during market stress periods in Istanbul stock exchange (Altay, 2008), (Doğukanlı & Ergün, 2011), (Kayalıdere, 2012), (Ergün & Doğukanlı, 2015), (Ergün & Doğukanlı, 2015) and (Özsu, 2015). The common objective of all these studies was to investigate the existence of herding behaviour when the market is in extreme stress periods. However, the empirical evidence of these studies is inconclusive. According to (Altay, 2008), (Kayalıdere, 2012) and (Doğukanlı & Ergün, 2015), there is herding behaviour towards market consensus in Istanbul stock exchange. On the other hand, (Doğukanlı & Ergün, 2011), (Ergün & Doğukanlı, 2015) and (Özsu, 2015), did not found the existence of herding behaviour in Istanbul stock exchange.

Unlike the above researchers, (Adem, 2020) and (Adem & Sarioğlu, 2020) investigated herding behaviour when the market return lies below zero (when the market return is negative) and above zero (when the market return is positive). To investigate herding behaviour in Istanbul stock exchange (Adem, 2020) and (Adem & Sarioğlu, 2020) used daily, weekly and monthly individual stock return as well as sectoral index return data for the period between January 1, 2000 and December 31, 2018. The empirical finding for both individual stock return and sectoral data shows that herding in the market is more prevalent and dominant when the market return falls below zero than when the market return rises above zero. This finding indicates that herding in Istanbul stock exchange is asymmetrical when the market rises and falls. At the same time, their empirical finding shows that herding is more dominant in the daily data than weekly and monthly data.

(Tan, Chiang, Mason, & Nelling, 2008) also investigated the existence of herding in the Chinese financial markets. Their finding shows the existence of herding in the two Chinese markets (Shangai and Shenzhen), especially in the daily data. However, they also documented the presence of herding in the weekly and monthly data but the magnitude of the coefficients is lower than the daily data coefficients.

Since the work of (Tan, Chiang, Mason, & Nelling, 2008), (Adem, 2020), and (Adem & Sarioğlu, 2020) shows herding is more prevalent in the daily data, in this study our objective is to investigate herding behaviour in Istanbul stock exchange at intraday level. Since there are a significant amount of empirical findings that shows bad information is stronger than positive information, I hypothesis that negative information and events plays a significant role for price formation as well as for herding formation than positive information and events, and when a news arrive to the market investors may see it in a binary ways i.e., a news which can help them to increase return as well as wealth or a news which can cause to lose money.

The remaining part of the paper is organized as follows. Section II gives a detail views about the role of information in a market for security price formation. Section III focus on the data and the research methodology employed. Section IV and section V deals about the empirical findings and conclusion respectively.

II. LITERATURE REVIEWS

The two parameter model shows that the price of securities is conditional on some relevant factor, i.e. the equilibrium expected return or price of a security is a function of its risk level (Fama, 1970). Thus, according to CAPM the relevant factor to determine the price of a security is the risk of an asset and the risk of an asset is divided in to systematic and non-systematic risk. Diversification enables investors to escape the risk of non-systematic risks but investors cannot avoid or reduce systematic risks. The responsiveness of an asset's expected rate of return to the level of changes in the economic activity or systematic risk is relevant in assessing its risk. So, the price of a security is proportional to the level of its systematic risk and it indicates that only the systematic risk of an asset is relevant to determine the expected return of any assets. Assets which are not affected by changes in the systematic risks will give a return equal to the pure interest rate or risk free rate. Those assets which moves with change in systematic risk will provide a higher expected rate of return. In other words, a security with a high level of risk has a high expected return in the future (Sharpe, 1964).

Even if the type or the nature of the asset determines the level of its risk (Sharpe, 1964), there is another factor that plays a significant role to cause the level of risk vary or change over time. According to (Fama, Fisher, Jensen, & Roll, 1969) and (Fama, 1970), that factor is information, and expected return or price of a security is formed based on information sets. However, for price of a security to fully reflect all available information and efficiently adjust to it, the market should fulfil the following conditions: there should not be transaction costs, all available information should be available to all market participants without cost and all market participants should agree on the implication of current information for current price and distribution of future price of each security (Fama, 1970).

A market in which prices always fully reflect the available information is called efficient market (Fama, 1970). In such like market the price of securities at any point in time fully reflect all available information. Thus, the main concern of efficient market hypothesis is whether a market or price of security at any point in time rapidly adjusts to new information (Fama, Fisher, Jensen, & Roll, 1969) and (Fama, 1970). This definition of efficient market indicates that information plays a major role for securities price formation. Here it is very important to stop and make brainstorming about the word ‘‘information’’, this is because it will help us to understand price adjustments process correctly. (Fama, 1970), in his pioneering work on efficient market hypothesis, classified information in to three subsets. These are: historical price information, all publicly available information and monopolistic or any privately accessible information relevant for price formation. According to this classification of information, (Fama, 1970) hypothesized the three level of market efficiency. A market where price of securities only adjust to historical price information is called weak form efficient market. In the weak form version of efficient markets model or random walk model, the current price of a security fully reflect available information implies successive price change are independent. On the other hand, if security prices adjust efficiently to other publicly available information, then the market is at semi strong level of market efficiency. Lastly, if security price adjusts efficiently to all available information including privately accessible information, the market is at strong level of market efficiency. Thus, the main conclusion of (Fama, 1970) was that no one can increase his/her expected returns using the three information type. Thus, while the efficient market hypothesis indicate the role of information for asset pricing, the two parameter or CAPM shows the role of systematic risk to determine or calculate the expected return or price of an asset in financial markets.

The basic theoretical foundation of market efficiency theory are: first, investors in the market are rational and value securities rationally. Second, even if some of the investors are irrational, their action is random and the effect is cancel out without affecting prices. Third, rational arbitrageurs can eliminate the irrational investors mispricing. The empirical foundation of efficient market hypothesis can be divided into two categories. First, when news about a security arrives to a market, then security prices should react and incorporate the news both quickly and correctly. The price adjustment in response to news announcement should be accurate i.e. the price should neither underreact nor overreact to a particular news. Second, security prices should not change without any news that affect the value of a security. Therefore, quick and accurate response of security prices to information as well as non-response to non-information were the main empirical prediction of efficient market hypothesis (Shleifer, 2000).

The efficient market hypothesis get an enormous theoretical and empirical success up to the end of 1970s. For example, (Jensen, 1978) make a strong statement saying that ‘‘there is no other proposition in economics which has more solid empirical evidence supporting it than the efficient market hypothesis’’. Although many theoretical and empirical findings support the efficient market hypothesis in the 1960s and 1970s, the foundations and evidences supporting the efficient market hypothesis have been challenged seriously starting from the end of 1970s. Arbitrage as one of the device that lead markets to efficiency does not work as it was explained by the efficient market hypothesis. Rather, in the real world arbitrage is costly, risky and limited (Shleifer & Vishny, 1997). The new empirical studies about stock prices formation have reversed some of the earlier evidence favouring the efficient market hypothesis. Economists called them anomalies because the observed patterns could not be expressed by the traditional theories (Szyszka, 2013).

Although efficient market hypothesis’s empirical evidence shows that stock prices do not change for non-information, latter on empirical evidences shows that stock prices react for non-information. The 1987 financial crash is an evidence for non-information reaction of markets (Shleifer, 2000). According to (Cutler, Poterba, & Summers, 1989), fifty largest one-day stock price movements in the United States after WWII occurs on the day of no major announcements. They conclude that moves in stock prices reflect something other than news about fundamental values. On the other hand, (Roll, 1984) studied whether futures price of orange juice is affected by weather news. His study shows that weather news account for a relatively small share of price movements. In addition, movements in prices of individual stocks are largely unrelated to public news as well as movements in potential substitutes. These empirical findings shows that stock prices change for non-information, which is against the efficient market hypothesis (Shleifer, 2000).

(Fama, 1991) agreed that the earlier conclusion was wrong. The weak form market hypothesis asserts that investors cannot earn excess expected returns by using past price information (Fama, 1970). However, according to (De Bondt & Thaler, 1985) a portfolio of prior losers are found to outperform prior winners in 3 to 5 years period. (Jegadeesh & Titman, 1993) also found that a strategy of buying past winners and selling past losers realize a significant returns in 6 to 12 months period. Therefore, to get excess returns investors can use past stock price information and apply contrarian or momentum strategy. Even if (Fama, 1970) showed the existence of many empirical evidence in strong support of weak form market efficiency, (Fama, 1991) accepts the predictability of stock returns from past returns and dividend yields. These empirical findings implies that the violation of weak form market efficiency premise.

According to the random walk theory, the way a stock price behaved in the past is not useful in defining how it will behave in the future. However, there seem to be some momentum in stock prices in the short run. The behaviourist view is that the short-run momentum is related to the psychological feedback mechanisms, that is, if individuals see a stock price rising and they are drawn into the market in a kind of “bandwagon effect.” The other explanation to the short run momentum is the tendency of investors to underreact to new information. Stock prices will exhibit a positive serial correlation when the full impact of an important news is not reflected in a stock price at once. On the other hand, many studies have showed the evidence of negative serial correlation (return reversals) in the long run (De Bondt & Thaler, 1985). Studies have associated the mean reversion to the tendency of stock market prices to overreaction to news (Malkiel, 2003). Important information about securities cannot be completely evaluated immediately or in the daily prices (Fama, 1970). Thus, investors can use past stock prices to get abnormal returns.

The semi strong form of market efficiency hypothesis assumes that investors cannot earn a superior risk adjusted return using any publicly available information. The main concern of this hypothesis is to know how stock prices efficiently and rapidly adjusts to publicly available information (Fama, 1970). Although, (Fama, 1991) clearly argued that event study (semi strong form efficiency) has the cleanest evidence in support of it, the following empirical evidences shows the inefficiency of markets at semi strong form level. One of the empirical finding against semi strong market hypothesis is that small stocks earn higher return than big stocks especially in January (Shleifer, 2000). According to (Fama & French, 1992) and (Fama & French, 1993) size of a firm (market price times number of outstanding share) and book-to-market equity (BE/ME) has a powerful and a strong role to explain the average return of a security. Thus, the company’s size, BE/ME and the coming of the month of January are known by the market and the evidence shows that investors can earn excess returns using publicly available information (Shleifer, 2000). The size and BE/ME evidence presents a serious challenge to the semi strong form of efficient market hypothesis because publicly available information helps to predict stock returns.

The strong form of market efficiency also hypothesized that investor cannot earn abnormal returns using private information because the insider information quickly leaks out and incorporated into prices (Fama, 1970). However, in reality private information has an important role to get an abnormal returns.

Although the market efficiency theory get a great empirical support to the end of 1970s, researches done in latter period clearly showed that efficient market hypothesis fail to sustain its strength and a lot of empirical works indicated the existence of anomaly in financial markets. Furthermore, these findings indicates that past security price, publicly available information as well as privately accessible information are relevant for price formation. Fama’s (1970) classification of information in to three miserably fails and such classification does not clearly articulate security price formation process in the market. So, (Fama, 1970)’s classification of information may not be enough to analyse the relevance of information for securities price formation process in financial markets. Although the work of (Fama, Fisher, Jensen, & Roll, 1969) and (Fama, 1970) showed the relevance of information, the empirical work of (Odean, 1999), (Hirshleifer & Teoh, 2003), (Peng & Xiong, 2006), (Barber & Odean, 2008), (Hou, Peng, & Xiong, 2009), (Barber & Odean, 2011), (Chakrabarty & Moulton, 2012), (Chemmanur & Yan, 2019) and (Padungsaksawasdi, Treepongkaruna, & Brooks, 2019) indicate that investors’ attention plays a significant role in price formation.

(Barber & Odean, 2008) tested the proposition that says ‘‘individual investors are more likely to buy than sell stocks that catch their attention.’’ The rationale for testing this proposition is that attention affects buying more than selling. In other words, each investor does not buy every single stock that grabs his/her attention rather individual investors are more likely to buy special attention-grabbing stocks than to sell them. According to (Barber & Odean, 2008), individual investors are net buyers of attention grabbing stocks like stocks in the news, stocks experiencing high abnormal trading volume and stocks with extreme one-day returns. Attention driven buying occurs due to the difficulty of searching from many stocks they can potentially buy. However, individual investors do not face the same search problem when selling because they tend to sell only stocks they already own. Accordingly, (Barber & Odean, 2008) hypothesize that many investors consider buying stocks only that have first caught their attention. In the existence of many alternatives, options that attract attention are more likely to be considered and more likely to be chosen while options that do not attract attention are often ignored. An attention grabbing event has a chance to be reported in the news and an event that attracts the attention of many investors is newsworthy. When there is a big price move, it is likely that whatever caused the move can caught investors’ attention. If price is responding to private information, the significant returns will often attract attention (Barber & Odean, 2008).

Many theoretical models of financial markets consider buying and selling as two sides of the same coin. But for actual investors, the decisions to buy and to sell are fundamentally different. When buying a stock, investors are faced with a formidable search problem. Like individual investors, institutional investors also face search problems. However, institutional investors devote more time to search for stocks to buy and sell than do most individuals. Institutional investors use computers to narrow their search and may limit their search to stocks in a particular sector or fulfil specific criteria such as low price to earnings ratio (Barber & Odean, 2008).

Due to the existence of many securities to be considered, investors face a formidable challenge when looking for a security to buy. Since there are limited resources to evaluate each security, investors are likely to consider purchasing securities to which their attention has been drawn. Investors may think about buying securities they have recently read about in the newspaper or heard about on the news. Those securities that have unusually well or poor performance are more likely to be discussed in the media, more likely to be considered by individual investors and more likely to be purchased. Accordingly, momentum investors may buy previous winners to which their attention has been directed and contrarian investors may buy previous losers to which their attention has been directed (Odean, 1999). An overconfident investor may overvalue the importance of events that catch their attention (Barber & Odean, 2008). For most investors the decision to buy a security is quite different from the decision to sell. The formidable search problems for purchasing does not apply to sales (Odean, 1999).

According to (Hou, Peng, & Xiong, 2009), high investors’ attention can exacerbate price overreaction in the up market. According to (Peng & Xiong, 2006), even though standard asset pricing models assume that markets distil new information with high speed and they provide the best possible estimate of securities price, recent studies suggest that investor attention could play an important role in determining asset prices. According to this new view, important news or information is not reflected in prices until investors pay attention to it. Due to the existence of vast amount of information and the inevitability of limited attention, investors have to be selective in information processing to come up with investment decisions. Limited attention leads investors to allocate or process more market and sector level information than firm specific factors. In an extreme case, investors allocate all attention to market and sector information and ignores all the firm specific information.

Thus, attention can affect the decision of investors in two distinct ways. Directing too little attention to important news can result in a delayed reaction to good and important information. Devoting too much attention to a particular type of news can lead to an overreaction to information. Individuals have a limited amount of attention that they can devote to investing (Barber & Odean, 2011).

According to (Chakrabarty & Moulton, 2012), humans have a difficulty in processing multiple sources of information or performing multiple tasks as the same time. This conditions of humans is considered as an important factor in financial markets. Investors have attention constraints that limit their ability to analyze all available information in the market. As a result, they focus only on information of their immediate interest. Investors’ attention is a necessary condition for stock trading and investors’ attention is the key for the decision they made to trade or not a particular asset (Padungsaksawasdi, Treepongkaruna, & Brooks, 2019). Attention is a scarce cognitive resource and market makers’ or specialists attention constraints affects asset pricing. Investors have limited attention and processing power (Hirshleifer & Teoh, 2003) and (Chemmanur & Yan, 2019). Thus, investors’ failure to pay attention or the limited investors’ attention to available information leads to mispricing in capital markets.

So far we have seen investors overreact to one type of news and underreact to another type of news; and they give much attention to one news and ignore or give less attention to another. Thus, it is very important to investigate why investors give special attention to one type of information and ignore another information? Which type of information attract investors’ attention to overreact and underreact? Do we have another theoretical and empirical explanation about information in other field of studies? Empirical findings in psychology and neuroscience shows a different ways to classify information. According to these field of studies information is divided into three: bad information, good information and neutral information. Sufficient number of empirical findings shows that human beings are not analysing good and bad information equally.

A. The Negativity Effect

According to (Tierney & Baumeister, 2019), human minds and lives are skewed by a fundamental imbalance that is just now becoming clear to scientists: bad is stronger than good. The power of bad has many names in the academic literature like the negativity bias, negativity dominance and the negativity effect. The power of bad refers the universal tendency of negative events and emotions to affect us more strongly than positive emotions and events (Tierney & Baumeister, 2019). According to (Hanson, 2013) through the evolution process, the human ancestors had to get things that were pleasurable such as the ‘‘carrots’’ of shelter, food, etc. In the same way, they had to stay away painful things such as the ‘‘sticks’’ of predators, starvation, aggression from other species of their own. Carrots and sticks are important, but there is a vital difference between the two. From survival point of views, sticks are more urgent and important than carrots. If you fail to get a carrot today, you will have another chance to get it the other day. However, if you fail to avoid a stick today, you will be wiped out and no more carrots forever. To help our ancestors survive, the brain evolved a negativity bias. In general the default setting of the brain is to overestimate threats and underestimate opportunities as well as underestimate resources both for coping with threats and for fulfilling opportunities. On the other hand, our brain is good at learning from bad experiences. However, it is bad at learning from good ones (Hanson, 2013). Bad is universally powerful. The negativity effect is a fundamental aspect of psychology and an important truth about life, yet it was a recent discovery (Tierney & Baumeister, 2019). Therefore, all these things shows that we humans are not treating the good and bad events equally.

According to (Tierney & Baumeister, 2019) bad health or bad parenting makes much more difference than good health or good parenting. The impact of bad events lasts longer than good events. A bad image stimulates more electrical activity in the brain than does a positive image. The pain of criticism is much stronger than the pleasure of praise. Punishments motivate students and workers more than rewards. A bad reputation is much easier to acquire and tougher to lose than a good reputation. It took little bad to contaminate something good or negative contaminates positive more than positive purifies negative (Hanson, 2013). This is similar to the old Russian saying ‘‘A spoonful of tar can spoil a barrel of honey, but a spoonful of honey does nothing for a barrel of tar.’’ All these different empirical findings shows that bad is relentlessly stronger than good (Tierney & Baumeister, 2019).

The greater power of bad events over good ones is found in our everyday events like major life events, marriage and love affairs, election campaign, research areas and outcomes, social network patterns, interpersonal interactions and learning process (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). The negativity bias causes humans to pay special attention to external threats and exaggerate those dangers (Tierney & Baumeister, 2019). In financial issues people normally perceive outcomes as gains and losses (Kahneman & Tversky, 1979). People become more irrational if they are at the risk of losing money (Tierney & Baumeister, 2019). According to (Kahneman & Tversky, 1979), respondents avert risk in the domain of gain and they seek risk in the domain of lose. They called this irrational phenomenon a loss aversion. Loss aversion indicates that losses loom larger than gains. This tendency of people preference is observed in the value function and it is concave for gains and convex for losses as well as it is steeper for losses than for gains. Furthermore, experiments tracking gamblers’ eye movement show that they pay more attention to potential loss than to gain (Tierney & Baumeister, 2019).

In financial markets investors sell winning stock earlier and hold a losing stock for a long period (Shefrin & Statman, 1985) and (Odean, 1998). Thus, all the above findings shows that investors does not treat gain and loss outcomes equally and it indicates there is an asymmetrical views of investors towards gain and loss.

Our minds evolved to focus on the negative (Tierney & Baumeister, 2019). Negativity bias creates two kinds of problems. First, it increases the negative and make people to overreact to it. It pulls people’s attention to what is or could be bad, and makes them to overreact to it. At the same time, the negative bias increases people stresses, worries, frustrations, irritations, hurts, sorrows, feelings of falling short, etc. Second, the negativity bias decreases the positive and it makes people underreact to the good facts they experience. In general, negativity bias make us over learn from bad experiences and under learn from good experiences (Hanson, 2013).

Positive and negative events evoke different patterns of physiological, affective, cognitive, and behavioural activity at different points in their occurrence. Negative events can cause more physiological, affective, cognitive, and behavioural activity and prompt more cognitive analysis than neutral or positive events. A negative event is the one that has the potential or actual ability to create adverse outcomes for an individual. Thus, negative events includes events that have not been occurred but are perceived as potentially threatening and those that have occurred and perceived as harmful (Taylor, 1991). Bad events can also be defined as an event that cause undesirable, harmful and unpleasant outcomes and a good event is the one that can cause desirable, beneficial and pleasant outcomes (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Even if previous researches assumed that both positive and negative events produces equal level of physical disorder; however, according to (Suls & Mullen, 1981) and (Taylor, 1991), negative events have substantially more impact to cause physical disorder, stress and illness than positive events. Negative events and expectation of future negative events appear to be more potent determinants of mood of a person than positive events. Furthermore, the negative mood evoked by negative events has the effect to dominate and suppress the influence of positive events on mood. This indicates that negative events have a greater role over positive events to cause emotional reactions and positive emotions are rarely experienced as intensely as negative emotions (Taylor, 1991). Furthermore, it takes between two and five good things to offset one bad thing. That means it is necessary to have between two and five good things to overcome one bad thing (Tierney & Baumeister, 2019).

In the experiment of (Taylor, 1991) subjects spent disproportionately more time to negative information by looking at it longer than positive or neutral information. So negative events lead people to narrow and focus their attention to features that elicit negative state at a greater degree than positive events and information. Moreover, a negative aspect of an object, event, or choice are weighted more heavily than positive aspects in any judgments. Negative information is weighted more heavily than positive information during evaluation of others. In investment decision also, people give more emphasis to costs than potential gains and they show a more conservative behaviour when choices are presented interms of costs. In general, negative information, in any area, is weighted more heavily than positive information (Taylor, 1991).

B. The tale of underreaction and overreaction of stock returns

In financial literatures we can find two stylized facts of stock returns: overreaction and underreaction. Overreaction refers to the long run negative autocorrelation in stock returns (De Bondt & Thaler, 1985); whereas, underreaction refers to the short run positive autocorrelation in stock returns (Jegadeesh & Titman, 1993). According to (De Bondt & Thaler, 1985), the overreaction effect is not symmetric. This effect is larger for losers than for winners. This means stocks that have the lowest return (losers) over the previous three to five years did better during the following three to five years than those stocks that had highest returns (winners) previously. The explanation given by (De Bondt & Thaler, 1985) to overreaction in stock return resemble the representative heuristic, in the sense of (Tversky & Kahneman, 1974) that investors give more weight to recent information and neglect or attribute less importance to past news. On the other hand, according to (Jegadeesh & Titman, 1993), investors underreact to recent information which create positive autocorrelation to stock returns and this behaviour of investors arises from conservatism heuristics. The underreaction finding indicates that over a short period, says one to twelve months, security prices underreact to news. Thus, a slow incorporation of news into prices gives the current good news the power to predict the positive returns (momentum) in the future (Barbaris, Shleifer, & Vishny, 1998). Conservatism refers to a situation where investors slowly adopt the arrival of recent news to the market and a gradual incorporation of their expectations into prices. According to (Jegadeesh & Titman, 1993), association or interpretation of long-term return reversal to overreaction and short-term return continuity to under reaction are probably very simplistic. They recommended that sophisticated model of investor behaviour is needed to explain the observed pattern of returns. Finally, they indicated the probable existence of other explanations for the patterns observed in stock returns.

(Barbaris, Shleifer, & Vishny, 1998) propose another explanation for an overreaction of stock returns with over optimism. According to them, after a subsequent announcement of good news, investors become overly optimistic that future news announcement will also be good and overreact accordingly. Such a behaviour of an investor makes stock prices high to unacceptable level. If the subsequent news announcements contradict to their expectation, then stock prices will go down. The main argument of overreaction hypothesis is that stocks with a consistent past record of good news are going to be overvalued and in the future, the price of overvalued security will return down to its fundamental value. With the same fashion, stock in the past with a consistent record of bad news become undervalued and undervalued stock will be priced up to its fundamental value. Thus, overreaction of stock prices occur for both good and bad news that makes stock prices to perform too extreme relative to their fundamental values and their subsequent actual return.

According to (Griffin & Tversky, 1992), people updates their beliefs based on the strength of the evidence or information and then make some adjustment based on the weight of an evidence or announcement. Strength refers to the salient (most important) and extremeness (very severe or bad) feature of an information, whereas weight refers to the statistical informativeness (credibility and reputational quality) of a news. People give too much focus to the strength of a news and too little to the weight of a news. Conservatism occurs when a news has high weight but its strength is low. People are unimpressed by the low strength of a news and in such condition they react slightly to the evidence, even if news weight require a large reaction. In some situations, people become under confident when the strength of the evidence is not extreme. However, overreaction occurs when the news has high strength but its weight is low. Thus, overreaction or representativeness occurs with an excessive attention to the strength of a particular news announcement, though the weight of the news is low. According to (Barbaris, Shleifer, & Vishny, 1998), the psychological evidence of (Griffin & Tversky, 1992) did not specifically explain what kind of information is strong and salient (which can cause to overreact) and what kind of information is low in weight to cause investors to underreact. Furthermore, their evidence did not mention the magnitude of the reaction to information. Since investors use heuristics during their decisions (Ackert & Deaves, 2010) and (Schwartz, 2010), the explanation of (Griffin & Tversky, 1992) is not practical for investors to categorize information based on its strength and weight. It is not always possible to separate the impact of news into strength and weight. There is still a need for better explanation why investors underreact and overreact to a particular news. So far, there is no clear evidence in finance literature that shows to what type of information investors' underreact and overreact. According to (Barbaris, Shleifer, & Vishny, 1998), underreaction may be a broader phenomenon than simply the delayed reaction to news announcement.

(Daniel, Hirshleifer, & Sabrahmanyam, 1998) proposed overconfidence and biased self-attributes to explain overreaction and underreaction of stock prices. They related overconfidence to negative long run autocorrelation or overreaction; whereas biased self-attribute is related to short term positive autocorrelation or underreaction. An overconfident investor is the one who overestimates the precision of his/her private information signal and underestimate the information signal received by all. Then, stock prices overreact to private information signal and underreact to publicly available information. Individuals too strongly attribute events that confirm the validity of their prior actions. Self-attribution occurs when the investor’s private information is consistent with the public information. People by nature attribute success to themselves and blame the external factors for their failures.

According to (Hong & Stein, 1999), there two types of agents in the stock markets: news watchers and momentum traders. Neither of them are rational because they are able to process a subset of the available public information. The news watchers forecast stock prices based on private signals they observed about future fundamental values but they did not involve historical price information; whereas, momentum traders only focus on change in past stock prices. Thus, when only news watchers are active in the market, prices adjust slowly to new information (underreaction) because such traders do not use historical price information. The gradual information flows are the main cause of underreaction. The underreaction phenomenon makes stock prices attractive for momentum traders and momentum traders try to correct the underreaction caused by news watchers. The upward price correction pushes stock prices towards their fundamental and a further positive news create an overreaction to prices in the long run. According to (Odean, 1999), (Peng & Xiong, 2006), (Hou, Peng, & Xiong, 2009) and (Barber & Odean, 2011) too little attention to important news can result in a delayed reaction to good news and important information. Devoting too much attention to a particular type of news can lead to an overreaction to information. Individuals have a limited amount of attention that they can devote to investing (Barber & Odean, 2011).

Both underreaction and overreaction hypothesis says investors underreact as well as overreact to news respectively. However, the news which arrive to the market may be either good, bad or neutral; thus, all the above explanations did not specifically explain to which type of news stock price underreact or overreact. There is a gap in explanation for the two return irregularities. Thus, based on the sound and consistent empirical findings from the field of Psychology and Neuroscience, I propose a new explanation for the two specified return patterns. Accordingly, stock returns underreact to good news or events because human being by nature gives less importance to good events or events. On the other hand, stock return overreaction is related to negative news or events arrival to the market. These phenomenon of human beings is a well-documented evidence in the field of Psychology and Neuroscience.

The default setting of our brain is to overestimate threats or negative events and to underestimate opportunities or positive events. In our daily life, we overreact to negative events than positive events. For this reason, throughout history political groups have played on fears to gain power or to win an election. Amazingly, humans learn faster from pain or bad than from pleasure. Strong dislikes are acquired faster than strong likes. In relationships, trust is easy to lose and hard to regain. Something bad about a person is better remembered than something is good. Negativity bias creates two types of problem. First, it increases or exaggerates the negative things. The negativity bias pulls our attention to the bad and make us to overreact to it as well as to store the negative experiences in our memory. Second, the negativity bias decreases the effect of positive events and make us underreact to the good things or news that we experienced (Hanson, 2013).

The power of bad events is greater than good events and it is found in everyday events, major life events, close relationship outcomes, social network patterns, interpersonal interactions, impression formation, sensory level and learning processes. Bad information is processed more thoroughly than good. As many empirical findings shows bad is greater than good but good events only prevail over the bad by superior force of numbers. That means in order to prevail the good events over the bad, the number of good events should outnumber the bad one. In general, there is asymmetrical effects of bad and good across a broad range of phenomenon (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001).

Likewise, the finance literatures and researches give more emphasis about Tulip crisis, the 1929 global financial crisis, the 1973 oil crisis, the 1980s debt crisis, the 1987 American financial crisis, the 1997 southeast Asian crisis, the 2000/01 Turkey financial crisis, the 2007/08 financial crisis as well as the 2010 European debt crisis. It is hard to find a detailed literature about the financial success of different countries and companies in history. Thus, this shows that there is a clear bias and focus towards financial crisis than financial success of countries or firms. The reason may be that the cost of crisis is huge and crisis occur relatively within a short period of time. Thus, people want to take measures in advance to reduce the cost of negative events. This is also another evidence to show bad is stronger than good and humans overreact or overemphasised to bad events and underreact to good events. Generally, our brain is wired to react more strongly too bad than good or our brain responds more strongly to bad things than good things.

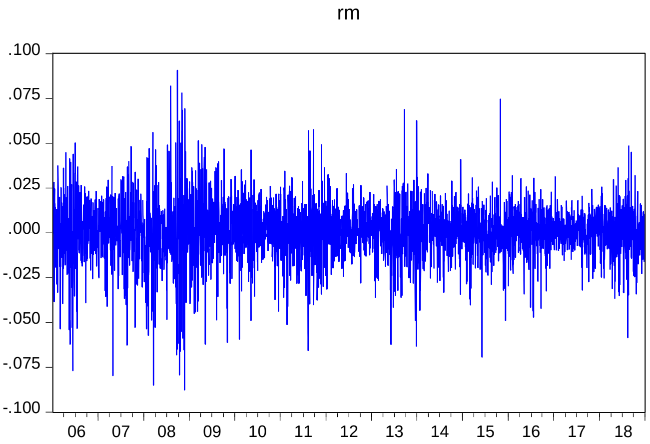
III. DATA ANDRESEARCH METHODOLOGY

A. Data

The intraday data for this analysis is collected from Finnet for the period between the beginning of 2006 and the end of

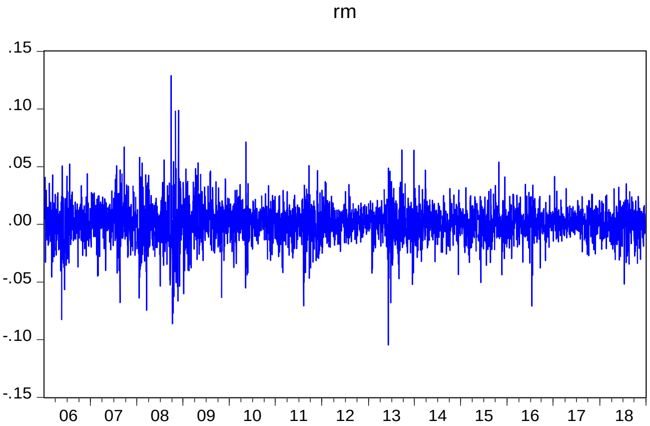
2018. The intraday data has two parts: the first session and the second session data. The first session and the second session refers the first half of a trading day or morning and the second half of a trading day or afternoon respectively. To take a particular firm’s stock data to the analysis, the firm should be listed in the market before the end of 2006. Thus, there are a total of 294 firms listed in Istanbul stock exchange before the end of 2006. However, in order to get a sound empirical results these firms should have a complete data. Therefore, firms which does not have a complete data are excluded from the sample. Accordingly in the first session, there should be a total of 3269 trading data and for the second session there should be 3243 trading data. Based on this criteria out of 294 firms there are 116 firms and 137 firms with a complete data for the first and the second session respectively. The following graphs shows the general situation of the market return for the two session. Based on graph 1 and 2 the level of market volatility is not the similar for the two session and there seems a high level of market volatility in the first session. As it can be seen from graph 3 and 4 the return distribution is also not similar for the two session.

Graph 1: Market volatility in the first session



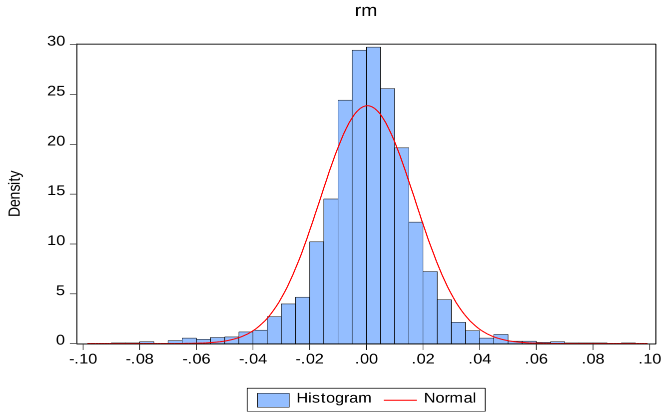
Source: Eviews

Graph 2: Market volatility in the second session



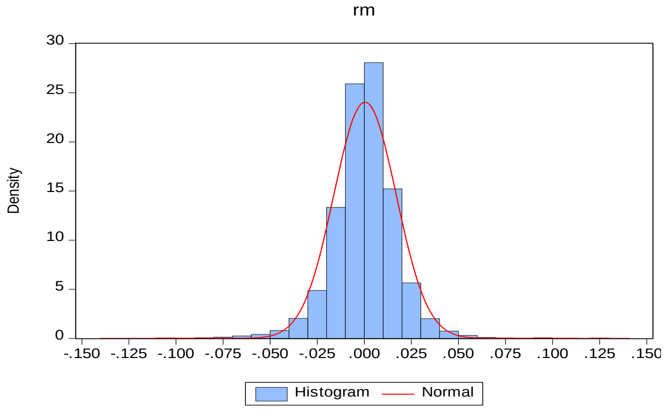
Source: Eviews

Graph 3: The distribution of market return in the first session



Source: Eviews

Graph 4: The distribution of market return in the second session



Source: Eviews

B. Research Methodology

In behavioral finance literatures, there are three different methods to test herding behavior of investors. The first method focus on the number of investors who made decisions in the same direction or it focuses on the percentage of investors who buy an asset while the other investor sells those assets and vice versa. The typical example of this method is the (Lakonishok, Shleifer, & Vishny, 1992) model or (LSV) model. The second method measures herding based on cross sectional stock’s return data. Thus, cross sectional dispersion of stock returns (CSSD) model and cross sectional absolute deviation (CSAD) of stock returns model are the models which use stock return data to test the existence of herding behavior. The third method uses the volatility of beta coefficient to test herding behavior. In this study CSSD and CSAD models are used.

Cross sectional dispersion of stock returns model or CH (1995) model

To measure the existence of herding in stock returns (Christie & Huang, 1995), hereafter CH (1995), developed a cross sectional standard deviation of stock returns model. According to CH model, the standard deviation is expected to be low when individuals herd around market consensus.

In essence, dispersion quantify the average proximity of individual returns to the mean of the market return. The lower limit of a dispersion is zero that indicates a perfect unison with the market. On the other hand, as individual returns begin to vary from the market return, the level of dispersion increases. According to CH (1995), individuals are most likely to suppress their own beliefs in favor of the market consensus during periods of unusual market movements and herd behavior would most likely emerge during market stress periods. The predictions concerning the behavior of dispersions during periods of market stress also comes from the rational asset pricing models. The rational asset pricing model relate the individual asset returns to one common factor i.e. market return. The rational asset-pricing model relates a large change in market returns to an increase in dispersion because individual assets differ in their sensitivity to the market return. In this way, herd behavior and rational asset pricing models offer conflicting predictions for the behavior of dispersions during periods of market stress.

To measure the return dispersion, CH (1995) proposed the cross-sectional standard deviation (CSSD) method, which is expressed as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(Ri,t-Rm,t)^2}{(N-1)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots eq(1)$$

Where N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the market return at time t. This model suggests that if herding occurs, investors will make similar decisions, leading to lower return dispersions. But low dispersion by itself do not guarantee the presence of herding. According to (Chang, Cheng, & Khorara, 2000), CSSD measure quantifies the average proximity of individual returns to the realized returns.

To test the existence of herding empirically, CH (1995) used the following model.

$$S_t = \alpha + \beta^L D^L_t + \beta^U D^U_t + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots eq(2)$$

Where S_t is the return dispersion at time t. D^L_t is a dummy variable at time t taking on the value of one when the market return at time t lies in the extreme lower tail of the distribution, and zero otherwise. Similarly, D^U_t is a dummy variable with a value of one when the market return at time t lies in the extreme upper tail of the distribution, and zero otherwise. The α coefficient denotes the average dispersion of the sample excluding the regions covered by the two dummy variables. The rational asset pricing models predict significantly positive coefficients for β^L and β^U; and statistically significant and negative values for β^L and β^U would indicate the presence of herding.

According to CH (1995), individuals herd to the market means that individuals suppress their own beliefs and their investment decisions; thereby only depends on the collective actions of the market, even when they disagree with its predictions. This way of herd formation implies that investors are attracted to the consensus of the market and it means that individual stock’s return would not move from the market return. CH (1995) believe that individuals are more likely to imitate the market consensus during periods of unusual market movements. Thus, herd behavior would most likely emerge during market stress periods. A natural candidate for market stress periods are those trading intervals characterized by large price swings in average prices. In such periods, security returns will move along with the market returns. Market stress is defined as an abnormally large price movement. Since the definition of market stress is arbitrary CH (1995) used the following criteria.

CH (1995) investigated the presence of herding when the market is in stress period. But, they define market stress in an arbitrary ways using a 1 or 5 percent criteria. The CH (1995) model uses a 1 or 5 percent upper or lower tail of the market return distribution as a criterion to specify market stress period. However, this model ignores that the impact of investors’ psychological factor is available throughout the investment decision process and herding does not only exist when a market is in a stress period. Many empirical findings revealed that during market stress period investors make decisions based on fundamentals rather than imitating an overall market consensus (Christie & Huang, 1995), (Hwanga & Salmon, 2004), (Doğukanlı & Ergün, 2011) and (Ergün & Doğukanlı, 2015). In addition, (Hwanga & Salmon, 2004) found herding when the market is quiet and investors are confident of the direction in which markets are heading. Therefore, it is important to study herding when the market return falls in the whole two half (negative and positive) of the return distribution. Using the same logic to CH (1995), this study developed the following modified version of CH (1995) model. Unlike CH (1995) model that uses a dummy variables to investigate herding, the following model uses an actual or realized stock return data.

$$CSSD_t = \alpha + \beta^n RM^n_t + \beta^p RM^p_t + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots eq(3)$$

Where, $CSSD_t$ is the cross sectional standard deviation at time t, α refers a constant when the market return is zero, RM^n_t is a realized negative market return at time t, RM^p_t is a realized positive market return at time t, β^n is the coefficient of RM^n, β^p is the coefficient of RM^p, and ε_t is the error term. A negative and statistically significant coefficient shows the presence of herding towards the market consensus. To measure the return dispersion the usual cross sectional standard deviation (CSSD) method is used.

The theoretical explanation of the above model is that when the market return rises, investors’ confidence will increase and they will make an independent decision. On the other hand, when the market performance falls, investors’ confidence will be eroded and they try to imitate the market consensus. The main theme of this argument is that psychological factors are available all the time when the market rises and falls.

Cross sectional absolute deviation (CSAD) of stock returns model

(Chang, Cheng, & Khorara, 2000), afterward CCK, have extended the work of CH (1995) to measure herding behavior and developed the cross sectional absolute deviation of stock returns model. The new model is a nonlinear model that is used to examine the relation between the level of equity return dispersions and the overall market return. CCK (2000) expect that in the presence of severe or moderate herding the return dispersion will decrease. The cross sectional absolute deviation model as a measure of return dispersion demonstrate that rational asset pricing models predict that the equity return dispersions are a linear and an increasing function of market returns. However, if investors follow (herd) the aggregate market behavior and ignore their own analysis during periods of large price movements, then the linear and increasing relation between dispersion and market return will no longer holds. In other words, the relation became non linearly increasing or even decreasing. Thus, the CSAD model is built on this premise. However, CSAD value by itself is not a measure of herding rather the relationship between CSAD and market return is used to detect herd behavior. CCK (2000) developed the following regression equation to allow for the possibility that the degree of herding may be asymmetric in the up versus the down market.

$$CSAD_t^{up} = \alpha + \gamma_1^{up}|R_{m,t}^{up}| + \gamma_2^{up}(R_{m,t}^{up})^2 + \varepsilon_t \ldots\ldots\ldots\ldots eq(4)$$

$$CSAD_t^{down} = \alpha + \gamma_1^{down}|R_{m,t}^{down}| + \gamma_2^{down}(R_{m,t}^{down})^2 + \varepsilon_t \ldots\ldots\ldots eq(5)$$

Where $CSAD_t$ is the average of the absolute value deviation of each stock relative to the return of market portfolio in period t, and $|R_{m,t}^{up}|$ ($|R_{m,t}^{down}|$) is the absolute value of an equally weighted realized return of all available securities on day t when the market is up (down). In addition, the CCK model facilitates the detection of herding over the entire distribution of market return with the following specification:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots eq(6)$$

$$CSADt = \frac{1}{N}\sum_{i=1}^{N} |Ri,t - Rm,t| \quad \ldots\ldots\ldots\ldots\ldots\ldots eq(7)$$

Thus, if herding exists, the coefficient γ2 is expected to be negative and statistically significant.

However, in this study we prefers to use the term positive market return (RMp) instead of ‘up market’ and negative market return (RMn) instead of ‘down market’ for the seek of simplicity. The following model is formulated by changing only up and down terms to positive and negative market return.

$$CSAD_t^{p} = \alpha + \gamma_1^{p}|RMp_t| + \gamma_2^{p}(RMp_t)^2 + \varepsilon_t \ldots\ldots\ldots\ldots eq(8)$$

$$CSAD_t^{n} = \alpha + \gamma_1^{n}|RMn_t| + \gamma_2^{n}(RMn_t)^2 + \varepsilon_t \ldots\ldots\ldots\ldots eq(9)$$

Where $CSAD_t$ is the average of an absolute value deviation of each stock relative to the return of the market portfolio in period t, and $|R_{m,t}^{P}|$ ($|R_{m,t}^{n}|$) is the absolute value of realized return of all available securities on day t when the market return is positive (negative). In addition, the CCK model facilitates the detection of herding over the entire distribution of market return with the following specification:

$$CSAD_t = \alpha + \gamma_1|RM_t| + \gamma_2 RM^2_t + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots eq(10)$$

In behavioral finance literature, there are two types of herding: spurious herding and intentional herding. Spurious herding or unintentional herding occurs when independent individuals arrived similar actions or decisions induced by the movement of fundamentals. An intentional herding occurs by a clear intent of an investor to imitate the action of others. There are two main question to be asked here. First, does a negative and significant coefficient for the above regression implies a spurious or intentional herding? Second, does investors make a similar investment decision because of having similar fundamental information?

Although investors get the same fundamental information equally, they cannot decide in the same direction and they cannot arrive at the same decision point. Thus, even if investors have similar fundamental information, they will not arrive to a similar investment decisions for the following reasons. First, (Fama, 1991) argued that transaction and information costs are not zero and this market condition can affect investors’ reaction to the arrival of new information. Second, investors are so diverse (heterogeneous) and each individual investor’s expectation, investment horizon, risk perception and the ability to analyze the same fundamental information is different. Accordingly, the result of investors’ analysis is different and their reaction time is different. Day traders make many investment decisions per day requiring fast information processing abilities and their reaction time is only a few seconds. Other investors have longer investment horizons (e.g., one or more years) (Hens & Rieger, 2010). According to (Goldberg & Nitzsch, 2001) different people evaluate the same information differently and reach to various decisions, may be completely opposite conclusions. When perceiving and processing information, people are always subject to misinterpretations and false conclusions. Third, the limitation of arbitrage (i.e. arbitrage is risky and costly) prevent investors’ decision to react identically for having similar fundamental information (Shleifer & Vishny, 1997). Fourth, when macroeconomic signals convince investors in either positive or negative way, investors might overreact or underreact and become too optimistic or pessimistic compared to the equilibrium price (Tversky & Kahneman, 1974), (De Bondt & Thaler, 1985), (Griffin & Tversky, 1992), (Jegadeesh & Titman, 1993), (Daniel, Hirshleifer, & Sabrahmanyam, 1998), (Barbaris, Shleifer, & Vishny, 1998) and (Hong & Stein, 1999). In such situation, investors may increase mispricing of assets, create and increase herding behavior in a market. Fifth, the effect of noise traders risk also affect the decision making process based on fundamental information. Noise traders may became too optimistic or too pessimistic about a particular fundamental information and make arbitrage so difficult (Black, 1986). Sixth, investors does not have a uniform understanding on the implication of current fundamental information on the price of a security (Hens & Rieger, 2010). Seventh, although market participants have similar fundamental information and all information relevant to the investment is publicly available to all investors, individual’s assessment about the quality of publicly available information is different from one investor to the other (Bikhchandani & Sharma, 2001). Individual investors are different in terms of preference, payoffs and belief on the precision of the information they receive (Bikhchandani, Hirshleifer, & Welch, 1998). Having all these reasons, the possibility of acting in similar fashions or the existence of spurious herding from having similar fundamental information is almost impossible. As a result the possibility of getting spurious herding in financial markets is almost zero. Therefore, the models used in this study are reasonable as well as valid, and they have a good ground for their applicability.

IV. EMPIRICAL FINDINGS

This section of the empirical analysis has two parts. The first part deals with the empirical findings of individual stock return data. In this section, firms with incomplete data and firms which are listed in the market since 2007 are not taken in to analysis. Thus, to avoid this problem the second section of the analysis uses sectoral index data and the use of sectoral data helps to compare the results of the two sections and to include the excluded firms’ data to the analysis. As it is mentioned in the methodology part, this section of the study employs the two models.

Table 1 below presents the summarized CSSD regression results and F-statistics for both session is statistically significant at 1% and 5% level that shows the model is valid. The R^2 value of the two session is almost close to each other. The coefficient of β^n is negative and statistically significant at 1% and 5% level for both session. The negative and stitistically significant result indicate that investors imitate the market consensus when the market return is negative or when the market falls. Thus, this shows that there is a significant level of herding at this market condition. Based on the coefficient of β^n, we can say that the level of herding is almost equal in the first and the second session. On the other hand, the coefficient of β^p is both positive and statistically significant at 1% and 5% level for the two session. A positive and statistically significant result shows that when the market return rises investors did not herd or follow the market consensus rather they make an indipendent decisions. Therefore, table 1 regression result indicates the asymmetrical behavior of investors when the market return rises and falls.

Table 1: Empirical findings using CSSD

Frequency	β^n	β^p	Prob(F-statistic)	R^2
Session 1	-0.013275 P-value (0.0000)	0.012230 P-value (0.0000)	0.000000	0.193184
Session 2	-0.013491 P-value (0.0000)	0.012308 P-value (0.0000)	0.000000	0.197388

Source: Eviews

Table 2, 3 and 4 below presents the summarized regression results of CSAD model. Table 2 summarizes the regression results when the market return is positive, and the F-statistics is statistically significant at 1% and 5% level and the model is valid for the two session. The R^2 value is 0.679286 and 0.635740 for the first and the second session respectively. According to the CSAD model, the coefficient of γ_2 is very important. As we can see from table 2, the coefficient of γ_2 is negative and statistically significant at 1% and 5% level. This result indicates that in both session investors herd towards the market consensus when the market return is positive. However, the coefficient of γ_2 is higher in the first session (-10.72428) than the second session (-6.992827). This result indicates that herding may be more prevalent in the first session than the second session.

Table 2: Empirical findings using CSAD when the market return is positive

Frequency	γ_1	γ_2	Prob(F-statistic)	R^2
Session 1	1.060425 P-value (0.0000)	-10.72428 P-value (0.0000)	0.000000	0.679286
Session 2	0.936029 P-value (0.0000)	-6.992827 P-value (0.0000)	0.000000	0.635740

Source: Eviews

Table 3 below presents the summarized regression results of CSAD model when the market return is negative. According to this table result, the F-statisitics is significant at 1% and 5% level for both session and the model has 0.631473 and 0.629263 R^2 values for the first and the second session respectively. The coefficient of γ_2 is negative and statistically significant for both sessions. This shows that investors follow (herd) the market consensus when the market return is negative. But the coefficient of γ_2 is a bit higher in the first session than the second session. This may show that herding behavior of investors is more dominant in the first session than the second session. On the other hand, if we compare the coefficient of γ_2 when the market return is positive and negative, the statistics in table 2 and 3 clearly shows that herding is strong and dominant when the market return falls or when it is negative.

Table 3: Empirical findings using CSAD when the market return is negative

Frequency	γ_1	γ_2	Prob(F-statistic)	R^2
Session 1	1.063817 P-value (0.0000)	-11.61058 P-value (0.0000)	0.000000	0.631473
Session 2	1.036940 P-value (0.0000)	-10.57318 P-value (0.0000)	0.000000	0.629263

Source: Eviews

Table 4 below presents a summarized regression results of CSAD model for entire market return or when the market return is not divided in to negative and positive returns. Accordingly, the model has a statisticallysignificant F-statistics for the two session and first session has 0.410980 R2 value and the second session has 0.400203 R2 value. The coefficient of $\gamma 2$ is positive and statistically significant at 1% and 5% level and this shows that there is no herding when the entire market return is regressed.

Table 4: Empirical findings using CSAD for the entire market return

Frequency	γ_1	γ_2	Prob(F-statistic)	R^2
Session 1	0.211001 P-value (0.0000)	0.884491 P-value (0.0001)	0.000000	0.410980
Session 2	0.206444 P-value (0.0000)	0.766616 P-value (0.0000)	0.000000	0.400203

Source: Eviews

So far we have seen, using individual stock return data, herding behavior is more dominant and strong when the market return falls and from the two session herding is more prevalent in the first session. In the following section sectoral index data is used to test herding behavior. Thus, from table 5 to 8 presents a summarized regression results using sectoral index data.

The models in table 5 has a statistically significant F-statistics at 1% and 5% level for both sessions and for all sectors, and the models are valid. For all sectors and for both session the coefficient of β^p is positive and statistically significant at 1% and 5% level. This shows that investors did not herd with the market consensus when the market return is positive. Thus, this finding is consistent with the findings of individual stock returns data in table 1. On the other hand, for both session the coefficient of β^n is negative and statistically significant at 1% and 5% level. This result indicates that when the market return falls investors herd towards the market consensus and this finding is consistent with table 1 findings.

Table 5: Empirical findings using CSSD for sectoral data

Sector	Session 1				Session 2			
	β^n	β^p	Prob(F-statistic)	R^2	β^n	β^p	Prob(F-statistic)	R^2
Banks	-0.000327 p-value (0.0000)	0.000448 p-value (0.0000)	0.000000	0.085742	-0.000300 p-value (0.0000)	0.000405 p-value (0.0000)	0.000000	0.082475
Real est.inv. trust	-0.000193 p-value(0.0000)	0.000227 p-value (0.0000)	0.000000	0.092280	-0.000192 p-value (0.0000)	0.000271 p-value (0.0000)	0.000000	0.095130
Food & beverage	-0.000534 p-value (0.0000)	0.000586 p-value (0.0000)	0.000000	0.121788	-0.000708 p-value (0.0000)	0.000761 p-value (0.0000)	0.000000	0.119434
Holding &investment	-4.84E-05 p-value (0.0000)	5.12E-05 p-value (0.0000)	0.000000	0.036893	-4.33E-05 p-value (0.0000)	5.86E-05 p-value (0.0000)	0.000000	0.034963
Chem. Petrol plastic	-0.000154 p-value (0.0000)	0.000220 p-value (0.0000)	0.000000	0.046097	-0.000164 p-value (0.0000)	0.000212 p-value (0.0000)	0.000000	0.032848
Basic metal	-0.000330 p-value	0.000367 p-value	0.000000	0.020455	-0.000296 p-value	0.000327 p-value	0.000000	0.019087

	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Metal product machine	-0.000106 p-value (0.0000)	0.000187 p-value (0.0000)	0.000000	0.044877	-0.000166 p-value (0.0000)	0.000216 p-value (0.0000)	0.000000	0.057026
Wood paper printing	-0.000447 p-value(0.0000)	0.000770 p-value (0.0000)	0.000000	0.067052	-0.000396 p-value (0.0000)	0.000673 p-value (0.0000)	0.000000	0.054576
Nonmetal mineral products	-0.000212 p-value (0.0000)	0.000340 p-value (0.0000)	0.000000	0.176570	-0.000233 p-value (0.0000)	0.000442 p-value (0.0000)	0.000000	0.271835
Technology	-0.000437 p-value(0.0000)	0.000404 p-value (0.0000)	0.000000	0.011396	-0.000317 p-value (0.0000)	0.000359 p-value (0.0000)	0.000000	0.013232
Textile teather	-0.000614 p-value (0.0000)	0.000713 p-value (0.0000)	0.000000	0.095368	-0.000607 p-value (0.0000)	0.000741 p-value (0.0000)	0.000000	0.128853
Wholesale and retail trade	-0.000654 p-value (0.0000)	0.000912 p-value (0.0000)	0.000000	0.121231	-0.000840 p-value (0.0000)	0.001066 p-value (0.0000)	0.000000	0.081369

Source: Eviews

Table 6 below summarizes the regression results when the market return is positive. Accordingly, for all sectors and for both session the F-statistics is statistically significant at 1% and 5% level. For all sectors the coefficient of γ_2 is both negative and statistically significant at 1% and 5% level and this shows that investors herd the market consensus when the market return is positive. However, except one sector (wood paper printing sector), the coefficient of γ_2 is higher in the first session than the second session. This may indicate that herding behavior is more dominant in the first session and the result is consistent with the result of table 2.

Table 6: Empirical findings using CSAD when the market return is positive

Sector	Session 1				Session 2			
	γ_1	γ_2	Prob(F-statistic)	R^2	γ_1	γ_2	Prob(F-statistic)	R^2
Banks	0.030485 p-value (0.0000)	-0.154805 p-value (0.0000)	0.000000	0.438860	0.029035 p-value (0.0000)	-0.113632 p-value (0.0000)	0.000000	0.405504
Real est.inv. trust	0.015980 p-value (0.0000)	-0.093290 p-value (0.0000)	0.000000	0.362306	0.016465 p-value (0.0000)	-0.072171 p-value (0.0000)	0.000000	0.358306
Food & beverage	0.032403 p-value (0.0000)	-0.220816 p-value (0.0000)	0.000000	0.389220	0.031720 p-value (0.0000)	-0.138448 p-value (0.0000)	0.000000	0.398952
Holding & investment	0.009928 p-value (0.0000)	-0.105100 p-value (0.0000)	0.000000	0.311575	0.008466 p-value (0.0000)	-0.056770 p-value (0.0000)	0.000000	0.264893
Chem. Petrol plastic	0.021503 p-value (0.0000)	-0.194607 p-value (0.0000)	0.000000	0.336899	0.018478 p-value (0.0000)	-0.091960 p-value (0.0000)	0.000000	0.338851
Basic metal	0.038056 p-value (0.0000)	-0.390985 p-value (0.0000)	0.000000	0.268022	0.034800 p-value (0.0000)	-0.273163 p-value (0.0000)	0.000000	0.258412
Metal product machine	0.016682 p-value	-0.130310 p-value	0.000000	0.321527	0.016957 p-value	-0.092913 p-value	0.000000	0.370266

	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Wood paper printing	0.040772 p-value (0.0000)	-0.165846 p-value (0.0000)	0.000000	0.365382	0.041553 p-value (0.0000)	-0.215300 p-value (0.0000)	0.000000	0.336564
Nonmetal mineral products	0.018648 p-value (0.0000)	-0.066442 p-value (0.0000)	0.000000	0.479436	0.018754 p-value (0.0000)	-0.024749 p-value (0.0091)	0.000000	0.534662
Technology	0.044242 p-value (0.0000)	-0.445880 p-value (0.0000)	0.000000	0.311850	0.041388 p-value (0.0000)	-0.338627 p-value (0.0000)	0.000000	0.317575
Textile leather	0.036667 p-value (0.0000)	-0.162651 p-value (0.0000)	0.000000	0.435340	0.035704 p-value (0.0000)	-0.121023 p-value (0.0000)	0.000000	0.447618
Wholesale and retail trade	0.034760 p-value (0.0000)	-0.074160 p-value (0.0113)	0.000000	0.430203	0.033838 p-value (0.0000)	-0.106473 p-value (0.0000)	0.000000	0.333650

Source: Eviews

Table 7 presents a summarized regression result when the market return is negative. The model for all sectors and for both session has a statistically significant F-statistics at 1% and 5% level. The coefficient of $\gamma 2$ is negative and statistically significant at 1% and 5% level for all sectors and both session. In addition, except four sectors (holding & investment, chemical petrol plastic, non-metal mineral products and technology sectors), the coefficient of $\gamma 2$ is higher in the first session than the coefficient of $\gamma 2$ in the second session. Generally, when we compare the coefficient of $\gamma 2$ when the market rises (from table 6) and falls (from table 7), it is clear that $\gamma 2$ is higher when the market falls, and from the two session $\gamma 2$ is higher in the first session. This shows that herding is more prevalent when the market falls and in the first session.

Table 7: Empirical findings using CSAD when the market return is negative

sector	Session 1				Session 2			
	γ_1	γ_2	Prob(F-statistic)	R^2	γ_1	γ_2	Prob(F-statistic)	R^2
Banks	0.033014 p-value (0.0000)	-0.358947 p-value (0.0000)	0.000000	0.361733	-0.000534 p-value (0.0000)	-0.004136 p-value (0.0000)	0.000000	0.559710
Real est.inv. trust	0.016874 p-value (0.0000)	-0.152321 p-value (0.0000)	0.000000	0.325845	0.015503 p-value (0.0000)	-0.113810 p-value (0.0000)	0.000000	0.318571
Food & beverage	0.034657 p-value (0.0000)	-0.311864 p-value (0.0000)	0.000000	0.408185	0.035985 p-value (0.0000)	-0.309304 p-value (0.0000)	0.000000	0.358857
Holding & investment	0.009847 p-value (0.0000)	-0.106657 p-value (0.0000)	0.000000	0.284108	0.010203 p-value (0.0000)	-0.113436 p-value (0.0000)	0.000000	0.300689
Chem. Petrol plastic	0.021486 p-value (0.0000)	-0.237341 p-value (0.0000)	0.000000	0.299998	0.023203 p-value (0.0000)	-0.276366 p-value (0.0000)	0.000000	0.278871
Basic metal	0.036068 p-value (0.0000)	-0.378073 p-value (0.0000)	0.000000	0.235625	-0.000627 p-value (0.0000)	-0.003904 p-value (0.0000)	0.000000	0.555619
Metal product machine	0.017425 p-value (0.0000)	-0.201866 p-value (0.0000)	0.000000	0.277466	-0.000215 p-value (0.0000)	-0.004290 p-value (0.0000)	0.000000	0.563354
Wood paper printing	0.047558 p-value (0.0000)	-0.552062 p-value (0.0000)	0.000000	0.290379	0.045373 p-value (0.0000)	-0.491224 p-value (0.0000)	0.000000	0.288125

Nonmetal mineral products	-0.000201 p-value (0.0000)	-0.006010 p-value (0.0000)	0.000000	0.651755	0.019483 p-value (0.0000)	-0.188316 p-value (0.0000)	0.000000	0.391101
Technology	0.042035 p-value (0.0000)	-0.415485 p-value (0.0000)	0.000000	0.261700	0.040439 p-value(0.0000)	-0.420224 p-value (0.0000)	0.000000	0.237744
Textile leather	0.044460 p-value (0.0000)	-0.486601 p-value (0.0000)	0.000000	0.327939	0.039641 p-value (0.0000)	-0.365305 p-value (0.0000)	0.000000	0.338516
Wholesale and retail trade	-0.000406 p-value (0.0000)	-0.013644 p-value (0.0000)	0.000000	0.623544	0.044300 p-value (0.0000)	-0.390460 p-value (0.0000)	0.000000	0.393400

Source: Eviews

Table 8 below presents a summarized regression results for the entire market return data. For all sectors and for both data the models have a statistically significant F-statistics at 1% and 5% level. According to the regression results, only banking sector has a negative and statistically significant γ_2 coefficient for both first and second session. Thus, we can conclude that using the entire market return data only the banking sector follows the market consensus in the first and second session.

Table 8: Empirical findings using CSAD for the entire market return

Sector	Session 1				Session 2			
	γ_1	γ_2	Prob(F-statistic)	R^2	γ_1	γ_2	Prob(F-statistic)	R^2
Banks	0.015699 p-value (0.0000)	-0.046353 p-value (0.0000)	0.000000	0.147260	0.013928 p-value (0.0000)	-0.010951 p-value (0.0000)	0.000000	0.129902
Real est.inv. trust	0.003866 p-value (0.0000)	0.051249 p-value (0.0003)	0.000000	0.106609	0.004227 p-value (0.0000)	0.049740 p-value (0.0000)	0.000000	0.108598
Food & beverage	0.011407 p-value (0.0000)	0.042893 p-value (0.0875)*	0.000000	0.140608	0.011616 p-value (0.0000)	0.051346 p-value (0.0191)	0.000000	0.128093
Holding & investment	0.002158 p-value (0.0000)	0.004213 p-value (0.6021)*	0.000000	0.045969	0.001668 p-value (0.0000)	0.009747 p-value (0.1392)*	0.000000	0.036416
Chem. Petrol plastic	0.006439 p-value (0.0000)	-0.005924 p-value (0.7340)*	0.000000	0.065401	0.005182 p-value (0.0000)	0.012548 p-value (0.3828)	0.000000	0.053455
Basic metal	0.004301 p-value (0.0000)	0.080630 p-value (0.0196)	0.000000	0.032629	0.007892 p-value (0.0000)	0.002155 p-value (0.9369)*	0.000000	0.028763
Metal product machine	0.004162 p-value (0.0000)	0.011064 p-value (0.4491)*	0.000000	0.055156	0.005303 p-value (0.0000)	0.012500 p-value (0.3042)	0.000000	0.075879
Wood paper printing	0.010560 p-value (0.0000)	0.088929 p-value (0.0207)	0.000000	0.079487	0.010900 p-value (0.0000)	0.049931 p-value (0.1000)*	0.000000	0.063903
Nonmetal mineral products	0.008178 p-value (0.0000)	0.018186 p-value (0.2039)*	0.000000	0.184383	0.008435 p-value (0.0000)	0.028378 p-value (0.0120)	0.000000	0.209398
Technology	0.011047 p-value (0.0000)	0.026622 p-value (0.4863)*	0.000000	0.055496	0.012223 p-value (0.0000)	-0.031160 p-value (0.2967)	0.000000	0.041817

Textile Leather	0.015771 p-value (0.0000)	0.007191 p-value (0.8236)	0.000000	0.123067	0.013569 p-value (0.0000)	0.057217 p-value (0.0178)	0.00000	0.139 490
Wholesale and retail trade	0.010353 p-value (0.0000)	0.143051 p-value (0.0000)	0.000000	0.146879	0.012878 p-value (0.0000)	0.079967 p-value (0.0028)	0.000000	0.123 279

Source: Eviews

*Shows insignificance at 1% and 5% level of significance

So far we have seen market trends: investors tend to show herding behavior during market downturns and it seems that they behave independently or they make rational decisions when the market rises. Here we need to ask whether investors themselves show a trend during any trading days. Does investors mood and emotions is equal and constant throughout the trading days? I think the above findings of this study can be viewed in the context of the following empirical findings.

The Day Reconstruction Method (DRM) is a new survey instrument that is developed by a group of researchers, (Stone, et al., 2006), to reconstruct the emotions of people in any given day. These researchers observed 12 emotions in 909 women over a working day. The finding shows that there are two positive emotion peaks at noon and evening. The women's positive affects rise in the morning hours and reach its optimal emotional points around midday, then the good moods quickly plummeted and stayed low throughout the afternoon until it rises again in the early evening. However, the negative emotion peaks found in mid morning and mid afternoon. But negative emotions reach low in the midday.

On the other hand, two Cornell University Sociologists (Golder & Macy, 2011), conducted a research to identify individual level daily moods using Tweeter messages from 84 countries, from different part of the world, and 2.4 millions individual. In this study, the researchers focused on identifying how positive affects (emotions like enthusiasm, confidence, hopefulness, active, engaged and alertness) and negative affects (emotions such as anger, lethargy and guilt) vary during workday and weekends. A total of 509 million messages were collected from February 2008 and January 2010, and the texts are analyzed using a prominent text analysis method, Linguistic Inquairy and Word Count (LIWC). The finding showed that positive affects has two peaks, one is early in the morning and the other is near the midnight. Positive affects are higher in the weekends than weekdays. Positive affects decreased in the midmorning, at the start of the work and increased in the evening, at the end of the work. In other words, positive affects rise in the morning but plummeted in the afternoon and rise again in the early evening. Furthermore, the shape of the positive affective cycle is similar on weekends and weekdays. On the other hand, negative affects are low in the morning or sharply drop the overnight hours, specially in the weekend and rise throughout the day to a peak at midnight. Unlike positive affects, negative affects less varied but steadily increases throughout the day. The main point is that positive and negative affects vary independently and they are not opposite to each other. The two affects have a small negative correlation (r = -0.08).

(Chen, Demers, & Levc, 2018) also investigated the moods of executives, investors and analysts during the quarterly earnings conference calls at different times of the day. The findings of the study showed that the executives, investors and analysts mood is systematically influenced by the time of the day and their moods become more negative as the days wears on. The negative mood of the economic agents in the latter part of the day create a misprising in stock prices. If we assume these economic agents act like rationational man (Chen, Demers, & Levc, 2018) conclude that the time of the day influences human emotions, biology, cognitive functions, communivcations, decision makings and compliance with professional standards like judiciary and medicine and other aspects of performance.

The study of (Dong, Feng, Ling, & Song, 2016) indicate that autocorrelation of intraday stock returns is 64% more negative during afternoon than during the morning and the overall serial correlation becomes less negative when sailent information arrives to the market. Informed trading and liquidity trading, the two types of trading, generate opposite short term serial correlation patterns (Dong, Feng, Ling, & Song, 2016). Informed trading, due to private information and market frictions, tend to generate zero or positive return correlation but liquidity trading tend to create a negative return correlation patterns. (Dong, Feng, Ling, & Song, 2016) argued that comparatively more trades are undertaken in the early hours of the day after the opening of the stock market. The huge trade is most likely motivated by the speculation on information because some informations may be released after the market is closed. Thus, most of the information based trading occurs immediately after the market is opened and for this reason the autocorrelation of intraday returns should be less negative early in the trading day. As the trading continues, fewer information based trading occurs in the latter part of the trading day and in the afternoon most of the tradings are liquidity based. However, towards the end of a trading day liquidity based rebalancing needs are likely to be strong and the autocorrelation of intraday stock return is more negative during the second half of the trading day.

V. CONCLUSIONS

The empirical findings of (Tan, Chiang, Mason, & Nelling, 2008), (Adem & Sarioğlu, 2020) and (Adem, 2020) showed that herding behavior is dominant in the daily data. In addition, the work of (Adem & Sarioğlu, 2020) and (Adem, 2020) revealed that herding behavior is strong and dominant when the market return falls than when it rises. In consistent with these findings, the empirical findings of this study shows that herding behavior in Istanbul stock exchange is more dominant when the market return is negative and also it is more domimant in the first session or in the morning than in afternoon. Therefore, under these two market conditions investors imitate the market consensus, and I can conclude that investors behave more irrationally when the market falls and in the first session. Therefore, the findings of this study may have the following implications. First, since there is a strong herding behavior, stock prices may not reflect the intrisnsic values in the intraday data, especially in the first session. Second, since stock prices deviate from their fundamental values, especially in the morning and when the market falls, the market is not efficient to reflect all the available information in the intraday trading. Third, the rise and fall of market return, especially big stock indexes like BIST 100, S&P 500 and others, deliver a signal to investors. Since stock indexes are economic indicators of overall stock market performance, a rise in the index of a leading economic indicators signal the economy is growing and the drop of an index signals the economy’s downturn. Indexes allows economists and investors to assess the current state of the economy as well as to predict the future. Therefore, the content and the implication of the signal is very important to determine the behavior of investors to set price for assets. Whatever the cause (information or non information causes) of the rise and fall of an index, a fall of an index is treated as bad and a rise in an index is considered as good. As we can see from the above findings, and the findings of (Adem, 2020) and (Adem & Sarioğlu, 2020), the fall of an index causes investors to imitate the market consensus. From this point of view I can conclude that the power of bad causes herding behavior in financial markets. The cause of such types of investors behavior may be to avoid the pain of loss and the pain of grievance as well as regret. However, herding behavior is not common when the market is rising. Thus, the behavior of investors is not symmetrical when the market return rises and falls.

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